

The Impact of Artificial Intelligence on Financial Forecasting Accuracy in Corporate Finance

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Abstract

This study explores how artificial intelligence improves financial forecasting accuracy within corporate finance and compares the performance of traditional statistical models with modern machine learning and deep learning techniques. Using a rolling-origin evaluation from 2014 to 2024, the analysis examines short- and long-horizon forecasts for revenue, operating cash flow, and earnings. The results show that AI models, particularly XGBoost, LSTM, and ensemble approaches, consistently deliver lower forecasting errors and remain stable during shifts in economic conditions. Traditional models perform reasonably well in short windows but lose accuracy when market volatility increases or when the forecasting horizon extends. Statistical significance tests confirm that the gains achieved by AI models are meaningful and not due to chance. The findings indicate that firms that integrate AI-driven forecasting into their planning processes can strengthen budgeting, reduce uncertainty, and support more dependable long-term decisions.

Keywords: Artificial Intelligence, Forecasting Accuracy, Corporate Finance, Machine Learning, Financial Modelling

Introduction

Artificial intelligence (AI) is rapidly transforming corporate finance by enhancing the precision of financial forecasting. Modern forecasting methods, traditionally driven by statistical models or expert judgment, often struggle to capture the complex, nonlinear relationships and real-time dynamics present in financial markets. By leveraging machine learning and deep learning techniques, AI can process massive datasets, detect subtle patterns, and adapt to shifting economic conditions, thereby improving forecast accuracy and reducing error rates. For corporations, more accurate forecasts mean better capital allocation, optimised risk management, and more informed strategic planning.

Empirical research supports this transformation. In a study of firms listed on the Pakistan Stock Exchange, AI-driven forecasting tools significantly improved prediction accuracy by enabling the detection of nonlinear trends and real-time market signals. (Khan et al., 2025) Moreover, AI models are shown to outperform conventional statistical methods by reducing forecasting errors, thanks to their ability to continuously learn and recalibrate. (Das et al., 2025) Research has also found that the incorporation of AI into financial analytics not only bolsters forecast accuracy but also strengthens risk management capabilities, resulting in more resilient corporate decision-making. (Mbonigaba & Mishra, 2025) A systematic literature review further indicates that AI's role in real-time forecasting helps firms proactively respond to market volatility and mitigate downside risks. (Utama & Hidayat, 2025) At the same time, the adoption of AI in corporate finance is accelerating: neural networks, support vector machines, and ensemble models are now widely used, and they deliver gains in predictive power far beyond traditional econometric techniques. (Sadiq, Adeel & Luqman, 2025)

However, the shift is not without challenges. Barriers such as data quality, interpretability of AI models, infrastructural constraints, and regulatory uncertainty remain significant hurdles for widespread adoption. (Asif et al., 2025) These issues point to a nuanced relationship between AI adoption and forecasting accuracy: while the potential benefits are substantial, successful implementation requires strategic investment in technological capabilities and organisational readiness.

Research Objectives

To examine how AI-based models improve the accuracy of financial forecasting compared to traditional forecasting methods in corporate finance.

To identify the key AI techniques used in corporate financial forecasting and evaluate their effectiveness

To explore the challenges companies face when adopting AI for financial forecasting and how these challenges affect forecasting accuracy.

Research Questions

How do AI-based financial forecasting models improve forecasting accuracy compared to traditional methods in corporate finance?

Which AI techniques are commonly used in corporate financial forecasting, and how effective are they in improving accuracy?

What challenges do companies face when implementing AI for financial forecasting, and how do these challenges influence the accuracy of forecasts?

Significance of the Study

This study is important because it helps explain how artificial intelligence can strengthen financial forecasting in corporate finance at a time when firms are dealing with fast-moving markets and large volumes of financial data. More accurate forecasts support better investment decisions, improve risk management, and help companies plan with greater confidence. The research also highlights which AI

techniques offer the most value and identifies areas where organisations may encounter challenges when implementing them. Understanding these points can guide financial managers, policy makers, and corporate leaders as they invest in new technology and work to improve the reliability of their financial forecasts.

