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Explainable and hybrid AI approaches for corporate financial performance forecasting: A structured literature review

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Abstract- Research on forecasting corporate financial performance has shifted from traditional econometric models toward machine learning, deep learning, and high-precision hybrid AI architectures. These methods can capture nonlinear relationships, high-dimensional structures, and regime shifts in financial data more effectively, which has driven their widespread adoption. At the same time, practical requirements for interpretability, regulatory transparency, and model risk governance have made explainable AI an essential component of modern forecasting systems. This Structured Literature Review synthesizes ninety-three empirical studies published between 2000 and 2025 using a PRISMA-informed selection procedure. It evaluates the actual contributions of hybrid AI and explainable AI to corporate financial performance forecasting. The review shows that econometric and machine learning hybrids, ensemble learning models, DEA-based machine learning frameworks, deep learning combined with signal processing, and multimodal architectures are extensively used and collectively improve predictive accuracy and stability. Methods such as SHAP, LIME, partial dependence, and individual conditional effect analyses, attention mechanisms, and counterfactual reasoning significantly enhance model interpretability, support managerial decision-making, and strengthen compliance with regulatory expectations. Despite these advances, challenges remain, including the predominance of static data analysis, limited generalizability, and the lack of architectures designed for realistic deployment. Future research should focus on multimodal data integration, causal AI, adaptive, real-time learning frameworks, and explainable hybrid systems aligned with regulatory and governance requirements.

Keywords-Corporate financial performance, Hybrid artificial intelligence, Explainable artificial intelligence, Machine learning, Forecasting

1. INTRODUCTION

In contemporary business environments, accurately assessing and forecasting corporate financial performance is essential for strategic planning, investment decision-making, risk management, regulatory compliance, and shaping market expectations. Beyond traditional indicators such as return on assets, return on equity, Tobin's Q, profit margins, and market returns, composite efficiency measures, including data envelopment analysis, have become widely used. These indicators enable a more comprehensive evaluation of a firm's value, sustainable growth prospects, and long-term competitive position.

As a result, producing high-precision forecasts for these measures is not merely a theoretical exercise but a practical necessity for policymakers at both macro and micro levels, as well as for investors, financial institutions, insurers, and corporate managers who rely on timely and evidence-based strategic decisions. Traditional econometric models have long served as the foundation for forecasting corporate financial performance. However, their reliance on linear assumptions limits their ability to capture nonlinear interactions among variables and to represent dynamic structural changes in financial data. As financial systems have become increasingly volatile and interconnected, driven by market psychology and complex behavioral patterns, machine learning and deep learning approaches have gained prominence. These methods have reshaped analytical practices in economics and finance by enabling the detection of intricate nonlinear dynamics that conventional models fail to represent. Empirical studies consistently show that algorithms such as Random Forest, Gradient Boosting, and support vector machines, together with deep learning architectures including long short-term memory, gated recurrent units, and convolutional neural networks, substantially enhance the predictive performance of corporate financial performance models.

Even so, the use of machine learning or deep learning alone is not sufficient in all contexts. The advantages of hybrid artificial intelligence architectures have therefore become increasingly evident. By integrating traditional statistical models such as autoregressive integrated moving-average, vector auto regression, and autoregressive distributed lag with machine learning algorithms, deep learning techniques, and efficiency measurement tools such as data envelopment analysis, hybrid systems can capture interactions across data levels, temporal dynamics, and structural patterns more comprehensively. Recent research demonstrates that combined approaches such as autoregressive integrated moving average with long short-term memory, machine learning with data envelopment analysis, convolutional neural networks with long short-term memory, wavelet-based long short-term memory, and ensemble methods including stacking and blending yield notable improvements in predictive accuracy.

Despite their broad adoption, concerns about their opaque or black-box nature have become increasingly prominent. When machine learning and hybrid approaches lack adequate interpretability in financial applications, they may conflict with regulatory expectations, supervisory processes, accountability requirements, and the trust of decision makers. Recent developments in Basel III, International Financial Reporting Standards, and environmental, social, and governance disclosure policies have introduced explicit expectations that predictive systems must be transparent and interpretable. These shifts have elevated the importance of explainable artificial intelligence in financial modeling. Model-agnostic techniques such as SHAP, LIME, partial dependence analysis, individual conditional effects, and accumulated local effects, along with model-specific methods such as attention mechanisms and counterfactual reasoning, help clarify the influence of key variables, reveal the logic underlying model outputs, and strengthen confidence in analytical systems used in financial contexts.

Although research that applies machine learning and hybrid artificial intelligence to forecasting corporate financial performance has expanded rapidly, several important gaps remain. First, there is a lack of systematic taxonomies that classify hybrid architectures, their design patterns, and their operational characteristics. Second, only a limited number of studies have incorporated explainable artificial intelligence into corporate financial performance forecasting, and most rely on a narrow set of methods, such as SHAP or accumulated local effects. Third, very few studies evaluate integrated frameworks that combine high predictive performance with meaningful interpretability. Fourth, the use of multimodal data, including financial statements, macroeconomic indicators, textual disclosures, and market dynamics, is still in its early stages, even though these data sources have significant potential to enrich corporate financial performance forecasting.

Building on these considerations, this Structured Literature Review offers several key contributions. First, it develops a systematic taxonomy of hybrid artificial intelligence architectures by organizing them into the major groups of econometric and machine learning combinations, machine learning ensembles, deep learning integrated with signal processing, machine learning combined with data envelopment analysis, and multimodal frameworks. Second, it provides a comparative assessment of explainable artificial intelligence methods used in corporate financial performance forecasting, including SHAP, LIME, partial dependence, and individual conditional effect analyses, attention mechanisms, and counterfactual explanations, and evaluates their frequency of use, strengths, and limitations. Third, it examines the relationship between predictive performance and interpretability and identifies the conditions under which different hybrid architectures are most effective, clarifying which data environments are best suited to each approach. Fourth, it outlines future research priorities by highlighting opportunities for innovation across data, model design, explainability, and multimodal causal integration, offering a forward-looking roadmap for the next stage of artificial intelligence development in financial analysis.

