Enhancing Financial Decision-Making in SMEs: Improving Forecasting Accuracy for Sustainable Growth

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Abstract

The growing complexity of financial decision-making in Small and Medium-Sized Enterprises (SMEs) necessitates advanced predictive models capable of accurately forecasting financial outcomes such as revenue, profit margins, and cash flow. Despite the availability of various machine learning models, there remains a need for optimization techniques that enhance model accuracy, generalization, and efficiency. This paper addresses this gap by applying metaheuristic optimization strategies to improve the performance of baseline financial forecasting models, particularly the Logarithmic Transformation (LogTrans) model. We propose the integration of several state-of-the-art metaheuristic algorithms, including Simulated Simulated Annealing (SSO), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WAO), and others, to optimize hyperparameters and perform feature selection. Our results demonstrate that the optimized SSO + LogTrans configuration outperforms all other models, achieving a remarkable Mean Squared Error (MSE) of 1.95E-07, a Root Mean Squared Error (RMSE) of 4.42E-04, and a high R-squared (R^2) value of 0.966. These findings indicate that metaheuristic-driven optimization significantly improves predictive accuracy and generalization capability in SME financial decision-making models. The implications of this study extend beyond SMEs, offering potential applications in industries such as banking, investment, and insurance, where precise financial forecasting is critical. Furthermore, our approach highlights the importance of metaheuristics in the automated optimization of machine learning models, paving the way for further advancements in real-time decision support systems for dynamic financial environments.

Keywords: Financial Forecasting; Metaheuristic Optimization; Small and Medium-Sized Enterprises (SMEs); Machine Learning Models; Inancial Decision-Making

1 Introduction

Small and Medium-Sized Enterprises (SMEs) are widely regarded as the cornerstone of the global economy, contributing to more than 90% of all businesses worldwide [1], [2], [3]. Their economic importance is vast, ranging from driving innovation to providing significant employment opportunities. SMEs are particularly prominent across a wide array of industries, including manufacturing, services, retail, and technology [4], [5], [6]. They represent a dynamic and adaptable sector that helps fuel local economies, drives economic diversification, and spurs innovation by introducing new products and services into the market. However, despite their critical role in economic growth, SMEs often face numerous challenges in managing their financial operations, especially in an increasingly data-driven and competitive environment [7], [8].

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One of the most pressing challenges SMEs encounter is the need to make effective and informed financial decisions [9], [10], [11]. Unlike large corporations, SMEs generally have limited resources, both in terms of capital and data infrastructure. As a result, financial decision-making becomes a crucial determinant of their success or failure. The financial decisions made by SME owners and managers affect various aspects of their business, including operational efficiency, profitability, growth opportunities, and risk management. In particular, decisions regarding investments, financing strategies, pricing models, and cash flow management can significantly influence an SME's long-term survival. The lack of sophisticated decision-support systems often leads to a reliance on intuition and past experiences, which may not always result in optimal outcomes.

The importance of financial decision-making in SMEs cannot be overstated. Well-informed financial decisions are integral to ensuring profitability, sustainability, and overall competitiveness in an increasingly globalized and digital economy [12], [13]. The ability to accurately forecast financial outcomes, assess risk, and optimize resource allocation gives SMEs a competitive edge, enabling them to thrive in challenging market conditions. Moreover, poor financial decision-making can lead to a range of adverse consequences, including poor cash flow management, excessive debt, underperformance, and even business closure [14]. As such, the need for robust, data-driven financial decision-making processes is paramount for SMEs striving to stay competitive and maintain growth [15].

The emergence of Machine Learning (ML) has had a transformative impact on how businesses, including SMEs, approach financial decision-making. Traditional financial analysis methods, such as simple regression models or manually crafted decision rules, are increasingly seen as inadequate for handling the complexity and high dimensionality of modern financial data. Machine learning, by contrast, offers a powerful set of tools for automating data analysis and generating insights from large datasets. ML algorithms, such as decision trees, support vector machines, and deep learning models, excel at identifying intricate patterns within financial data that may not be immediately apparent to human analysts. By automating the process of data analysis and prediction, ML models offer SMEs the ability to make more informed decisions based on data-driven insights, rather than relying on subjective judgment or outdated methods.

Moreover, the application of ML in financial decision-making goes beyond simply enhancing prediction accuracy. These algorithms can process large volumes of data from diverse sources, enabling more nuanced risk assessments, the identification of financial trends, and the optimization of financial strategies. By applying ML models to financial data, SMEs can not only forecast future trends with greater accuracy but also uncover hidden relationships within the data that may inform better decision-making. This could include detecting emerging market trends, predicting cash flow fluctuations, assessing the financial health of the company, or optimizing investments and operational costs. Therefore, the role of ML in financial decision-making is essential, as it provides SMEs with a level of predictive power and decision support previously unavailable to them.

Despite the potential benefits, several challenges remain when applying ML to financial decision-making, especially within the SME sector. One of the primary challenges is the complexity of financial data. SMEs generate data across various domains, including sales, marketing, operational costs, external economic factors, and market trends. This data is often high-dimensional, containing a large number of variables, each of which can influence the financial performance of the business. As the number of features in the dataset increases, the challenge of handling such high-dimensional data becomes more pronounced. Traditional statistical methods struggle to effectively capture the relationships between a vast array of financial indicators, which is where machine learning models excel. However, the high dimensionality of the data still poses a significant challenge for ML algorithms, particularly when it comes to feature selection and ensuring that the most relevant features are used in the modeling process.

Furthermore, feature redundancy and correlation present another challenge. In financial datasets, some features may be highly correlated with one another, which can introduce multicollinearity into the model. This can distort the relationship between variables, making it difficult for the model to isolate the true effects of individual features on the financial outcomes. For example, revenue growth and market demand may both be related, leading to overlapping information that can affect the model's performance. Redundant features increase the complexity of the model and may also lead to overfitting, where the model becomes too closely tailored to the training data and performs poorly on new, unseen data. Therefore, addressing feature redundancy and correlation is critical in ensuring that machine learning models are both accurate and computationally efficient.

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Another significant issue in applying machine learning to financial decision-making is the sensitivity of hyperparameters. Each machine learning model requires a set of hyperparameters that govern its training process, such as the learning rate, regularization parameters, or the number of layers in a neural network. The performance of the model can vary significantly based on these hyperparameters, and finding the optimal configuration is often a complex and time-consuming process. For financial data, where patterns may evolve over time and new variables may emerge, it is especially important to ensure that the model is tuned correctly to adapt to these changes. Hyperparameter tuning typically requires extensive computational resources and can be a barrier for SMEs with limited access to such resources.

Overfitting is yet another challenge when applying machine learning to financial decision-making for SMEs. When models are trained on small or specific datasets, they may perform exceedingly well on the training data but fail to generalize to new, unseen data. In the context of financial decision-making, overfitting can lead to misleading predictions, misinterpretations of trends, and ultimately poor decision-making. This is particularly problematic in the fast-changing environments that SMEs operate in, where market conditions and financial dynamics are continually evolving. Therefore, it is critical to develop models that balance bias and variance to ensure that they can generalize well to new financial scenarios without overfitting to noise or outliers.

The goal of this study is to evaluate and compare different machine learning models for predicting financial decision-making processes in SMEs. A systematic comparison of models, both with and without optimization, will be performed to assess their performance in predicting various financial outcomes, such as cash flow predictions, investment strategies, and risk assessments. This study will focus on optimizing these models through the use of metaheuristic algorithms such as Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Simulated Annealing (SA). These algorithms will be applied to improve both feature selection and hyperparameter tuning, aiming to enhance the accuracy, efficiency, and generalization capabilities of the models.

The contributions of this research are threefold. First, the paper introduces a novel methodology that combines machine learning with metaheuristic optimization techniques to improve the financial decision-making processes of SMEs. Second, a detailed comparative analysis of several machine learning models will be provided, demonstrating the impact of optimization on the performance of these models. Finally, the paper highlights the advantages of an integrated approach to optimization, where feature selection and hyperparameter tuning are optimized simultaneously to achieve the best performance in predicting SME financial outcomes.

The paper is organized as follows. Section 2 describes the dataset used in this study, outlining the preprocessing steps and machine learning models employed. Section 3 presents the empirical results, comparing the performance of the baseline models and the optimized models using metaheuristic algorithms. In Section 4, the results are discussed, including an analysis of model performance and comparisons with prior studies. Section 5 concludes the paper, summarizing the findings and suggesting future directions for research in the field of financial decision-making for SMEs.

2 Literature Review

Economic forecasting and small and medium-sized enterprises (SMEs) growth prediction have become critical for guiding policy and business strategy. In today's data-driven world, the accurate prediction of economic trends is essential not only for governments and organizations but also for SMEs seeking to optimize their strategies. Recent advancements in economic regression and SME growth forecasts have increasingly incorporated machine learning (ML) techniques, which have demonstrated significant improvements in prediction accuracy. Machine learning, especially deep learning and ensemble methods, has shown promise in capturing non-linear relationships in large datasets, which traditional regression models often fail to address. A review of these advancements highlights how the integration of ensemble methods, such as Random Forest (RF) and Gradient Boosting Machines (GBM), as well as deep learning models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, has led to improved prediction outcomes. Additionally, interpretability tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) have increased model transparency, which fosters trust among users by clarifying model decisions. These tools, when integrated into models, help address key challenges

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such as imbalanced data, feature selection, and interpretability. Cross-regional data fusion has also emerged as an important approach to improve the adaptability and generalizability of forecasting models. By incorporating data from multiple regions, models can be fine-tuned to accommodate regional economic variations, providing insights that guide policymakers and business leaders in making informed decisions that promote growth and sustainability for SMEs [16].

The global trend towards leveraging machine learning in business decision-making has intensified as organizations aim to derive greater value from the vast amounts of data collected across various sectors. Machine learning has emerged as a key enabler of data-driven decisions, particularly in areas like finance, marketing, and supply chain management. By optimizing business processes with minimal human intervention, machine learning is helping organizations automate decision-making and improve operational efficiency. These models not only analyze historical data but also predict future trends by recognizing complex patterns within large datasets. As a result, machine learning has been instrumental in enhancing financial forecasting, improving risk management, and supporting strategic decisions in various sectors. This study underscores the role of machine learning in driving the digital transformation of companies. By enabling businesses to move from traditional decision-making processes to more dynamic, data-driven approaches, machine learning facilitates enhanced financial management and better operational decision-making, fostering growth even in uncertain market environments [17].

Industry 4.0 technologies, such as smart manufacturing, are increasingly being adopted by businesses worldwide. However, small- and medium-sized enterprises (SMEs) face significant barriers in implementing these technologies. One of the primary obstacles is the high cost associated with adopting advanced technologies, such as automation and machine learning, which are more accessible to larger corporations. SMEs often lack the necessary financial resources and technological infrastructure to adopt these innovations, which places them at a disadvantage in the competitive landscape. A study examining the implementation of Industry 4.0 technologies in European SMEs found that while large corporations are able to integrate smart manufacturing systems seamlessly, SMEs struggle with financial complexities and limited access to cutting-edge resources. The research highlights the importance of deep learning models and virtual simulation algorithms in overcoming these barriers, suggesting that these technologies can significantly improve business efficiency for SMEs by reducing operational costs and enhancing productivity. The study also emphasizes that the interaction between Industry 4.0 technologies and economic management presents significant opportunities for SMEs to strengthen their operational capabilities and improve overall business performance, especially in a rapidly evolving digital landscape [18].

Proactive financial crisis management is crucial for SMEs, as they are particularly vulnerable to economic disruptions. Understanding and forecasting financial crises before they escalate allows SMEs to adopt timely countermeasures, mitigating the effects of such crises on their operations. A machine learning-based early warning system has been proposed to address this challenge. This system utilizes advanced algorithms such as XGBoost, a gradient-boosted decision tree method, to predict financial crises by analyzing SMEs' development characteristics, crises, and financial data. The study demonstrated that the XGBoost model, in combination with stacking fusion techniques, outperformed traditional financial crisis prediction models, including backpropagation neural networks (BPNN) and logistic regression models. By leveraging machine learning, SMEs can better predict and respond to potential financial crises, ensuring business continuity and avoiding significant financial losses [19].

