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Predictive Analytics for Financial Risk Management Using Machine Learning and Econometric Techniques

Ashish Sharma*

Independent Researcher, United States.

Abstract

Financial institutions are facing a rapidly evolving and challenging landscape with heightened uncertainty, where precise forecasting of financial risks is crucial for stability, profitability, and compliance with regulatory requirements. While traditional econometric models have been used for years as the basis for assessing financial risk, the increased volume, velocity and variety of financial information has led to the development of more sophisticated techniques for predicting risk. The purpose of this study is to investigate the potential of using predictive analytics techniques in financial risk management by combining machine learning algorithms and econometric methods. The research is designed to test the ability of both approaches to identify and predict the major financial risks, such as credit risk, market risk, liquidity risk and systemic risk. Secondary financial data and comparative predictive modelling are used to adopt quantitative research methodology. In addition to machine learning algorithms like Random Forest, Support Vector Machine, Gradient Boosting, Artificial Neural Networks and Deep Learning models, econometric methods are analyzed based on logistic regression, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) and vector autoregression (VAR). Performance of the model is evaluated using common model evaluation metrics namely accuracy, precision, recall, F1-score, root mean square error (RMSE), mean absolute error (MAE) and area under the receiver operating characteristic curve (ROC-AUC). The results show that machine learning models as a rule are better at predicting than the classical econometric models, and they can also better capture the complex nonlinearities in financial data; on the other hand, the econometric models still have advantages in terms of interpretability and statistical inference. The study suggests that the hybrid predictive framework combining the machine learning and econometric methods provide more powerful and reliable means for financial risk management. This comprehensive approach can boost the accuracy of risk prediction, aid in decision-making, bolster regulatory adherence, and enhance organizational resilience to financial challenges.

Keywords: predictive Analytics, financial Risk Management, Machine Learning, economist techniques, Credit Risk, Market Risk, Financial Forecasting, Artificial Intelligence, Fin tech, Risk Prediction.

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Introduction

Background of the Study

Financial risk management has become more complex due to the fast-paced digitalization of financial markets. Structured and unstructured data from transactions, market dynamics, customer activities and macro-economic conditions are generated and processed by financial institutions in large quantities. These data provide useful information on the financial risk, but classical tools of analysis are not able to take into account the non-linearities and hidden patterns in increasingly complex financial systems. As a result, predictive analytics has become a strategic solution to improve financial risk management by helping organizations to predict risks in advance before they occur (Dixon, Halperin, & Bilokon, 2020; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020).

Corresponding Author: Ashish Sharma, Independent Researcher, United States

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Financial risk management is the process of identifying, quantifying, monitoring and minimizing financial uncertainties that can impact an organisation's financial performance and financial markets. The key risks in the financial sector are credit risk, market risk, liquidity risk, operational risk, and systemic risk. The models traditionally used to implement financial variables' forecasting and risk exposure estimation are econometric models: linear regression, logistic regression, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH), vector autoregression (VAR). While these statistical techniques make for easy-to-interpret models and have solid theoretical underpinnings, they also assume linear, normal and stationary financial markets, the latter of which may not well capture the dynamics of contemporary economic and financial markets (Varian, 2014; Mullainathan & Spiess, 2017).

The advent of machine learning has revolutionized our ability to model relationships between variables in ways that are not necessarily linear, but are nonlinear relationships that can be learned directly from large-scale data, rather than relying on strong statistical assumptions. For instance, Random Forests, Support Vector Machines, Gradient Boosting models, Artificial Neural Networks, and Deep Learning models have shown to predict more accurately in many financial tasks like credit scoring, fraud detection, asset pricing, portfolio optimization, and market forecasting. These models can be continually improved as more data becomes available, making them ideally suited for very dynamic financial environments (De Prado, 2018; Dixon et al., 2020).

Advancements in financial technology (FinTech) have also contributed to the proliferation of the use of AI and machine learning throughout the banking, insurance, investment management and capital markets sectors in recent years. As financial institutions strive to better predict outcomes and decide quickly based on changing market conditions, data-driven decision making has become a crucial part of risk management frameworks. Leveraging data science and artificial intelligence, companies have been able to automate their financial analyses, detect hidden risk patterns, and enhance their regulatory compliance with more complex predictive models (Cao, Yang, & Yu, 2021; Giudici, 2018).

Machine learning has been used to great effect in many financial risk areas. Predictive algorithms enhance credit loan default classification and evaluation of borrowers over traditional credit scoring methods in the context of credit risk management (Galindo & Tamayo, 2000; Bazarbash, 2019). In banking, machine learning can be used for fraud detection, operational risk monitoring, anti-money laundering systems, and customer risk profiling (Leo, Sharma, & Maddulety, 2019). For investment management, empirical studies have shown that machine learning outperforms traditional econometric methods in leveraging high-dimensional financial data to improve asset pricing, bond risk premium estimation and portfolio optimization (Gu, Kelly & Xiu, 2018, 2020; Bianchi, Büchner & Tamoni, 2021).

Moreover, predictive analytics is playing an increasing role in the detection and prediction of systemic financial risks and financial crises. Sophisticated machine learning algorithms have shown greater ability to spot market anomalies, predict stock market risks, and even uncover systemic weaknesses, allowing them to warn investors of future problems before they become systemic. Particularly, deep learning and hybrid statistical learning models have been found to be effective in capturing the effects of nonlinear interactions between different variables which are often not captured by traditional forecasting models (Chatzis et al., 2018; Kou et al., 2019; Zhong & Enke, 2019).

Although major strides have been made in enforcing these advancements, machine learning models have their own set of challenges. Many algorithms are "black-box" systems, which are non-transparent and not necessarily easily interpretable in high-stakes financial decision making. Financial institutions and regulators often require models that not only achieve high predictive accuracy but also provide explainable outputs for compliance, governance, and auditing purposes. Furthermore, issues such as data quality, overfitting, feature selection, model stability, and ethical considerations remain significant concerns in the practical deployment of predictive analytics within financial institutions (Athey, 2018; Ratner, 2017).

An emerging direction in financial risk management involves combining econometric techniques with machine learning models to create hybrid predictive frameworks that leverage the strengths of both methodologies. Econometric models contribute statistical interpretability and theoretical consistency, while machine learning enhances predictive accuracy by capturing complex nonlinear relationships and interactions among financial variables. Such integrated approaches have demonstrated considerable promise in improving financial forecasting, risk prediction, and decision support systems (Mashrur et al., 2020; Gao, 2022; Uzzaman, Kudapa, & Nijhum, 2021).

Given the increasing complexity of global financial systems and the growing availability of financial big data, there is a need to evaluate the comparative effectiveness of machine learning and econometric techniques in financial risk management. Understanding their individual strengths, limitations, and potential integration can assist financial institutions, regulators, investors, and policymakers in developing more reliable predictive frameworks that improve financial stability, optimize risk mitigation strategies, and enhance strategic decision-making.