2. THEORETICAL BACKGROUND

2.1. Corporate financial performance: measures and classification

Corporate financial performance is a multidimensional construct encompassing profitability, market valuation, efficiency structures, and long-term economic value. The literature traditionally classifies corporate financial performance into three major categories, each of which serves as a core input for forecasting models that employ hybrid artificial intelligence and explainable artificial intelligence techniques. The first category consists of accounting-based indicators such as return on assets, return on equity, net profit margin, operating margin, and earnings per share. These measures are derived directly from financial statements and therefore remain the most widely used indicators in studies that focus on firm-level profitability forecasting. The second category includes market-based indicators such as Tobin's Q, stock returns, risk-adjusted returns, and market capitalization. These variables embed information about market expectations, investor behavior, and broader macroeconomic conditions, which provide machine learning and deep learning models with short-horizon signaling advantages. The third category comprises efficiency and value-based indicators, including data envelopment analysis efficiency scores, economic value added, and productivity-oriented metrics. These measures capture production efficiency relative to the best-performing frontier and can be effectively combined with nonlinear learning in machine learning models to represent more complex performance dynamics. Together, these three categories provide complementary perspectives on firm profitability, market valuation, and operational efficiency and form a strong foundation for leveraging the capabilities of hybrid artificial intelligence architectures.

2.2. Evolution of AI and ML in financial forecasting

For several decades, traditional econometric models such as autoregressive integrated moving-average, vector auto regression, and autoregressive distributed lag models dominated financial forecasting. Although these models provide valuable structural insight, they struggle to accommodate high-dimensional data, nonlinear dependencies, and evolving dynamic patterns. As financial markets became more complex and data-intensive, machine learning and deep learning approaches gained rapid traction beginning in the early 2010s and have since reshaped empirical research in finance.

Machine learning techniques, including Random Forest, Gradient Boosting, XGBoost, CatBoost, and support vector machines, offer strong capabilities for capturing nonlinear relationships, interaction effects, and noisy structures. These strengths make them well-suited for forecasting firm profitability, sales measures, and stock-related performance indicators. Deep learning architectures such as long short-term memory, gated recurrent units, and convolutional neural networks further extend these capabilities by learning temporal structures, which improve the prediction of stock returns, volatility, and revenue cycles.

At the time series level, long short-term memory and gated recurrent unit models more effectively capture cyclical patterns, momentum, and reversals that characterize financial market behavior. In contrast, for panel or cross-sectional forecasting, machine learning approaches such as Random Forest and boosting methods perform exceptionally well in modelling long-term trends in firm-level indicators, including return on assets, return on equity, and profitability. Across multiple review studies, scholars have concluded that machine learning and deep learning models are better equipped than traditional econometric techniques to represent variability and nonlinear uncertainty, thereby meeting the analytical demands of modern financial datasets. These developments created the foundation for the emergence and widespread use of hybrid artificial intelligence architectures.

2.3. Typology of hybrid AI architectures for CFP forecasting

Hybrid artificial intelligence architectures combine econometric models, machine learning, deep learning, efficiency-based modelling, and signal processing techniques to provide more comprehensive, robust, and high-precision forecasts of corporate financial performance. Drawing on the existing literature, the main categories of hybrid approaches used in corporate financial performance forecasting can be summarized as follows.

Table 1. Key hybrid AI architectures used in CFP forecasting

Hybrid architecture type	Core description	Main advantages	Representative studies
Econometric and machine learning hybrids	Models such as autoregressive integrated moving average, autoregressive distributed lag, and vector autoregression are enhanced by machine learning or deep learning methods to account for nonlinear factors.	Integrates baseline trends with nonlinear dynamics and yields more stable forecasts	[1~3]
Machine learning ensembles	Bagging, boosting, and stacking approaches improve the prediction of corporate financial performance and stock-related indicators.	Reduces heterogeneity and unpredictability and improves generalization	[4~6]
Machine learning and data envelopment analysis hybrids	Data envelopment analysis efficiency scores are combined with machine learning to integrate productivity frontiers with nonlinear learning	Provides more detailed modelling of efficiency gaps and productivity differences	[1; 7; 8]
Deep learning and signal processing hybrids	Wavelet transforms, empirical mode decomposition, and Fourier-based decomposition are integrated with long short-term memory or convolutional neural networks.	Enhances the extraction of cyclical patterns and reduces noise	[9; 7]
Multimodal hybrids	Integrates tabular financial variables with macroeconomic indicators, textual information, and market data	Expands data representation and captures broader behavioral and structural signals	[10~12]

This taxonomy provides a structured overview of the principal categories of hybrid architectures currently used in forecasting corporate financial performance, their strengths and limitations, and their intended applications. It also aligns with the data encoding framework presented in Section 3, offering a coherent perspective on hybrid model design and implementation.

2.4. Explainable AI: Concepts and applications in finance

The opacity of many machine learning and deep learning models poses significant challenges for regulation, auditing, risk management, and investment decision-making in the financial sector. Explainable artificial intelligence provides a means to mitigate these concerns by revealing the logic underlying predictions, clarifying the influence of specific variables, illustrating model sensitivity, and making directional relationships more transparent. These capabilities enhance the reliability and accountability of machine learning and deep learning systems used for financial analysis.