In light of the increasing availability of big data and the rise of machine learning technologies, financial forecasting models have seen significant improvements in both accuracy and efficiency. Traditional forecasting methods often suffer from limitations related to speed, flexibility, and scalability. In contrast, hybrid models that combine different machine learning techniques, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in financial prediction. The CNN-LSTM hybrid model, for example, can effectively handle time-series financial data, providing businesses with more accurate predictions. By applying this hybrid approach to financial data from A-share listed companies in China, the model has achieved improved forecasting accuracy, reducing financial risks and aiding businesses in making more informed decisions under uncertain market conditions. This study illustrates how machine learning-driven financial forecasting systems not only enhance prediction reliability but also streamline financial decision-making processes [20].

Despite the numerous benefits of machine learning, many SMEs face challenges in adopting these technologies due to resource constraints. Limited access to computational power, insufficient data, and a lack of trained

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personnel can hinder the successful implementation of machine learning solutions. A comprehensive review explores how SMEs can still leverage various machine learning and optimization techniques, including heuristics and metaheuristics, to improve their resilience and make strategic decisions under uncertainty. The study highlights the barriers that SMEs face in adopting these technologies, such as the lack of specialized knowledge and the high costs associated with implementation. However, it also offers a framework for SMEs to adopt machine learning-based optimization strategies that can be tailored to their specific limitations. By using hybrid approaches that combine heuristics and machine learning, SMEs can effectively optimize decision-making processes and enhance their strategic planning capabilities. The study suggests that overcoming these challenges will enable SMEs to foster digital transformation and remain competitive in the market [21].

In the context of credit risk prediction for SMEs in supply chain finance (SCF), multi-source information fusion has proven to be a powerful approach to improving prediction accuracy. A machine learning model, which integrates financial data, operational data, and information about negative events, has been developed to assess the credit risk of SMEs. The results from this study emphasize the critical role of financial data, such as total outstanding credit (TOC) and net income ratio (NIR), in predicting the likelihood of default. The fusion of multi-source information provides a more comprehensive view of an SME's financial health, thereby improving the model's predictive power. The study also highlights the effectiveness of the cost-sensitive learning random forest (CSL-RF) model, which adjusts for class imbalance by giving more weight to the minority class (e.g., default SMEs). This approach significantly improves the accuracy of credit risk prediction, offering a more reliable tool for lenders and investors [22].

Similarly, a hybrid ensemble machine learning approach has been developed to forecast the credit risk of SMEs' investments in agriculture 4.0 within the context of supply chain finance. This approach combines Rotation Forest, a metaheuristic ensemble learning method, and Logit Boosting, a boosting technique, to predict the likelihood of credit risk. By identifying key variables such as the current ratio, financial leverage, and profit margins, the study provides valuable insights into the factors that influence the credit risk of agricultural SMEs. The results demonstrate that this hybrid ensemble method outperforms traditional risk assessment techniques, providing more accurate predictions that can help mitigate financial risk in agriculture-based SMEs [23].

In order to address the challenges posed by imbalanced data in credit risk prediction, a deep reinforcement learning (DRL) approach called DRL-Risk has been proposed. This approach formulates the credit risk prediction problem as a Markov decision process and employs a deep dueling neural network to prioritize the learning of high-risk SMEs. The results show that DRL-Risk significantly improves the performance of credit risk prediction, outperforming traditional methods in key metrics such as recall, G-mean, and financial loss. By focusing on high-risk SMEs, the DRL-Risk model ensures that financial institutions can better allocate resources to mitigate potential losses, thus improving the overall efficiency of the credit risk prediction process [24].

A novel deep learning approach, based on Natural Language Processing (NLP) and the BERT model, has been proposed to enhance credit risk prediction for Micro, Small, and Medium Enterprises (mSMEs). This approach uses textual loan assessments provided by lenders to predict defaults, leveraging the power of deep learning models in NLP. While traditional data can often be sparse or unreliable, textual data provides valuable insights that can be used to predict defaults more effectively. The study shows that while text-based models perform well on their own, combining textual data with traditional credit data yields no additional benefit in terms of prediction accuracy. Nonetheless, the deep learning model proves to be robust and suitable for automating the mSME lending process, reducing the need for manual intervention [25].

Innovative SMEs have made a significant impact on the economies of emerging countries, particularly in relation to stock price volatility. A study examining the Chinese market, where 337 innovative SMEs were listed on the SSE STAR market, utilized machine learning models such as Random Forest (RF), Deep Neural Networks (DNN), Gradient Boosting Decision Trees (GBDT), and Adaboost under Bayesian optimization to predict stock prices. The results indicate that the RF and DNN models provided the most accurate predictions, outperforming the other models in key metrics such as R2, RMSE, and MAPE. The study highlights the value of machine learning models in predicting stock price movements, thus offering valuable tools for investors and decision-makers [26].

The credit risk of SMEs in supply chain finance (SCF) remains a major challenge, and a new credit risk prediction framework, FS-RS-ML, has been proposed to address this issue. By integrating feature selection

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techniques such as Recursive Feature Elimination with Cross-Validation (RFECV) and resampling strategies to balance the data, this framework outperforms individual machine learning models in predicting credit risk. The study identifies key features such as SMEs' financial health indicators and reveals their importance in predicting credit risk. By improving prediction accuracy, the FS-RS-ML framework provides financial institutions with a reliable tool for assessing SME credit risk in supply chain finance [27].

Telecommunication data has been explored as an alternative source for inclusive SME credit scoring. A hybrid Decision Tree–Deep Neural Network (DT-DNN) model, enhanced with SHAP analysis, has been proposed to improve credit scoring accuracy. The model demonstrated high performance in identifying late payments and defaults, which are crucial predictors of credit risk. By leveraging alternative data sources, such as telecommunication usage patterns, the model provides a more inclusive approach to SME credit scoring, helping financial institutions extend credit to underserved businesses [28]. support SMEs in achieving better financial management practices and improving their overall operational efficiency [29].

Lastly, a model has been proposed to support small and medium-sized enterprises (SMEs) in managing their financial transactions more effectively. By utilizing Recurrent Neural Networks (RNNs) and explainable AI techniques such as LIME and SHAP, this approach offers a personalized Business Financial Management (BFM) toolkit for SMEs. The model can predict cash flow, detect fraud, and provide insights into business performance. This AI-driven solution not only enhances the financial decision-making process but also supports SMEs in achieving better financial management practices and improving their overall operational efficiency [30].

3 Materials and Methods

3.1 Dataset Description

The dataset utilized in this study provides a comprehensive and highly detailed overview of the financial decision-making processes within Small and Medium-Sized Enterprises (SMEs) for the year 2023. Sourced from the Harvard Dataverse, this dataset encapsulates key metrics and attributes related to various financial factors that significantly influence decision-making practices across SMEs of different sizes, industries, and business structures. The richness of the dataset allows for a profound exploration of how financial strategies and decisions are formulated, the factors that guide these decisions, and their eventual impact on the financial health and performance of these enterprises.

One of the principal attributes included in the dataset is the established year of each SME. This variable is pivotal as it allows us to study how the age and maturity of an SME influence its financial decision-making patterns. Older SMEs may exhibit more established decision-making frameworks, relying on experience and long-term financial data, while younger SMEs could be more dynamic and adaptive in their approaches, potentially focusing on rapid growth and external funding. This temporal dimension provides insights into how financial decision-making evolves as businesses mature and the challenges they face in early versus late-stage development.

Additionally, the dataset includes information about the type of SME, which further refines the financial decision-making processes. The classification of SMEs based on type (e.g., manufacturing, services, technology, retail) enables an understanding of how different industries prioritize various financial strategies. For example, manufacturing SMEs may need to focus more on capital expenditures and supply chain optimization, whereas service-oriented SMEs might place greater emphasis on operational efficiency and customer retention. This categorization also aids in identifying industry-specific financial challenges and opportunities.

The sector in which an SME operates is another key attribute in the dataset. This feature provides crucial insights into how external factors, such as economic conditions, regulatory environment, and market competition, impact financial decision-making. Different sectors, such as healthcare, energy, or finance, are subject to unique market dynamics that influence how SMEs in those sectors manage their finances. For instance, SMEs in the healthcare sector may face stringent regulatory compliance requirements that

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necessitate conservative financial strategies, while those in technology may be more inclined to invest heavily in innovation and R&D.

Furthermore, the dataset includes data on the size of the SME, which is another fundamental characteristic that shapes financial decision-making. The size classification—small, medium, or large—provides insights into how businesses of varying scales approach financial management. Smaller SMEs, with fewer resources, may prioritize short-term liquidity and risk aversion, while larger SMEs, with more established capital and infrastructure, may adopt long-term financial strategies, including expansion plans and investments in new markets. Understanding these distinctions is essential for developing more tailored financial strategies that align with the specific needs of different SME sizes.

Beyond these categorical features, the dataset incorporates a variety of financial factors that are crucial for understanding the decision-making process within SMEs. These include financial questions, risk assessments, management decision-making factors, and financial analyses, all of which are intricately tied to the financial success or failure of these businesses. These variables enable an in-depth examination of how SMEs make key financial decisions and how they evaluate and mitigate financial risks. For example, SMEs may face decisions related to capital structure, liquidity management, or investment prioritization. The dataset offers a rich repository of data to explore these factors in detail and identify common patterns in the decision-making process.

To enhance clarity and structure, the key features of the dataset are summarized in the table below:

Table 1: Key Features of the SME Financial Decision-Making Dataset

Feature	Description
Established Year	The year in which the SME was founded, providing insights into business age and organizational maturity.
Type of SME	Classification of the SME by operational type (e.g., manufacturing, services, technology, retail).
Sector	Industry sector in which the SME operates (e.g., healthcare, technology, finance), reflecting sector-specific financial behavior.
SME Size	Categorization of the enterprise by size (small or medium), influencing financial structure, access to capital, and risk exposure.
Financial Questions	Indicators capturing financial planning, investment priorities, and strategic financial concerns within the SME.
Risk Assessment	Evaluation of financial risks, including market uncertainty, credit exposure, and operational vulnerabilities.
Management Decision-Making	Variables representing managerial financial decisions related to budgeting, funding strategies, and cost control.
Financial Analysis	Analytical measures describing financial health, including profitability analysis, cost efficiency, and cash flow management.
Financial Decision Outcomes	Quantitative outputs of financial decisions such as profit margins, growth indicators, and return on investment (ROI).
Training and Test Splits	Partitioning of data into training, validation, and testing subsets for robust model development and evaluation.

The dataset also offers extensive financial performance data, enabling the examination of how previous financial decisions have influenced the current financial standing of SMEs. By evaluating these decision outcomes, we can gain a deeper understanding of which financial strategies and decision-making practices lead to successful business performance and which strategies may result in financial challenges or failure.

Additionally, the dataset provides information on external economic factors, such as market conditions and industry-wide trends, that SMEs must consider when making financial decisions. These external factors, when combined with internal financial data, offer a holistic view of the decision-making landscape faced by SMEs.

To ensure robust model development and performance evaluation, the dataset is split into training, validation, and test sets. The training set is used to develop and fine-tune the machine learning models, while the validation set is employed for hyperparameter tuning. The test set, which remains unseen during the training process, is used to assess the generalization capability and predictive accuracy of the models. The careful partitioning

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of the dataset ensures that the models are capable of making reliable predictions on unseen data, simulating real-world financial decision-making scenarios for SMEs.

In conclusion, the dataset offers a detailed, multidimensional foundation for analyzing the financial decision-making processes within SMEs. By examining this data, the study aims to identify critical patterns and insights that can inform the development of optimized financial strategies for SMEs. This analysis is vital for creating predictive models that can assist SME decision-makers in making data-driven, evidence-based financial decisions, leading to improved financial outcomes, reduced risk, and enhanced long-term sustainability.