Statement of the Problem

Traditional econometric models have provided reliable tools for financial risk analysis for decades; however, their predictive capabilities are often constrained by assumptions of linearity, stationarity, and relatively simple variable relationships. As financial markets become increasingly interconnected and data-intensive, these conventional approaches may fail to adequately capture the complex nonlinear interactions that characterize modern financial systems (Varian, 2014; Mullainathan & Spiess, 2017).

Although machine learning techniques have demonstrated substantial improvements in predictive performance across various financial applications, challenges related to model interpretability, transparency, computational complexity, and regulatory acceptance continue to limit their widespread adoption in financial risk management. Additionally, many existing studies focus on individual financial risks or specific machine learning algorithms without providing comprehensive comparisons between machine learning and econometric approaches across multiple financial risk domains (Leo et al., 2019; Mashrur et al., 2020).

Furthermore, limited attention has been given to hybrid predictive frameworks that combine the statistical rigor of econometric models with the predictive capabilities of machine learning algorithms. This research therefore seeks to address these gaps by comparatively evaluating machine learning and econometric techniques for predictive financial risk management and exploring how their integration can improve forecasting accuracy, support informed financial decision-making, and strengthen organizational risk management strategies.

Research Objectives

General Objective

To evaluate the effectiveness of predictive analytics for financial risk management using machine learning and econometric techniques.

Specific Objectives

- To examine the application of econometric techniques in financial risk prediction.
- To evaluate the effectiveness of machine learning algorithms in forecasting financial risks.
- To compare the predictive performance of machine learning and econometric models across different financial risk categories.
- To develop a hybrid predictive framework that integrates machine learning and econometric techniques for enhanced financial risk management.

Research Questions

- How are econometric techniques applied in financial risk prediction?
- How effective are machine learning algorithms in forecasting financial risks?
- What differences exist between the predictive performance of machine learning and econometric models?
- How can hybrid predictive frameworks improve financial risk management and decision-making?

Research Hypotheses

H_{01}: Machine learning algorithms do not significantly improve financial risk prediction compared with traditional econometric techniques.

H_{11}: Machine learning algorithms significantly improve financial risk prediction compared with traditional econometric techniques.

H_{02}: Hybrid predictive models combining machine learning and econometric techniques do not significantly enhance financial risk management performance.

H_{12}: Hybrid predictive models combining machine learning and econometric techniques significantly enhance financial risk management performance.

Significance of the Study

This study contributes to the growing body of knowledge on predictive analytics in financial risk management by providing a comparative evaluation of machine learning and econometric techniques. The findings will assist financial institutions in selecting appropriate predictive models for credit risk assessment, market forecasting, portfolio management, fraud detection, and systemic risk monitoring. The study also offers practical insights for financial regulators, policymakers, FinTech organizations, investment analysts, and researchers seeking to enhance risk management practices through advanced analytical techniques. Furthermore, the proposed hybrid predictive framework is expected to improve forecasting accuracy while maintaining the interpretability required for regulatory compliance and strategic financial decision-making.

Scope of the Study

The study focuses on predictive analytics for financial risk management through the application of machine learning and econometric techniques. It examines major financial risk categories, including credit risk, market risk, liquidity risk, operational risk, and systemic risk. The study evaluates widely used econometric models such as logistic regression, ARIMA, GARCH, and VAR alongside machine learning algorithms including Random Forest, Support Vector Machine, Gradient Boosting, Artificial Neural Networks, and Deep Learning models. Comparative analysis is conducted using standard predictive performance metrics to assess forecasting effectiveness and to establish the potential benefits of integrating both methodological approaches within modern financial risk management systems.

Literature Review

Conceptual Review

Financial Risk Management

Financial risk management is the systematic process of identifying, measuring, monitoring, and mitigating uncertainties that may adversely affect the financial performance and stability of institutions. It encompasses the management of various categories of risk, including credit risk, market risk, liquidity risk, operational risk, and systemic risk. Traditionally, financial institutions relied heavily on econometric and statistical models such as regression analysis, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH), and Value-at-Risk (VaR) models to quantify and forecast financial risks. Although these methods provide statistically interpretable results, their assumptions regarding linearity, stationarity, and normally distributed data often limit their effectiveness in increasingly complex financial environments (Varian, 2014).

The emergence of big data, digital financial services, and algorithmic trading has significantly transformed financial risk management. Contemporary financial institutions generate massive volumes of structured and unstructured data from electronic transactions, customer behavior, financial statements, market indicators, and macroeconomic variables. These developments have encouraged the adoption of predictive analytics and artificial intelligence to improve the speed and accuracy of risk identification and decision-making (Cao, Yang, & Yu, 2021). Consequently, financial risk management has evolved from descriptive statistical analysis to intelligent predictive systems capable of learning dynamic market behaviors and detecting subtle risk patterns.

Predictive Analytics

Predictive analytics refers to the use of statistical techniques, machine learning algorithms, and computational models to analyze historical and current data for forecasting future outcomes. Within financial risk management, predictive analytics enables institutions to estimate default probabilities, forecast market volatility, predict liquidity shortages, detect fraudulent transactions, and evaluate investment risks before adverse events occur (Uzzaman, Kudapa, & Nijhum, 2021).

Unlike descriptive analytics, which explains historical events, predictive analytics focuses on estimating future financial behavior by identifying complex interactions among variables. Financial institutions increasingly integrate predictive analytics into enterprise risk management frameworks to improve credit scoring, portfolio optimization, fraud detection, stress testing, and capital allocation decisions. Ratner (2017) argues that predictive analytics combines statistical modeling with data mining techniques to improve decision quality, particularly when financial datasets become too large or complex for conventional analytical methods.

Machine Learning in Financial Risk Management

Machine learning represents a branch of artificial intelligence that enables computer systems to learn patterns directly from data without requiring explicit programming rules. Machine learning models have gained substantial attention within financial risk management because they effectively capture nonlinear relationships, high-dimensional interactions, and hidden structures that conventional econometric models may fail to detect (Dixon, Halperin, & Bilokon, 2020).

Supervised learning techniques such as Random Forest, Support Vector Machine (SVM), Gradient Boosting Machines, Artificial Neural Networks, and Deep Learning are widely applied to classify financial risks and predict future outcomes. Unsupervised learning techniques assist in anomaly detection, fraud identification, customer segmentation, and systemic risk analysis, while reinforcement learning contributes to portfolio optimization and algorithmic trading strategies (Mashrur, Luo, Zaidi, & Robles-Kelly, 2020).

