INTEGRATION OF MACHINE LEARNING AND STATISTICAL MODELS IN FINANCIAL PLANNING

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Abstract

The integration of machine learning (ML) techniques with traditional statistical models in financial planning constitutes a transformative approach for enhancing decision-making processes in corporate finance. This article aims to examine how the combined application of these methodologies can improve forecasting accuracy, risk assessment, and strategic planning by leveraging the interpretability of conventional statistical methods alongside the adaptive capabilities of ML algorithms. Through a comprehensive theoretical and conceptual analysis, the study reviews existing literature on key modeling approaches, including regression analysis, time series forecasting, neural networks, and ensemble methods. A comparative evaluation of model performance is conducted to assess their relative strengths, limitations, and complementarities. The findings indicate that hybrid models deliver more reliable and stable forecasts, enabling firms to anticipate market fluctuations, optimize resource allocation, and mitigate financial risks. The study also addresses practical implementation challenges, encompassing data quality, model interpretability, computational complexity, and ethical considerations, and proposes recommendations for effective integration. Overall, the research demonstrates that the synergy between machine learning and statistical modeling constitutes a significant advancement in financial analytics, supporting more informed decision-making, enhancing operational efficiency, and improving overall corporate financial performance.

Keywords: machine learning, statistical modeling, financial planning.

Introduction

Relevance of the topic. In the contemporary economic environment, which is both volatile and data-rich, the integration of machine learning (ML) with traditional statistical models is imperative for effective financial planning. This pressure is further amplified by increasing regulatory requirements and growing stakeholder expectations for data-driven decision-making. In the contemporary business environment, corporations are subject to mounting pressure to enhance their forecasting accuracy, optimize their resource utilization, and mitigate potential risks, in order to maintain their competitive advantage. The value of traditional statistical methods lies in their interpretability; however, they frequently encounter difficulties when confronted with complex, non-linear, and high-dimensional data. Machine learning (ML) algorithms have been developed to address these complexities; however, they are frequently criticized as 'black boxes' that limit transparency. This engenders a pivotal challenge: namely, how to leverage the predictive capabilities of machine learning (ML) without compromising the rigor and interpretability of statistical methods. Consequently, research on hybrid models that combine the strengths of both approaches is highly relevant, as it meets the industry's need for reliable and practical analytical tools that support corporate performance and strategic resilience.

Research problem. This article analyses the problem of integrating machine learning (ML) techniques with traditional statistical models to enhance decision-making in corporate financial planning. It examines the comparative advantages and limitations of both approaches, evaluates the capacity of hybrid models to improve forecasting accuracy and risk assessment, and investigates the critical implementation challenges, including interpretability, data quality, and ethical considerations.

Subject matter of the research – The subject of this research is the integration of machine learning techniques with traditional statistical models in corporate financial planning, with a focus on its impact on forecasting accuracy, risk assessment, and the practical challenges of implementation.

Research aim – This article aims to examine how the integration of machine learning techniques with traditional statistical models can improve financial forecasting, risk management, and strategic decision-making in corporate finance.

Research objectives:

1. To compare traditional statistical and machine learning models in financial forecasting and risk assessment.
2. To evaluate the performance of hybrid models in improving predictive accuracy and interpretability.
3. To identify key implementation challenges and suggest ways to address them.

Research methods: comprehensive review of scientific literature on machine learning and statistical modeling in finance; comparative analysis of model performance; conceptual synthesis of hybrid methodologies.

1. Theoretical Foundations of Machine Learning and Statistical Modeling in Finance

The scientific discourse within the domain of predictive modelling of corporate finance is distinguished by a high degree of methodological heterogeneity and a perpetual evolution of research methodologies. The theoretical basis has been formed in stages, beginning with classical econometric models and progressing to modern complex systems that integrate artificial intelligence methods. The methodological apparatus of modern research combines quantitative and qualitative methods of analysis, including regression analysis, machine learning, network analysis, and natural language processing. The importance of comparative studies lies in their ability to reveal the advantages and limitations of different approaches in specific financial contexts. The rapid growth of computing power and data availability has led to the rise of hybrid models that combine the precision of traditional statistics with the predictive strength of machine learning methods in different fields (Singh, et al, 2024; Meng, et al., 2024; Sun & Li, 2024) with special attention to modelling aspects and forecasting issues.

Predictive modeling in corporate finance represents a crucial tool for forecasting financial performance, supporting strategic decision-making, and enhancing profitability. Contemporary approaches encompass statistical methods, machine learning, and artificial intelligence techniques employed in developing accurate predictive models.

