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MACHINE LEARNING IN CORPORATE FINANCIAL DECISION-MAKING: A CRITICAL NARRATIVE REVIEW OF PREDICTIVE MODELS FOR INVESTMENT, VALUATION, AND RISK ASSESSMENT

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ABSTRACT

Machine learning is increasingly applied to support corporate financial decisions under conditions of high dimensionality, nonlinearity, and rapid information change. This critical narrative review examines how predictive models have been used across three core domains: investment decision-making, valuation, and risk assessment. Drawing on a validated corpus of empirical and conceptual studies, the review compares traditional financial models, classical machine learning methods, ensemble techniques, and deep learning architectures, and analyzes how their suitability varies by decision context. The evidence shows that ensemble and deep learning approaches frequently improve predictive performance relative to linear benchmarks when relationships are complex or sequential, yet these gains are conditional on data regime, validation discipline, and integration into actual decision processes. A structural tension persists between predictive accuracy and the transparency, governance, and regulatory requirements that shape organizational trust and adoption, particularly in risk applications. The review consolidates dispersed findings, clarifies the boundary conditions under which machine learning contributes to corporate financial decisions, and identifies the prediction-to-decision gap and explainability constraints as central unresolved issues. Scholarly and practical contributions lie in the comparative synthesis across models and decision domains and in the articulation of evidence-based priorities for more decision-relevant and responsibly governed research and practice.

Keywords: Predictive Analytics, Corporate Finance, Investment Decision-Making, Valuation, Financial Risk Assessment, Explainable AI

1 INTRODUCTION

Corporate financial decisions have grown more complex as firms navigate information-rich, fast-moving, and interconnected markets. Investment appraisal, capital allocation, valuation, and risk assessment now demand the processing of high-dimensional data that extend well beyond traditional accounting and market variables to include alternative signals and sequential information streams. Managers, analysts, and risk functions operate under continuous pressure to anticipate outcomes amid uncertainty, allocate scarce capital efficiently, and manage exposures

that can shift abruptly across regimes. The quality of the predictive support available to them carries direct consequences for firm performance and resilience.

For decades, conventional financial modeling supplied the analytical foundation for these choices. Ratio analysis, linear and logistic regression, discriminant models, discounted cash-flow frameworks, and parametric risk measures remain widely taught and institutionally embedded. Transparency, modest computational demands, and ease of communication with boards and regulators constitute their enduring strengths. Those same models, however, rest on assumptions of linearity, limited interaction among predictors, and relative stability of relationships over time. When financial data display nonlinear dependencies, regime shifts, or high dimensionality, traditional specifications frequently lose discriminatory power and generate forecasts or classifications that lag flexible alternatives (Gu et al., 2020; de Oliveira & Basso, 2025). The mismatch between the complexity of contemporary financial environments and the representational limits of classical models has become difficult to ignore.

Machine learning and predictive analytics emerged in response. Expanded computational capacity together with the wider availability of structured and alternative financial data enabled algorithms capable of detecting patterns that linear models systematically overlook. Ensemble methods, deep sequential architectures, and hybrid approaches have been applied to investment screening, earnings and ratio forecasting, credit-risk assessment, distress prediction, and portfolio-risk estimation (Ross et al., 2021; Fatouros et al., 2022; Jalali et al., 2026). Concurrent work on explainable artificial intelligence underscores a related recognition: predictive power alone rarely secures organizational adoption. Transparency, auditability, and alignment with governance expectations also matter (Pamuk & Schumann, 2023).

Even so, the research landscape remains fragmented. Contributions surface across finance, accounting analytics, artificial intelligence, information systems, and business analytics outlets, often with limited cross-reference. Many studies concentrate on a single decision domain or a narrow class of algorithms, yielding a literature rich in local performance results yet thin in comparative synthesis. Questions about when machine learning actually improves decisions, how model requirements differ across investment, valuation, and risk contexts, and how organizations should manage the tension between accuracy and interpretability receive uneven attention. Surveys of deep learning in finance and banking document technical progress while simultaneously highlighting the incomplete translation of laboratory gains into institutional practice (Huang et al., 2020; Olorunnimbe & Viktor, 2023).

A critical narrative review is therefore needed. Systematic comparison of predictive modeling approaches and their application across the principal domains of corporate financial decision-making, together with examination of the implementation and governance conditions that shape realized value, can consolidate dispersed findings, clarify the conditions under which machine learning improves (or fails to improve) investment, valuation, and risk decisions, and identify the unresolved tensions that future research must confront. The analysis that follows pursues that objective.

2 PURPOSE AND SCOPE OF THE REVIEW

The purpose of this review is to examine critically how machine learning-driven predictive analytics has been applied to support corporate financial decision-making, with particular attention to investment, valuation, and risk assessment. It synthesizes the current state of knowledge, evaluates the strengths and limitations of existing approaches, identifies unresolved scholarly and practical challenges, and develops an integrated understanding intended to advance both research and practice.

Five questions guide the analysis. How is machine learning currently applied to support strategic financial decisions across investment, valuation, and risk domains? Which modeling approaches demonstrate comparative advantages under different data and decision conditions? How do requirements and outcomes differ across the three decision contexts? What implementation, explainability, and governance factors condition the translation of predictive gains into organizational value? What priorities should guide future research?

Corporate financial decision-making is understood here as the set of choices through which firms allocate capital, determine the value of assets or enterprises, and measure and manage financial risk. Machine learning is treated as a family of computational methods capable of learning patterns from data for prediction or classification, encompassing classical algorithms, ensemble techniques, and deep learning architectures. Purely algorithmic innovation detached from financial decision problems falls outside the scope, as do consumer lending, high-frequency trading, and macroeconomic forecasting except where such work directly informs corporate-level decisions.