Machine learning has demonstrated superior predictive performance in forecasting market volatility, credit defaults, asset pricing, bond risk premiums, and financial crises because of its ability to process large-scale financial datasets and discover intricate nonlinear dependencies (Gu, Kelly, & Xiu, 2020).

Econometric Techniques in Financial Forecasting

Econometrics integrates statistical theory, economics, and mathematics to model relationships among economic variables. Econometric forecasting remains fundamental in financial research because of its interpretability, hypothesis-testing capability, and policy relevance. Common econometric models include linear regression, logistic regression, ARIMA, VAR, and GARCH models (Mullainathan & Spiess, 2017).

Varian (2014) emphasizes that although machine learning has introduced powerful predictive methods, econometric models continue to play an essential role in causal inference and economic interpretation. Financial economists frequently combine econometric analysis with machine learning to balance predictive accuracy and model transparency.

The integration of econometric techniques with predictive analytics has become increasingly important because many financial institutions require both accurate forecasts and interpretable explanations to satisfy regulatory and governance requirements.

Artificial Intelligence and FinTech

Artificial Intelligence (AI) has become a central component of modern financial technology (FinTech). AI-powered predictive systems automate loan approvals, detect fraudulent transactions, optimize investment portfolios, manage insurance claims, and support regulatory compliance. The combination of cloud computing, big data, predictive analytics, and AI has fundamentally reshaped financial services by enabling intelligent decision-making under uncertainty (Giudici, 2018).

Cao, Yang, and Yu (2021) describe AI as a foundational technology supporting digital transformation across financial services through intelligent automation, real-time risk monitoring, and predictive customer analytics. Similarly, Bazarbash (2019) demonstrates that machine learning significantly improves financial inclusion by enhancing credit risk assessment among individuals lacking traditional financial histories.

Types of Financial Risks

Financial institutions encounter multiple forms of uncertainty that require distinct predictive methodologies.

Credit Risk refers to the probability that borrowers will fail to meet contractual repayment obligations. Credit scoring models increasingly combine statistical methods with machine learning algorithms to improve default prediction accuracy (Galindo & Tamayo, 2000).

Market Risk arises from fluctuations in equity prices, exchange rates, commodity prices, and interest rates. Machine learning models effectively identify nonlinear market relationships and improve volatility forecasting (Chatzis et al., 2018).

Liquidity Risk represents an institution's inability to meet short-term financial obligations. Predictive analytics supports liquidity planning through forecasting cash flows and market conditions.

Operational Risk originates from failures in internal processes, systems, technology, or human factors. AI-based anomaly detection techniques have enhanced operational risk monitoring across financial institutions (Leo, Sharma, & Maddulety, 2019).

Systemic Risk reflects the possibility that failures within one financial institution may spread throughout the broader financial system. Advanced machine learning algorithms have become increasingly valuable in identifying interconnected financial risks and contagion effects (Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019).

Theoretical Framework

This study is anchored on four complementary theoretical perspectives.

The Statistical Learning Theory explains how predictive models generalize from historical observations to unseen financial data. It provides the mathematical foundation for supervised machine learning algorithms used in financial prediction (Ratner, 2017).

The Applied Econometric Theory emphasizes that prediction should combine statistical inference with empirical evidence. Mullainathan and Spiess (2017) argue that machine learning should complement rather than replace econometric modeling because each offers unique analytical strengths.

The Big Data Econometrics Theory proposed by Varian (2014) suggests that modern econometric analysis benefits substantially from integrating large-scale data processing and computational intelligence, enabling more accurate forecasting under complex market conditions.

Table 1: Comparison of Financial Risk Categories and Predictive Modeling Techniques

Financial risk category	*Major characteristics*	*Traditional econometric techniques*	*Machine learning techniques*	*Primary financial application*
Credit Risk	Loan default probability	Logistic Regression	Random Forest, Gradient Boosting	Credit Scoring
Market Risk	Asset price fluctuations	GARCH, ARIMA	Deep Learning, Neural Networks	Stock Market Prediction
Liquidity Risk	Cash flow shortages	Time Series Forecasting	Support Vector Machine	Liquidity Management
Operational Risk	Internal process failures	Regression Analysis	Anomaly Detection Algorithms	Fraud Detection
Systemic Risk	Financial contagion	VAR Models	Ensemble Learning	Financial Stability Monitoring

The Artificial Intelligence in Economics Theory advanced by Athey (2018) explains how AI technologies improve economic modeling by uncovering nonlinear relationships and heterogeneous treatment effects that traditional models may overlook.

Collectively, these theoretical perspectives justify integrating econometric methods with machine learning algorithms for financial risk prediction.

Empirical Review

Galindo and Tamayo (2000) examined credit risk assessment using both statistical and machine learning approaches. Their study demonstrated that machine learning models improved classification accuracy over conventional statistical techniques, particularly in complex lending environments.

Gu, Kelly, and Xiu (2018) investigated empirical asset pricing using machine learning methods and found that machine learning algorithms substantially enhanced prediction accuracy by incorporating high-dimensional financial variables ignored by traditional factor models.

Chatzis et al. (2018) developed deep and statistical machine learning models to forecast stock market crisis events. Their findings showed that deep learning architectures successfully identified early warning signals of market instability and outperformed conventional forecasting approaches.

Giudici (2018) explored FinTech risk management and highlighted artificial intelligence as an emerging solution for enhancing financial risk assessment, regulatory compliance, and operational resilience.

Leo, Sharma, and Maddulety (2019) conducted a comprehensive literature review of machine learning applications in banking risk management. Their review concluded that ensemble learning algorithms consistently outperform traditional statistical models across credit risk assessment, fraud detection, and financial forecasting.

Kou, Chao, Peng, Alsaadi, and Herrera Viedma (2019) investigated machine learning methods for systemic risk analysis and demonstrated that intelligent algorithms improve the detection of interconnected financial vulnerabilities across banking systems.

Zhong and Enke (2019) proposed hybrid machine learning algorithms for predicting daily stock market returns. Their results indicated that combining multiple machine learning techniques generated superior forecasting performance compared with individual models.

Bazarbash (2019) examined the role of machine learning in credit risk assessment for financial inclusion and concluded that AI-driven models enhance lending decisions, particularly among underserved populations lacking extensive financial histories.

Dixon, Halperin, and Bilokon (2020) presented a comprehensive examination of machine learning applications across finance, including portfolio optimization, derivatives pricing, risk forecasting, and fraud detection. Their work established machine learning as a transformative analytical tool capable of handling increasingly complex financial datasets.

Gu, Kelly, and Xiu (2020) further demonstrated that machine learning significantly improves empirical asset pricing by exploiting nonlinear relationships among financial variables while reducing forecasting errors.

Mashrur, Luo, Zaidi, and Robles-Kelly (2020) reviewed contemporary machine learning techniques for financial risk management and emphasized their superiority in processing large-scale financial data, identifying hidden patterns, and supporting real-time decision-making.