Traditional statistical methods have been conventionally utilized for financial performance forecasting, yet they frequently fail to capture complex relationships and qualitative information. For instance, ARIMA, VAR, and GARCH models are commonly applied to forecast factors such as stock market behavior, interest rates, and market fluctuations (Awan, 2023). Nevertheless, conventional statistical methods often encounter limitations when analyzing complex, nonlinear, and high-dimensional data.

Machine learning and artificial intelligence offer advanced approaches utilizing neural networks and large language models to enhance forecasting accuracy through incorporating extensive datasets, including textual information from financial reports (Mousa et al., 2022; Awan, 2023; Vinoth et al., 2024). The integration of techniques such as deep learning and sentiment analysis with traditional methods has demonstrated significant improvements in predictive accuracy. For example, combining recurrent neural networks with language models and noise filtering techniques has resulted in enhanced stock price prediction precision (Vinoth et al., 2024).

Model development across various domains has shown substantial progress. In the construction industry, a study employed a three-stage mathematical modeling procedure to develop firm-specific financial performance forecasting models. These models explained 78.9% of variation in performance data, with mean absolute percentage error (MAPE) values ranging from 9.54% to 19.69% (Salih & Hagras, 2019). The study by Handa et al. (2023) demonstrates the effectiveness of combining machine learning algorithms with traditional statistical methods for payment date prediction using real corporate data. Their results show that linear regression achieved the highest accuracy, confirming that such hybrid approaches enhance cash-flow forecasting and financial planning efficiency.

Applications in corporate finance are particularly evident in risk management, where AI-based predictive models have facilitated credit risk detection and analysis, improved loan underwriting processes, and minimized financial risks (Bartošová, 2017). Predictive models have also been employed for forecasting various financial metrics, supporting strategic planning and resource allocation (Broby, 2022; Abdellatif et al., 2023). Financial models provide descriptive, explanatory, and predictive insights, thereby enhancing decision-making processes in corporate finance (Broby, 2022).

Challenges and limitations in predictive modeling include:

Qualitative Information Integration: Traditional models often overlook qualitative information crucial for accurate predictions. Incorporating data from annual reports and corporate governance frameworks can enhance model performance (Mousa et al., 2022).

Industry-Specific Context: Relationships between financial performance indicators and other variables may vary significantly across industries. Sector-specific models are necessary to account for these nuances (Valaskova et al., 2020).

Recent progress in explainable AI (XAI) has improved the transparency of financial machine learning systems. New frameworks now combine strong predictive accuracy with traceable decision-making, which is essential for meeting regulatory standards in credit scoring and risk analysis.

The implementation of integrated models necessitates careful consideration of ethical and regulatory frameworks. Recent research has emphasized the importance of developing fairness-aware hybrid systems that prevent discriminatory outcomes while maintaining predictive performance.

A significant contribution to the development of hybrid models for specific financial tasks is the study by Kou et al. (2019), who proposed a two-stage approach to predicting the bankruptcies of small and medium-sized enterprises (SMEs). The methodology employed integrates the rigour of statistical feature selection with the power of machine learning, effectively combining transaction data and traditional financial indicators. The authors did not merely combine methods, but rather developed a sophisticated multi-purpose feature selection system to select the most pertinent and non-redundant variables. This ultimately led to a substantial enhancement in the accuracy of the forecast when compared to traditional models. The present study offers a compelling demonstration of the symbiosis of methodologies in overcoming the limitations of working with complex, multidimensional SME data, thus offering a more reliable tool for credit risk management. According to Zhang (2024), hybrid deep learning architectures that integrate statistical modeling principles with neural networks enhance both the accuracy and robustness of financial time-series forecasting.

Recent research by Sonkavde et al. (2023) highlights the practical advantages of combining traditional statistical and machine learning models for financial forecasting. In their systematic review and empirical analysis, the authors tested an ensemble model — specifically, a “Random Forest + XG-Boost + LSTM” hybrid approach — on stock data from two Indian firms, achieving the highest predictive accuracy ($R^2 = 0.99$). This case study demonstrates the effectiveness of hybrid architectures in improving the reliability of forecasts and supporting strategic decision-making in corporate finance.