Three analytical domains structure the review. Investment decision-making covers capital investment appraisal, opportunity evaluation, capital allocation, and portfolio-related choices at the corporate or strategic level. Valuation includes firm valuation, startup and venture valuation, acquisition-related valuation, and market-based relative valuation approaches that support corporate transactions or reporting. Risk assessment encompasses bankruptcy and

financial-distress prediction, credit-risk evaluation, corporate financial-health diagnosis, and related monitoring applications that inform risk management and capital decisions.

Only studies that apply machine learning methods to one or more of these domains and that supply sufficient methodological and empirical detail for comparative evaluation are examined. The intended scholarly contribution resides in the critical comparative synthesis of modeling approaches and decision contexts, the clarification of boundary conditions under which machine learning improves predictive and decision outcomes, and the identification of structural tensions around explainability and governance. The practical contribution is to equip decision makers, practitioners, technology developers, and policymakers with an evidence-based understanding of when and how machine learning can support corporate financial decisions, and of the organizational conditions required for responsible use.

3 REVIEW APPROACH AND LITERATURE SELECTION

This Critical Narrative Review followed a structured literature selection process to ensure methodological rigor and evidence traceability. Although narrative in design, the review applied systematic principles of identification, screening, validation, and thematic analysis.

Literature was searched across Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, Wiley Online Library, Taylor & Francis Online, Emerald Insight, Google Scholar, and related repositories. Search terms combined machine learning, predictive analytics, corporate financial decision-making, investment decision support, financial forecasting, valuation, risk assessment, technology markets, and strategic capital allocation. Reference tracking and citation networks supplemented the search. The corpus was limited to studies published between 2020 and 2026.

The initial search and compilation identified 112 candidate records. After removal of duplicates and title/abstract screening for relevance to corporate financial decision-making, 47 studies remained for full-text assessment. Studies were excluded at this stage if they lacked relevance to predictive financial decision-making, focused solely on algorithm development without financial application, duplicated prior evidence, or provided insufficient methodological detail. Priority was given to U.S. markets, firms, investors, or technology-driven industries; studies from other contexts were retained only when findings were transferable. This focused scope prioritizes methodological relevance and direct application to corporate financial decision-making rather than comprehensive coverage of the broader machine learning finance literature. After full-text screening, quality validation, and confirmation of source authenticity and publication quality, 17 studies constituted the final corpus.

Evidence was analyzed through critical narrative synthesis, comparing methods, identifying patterns, evaluating limitations, examining competing perspectives, and interpreting emerging trends. This approach enabled assessment of how machine learning-based predictive models are reshaping investment, valuation, and risk-related financial decisions.

Table 1: Summary of 17 Retained Studies by Decision Domain, Methodological Approach, and Key Contribution

Study (Author, Year)	Domain	Method(s) Applied	Focus / Key Contribution
Abdul-Kareem et al. (2024)	Risk Assessment	Multi-layer perceptron with particle swarm optimization	Insolvency prediction for financial investment firms
Chahuán-Jiménez (2024)	Investment	LSTM, CNN, ANN, RNN, GRU (comparative)	Neural-network forecasting of the S&P 500 index
de Oliveira & Basso (2025)	Risk Assessment	Ensemble machine learning (gradient boosting and related methods)	Corporate credit rating prediction across 20 countries
Fatouros et al. (2022)	Risk Assessment	Probabilistic deep neural networks (DeepVaR)	Portfolio Value-at-Risk estimation
Geertsema & Lu (2022)	Valuation	Gradient-boosting-based machine learning	Relative valuation and peer-firm selection

Gu, Kelly & Xiu (2020)	Investment	Trees, neural networks, regularized regression (comparative)	Empirical asset pricing and return prediction
Hair et al. (2025)	Risk Assessment	Deterministic vs. stochastic classifiers (comparative)	Capital-structure (debt-level) classification
Horváthová et al. (2024)	Risk Assessment	AdaBoost, Gradient Boosting (comparative)	Financial health diagnosis in construction firms
Huang et al. (2020)	Cross-Cutting Background /	Literature review	Deep learning applications across finance and banking
Jalali et al. (2026)	Investment	Machine learning with thematic feature grouping	Return forecasting for the “Magnificent Seven” firms
Li (2022)	Risk Assessment	Deep neural network	Early-warning corporate financial risk model
Liapis et al. (2023)	Valuation	Dynamic forecasting-method selection algorithms	Forecasting key ratios to support firm valuation
Olorunnimbe & Viktor (2023)	Cross-Cutting Background /	Systematic survey	Deep learning practice and backtesting in stock markets
Pamuk & Schumann (2023)	Risk Assessment	Multi-class machine learning classification models	Corporate credit rating forecasting; explainability considerations
Qin (2022)	Risk Assessment	XGBoost	Corporate financial management risk model
Ross et al. (2021)	Investment	Ensemble machine learning (CapitalVX)	Startup selection and exit prediction
Wasserbacher & Spindler (2022)	Cross-Cutting Implementation /	Double machine learning	Financial forecasting and planning; prediction vs. causal inference

4 EVOLUTION OF MACHINE LEARNING IN CORPORATE FINANCIAL DECISION-MAKING

Structured quantitative models have long underpinned corporate financial analysis. Ratio analysis, statistical forecasting, econometric specifications, and established valuation frameworks such as discounted cash flow and multiple-based methods supplied transparency and institutional familiarity. Those tools, however, rested on relatively strong assumptions of linearity, stationarity, and limited interaction among predictors. As financial environments grew more complex and data volumes expanded, the constraints of those assumptions became increasingly visible.

Improved computational capacity and the growing availability of large, structured datasets accelerated the move toward data-driven finance. Researchers and practitioners began testing methods capable of detecting patterns that linear specifications systematically missed. Classical machine learning techniques (decision trees, support vector machines, and early neural networks) entered the literature as flexible alternatives for classification and prediction. Work on bankruptcy prediction, credit assessment, and return forecasting showed that nonlinear methods could improve discriminatory power relative to traditional statistical benchmarks (Huang et al., 2020; Olorunnimbe & Viktor, 2023). Algorithmic pattern discovery began to complement, and in some settings challenge, purely theory-driven specification.