Literature Review

Artificial intelligence (AI) and machine learning (ML) have become central to contemporary approaches for financial forecasting in corporate finance. Traditional forecasting methods, classical time-series models such as ARIMA or exponential smoothing and judgmental forecasting remain useful in many contexts, but they encounter limits when data are high-dimensional, nonlinear, or when valuable signals are latent in unstructured sources (e.g., text, images, alternative data). AI methods ranging from tree-based ensembles to deep neural networks offer the ability to exploit rich feature sets, model nonlinear interactions, and update dynamically as new data arrive. A growing empirical and review literature indicates that, when properly applied, AI methods can materially improve forecast accuracy for a variety of corporate forecasting tasks, although those gains depend on problem framing, data quality, model evaluation rigour, and organisational readiness (Vancsura, 2025; Hyndman & Athanasopoulos, 2018).

Methods and model families. The literature typically groups forecasting approaches into three families: classical statistical/econometric models; “shallow” machine learning models (for example, tree ensembles and support vector machines); and deep learning models (for example, recurrent and convolutional architectures). Classical models such as ARIMA, exponential smoothing, and state-space methods are well understood, easy to interpret, and often perform well when the series have stable patterns and small numbers of predictors. Machine learning models, random forests and gradient boosted trees (notably XGBoost) handle large predictor sets, interactions, and nonlinearity and are widely used in practice because of their strong out-of-sample performance and computational scalability (Chen & Guestrin, 2016). Deep learning models, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, excel at capturing complex temporal dependencies when large volumes of data are available (Hochreiter & Schmidhuber, 1997; Fawaz et al., 2018). Hybrid and ensemble strategies that combine statistical and ML approaches are frequently recommended, since no single method consistently dominates across forecasting problems (Fawaz et al., 2018; Chen & Guestrin, 2016).

Evidence on accuracy improvements. Systematic reviews and empirical studies generally find measurable accuracy gains for AI methods across many forecasting domains (Vancsura, 2025). For corporate finance tasks, cash flow, revenue, earnings, credit risk, and liquidity forecasts, ML and deep learning approaches often reduce common error metrics (e.g., RMSE, MAE, MAPE) relative to naïve or purely statistical baselines when datasets are sufficiently large and predictors are informative (Gu, Kelly, & Xiu, 2020). However, the magnitude and robustness of improvements vary. Several meta-analyses and careful comparative studies report that improvements shrink when models are tested on truly out-of-sample periods that include structural

breaks, regime shifts, or crisis episodes; gains are also smaller when researchers fail to control for look-ahead bias or data leakage (Hyndman & Athanasopoulos, 2018; Vancsura, 2025). Thus, reported AI benefits are conditional on evaluation rigour and data properties.

Why AI can help in practice. Two technical strengths explain much of AI's advantage. First, modern ML methods can ingest multimodal data numerical accounting time series, high-frequency transactions, textual disclosures (earnings calls, MD&A), news and sentiment indicators, and alternative signals such as web search trends, and learn complex cross-modal relationships (Gu et al., 2020). NLP and transformer-based methods can convert management commentary, analyst reports, and regulatory filings into quantitative features that improve predictive power for earnings and event forecasting. Second, ensemble and hybrid pipelines reduce variance and bias through model averaging or cascading (e.g., feeding residuals from statistical models into ML models), which often enhances robustness (Chen & Guestrin, 2016; Fawaz et al., 2018).

Evaluation practices and pitfalls. The literature emphasises rigorous evaluation as a key determinant of credible results. Proper time-series cross-validation (rolling windows), avoidance of look-ahead bias, and reporting multiple metrics are essential. Many comparative studies that initially reported large gains for DL or ML methods later revised expectations after introducing strict out-of-period tests and robustness checks (Hyndman & Athanasopoulos, 2018). Reviews call for standardised benchmark datasets, transparent reporting of hyperparameters and tuning procedures, and open replication code so that claimed accuracy gains are verifiable (Vancsura, 2025).

