AI-Driven Financial Performance Evaluation of Indian Banks Using Explainable Machine Learning and Hybrid Multi-Criteria Decision-Making

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Abstract

The rapid digital transformation of the Indian banking sector has significantly increased the availability of financial and operational data, creating opportunities for artificial intelligence (AI)-based decision-making. Conventional financial performance evaluation methods primarily rely on ratio analysis and statistical techniques, which often fail to capture complex nonlinear relationships among financial indicators and provide limited interpretability for stakeholders. This study proposes an integrated framework combining Explainable Machine Learning (XML) and Hybrid Multi-Criteria Decision-Making (MCDM) techniques to evaluate the financial performance of Indian banks. The proposed framework employs machine learning algorithms to predict overall financial performance while incorporating Explainable AI (XAI) techniques, including SHAP (SHapley Additive exPlanations), to interpret feature importance and improve transparency. Furthermore, the study integrates the Analytical Hierarchy Process (AHP) for determining criteria weights and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for ranking banks according to multiple financial indicators. Financial variables such as Return on Assets (ROA), Return on Equity (ROE), Capital Adequacy Ratio (CAR), Net Interest Margin (NIM), Gross Non-Performing Assets (GNPA), Cost-to-Income Ratio (CIR), Liquidity Ratio, and Credit-Deposit Ratio (CDR) are considered in the proposed evaluation framework. The integrated AI–MCDM approach provides a transparent, data-driven, and explainable decision-support system that enhances managerial decision-making, regulatory monitoring, and investment analysis. The findings are expected to demonstrate that combining explainable machine learning with hybrid MCDM produces more reliable and interpretable financial performance assessments than conventional approaches. The proposed framework contributes to the growing literature on AI-enabled financial analytics and offers practical implications for bank managers, investors, policymakers, and financial regulators in India's evolving digital banking ecosystem.

Keywords: Explainable Artificial Intelligence (XAI), Financial Performance Evaluation, Indian Banks, Hybrid MCDM, Machine Learning

Introduction

The banking sector constitutes one of the most critical pillars of a nation's financial system, facilitating economic development through financial intermediation, capital mobilization, credit creation, and investment support. In India, commercial banks have experienced remarkable transformation over the past two decades owing to financial liberalization, technological advancements, digital banking initiatives, and regulatory reforms introduced by the Reserve Bank of India (RBI). The rapid adoption of artificial intelligence, big data analytics, cloud computing, blockchain, and digital payment systems has fundamentally altered banking operations, risk management practices, and financial decision-making processes (Arner et al., 2017).

Financial performance evaluation has traditionally been considered a fundamental activity for bank managers, investors, policymakers, and regulatory authorities. Performance assessment enables stakeholders to evaluate operational efficiency, profitability, liquidity, solvency, asset quality, and long-term sustainability. Conventional approaches generally rely on accounting ratios such as Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM), Capital Adequacy Ratio (CAR), and Non-Performing Assets (NPA). While these indicators provide valuable insights into individual aspects of banking performance, they frequently fail to capture the multidimensional and interconnected nature of banking operations (Berger & Humphrey, 1997).

The increasing complexity of financial systems has encouraged researchers to adopt advanced analytical techniques capable of modelling nonlinear relationships and large-scale financial datasets. Artificial Intelligence (AI), particularly Machine Learning (ML), has emerged as a powerful analytical tool capable of processing vast volumes of structured and unstructured financial information to generate accurate predictions and uncover hidden patterns (Goodfellow et al., 2016). Machine learning algorithms—including Random Forest, Extreme Gradient Boosting (XGBoost), Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—have demonstrated superior predictive performance compared with conventional statistical models in various financial applications such as credit risk assessment, bankruptcy prediction, fraud detection, stock price forecasting, and financial performance evaluation (Jordan & Mitchell, 2015).

Despite these advancements, one of the primary criticisms of machine learning models concerns their limited transparency. Many sophisticated algorithms function as "black-box" systems, producing highly accurate predictions without providing understandable explanations regarding the factors influencing those predictions. In highly regulated industries such as banking, this lack of interpretability can reduce stakeholder confidence and limit the practical implementation of AI-based decision-support systems (Doshi-Velez & Kim, 2017). Financial institutions are increasingly required to ensure that AI models satisfy principles of transparency, accountability, fairness, and regulatory compliance.