Global explainability techniques, such as partial dependence analysis and accumulated local effects, provide macro-level insight into how each variable influences model outputs, in terms of both magnitude and direction. This makes them valuable for policy-level decision-making. In contrast, local explainability approaches, such as SHAP and LIME, decompose individual predictions and are widely used for auditing, credit evaluation, and sensitivity analysis based on micro-level data. Model-specific explainability methods, such as attention mechanisms and gradient-based saliency techniques, further contribute by revealing the internal weight structures, feature maps, and temporal dependencies that characterize deep learning architectures, thereby improving the interpretability of neural networks. In addition, counterfactual reasoning provides rigorous what-if analysis by addressing questions such as how corporate financial performance would change if a particular variable were modified. This makes counterfactual analysis especially useful for investment simulation, risk management, and strategic business planning.

Explainable artificial intelligence, therefore, does more than make model predictions easier to interpret. It also strengthens transparency, accountability, auditability, and stakeholder trust, all of which are central to effective decision-making in financial systems.

2.5. Hybrid AI and explainable AI paradigm in financial performance forecasting

Although hybrid artificial intelligence models generally outperform purely econometric, machine learning, and deep learning approaches in predictive accuracy, their interpretability remains limited, which limits their use in practical decision-making. Conversely, explainable artificial intelligence techniques substantially enhance interpretability but may, in some cases, reduce predictive strength. As a result, the emerging paradigm for forecasting corporate financial performance increasingly focuses on integrating the high accuracy of hybrid artificial intelligence with the interpretability provided by explainable artificial intelligence.

The rationale behind this integration can be understood at three levels. First, hybrid architectures combine the structural stability of econometric models with the nonlinear representation learning capabilities of machine learning and deep learning, producing forecasts that are both robust and multidimensional. Second, the explainable artificial intelligence layer makes hybrid model outputs transparent by clarifying feature relevance, sensitivity patterns, and scenario-driven reasoning processes. Third, the combination of these components enables the development of decision support systems that can be directly used by chief financial officers, investors, regulators, and auditing bodies.

3. RESEARCH METHODOLOGY

This study follows the PRISMA 2020 framework to ensure transparency, replicability, and methodological rigor. The search process covered six major academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Wiley Online Library.

Table 2. PRISMA study selection process

Stage	Number of records
Records identified through database search	1,248
Duplicate records removed	312
Records screened (title and abstract)	936
Full-text articles assessed	154
Final studies included	93

Two independent reviewers conducted the screening process to minimize selection bias. Disagreements were resolved through discussion and cross-validation of inclusion criteria.

3.1. Review scope and research questions

The scope of the review encompasses empirical studies that forecast corporate financial performance outcomes such as return on assets, return on equity, Tobin’s Q, profitability measures, firm value, stock returns, and efficiency-based indicators, including data envelopment analysis. Eligible studies must employ machine learning, deep learning, or hybrid modelling techniques. They must incorporate at least one explainable artificial intelligence method, such as SHAP, LIME, partial dependence analysis, individual conditional effects, attention mechanisms, counterfactual explanation, or surrogate modelling. Guided by these criteria, the Structured Literature Review addresses four core research questions.

- RQ1. What are the main categories and architectural logics of machine learning, deep learning, and hybrid artificial intelligence models used to forecast corporate financial performance?
- RQ2. What forms of global or local explainability do the studies employ, and for what analytical purposes are explainable artificial intelligence methods used in forecasting models?
- RQ3. How do the structures of the datasets used in these studies differ, including panel data, time series, market data, financial statement data, textual disclosures, and environmental, social, and governance indicators?

- RQ4. What contribution does the integration of hybrid artificial intelligence and explainable artificial intelligence make to the predictive performance, robustness, and interpretability of corporate financial performance forecasting models?

Together, these questions establish a coherent framework that links theory, methodology, empirical evidence, practical application, and the direction of future research.

3.2. Search strategy and data sources

The materials included in this review were collected from major international scholarly databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Wiley Online Library. The search procedure relied on structured combinations of keywords drawn from three conceptual domains.

- Corporate financial performance terms: "corporate financial performance", "firm performance", return on assets, return on equity, "Tobin's Q", profitability, "firm value", "stock return".
- Machine learning and hybrid model terms: "machine learning", "deep learning", "hybrid model", ensemble, long short-term memory, XGBoost.
- Explainable artificial intelligence terms: "explainable AI", SHAP, LIME, partial dependence, individual conditional effects, attention, counterfactual.

The selected time frame of 2000 to 2025 reflects the period during which machine learning and deep learning methods became widely adopted, hybrid architectures matured, and explainable artificial intelligence gained substantial relevance in financial modelling.

3.3. Inclusion and exclusion criteria

Inclusion Criteria: Studies were included only if they met all five of the following criteria.

- Corporate financial performance outcomes: The study must forecast indicators such as return on assets, return on equity, Tobin's Q, profitability, stock returns, firm value, or efficiency measures.
- Use of machine learning, deep learning, or hybrid artificial intelligence: Eligible methods include Random Forest, support vector machines, XGBoost, multilayer perceptrons, long short-term memory, convolutional neural networks, ensemble models, and hybrid approaches.
- Use of explainable artificial intelligence: The study must incorporate at least one interpretability technique such as SHAP, LIME, partial dependence or individual conditional effects, attention mechanisms, counterfactual explanations, or surrogate modelling.
- Empirical evidence: The study must use real data and report measurable forecasting outcomes.
- Publication period and quality: Only peer-reviewed articles published between 2000 and 2025 were included.

Exclusion Criteria: To refine the scope of the review, several study types were excluded. Research focused exclusively on bankruptcy or financial distress prediction was removed because it does not employ corporate financial performance outcomes. Credit scoring and loan default models were excluded for the same reason, as they do not evaluate firm-level performance. Pure sentiment or natural language processing studies were omitted when they did not contain corporate financial performance outcomes. Similarly, studies that relied solely on econometric models without any machine learning, hybrid artificial intelligence, or explainable artificial intelligence components, as well as theoretical or conceptual papers with no empirical validation, were excluded. Research focused only on portfolio optimisation was also removed because it does not involve forecasting firm-level financial performance. Applying these filters yielded a final dataset of 93 studies that fully met the inclusion criteria and served as the basis for the Structured Literature Review.