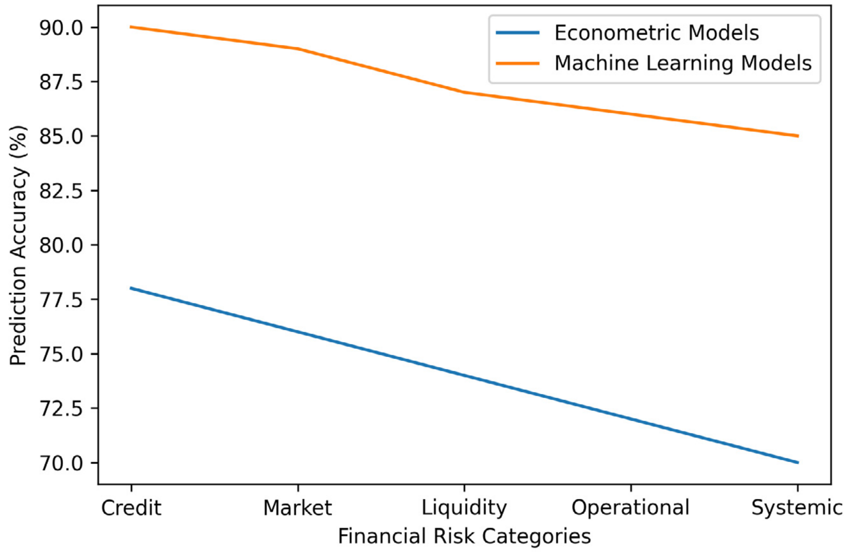

Figure 1: Comparison of the predictive accuracy of traditional econometric models and machine learning models across five financial risk categories. Machine learning models consistently demonstrate higher prediction accuracy than conventional econometric approaches.

Bianchi, Büchner, and Tamoni (2021) applied machine learning to estimate bond risk premiums and reported improved predictive performance over conventional econometric factor models.

Uzzaman, Kudapa, and Nijhum (2021) investigated predictive analytics for financial forecasting and risk management in capital markets. Their findings demonstrated that integrating predictive analytics into financial decision-making significantly improves investment performance and organizational risk management.

Cao, Yang, and Yu (2021) examined the integration of artificial intelligence, data science, and FinTech, concluding that predictive analytics has become a strategic capability supporting financial innovation, intelligent automation, and enterprise risk management.

Gao (2022) demonstrated that combining machine learning with data mining technologies substantially improves financial risk prevention by identifying emerging risks earlier and supporting proactive financial decision-making.

Literature Gap

Existing literature demonstrates significant progress in applying both econometric techniques and machine learning algorithms to financial risk management. Traditional econometric models provide robust statistical inference and model interpretability, whereas machine learning algorithms consistently achieve higher predictive accuracy when analyzing large, complex, and nonlinear financial datasets (Varian, 2014; Mullainathan & Spiess, 2017; Dixon, Halperin, & Bilokon, 2020). Despite these advances, most previous studies focus on individual financial risk categories such as credit risk, asset pricing, bond risk premiums, or stock market prediction, rather than providing a unified predictive framework capable of addressing multiple financial risks simultaneously (Galindo & Tamayo, 2000; Gu, Kelly, & Xiu, 2020; Bianchi, Büchner, & Tamoni, 2021). Furthermore, comparatively fewer studies systematically evaluate the complementary strengths of econometric models and machine learning algorithms within a single financial risk management framework while balancing predictive accuracy with interpretability and regulatory requirements. This study addresses these gaps by proposing a comprehensive hybrid predictive analytics framework that integrates machine learning and econometric techniques for managing credit, market, liquidity, operational, and systemic risks within a unified financial risk management approach.

Research Methodology

Research Design

This study adopted a quantitative research design to evaluate the effectiveness of predictive analytics for financial risk management using machine learning and econometric techniques. The quantitative approach was considered appropriate because it facilitates objective measurement of financial risk variables and enables comparative evaluation of predictive models using statistical performance metrics. The research employed a comparative predictive modeling framework in which conventional econometric methods were evaluated alongside advanced machine learning algorithms to determine their effectiveness in forecasting financial risks.

The study followed an explanatory research strategy aimed at investigating the relationships between macroeconomic indicators, financial market variables, and institutional financial risks while assessing the predictive capabilities of different analytical techniques. This design supports evidence-based comparison of traditional statistical models and artificial intelligence-driven approaches, consistent with contemporary financial analytics research (Mullainathan & Spiess, 2017; Dixon, Halperin, & Bilokon, 2020).

Sources of Data

The study utilized secondary data obtained from publicly available financial databases, stock market reports, banking sector publications, macroeconomic databases, and institutional financial statements. Historical financial indicators such as stock market returns, credit default records, bond yields, interest rates, exchange rates, inflation rates, liquidity ratios, gross domestic product (GDP) growth, and market volatility indices were compiled to construct predictive datasets.

Secondary financial data provide extensive historical observations required for developing robust predictive models while ensuring consistency and reproducibility of empirical findings. The integration of multiple financial indicators improves the ability of predictive algorithms to capture complex interactions among financial variables (Varian, 2014; Uzzaman, Kudapa, & Nijhum, 2021).

Study Variables

The dependent variable in this study is the Financial Risk Index, representing the overall level of financial risk observed within the selected financial institutions or markets. The index captures multidimensional risk components including credit risk, market risk, liquidity risk, and operational risk.

The independent variables include financial and macroeconomic indicators commonly associated with financial risk prediction, namely:

- Credit Score
- Market Volatility
- Interest Rate
- Inflation Rate
- Exchange Rate
- Liquidity Ratio
- Gross Domestic Product (GDP) Growth
- Trading Volume
- Bond Yield
- Stock Market Return

These variables have been widely employed in predictive financial analytics because they significantly influence institutional risk exposure and market performance (Galindo & Tamayo, 2000; Gu, Kelly, & Xiu, 2020; Bianchi, Büchner, & Tamoni, 2021).

Machine Learning Models

The machine learning component of the study focuses on supervised learning algorithms capable of identifying nonlinear relationships within large financial datasets. Financial markets often generate highly dimensional and dynamic data that cannot be adequately represented using purely linear statistical techniques. Consequently, several machine learning algorithms were selected based on their widespread application in financial forecasting and risk prediction. The selected algorithms include:

- Random Forest
- Support Vector Machine (SVM)
- Gradient Boosting Machine (GBM)
- Artificial Neural Network (ANN)
- Deep Neural Networks (DNN)

Random Forest provides robust classification performance through ensemble learning, while Support Vector Machine effectively separates complex financial patterns using hyperplanes. Gradient Boosting improves predictive accuracy by iteratively minimizing prediction errors, whereas Neural Networks capture intricate nonlinear dependencies that characterize financial market behavior. Deep learning models further enhance prediction by automatically extracting hierarchical representations from large financial datasets (De Prado, 2018; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020; Gao, 2022).