Ensemble methods subsequently gained prominence. Random forests, gradient boosting, and related techniques proved effective on tabular financial data, delivering predictive strength at manageable computational cost. Applications to corporate financial management risk modeling and early-warning systems further illustrated the practical reach of these methods (Qin, 2022; Li, 2022). Deep learning architectures extended the frontier for sequential and high-dimensional problems. Long short-term memory networks, convolutional models, and hybrid designs were applied to earnings forecasting, index prediction, and advanced risk estimation, revealing advantages in capturing temporal dependence and complex latent structure (Olorunnimbe & Viktor, 2023; Chahuán-Jiménez, 2024). Both the range of financial problems addressed and the sophistication of the algorithms deployed expanded markedly.

Data ecosystems evolved in parallel. Beyond conventional accounting and market variables, researchers incorporated textual information, patent records, and venture-specific attributes. Startup and innovation-focused studies illustrated how non-traditional signals could improve screening and exit prediction when combined with standard firm characteristics (Ross et al., 2021). Studies examining insolvency among financial investment firms and industry-specific financial health diagnosis similarly expanded the empirical base (Abdul-Kareem et al., 2024; Horváthová et al., 2024). Comparative work on deterministic versus stochastic classifiers for capital-structure decisions further underscored the importance of matching model families to decision characteristics (Hair et al., 2025). The rising use of high-capacity models simultaneously intensified concerns about opacity. As ensemble and deep learning systems produced stronger predictive results, questions of interpretability, auditability, and managerial trust moved from the periphery toward the center of scholarly and practical discussion.

Since roughly 2020, literature has pursued two concurrent emphases. One strand continues to seek gains in predictive performance through more elaborate architectures, richer feature sets, and refined validation designs. The other focuses on the conditions of responsible deployment (explainability, governance arrangements, regulatory alignment, and the organizational processes needed to convert predictions into decisions) (Pamuk & Schumann, 2023; Wasserbacher & Spindler, 2022). Reviews of deep learning in finance and banking document both technical progress and the persistent gap between laboratory performance and institutional adoption (Huang et al., 2020; Olorunnimbe & Viktor, 2023). Tax-payment forecasting and related cash-management applications further demonstrated the extension of machine learning into operational financial planning (Wasserbacher & Spindler, 2022).

The overall trajectory is not a simple replacement of traditional models by machine learning. It is an expansion of the analytical toolkit accompanied by rising awareness of the institutional requirements that determine whether expanded predictive capacity improves actual financial decisions. Early studies established that nonlinear methods could outperform linear benchmarks on selected tasks. Later work has shown that such outperformance is conditional on data regime, validation discipline, and decision-process integration, while also underscoring the structural tension between accuracy and transparency. That evolutionary pattern supplies the context for the application mapping and comparative analyses that follow.

5 MACHINE LEARNING APPLICATIONS ACROSS CORPORATE FINANCIAL DECISION-MAKING

Applications of machine learning now span a widening range of corporate financial problems, yet the distribution remains uneven. Risk assessment accounts for the largest share of empirical work, investment decision-making forms a substantial second cluster, and valuation support, while coherent, is more limited. The mapping below organizes the evidence around decision problems rather than algorithms and identifies the patterns that later comparative analysis will examine.

5.1 Investment Decision-Making

Investment applications focus on the identification and evaluation of capital allocation opportunities. Predictive tasks include return and risk-premia forecasting, screening of projects or ventures, and support for portfolio construction under concentration constraints. Firm characteristics such as profitability, momentum, liquidity, and size appear frequently, sometimes augmented by sequential price data or alternative indicators including patent activity (Gu et al., 2020; Ross et al., 2021). Data sources range from standard equity panels to venture-capital databases.

Ensemble methods and tree-based models are common when the task involves classification or ranking of opportunities; sequential architectures have been applied to index-level and return forecasting (Chahuán-Jiménez, 2024). In constrained samples (particularly those involving a small number of systemically important firms), unrestricted high-dimensional models tend to overfit unless economic structure is imposed through thematic grouping or related constraints (Jalali et al., 2026). Startup and venture screening studies further illustrate the value of combining conventional firm attributes with innovation-related signals (Ross et al., 2021). Tax-payment forecasting studies similarly demonstrate the applicability of machine learning to cash-management and planning decisions that support broader investment and capital-allocation processes (Wasserbacher & Spindler, 2022). Claimed business value lies in sharper discrimination among competing uses of capital and earlier identification of high-potential or high-risk opportunities. Whether that value is realized depends on the actual embedding of screening outputs in allocation processes.

5.2 Corporate Valuation

In valuation settings, machine learning functions chiefly as a means of improving the inputs that feed established frameworks rather than as a replacement for those frameworks. Typical targets include forecasts of earnings, key financial ratios, and relative valuation multiples (Liapis et al., 2023; Geertsema & Lu, 2022). Sequential models, including long short-term memory networks and temporal convolutional networks, have reduced forecast error relative to

traditional time-series benchmarks in earnings prediction. Dynamic algorithms that select among competing forecasting methods for individual ratio series have been proposed to strengthen discounted-cash-flow inputs (Liapis et al., 2023).

Relative valuation research has tested whether machine learning can extract more accurate cross-sectional pricing relationships from accounting and market data than conventional multiples approaches (Geertsema & Lu, 2022). In that study, the data are drawn primarily from Compustat-style accounting sources supplemented by market prices, and evaluation focuses on out-of-sample valuation accuracy, as well as whether the resulting valuations behave like fundamental values. The comparatively limited attention given to full valuation applications in the broader literature is consistent with the technical difficulty of linking improved input forecasts to final firm-value estimates that are then used in actual decisions. This slower evolution relative to investment and risk applications also reflects the continued institutional dependence on traditional discounted cash-flow and multiples frameworks, which remain deeply embedded in professional practice, auditing standards, and transaction processes. Valuation problems are inherently multi-stage and continuous rather than discrete classification or ranking tasks, making it harder both to isolate the contribution of any single algorithmic improvement and to demonstrate downstream effects on prices or decisions. In addition, regulatory and professional conservatism in formal valuation settings has limited the willingness of practitioners and researchers to treat machine learning outputs as primary valuation engines rather than as supplementary inputs. Where machine learning has been applied, its clearest contribution lies in more disciplined preparation of the numbers that traditional valuation models require. At present, however, evidence that these input improvements reliably alter transaction prices, reporting outcomes, or capital-allocation decisions remains largely absent.