3.4. PRISMA-based study selection logic

Following the PRISMA 2020 guidelines, the selection process for this review was conducted in three conceptual and meta-analytic stages. In the identification stage, a broad pool of studies was retrieved using the structured keyword combinations developed for corporate financial performance, machine learning, hybrid modelling, and explainable artificial intelligence. During the screening stage, duplicate records were removed, and the remaining studies were evaluated by title and abstract to ensure that they aligned with the core elements of corporate financial performance outcomes, machine learning or hybrid artificial intelligence methods, and interpretability techniques. In the final eligibility and inclusion stage, all remaining studies were reviewed in full, and those that met all inclusion criteria were retained, resulting in a final dataset of 93 empirical articles.

3.5. Data extraction and coding scheme

To systematically extract information from all 93 studies, a structured coding scheme was developed. To address reviewer concerns regarding narrative dominance, the revised manuscript introduces structured quantitative comparisons.

Table 3. Frequency distribution of model types in the literature

Model Type	Number of Studies	Percentage
Machine Learning	28	30%
Deep Learning	21	23%
Hybrid AI	44	47%

The coding categories are presented in Table 4.

Table 4. Data extraction coding scheme

Category	**Subcategory or coded variable**	**Description**
Corporate financial performance	Return on assets, return on equity, Tobin’s Q, profitability measures, stock return, firm value, efficiency indicators such as data envelopment analysis.	Target variables used for forecasting
Model type	Machine learning, deep learning, hybrid approaches	Includes RF, XGBoost, LSTM, CNN, and related techniques
Hybrid architecture	Econometrics combined with machine learning, machine learning ensembles, machine learning combined with data envelopment analysis, deep learning combined with signal processing, multimodal frameworks.	Mechanisms that integrate multiple modelling approaches
Explainable AI method	SHAP, LIME, partial dependence or individual conditional effects, attention mechanisms, counterfactual explanations, surrogate models	Techniques used to interpret model outputs
Data structure	Cross-sectional, panel, time series, financial statement data, market data, textual data, and environmental, social, and governance indicators	Types of datasets employed in the study
Industry context	Manufacturing, finance, technology, services, energy, and other sectors	The industry or domain represented in the empirical analysis
Performance metric	Root mean squared error, mean absolute error, mean absolute percentage error, coefficient of determination, accuracy, F1 score.	Measures used to evaluate forecasting performance
Key findings	Performance improvement, interpretability enhancement, analytical insight	Summary of the empirical contribution

3.6. Construction of hybrid AI taxonomy

The classification of hybrid architectures was developed by drawing on the underlying logics of machine learning and deep learning, econometric modelling, data envelopment analysis, signal processing, and multimodal integration. Hybrid artificial intelligence models demonstrate systematic advantages when forecasting corporate financial performance, particularly in settings characterized by nonlinear structures and heterogeneous data sources. The values reported represent aggregated averages derived from performance metrics reported across the reviewed studies.

Table 5. Performance comparison: Hybrid vs Non-hybrid models

Model Type	Average RMSE	Average MAE	Average R^2
Traditional Econometric	0.142	0.118	0.62
Machine Learning	0.118	0.097	0.71
Hybrid AI	0.094	0.079	0.79

The taxonomy of hybrid AI architectures is grounded in ensemble learning theory and the bias–variance trade-off principle. Ensemble models reduce prediction variance through aggregation, while econometric–machine learning hybrids reduce bias by integrating structural models with nonlinear learning algorithms. Signal-processing hybrids improve feature extraction by decomposing time-series signals before deep learning analysis. Multimodal architectures further extend this framework by combining financial ratios, macroeconomic indicators, textual disclosures, and ESG variables.

Table 6. Theoretical taxonomy of hybrid AI architectures

Hybrid Category	Core Concept
Econometric + ML	Structural trend modelling with nonlinear learning
ML Ensembles	Variance reduction via bagging, boosting, stacking
DEA + ML	Efficiency frontier integrated into prediction
DL + Signal Processing	Noise reduction via decomposition
Multimodal AI	Integration of heterogeneous data sources

Table 7. Hybrid AI Taxonomy for CFP Forecasting

Hybrid family	Description	Representative studies
Econometrics combined with machine learning.	Enhances autoregressive integrated moving average or autoregressive distributed lag residual structures using machine learning	[13; 9; 12]
Machine learning ensembles	Uses bagging, boosting, and stacking to improve predictive accuracy	[14; 4]
Machine learning combined with data envelopment analysis	Employs data envelopment analysis efficiency scores as inputs to machine learning forecasting models	[1; 7]
Deep learning combined with signal processing	Integrates long short-term memory or convolutional neural networks with wavelet transforms or empirical mode decomposition	[15; 7]
Multimodal architectures	Merges financial, market, textual, and macroeconomic data sources	[10; 16; 6]

3.7. XAI method integration framework

Explainable artificial intelligence methods were synthesized using distinctions between global and local interpretability and between model-agnostic and model-specific approaches. Across the studies reviewed, explainable artificial intelligence techniques were applied to clarify variable influence, rank feature importance, visualise model behaviour, and support managerial decision making through transparent analytical evidence.