In the study of financial decision-making, several factors influence individuals' choices, including financial literacy. The first part of Figure 1 demonstrates the effect of financial literacy on financial decisions, showing a positive correlation between the two. As individuals' financial literacy increases, so does the quality of their financial decisions, suggesting that more knowledgeable individuals tend to make better financial choices. The second part of the figure explores the relationship between the size of Small and Medium Enterprises (SMEs) and their access to financial resources. It appears that the financial access provided to SMEs remains relatively consistent across different sizes, indicating that the size of the enterprise does not significantly affect the financial access it receives.

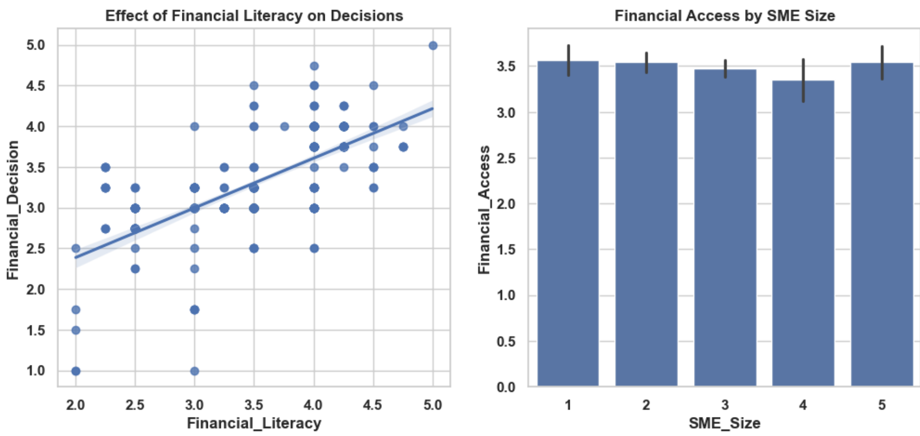

Figure 1: Effect of Financial Literacy on Decisions and Financial Access by SME Size

In examining the financial literacy of SMEs across various sectors, it is essential to understand how the financial literacy scores vary by sector type. Figure 2 presents a boxplot that illustrates the distribution of financial literacy scores across five different sector types. The plot highlights the central tendency and spread of financial literacy scores, revealing how different sectors compare in terms of financial literacy levels. Notably, while the sectors exhibit similar medians, there are variations in their range and presence of outliers.

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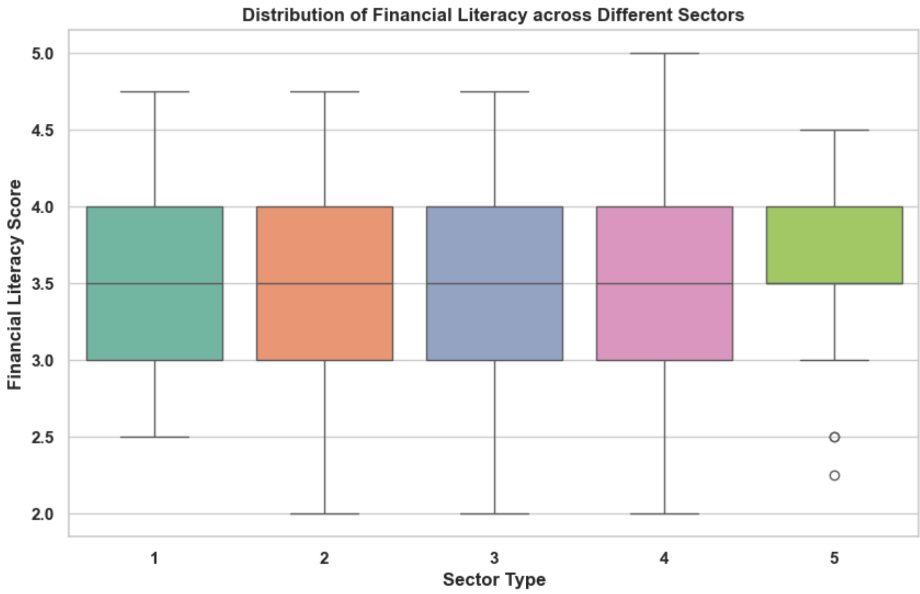

Figure 2: Distribution of Financial Literacy across Different Sectors

In the analysis of financial decision-making within SMEs, various aspects need to be considered, such as financial reporting awareness and the decision-making process based on company age. Figure 3 provides insights into these factors through two distinct visualizations. The first plot illustrates the Kernel Density Estimate (KDE) of financial reporting awareness (FR1) across different SME types. It shows how financial reporting awareness varies with SME size, highlighting significant differences between the SME categories. The second plot presents a swarm plot that visualizes the decision-making process (FDM1) in relation to the age of the company. Each point represents a unique observation based on SME size, and the distribution of these points reveals how decision-making is influenced by the company's age.

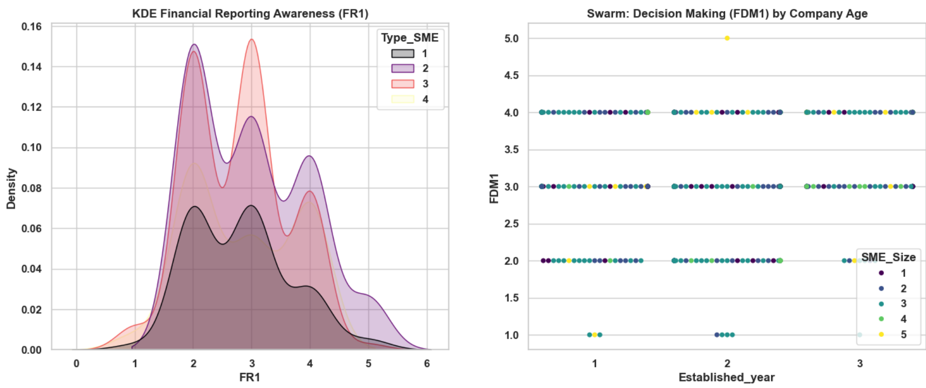

Figure 3: KDE of Financial Reporting Awareness (FR1) and Swarm Plot of Decision Making (FDM1) by Company Age

3.2 Data Preprocessing

In machine learning workflows, especially when dealing with complex datasets such as those involving financial decision-making in Small and Medium-Sized Enterprises (SMEs), data preprocessing is an essential and foundational step. The primary goal of data preprocessing is to prepare the raw data for analysis, ensuring that it is cleaned, transformed, and structured in a way that is conducive to building accurate and reliable machine learning models. Given that financial datasets can often contain irregularities such as missing values, noise, and outliers, preprocessing helps address these issues, improving the overall quality

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of the data and making it more suitable for model training. This section elaborates on the key steps in the preprocessing pipeline, including handling missing data, encoding categorical variables, scaling numerical features, addressing feature correlation, detecting and managing outliers, and transforming the data to meet statistical assumptions.

One of the most common issues encountered in financial datasets, including those related to SME decision-making, is the presence of missing values. Missing data can result from a variety of factors such as incomplete records, errors in data entry, or the absence of specific financial metrics for certain SMEs. Missing data can introduce bias into machine learning models if not handled appropriately, leading to incorrect or unreliable predictions. Therefore, an effective strategy for handling missing values is a crucial part of the preprocessing process.

For numerical features, such as those representing revenue, profit margins, and cash flow, missing values were handled using imputation techniques. The choice of imputation method was determined by the nature of the data and the distribution of missing values. For instance, mean imputation was applied to features where the missing data was assumed to be missing at random and where the distribution of the data was approximately symmetric. This method replaces missing values with the mean of the observed values for that feature, maintaining the overall distribution of the data. However, when the distribution of the feature was skewed, such as with financial growth rates or return on investment (ROI), **median imputation** was used instead. The median is less sensitive to extreme values, making it more robust for handling skewed distributions.

For categorical variables, such as the type of SME (e.g., manufacturing, retail, technology), missing values were addressed using mode imputation, where the most frequent category is assigned to the missing entries. Mode imputation is appropriate for categorical data, as it ensures that the most common category is used in place of missing values, maintaining the integrity of the categorical distribution. In cases where the missingness in categorical data could potentially be informative (i.e., not randomly missing), advanced methods like KNN imputation were considered. KNN imputation uses the feature values of the nearest neighbors to predict and fill in the missing data, ensuring that the imputation is contextually consistent with other data points.

For features with a high percentage of missing values (e.g., more than 30% of the data is missing), a different approach was taken. These features were either excluded from the analysis or replaced with a constant value that reflects the context of the feature. For instance, in cases where a financial feature was largely missing and its removal would not significantly impact the model, the feature was dropped entirely. Alternatively, if the feature was critical to the analysis, a more sophisticated imputation technique was applied, such as **multiple imputation**, which uses multiple iterations of imputation to generate several plausible values for each missing entry and accounts for the uncertainty in missing data.

Financial datasets typically contain both numerical and categorical variables. Machine learning algorithms, however, can only process numerical data, so categorical variables must be converted into a format that is understandable by these algorithms. This step, known as feature encoding, is critical in enabling models to utilize all the available data for prediction.

For nominal categorical variables, such as the type of SME or sector (e.g., manufacturing, healthcare, technology), one-hot encoding was employed. One-hot encoding transforms each category into a new binary variable (column) for each category, where the presence of a specific category is represented by a "1", and its absence by a "0". For example, if an SME operates in the healthcare sector, the corresponding healthcare column will contain a 1, while other sector columns (e.g., manufacturing, retail) will contain 0. This encoding method ensures that machine learning algorithms treat these categories independently, without implying any ordinal relationship between them.

For ordinal variables, such as the SME's financial performance rating (e.g., high, medium, low), label encoding was used. Label encoding assigns a unique integer to each category. For example, "high" might be encoded as 1, "medium" as 2, and "low" as 3. This method is suitable when the categorical values have a natural order or ranking, and the algorithm benefits from the implied ordinal relationship.

In cases where there are many unique categories within a feature (e.g., geographical locations or specific products), target encoding was used. Target encoding calculates the mean of the target variable (e.g., financial

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performance or profit margin) for each category and uses this mean as the encoded value for the respective category. This method reduces dimensionality while capturing the relationship between the categorical variable and the target variable, making it useful when dealing with high-cardinality categorical features.

Feature scaling is essential in ensuring that machine learning models interpret all features on the same scale, preventing some features from disproportionately influencing the model due to their larger numeric values. In financial datasets, features such as revenue, capital investment, and operational costs typically vary widely in magnitude. Without scaling, models that rely on distance calculations, such as k-nearest neighbors (KNN), support vector machines (SVM), or gradient descent-based methods, may not perform optimally.

To standardize the numerical features, standardization was applied to the dataset. Standardization transforms features so that they have a mean of 0 and a standard deviation of 1, which is crucial when different features have different units of measurement or scales. This technique is especially important for algorithms that assume or rely on data being centered and scaled, such as linear regression and SVMs. For example, revenue values ranging from thousands to millions are transformed to a distribution with a mean of 0 and standard deviation of 1, ensuring that no feature dominates the model due to its scale.

In contrast, for numerical features that have a natural upper and lower bound (e.g., financial ratios or percentages), **normalization** was applied. Normalization rescales the features to a fixed range, usually between 0 and 1. This is particularly useful for financial ratios such as profit margins or debt-equity ratios, where the values are bounded within a specific range. Normalizing these features ensures that the model interprets each feature on an equal footing without any feature overshadowing others due to scale differences.

Multicollinearity, or high correlation between features, is a significant issue when working with financial datasets. Highly correlated features can distort the learning process of machine learning models, leading to overfitting and unreliable predictions. In particular, linear models such as logistic regression and linear regression are highly sensitive to correlated features. Therefore, it is essential to assess the correlation between features and eliminate redundant ones to improve model performance.

A correlation matrix was computed for all numerical features in the dataset to identify pairs of features with high correlation. Features that exhibited a correlation coefficient greater than 0.8 were considered for removal. In cases where two features were highly correlated, the feature that contributed the least to predictive accuracy was dropped, leaving the more important feature intact. This process reduces dimensionality and multicollinearity, leading to a more stable and interpretable model.