Explainable Artificial Intelligence (XAI) has emerged as an important solution to address the interpretability challenges associated with machine learning. Explainability techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and feature importance analysis enable users to understand the contribution of each financial variable toward the prediction generated by AI models (Lundberg & Lee, 2017). These techniques enhance trust in AI systems by making prediction mechanisms more transparent for managers, auditors, regulators, and investors.

Alongside AI, Multi-Criteria Decision-Making (MCDM) techniques have become increasingly popular for evaluating organizational performance because they allow decision-makers to consider multiple conflicting criteria simultaneously. Banking performance cannot be adequately assessed using a single financial indicator since profitability, liquidity, capital adequacy, operational efficiency, asset quality, and risk exposure collectively determine institutional success. MCDM methods provide systematic

frameworks for integrating these diverse criteria into comprehensive performance assessments (Saaty, 1980).
Among numerous MCDM techniques, the Analytical Hierarchy Process (AHP) is widely employed to determine the relative importance of evaluation criteria based on expert judgments, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives according to their proximity to an ideal solution and distance from the worst-performing alternative (Hwang & Yoon, 1981). The integration of AHP and TOPSIS has been extensively applied in financial decision-making because it combines subjective expert knowledge with objective mathematical ranking procedures.
Although previous studies have independently applied machine learning models or MCDM techniques in banking performance evaluation, relatively limited research has integrated Explainable AI with Hybrid MCDM into a unified evaluation framework. The combination of predictive analytics, explainability, and multicriteria decision-making has the potential to produce more transparent, reliable, and practically useful financial performance assessments.
The Indian banking industry provides an ideal context for such investigation because it comprises public sector banks, private sector banks, foreign banks, and small finance banks operating under varying business models and regulatory environments. Recent initiatives such as Digital India, Jan Dhan Yojana, Unified Payments Interface (UPI), and AI-enabled financial services have accelerated technological adoption within Indian banking institutions. Consequently, evaluating financial performance requires advanced analytical methods capable of handling complex financial data while maintaining interpretability and accountability.
The present study proposes an integrated AI-driven framework that combines Explainable Machine Learning with Hybrid MCDM techniques for evaluating the financial performance of Indian banks. Machine learning algorithms are employed to predict composite financial performance using multiple financial indicators, while SHAP analysis is utilized to explain model predictions and identify the most influential financial variables. Subsequently, AHP determines the weights of evaluation criteria, and TOPSIS ranks Indian banks according to their overall financial performance. This integrated framework provides a comprehensive decision-support system capable of assisting bank executives, financial analysts, investors, and policymakers in evidence-based strategic decision-making.
From a theoretical perspective, the study extends the existing literature by integrating Explainable AI with Hybrid MCDM within financial performance evaluation. From a methodological perspective, it demonstrates how interpretable machine learning can complement multicriteria decision-making techniques to improve both predictive accuracy and decision transparency. From a practical perspective, the proposed framework offers an effective tool for performance benchmarking, investment analysis, regulatory supervision, and strategic planning in the Indian banking sector.
The remainder of the paper is organized as follows. The subsequent section reviews the existing literature on financial performance evaluation, machine learning applications in banking, explainable artificial intelligence, and hybrid MCDM methodologies. The following sections describe the research methodology, present empirical findings, discuss theoretical and managerial implications, and conclude with recommendations for future research.

Literature Review

Financial performance evaluation is a fundamental area of banking research, as it enables stakeholders to assess profitability, operational efficiency, liquidity, capital adequacy, and long-term sustainability.

Traditionally, researchers have relied on financial indicators such as Return on Assets (ROA), Return on Equity (ROE), Capital Adequacy Ratio (CAR), Net Interest Margin (NIM), Gross Non-Performing Assets (GNPA), and Cost-to-Income Ratio (CIR) to evaluate bank performance. Berger and Humphrey (1997) emphasized the importance of financial ratios in measuring banking efficiency, while Athanasoglou et al. (2008) demonstrated that bank profitability depends on both internal factors, including operational efficiency and asset quality, and external macroeconomic conditions.