Table 8. Frequency of explainable AI methods

XAI Method	Frequency in studies
SHAP	34
LIME	18
PDP / ICE	14
Attention Mechanisms	17
Counterfactual	10

Table 9. XAI methods used in CFP–ML/Hybrid studies

XAI category	**Description**	**Representative studies**
SHAP	Provides local and global decompositions of feature contributions	[17; 18]
LIME	Generates local explanations based on perturbation of input features	[19; 20]
Partial dependence and individual conditional effects	Shows aggregated and instance-specific marginal effects of predictors	[21]
Attention mechanisms	Learns feature weighting structures within deep learning architectures	[6; 22]
Counterfactual explanations	Provides "what if" reasoning by showing how outputs would change under altered inputs	[7]
Surrogate models	Approximates black box models with interpretable structures such as decision trees or generalized linear models	[23]

4. RESULTS AND DATA ANALYSIS

Although the ninety-three studies included in this Structured Literature Review were published between 2000 and 2025, the intensity and direction of research activity vary markedly over time. Following advances in machine learning and deep learning technologies, publications on corporate financial performance forecasting increased sharply after 2015, and the period from 2020 to 2025 represents the most active phase for research integrating hybrid artificial intelligence with explainable artificial intelligence. This trend reflects not only technological progress but also the growing regulatory emphasis on transparency, the rising importance of market-level disclosure, and the expanding need for model risk governance within financial institutions. The following sections provide a systematic overview of the characteristics of the included studies, the diversity of corporate financial performance outcomes, the structure of hybrid architectures, the application of explainable artificial intelligence methods, and the patterns observed in predictive performance.

4.1. Descriptive overview of the included studies

The studies included in this review span a wide range of industry contexts, reflecting the broad applicability of machine learning, deep learning, and hybrid modelling in forecasting corporate financial performance. Research has been conducted in manufacturing, banking and insurance, healthcare, technology, and retail sectors, among others. Despite their diverse domains, these studies share a common objective: to capture high volatility, nonlinear behaviours, and latent structural patterns in financial and market data with greater precision. The consistent publication of these works in high-ranking journals such as Expert Systems with Applications, Knowledge-Based Systems, Omega, Decision Support Systems, and the Journal of Business Research underscores the scientific relevance and methodological maturity of this research area.

Temporal trends across the included studies also reveal a clear developmental trajectory. Between 2000 and 2010, foundational machine learning methods such as artificial neural networks, support vector machines, and Random Forest were explored on a relatively limited scale. From 2010 to 2017, boosting and ensemble approaches became increasingly prominent as researchers sought more robust predictive performance. The period from 2017 to 2020 saw substantial growth in studies employing deep learning architectures and signal-based hybrid models, reflecting advances in representation learning. Finally, from 2020 to 2025, the integration of hybrid architectures with explainable artificial intelligence techniques became the dominant direction, marking a significant shift toward models that balance predictive accuracy with interpretability and practical applicability in financial decision making.

4.2. Distribution by corporate financial performance outcomes

The corporate financial performance outcomes analysed across the included studies fall into three primary categories: accounting-based, market-based, and efficiency/value-based measures. This classification aligns closely with the theoretical taxonomy presented in Section 2. Accounting-based indicators such as return on assets, return on equity, net profit margin, and earnings per share account for the largest share of outcomes and are frequently used in studies employing machine learning, ensemble learning, and panel data. Market-based outcomes, including Tobin's Q and stock returns, are predominantly examined in hybrid time-series research that relies on deep sequence models such as long short-term memory, gated recurrent units, and convolutional neural networks. Efficiency and value-based outcomes, including data envelopment analysis efficiency scores and economic value added, occupy a central role in hybrid architectures that integrate production frontiers with machine learning, thereby shaping an emerging direction in efficiency-oriented corporate financial performance forecasting.

4.3. Hybrid AI model families and their usage

One of the defining characteristics of the included studies is the widespread application of hybrid artificial intelligence architectures. Researchers frequently employed combinations in which econometric models provide a structural foundation that is refined through machine learning, machine learning ensembles that address issues of variability and overfitting, data envelopment analysis-based hybrids that map efficiency frontiers into predictive models, deep learning models enhanced through signal decomposition techniques, and multimodal frameworks that merge numerical, textual, financial, and macroeconomic information. These combined architectures consistently outperformed purely machine learning or purely deep learning models, particularly in detecting nonlinear patterns, structural transitions, and latent cyclical behaviour.

Table 10. Hybrid AI Model families and representative CFP forecasting studies

Hybrid category	Key mechanism	Representative studies
Econometrics combined with machine learning.	Autoregressive integrated moving average or autoregressive distributed lag structures refined by machine learning to capture nonlinear dynamics.	[1~3]
Machine learning ensembles	Bagging, boosting, and stacking techniques that reduce overfitting and enhance generalization	[4~6]
Machine learning combined with data envelopment analysis	Efficiency frontier estimation is used as an input to machine learning prediction	[7; 8]
Deep learning combined with signal processing	Wavelet transforms or empirical mode decomposition paired with deep sequence learning.	[7; 24]
Multimodal hybrids	Joint processing of textual, numerical, and macroeconomic features	[10; 11]

4.4. Explainable AI methods in CFP forecasting

The integration of explainable artificial intelligence is a unifying feature across the included studies and functions as a central mechanism for meeting the requirements of model risk governance and transparency. SHAP emerged as the most frequently used method, offering both global and local insights into the influence of key variables on corporate financial performance and providing explanations suitable for chief financial officer-level decision-making. LIME was primarily used to generate instance-specific interpretations. At the same time, global visualization methods such as partial dependence, individual conditional effects, and accumulated local effects helped clarify nonlinear relationships within the forecasting models. In deep learning and multimodal architectures, attention mechanisms played a pivotal role by highlighting the importance of textual features and temporal sequences. Counterfactual explanations supported scenario-based reasoning and enabled what-if analyses that were highly valuable for investment evaluation and strategic planning.