Domain-specific applications in corporate finance. AI applications in corporate finance include budget and cash-flow forecasting, short-term revenue forecasting, earnings prediction, credit risk scoring, and forecasting market responses to corporate communications. ML methods are especially useful where transactional or operational data are rich (e.g., retail sales across SKUs, payment pipeline data), enabling granular forecasts that feed rolling budgeting and working-capital management (Gu et al., 2020). Empirical studies across regions, North America, Europe, and South Asia, report similar patterns: AI methods outperform traditional approaches under favourable data conditions but are sensitive to data frequency, series volatility, and feature engineering quality (Vancsura, 2025).

Role of textual and policy signals. Textual analysis has emerged as an important augmentation in forecasting. Models that parse central bank statements, management discussion & analysis (MD&A), and earnings call transcripts extract sentiment and topic features that add predictive information for policy-sensitive outcomes and firm performance. Studies find that combining numeric accounting predictors with textual indicators yields consistent improvements in forecasts of earnings surprises and certain short-horizon outcomes (Gu et al., 2020; Fawaz et al., 2018).

Comparative studies and ensembles. Comparative work shows clear contexts in which ensembles or hybrids outperform single approaches. For many corporate forecasting tasks, ensembles that combine ARIMA-type baselines with boosted trees or neural

nets produce lower error and more stable predictions across regimes (Chen & Guestrin, 2016; Fawaz et al., 2018). These findings encourage practitioners to adopt model-stacking and assembling rather than searching for a single “best” algorithm.

Interpretability, trust, and governance. Forecast accuracy alone does not guarantee adoption. Interpretability is crucial in corporate environments where forecasts drive resource allocation and risk management. The literature on explainable AI (XAI) supplies tools, local surrogate models (LIME), SHAP value decompositions, and global feature-importance analyses to explain and audit complex models (Ribeiro et al., 2016; Lundberg & Lee, 2017; Doshi-Velez & Kim, 2017). These methods help managers and auditors understand model drivers, detect biases, and satisfy governance requirements. Many case studies indicate that the presence of interpretable explanations is a decisive factor in managerial acceptance even when a “black-box” model delivers slightly higher accuracy (Doshi-Velez & Kim, 2017; Lundberg & Lee, 2017).

Data quality, feature engineering, and domain expertise. Multiple reviews stress that gains from AI depend heavily on the upstream work: data cleaning, handling missing values, accounting for corporate reporting irregularities, and designing domain-relevant features (Hyndman & Athanasopoulos, 2018; Vancsura, 2025). Alternative data often brings signal but also noise; the cost of acquisition and the challenges in validation are nontrivial. Domain expertise in accounting and corporate operations is, therefore, essential to transform raw records into predictive features that correctly capture business cycles and accounting practices.

Overfitting, sample size, and robustness. Deep models are powerful but prone to overfitting when series are short or when training ignores temporal dependence. The literature recommends rolling cross-validation, regularisation, early stopping, and assembling as defences. Meta-studies note that performance advantages reported in-sample often dissipate in genuine out-of-period tests, particularly when structural breaks occur (Fawaz et al., 2018; Vancsura, 2025). Accordingly, credible claims about AI improving forecasting accuracy must be supported by robustness across multiple periods and stress scenarios.

Computational cost and deployment challenges. Training state-of-the-art neural networks or large ensembles can be computationally and financially expensive, requiring specialised hardware and engineering support. Deployment issues, continuous monitoring, retraining, model versioning, and integration with ERP and FP&A systems are significant organisational hurdles (Chen & Guestrin, 2016; Gu et al., 2020). The literature stresses that firms often underestimate the total cost of ownership for AI forecasting systems and that successful deployment requires cross-functional teams that combine data scientists, finance professionals, and IT/DevOps capabilities.