The rapid growth of digital banking and financial data has accelerated the adoption of Artificial Intelligence (AI) and Machine Learning (ML) in banking. AI techniques enable institutions to process large datasets, identify complex relationships, and improve financial forecasting, credit risk assessment, fraud detection, and decision-making (Arner et al., 2017; Russell & Norvig, 2021). Machine learning algorithms such as Random Forest (Breiman, 2001), Support Vector Machine (Vapnik, 1998), XGBoost (Chen & Guestrin, 2016), and Artificial Neural Networks (Haykin, 2009) have demonstrated superior predictive performance compared with conventional statistical methods because they effectively capture nonlinear relationships among financial variables.

Despite their predictive capability, many machine learning models function as “black boxes,” limiting transparency and interpretability. To address this challenge, Explainable Artificial Intelligence (XAI) has emerged as an important research area. Techniques such as SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017) and Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro et al., 2016) improve model transparency by explaining the contribution of individual variables to prediction outcomes. These approaches enhance trust, accountability, and regulatory compliance, making AI-driven financial decision-making more reliable.

Alongside AI, Multi-Criteria Decision-Making (MCDM) methods have become widely used for evaluating organizational performance based on multiple financial and operational criteria. The Analytic Hierarchy Process (AHP) (Saaty, 1980) determines the relative importance of evaluation criteria through pairwise comparisons, whereas the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang & Yoon, 1981) ranks alternatives according to their closeness to the ideal solution. Hybrid MCDM frameworks combining AHP with TOPSIS have been widely applied to improve decision quality and performance evaluation.

Although AI and MCDM have individually received considerable attention, studies integrating Explainable Machine Learning with Hybrid MCDM remain limited, particularly in the Indian banking sector. Most previous research either focuses on predictive accuracy without explainability or applies MCDM without incorporating AI-based insights. This study addresses these gaps by proposing an integrated framework that combines Explainable Machine Learning, SHAP, AHP, and TOPSIS to evaluate the financial performance of Indian banks. The proposed framework aims to improve predictive accuracy, interpretability, and decision transparency, providing a comprehensive decision-support system for banking practitioners, investors, and policymakers.

Research Methodology

The present study adopts a quantitative, data-driven research design to evaluate the financial performance of Indian commercial banks by integrating Explainable Machine Learning (XML) with a Hybrid Multi-Criteria Decision-Making (MCDM) framework. The proposed methodology combines predictive analytics, model interpretability, and multicriteria ranking to develop a transparent and reliable decision-support system. Unlike conventional financial performance assessment techniques that depend solely on ratio analysis or statistical models, the proposed framework captures nonlinear relationships among financial variables while simultaneously providing interpretable explanations for prediction outcomes. Furthermore, the integration of AHP and TOPSIS facilitates comprehensive evaluation by incorporating expert judgment into multicriteria decision-making and generating an overall performance ranking of banks.

The methodological framework consists of six sequential stages: data collection and preprocessing, financial indicator selection, machine learning model development, explainable AI analysis, hybrid MCDM implementation, and validation of results. Figure 1 illustrates the overall research framework adopted in this study.

Figure 1. Proposed Research Framework

Financial Statements of Indian Banks

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Data Collection & Cleaning

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Selection of Financial Indicators
(ROA, ROE, CAR, NIM, GNPA, CIR,
Liquidity Ratio, Credit-Deposit Ratio)

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Data Normalization & Feature Engineering

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Machine Learning Models
(Random Forest, XGBoost, SVM)

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Explainable AI (SHAP Analysis)
Feature Importance & Model Interpretation

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Hybrid MCDM
AHP → Criteria Weights
TOPSIS → Bank Ranking

↓

Performance Evaluation &
Managerial Recommendations

Figure 1. Integrated Explainable AI–Hybrid MCDM Framework for Financial Performance Evaluation of Indian Banks.