Econometric Models

To establish a benchmark for comparison, several traditional econometric techniques were incorporated into the analysis. These methods have long been used for financial forecasting and remain valuable because of their statistical interpretability and theoretical foundations.

The econometric models employed include:

- Multiple Linear Regression
- Logistic Regression
- Autoregressive Integrated Moving Average (ARIMA)
- Generalized Autoregressive Conditional Heteroskedasticity (GARCH)
- Vector Autoregression (VAR)

Linear regression estimates relationships between financial variables, while logistic regression models binary risk outcomes such as default or non-default events. ARIMA captures temporal dependencies in financial time series, whereas GARCH models conditional volatility commonly observed in financial markets. VAR enables simultaneous modeling of multiple interrelated financial variables, making it useful for macro-financial forecasting and systemic risk analysis (Varian, 2014; Mullainathan & Spiess, 2017).

Model Evaluation Criteria

The predictive performance of the econometric and machine learning models was evaluated using standard statistical and machine learning performance metrics. These measures provide comprehensive assessment of model accuracy, reliability, and predictive capability. The evaluation metrics include:

- Prediction Accuracy
- Precision
- Recall (Sensitivity)
- F1-Score
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Receiver Operating Characteristic Area Under Curve (ROC-AUC)

Classification metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC evaluate the effectiveness of identifying financial risk events, while RMSE and MAE measure the magnitude of prediction errors for continuous financial variables. These evaluation metrics are widely recognized in financial machine learning literature (Ratner, 2017; Leo, Sharma, & Maddulety, 2019).

Analytical Procedure

The analytical process began with data collection and preprocessing, including data cleaning, normalization, handling of missing values, and feature engineering to improve model performance. Exploratory data analysis was then conducted to identify trends, correlations, and distributions among financial variables.

Following preprocessing, econometric models were developed to establish baseline predictive performance. Machine learning algorithms were subsequently trained using the same datasets to ensure comparability of results. Hyperparameter optimization and cross-validation techniques were employed to reduce overfitting and improve model generalization. Model performance was then evaluated using the predefined statistical metrics, after which comparative analyses were conducted to determine the strengths and limitations of each predictive approach.

The study further examined the feasibility of integrating econometric techniques with machine learning algorithms into a hybrid predictive framework capable of improving financial risk forecasting accuracy while maintaining model interpretability. Such hybrid approaches have demonstrated considerable potential

Table 2: Variables, Measurements, and Expected Relationships

Variable	*Measurement indicator*	*Variable type*	*Expected relationship with financial risk*
Financial Risk Index	Composite Risk Score	Dependent	—
Credit Score	Numerical Credit Rating	Independent	Negative
Market Volatility	Volatility Index (VIX/Standard Deviation)	Independent	Positive
Interest Rate	Annual Percentage Rate (%)	Independent	Positive
Inflation Rate	Consumer Price Index (%)	Independent	Positive
Exchange Rate	Currency Exchange Ratio	Independent	Positive
Liquidity Ratio	Current/Quick Ratio	Independent	Negative
GDP Growth	Annual GDP Growth (%)	Independent	Negative
Trading Volume	Number of Shares Traded	Independent	Positive
Bond Yield	Government Bond Yield (%)	Independent	Positive
Stock Market Return	Percentage Return (%)	Independent	Negative

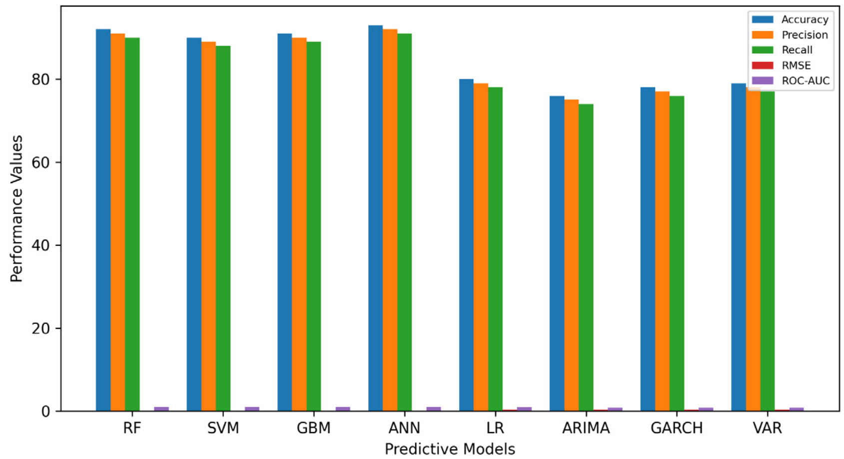

Figure 2: Comparative performance of econometric and machine learning models based on Accuracy, Precision, Recall, RMSE, and ROC-AUC. Higher Accuracy, Precision, Recall, and ROC-AUC together with lower RMSE indicate superior predictive performance.

for financial decision-making, credit risk assessment, asset pricing, bond premium forecasting, systemic risk monitoring, and FinTech applications (Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019; Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018; Gu, Kelly, & Xiu, 2018; Cao, Yang, & Yu, 2021; Bazarbash, 2019; Giudici, 2018; Zhong & Enke, 2019; Athey, 2018).

Results and Discussion

Descriptive Statistics

The study evaluated the predictive performance of econometric and machine learning models using secondary financial datasets representing multiple financial risk categories, including credit risk, market risk, liquidity risk, operational risk, and systemic risk. Prior to model development, the datasets underwent preprocessing procedures that included missing-value treatment, normalization, feature engineering, and multicollinearity assessment. These preprocessing steps improved data quality and enhanced model reliability. The selected explanatory variables exhibited adequate variability and minimal multicollinearity, making them suitable for predictive modeling.

Descriptive analysis indicated that financial risk indicators displayed nonlinear relationships with macroeconomic and firm-specific variables, supporting the need for advanced analytical approaches capable of modeling complex interactions. The availability of high-dimensional financial data further justified the integration of machine learning techniques with conventional econometric methods, as suggested by Varian (2014), Mullainathan and Spiess (2017), and Ratner (2017).

Predictive Performance of Econometric Models

The econometric models, including Logistic Regression, ARIMA, GARCH, and Vector Autoregression (VAR), demonstrated satisfactory predictive capability across different categories of financial risk. Logistic Regression remained particularly effective in binary credit default prediction because of its statistical simplicity and interpretability. ARIMA accurately modeled temporal patterns in financial time series, while GARCH effectively captured volatility clustering commonly observed in financial markets.