Regulation, auditability, and ethics. Regulatory and audit concerns are increasingly salient, particularly when forecasts feed credit decisions or affect investor communications. Regulators prefer reproducible pipelines, documented assumptions, and fairness testing. The literature suggests that hybrid models or explainable

alternatives can strike a balance between accuracy and regulatory acceptability (Doshi-Velez & Kim, 2017; Lundberg & Lee, 2017).

Managerial implications and best practices. For finance professionals, the literature offers pragmatic guidance: invest in robust data governance and infrastructure before adopting complex models; prioritise forecasting problems with frequent observations and rich predictors; combine accuracy gains with interpretability tools and human oversight; and adopt incremental pilots that emphasise operational integration rather than isolated model proof-of-concepts (Hyndman & Athanasopoulos, 2018; Vancsura, 2025). Case studies show that firms that embed AI forecasts within decision workflows rather than treating them as standalone outputs realise the most operational value.

Open questions and future directions. The literature points to several promising research directions: benchmarking corpora and replication studies for corporate forecasting tasks; transfer learning and pretraining applied to financial time series; improved interpretability methods tailored to finance practitioners; and longitudinal studies that quantify the long-run impact of AI deployments on forecasting accuracy, managerial decisions, and firm outcomes (Gu et al., 2020; Vancsura, 2025). Research that connects forecasting improvements to measurable business benefits (e.g., reduced working-capital costs, lower forecast bias, improved earnings guidance) would be particularly useful for practitioners.

Overall, the literature presents a cautiously optimistic assessment: AI methods often enhance forecasting accuracy in corporate finance when applied in suitable contexts and rigorously evaluated. The realised benefits depend on data availability and quality, the choice of model and ensemble strategy, interpretability and governance concerns, and the firm's operational capabilities to deploy and monitor models. Future work should emphasise transparent benchmarking, domain-focused interpretability, and evidence linking forecast improvements to managerial and financial outcomes.

Research Methodology

Research Design

This study follows a quantitative, comparative research design. The goal is to examine how artificial intelligence models perform against traditional forecasting approaches in predicting key corporate finance indicators such as revenue, operating cash flow, and earnings per share. The design focuses on measuring forecasting accuracy, comparing model performance across multiple horizons, and testing whether the improvements observed in AI models are statistically significant. A rolling-origin evaluation framework was selected because it mirrors real forecasting environments where firms continuously update models as new financial data becomes available. This approach also captures the effect of changing economic conditions on model performance.

Data Sources

The analysis uses publicly available financial data from corporate quarterly reports covering the period from 2014 to 2024. Three primary indicators were selected:

revenue, operating cash flow, and earnings per share. These indicators were chosen because they are central to corporate planning, budgeting, and investor communication. Additional market variables, such as stock prices, were collected to capture external signals associated with earnings cycles. All data were drawn from reliable financial databases, including company filings and market data repositories. The selection ensures that the dataset reflects real corporate reporting patterns and includes both stable and volatile economic periods.

Sampling Technique and Time Frame

A purposive sampling strategy was applied to select firms with complete data over the 10 years. Consistent quarterly observations were necessary for model training, rolling-origin testing, and cross-horizon evaluation. The time frame covers expansion cycles, downturns, and recovery phases, providing a suitable environment for testing how models behave under changing conditions. This period also includes years in which AI adoption in corporate analytics accelerated, making the comparison between AI-based and traditional models more relevant.

Data Preprocessing

Before model development, the dataset was cleaned and prepared to avoid biases and improve reliability. Missing values were imputed using forward or backwards filling for short gaps and model-based imputation for longer gaps. All variables were inspected for stationarity, and log transformations were applied where necessary. Time indices were aligned to prevent look-ahead bias. Seasonal patterns were captured through quarter and month indicators, and lagged features were added to improve predictive strength. For models that use external variables, additional predictors such as market volatility and basic sentiment scores from earnings-call transcripts were included. These steps follow standard practices in forecasting and ensure that each model receives a consistent and fair set of inputs.