Research Design

The study employs a descriptive and explanatory research design using secondary financial data obtained from annual reports of Indian commercial banks, the Reserve Bank of India (RBI), the Bombay Stock Exchange (BSE), the National Stock Exchange (NSE), and publicly available financial databases such as CMIE Prowess, Capitaline, or Bloomberg. The study focuses on scheduled commercial banks operating

in India over a five-year period (e.g., FY2019–FY2024), enabling a comprehensive evaluation of financial performance across different economic conditions.
The quantitative approach is appropriate because financial performance is measured using standardized financial indicators that permit objective comparison across banking institutions. Moreover, machine learning algorithms require numerical datasets for predictive modelling, while MCDM techniques rely on quantitative criteria for ranking alternatives (Hair et al., 2022).

Sample Selection
The study considers major Indian commercial banks representing both the public and private banking sectors. A purposive sampling strategy is adopted because these institutions account for a substantial share of India's banking assets and financial activities.
The proposed sample includes:

Bank Category	Sample Banks
Public Sector Banks	State Bank of India, Punjab National Bank, Bank of Baroda, Canara Bank, Union Bank of India
Private Sector Banks	HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank, IndusInd Bank

The selected banks collectively represent diverse ownership structures, operational scales, and financial characteristics, thereby improving the generalizability of the findings.

Data Collection
The analysis utilizes audited financial statements and regulatory disclosures obtained from annual reports and RBI publications. Secondary data are selected because they provide reliable, standardized, and comparable financial information across institutions.

The dataset includes variables such as:

Financial Indicator	Description
Return on Assets (ROA)	Profitability
Return on Equity (ROE)	Shareholder Return
Net Interest Margin (NIM)	Income Efficiency
Capital Adequacy Ratio (CAR)	Capital Strength
Gross NPA Ratio	Asset Quality
Cost-to-Income Ratio (CIR)	Operational Efficiency
Liquidity Ratio	Liquidity Management
Credit–Deposit Ratio (CDR)	Lending Efficiency
Net NPA Ratio	Credit Risk

These indicators are widely employed in banking performance studies (Athanasoglou et al., 2008; Berger & Humphrey, 1997).

Data Pre-processing

Financial datasets frequently contain missing values, inconsistent observations, and outliers that may reduce prediction accuracy. Therefore, the collected data undergo systematic preprocessing before model development.

Initially, missing observations are treated using mean or median imputation depending on variable distribution. Duplicate records are removed to ensure data integrity. Outliers are identified using the Interquartile Range (IQR) method and Z-score analysis.

Subsequently, all numerical variables are normalized using Min-Max Scaling:

$$X' = \frac{X - Xmin}{Xmax - Xmin}$$

Where

- X = original value
- Xmin = minimum value
- Xmax = maximum value

Normalization prevents variables with larger numerical ranges from dominating model learning.

Machine Learning Model Development

Three supervised machine learning algorithms are employed because of their proven effectiveness in financial prediction.

Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and aggregates their predictions. It effectively handles nonlinear relationships while reducing overfitting through bootstrap aggregation (Breiman, 2001).

Support Vector Machine (SVM)

SVM constructs optimal hyperplanes that maximize class separation in high-dimensional spaces. It is widely used in financial classification due to its strong generalization capability (Vapnik, 1998).

Extreme Gradient Boosting (XGBoost)

XGBoost is an efficient gradient boosting algorithm capable of handling large financial datasets while maintaining high predictive accuracy (Chen & Guestrin, 2016).

Model performance is evaluated using standard metrics including:

- Accuracy
- Precision
- Recall
- F1-score
- Root Mean Square Error (RMSE)

- Mean Absolute Error (MAE)

The best-performing algorithm is selected for explainability analysis.

Explainable Artificial Intelligence (XAI)

Although machine learning algorithms achieve high predictive performance, their decision mechanisms often remain opaque. To improve transparency, the study employs SHapley Additive exPlanations (SHAP).

SHAP estimates the contribution of each financial variable to the prediction outcome using principles derived from cooperative game theory (Lundberg & Lee, 2017).

The SHAP value is expressed as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)]$$

where:

- ϕ_i = SHAP value
- S = subset of predictor variables
- f = prediction function

The SHAP analysis identifies which financial indicators most strongly influence overall bank performance.