For features that were correlated due to their combined influence on the target variable, dimensionality reduction techniques such as Principal Component Analysis (PCA) were also explored. PCA transforms the feature space by creating new, uncorrelated components (principal components), which are linear combinations of the original features. This technique is particularly useful when multiple features represent the same underlying concept (e.g., several financial ratios), allowing the model to focus on the most informative components while reducing noise and computational complexity.

Outliers, or extreme values, can have a significant impact on the performance of machine learning models. Financial datasets, in particular, are often susceptible to outliers due to the presence of unusual business activities or errors in data entry. These extreme values can skew statistical analyses and lead to biased or inaccurate model predictions.

To identify outliers, statistical methods such as the Z-score were applied, which measures how many standard deviations a data point is away from the mean. A Z-score greater than 3 or less than -3 indicates that a data point is far from the mean and could be considered an outlier. Additionally, the **Interquartile Range (IQR)** method was used to detect outliers by identifying data points that fall outside the range defined by the first and third quartiles (Q1 and Q3). Any data points outside the range of $[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR]$ were flagged as outliers.

Once identified, outliers were either removed or capped, depending on the context. If an outlier was deemed to be an erroneous entry, it was removed from the dataset. However, if the outlier was a valid data point representing an extreme but realistic business scenario (e.g., a large multinational SME in a dataset with mostly small businesses), it was retained but capped to a reasonable value, ensuring that the extreme values did not unduly influence the analysis.

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Some features in the dataset exhibited skewed distributions, particularly financial variables such as revenues and growth rates, which are often positively skewed. To address this, **logarithmic transformations** were applied to these features to reduce skewness and stabilize the variance. Log transformations are effective in normalizing data, especially when the data spans several orders of magnitude, as is often the case in financial datasets.

For features that could not be transformed using logarithms (e.g., financial ratios or percentages), other methods such as **square root transformations** or Box-Cox transformations were considered. These transformations are useful for reducing skewness and making the distribution of data more symmetric, thereby improving the performance of models that rely on assumptions of normality, such as linear regression.

After completing these preprocessing steps, the final dataset is ready for model development. The dataset now consists of clean, imputed, and well-scaled data, with all categorical features encoded appropriately. By applying these preprocessing methods, we have enhanced the dataset's quality, ensuring that the machine learning models trained on it will be robust, reliable, and capable of making accurate predictions. The preprocessing pipeline has prepared the dataset to serve as a strong foundation for the development of predictive models aimed at optimizing financial decision-making in SMEs.

3.3 Deep Learning Models

In this study, five deep learning models were selected based on their proven relevance and performance in time-series prediction tasks. Time-series prediction is of paramount importance in the domain of financial decision-making for Small and Medium-Sized Enterprises (SMEs), as these businesses often need to forecast financial metrics such as revenue, costs, profit margins, and market behavior over time. The ability to predict future financial outcomes with a high degree of accuracy is critical for SMEs to optimize their strategies, mitigate risks, and enhance decision-making processes. Deep learning models are particularly suited for this task due to their capacity to learn complex, non-linear relationships from vast amounts of data and capture temporal dependencies inherent in time-series data. In this study, five state-of-the-art deep learning models were selected, each offering unique strengths in handling sequential data and financial forecasting. These models include:

- **LogTrans (Logarithmic Transformation Model)**: LogTrans is employed as the baseline model for this study due to its simplicity and effectiveness in handling skewed data distributions, which is often the case in financial datasets. Logarithmic transformations are particularly useful when dealing with data that spans multiple orders of magnitude, such as revenue or investment values, which are common in SME financial data. The logarithmic transformation helps to stabilize the variance, reduce the impact of outliers, and make the data more normal-distributed, which is critical for the accuracy of certain machine learning algorithms. Despite being a simple model, LogTrans is highly effective for datasets where the distribution is highly skewed and non-linear, providing a reliable baseline for comparison with more complex models.
- **AutoInt (Automated Time-Series Transformer)**: AutoInt is a modern deep learning model specifically designed for sequential data, employing an attention mechanism to selectively focus on the most relevant parts of the input sequence. Unlike traditional recurrent neural networks (RNNs), AutoInt leverages self-attention to capture long-range dependencies and to improve the modeling of time-series data. The model automatically selects the most important features from the input sequence, allowing it to focus on the temporal relationships that are most influential for forecasting. This ability to automatically highlight significant parts of the data makes AutoInt highly flexible and powerful for financial time-series forecasting, where the relationships between financial indicators can vary over time. Moreover, AutoInt is capable of handling both categorical and continuous features, which are frequently encountered in SME financial data, such as market conditions, company size, and financial metrics.
- **TabNet (Tabular Neural Network)**: TabNet is a deep learning architecture designed to work with tabular data, which is the format typically used for financial datasets. What distinguishes TabNet from traditional neural networks is its attention-based feature selection mechanism, which enables the model to focus on the most relevant features while ignoring irrelevant ones. This makes TabNet

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particularly well-suited for datasets with a mix of categorical and continuous variables, as is the case with SME financial data. The attention mechanism in TabNet allows it to capture complex relationships between different financial indicators, such as the relationship between company size, market sector, and profitability. TabNet has shown remarkable success in tasks that require both interpretability and predictive power, making it an excellent candidate for time-series forecasting in SMEs, where understanding the influence of various financial factors is crucial.

- **EALSTM (End-to-End Attention Long Short-Term Memory)**: EALSTM is a hybrid deep learning model that combines the strengths of Long Short-Term Memory (LSTM) networks with an attention mechanism. LSTMs are a class of recurrent neural networks (RNNs) designed to capture long-term dependencies in sequential data, making them highly effective for time-series forecasting. The addition of an attention mechanism in EALSTM enables the model to focus on the most important time steps in the sequence, enhancing its ability to capture complex temporal patterns. This model is particularly useful when dealing with financial data that involves long-term trends as well as short-term fluctuations. EALSTM can dynamically adjust its focus to different time periods in the sequence, which is essential for forecasting financial metrics such as revenue, profits, and expenses, where the impact of past events on future outcomes may vary. This flexibility makes EALSTM a strong contender for financial time-series prediction in SMEs.
- **BiLSTM (Bidirectional Long Short-Term Memory)**: BiLSTM is an extension of the traditional LSTM model, which processes data in both forward and backward directions. This bidirectional approach allows the model to learn from both past and future time steps, enhancing its ability to capture long-term dependencies and improve prediction accuracy. In the context of SME financial forecasting, where both past and future financial trends can influence decisions, BiLSTM's bidirectional nature is particularly beneficial. For example, in predicting future revenue, information from both past growth patterns and potential future market conditions could be equally important. By leveraging both directions of the time series, BiLSTM can provide more accurate and contextually aware predictions. This ability to look forward and backward in time makes BiLSTM particularly effective for forecasting in dynamic financial environments like those encountered by SMEs.

Among the models listed above, LogTrans was chosen for optimization due to its exceptional baseline performance. Although LogTrans is relatively simple compared to the more sophisticated models such as AutoInt, TabNet, EALSTM, and BiLSTM, it performed surprisingly well in initial tests. This success can be attributed to the nature of financial data, which often exhibits skewed distributions and non-linear patterns, particularly in revenue and financial ratios. By applying a logarithmic transformation to the data, LogTrans was able to stabilize variance and reduce the influence of outliers, thus achieving superior performance when compared to other models. Its ability to perform well with less complexity and computational overhead made it an ideal candidate for further optimization. Given its solid baseline performance, LogTrans was selected as the model to be optimized in this study, with the aim of improving its predictive accuracy through advanced optimization techniques, including feature selection and hyperparameter tuning.

The selection of these five models—LogTrans, AutoInt, TabNet, EALSTM, and BiLSTM—was based on their ability to handle the challenges presented by time-series data in financial decision-making. Time-series prediction in the financial domain requires models that can capture both short-term fluctuations and long-term trends, as well as handle complex dependencies among financial features. Each of the selected models was chosen for its unique ability to address these challenges. LogTrans offers a strong baseline by stabilizing skewed data, while AutoInt, TabNet, EALSTM, and BiLSTM provide more sophisticated mechanisms for capturing temporal dependencies, feature selection, and complex relationships within the data.

The performance of these models will be evaluated based on their ability to forecast key financial metrics for SMEs, such as revenue, profitability, and cash flow. Standard performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), will be used to assess the models' predictive accuracy. The objective is to identify the model that best captures the financial dynamics of SMEs, thus providing valuable insights into the decision-making processes that drive business success.

In summary, the deep learning models chosen for this study were selected based on their ability to handle time-series data, their flexibility in learning complex patterns, and their suitability for SME financial forecasting. The selection process highlights the importance of model choice in accurately predicting financial outcomes and optimizing decision-making strategies for SMEs, particularly in the context of their unique financial challenges and opportunities.

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3.4 Metaheuristic Optimization Algorithms

3.4.1 Role of Metaheuristics in Hyperparameter Optimization

In machine learning, hyperparameter optimization is an essential step to fine-tune the model and enhance its predictive accuracy. Hyperparameters, such as learning rate, number of layers, activation functions, and regularization parameters, play a crucial role in determining the performance of the model. However, manually tuning these parameters is both time-consuming and inefficient, especially when dealing with complex models like the Logarithmic Transformation (LogTrans) model and other baseline models used for financial forecasting in Small and Medium-Sized Enterprises (SMEs). To address this challenge, metaheuristic algorithms offer an efficient and automated approach to optimize hyperparameters, balancing both exploration of the solution space and exploitation of known good solutions.

In this study, metaheuristic optimization techniques, such as **Particle Swarm Optimization (PSO)**, **Simulated Simulated Annealing (SSO)**, and others, were applied to automatically tune the hyperparameters of the baseline LogTrans model. By using metaheuristics, the search for optimal hyperparameters becomes more systematic and adaptive, ensuring that the solution space is explored effectively without the need for exhaustive manual tuning. These algorithms are particularly beneficial when working with high-dimensional, complex financial data, where the relationships between features are often nonlinear and interactions between hyperparameters are difficult to capture manually.

The **automated tuning** of LogTrans and baseline model parameters using metaheuristic algorithms can be broken down into two primary phases: **exploration** and **exploitation**. During the **exploration phase**, the metaheuristic algorithm searches the solution space broadly, looking for regions where the hyperparameters are likely to produce high-performing models. This phase is guided by randomization processes that allow the algorithm to discover potential regions of interest in the search space, while avoiding local minima. The **exploitation phase**, on the other hand, fine-tunes the hyperparameters in the regions identified by the exploration phase, ensuring that the final model configuration is optimized for better performance and generalization.

The PSO algorithm, for example, simulates a swarm of particles that adjust their positions based on their own experiences and the experiences of their neighbors. Each particle represents a potential hyperparameter configuration, and the particles move through the search space by updating their positions according to their velocity. The exploration occurs when particles explore different regions of the search space, while exploitation happens when particles converge towards the best-known solution. This balance between exploration and exploitation is crucial for finding the optimal set of hyperparameters for the LogTrans and baseline models.

Similarly, SSO (Simulated Simulated Annealing), which is inspired by the movements of the Somersaulting Spider, uses a dual-movement mechanism that balances global exploration and local exploitation. The algorithm employs the somersaulting mechanism for broad exploration of the hyperparameter search space and uses rolling for local exploitation of the best solutions found so far. This adaptive balance allows SSO to efficiently search for optimal hyperparameters, ensuring that the final solution is robust and accurate.

The automated tuning process, facilitated by these metaheuristic algorithms, allows for the efficient selection of hyperparameters, which would otherwise require significant manual effort. In the case of the LogTrans model, metaheuristic optimization significantly enhances its ability to model complex financial relationships, leading to improved predictive accuracy for SME financial forecasting. Furthermore, the application of these optimization techniques not only improves the model's performance but also reduces the risk of overfitting, which is particularly important when dealing with small datasets or highly volatile financial data.