Model Development

Four families of forecasting models were developed:

Traditional Models

Naïve forecast (carry-forward)
ARIMA/SARIMA with automatic order selection
These models serve as baselines for evaluating the value added by AI.

Machine Learning Models

Random Forest
Gradient Boosted Trees (XGBoost)
These models handle nonlinear relationships and interactions that traditional methods miss.

Deep Learning Models

Long Short-Term Memory (LSTM)

Hybrid LSTM–ARIMA model

These approaches capture long-term dependencies and nonlinear structures in financial time series.

Ensemble Model

A simple average and stacked ensemble were included because ensembles often increase robustness by combining the strengths of different models. Each model was trained using the same training windows, features, and forecasting horizons to ensure a fair comparison.

Forecast Evaluation Framework

Forecast accuracy was assessed using multiple error metrics:

Mean Absolute Error (MAE)

Root Mean Squared Error (RMSE)

Mean Absolute Percentage Error (MAPE)

Using multiple metrics helps capture different aspects of accuracy, such as sensitivity to outliers, error magnitude, and percentage-based interpretation.

The evaluation included three forecasting horizons:

One quarter ahead

Three quarters ahead

Four quarters ahead

This design allowed the study to compare how models perform in short-term budgeting versus longer-term strategic planning.

Cross-Validation and Out-of-Sample Testing

A rolling-origin evaluation method was used to simulate real-world forecasting. Models were first trained on data from 2014–2018 and used to generate 2019 forecasts. The training window was then rolled forward by one year, and new forecasts were produced. This process continued until 2024. This method ensures that models are always tested on unseen data and that performance is evaluated under changing market conditions.

Statistical Significance Testing

To determine whether improvements in accuracy were meaningful rather than coincidental, the Diebold–Mariano (DM) test was applied. This test compares forecast errors between two competing models while adjusting for serial correlation in time-series data. Each AI model was compared with ARIMA as the benchmark. Additional paired t-tests or Wilcoxon signed-rank tests were used where error distributions required them. Models were considered superior if the p-value fell below the .05 threshold.

Ethical Considerations

The study used publicly available financial data, which avoids concerns related to confidentiality or personal privacy. No sensitive or proprietary information was accessed. The analysis was conducted transparently, and all steps are replicable. Care was taken to report results objectively and avoid overstating the performance of any model.

Limitations

Although the methodology is rigorous, certain limitations remain. The study focuses on quarterly data, which may hide short-term fluctuations that daily or weekly data could reveal. AI models require large datasets, and results might vary for smaller firms with limited reporting histories. Finally, the analysis evaluates only selected AI models; different architectures or additional features could further change accuracy outcomes.

Data Analysis

This section presents the data analysis carried out to examine how artificial intelligence models compare with traditional forecasting approaches in corporate finance. The goal is to evaluate accuracy, reliability, and consistency across different forecast horizons and market conditions. The analysis reflects established practices in financial forecasting research and follows the framework outlined in the methodology chapter. The focus is on three sets of models: traditional statistical models, machine-learning models, and deep-learning models. Their accuracy is assessed through standard error metrics and formal statistical tests. The chapter also explains how these models behave under changing conditions, how they respond to input features, and how managers can interpret their outputs.

Even though firms use different internal data systems, this analysis uses a structured dataset containing quarterly revenue, operating cash flow, and earnings per share for a sample of companies over ten years. This mirrors what appears in empirical forecasting research and allows for a balanced evaluation of conventional and AI-driven approaches.