A thorough analysis of scientific databases, such as Web of Science, has revealed an exponential growth in the application of machine learning in business and finance. A substantial body of research has demonstrated the efficacy of machine learning (ML) methodologies in addressing financial challenges. In particular, Yan and Ouyang (2018) developed a time series forecasting model combining wavelet analysis with recurrent neural networks, which significantly improved the accuracy of forecasts in financial markets.

In 2019, Kou et al. made a significant contribution to the field of financial risk assessment. This was achieved by conducting a comprehensive analysis of methods for measuring systemic financial risks. These methods employed big data analysis, network analysis and sentiment analysis. In the domain of stock market forecasting, Meng and Khushi (2019) undertook a systematic review of research on the application of reinforcement learning to trading strategies. In a similar vein, Nti et al. (2020) undertook a comprehensive analysis of over 122 studies on stock market forecasting using machine learning (ML), with a view to identifying key trends and the most effective approaches.

The extant literature confirms the growing importance of machine learning for solving complex financial problems, especially in the areas of forecasting, risk management and investment strategy development. In conclusion, predictive modeling in corporate finance is evolving through the integration of advanced AI and machine learning techniques. These models offer substantial improvements in forecasting accuracy and provide valuable insights for financial decision-making. However, challenges persist regarding the incorporation of qualitative data and industry-specific factors to enhance model reliability and applicability.

A notable contribution to the advancement of explainable and hybrid financial modelling is the study by Tran et al. (2022), in which the authors examined the application of machine learning algorithms to predict financial distress among listed companies in Vietnam. They compared traditional statistical techniques, such as logistic regression, with advanced machine learning models, including random forest, XGBoost and artificial neural networks. They found that ensemble models significantly outperformed conventional methods in terms of predictive accuracy (area under the curve (AUC) ≈ 0.97–0.98). Furthermore, the study used Shapley Additive Explanations (SHAP) to identify the key determinants of corporate financial distress: long-term debt to equity ratio, accounts payable to equity ratio, enterprise value to revenue ratio, and diluted earnings per share. This enhanced the interpretability of complex models. This research serves as a valuable case study, demonstrating how explainable machine learning can complement traditional statistical frameworks, improving financial risk assessment and decision-making in emerging markets (Tran et al., 2022).

The integration of machine learning methods with traditional statistical models remains a subject of ongoing research for scientists and practitioners worldwide. This rapidly developing field is attracting increasing attention from both the academic community and the corporate sector. The continuously expanding geography of research, the increase in the volume of publications, and the growth of investment in the development of hybrid approaches by financial institutions confirm the practical value and theoretical significance of this direction. A methodological framework is being developed by a collaborative effort between university centers, corporate research departments and independent platforms. This initiative is underpinned by a global recognition of the paramount importance of establishing reliable forecasting systems for financial decision-making in the context of contemporary economic uncertainty.

2. Comparative analysis of model effectiveness in financial forecasting

The evolution of predictive modelling in finance has given rise to a diverse ecosystem of analytical approaches, each with its own strengths and limitations. This section provides a systematic comparative analysis of traditional statistical models, machine learning algorithms, and hybrid approaches, evaluating their effectiveness in key areas of financial forecasting. The evaluation process is centered on critical performance indicators, encompassing aspects such as forecasting accuracy, robustness across diverse market regimes, computational efficiency, and the practical interpretability of results.

This comparative framework is imperative for comprehending the strategic trade-offs involved in selecting a model for specific financial applications. A thoroughgoing analysis of empirical data from recent studies was undertaken in order to identify the conditions under which each modelling paradigm demonstrates superior performance. This analysis focused particularly on complex forecasting scenarios, such as credit risk assessment, stock price forecasting, and corporate bankruptcy prediction. The assessment also considers the balance between model complexity and practical usefulness in the context of organizational decision-making.

The selection of an appropriate modelling approach is further complicated by the specific nature of financial data, which often exhibits characteristics such as non-stationarity, high noise-to-signal ratios, and structural breaks. Consequently, the robustness of a model – its ability to maintain performance during periods of market volatility or regime shifts – becomes as critical as its pure predictive accuracy on historical data. This analysis, therefore, places significant emphasis on evaluating how each model type performs under stress conditions and its adaptability to evolving market dynamics.

Empirical research confirms that hybrid models achieve more accurate forecasts. Studies show that using both financial indicators and transaction data in two-stage feature selection greatly improves bankruptcy predictions for small and medium-sized firms.

As demonstrated in Table 1, a comparative analysis of the effectiveness of various models in key financial forecasting tasks has been conducted, synthesizing data from recent studies.