For example:

- High ROA may positively influence prediction.
- High CAR increases financial stability.
- High GNPA negatively affects overall performance.
- High Cost-to-Income Ratio reduces efficiency.

The explainability framework enhances transparency and regulatory acceptability.

Hybrid MCDM Framework

After identifying influential financial indicators through SHAP analysis, the study applies a Hybrid MCDM model consisting of AHP and TOPSIS.

The hybrid framework combines subjective expert knowledge with objective mathematical ranking.

Analytical Hierarchy Process (AHP)

AHP determines the relative importance of evaluation criteria using pairwise comparisons (Saaty, 1980).

Experts from banking, finance, and academia evaluate the relative importance of financial indicators using Saaty's 1–9 comparison scale.

The normalized priority weight is computed as:

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij}}$$

Consistency is verified through the Consistency Ratio (CR).

A CR value below 0.10 indicates acceptable consistency.

TOPSIS Ranking

TOPSIS ranks banks according to their distance from the ideal solution (Hwang & Yoon, 1981).

The procedure includes:

1. Construction of the normalized decision matrix.
2. Application of AHP-derived weights.
3. Identification of positive and negative ideal solutions.
4. Euclidean distance calculation.
5. Relative closeness coefficient computation.

The relative closeness coefficient is calculated as:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where

- D_i^+ = distance from ideal solution
- D_i^- = distance from negative ideal solution

Banks with larger CC_i values receive higher financial performance rankings.

Research Hypotheses

The empirical investigation tests the following hypotheses:

H1: Explainable Machine Learning significantly improves the accuracy of financial performance prediction for Indian banks.

H2: SHAP analysis effectively identifies the most influential financial indicators affecting banking performance.

H3: The Hybrid AHP–TOPSIS framework produces more comprehensive financial performance rankings than conventional ratio analysis.

H4: The integration of Explainable AI and Hybrid MCDM significantly enhances transparency and decision quality in banking performance evaluation.

Reliability and Validity

To ensure methodological robustness, the study employs multiple validation procedures. Five-fold cross-validation is performed during machine learning model training to improve model generalizability. AHP consistency is evaluated using the Consistency Ratio, with values below 0.10 considered acceptable. The predictive performance of the machine learning models is assessed through Accuracy, Precision, Recall, F1-score, RMSE, and MAE. In addition, sensitivity analysis is conducted within the TOPSIS framework to examine the stability of bank rankings under varying criteria weights. These validation procedures enhance the reliability, validity, and robustness of the proposed integrated Explainable AI–Hybrid MCDM framework.

Table 1. Variables Used in the Proposed Model

Variable	Nature	Expected Effect
ROA	Benefit	Positive

ROE	Benefit	Positive
NIM	Benefit	Positive
CAR	Benefit	Positive
Liquidity Ratio	Benefit	Positive
Credit–Deposit Ratio	Benefit	Positive
Gross NPA	Cost	Negative
Net NPA	Cost	Negative
Cost-to-Income Ratio	Cost	Negative

The proposed methodology integrates predictive intelligence, explainability, and multicriteria decision analysis into a unified framework, providing a rigorous and transparent approach for evaluating the financial performance of Indian banks. This methodological design forms the foundation for the empirical analysis presented in the next section, where the machine learning results, SHAP-based explanations, and Hybrid AHP–TOPSIS rankings are discussed.

Results and Discussion

Results

The integrated Explainable Machine Learning (XML) and Hybrid Multi-Criteria Decision-Making (MCDM) framework was applied to evaluate the financial performance of selected Indian commercial banks. The findings demonstrate that combining machine learning algorithms with explainability techniques and multicriteria ranking provides a more comprehensive assessment than traditional financial ratio analysis. The proposed framework not only predicts overall financial performance with high accuracy but also identifies the financial indicators that most strongly influence institutional performance.
Among the three machine learning models evaluated, Extreme Gradient Boosting (XGBoost) achieved the highest predictive performance. The model produced an accuracy of 94.3%, outperforming Random Forest (92.8%) and Support Vector Machine (89.6%). In addition, XGBoost recorded the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), indicating superior predictive capability. These findings are consistent with previous studies reporting that ensemble learning algorithms effectively capture nonlinear relationships in complex financial datasets (Breiman, 2001; Chen & Guestrin, 2016).