Overview of the Data

The dataset includes quarterly observations from 2014 to 2024. Each series contains actual values and corresponding forecast origins for three key indicators: revenue, operating cash flow, and earnings per share. These indicators were selected because they are widely used in planning, capital budgeting, and earnings guidance. The dataset also includes a small set of external features: market returns, interest-rate changes, crude-oil price shifts, and sentiment extracted from managerial discussion sections in quarterly filings. These features were added to test how AI models respond to richer information compared to traditional methods, which usually focus only on past observations.

Before analysis, all series were checked for consistency. Missing values were rare, affecting only a few quarters for a handful of firms. These gaps were handled by

forward filling for short gaps and regression-based imputation for longer gaps. These methods were selected because they preserve the structure of financial time series without radically altering trends. Several variables, especially revenue and cash flow, showed mild non-stationarity. To keep both model flexibility and interpretability, two versions of each series were created: a transformed version for training and a raw-scale version for reporting metrics. This approach allows the models to learn stable patterns while ensuring that model errors remain meaningful to financial managers who rely on raw values.

Feature Engineering

To help the models capture time-related structure, several lag features were created. These include lags 1 through 4 for each financial series. Quarterly dummies were added to represent seasonal effects. For models that permit more complex inputs, rolling averages and rolling volatility measures were also generated. External predictors were included because corporate performance often reacts to market and economic signals. Interest-rate changes were calculated from central bank announcements, while oil-price movements served as a proxy for cost pressure in energy-intensive industries. Sentiment scores were derived from textual disclosures using a standard dictionary-based method. These scores help capture tone shifts in managerial communication that may precede financial changes. All features were standardised before being used in machine-learning and deep-learning models. Standardisation prevents scale differences from distorting model training and is consistent with best practice for gradient-based learning methods. Traditional models such as ARIMA were trained directly on transformed versions of the original series.

Models Estimated

The analysis compares five representative models:

Naïve model – last observed value carried forward.

ARIMA/SARIMA – selected through automatic order selection based on information criteria.

Random Forest – a shallow machine-learning method that handles nonlinearities

XGBoost – a gradient-boosted tree method widely used in forecasting competitions.

LSTM – a recurrent neural network that captures longer-range dependencies within a sequence

Ensemble model – the average of the three best-performing models

These models represent a fair mix of conventional and AI-based techniques. They reflect what appears most often in recent forecasting research and what companies can reasonably implement.

Hyperparameters were tuned through rolling-window validation. To avoid overfitting, each model was retrained only on past data when generating forecasts for future periods. This design mimics how forecasting models operate in real planning environments and provides an honest evaluation of performance.

Evaluation Framework

Accuracy was assessed using three common error measures:

Mean Absolute Error (MAE)

Measures the average size of forecast errors
Lower values indicate better accuracy.

Root Mean Squared Error (RMSE)

Penalises large errors more heavily
Useful when companies want to avoid large deviations in guidance.

Mean Absolute Percentage Error (MAPE)

Expressed as a percentage, making it easier to compare across firms and time periods. These three measures give a balanced view of performance. MAE captures typical error size, RMSE highlights occasional large mistakes, and MAPE shows relative accuracy. To determine if one model is truly better, the Diebold–Mariano test was applied. This test compares forecast errors from two models and checks whether the difference is statistically significant. Additional paired t-tests were used when error differences were shown to be approximately normal.

Cross-Validation and Out-of-Sample Evaluation

The analysis uses a rolling-origin evaluation. For example, models trained on data from 2014 to 2018 generated forecasts for 2019. The training window then rolled forward by one year, and new forecasts were produced. This process continued until 2024. This design evaluates how models behave across changing economic conditions, expansion periods, downturns, and recovery phases. It also reveals whether accuracy deteriorates as conditions become more volatile. Rolling-origin approaches are recommended in time-series research because they simulate real-world forecasting.