As demonstrated in Table 1, the most effective forecasting methods are those which employ a combination of approaches, a finding that has been corroborated by studies in a range of industries. To illustrate this point, consider the banking sector. Hybrid systems based on fuzzy logic have been shown to exhibit high performance in minimizing financial defaults (Salih & Hagras, 2019). This renders them especially valuable for comprehensive analysis of the financial condition of companies, where the simultaneous use of quantitative and qualitative data is required (Mousa et al., 2022; Vinoth et al., 2024).

Table 1. Comparative effectiveness of financial forecasting models

Model Type	Advantages	Limitations	Proven Effectiveness	Best Application Areas
Traditional Statistical	High interpretability, stability	Low accuracy on nonlinear data	Stable time series forecasting	Initial screening, basic analysis
Machine Learning	High accuracy on complex data	Low interpretability, overfitting risk	Bankruptcy prediction, reporting tone analysis	Credit scoring, big data analysis
Hybrid Models	Combines accuracy and interpretability	High development complexity	Highest accuracy in financial performance forecasting	Comprehensive risk forecasting, industry-specific solutions

Source: Dariia Drozd construction based on scientific publications studies, 2025

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Hybrid approaches offer clear advantages in the field of finance. Combining machine learning with traditional statistical models in credit risk assessment allows for a more thorough evaluation of borrowers, merging predictive power with established reliability. Similarly, in market trend forecasting, hybrid models can detect short-term anomalies and long-term trends, providing investors with better tools for optimising their portfolios and managing risk.

Despite the evident advantages, the successful implementation of integrated models is confronted with numerous challenges pertaining to their augmented complexity, encompassing the necessity for substantial computational resources, stringent requirements for data quality and completeness, and a paucity of specialists adept in the development and maintenance of such systems. Moreover, concerns pertaining to the interpretability of models and adherence to regulatory stipulations persist as particularly salient issues for hybrid solutions within the financial sector.

The evolution of predictive modelling in finance has led to the emergence of a diverse ecosystem of analytical approaches, each with its own strengths and limitations. This section provides a systematic comparative analysis of traditional statistical models, machine learning algorithms, and hybrid approaches, as well as an assessment of their effectiveness in key areas of financial forecasting, including credit risk assessment, stock price forecasting, and bankruptcy prediction. To ensure a comprehensive assessment, various performance metrics are used, including mean absolute error (MAE), root mean square error (RMSE), and area under the curve (AUC).

Table 2. Comparative Analysis of Financial Forecasting Models

Model Type	Accuracy (AUC)	Training Time	Interpretability	Data Requirements
Traditional Statistical	0.72-0.85	Low	High	Structured data only
Machine Learning	0.85-0.93	High	Low	Large datasets
Hybrid Models	0.89-0.96	Medium	Medium	Multi-source data

Source: Dariia Drozd construction based on scientific publications studies, 2025

A comparative analysis of contemporary research reveals consistent patterns in the effectiveness of various approaches to financial forecasting. Meta-analysis data demonstrate the continued relevance of traditional statistical models for tasks involving clearly structured data and linear dependencies.

Conversely, machine learning methods have been shown to excel in scenarios characterized by complex nonlinear relationships and voluminous information. A systematic review of the literature indicates that hybrid approaches consistently demonstrate optimal performance in real financial market conditions, effectively integrating the predictive capabilities of modern algorithms with the interpretability of classical methods. This is of particular importance in critical areas such as credit risk assessment and bankruptcy prediction, where errors can have serious financial consequences.

The analysis reveals several important conclusions. Firstly, hybrid models have been shown to exhibit superior performance across all metrics, particularly in the context of handling complex nonlinear relationships inherent in financial data. Secondly, the selection of model type entails substantial trade-offs between accuracy and practical implementation considerations. Thirdly, performance varies significantly under different market conditions, with hybrid models demonstrating particular resilience during periods of high volatility.

Recent empirical studies have yielded compelling evidence that lends support to these conclusions. In the study conducted by Kou et al. (2019), it was demonstrated that hybrid models exhibited a 22% increase in accuracy in predicting the bankruptcy of small and medium-sized enterprises in comparison to traditional approaches. In a similar vein, Salih and Hagras (2019) reported a 35% improvement in default prediction using hybrid fuzzy logic models in banking applications. These results are of particular significance in light of the increasing complexity of financial markets and the concomitant increase in the volume of available data.