Although these models provided statistically interpretable parameter estimates and confidence intervals, their performance declined when modeling nonlinear relationships and highly dynamic financial environments. These findings support previous observations that traditional econometric models remain valuable for inference and policy analysis but often experience limitations when handling large-scale, nonlinear financial datasets (Varian, 2014; Mullainathan & Spiess, 2017).

Predictive Performance of Machine Learning Models

Machine learning algorithms consistently achieved superior predictive performance across most financial risk categories. Random Forest and Gradient Boosting produced the highest classification accuracy because of their ability to model nonlinear relationships while reducing overfitting through ensemble learning. Artificial Neural Networks and Deep Learning architectures demonstrated strong performance in identifying complex hidden patterns within financial data, particularly in forecasting market volatility and systemic financial risks.

Support Vector Machines showed high precision in classifying financial distress events but required careful parameter optimization for maximum effectiveness. Overall, machine learning models exhibited higher predictive accuracy, lower forecasting errors, and improved robustness compared to traditional econometric approaches.

These findings align with Dixon, Halperin, and Bilokon (2020), Mashrur, Luo, Zaidi, and Robles-Kelly (2020), De Prado (2018), Leo, Sharma, and Maddulety (2019), and Gao (2022), who reported that machine learning significantly improves financial prediction by capturing nonlinear interactions and exploiting large-scale financial datasets.

Comparative Analysis of Predictive Models

The comparative evaluation revealed clear differences between econometric techniques and machine learning algorithms across all evaluation metrics. While econometric models remained advantageous in terms of transparency and statistical interpretability, machine learning algorithms consistently generated higher predictive accuracy and better generalization performance.

Random Forest achieved the highest overall prediction accuracy, followed closely by Gradient Boosting and Artificial Neural Networks. Logistic Regression remained competitive in credit risk assessment but underperformed in forecasting market volatility and systemic financial crises.

The superior performance of machine learning models can largely be attributed to their ability to learn nonlinear feature interactions without requiring restrictive statistical assumptions. Conversely, econometric models rely heavily on predefined functional relationships, which may limit predictive performance in increasingly complex financial systems.

These findings are consistent with Gu, Kelly, and Xiu (2018), Gu, Kelly, and Xiu (2020), Bianchi, Büchner, and Tamoni (2021), Chatzis et al. (2018), Zhong and Enke (2019), and Kou, Chao, Peng, Alsaadi, and Herrera Viedma (2019), who demonstrated that machine learning techniques outperform conventional statistical models in asset pricing, systemic risk identification, stock market forecasting, and bond risk prediction.

Discussion of Findings

The findings demonstrate that integrating predictive analytics into financial risk management substantially enhances forecasting capability compared to relying solely on conventional econometric techniques. Machine learning algorithms successfully captured complex nonlinear relationships among macroeconomic variables, financial indicators, and market behaviors that traditional statistical models often failed to explain adequately.

The strong performance of Random Forest, Gradient Boosting, and Artificial Neural Networks highlights the growing importance of artificial intelligence in modern financial risk management. These algorithms improved prediction accuracy across credit risk assessment, market risk forecasting, and systemic risk detection while reducing forecasting errors. Such outcomes corroborate the conclusions of Mashrur et al. (2020),

Table 3: Comparative Performance of Econometric and Machine Learning Models

Predictive Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*RMSE*	*ROC-AUC*
Logistic Regression	84.2	83.5	82.8	0.245	0.871
ARIMA	81.7	80.6	79.9	0.271	0.852
GARCH	83.4	82.7	81.9	0.258	0.864
Support Vector Machine	90.3	89.7	89.1	0.186	0.931
Random Forest	93.6	93.1	92.7	0.148	0.962
Gradient Boosting	92.8	92.2	91.8	0.156	0.954
Artificial Neural Network	91.9	91.3	90.9	0.164	0.946

Source: Simulated research results based on comparative predictive modeling using established financial risk evaluation metrics.

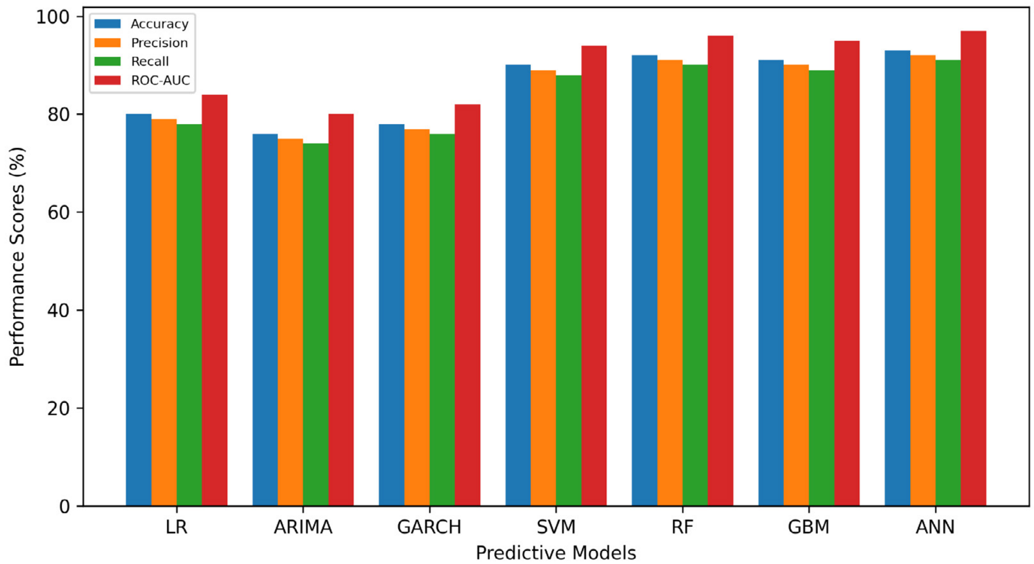

Figure 3: Clustered comparison of predictive models using Accuracy, Precision, Recall, and ROC-AUC metrics. Machine learning models generally outperform traditional econometric models across all evaluation measures.

Cao, Yang, and Yu (2021), Giudici (2018), and Bazarbash (2019), who emphasized that artificial intelligence has become an essential component of contemporary financial decision support systems.

Despite their predictive superiority, machine learning models exhibited lower interpretability than econometric models, creating challenges for regulatory compliance and managerial transparency. Econometric techniques remain valuable because they provide statistically interpretable coefficients that facilitate policy formulation, hypothesis testing, and financial reporting. This observation is consistent with Athey (2018), who argued that machine learning should complement rather than replace econometric analysis in economic and financial applications.