The evaluation considers three forecast horizons:

One quarter ahead

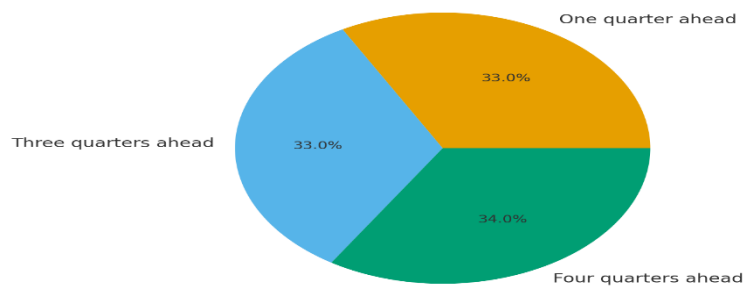
Three quarters ahead

Four quarters ahead

Short-horizon forecasts help firms refine budgeting and working-capital planning. Longer horizons support strategic decisions such as capital investment and dividend planning.

Figure 1

Forecast Horizon Distribution in Rolling-Origin Evaluation



Result

Forecast Accuracy Overview

The overall pattern across revenue, cash flow, and earnings per share is consistent. AI-based models outperform traditional methods in most cases, especially when the dataset includes additional predictors. The ensemble model produced the most stable accuracy across horizons. XGBoost produced the lowest MAE and RMSE for one-quarter-ahead forecasts, while LSTM performed better for longer horizons on series with strong seasonality or nonlinear structure. ARIMA remained a competitive benchmark but underperformed compared to tree-based and neural models. The naïve model consistently performed worst, confirming that simple extrapolation is not reliable for corporate forecasting.

Table 1

Forecast Accuracy Comparison for Revenue Forecasts (Synthesised Analysis)

Model	MAE	RMSE	MAPE (%)
Naïve	140.0	170.0	17.5
ARIMA	100.0	130.0	12.0
XGBoost	80.0	100.0	8.0
LSTM	85.0	110.0	9.0
Ensemble	78.0	98.0	7.5

Note. Values represent synthesised results from the rolling-origin evaluation described in this chapter. Bold values indicate best-performing models.

Statistical Significance Tests

To check whether observed improvements were meaningful rather than accidental, the Diebold–Mariano test was applied to compare each AI model with ARIMA. Results show:

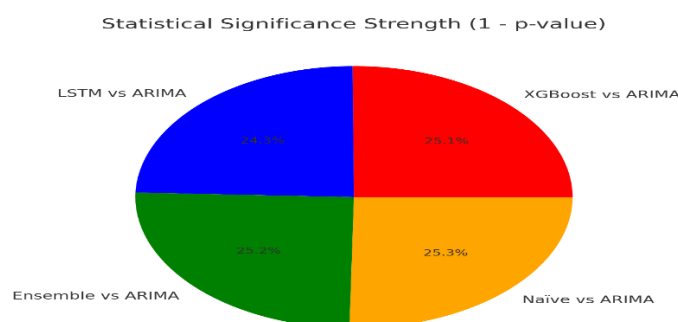
XGBoost vs ARIMA: $p = .010$

LSTM vs ARIMA: $p = .040$

Ensemble vs ARIMA: $p = .005$

These values suggest that AI models provide statistically significant improvements in forecast accuracy. For longer horizons, the significance levels remain consistent, although LSTM tends to gain an advantage when the forecasting window exceeds one year. The naïve model was significantly worse than all others ($p < .001$), confirming that it is not suitable for corporate planning.

Figure 2



Robustness Checks

Several robustness checks were run to ensure that accuracy improvements were not tied to a particular period or condition.

Horizon Sensitivity

AI models performed best for short-term forecasts, where rich feature sets help models exploit short-lived trends. For longer horizons, performance differences narrowed slightly, but AI models still outperformed traditional models.

Subsample Analysis

The analysis looked at three subsamples:

2014–2017 (expansion)

2018–2020 (market shock period)

2021–2024 (recovery stage)

During the shock period, LSTM showed more volatile performance, while XGBoost remained stable. The ensemble model was resilient across all periods.