5.3 Risk Assessment

Risk assessment is the most extensively studied domain. Applications encompass credit-rating prediction, bankruptcy and financial-distress classification, portfolio Value-at-Risk estimation, financial-health diagnosis, and early-warning systems. Financial ratios that capture liquidity, leverage, profitability, and coverage dominate the predictor sets, occasionally extended by business-risk indicators or macroeconomic variables. Data sources include multi-country commercial databases, annual financial statements, standard bankruptcy datasets, and industry-specific panels from both developed and emerging markets (de Oliveira & Basso, 2025; Fatouros et al., 2022; Horváthová et al., 2024; Li, 2022; Abdul-Kareem et al., 2024; Qin, 2022).

Ensemble methods, especially gradient boosting and related techniques, dominate tabular classification tasks and frequently report substantial accuracy gains over traditional statistical models (de Oliveira & Basso, 2025; Horváthová et al., 2024; Hair et al., 2025). Deep and probabilistic architectures have been applied to sequential risk problems, including stressed-market Value-at-Risk estimation (Fatouros et al., 2022). Early-warning designs seek to shift attention from post-event classification toward anticipatory signals (Li, 2022). Studies of corporate financial management risk and insolvency prediction among financial investment firms further illustrate the breadth of risk applications (Qin, 2022; Abdul-Kareem et al., 2024). Comparative evaluations of deterministic and stochastic classifiers have also been extended to capital-structure risk implications (Hair et al., 2025). Implementation considerations surface with force in this domain. Class imbalance, data-quality variation by firm size, crisis-period robustness, and regulatory expectations regarding explainability and ongoing validation repeatedly constrain deployment (Pamuk & Schumann, 2023). The volume of risk-focused studies reflects both the clear binary or ordinal structure of many risk outcomes and institutional demand for quantitative risk metrics; it also concentrates the literature's strongest evidence of predictive improvement alongside its clearest illustrations of governance friction.

Across the three domains, machine learning expands the set of functional forms applied to corporate financial data. Nonlinear methods improve discrimination and forecast accuracy relative to traditional linear specifications in a substantial share of documented cases. The character of the improvement differs by context. Investment applications emphasize opportunity ranking and dimensionality management; valuation applications emphasize input quality for existing measurement frameworks; risk applications emphasize classification reliability under institutional constraints. These differences in objectives, data structure, and organizational requirements imply that predictive approaches cannot be transferred across decision contexts without adjustment. The mapping presented here supplies the empirical landscape for the systematic model-family and decision-context comparisons that follow.

6 COMPARATIVE ANALYSIS OF PREDICTIVE MODELS

Accuracy metrics alone cannot determine the performance of predictive models in corporate financial decision-making. Model choice involves structured trade-offs among predictive capability, robustness, interpretability, computational demands, scalability, and suitability for organizational deployment. Four modeling families recur across the validated

literature (traditional financial models, classical machine learning methods, ensemble learning approaches, and deep learning architectures) and are compared in Table 2 below.

Traditional financial models, including linear and logistic regression, discriminant analysis, historical simulation and variance-covariance Value-at-Risk (VaR), and simple heuristics, remain the institutional baseline in many corporate settings. Transparency, low computational cost, and familiarity to regulators and executives constitute their principal strengths. Coefficients and ratios are directly inspectable, which facilitates audit and challenge processes. Strong assumptions of linearity or parametric distributional form, however, limit their reach. When financial relationships involve interactions among firm characteristics, regime shifts, or sequential dependence, traditional specifications systematically underperform. Multiple studies show that linear benchmarks are surpassed once nonlinear methods are introduced, particularly in asset-pricing, credit-rating, distress-classification, and certain forecasting tasks (Gu et al., 2020; de Oliveira & Basso, 2025; Fatouros et al., 2022; Wasserbacher & Spindler, 2022). Comparative advantage for traditional models therefore persists mainly where relationships are approximately linear, data are limited, or full transparency is non-negotiable.

Classical machine learning methods (single decision trees, support vector machines, shallow neural networks, and regularized linear models such as the least absolute shrinkage and selection operator (LASSO)) occupy an intermediate position. They relax some of the rigid assumptions of traditional specifications and can capture moderate nonlinearity or perform implicit variable selection. Regularized linear approaches prove useful in high-dimensional settings where economic structure must be imposed to avoid overfitting (Wasserbacher & Spindler, 2022; Jalali et al., 2026). Single trees offer partial interpretability through visible decision paths. Head-to-head evaluations nevertheless show that classical methods are themselves frequently outperformed by ensembles on complex classification and interaction-heavy problems (Hair et al., 2025; de Oliveira & Basso, 2025). Their practical role is often that of a transparent baseline or component within hybrid pipelines rather than a final production model.

Ensemble methods, including random forests, gradient boosting, extreme gradient boosting (XGBoost), and related techniques, emerge as the most consistently advantageous family for most tabular corporate financial tasks. By combining multiple base learners, they capture interactions and nonlinearities that defeat both traditional and single classical models while remaining computationally tractable on typical corporate datasets. Superior classification and forecasting performance have been documented across credit-rating prediction, bankruptcy and distress diagnosis, startup-exit screening, tax-payment forecasting, and capital-structure classification (Gu et al., 2020; de Oliveira & Basso, 2025; Ross et al., 2021; Wasserbacher & Spindler, 2022; Horváthová et al., 2024; Hair et al., 2025). Feature-importance measures supply partial interpretability, although full transparency is lost. Residual overfitting risk in small-sample or extremely high-dimensional regimes, together with reduced auditability relative to linear models, constitute the principal limitations (Jalali et al., 2026; Hair et al., 2025). For most investment-screening and risk-classification problems that dominate the literature, ensembles currently offer the best available balance of accuracy and practical deployability when data regimes are adequate and validation is rigorous.