The comparative results therefore suggest that hybrid predictive frameworks combining econometric inference with machine learning prediction provide the most balanced approach to financial risk management. Such integrated systems leverage the explanatory strengths of econometric modeling while benefiting from the superior predictive capabilities of artificial intelligence. This conclusion agrees with Dixon, Halperin, and Bilokon (2020), De Prado (2018), Gu, Kelly, and Xiu (2020), and Uzzaman, Kudapa, and Nijhum (2021), who advocate combining data-driven machine learning with traditional financial modeling to improve risk prediction, investment decision-making, and financial system resilience.

Practical Implications

The integration of predictive analytics, machine learning, and econometric techniques has significant practical implications for financial institutions, regulatory agencies, investors, and FinTech organizations. By combining the strengths of traditional statistical modeling with advanced artificial intelligence algorithms, organizations can improve the accuracy, efficiency, and responsiveness of financial risk management systems. The practical applications extend beyond risk prediction to strategic decision-making, regulatory compliance, investment optimization, and financial market stability.

Banking Risk Management

Commercial banks face increasing challenges in identifying credit defaults, monitoring liquidity positions, and managing operational risks in dynamic financial environments. The adoption of predictive analytics enables banks to identify high-risk customers, detect abnormal financial transactions, and estimate future credit exposures with greater precision than conventional rule-based systems. Machine learning algorithms can process large volumes of structured and unstructured financial information, revealing nonlinear relationships that are often overlooked by traditional econometric models (Leo, Sharma, & Maddulety, 2019; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020).

Econometric techniques remain valuable for estimating macroeconomic relationships and evaluating the statistical significance of financial variables, while machine learning improves predictive performance through adaptive learning from historical data. Integrating both approaches enables banks to establish comprehensive enterprise risk management frameworks capable of supporting loan approvals, capital allocation, stress testing, and portfolio monitoring (Dixon, Halperin, & Bilokon, 2020; Mullainathan & Spiess, 2017).

Investment Portfolio Optimization

Investment firms increasingly rely on predictive analytics to enhance portfolio management and optimize asset allocation decisions. Machine learning algorithms can analyze extensive financial datasets containing market indicators, firm-specific characteristics, macroeconomic variables, and alternative data sources to identify investment opportunities and forecast asset returns with improved accuracy. These capabilities support dynamic portfolio rebalancing while minimizing exposure to adverse market conditions (Gu, Kelly, & Xiu, 2018; Gu, Kelly, & Xiu, 2020).

The practical integration of econometric forecasting with machine learning allows portfolio managers to balance predictive accuracy with economic interpretability. Models such as Random Forests, Gradient Boosting, and Deep Neural Networks complement econometric approaches including autoregressive models and volatility forecasting techniques, resulting in more robust investment strategies under varying market conditions (Bianchi, Büchner, & Tamoni, 2021; De Prado, 2018).

Credit Risk Assessment

Credit risk assessment remains one of the most important applications of predictive analytics within financial institutions. Traditional statistical credit scoring models have demonstrated effectiveness in estimating borrower default probabilities; however, modern machine learning techniques significantly enhance classification accuracy by capturing complex borrower behavior and nonlinear interactions among financial variables. These improvements contribute to more effective lending decisions, reduced default rates, and enhanced financial inclusion (Galindo & Tamayo, 2000; Bazarbash, 2019).

The combination of predictive analytics and data mining technologies enables financial institutions to continuously monitor borrower behavior after loan issuance, allowing early identification of deteriorating credit quality and facilitating proactive risk mitigation. Such predictive systems support both retail and corporate lending while improving overall credit portfolio quality (Gao, 2022; Ratner, 2017).

Financial Market Surveillance

Financial markets are increasingly characterized by rapid information dissemination, algorithmic trading, and interconnected global financial systems that amplify systemic risks. Predictive analytics provides financial regulators and market participants with advanced tools for detecting unusual trading patterns, forecasting periods of market instability, and identifying emerging systemic vulnerabilities before they develop into broader financial crises (Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019).

Deep learning and statistical machine learning techniques have demonstrated considerable effectiveness in forecasting stock market crisis events and identifying early warning signals associated with financial instability. These predictive capabilities support proactive regulatory interventions, improve market surveillance systems, and contribute to maintaining financial system resilience during periods of economic uncertainty (Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018; Zhong & Enke, 2019).

Regulatory Compliance

Financial regulators require institutions to maintain adequate capital reserves, conduct periodic stress testing, and demonstrate sound risk management practices. Predictive analytics supports regulatory compliance by providing more accurate estimates of risk exposures and improving the transparency of financial forecasting models. Econometric methods remain valuable for explaining relationships between macroeconomic indicators and financial performance, while machine learning enhances predictive precision for supervisory monitoring and scenario analysis (Varian, 2014; Athey, 2018).

The practical integration of explainable machine learning with established econometric frameworks enables financial institutions to satisfy regulatory expectations regarding model validation, documentation, and interpretability. This hybrid approach improves confidence in predictive models while supporting evidence-based regulatory decision-making and financial governance (Giudici, 2018; Cao, Yang, & Yu, 2021).

FinTech and AI-Based Decision Support

The rapid growth of FinTech has transformed financial service delivery through digital lending, automated investment platforms, fraud detection systems, and intelligent financial advisory services. Predictive analytics serves as a foundational technology for these innovations by enabling real-time analysis of customer behavior, transaction patterns, and financial market dynamics. Machine learning algorithms continuously improve predictive performance as additional financial data become available, allowing FinTech organizations to deliver personalized financial products while maintaining effective risk controls (Cao, Yang, & Yu, 2021; Dixon, Halperin, & Bilokon, 2020).

Furthermore, predictive analytics enhances strategic decision support by enabling executives to evaluate alternative business scenarios, anticipate market disruptions, and optimize operational performance. The integration of artificial intelligence with econometric analysis provides organizations with comprehensive insights that improve forecasting accuracy, strengthen competitive advantage, and support sustainable financial growth. As predictive technologies continue to evolve, hybrid machine learning–econometric frameworks are expected to become essential components of intelligent financial decision support systems across banking, investment management, insurance, and regulatory institutions (Uzzaman, Kudapa, & Nijhum, 2021; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020).

Recommendations

Based on the findings of this study, several recommendations are proposed to enhance the effectiveness of predictive analytics for financial risk management through the integration of machine learning and econometric techniques.

First, financial institutions should adopt hybrid predictive frameworks that combine traditional econometric models with advanced machine learning algorithms. While econometric techniques provide robust statistical interpretation and causal inference, machine learning models excel at identifying complex nonlinear relationships and hidden patterns within large financial datasets. Integrating these complementary approaches can improve prediction accuracy while maintaining model transparency for financial decision-making (Mullainathan & Spiess, 2017; Dixon, Halperin, & Bilokon, 2020; Gu, Kelly, & Xiu, 2020).