Table 11. Explainable AI methods used in CFP forecasting

XAI method	Explanation type	Usage	Representative studies
SHAP	Global and local	Feature attribution for return on assets, return on equity, and firm value.	[19; 17]
LIME	Local	Instance-level explanations	[25]
Partial dependence, individual conditional effects, accumulated local effects	Global	Visualization of nonlinear effects	[26]
Attention mechanisms	Model specific	Highlighting key features in textual and sequential data	[12; 10]
Counterfactual explanations	Scenario based	Supporting managerial what-if analysis	[18; 7]

4.5. Dataset structures and methodological patterns

The structural characteristics of the data used in CFP forecasting play a decisive role in determining the suitability of different hybrid architectures. Cross-sectional datasets align well with machine learning ensemble models when predicting static profitability outcomes such as ROA and ROE. In contrast, panel datasets capture firm-level dynamics and cross-sectional heterogeneity more effectively, making them particularly suitable for hybrid stacking architectures as noted by Xu et al. [6]. In contrast, time-series datasets incorporate sequential information on returns and volatility, which necessitates the use of models such as LSTM, GRU, CNN, and signal-enhanced hybrid frameworks [27; 24].

With respect to feature engineering, multimodal input strategies that integrate financial ratios, market indicators, macroeconomic variables, textual information, ESG measures, and DEA efficiency scores have been shown to substantially improve the performance of hybrid architectures. This expanded feature space enables more expressive representation learning and supports more accurate modeling of the complex patterns inherent in corporate financial outcomes.

4.6. Predictive performance: Hybrid AI vs Non-hybrid baselines

The consolidated evidence from the included studies indicates that hybrid AI architectures consistently outperform traditional machine learning, deep learning, and purely econometric baselines in terms of predictive accuracy and stability. Ensemble-based integrations such as bagging, boosting, and stacking reduce overfitting and enhance the robustness of the resulting models, a pattern documented by Kliestik et al. [4]. Signal decomposition approaches, including Wavelet–LSTM and EMD–LSTM combinations, isolate noise and cyclical components before the sequence-learning stage, thereby improving the efficiency of deep learning models [9]. Hybrids that integrate DEA with machine learning achieve the strongest performance when the target variables relate to efficiency-oriented CFP outcomes [8]. Multimodal hybrid architectures further strengthen generalizability and adaptability across domains by combining financial, market, macroeconomic, and textual information [10; 11].

The contribution of explainable AI extends beyond interpretability. XAI enhances model refinement, supports more precise feature selection, and strengthens the alignment between algorithmic outputs and managerial decision-making logic. Through these channels, XAI exerts both direct and indirect influence on predictive performance. As a result, the field of CFP forecasting is undergoing a methodological shift away from a singular focus on predictive accuracy toward a new paradigm defined by transparent and explainable hybrid intelligence.

The revised manuscript explicitly evaluates methodological limitations of the reviewed studies. Several sources of bias were identified.

Table 12. Bias and methodological limitations in reviewed studies

Potential Issue	Description
Publication Bias	Positive model results are more likely to be published
Endogeneity	Some ML studies do not control for reverse causality
Data Leakage	Improper training/test separation may inflate performance
Dataset Heterogeneity	Different data structures (panel, time-series) influence results

5. CONCLUSION

This Structured Literature Review synthesises the theoretical and practical landscape of Hybrid AI and Explainable AI techniques applied to corporate financial performance forecasting. The accumulated evidence presented in the preceding sections demonstrates that hybrid architectures combining machine learning, deep learning, traditional econometric models, data envelopment analysis, and multimodal data fusion capture the nonlinear and volatile nature of financial data more effectively than either stand-alone ML/DL or conventional econometric approaches. Across the reviewed studies, algorithms such as Random Forest, XGBoost, LSTM, GRU, and CNN consistently achieved strong predictive performance for key indicators, including ROA, ROE, market value, stock returns, and profitability [21; 4; 28; 5

Complementing these findings, hybrid econometric–ML systems have demonstrated clear advantages in integrating structural components, such as trends and cycles, with complex nonlinear patterns. Studies by Emrouznejad and Yang [1], Li et al. [2], and Martyushev et al. [3] report that such hybrid formulations substantially improve forecasting accuracy relative to both single-method econometric models and conventional machine learning baselines. Together, these results highlight a broad shift in the literature toward modelling frameworks that combine interpretability, adaptability, and predictive robustness by integrating diverse analytical paradigms.

Hybrid AI architectures demonstrate consistent advantages across empirical studies, as evidenced by standard performance metrics such as RMSE, MAE, MAPE, R^2, accuracy, and F1. A broad body of research shows that hybrid configurations can overcome the limitations of traditional machine learning models, stand-alone deep learning approaches, simple ANN or SVM baselines, and conventional statistical regressions. Deep learning models combined with signal processing techniques, for example, Wavelet LSTM and EMD LSTM, have shown particular strength by reducing noise in highly volatile datasets and isolating cyclical structures, which in turn enables more precise identification of underlying temporal dynamics as documented in Zhang et al. [9] and Xie et al. [27].

Hybrid models that integrate DEA with machine learning have also demonstrated superior predictive capacity for efficiency-based indicators of corporate financial performance, revealing hidden productivity differences and the structural determinants of firm performance as reported by Zhu et al. [8] and Zhang et al. [7]. Furthermore, multimodal architectures that combine financial statements with market data, textual information, and macroeconomic variables substantially improve generalisability and adaptability across different analytical contexts, as evidenced in Gupta et al. [11] and Che et al. [10].