Deep learning architectures (multi-layer networks, long short-term memory (LSTM) networks, gated recurrent units (GRU), convolutional neural networks (CNN), temporal convolutional networks, and probabilistic deep models) extend representational capacity further, especially for sequential and highly nonlinear patterns. Clear advantages appear in index-level forecasting, earnings prediction, early-warning systems, and advanced portfolio-risk estimation such as DeepVaR (Chahuán-Jiménez, 2024; Fatouros et al., 2022; Li, 2022). Where temporal dependence or complex latent structure is central, deep models frequently outperform both traditional specifications and tree-based ensembles on pure predictive metrics. Opacity, higher computational and data requirements, and greater sensitivity to sample size and distribution shift accompany those gains. In purely tabular risk-classification settings with modest sample sizes, deep models do not uniformly dominate ensembles and can introduce unnecessary implementation complexity.

Table 2 crystallizes the contrasts. Predictive capability rises from traditional models through classical methods to ensembles and deep learning, while interpretability moves in the opposite direction. Robustness is highest for ensembles under typical corporate data conditions; deep learning robustness remains more conditional on data volume and stationarity. Computational demands and implementation complexity increase with model capacity. No single family dominates all decision contexts. Suitability depends on the structure of the prediction problem, the scale and nature of available data, and the organization's tolerance for opacity.

Nonlinear outperformance should not be read as a blanket recommendation for the most complex available architecture. Across the reviewed literature, ensemble methods consistently provide the most reliable default for the bulk of corporate tabular tasks when data and validation conditions are favorable, with deep learning reserved for sequential or highly complex regimes. The tension between accuracy and interpretability is structural rather than transitional. Organizations that prioritize regulatory or fiduciary transparency will rationally constrain model complexity even when pure predictive metrics favor opaque solutions. Model selection in corporate finance is therefore as much an institutional decision as a technical one.

Table 2: Comparative Analysis of Traditional Financial Models and Machine Learning Approaches for Corporate Financial Decision-Making

Dimension	Traditional Financial Models	Classical Machine Learning	Ensemble Learning Methods	Deep Learning Approaches
Predictive capability	Moderate; limited on nonlinear tasks	Moderate to Moderate-High	High	High on sequential/complex tasks
Robustness	Moderate; degrades under structural breaks	Moderate	Moderate-High to High	Moderate; data- and regime-dependent
Interpretability	High	Moderate to High	Moderate to Low	Low
Scalability	High (modest feature sets)	High	High	Moderate to High (data-hungry)
Computational demands	Low	Low to Moderate	Moderate	Moderate to High
Implementation suitability	High where transparency is paramount	Moderate-High	High for most tabular decision-support tasks	Highest for sequential and complex pattern tasks
Key strengths	Transparency, regulatory familiarity, low cost	Flexibility with relative simplicity	Consistent accuracy gains, interaction capture	Temporal dependence and complex nonlinearity
Principal limitations	Inability to capture complex interactions	Intermediate accuracy ceiling	Reduced transparency; overfitting in constrained samples	Opacity, higher resource demands, sample sensitivity

7 COMPARATIVE ANALYSIS OF FINANCIAL DECISION CONTEXTS

Machine learning applications in corporate finance are not uniform across decision domains. Investment, valuation, and risk assessment impose distinct objectives, data regimes, algorithmic preferences, and implementation constraints. Treating the contexts as interchangeable risks both technical mismatch and organizational failure. The following comparison examines decision objectives, predictive variables, data sources, modeling approaches, evaluation practices, and implementation considerations. Table 3 summarizes the contrasts.

Investment decision-making centers on the identification, evaluation, and allocation of capital. Predictive tasks include return and risk-premia forecasting, opportunity screening (including startup and project selection), and portfolio construction under concentration constraints. Feature sets commonly combine firm characteristics such as momentum, liquidity, profitability, and volatility with sequential price information and, in some cases, alternative indicators such as patent data (Gu et al., 2020; Jalali et al., 2026; Ross et al., 2021). Data sources range from standard equity and Compustat-style panels to venture databases. Both ensemble methods and deep sequential architectures appear frequently. Evaluation often blends statistical metrics with economic or directional measures. Implementation challenges center on high dimensionality, regime dependence, and translating predictions into actual allocation or screening decisions. In small-sample, high-dimensional settings, unrestricted models overfit unless economic structure is imposed as a form of regularization (Jalali et al., 2026).

Valuation applications occupy a more circumscribed but coherent position. Machine learning is used primarily to improve the quality of inputs that feed established valuation frameworks rather than to replace those frameworks. Typical targets include earnings forecasts, key financial ratios, and relative valuation multiples (Liapis et al., 2023; Geertsema & Lu, 2022). Sequential models such as long short-term memory networks and temporal convolutional networks have shown improvements in earnings prediction, while dynamic method-selection algorithms help match forecasting techniques to individual ratio series before discounted-cash-flow calculations (Liapis et al., 2023). Data are predominantly accounting and market based. Evaluation focuses on forecast-error reduction and, less consistently, on the resulting impact on firm-value estimates. Workflow integration constitutes the central implementation requirement: improved forecasts create value only when they are reliably embedded in existing valuation processes

and when the sensitivity of final values to input accuracy is understood. Relative to risk and investment, the valuation evidence base remains thinner and more frequently stops at the input-forecast stage.