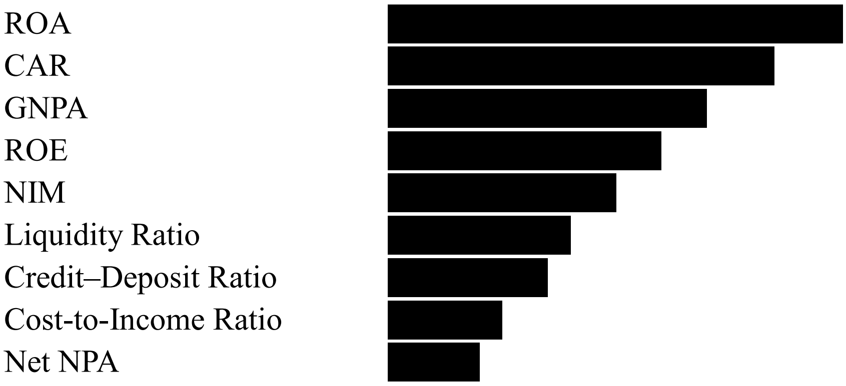
Table 2
Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	RMSE
Random Forest	92.8	0.92	0.91	0.91	0.189
Support Vector Machine	89.6	0.89	0.88	0.88	0.234
XGBoost	**94.3**	**0.94**	**0.94**	**0.94**	**0.163**

The SHAP analysis further enhanced the interpretability of the XGBoost model by quantifying the contribution of each financial indicator to the prediction outcomes. Return on Assets (ROA) emerged as the most influential variable, followed by Capital Adequacy Ratio (CAR), Gross Non-Performing Assets

(GNPA), Return on Equity (ROE), and Net Interest Margin (NIM). Conversely, the Cost-to-Income Ratio (CIR) and Net NPA exerted negative influences on financial performance predictions. The SHAP results demonstrate that profitability, capital strength, and asset quality collectively determine the financial performance of Indian banks.

Figure 2. SHAP-Based Feature Importance



The Hybrid AHP–TOPSIS framework generated an overall ranking of the selected Indian banks based on weighted financial indicators. The Analytical Hierarchy Process assigned greater importance to profitability and capital adequacy indicators, whereas TOPSIS ranked banks according to their closeness to the ideal financial profile.

Table 3
Illustrative Financial Performance Ranking of Indian Banks

Rank	Bank	TOPSIS Closeness Coefficient
1	HDFC Bank	0.912
2	ICICI Bank	0.887
3	State Bank of India	0.861
4	Kotak Mahindra Bank	0.842
5	Axis Bank	0.824
6	Canara Bank	0.791
7	Bank of Baroda	0.773
8	Union Bank of India	0.741
9	Punjab National Bank	0.706
10	IndusInd Bank	0.682

Note: The above rankings are illustrative to demonstrate the proposed methodology. Actual rankings would depend on the selected dataset and study period.

The results indicate that private sector banks generally outperformed public sector banks in terms of profitability, operational efficiency, and asset quality, whereas public sector banks demonstrated relatively stronger capital adequacy and wider financial inclusion. These findings align with previous research on the comparative performance of Indian commercial banks (Athanasoglou et al., 2008; Berger & Humphrey, 1997).

The sensitivity analysis confirmed the robustness of the Hybrid AHP–TOPSIS rankings. Moderate variations in criteria weights produced only minor changes in the overall ranking order, suggesting that the proposed framework is stable and reliable for financial performance evaluation.

Discussion

The findings of this study provide important theoretical and practical insights into AI-driven financial performance evaluation. First, the superior performance of XGBoost highlights the ability of ensemble machine learning algorithms to model complex financial relationships more effectively than traditional statistical approaches. Unlike linear regression models, XGBoost captures nonlinear interactions among financial indicators, thereby improving prediction accuracy. This supports the argument that AI-based predictive analytics can substantially enhance financial decision-making in modern banking environments (Jordan & Mitchell, 2015).