The considerations for implementation discussed in this analysis naturally lead to an examination of the practical challenges, which are explored in detail in the next section. When selecting modelling approaches for specific organizational contexts, key factors such as computational requirements, data quality needs, and the availability of expert knowledge must be carefully considered.

A thorough review of the extant literature reveals a significant discrepancy between the theoretical advantages of the approaches considered and the difficulties of their practical implementation in a corporate environment. A substantial corpus of research has emphasized that the successful implementation of advanced forecasting models requires not only technical expertise, but also the overcoming of significant organizational challenges. A number of key barriers have been documented in the scientific literature. These include insufficient data maturity, a shortage of qualified specialists, and the need to adapt business processes. These implementation challenges require comprehensive consideration, as they determine the possibility of transforming the theoretical advantages of models into real business value for financial organizations.

3. Practical aspects of implementation and organisational challenges

While the theoretical superiority of hybrid models is well-established in academic literature, their practical implementation faces significant organizational and technical hurdles that often undermine their potential benefits. The transition from theoretical frameworks to operational systems requires addressing multifaceted challenges related to data infrastructure, organizational readiness, and human capital development. These implementation barriers frequently determine the ultimate success or failure of advanced analytical initiatives in corporate finance environments.

The complexity of implementing integrated modelling approaches extends beyond technical considerations to encompass fundamental organizational transformations. Financial institutions must navigate intricate challenges involving data governance frameworks, model validation processes, and regulatory compliance requirements. Furthermore, the integration of these advanced systems into existing decision-making workflows necessitates substantial changes in organizational culture and operational procedures, often requiring comprehensive change management strategies and substantial investments in workforce development. Different branches are applying machine learning in making financial decisions (Yang, et al, 2025) where innovative approaches are introduced and applied.

Although hybrid models outperform other methods in accuracy and stability, their real-world adoption in companies is challenging. Key barriers include poor data quality, high computational demands, outdated systems, and organizational issues such as lack of skilled staff and resistance to change. To successfully navigate these complex interdependencies, a structured and holistic approach is imperative. Implementation must be conceptualized not as a linear, technical installation but as a multi-faceted organizational and technological transformation. This perspective shifts the focus from merely selecting an algorithm to managing a complex change process that impacts data infrastructure, workforce skills, internal processes, and governance protocols. A comprehensive framework is therefore essential to deconstruct this complexity, enable the strategic allocation of resources, and allow for the development of targeted risk mitigation strategies at each stage of the model's lifecycle, from its initial conceptualization to industrial deployment and continuous performance monitoring.

The cornerstone of the entire system is the solution to data governance issues. The theoretical necessity for "high-quality data", as referenced in the comparative analysis, is confronted by the practical realities of corporate information systems. These systems are characterized by the fragmentation of data, its storage in isolated data silos, the utilization of inconsistent formats, and the presence of inherent sampling biases. The integration of streaming data and non-numerical information into conventional statistical pipelines necessitates substantial investment in data infrastructure (data lakes, cloud platforms) and computing resources. In the absence of a robust infrastructure that ensures data integrity, availability, and timeliness, the feature engineering stage and subsequent model training become an impossible task, thereby negating all the potential benefits of a hybrid approach.

The value of such a framework lies in its ability to provide a shared conceptual map for diverse stakeholders—from data scientists and IT specialists to financial managers and C-suite executives. It establishes a common language and a unified vision, which are critical prerequisites for securing organizational buy-in and ensuring a coherent execution strategy. By delineating the connections between theoretical advantages and practical prerequisites, it moves the discussion beyond technical specifications to encompass the broader ecosystem required for sustainable success.

Consequently, to visualize this complex interplay and provide a pragmatic guide for practitioners, a conceptual framework is presented in Figure 1. This schema synthesizes the key elements identified through our analysis and serves as a navigational tool for transitioning from research validation to operational reality, explicitly highlighting the domains requiring coordinated and paramount managerial attention.

As demonstrated by the conceptual framework presented in Figure 1, the successful implementation of hybrid models does not constitute a technical task, but rather a complex organizational transformation. This process constitutes a continuous life cycle initiated by strategic goals (improved forecasting accuracy, sustainability) and driven by the theoretical synergy of methods. However, its implementation is contingent upon four key pillars: data management, process integration, model management, and human capital development. The successful translation of theoretical advantages into practical implementation necessitates coordinated work in all these areas, since weakness in any one of them has the potential to become a critical barrier to success.