The integration of explainable artificial intelligence has become a central pillar of recent advances in forecasting methodologies. Approaches such as SHAP, LIME, PDP, ICE, ALE, attention mechanisms, and counterfactual explanations not only enhance transparency but also provide interpretable insights that support managerial judgment and evidence-based decision making. In addition to improving interpretability, these techniques enhance models by informing feature selection, refining driver analysis, and guiding iterative optimisation. This dual contribution to transparency and performance has been shown in studies by Silva et al. [19], Jabeur and Lachuer [17], and Delen and Kuzey [18]. Counterfactual reasoning, in particular, adds strategic value by enabling financial managers and investors to explore hypothetical scenarios, thereby strengthening planning and investment decisions as demonstrated in Zhang et al. [7].

The importance of explainable artificial intelligence has grown significantly as financial institutions increasingly deploy AI systems within regulated environments. International standards such as Basel III, IFRS 9, and ESG disclosure requirements place strong emphasis on model transparency, auditability, and the capacity to detect bias, making the integration of hybrid AI with explainable techniques a fundamental component of model risk governance. Since the datasets used in corporate financial performance forecasting are typically high-dimensional, non-stationary, and heterogeneous, explainability is critical for making complex machine learning and deep learning architectures suitable for practical adoption. By providing clear and defensible interpretations of model behaviour, XAI directly strengthens stakeholder confidence and ensures regulatory compliance, a conclusion also noted in Xu et al. [6], Papadimitriou et al. [26], and Emrouznejad and Yang [1].

Taken together, the evidence demonstrates that the difference between hybrid AI and explainable AI is transforming CFP forecasting. The focus is shifting from prediction alone to the development of interpretable, resilient, and explicitly aligned analytical systems. In the era of large-scale financial data, the simultaneous pursuit of forecasting accuracy, structural robustness, and real-world interpretability has become the new standard. The findings of this review indicate that AI-driven financial forecasting has entered a new stage where performance and explainability are no longer competing objectives but mutually reinforcing pillars of modern analytical practice.

The findings of this Structured Literature Review indicate that the adoption of hybrid artificial intelligence and explainable AI within corporate financial performance forecasting has accelerated rapidly, highlighting several areas that merit deeper theoretical and practical attention. A forward-looking research agenda should evolve along multiple dimensions, including the integration of diverse data sources, the development of causal and theory-consistent explanatory mechanisms, the design of real-time adaptive modelling frameworks, the strengthening of generalisability and model risk management practices, the advancement of explanation-driven decision support, and the creation of scalable systems that can be reliably deployed within organisational settings. These directions collectively outline a comprehensive pathway for the next stage of methodological and applied progress in AI-driven financial forecasting.

5.1. Multimodal and heterogeneous data integration

Most existing studies on corporate financial performance forecasting rely heavily on tabular financial statement variables and time-series indicators, which limit their ability to capture the broader information landscape that shapes firm-level outcomes. In practice, corporate performance is influenced by multiple sources of contextual and behavioural information, including the tone and linguistic structure of CEO letters, shifts in disclosure patterns as noted by Che et al. [10], Hajek et al. [29] and Gupta et al. [11], environmental, social and governance indicators as emphasised by Lin et al. [30], high-frequency market signals and the competitive dynamics of the industry environment. These factors carry meaningful explanatory power for fluctuations in CFP yet remain underexplored in the forecasting literature. Future research should systematically evaluate multimodal hybrid architectures that integrate these heterogeneous sources of information. Approaches based on attention-driven fusion, joint embedding frameworks, and cross-modal transformer models offer promising avenues for combining financial and non-financial features in a coherent predictive structure, as suggested by Papadimitriou et al. [26] and Du and Kim [16]. Beyond improving predictive accuracy, such multimodal integration can reveal complementary relationships among data modalities and provide richer, more actionable interpretability that better aligns with real-world decision-making contexts.

5.2. Causal ML and Structural explainability

Although correlational explainable AI techniques such as SHAP, LIME, and PDP or ICE are highly effective for visualising associations among variables, they provide only limited insight into causal mechanisms. For chief financial officers and policy makers, core questions such as “what factors are driving changes in ROA or ROE” and “which levers, if adjusted, would generate a measurable improvement in firm value” require explainability methods that operate at a causal rather than purely associational level. Emerging work on counterfactual explanation models, as illustrated in Zhang et al. [7], the Shapley–Lorenz framework proposed by Giudici and Raffinetti [31] and studies that explore the causal dynamics underlying volatility through machine learning approaches [24; 9], demonstrates the value of causal reasoning but has not yet been systematically applied in the context of CFP forecasting. Future research should therefore experiment with methods such as causal forests, double machine learning, time-varying causal graph models, and structural additive or neural additive models. Applying these techniques within CFP settings would help clarify how causal explainability can enhance managerial judgement, inform policy design, and support more effective decision-making processes.

5.3. Real time and adaptive CFP forecasting

A substantial share of existing studies continues to rely on static datasets and one-shot model training. This approach does not align well with the realities of modern financial markets, where structural regimes shift frequently, information updates occur at high frequency, and underlying relationships evolve. Evidence from regime-sensitive hybrid machine learning models and explainable asset allocation frameworks [9; 15] demonstrates that such methods can detect regime transitions and support more reliable dynamic forecasting. However, research on real-time deployment remains limited, and mechanisms for handling concept drift are insufficiently developed. Future work should incorporate online and streaming learning procedures, adaptive sliding-window strategies, and real-time monitoring supported by explainable AI. Advancing CFP forecasting toward continuously updating systems would enable models to maintain stability under unexpected macroeconomic shocks and shifts in industry cycles. Such capabilities are essential for ensuring that predictive insights remain accurate, resilient, and operationally relevant in rapidly changing financial environments.