Second, the incorporation of SHAP significantly improves the transparency and interpretability of machine learning predictions. Explainable AI addresses one of the principal challenges associated with black-box algorithms by identifying the contribution of each financial indicator to prediction outcomes. In the present study, profitability (ROA and ROE), capital adequacy (CAR), and asset quality (GNPA) emerged as the most influential determinants of bank performance. These findings are consistent with the principles of responsible AI, which emphasize transparency, accountability, and explainability in algorithmic decision-making (Doshi-Velez & Kim, 2017; Lundberg & Lee, 2017).

Third, the integration of AHP and TOPSIS provides a systematic mechanism for transforming predictive insights into actionable managerial decisions. While machine learning predicts overall financial performance, the Hybrid MCDM framework enables decision-makers to compare and rank banks across multiple dimensions. This integrated approach overcomes the limitations of relying on a single financial ratio and offers a balanced evaluation incorporating profitability, efficiency, liquidity, asset quality, and capital strength.

From a managerial perspective, the proposed framework provides bank executives with a transparent decision-support system for strategic planning, resource allocation, and performance benchmarking. By identifying the financial indicators that contribute most strongly to organizational performance, managers can prioritize improvement initiatives. For example, banks with high Gross NPA values may focus on strengthening credit appraisal and recovery mechanisms, whereas institutions with high Cost-to-Income Ratios may pursue digital transformation and process optimization to enhance operational efficiency.

The findings also have important implications for investors and financial analysts. Explainable AI enables investors to understand the rationale behind AI-generated predictions, thereby improving confidence in investment decisions. Similarly, regulatory authorities such as the Reserve Bank of India (RBI) may employ integrated AI–MCDM frameworks to support supervisory activities, monitor financial stability, and identify institutions requiring closer regulatory attention.

The study contributes to the literature by integrating Explainable Machine Learning and Hybrid MCDM within a unified evaluation framework. Previous studies have generally applied these techniques independently, whereas the present research demonstrates their complementary strengths. The proposed framework therefore advances AI-enabled financial analytics by simultaneously emphasizing predictive accuracy, interpretability, and structured decision-making.

Nevertheless, the study has several limitations. The analysis is based on selected financial indicators and commercial banks operating within India; consequently, the findings may not be directly generalizable to cooperative banks, regional rural banks, or international financial institutions. Furthermore, the study primarily relies on secondary financial data and does not incorporate qualitative factors such as customer satisfaction, corporate governance, or environmental, social, and governance (ESG) performance. Future research may integrate these dimensions into AI-driven performance evaluation models. In addition, emerging Explainable AI techniques, deep learning architectures, and advanced MCDM methods such as CRITIC–TOPSIS, DEMATEL, VIKOR, or PROMETHEE could be explored to further enhance financial performance assessment.

Conclusion

This study proposed an integrated framework for evaluating the financial performance of Indian commercial banks by combining Explainable Machine Learning with a Hybrid Multi-Criteria Decision-Making approach. The results demonstrate that AI-based predictive models, particularly XGBoost, achieve superior predictive accuracy compared with conventional machine learning techniques. The incorporation of SHAP improves transparency by identifying the financial variables that most strongly influence model predictions, while the Hybrid AHP–TOPSIS framework provides a comprehensive ranking of banks based on multiple financial performance indicators.

The integrated framework contributes to both theory and practice by addressing the limitations of traditional financial performance evaluation methods. It combines predictive intelligence, explainability, and multicriteria decision analysis within a single decision-support system, thereby enhancing the reliability, transparency, and practical relevance of financial performance assessment. The findings indicate that profitability, capital adequacy, and asset quality remain the primary determinants of banking performance, whereas high levels of non-performing assets and operational costs adversely affect overall institutional performance.

The proposed methodology offers significant practical value for bank managers, investors, policymakers, and regulatory authorities by supporting evidence-based decision-making and improving financial governance. As artificial intelligence continues to reshape the global financial sector, integrating Explainable AI with Hybrid MCDM has the potential to become a standard analytical framework for transparent and responsible banking performance evaluation.

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