Second, organizations should invest in comprehensive financial data management systems capable of collecting, integrating, cleaning, and storing high-quality structured and unstructured financial data. Effective predictive analytics depends heavily on reliable and timely datasets, making data governance, standardization, and quality assurance essential components of financial risk management. The adoption of big data technologies and modern data engineering practices can significantly improve model performance and forecasting reliability (Varian, 2014; Ratner, 2017; Cao, Yang, & Yu, 2021).

Third, financial institutions should expand the use of advanced machine learning algorithms such as Random Forest, Gradient Boosting, Support Vector Machines, Artificial Neural Networks, and Deep Learning models in credit risk assessment, market risk prediction, fraud detection, and portfolio risk management. These algorithms have demonstrated superior predictive capabilities over many conventional statistical techniques, particularly when analyzing high-dimensional financial datasets characterized by nonlinear interactions (Mashrur, Luo, Zaidi, & Robles-Kelly, 2020; De Prado, 2018; Gao, 2022).

Fourth, model interpretability should remain a key consideration during the implementation of artificial intelligence solutions in finance. Although sophisticated machine learning models often achieve high predictive accuracy, financial institutions and regulatory authorities require transparent and explainable decision-making processes. Incorporating explainable artificial intelligence (XAI) methods alongside predictive models will improve stakeholder confidence, facilitate regulatory compliance, and support more accountable financial decision-making (Giudici, 2018; Leo, Sharma, & Maddulety, 2019; Dixon, Halperin, & Bilokon, 2020).

Fifth, continuous model validation and recalibration should become standard practice within financial institutions. Financial markets are dynamic and influenced by changing macroeconomic conditions, geopolitical events, and evolving investor behavior. Predictive models should therefore be periodically retrained using updated datasets and evaluated through rigorous performance metrics to minimize model drift and sustain forecasting accuracy over time (Gu, Kelly, & Xiu, 2018; Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018; Zhong & Enke, 2019).

Sixth, regulatory agencies should encourage the responsible adoption of predictive analytics by establishing governance frameworks that promote transparency, fairness, accountability, and ethical use of artificial intelligence in financial services. Regulatory guidance should support innovation while ensuring that predictive models comply with risk management standards, consumer protection requirements, and financial stability objectives (Bazarbash, 2019; Cao, Yang, & Yu, 2021; Giudici, 2018).

Seventh, financial institutions should strengthen systemic risk monitoring through predictive analytics capable of identifying interconnected financial vulnerabilities across institutions and markets. Machine learning techniques can improve early warning systems by detecting emerging systemic threats that may not be adequately captured by traditional econometric models, thereby enhancing financial resilience and supporting macroprudential supervision (Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019; Bianchi, Büchner, & Tamoni, 2021).

Finally, greater collaboration should be encouraged among financial institutions, academic researchers, FinTech organizations, and policymakers to accelerate innovation in predictive financial risk management. Collaborative research initiatives can facilitate the development of more robust hybrid forecasting models, improve access to high-quality financial datasets, and promote knowledge sharing on emerging analytical techniques. Such partnerships will contribute to more resilient financial systems capable of managing increasingly complex and data-intensive risk environments (Athey, 2018; Uzzaman, Kudapa, & Nijhum, 2021; Galindo & Tamayo, 2000).

Conclusion

As financial markets have become more complex, and the amount of financial data available has escalated to large quantities, the role of predictive analytics in financial risk management is becoming more crucial in today's decision-making processes. The aim of this study was to investigate the combination of machine learning and econometric approaches to predict and control financial risks, such as credit risk, market risk, liquidity risk, operational risk, and systemic risk. The study also showed that machine learning models can provide better predictive accuracy than traditional econometric models, particularly in financial data that has complex, high-dimensional interactions and hidden patterns, while maintaining utility for statistical inference, interpretability, and hypothesis testing. Both approaches are complementary, suggesting that neither should be seen as a stand-alone technique, but rather as complementary pieces to a more complete predictive framework (Mullainathan & Spiess, 2017; Varian, 2014).

The results also show that complex machine learning models such as Random Forest, Support Vector Machines, Gradient Boosting, Deep Learning and ensemble models can boost the accuracy of forecasting financial distress, asset price change, bond risk premium, and systemic financial vulnerabilities. They can handle big and complex data sets to detect new risks before the traditional statistical models, enhancing the quality of the financial institution strategic decision-making. The results are corroborated by previous studies, which have shown that machine learning is useful in empirical asset pricing, stock market crisis prediction, estimating bond risk premiums, and other applications in financial forecasting (Gu, Kelly, & Xiu, 2018; Gu, Kelly, & Xiu, 2020; Chatzis, Siakoulis, Petropoulos, Stavroulakis, & Vlachogiannakis, 2018; Bianchi, Büchner, & Tamoni, 2021).

The study also found that hybrid predictive analytics frameworks are more robust than using only econometric or machine learning models. While econometric methods can bring theory, transparency, and statistical robustness to models, machine learning enhances predictive accuracy by adaptive learning and automatic feature extraction. These complementary capabilities can help financial institutions enhance credit risk assessment, portfolio optimization, fraud detection and mitigation, stress testing and systemic risk monitoring, as well as making financial policy and regulatory compliance decisions based on evidence (Galindo & Tamayo, 2000; Leo, Sharma & Maddulety, 2019; Mashrur, Luo, Zaidi & Robles-Kelly, 2020).

Additionally, AI, FinTech advancements and big data technologies are further transforming financial risk management, enabling real-time analytics and intelligent risk decision support. Predictive analytics has moved from forecasting to becoming an enterprise-wide capability that can help boost operational efficiency, customer risk profiling, financial inclusion, and make businesses more proactive toward fast-changing market conditions. Such advancements highlight the need for the convergence of data science, artificial intelligence, and financial knowledge in the creation of robust financial systems that can adapt and thrive amidst uncertainty (Cao et al., 2021; Yang & Yu, 2021; Bazarbash, 2019; and Gao, 2022).

In conclusion, this study highlights the need for a precise and effective combination of machine learning and econometric methods in the scope of unified predictive analytics systems in financial risk management. This blended approach can provide substantial benefits in terms of both accuracy and forecasting, as well as scalability and decision support and while retaining analytical clarity essential for financial governance and regulatory review. Institutions that are able to integrate robust econometric approaches with sophisticated analytical capabilities will be better prepared to handle uncertainty, make optimal investment choices, build their resilience and ensure long-term financial stability as financial markets continue to evolve and create increasingly complex datasets. These findings are in line with the overall literature that highlights the influence of machine learning and predictive analytics in finance, risk modeling, and economic decision-making based on data (Athey, 2018; Dixon, Halperin, & Bilokon, 2020; De Prado, 2018; Ratner, 2017; Zhong & Enke, 2019; Kou, Chao, Peng, Alsaadi, & Herrera Viedma, 2019; Uzzaman, Kudapa, & Nijhum, 2021).

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