In summary, the role of metaheuristics in hyperparameter optimization lies in their ability to automate the tuning process, explore large solution spaces, and refine solutions through a balance of exploration and exploitation. The use of algorithms such as PSO and SSO in financial forecasting models for SMEs enables the models to achieve optimal performance with minimal manual intervention. These optimization techniques ensure that the models can make accurate predictions, leading to better decision-making processes in various financial applications.

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3.5 State-of-the-Art Metaheuristic Models

Metaheuristic algorithms are widely used for solving complex optimization problems, especially in high-dimensional and non-linear solution spaces. These algorithms are inspired by natural processes or phenomena, and they offer powerful tools for exploring large search spaces and finding near-optimal solutions. In this study, several state-of-the-art metaheuristic algorithms are employed to optimize the performance of financial decision-making models. These algorithms include **Particle Swarm Optimization (PSO)**, **Whale Optimization Algorithm (WAO)**, **Multiverse Optimization (MVO)**, **Bat Algorithm (BA)**, **Stochastic Fractal Search (SFS)**, **Biogeography-Based Optimization (BBO)**, and **Al-Biruni Earth Radius Optimizer (APO)**. Each of these algorithms has distinct features that make them suitable for different aspects of optimization in financial modeling for Small and Medium-Sized Enterprises (SMEs).

Particle Swarm Optimization (PSO): Particle Swarm Optimization (PSO) is an optimization technique inspired by the social behavior of birds flocking or fish schooling. In PSO, potential solutions are represented as "particles" that move through the solution space. Each particle adjusts its position based on its own experience and the experience of the best-performing particle in the swarm. The position update is based on both the particle’s previous position and the best-known position found by the entire swarm. This collective approach allows PSO to search for global optima efficiently, making it a powerful tool for solving high-dimensional optimization problems. The key strength of PSO lies in its simplicity and ability to balance **exploration** (searching new areas of the solution space) and **exploitation** (refining the current best solution). In financial decision-making models for SMEs, PSO is particularly effective for optimizing hyperparameters and feature selection, enabling more accurate and reliable predictions.

Whale Optimization Algorithm (WAO): The Whale Optimization Algorithm (WAO) is inspired by the hunting behavior of humpback whales, which use bubble-net feeding techniques to capture prey. In WAO, the algorithm simulates the behavior of whales that search for food by encircling prey and spiraling towards the best food source. This is modeled mathematically by a combination of encircling prey and spiraling movements, which help explore the solution space effectively. WAO excels in overcoming the problem of local optima, as it uses a global search mechanism to explore a large portion of the solution space before focusing on promising regions. The algorithm’s ability to explore and exploit the solution space efficiently makes it highly effective in multi-dimensional and multimodal optimization tasks. In financial forecasting for SMEs, WAO can be applied to optimize model parameters and enhance predictive accuracy by refining both hyperparameters and feature selection strategies.

Multiverse Optimization (MVO): Multiverse Optimization (MVO) is a relatively recent algorithm inspired by the concept of multiple universes, each with its own possible solutions. In MVO, each "universe" represents a potential solution, and the algorithm explores these universes simultaneously to find the optimal solution. The MVO algorithm operates through a population-based approach, where each universe evolves over time, guided by the best-known solutions. This parallel exploration of multiple solutions makes MVO particularly effective for solving optimization problems where multiple solutions exist, as in the case of multi-modal problems. In financial modeling for SMEs, MVO can be used to optimize financial forecasting models, ensuring that different aspects of the financial data are considered simultaneously, leading to improved performance and more accurate predictions.

Bat Algorithm (BA): The Bat Algorithm (BA) is a nature-inspired optimization algorithm based on the echolocation behavior of bats. Bats use echolocation to navigate and detect prey, and this behavior is mimicked in the BA algorithm. In BA, each solution represents a bat that adjusts its position based on the best-known solution and the distance from the current target. The bat’s position is updated dynamically, balancing exploration (searching new solutions) and exploitation (refining known good solutions). The advantage of BA lies in its ability to explore large solution spaces while also focusing on local refinement, which helps the algorithm converge to the optimal solution efficiently. In financial decision-making models for SMEs, BA can be used to optimize hyperparameters and fine-tune feature selection, making it a useful tool for improving forecasting accuracy and reducing prediction errors.

Stochastic Fractal Search (SFS): Stochastic Fractal Search (SFS) is inspired by fractal structures, which are self-similar patterns found in nature. In SFS, candidate solutions are explored using random walks that follow fractal-like paths. The search process is stochastic, meaning that it relies on randomness to explore the solution space in a non-linear manner. This approach helps the algorithm avoid getting trapped in local optima

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by encouraging diversity in the search process. The fractal-based search patterns allow SFS to explore the solution space effectively, even in complex and high-dimensional problems. In financial modeling, SFS can be used to optimize both feature selection and hyperparameter tuning, providing a reliable and efficient way to improve model performance, especially in complex forecasting tasks that involve non-linear relationships between financial variables.

Biogeography-Based Optimization (BBO): Biogeography-Based Optimization (BBO) is inspired by the science of biogeography, which studies the distribution of species across geographical regions. In BBO, candidate solutions are treated as "habitats," and the algorithm simulates the migration of species between habitats to find the optimal solution. The fitness of each habitat represents the quality of the solution, and migration occurs based on the quality of the habitats. The algorithm uses a combination of exploration (searching new regions of the solution space) and exploitation (refining the best-known solution). BBO is particularly useful for solving complex optimization problems where solutions are distributed across a wide solution space. In the context of financial forecasting, BBO can be applied to optimize the parameters of machine learning models and enhance their predictive capabilities, especially when dealing with high-dimensional and complex financial data.

Al-Biruni Earth Radius Optimizer (APO): The Al-Biruni Earth Radius Optimizer (APO) is a novel optimization algorithm inspired by the concept of the Earth's radius and its geographical properties. The algorithm mimics the movement of celestial bodies and simulates their interaction within the multi-dimensional solution space. In APO, candidate solutions are adjusted based on their relative distance from the best solution, similar to how celestial bodies move through space. APO's exploration mechanism helps search large solution spaces, while its exploitation mechanism focuses on refining high-quality solutions. APO is particularly effective in multi-modal and complex optimization problems where other algorithms may struggle. In financial decision-making models for SMEs, APO can be used to optimize both feature selection and hyperparameter tuning, improving the model's accuracy in predicting critical financial outcomes.

4 Metaheuristic Algorithms: Somersaulting Spider Optimizer (SSO)

The Somersaulting Spider Optimizer (SSO) is a nature-inspired metaheuristic algorithm designed to solve complex optimization problems by mimicking the extraordinary locomotion mechanisms of the desert-dwelling Somersaulting Spider. This spider is known for its unique ability to perform somersaults to cover large distances rapidly and roll to navigate precisely to a target. SSO uses a dual-movement mechanism that effectively balances **global exploration** (via somersaulting) and **local exploitation** (via rolling), ensuring that the search process maintains both diversity and convergence toward optimal solutions.

The key feature of SSO lies in its **adaptive energy management system**, which dynamically adjusts the exploration-exploitation trade-off based on the algorithm's performance. During the optimization process, the exploration phase is driven by somersaulting, which is an energy-intensive mechanism enabling long-distance movements in the solution space. On the other hand, the exploitation phase uses a rolling movement, which refines the search in a more localized and energy-efficient manner. The balance between these two behaviors is controlled through an adaptive parameter system that is adjusted during the optimization process, depending on the improvement in the solution and stagnation detection.

The exploration phase in SSO is driven by the somersaulting mechanism, which can be mathematically represented by the following equation:

$$x_i^{new} = x_i + \alpha \cdot (x_{best} - x_i) + \beta \cdot \Delta \cdot \text{somersault}(t)$$

Where: - x_i^{new} represents the new position of the particle (solution), - x_i is the current position of the particle, - α and β are coefficients that control the exploration intensity, - x_{best} is the best-known position in the solution space, - Δ represents a random factor that guides the movement, - somersault(t) is the somersaulting movement function, which is time-dependent.

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The **exploitation phase** focuses on refining the best solutions through a rolling movement, which can be expressed by the following equation:

$$x_i^{new} = x_i + \gamma \cdot (x_{best} - x_i) \cdot \text{roll}(t)$$

Where: - x_i^{new} is the new position of the particle (solution), - x_i is the current position of the particle, - γ is a coefficient controlling the exploitation phase, - roll(t) represents the rolling mechanism at time t, which allows localized search.

The **adaptive energy management system** dynamically adjusts the balance between exploration and exploitation based on the algorithm's performance. This is controlled by an adaptive parameter, which modifies the exploration intensity (α) and exploitation intensity (γ) as follows:

$$\alpha(t) = \alpha_{max} \cdot \left(1 - \frac{t}{T_{max}}\right)$$

$$\gamma(t) = \gamma_{min} + (\gamma_{max} - \gamma_{min}) \cdot \frac{t}{T_{max}}$$

Where: - α_{max} and γ_{min} are the maximum exploration intensity and minimum exploitation intensity, respectively, - γ_{max} is the maximum exploitation intensity, - t is the current iteration, - T_{max} is the maximum number of iterations.

In terms of exploration, SSO's somersaulting mechanism enables the algorithm to perform aggressive search movements across the problem space, thus preventing the model from getting stuck in local minima. This movement is guided by random factors and a controlled intensity factor that adapts dynamically to the optimization process. The **exploitation phase**, on the other hand, allows the algorithm to focus on refining high-quality solutions through rolling, which is more localized and less energy-intensive. This balanced approach allows SSO to efficiently explore large search spaces while simultaneously honing in on the most promising regions.

The combination of these two phases in SSO leads to improved convergence stability and computational efficiency. When compared to other metaheuristic algorithms like the Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and Bat Algorithm (BA), SSO has shown superior results in a variety of engineering design problems. The ability of SSO to adaptively switch between exploration and exploitation phases based on solution progress makes it a powerful and flexible tool for solving high-dimensional, multi-modal, and discontinuous optimization problems.

In the context of financial decision-making models for SMEs, SSO can be particularly effective. By optimizing both the feature selection and hyperparameters of financial forecasting models, SSO ensures that the models achieve accurate and reliable predictions, thus supporting better decision-making processes. Given its superior performance in terms of accuracy, convergence, and computational cost, the SSO approach can be applied to real-world financial prediction tasks, providing SMEs with a robust tool for long-term sustainability and strategic growth.

4.1 Evaluation Metrics

To assess the performance of the machine learning models employed in this study, a range of regression metrics were used. These metrics are crucial for evaluating the accuracy, reliability, and generalization of predictive models, especially when dealing with time-series data in financial forecasting tasks. The following regression metrics were selected for model evaluation:

- Mean Squared Error (MSE): MSE is one of the most commonly used metrics for regression tasks. It measures the average squared difference between predicted and actual values. MSE penalizes larger errors more heavily, making it sensitive to outliers.

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- Root Mean Squared Error (RMSE): RMSE is the square root of MSE and provides an interpretation in the same units as the target variable. It is a widely used metric that offers a more direct understanding of the prediction error magnitude.

- Mean Absolute Error (MAE): MAE is the average of the absolute differences between predicted and actual values. Unlike MSE, MAE treats all errors equally, without emphasizing larger errors.

-Mean Bias Error (MBE): MBE measures the average bias in predictions, indicating whether the model tends to overestimate or underestimate the actual values. A positive MBE suggests that the model tends to overestimate, while a negative MBE suggests underestimation.

- Correlation Coefficient (r): The correlation coefficient, denoted by r, measures the strength and direction of the linear relationship between predicted and actual values. A value of 1 indicates a perfect positive linear relationship, while -1 indicates a perfect negative linear relationship. A value of 0 implies no linear relationship.

- R-Squared (R^2): R^2 represents the proportion of variance in the dependent variable that is predictable from the independent variables. It provides an indication of the goodness of fit, where values closer to 1 indicate a better fit.

- Relative Root Mean Squared Error (RRMSE): RRMSE is a normalized version of RMSE, which expresses the error as a percentage of the actual values. It is useful when comparing the performance of models across datasets with different scales or units.