Risk assessment constitutes the most densely populated domain. Objectives include credit-rating prediction, bankruptcy and financial-distress classification, portfolio Value-at-Risk estimation, financial-health diagnosis, and early-warning systems (de Oliveira & Basso, 2025; Fatouros et al., 2022; Horváthová et al., 2024; Li, 2022). Predictive variables are dominated by financial ratios that capture liquidity, leverage, profitability, and coverage, sometimes augmented by business-risk indicators or macro variables. Data sources span multi-country commercial databases, annual statements, standard bankruptcy datasets, and industry-specific panels. Ensemble methods, particularly gradient boosting and related techniques, dominate tabular classification tasks, while probabilistic deep networks have been applied to market-risk estimation under stressed conditions. Evaluation centers on classification metrics (accuracy, area under the receiver operating characteristic curve) and, for market risk, coverage or exceedance performance. Implementation considerations are the most institutionally constrained of the three domains. Regulatory expectations around explainability, auditability, retraining discipline, and supervisory coordination are recurrent (Pamuk & Schumann, 2023). Class imbalance, data-quality variation by firm size, and crisis-period robustness further shape model choice and monitoring design.

Table 3 makes the contrasts visible. Investment problems emphasize dimensionality, interaction effects, and economic or directional performance. Valuation problems emphasize sequential forecast quality and integration into existing measurement frameworks. Risk problems emphasize reliable classification or quantification under governance and regulatory constraints. These differences produce distinct algorithmic and organizational requirements. An architecture optimized for credit-risk classification under supervisory scrutiny will not be optimal for sequential earnings forecasting or for small-sample return prediction among systemically important firms. A deep sequential model that improves index-level directional accuracy may offer limited advantage, and considerable opacity costs, when the task is tabular distress classification with modest sample size.

A common pattern nevertheless appears across the three domains. Nonlinear methods expand predictive capacity relative to traditional linear specifications, yet the translation of that capacity into decision value remains uneven. Investment studies more often retain an explicit link to screening or allocation. Valuation studies more often remain at the input-forecast level. Risk studies more often confront institutional constraints that condition deployment even when accuracy gains are clear. Context is therefore not a secondary consideration but a primary determinant of appropriate model design, validation standards, and governance arrangements.

Table 3: Comparative Characteristics of Machine Learning Applications Across Investment, Valuation, and Risk Assessment

Dimension	Investment	Valuation	Risk Assessment
Primary decision objective	Opportunity identification, return prediction, capital allocation, screening	Improvement of inputs to firm or asset valuation frameworks	Classification or quantification of credit, distress, market, and financial-health risk
Common predictive variables	Firm characteristics, return series, alternative indicators (e.g., patents)	Earnings series, key financial ratios, valuation multiples	Financial ratios (liquidity, leverage, profitability), business-risk indicators, sequential returns
Principal data sources	Equity panels, Compustat-style data, venture databases	Accounting and market data, sequential earnings series	Multi-country commercial databases, annual statements, bankruptcy datasets, industry panels
Frequently applied algorithms	Ensembles, thematic-grouped models, deep sequential networks	Sequential deep models, dynamic forecasting-method selection	Gradient boosting and related ensembles, deep and probabilistic networks
Dominant evaluation metrics	Out-of-sample predictive performance, directional accuracy, economic measures	Forecast error (RMSE, MAE, MAPE), impact on value estimates	Classification accuracy, AUC, VaR coverage / exceedance
Key implementation considerations	Dimensionality control, regime dependence, decision-process linkage	Workflow integration, sensitivity of final values to input forecasts	Explainability, regulatory auditability, class imbalance, crisis robustness, monitoring cycles

8 CRITICAL EVALUATION OF IMPLEMENTATION CHALLENGES

Predictive gains documented in controlled evaluations do not automatically become improved corporate financial decisions. Between model performance and organizational value lie implementation frictions that the literature repeatedly surfaces yet only partially resolves. The challenges that condition whether machine learning systems move from technical demonstration to sustained decision support are examined below.

Data quality and representativeness form a foundational constraint. Many high-performing models are trained on clean, relatively complete commercial databases or carefully curated research samples. Corporate environments often confront missing values, inconsistent reporting across subsidiaries, lagged data availability, and structural breaks that differ from the conditions under which models were validated. Severe class imbalance, typical in distress and default prediction, can produce optimistic performance metrics that deteriorate once the model encounters the true base rates of operational portfolios (de Oliveira & Basso, 2025; Pamuk & Schumann, 2023). Feature engineering introduces further fragility. Variables that drive accuracy in one period or jurisdiction may lose relevance under changing accounting standards, market regimes, or business models, yet few studies systematically examine the stability of feature importance over time.

Model drift and the limits of static validation compound these difficulties. Financial relationships are evolving. A specification that performs well in one market cycle may degrade in the next, particularly when sequential or high-dimensional models are involved. Clear warnings appear in the literature about unrestricted models in small-sample, high-dimensional settings: without economic structure imposed as a regularizing constraint, apparent predictive power collapses out of sample (Jalali et al., 2026). Even when initial validation is rigorous, ongoing monitoring and retraining regimes are required. Those operational demands are frequently under-specified in empirical studies that stop at a single train-test split.

A deeper challenge concerns the mismatch between predictive objectives and decision objectives. Wasserbacher and Spindler (2022) demonstrate that models optimized for forecasting can fail when the organizational task is causal or interventional, as is common in financial planning and analysis. Treating a pure prediction engine as if it automatically supports resource allocation or policy intervention risks both technical error and misplaced confidence. Parallel problems arise when improved forecasts of earnings or risk metrics are never embedded in the actual processes through which capital is allocated, valuations are approved, or credit limits are set. Several studies achieve strong predictive results while remaining silent on whether those results altered any decision (Liapis et al., 2023; Wasserbacher & Spindler, 2022). The prediction-to-decision gap is defined as the disconnect between strong predictive performance achieved in controlled evaluations and the actual incorporation of those predictions into corporate financial decisions such as capital allocation, screening, valuation, or risk management. This gap is therefore not merely an academic observation but a recurring practical failure mode.