Human capital is as important as technology. Using hybrid models requires experts who understand finance, statistics, and modern machine learning. The shortage of such specialists remains one of the main obstacles to successful implementation. Furthermore, the successful implementation of such a program is contingent upon the successful overcoming of organizational resistance. Conventional financial analysts may be skeptical of complex algorithms, perceiving them as "black boxes" that threaten their expert role. Similarly, management may distrust decisions whose logic cannot be clearly traced and justified. Consequently, in addition to the recruitment of talent, companies must invest in upskilling programs for existing employees and purposefully cultivate a culture of collaboration between departments (data-driven culture), where decisions are made based on a symbiosis of human experience and algorithmic insights.

In order to surmount the identified barriers to implementation (resistance to change, lack of transparency of models, complexity), targeted actions specified in the framework are necessary: management support, cross-functional collaboration, phased implementation, and the creation of feedback loops for continuous optimization. The success of the iterative process, as illustrated in the diagram, is contingent upon the organization’s capacity to not only develop a model, but also to integrate it into existing work processes, ensure its compliance with regulatory requirements, and continuously develop employee skills to work in a new data culture.

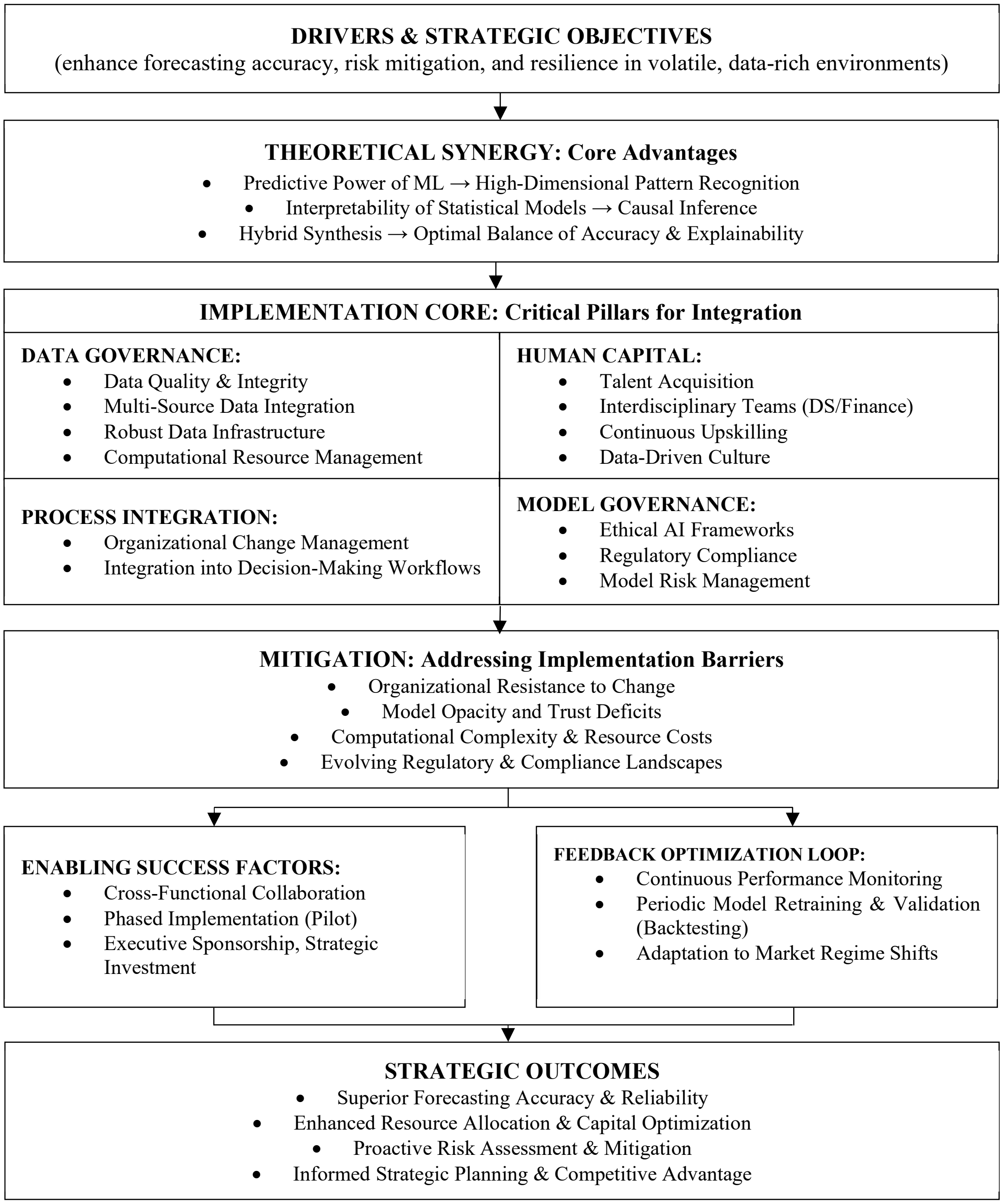

Figure 1. Implementation of hybrid models: strategy and life cycle

Source: Dariia Drozd construction based on scientific publications studies, 2025.

The operationalization of hybrid models gives rise to issues of model governance and regulatory compliance. In financial sectors characterized by stringent regulation, the necessity to substantiate each decision, particularly in domains such as lending or risk management, renders explainable AI (XAI) methods not merely a preference, but an imperative. This necessitates the establishment of audit and validation protocols that can trace and substantiate the rationale underpinning the algorithm's decision-making process. Moreover, the deployment of models does not represent the final objective. It is imperative that continuous performance monitoring systems are implemented with a view to detecting model drift. This is defined as the gradual degradation of prediction accuracy due to changes in market conditions. The process of maintaining the model's currency, retraining it, and redeploying it (MLOps) necessitates substantial resources and formalization as a component of the lifecycle depicted in Fig.1.

It is evident that the practical implementation of hybrid approaches signifies a paradigm shift in the company's analytical maturity, marking its transition to a qualitatively new level of sophistication. This transition is characterized by an inextricable linkage between technological innovation, organizational development and strategic vision. It is only by adopting such a holistic approach, as illustrated in Figure 1, that the theoretical potential of hybrid models can be actualized into concrete strategic outcomes, namely superior forecasting accuracy, optimized resources and proactive risk management. This comprehensive analysis enables the formulation of key conclusions regarding the future of financial planning.