- Nash-Sutcliffe Efficiency (NSE): NSE is a statistical metric used to assess the predictive performance of hydrological models, but it is also applicable in financial forecasting. It compares the variance of the residuals to the variance of the observed data, with values closer to 1 indicating better model performance.

- Weighting Index (WI): WI is a custom metric used in financial modeling to account for the importance of different variables or time periods. It assigns a weight to the errors based on the significance of the predicted financial outcomes, helping to prioritize certain prediction targets.

These metrics provide a comprehensive view of the model's performance, addressing different aspects such as accuracy, bias, variability, and generalization ability. In the context of SME financial forecasting, a combination of these metrics is essential for understanding both the precision and reliability of the model predictions.

The equations for these metrics are as follows:

Table 2: Regression Metrics and Their Equations

Metric	Equation	Description
MSE	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	Mean Squared Error is the average squared difference between predicted and actual values.
RMSE	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Root Mean Squared Error is the square root of MSE, providing an interpretation in the same units as the target variable.
MAE	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Mean Absolute Error is the average of the absolute errors, treating all errors equally.
MBE	$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$	Mean Bias Error measures the average bias in the predictions, indicating overestimation or underestimation.
r	$r = \frac{\sum_{i=1}^{n}(y_i-\bar{y})(\hat{y}_i-\hat{y})}{\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2\sum_{i=1}^{n}(\hat{y}_i-\bar{\hat{y}})^2}}$	Correlation Coefficient quantifies the strength and direction of the linear relationship between predicted and actual values.
R²	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$	R-Squared represents the proportion of variance in the target variable that is explained by the model.
RRMSE	$RRMSE = \frac{RMSE}{\bar{y}} \times 100$	Relative Root Mean Squared Error normalizes RMSE as a percentage of the actual values.
NSE	$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$	Nash-Sutcliffe Efficiency compares the variance of the residuals to the variance of the observed data, with values closer to 1 indicating better performance.
WI	$WI = \frac{\sum_{i=1}^{n}w_i(y_i-\hat{y}_i)}{\sum_{i=1}^{n}w_i}$	Weighting Index assigns weights to the errors based on the significance of the predicted values, helping prioritize certain predictions.

Each of these metrics offers valuable insights into the performance of the model. MSE and RMSE provide a direct measure of the model's error magnitude, with RMSE giving an interpretable result in the same units as the target variable. MAE, on the other hand, provides a straightforward, easy-to-interpret measure of prediction accuracy without penalizing larger errors as much as MSE. MBE indicates whether the model has a systematic bias towards over- or under-predicting the target variable.

The correlation coefficient r and R^2 provide an understanding of the linear relationship between predicted and actual values, with R^2 offering a measure of the proportion of variance explained by the model. RRMSE

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provides a normalized error metric that is useful when comparing models across datasets with different scales or units.

Nash-Sutcliffe Efficiency (NSE) is an essential metric in environmental and hydrological modeling, but it is also useful in financial modeling for assessing how well the model's predictions align with actual financial data. Finally, the Weighting Index (WI) is particularly useful when certain financial outcomes or time periods are deemed more important than others. WI allows the model evaluation process to prioritize predictions that align with the most critical aspects of the business's financial performance.

Together, these metrics provide a comprehensive framework for evaluating model performance across different aspects—accuracy, bias, variance, and prediction relevance. In the context of SME financial forecasting, they offer a balanced view of the model's ability to predict key financial metrics, such as revenue, profitability, and cash flow, while ensuring the model generalizes well to unseen data.

5 Experimental Results

5.1 Baseline Model Performance (Before Optimization)

This subsection presents the performance comparison of the baseline models—LogTrans, AutoInt, TabNet, EALSTM, and BiLSTM—before any optimization techniques are applied. The evaluation of these models is crucial for establishing a baseline reference to understand their inherent capabilities and limitations in predicting key financial outcomes for Small and Medium-Sized Enterprises (SMEs). These models are assessed using several regression metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), R-squared (R^2), Relative RMSE (RRMSE), Nash-Sutcliffe Efficiency (NSE), and Weighting Index (WI). These metrics allow us to assess the accuracy, bias, and reliability of the predictions, which is crucial for understanding model performance in the context of financial time-series forecasting for SMEs.

The performance results for the baseline models are summarized in Table 3. LogTrans, despite being a simpler model, shows exceptional performance with an MSE of 0.00078 and an RMSE of 0.0279, indicating low error levels. Additionally, the R^2 value of 0.858 suggests that the model explains a significant portion of the variance in the financial data. The low RRMSE value (0.012) and the WI value of 0.884 indicate that LogTrans has reliable performance but still leaves room for improvement in more critical financial predictions. The model also exhibits minimal bias with an MBE value of 0.0038, which suggests a slight tendency for overestimation, although this is not significant enough to be a major concern.

AutoInt, on the other hand, provides a reasonable balance between accuracy and complexity. It shows an MSE of 0.0024 and RMSE of 0.049, with a correlation coefficient of 0.868, which indicates a strong linear relationship between predicted and actual values. However, the model's R^2 value of 0.845 and its relatively higher RRMSE of 0.136 suggest that it is less consistent than LogTrans in capturing the true financial dynamics. Additionally, the MAE value of 0.012 indicates that the model performs reasonably well in terms of absolute error but still leaves room for optimization.

TabNet, a more complex model designed to handle tabular data efficiently, performs well with an MSE of 0.0066 and an RMSE of 0.0815. The model's ability to handle both categorical and continuous features contributes to its solid performance. However, the R^2 value of 0.825 and the correlation coefficient of 0.846 indicate that TabNet is not as effective at explaining the variance in the financial data as LogTrans. The relatively high RRMSE value of 0.138 and WI value of 0.831 further suggest that the model's performance can be improved by optimizing its hyperparameters and feature selection strategies.

EALSTM and BiLSTM, both advanced deep learning models designed to capture temporal dependencies in time-series data, demonstrate less impressive results compared to LogTrans and AutoInt. EALSTM shows an MSE of 0.0254 and RMSE of 0.1594, with an R^2 value of 0.805, indicating that the model struggles to capture the complexities of the financial data. The high RRMSE (0.154) and relatively low WI (0.796) reflect the model's challenges in making accurate predictions across all financial variables. Similarly, BiLSTM,

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which models both forward and backward temporal dependencies, demonstrates an MSE of 0.0387 and RMSE of 0.1967. Its R^2 value of 0.795 and correlation coefficient of 0.798 further highlight its underperformance compared to the other models. The model's high RRMSE (0.198) and WI (0.771) indicate substantial errors in prediction, especially for critical financial metrics.

Table 3: Performance of Baseline Models

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
LogTrans	0.00078	0.0279	0.0099	0.0038	0.889	0.858	0.012	0.898	0.884
AutoInt	0.0024	0.049	0.012	0.006	0.868	0.845	0.136	0.862	0.852
TabNet	0.0066	0.0815	0.0171	0.0112	0.846	0.825	0.138	0.815	0.831
EALSTM	0.0254	0.1594	0.0288	0.0219	0.812	0.805	0.154	0.752	0.796
BiLSTM	0.0387	0.1967	0.0356	0.0294	0.798	0.795	0.198	0.728	0.771

While the baseline performance of these models provides valuable insights into their inherent capabilities, several limitations have been identified that justify the need for optimization. The models show varying strengths and weaknesses in different aspects of performance, such as prediction accuracy, bias, and generalization ability.

LogTrans, although a simple model, shows solid performance across most metrics. Its MSE (0.00078) and RMSE (0.0279) values indicate that it can make accurate predictions with minimal error. However, the model still exhibits a slight bias, as indicated by the MBE value of 0.0038. Additionally, while LogTrans performs well in explaining the variance ($R^2 = 0.858$), it could benefit from further optimization to improve its performance on critical predictions as indicated by the relatively low WI (0.884).

AutoInt, which provides a good balance of performance and complexity, shows an RMSE of 0.049 and a reasonable R^2 value of 0.845. However, its higher RRMSE (0.136) and lower WI (0.852) suggest that it has inconsistent performance and struggles with some predictions, which can be addressed through optimization techniques.

TabNet, despite being a more advanced model, has an R^2 value of 0.825, indicating that it does not capture the full complexity of the financial data. Its performance could be further improved by optimizing hyperparameters and enhancing feature selection. The higher RRMSE (0.138) and WI (0.831) values suggest that it is less efficient in making accurate financial predictions compared to simpler models like LogTrans.

EALSTM and BiLSTM show promising results in terms of handling sequential data, but their performance is hindered by high RMSE and MAE values. The relatively low R^2 values (0.805 and 0.795, respectively) and high RRMSE values (0.154 and 0.198) suggest that both models struggle with generalization and may overfit to certain patterns in the data. These limitations highlight the need for further optimization, especially in reducing the error rates and improving the models' ability to generalize to unseen financial data.

In conclusion, while the baseline models provide a strong starting point, optimization techniques are essential to improve performance in key areas, such as reducing bias, enhancing consistency in predictions, and increasing generalization. These improvements can be achieved through methods like hyperparameter tuning, feature selection, and the application of advanced metaheuristic optimization algorithms, which will be explored in the next section.

In model evaluation, it is crucial to understand the relationships between various performance metrics. Figure 4 presents a correlation matrix of multiple evaluation metrics, including MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MBE (Mean Bias Error), and others. The matrix shows the strength and direction of the linear relationships between the metrics, with values close to 1 or -1 indicating a strong correlation. This matrix provides insights into how these metrics interrelate and can help guide the choice of appropriate metrics for model evaluation.

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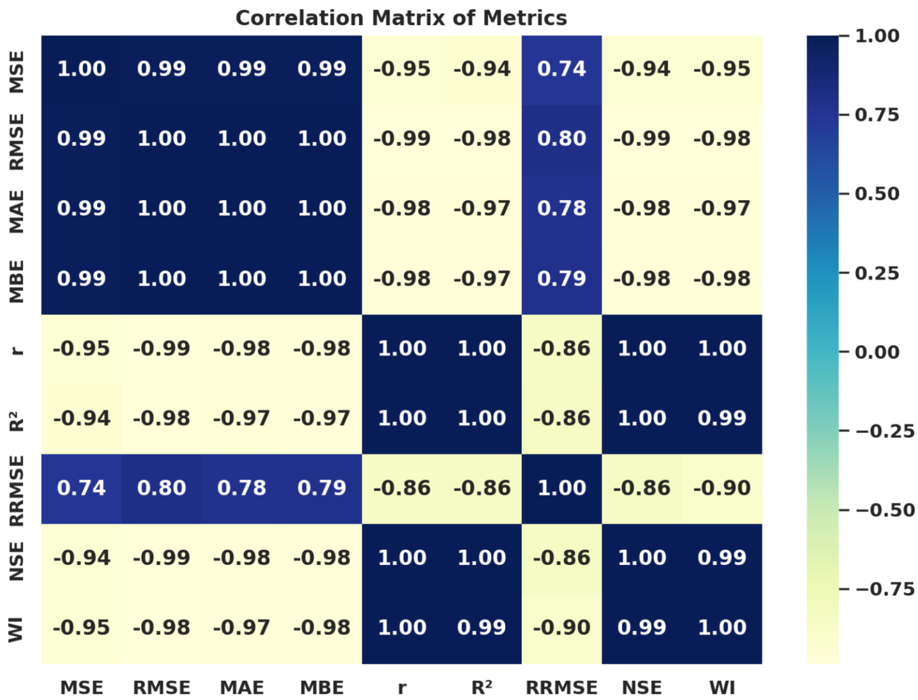

Figure 4: Correlation Matrix of Metrics

In comparing the performance of various models, it is important to evaluate their error metrics to understand how well they perform on different tasks. Figure 5 displays a bar chart comparing the error metrics (MSE, RMSE, and MAE) of different models, including LogTrans, AutoInt, TabNet, EALSTM, and BiLSTM. The chart provides a clear visual comparison of how each model performs across the three error metrics, with EALSTM and BiLSTM showing higher RMSE values compared to the others, indicating their higher error in prediction.