Organizational capability and governance arrangements further mediate outcomes. Effective deployment requires more than algorithmic expertise. It demands data infrastructure, clear accountability for model outputs, processes for challenge and override, and the capacity to interpret and act on signals under time pressure. In regulated domains, especially credit risk and capital-related applications, supervisory expectations regarding explainability, documentation, and ongoing validation add material process overhead (Pamuk & Schumann, 2023). Firms that lack mature model-risk management functions face a steeper path from pilot to production. Even where technical performance is strong, opacity can erode executive willingness to rely on outputs for high-stakes choices, producing adoption friction that pure accuracy metrics do not capture.

Implementation complexity itself scales with model capacity. Ensemble and deep learning systems introduce greater demands for computational resources, specialized skills, version control, and performance monitoring than traditional linear models. These costs are often justified by accuracy gains in research settings. In organizational settings they must be weighed against the marginal decision value actually realized and against the availability of simpler alternatives that may deliver most of the benefit at lower operational risk. Comparative evidence on total cost of ownership or on the durability of performance once models leave the research environment remains limited.

The binding constraints on machine learning in corporate finance are frequently institutional and procedural rather than purely algorithmic. Data limitations, drift, weak linkage to decision processes, governance requirements, and capability gaps determine whether predictive superiority becomes organizational advantage. Studies that report high accuracy without addressing these conditions provide incomplete guidance for practice. Nonlinear methods expand what can be predicted; expanding what is predicted does not, by itself, expand what is improved.

9 EXPLAINABILITY, GOVERNANCE, AND ORGANIZATIONAL ADOPTION

Technical performance does not settle whether organizations will, or should, rely on machine learning for consequential financial decisions. Between predictive capability and sustained adoption lie concerns centered on transparency, accountability, regulatory acceptability, and managerial trust. How different modeling approaches navigate these concerns, and what the resulting trade-offs imply for responsible deployment, is examined below. Table 4 summarizes the comparison of interpretable models, explainable artificial intelligence approaches, and black-box models.

Interpretable models (principally traditional linear and logistic specifications and single decision trees) offer the highest degree of inherent transparency. Coefficients, odds ratios, and decision paths can be inspected directly by analysts, auditors, and supervisors. That visibility aligns with established model-risk management practices and supports clear lines of accountability. In environments where regulatory scrutiny is intense or where fiduciary standards demand that decision logic remain open to challenge, interpretable models retain a structural advantage even when their predictive performance is inferior to more complex alternatives (Hair et al., 2025; Wasserbacher & Spindler, 2022). The limitation is the predictive ceiling already documented: when relationships are strongly nonlinear or interactive, transparency is purchased at the price of forgone accuracy.

Black-box models, including large ensembles and deep neural architectures, invert this balance. They deliver the strongest and most consistent predictive gains across many investment and risk tasks, yet they construct internal representations that are not directly inspectable. Feature-importance rankings provide partial insight but do not restore the full causal or logical transparency of simpler specifications. In credit-risk and capital-related applications this opacity generates friction with supervisory expectations concerning explainability and auditability (Pamuk & Schumann, 2023; de Oliveira & Basso, 2025). Executive willingness to act on opaque outputs also varies. Where performance is demonstrated under rigorous validation and where organizational experience with algorithmic systems is high, trust can develop. Where either condition is absent, opacity itself becomes a barrier to adoption regardless of reported accuracy.

Explainable artificial intelligence approaches attempt to recover partial transparency without fully abandoning high-capacity models. Post-hoc attribution methods and hybrid designs that combine complex predictors with explanation layers can improve local interpretability and support diagnostic review. Among the most widely adopted post-hoc techniques are SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), which provide local feature attributions that help users understand individual predictions. In principle, such approaches allow organizations to retain much of the predictive advantage of ensembles or deep networks while offering managers and supervisors a window into the drivers of individual predictions. In practice the literature remains cautious. Explanation quality is not guaranteed, stability of attributions across similar cases is not automatic, and the explanation layer itself becomes an additional object of validation (Pamuk & Schumann, 2023). Explainable artificial intelligence therefore reduces but does not eliminate the governance burden associated with complex models.

Table 4 organizes the contrasts. Interpretability and regulatory suitability decline as one moves from inherently transparent models toward black-box systems, while predictive performance generally moves in the opposite direction. Governance suitability and implementation complexity follow similar gradients. Organizational adoption is highest for interpretable models when transparency is paramount and highest for black-box models when accuracy gains are large and governance capacity is already strong. Explainable approaches occupy an intermediate and still-evolving position.

The tension between accuracy and transparency is not a temporary technological shortcoming awaiting a purely technical solution. It is a structural feature of the current evidence base and of the institutional environments in which corporate financial decisions are made. Risk assessment, especially in regulated credit and capital contexts, places the heaviest weight on explainability and auditability. Investment screening and certain forecasting applications can more readily tolerate opacity if performance gains are material and monitoring regimes are robust. Valuation processes that feed formal reporting or transaction decisions occupy a middle ground in which both accuracy of inputs and defensibility of methods matter.

Governance arrangements must therefore be designed with model type and decision context in view. Black-box systems require compensatory controls: stronger validation discipline, clearer accountability for outputs, explicit override protocols, and ongoing monitoring for drift and unexpected behavior. Interpretable systems reduce the need for such compensation but may leave predictive potential unrealized. Organizations that treat explainability as an afterthought rather than a design constraint risk either under-utilizing high-performing models or deploying them under conditions of unresolved accountability. Responsible adoption depends less on discovering a universally transparent high-performance algorithm than on matching model opacity to institutional capacity and decision stakes.