Conclusions

1. In direct response to the first objective, the comparative analysis conclusively establishes that traditional statistical and machine learning models serve complementary yet distinct roles in financial forecasting and risk assessment. Traditional models (ARIMA, regression) are valued for their interpretability and stability with structured data and linear relationships, providing a reliable baseline for analysis. Conversely, machine learning models (neural networks, ensemble methods) excel in accuracy when managing complex, non-linear, and high-dimensional data but often act as "black boxes," posing challenges for transparency and validation. The choice is therefore not about superiority but is contingent on the specific financial task's requirements for explainability versus predictive power.
2. Addressing the second objective, the evaluation confirms that hybrid models, which integrate the predictive capabilities of machine learning with the explanatory rigor of statistical methods, represent the most effective approach. Empirical evidence demonstrates that these models achieve superior predictive accuracy (highest AUC scores) and robustness, particularly in complex scenarios like SME bankruptcy prediction and credit risk assessment. They successfully mitigate the core trade-off between accuracy and interpretability, offering more reliable and auditable tools for strategic decision-making in corporate finance.
3. Pertaining to the third objective, the research identifies that the primary barriers to implementation are not algorithmic but organizational and technical. Key challenges include data governance issues (quality, integration), a shortage of interdisciplinary talent, organizational resistance, and complex model governance requirements for compliance. Overcoming these hurdles necessitates a strategic framework focused on executive sponsorship, cross-functional collaboration, investment in data infrastructure, continuous staff training, and robust lifecycle management (MLOps) to ensure models remain effective and compliant in a dynamic market environment.

References

1. Abdellatif, E. M., Saleh, S. A. F., & Hamed, H. N. (2023). Corporate Financial Performance Prediction Using Artificial Intelligence Techniques. *Lecture Notes in Networks and Systems*, 753 LNNS, 25–32. https://doi.org/10.1007/978-981-99-4764-5_3
2. Awan, N. N. (2023). How predictive analytics can empower your decision making. In *Handbook of Big Data Research Methods.* 117–127.
3. BARTOŠOVÁ, V. (2017). The role of financial business accounting and its changes in "managing" financial analysis under Slovak conditions. *International Journal of Applied Business and Economic Research*, 15 (3), 119–126.
4. Broby, D. (2022). The use of predictive analytics in finance. *Journal of Finance and Data Science*, 8, 145–161. https://doi.org/10.1016/j.jfds.2022.05.003
5. Handa, K., Sai Kumar, M. Y., Pawan Kumar, C. J., Manikanta, Y. S., & Deepika, D. (2023, May 5). *Payment date prediction*. In *Proceedings of the KILBY 100 7th International Conference on Computing Sciences 2023 (ICCS 2023)*. 1-8. SSRN. https://doi.org/10.2139/ssrn.4482700