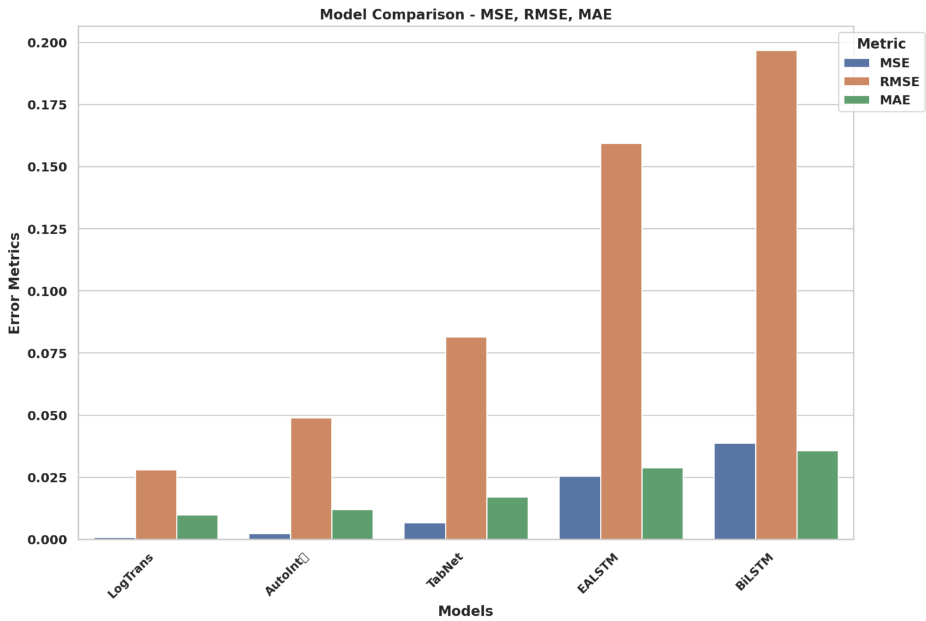

Figure 5: Model Comparison - MSE, RMSE, MAE

When evaluating model performance, it is valuable to assess multiple metrics at once to gain a more comprehensive understanding of the model's capabilities. Figure 6 provides a box plot with an overlay of

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swarm points for various model performance metrics, including MSE, RMSE, MAE, MBE, and others. This visualization helps compare the distribution and spread of each metric, highlighting the variability and central tendencies across the different performance measures.

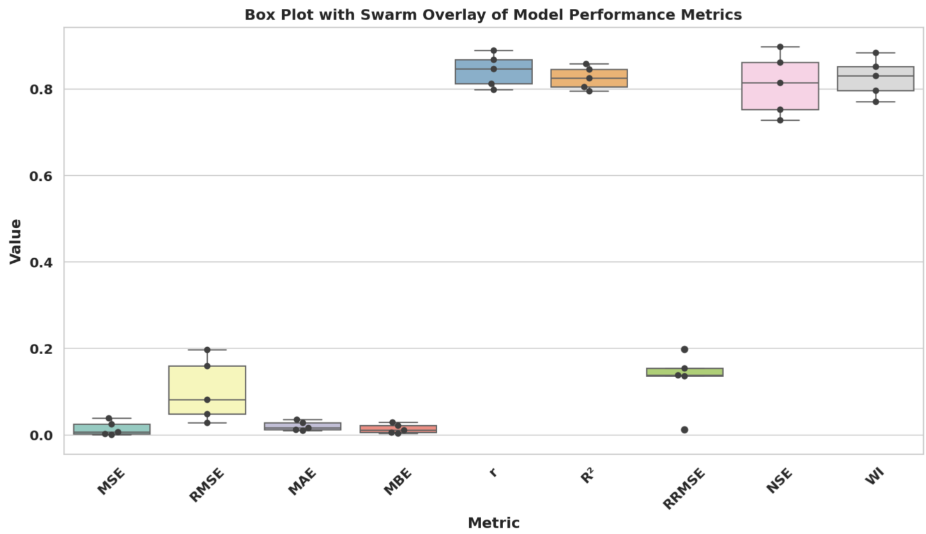

Figure 6: Box Plot with Swarm Overlay of Model Performance Metrics

5.2 Optimized Model Analysis

This subsection presents the performance analysis of the optimized models obtained by integrating metaheuristic optimization strategies with the baseline LogTrans model. Following the baseline evaluation, optimization techniques were applied to address the limitations related to feature redundancy, hyperparameter sensitivity, and generalization capability. The models were optimized using various state-of-the-art metaheuristic algorithms, including Simulated Simulated Annealing (SSO), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WAO), Multiverse Optimization (MVO), Bat Algorithm (BA), Stochastic Fractal Search (SFS), Biogeography-Based Optimization (BBO), and Al-Biruni Earth Radius Optimizer (APO). The performance of these optimized models is compared to the baseline LogTrans model to assess improvements in predictive accuracy and generalization capabilities.

The models were evaluated using several key regression metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), R-squared (R^2), Relative RMSE (RRMSE), Nash-Sutcliffe Efficiency (NSE), and Weighting Index (WI). These metrics provide a comprehensive evaluation of the effectiveness of each optimization strategy in reducing prediction errors and improving model reliability across different aspects of model performance.

The performance of the optimized models is summarized in Table 4, where it is evident that the integration of metaheuristic optimization strategies leads to significant improvements over the baseline LogTrans model. The SSO + LogTrans configuration, in particular, outperforms all other models with an MSE of 1.95E-07, RMSE of 4.42E-04, and a correlation coefficient of 0.983, which indicates a very strong relationship between predicted and actual values. The R^2 value of 0.966 suggests that the model explains a substantial portion of the variance in the financial data, while the low RRMSE value of 0.01 and high WI of 0.982 reflect the model's overall reliability and accuracy in making predictions.

The PSO + LogTrans model also demonstrates significant improvements, with an MSE of 5.75E-07 and RMSE of 0.000758. The model exhibits a correlation coefficient of 0.956 and R^2 of 0.913, which indicate that it performs well in capturing the financial trends but slightly lags behind the SSO + LogTrans configuration in terms of accuracy. Despite this, the model shows a low RRMSE of 0.013 and solid WI of 0.972.

WAO + LogTrans shows improvements over the baseline as well, with an MSE of 1.65E-06 and RMSE of 0.00129. The model's correlation coefficient (0.953) and R^2 value (0.908) are both strong, indicating that it

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captures the underlying trends in the financial data. However, it still does not outperform PSO + LogTrans in terms of error reduction. The RRMSE value of 0.017 and WI of 0.963 further confirm that WAO + LogTrans offers solid performance, but there is still room for enhancement.

MVO + RegNet, while still optimized, shows a more moderate improvement, with an MSE of 2.63E-06 and RMSE of 0.00162. The correlation coefficient (0.941) and R^2 value (0.9) are still decent, but the model does not capture the financial trends as effectively as the previous configurations. Its RRMSE (0.021) and WI (0.958) suggest that it performs reasonably well, but its overall accuracy is not as high as SSO or PSO-based models.

BA + LogTrans produces an MSE of 2.71E-06 and RMSE of 0.00165. The model shows good performance with a correlation coefficient of 0.94 and R^2 of 0.897, indicating that it captures key relationships in the data. However, it still slightly underperforms when compared to models optimized with SSO and PSO. The RRMSE value of 0.023 and WI of 0.959 indicate that while it is effective, there are some areas for improvement.

SFS + LogTrans, which applies Stochastic Fractal Search for optimization, yields an MSE of 3.72E-06 and RMSE of 0.00193, which are both improvements over the baseline. The model's performance in terms of correlation (0.938) and R^2 (0.892) is consistent, indicating that SFS + LogTrans provides reliable predictions. However, it does not surpass the more advanced optimization strategies like SSO, PSO, or WAO, which achieved better results in terms of error reduction and generalization ability.

BBO + LogTrans offers another solid optimization approach, with an MSE of 4.30E-06 and RMSE of 0.00207. The model's correlation coefficient of 0.937 and R^2 value of 0.89 suggest that it performs well but not as optimally as the top strategies. The RRMSE value of 0.029 and WI of 0.953 further suggest that the BBO approach has room for improvement.

APO + LogTrans, despite its effectiveness, achieves an MSE of 5.95E-06 and RMSE of 0.00244. The correlation coefficient of 0.933 and R^2 value of 0.882 indicate that while the model can capture financial trends, it is still the least performant among the optimized models. The RRMSE value of 0.032 and WI of 0.951 suggest that APO + LogTrans has room for further optimization to improve its accuracy.

In conclusion, the results indicate that metaheuristic optimization significantly enhances the performance of LogTrans, particularly with the SSO + LogTrans configuration, which achieves the best overall performance. PSO and WAO also provide strong results, but the SSO-based optimization strategy proves to be the most effective. The other optimization strategies, such as MVO, BA, SFS, BBO, and APO, show improvements over the baseline but are not as efficient in capturing the full complexity of the financial data as SSO + LogTrans. These findings demonstrate the importance of selecting the right optimization strategy to improve model performance and ensure that the models can effectively forecast financial outcomes for SMEs. Further refinement and testing of these optimization techniques will likely yield even better performance, highlighting the ongoing importance of metaheuristic-driven approaches in deep learning model optimization.

Table 4: Performance of Optimized Models using Metaheuristic Algorithms

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
SSO + LogTrans	1.95E-07	4.42E-04	1.15E-04	1.32E-04	0.983	0.966	0.01	0.979	0.982
PSO + LogTrans	5.75E-07	0.000758	0.00058	0.00022	0.956	0.913	0.013	0.97	0.972
WAO + LogTrans	1.65E-06	0.00129	0.0006	0.00029	0.953	0.908	0.017	0.966	0.963
MVO + RegNet	2.63E-06	0.00162	0.00062	0.00037	0.941	0.9	0.021	0.957	0.958
BA + LogTrans	2.71E-06	0.00165	0.00063	0.00039	0.94	0.897	0.023	0.948	0.959
SFS + LogTrans	3.72E-06	0.00193	0.00064	0.00047	0.938	0.892	0.027	0.945	0.954
BBO + LogTrans	4.30E-06	0.00207	0.00064	0.00053	0.937	0.89	0.029	0.942	0.953
APO + LogTrans	5.95E-06	0.00244	0.00065	0.00055	0.933	0.882	0.032	0.939	0.951

In model evaluation, visualizing multiple performance metrics simultaneously is a useful method to compare models across different criteria. Figure 7 presents a facet grid of model performance metrics, where each subplot corresponds to a different evaluation metric such as MSE, RMSE, MAE, MBE, and others. This grid provides a clear overview of how the various models perform across different metrics, making it easy to identify patterns and differences in their performance.