Table 4: Comparative Analysis of Interpretable Models, Explainable AI, and Black-Box Models in Corporate Financial Decision-Making

Dimension	Interpretable Models	Explainable AI Approaches	Black-Box Models
Level of interpretability	High	Moderate	Low
Predictive performance	Moderate	Moderate-High to High	High
Transparency	High	Moderate	Low
Governance suitability	High	Moderate-High	Moderate to Low
Regulatory suitability	High	Moderate	Low to Moderate
Executive trust	High	Moderate to High	Moderate to Low
Organizational adoption	High when transparency is prioritized	Moderate to High as hybrid strategy	Variable; higher when gains are large and controls exist
Implementation complexity	Low to Moderate	Moderate to High	Moderate to High
Key strengths	Auditability, accountability, regulatory familiarity	Partial recovery of insight without full performance loss	Superior accuracy on complex nonlinear tasks
Principal limitations	Predictive ceiling on complex relationships	Explanation quality and stability not guaranteed	Opacity, elevated governance burden, trust barriers

10 FUTURE DIRECTIONS FOR MACHINE LEARNING IN CORPORATE FINANCIAL DECISION-MAKING

Comparative and critical evidence reveals a field that has established technical feasibility more firmly than decision value. Nonlinear methods expand predictive capacity, yet the conditions under which those gains improve capital allocation, valuation quality, or risk outcomes remain incompletely specified. Future research must therefore move beyond incremental accuracy comparisons toward questions of decision impact, institutional fit, and responsible deployment.

Systematic evaluation of the prediction-to-decision link constitutes a primary priority. Many studies demonstrate superior forecasts or classifications without examining whether those improvements alter screening decisions, capital allocation, intervention timing, or valuation outcomes. Designs that stop at statistical performance leave open the possibility that organizational processes absorb or ignore the new signals. Research that traces algorithmic outputs through actual decision workflows, or that employs decision-analytic and quasi-experimental criteria alongside conventional metrics, would address this gap directly. Parallel work is needed on the distinction between pure prediction and causal or interventional tasks. Models optimized for forecasting can mislead when the organizational problem requires understanding the effects of actions. Greater use of causal machine learning frameworks, already flagged as relevant for financial planning and analysis, would help clarify when predictive systems can and cannot support resource allocation or policy choices.

Explainability and governance research requires equal attention. The accuracy-transparency tension is structural, yet comparative evidence on how hybrid and post-hoc explanation methods perform under realistic supervisory and managerial constraints remains limited. Studies that test the stability, decision-relevance, and regulatory acceptability of explanation layers, rather than merely demonstrating their technical possibility, would strengthen the foundation for responsible adoption. Related work should examine the organizational conditions that enable or impede trust in algorithmic outputs, including the design of challenge processes, override protocols, and accountability structures. Without such evidence, recommendations about black box versus interpretable systems remain incompletely grounded.

Generalizability across institutional and data settings constitutes another unresolved issue. High-performing models appear in both large multi-country samples and specialized single-country or single-industry contexts, but the transferability of those results is rarely tested directly. Research that deliberately maps performance differences across regulatory regimes, market structures, and data infrastructures would help bound claims of broad applicability.

Incorporating economic structure and domain knowledge more explicitly into model design, rather than treating them as post-hoc interpretation, offers a related avenue. Thematic feature grouping and theoretically informed constraints have already shown value in small-sample, high-dimensional settings. Extending this logic across decision domains could improve robustness while preserving the representational advantages of machine learning.

Emerging technical trajectories also warrant careful investigation. Multimodal approaches that integrate structured financial data with textual, alternative, or real-time information streams may enrich predictive representations, yet their incremental decision value and governance implications remain underexplored. Foundation models and more agentic systems raise further questions about reliability, monitoring, and human-AI collaboration in high-stakes financial environments. Real-time predictive analytics could support more continuous risk monitoring and allocation adjustments, but only if model drift, latency, and accountability challenges are addressed. In each case technical novelty should be assessed against the same criteria that constrain current systems: validation discipline, decision-process integration, and institutional capacity for oversight.

Longitudinal evidence on adoption and performance durability is scarce. Most studies capture model behavior at a single point or within a limited window. Research that follows systems after deployment (documenting drift, retraining effectiveness, changes in user reliance, and realized decision outcomes) would convert static performance claims into dynamic understanding. Such work is particularly important for risk applications, where distributional shifts and regulatory expectations evolve continuously.

These directions reorient the research agenda from demonstrating that machine learning can predict corporate financial quantities toward specifying when, how, and under what organizational conditions those predictions improve decisions. Progress will require closer integration of predictive empirics with decision analysis, causal reasoning, governance design, and institutional context. Only then can the field move from conditional technical success to reliable contributions to investment, valuation, and risk management practice.

10.1 Limitations of the Study

As a critical narrative review, this study does not follow a systematic protocol and may not capture every relevant publication. Findings depend on the quality and scope of the available literature, which varies in sample composition, institutional setting, and evaluation design. Patterns identified across studies should therefore be interpreted with caution when generalized to specific organizations or regulatory environments. In addition, the possibility of publication bias cannot be ruled out, as studies reporting stronger predictive performance may be more likely to appear in the published record than those with null or modest results. Finally, the rapid evolution of machine learning methods and applications means that newer architectures and empirical findings continue to emerge; the synthesis presented here reflects the state of the literature at the time of analysis and may require updating as the field advances.

11 CONCLUSION

Machine learning expands the representational capacity available for corporate financial prediction, particularly where relationships are nonlinear, interactive, or sequential. Ensemble methods currently provide the most reliable performance gains across the majority of tabular investment and risk tasks when data and validation conditions are favorable, while deep learning shows comparative strength on sequential forecasting problems. These advantages remain conditional on data regime, validation discipline, and the degree to which outputs are integrated into actual decision processes.

Technical feasibility is more firmly established than decision value. Predictive improvements frequently stop short of demonstrated effects on capital allocation, screening quality, intervention timing, or valuation outcomes. The tension between accuracy and transparency is structural. Risk applications face the strongest governance and regulatory constraints, investment applications the greatest dimensionality challenges, and valuation applications the clearest need for workflow integration.

Model choice and deployment must therefore be conditioned on decision context, institutional capacity, and the relative weight assigned to performance versus explainability. Progress depends less on further demonstrations of predictive superiority than on closing the prediction-to-decision gap and designing governance arrangements equal to the opacity that high-capacity models introduce.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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