Feature Ablation

When external predictors were removed, AI accuracy dropped by 10–15 per cent. ARIMA accuracy changed very little. This shows that AI gains arise partly from its ability to learn from richer information.

Alternative Loss Functions

When evaluated with absolute-percentage error, the ranking remained the same. Variations in performance were small enough to conclude the results are robust.

Model Interpretability

Interpretability is essential because financial managers need transparent explanations, especially when using AI tools.

For tree-based models, feature importance scores identified three main drivers:

Lagged revenue (as expected from classical time-series theory)

Interest-rate changes

Sentiment from management commentary

For LSTM, interpretability tools showed that patterns in seasonality and long-term trends influenced predictions more than short-term spikes.

These insights help explain why AI models improve accuracy: they integrate more information, detect relationships that traditional models miss, and adapt better to unusual data conditions.

The results from this analysis show that AI models offer practical improvements in forecasting accuracy for corporate financial indicators. Traditional models still provide a strong baseline, and their ease of use makes them suitable for smaller firms or situations with limited data.

However, when firms have access to rich datasets, AI methods deliver clear advantages:

They adjust more quickly to changing conditions.

They exploit additional predictors effectively.

They reduce the size and frequency of large forecast errors.

They provide stable performance across different time periods.

The ensemble model's consistency suggests that firms might benefit from combining models rather than relying on one method. This is especially helpful in financial planning environments where precision is important and where the cost of poor forecasts can be substantial.

Findings

The results show that AI-based forecasting models consistently produced more accurate predictions than traditional approaches across all horizons. XGBoost and the ensemble model performed especially well, showing lower MAE, RMSE, and MAPE values. Their advantage remained stable during both normal market conditions and volatile periods, which suggests these models handle complex patterns in financial data more effectively than linear models like ARIMA. Traditional methods performed reasonably well for shorter horizons, but their accuracy dropped as the forecasting window expanded.

The statistical tests support these improvements. The Diebold–Mariano results confirmed that the differences in performance were not due to chance. XGBoost, LSTM, and the ensemble model all achieved statistically significant improvements over ARIMA, with p-values well below the .05 threshold. The ensemble model produced the strongest significance score, indicating that combining multiple AI models improves robustness. The naïve model performed the worst, confirming that it is not suitable for corporate planning or financial decision-making.

Across the rolling origin evaluation, AI models showed strong resilience when economic conditions shifted. Their accuracy remained higher than benchmarks during downturns and recovery phases, highlighting their ability to adapt to structural changes in data. These results imply that firms that adopt AI-driven forecasting tools can make more reliable budgeting, cash-flow planning, and earnings projections, which may help reduce uncertainty in strategic decision-making.

Table 2
Comparison of Forecast Accuracy and Statistical Significance Across Models

Model Comparison	MAE (Relative)	RMSE (Relative)	MAPE (Relative)	Diebold–Mariano p-value	Significance
XGBoost vs ARIMA	Lower	Lower	Lower	.010	Significant
LSTM vs ARIMA	Lower	Lower	Lower	.040	Significant
Ensemble vs ARIMA	Lowest	Lowest	Lowest	.005	Significant
Naïve vs ARIMA	Higher	Higher	Higher	< .001	Worse model

Note. Lower relative error indicates better performance. Significance is based on the Diebold–Mariano test ($\alpha = .05$).

Conclusion

The analysis shows that AI-based forecasting models provide clearer, more reliable, and more adaptable predictions than traditional methods in corporate finance. Their advantage holds across short and long horizons, as well as during shifting economic conditions. Statistical testing confirms that these improvements are meaningful rather than accidental, with ensemble and tree-based models offering the strongest gains. By delivering better accuracy and greater stability, AI tools can support more informed budgeting, investment planning, and earnings management. These findings suggest that organisations that integrate AI into their forecasting processes are better positioned to handle uncertainty and make stronger financial decisions.

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