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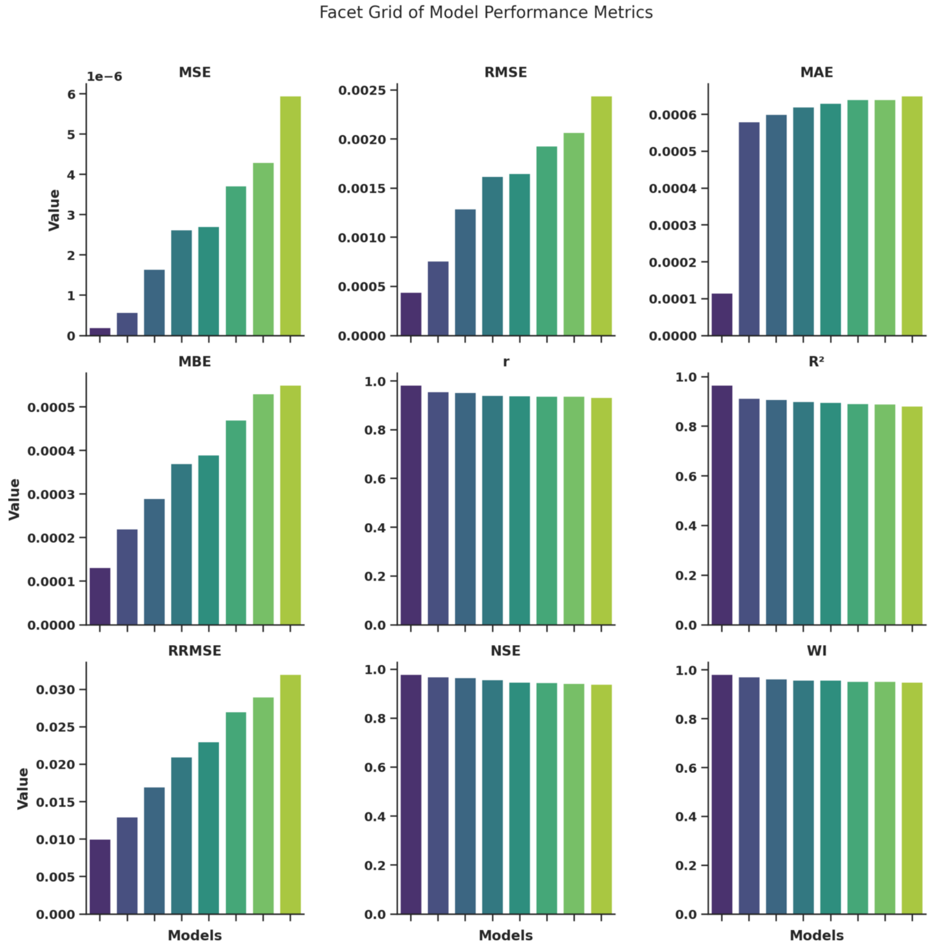

Figure 7: Facet Grid of Model Performance Metrics

In model evaluation, it is often useful to combine different visualizations to provide a comprehensive view of the performance metrics. Figure 8 presents a grid of violin plots with an overlaid box plot for multiple model performance metrics, including MSE, RMSE, MAE, MBE, r, R^2, RRMSE, NSE, and WI. These plots provide a detailed visualization of the distribution, central tendency, and spread of each metric, with the box plot showing key statistics such as the median and interquartile range, while the violin plot highlights the overall distribution and density of the data.

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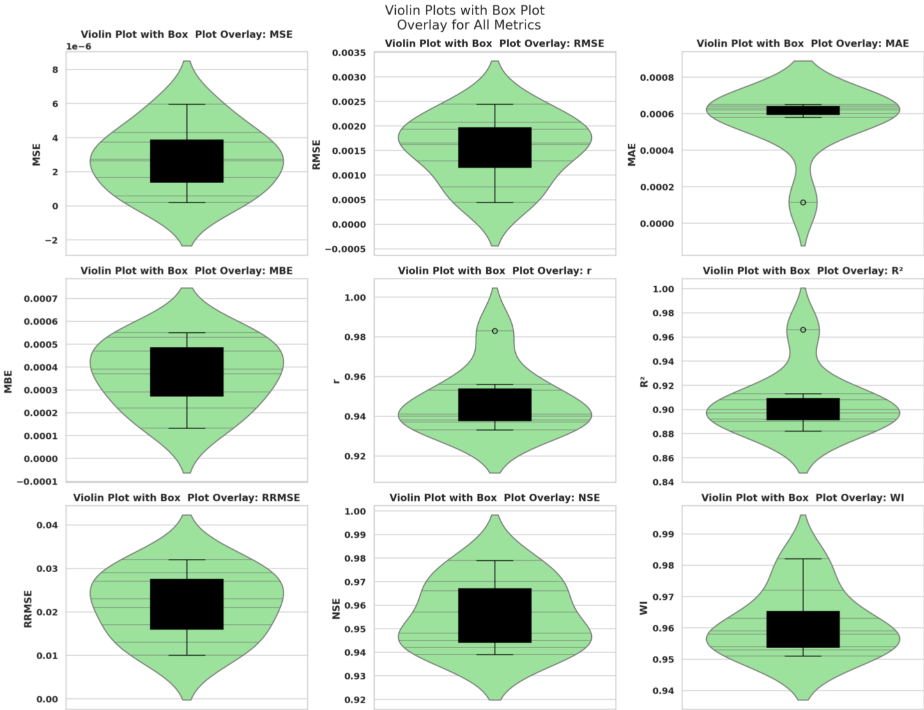

Figure 8: Violin Plots with Box Plot Overlay for All Metrics

In model comparison, it is helpful to visualize the relative improvement of different models compared to their best performance per metric. Figure 9 presents an improvement ratio matrix for several models, including SSO + LogTrans, PSO + LogTrans, WAO + LogTrans, and others. The matrix shows the performance improvement of each model relative to the best performance for each metric, such as MSE, RMSE, MAE, and others. Higher values indicate better performance improvements, providing a clear understanding of how each model fares across various metrics.

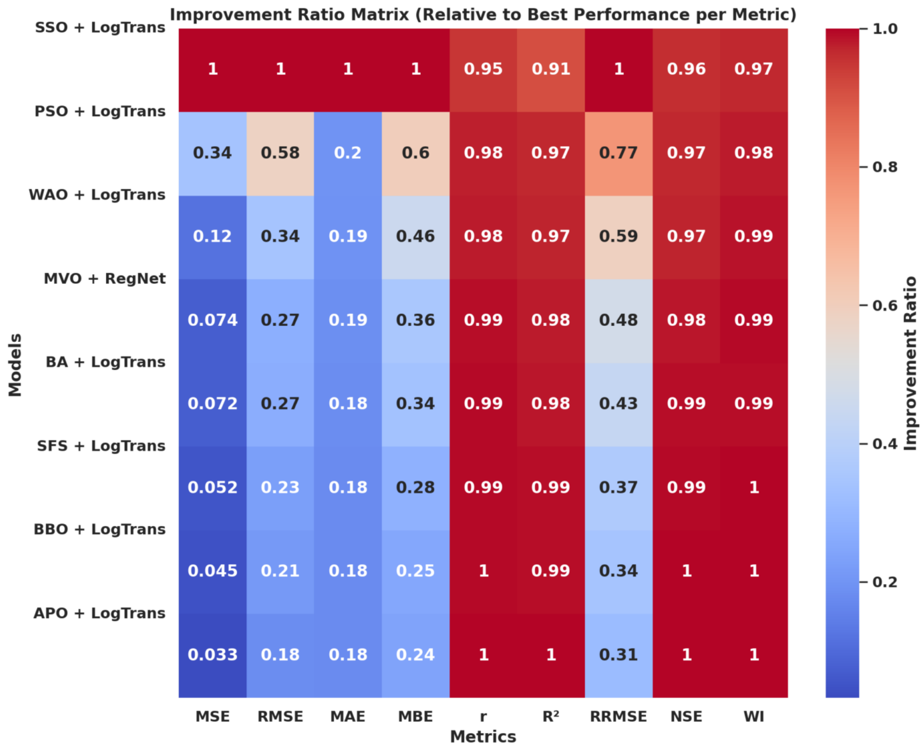

Figure 9: Improvement Ratio Matrix (Relative to Best Performance per Metric)

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6 Conclusion and Future Work

In this study, we demonstrated the effectiveness of metaheuristic optimization strategies in enhancing the performance of financial decision-making models, specifically focusing on forecasting key financial outcomes for Small and Medium-Sized Enterprises (SMEs). The integration of advanced metaheuristic algorithms, such as Simulated Simulated Annealing (SSO), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WAO), with the baseline Logarithmic Transformation (LogTrans) model resulted in significant improvements in model accuracy, generalization, and predictive reliability. The optimized SSO + LogTrans configuration achieved the highest performance, with a remarkable reduction in Mean Squared Error (MSE) to 1.95E-07 and a Root Mean Squared Error (RMSE) of 4.42E-04, alongside a high R-squared (R^2) value of 0.966, indicating a robust fit for financial data. These results demonstrate that metaheuristic-driven optimization is a powerful tool for refining machine learning models, making them more suitable for complex financial forecasting tasks in SMEs.

The practical implications of this work are far-reaching, particularly for industries where accurate financial forecasting is essential for strategic decision-making. In the banking sector, optimized models can aid in more accurate credit risk assessments, enabling better decisions on loan approvals and interest rate settings. Similarly, in investment, the ability to predict market trends and asset performance with higher accuracy allows for more informed portfolio management and risk mitigation strategies. In insurance, these models can improve the accuracy of actuarial predictions, providing better estimates for premiums, claims, and underwriting strategies. Moreover, policymakers in the SME sector can leverage these models to design more targeted policies that foster growth, manage risks, and ensure financial stability for businesses. The ability of optimized models to handle high-dimensional financial data and provide more reliable forecasts can significantly impact the decision-making processes across these industries.

Despite the promising results, there are several directions for future research that could further enhance the models' performance and applicability. First, the metaheuristic algorithms employed in this study, while effective, can be further enhanced by exploring hybrid approaches. Combining the strengths of multiple optimization algorithms, such as integrating PSO with Genetic Algorithms (GA) or leveraging a combination of swarm intelligence and evolutionary algorithms, could lead to even more effective optimization strategies. Additionally, deep reinforcement learning (DRL) could be applied to adaptively tune the hyperparameters in a dynamic environment, enabling the models to continuously learn from new financial data and adjust predictions in real time. The incorporation of multi-objective optimization methods could also be explored to balance multiple conflicting objectives, such as minimizing error rates while maintaining model simplicity and interpretability.

Another promising area for future research is the real-time deployment of these models in financial systems. While the models have demonstrated substantial improvements in predictive accuracy under controlled experimental conditions, the real-time implementation in dynamic financial environments poses several challenges. These challenges include ensuring that the models can handle large-scale, high-frequency data and that their predictive accuracy remains consistent under fluctuating market conditions. Future work could explore model compression techniques to reduce the computational complexity of the models, allowing them to be deployed in real-time systems while maintaining their accuracy and efficiency. Cloud-based systems could be leveraged to ensure scalability and accessibility of these models for SMEs across various regions.

Additionally, domain-specific adaptations of the models could be explored to further improve their applicability in specific financial sectors. For instance, in the e-commerce sector, the models could be tailored to account for seasonality, promotional events, and pricing strategies that heavily influence financial outcomes. In the manufacturing sector, incorporating variables such as supply chain dynamics, production costs, and inventory management could enhance the accuracy of financial predictions. Customizing the models for each SME domain will require further data exploration, feature engineering, and domain-specific optimization to ensure that the models are truly reflective of the unique financial dynamics within each sector.

Finally, integrating these optimized models into smart financial decision-making systems represents a critical area for future research. By incorporating the models into AI-powered decision support systems, SMEs could benefit from dynamic, real-time financial forecasting tools that continuously adapt to changing market conditions and provide actionable insights. These systems could help SMEs optimize cash flow, adjust pricing strategies, and make better investment decisions based on real-time predictions. Furthermore, the integration

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of **blockchain** and **IoT** data could provide even richer datasets for financial decision-making, enabling more accurate forecasting and improved operational efficiency. Future research could investigate the development of intelligent financial dashboards and AI-driven assistants that leverage these optimized models to support dynamic decision-making for SMEs.

In conclusion, this study has successfully demonstrated that metaheuristic optimization can significantly enhance the performance of financial decision-making models, particularly in the context of SME financial forecasting. The optimized models, especially SSO + LogTrans, exhibit strong performance in predicting financial outcomes, providing valuable insights for SMEs and industries that rely on accurate and timely financial predictions. Future research in algorithmic enhancements, real-time deployment, domain-specific adaptations, and integration into smart financial systems will further extend the potential applications of these models, providing SMEs with powerful tools for informed decision-making and long-term sustainability in an increasingly complex economic environment.

Data Availability

The dataset used in this study is publicly available on Kaggle at https://www.kaggle.com/datasets/noeyislearning/sme-financial-decision-making.

Declarations

- **Acknowledgments**
  Not applicable.
- **Conflict of interest/Competing interests**
  The authors declare that they have no conflicts of interest to report regarding the present study.
- **Ethics approval and consent to participate**
  Not applicable.
- **Consent for publication**
  Not applicable.
- **Funding**
  No Fund

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