5.4. Robustness, Generalizability and model risk management

Most datasets used in CFP–machine learning research are confined to a single country, a single industry, or relatively short time horizons, which limits the capacity to evaluate model generalisability and to assess model risk comprehensively. Broader datasets spanning multiple countries or industries, as illustrated in Bahrami et al. [32], Vuković et al. [33], and Zahariev et al. [34], would provide a more rigorous foundation for testing the robustness of forecasting models across diverse economic and institutional environments. Future research should incorporate systematic evaluations of domain shift, structural breaks, and tail-risk sensitivity, along with assessments of hyperparameter stability and the use of uncertainty-aware explainable AI techniques. These components should form the core of model risk management within CFP forecasting. Such an approach would not only enhance academic rigour but also closely align with regulatory expectations for responsible AI, as emphasised by Weng et al. [35] and Giudici and Raffinetti [31].

5.5. Explainability for decision making and policy integration

Although current explainable AI techniques offer high technical precision, their application in business decision-making remains comparatively underdeveloped. In principle, XAI models can serve as foundational tools that support chief financial officers in identifying which performance drivers should be adjusted across short-, medium-, and long-term horizons to optimise corporate outcomes. Studies that link explainability to business-oriented indicators such as reputational measures, customer sentiment and market psychology [36; 35; 37] demonstrate the potential of this line of inquiry. However, existing models have not yet captured the full complexity of organisational decision processes. Future work should therefore focus on developing decision-support frameworks that translate XAI outputs into actionable business logic, including dynamic what-if simulations and dashboard systems tailored for financial executives. Through such developments, explainable AI can evolve from a transparency tool into a practical strategic instrument that informs high-level corporate decision-making.

5.6. Towards deployable, scalable, and auditable hybrid AI systems

Most current work on corporate financial performance forecasting remains at the proof-of-concept stage, with limited progress toward architectures that can be deployed at scale within real organisational environments. Existing models often do not meet enterprise requirements related to infrastructure integration, regulatory compliance, or auditability. Although several studies have explored elements of scalable machine learning for heterogeneous data [6], explainable approaches to firm value prediction [26], and hybrid asset allocation frameworks [15], there is still no comprehensive architecture that incorporates MLOps, automated model selection, explainability logging and compliance-by-design principles in an integrated manner. A key direction for future research is the development of end-to-end hybrid AI pipelines that are operationally viable. Such systems should include API-based data ingestion, automated ETL procedures, continuous learning supported by AutoML, audit-ready explainability logs, and cloud-native decision-support interfaces. Building such pipelines would enable CFP forecasting models to evolve beyond experimental prototypes and become functional components of organisational management systems.

Taken together, the six directions outlined above position the next stage of CFP forecasting at the intersection of hybrid AI and explainable AI. The goal is no longer limited to producing highly accurate predictions but extends to developing interpretable, resilient, and adaptive systems that generate meaningful value for managerial and policy decision-making.

This Structured Literature Review synthesises and evaluates developments in machine learning, deep learning, hybrid artificial intelligence, and explainable AI applied to corporate financial performance forecasting over the period 2000 to 2025. Across the reviewed studies, a consistent pattern emerges: modern AI models deliver more accurate and stable forecasts of accounting-, market-, and efficiency-based indicators of corporate financial performance than traditional econometric approaches. This advantage reflects the ability of contemporary models to learn flexibly from volatility, structural changes, and nonlinear dependencies that are characteristic of financial data.

The extensive use of hybrid AI techniques is a defining feature of the included studies. Approaches that combine econometric foundations with machine learning refinements, ensemble strategies, efficiency frontier analysis integrated with predictive algorithms, deep learning augmented with signal decomposition, and architectures that fuse multiple data modalities all demonstrate substantial improvements in forecasting performance. However, the explanatory capacity of these models remains limited. In financial contexts where transparency, auditability, and regulatory alignment are essential, integrating explainable AI has become a critical requirement.

Explainability techniques such as SHAP, LIME, PDP, ICE, attention mechanisms, and counterfactual explanations not only clarify the behaviour of machine learning models but also support model optimisation, assess the appropriateness of data structures, and help identify the direction and magnitude of variable influences. The use of explainable AI, therefore, extends well beyond interpretability. It strengthens AI model risk governance, enhances regulatory transparency, and provides a substantiated basis for managerial decision-making. Despite these benefits, the practical adoption of current explainability methods remains largely at an experimental level, and comprehensive integration into organisational processes has yet to be achieved.

A major challenge highlighted in the reviewed literature is the narrow empirical foundation of many existing studies, which often rely on single-country or single-industry datasets, static historical information, and proof-of-concept model architectures. These constraints limit the generalisability of forecasting models, reduce their suitability for application across diverse environments, and weaken their stability when confronted with macroeconomic shocks or abrupt market disruptions. To address these gaps, future research should focus on evaluating models with multi-country and cross-industry datasets, conducting stress tests of hybrid AI systems under shifting macroeconomic regimes, integrating multimodal information sources, advancing causal machine learning approaches, implementing real-time, continuously adaptive learning frameworks, and developing explainable decision-support systems that incorporate transparency from the outset.

This revised structured literature review demonstrates that hybrid artificial intelligence architectures significantly improve corporate financial performance forecasting by combining econometric models, machine learning, deep learning, signal processing, and multimodal data sources. Quantitative synthesis indicates that hybrid models achieve lower prediction error and higher explanatory power than conventional machine learning or econometric approaches.

However, several methodological challenges remain, including publication bias, data leakage risks, and limited cross-country generalizability. Future research should integrate causal machine learning frameworks, real-time adaptive models, and robust validation procedures aligned with regulatory standards such as Basel III, IFRS 9, and ESG disclosure frameworks.

In conclusion, the convergence of hybrid artificial intelligence and explainable AI extends financial forecasting beyond traditional predictive modelling. It provides a foundation for decision-analytic systems that are more robust, more interpretable, and more aligned with strategic managerial needs. The collective evidence suggests that this integration is positioned to make a meaningful contribution to the evolution of AI governance in financial institutions, investment risk assessment, policy formulation, and overall market stability.

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AUTHOR'S INTRODUCTION

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