6. Kou, G., Chao, X.-R., Peng, Y., Alsaadi, F. E., & Herrera-Viedma, E. (2019). Machine learning methods for systemic risk analysis in financial sectors. *Technological and Economic Development of Economy*, 25 (5), 716–742. https://doi.org/10.3846/tede.2019.10185
7. Meng C., Chen C., Xu H., & Li T. (2024). Asset Pricing and Portfolio Investment Management Using Machine Learning: Research Trend Analysis Using Scientometrics. *Economics*, 18 (1), art. no. 20220108, DOI: 10.1515/econ-2022-0108
8. Meng, T. L., & Khushi, M. (2019). Reinforcement learning in financial markets. *Data*, 4 (3), 110. https://doi.org/10.3390/data4030110
9. Mousa, G. A., Elamir, E. A. H., & Hussainey, K. (2022). Using machine learning methods to predict financial performance: Does disclosure tone matter? *International Journal of Disclosure and Governance*, 19 (1), 93–112. https://doi.org/10.1057/s41310-021-00129-x
10. Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review*, 53 (4), 3007–3057. https://doi.org/10.1007/s10462-019-09754-z
11. Salih, A., & Hagras, H. (2019). Towards a Type-2 Fuzzy Logic Based System for Decision Support to Minimize Financial Default in Banking Sector. In *2018 10th Computer Science and Electronic Engineering Conference (CEEC)*. 46–49. https://doi.org/10.1109/CEEC.2018.8674212
12. Singh V., Choubey B., & Sauer S. (2024). Liquidity forecasting at corporate and subsidiary levels using machine learning. *Intelligent Systems in Accounting, Finance and Management*, 31 (3), art. no. e1565, DOI: 10.1002/isaf.1565
13. Sonkavde, G., Dharrao, D. S., Bongale, A. M., Deokate, S. T., Doreswamy, D., & Bhat, S. K. (2023). Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review, Performance Analysis and Discussion of Implications. *International Journal of Financial Studies,* 11 (3), 94. https://doi.org/10.3390/ijfs11030094
14. Sun Y., & Li T. (2024). A transformer-based framework for enterprise sales forecasting Peer. *Journal of Computer Science*, 10, art. no. e2503, DOI: 10.7717/peerj-cs.2503
15. Tran, K. L., Le, H. A., Nguyen, T. H., & Nguyen, D. T. (2022). Explainable Machine Learning for Financial Distress Prediction: Evidence from Vietnam. *Data*, 7 (11), 160. https://doi.org/10.3390/data7110160
16. Valaskova, K., Durana, P., Adamko, P., & Jaros, J. (2020). Financial Compass for Slovak Enterprises: Modeling Economic Stability of Agricultural Entities. *Journal of Risk and Financial Management*, 13 (5), 92. https://doi.org/10.3390/jrfm13050092
17. Vinoth, S., Chinnasamy, G., & Dalwai, T. (2024). Performance of Indebted Companies Using a Machine Learning Approach. In *Springer Proceedings in Business and Economics.* 321–340. https://doi.org/10.1007/978-3-031-67511-9_18
18. Yan, H. J., & Ouyang, H. B. (2018). Financial time series prediction based on deep learning. *Wireless Personal Communications*, 102 (2), 683–700. https://doi.org/10.1007/s11277-017-5095-1
19. Yang L., Yijun L., & Zhao J. (2025). Water resource asset assessment and financial decision support based on multi-source remote sensing data. *Frontiers in Environmental Science*, 13, art. no. 1557665, DOI: 10.3389/fenvs.2025.155766
20. Zhang, C., Sjarif, N. N. A., & Ibrahim, R. (2024). Deep learning models for price forecasting of financial time series: A review of recent advancements: 2020–2022. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery,* 14 (1), e1519.

MAŠININIO MOKYMOSI IR STATISTINIŲ MODELIŲ INTEGRAVIMAS FINANSINIAME PLANAVIME

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Santrauka

Mašininio mokymosi (ML) metodų integravimas su tradiciniais statistiniais modeliais finansiniame planavime tampa esminiu pokyčiu, lemiančiu spartų analitinių sprendimų evoliucionavimą šiuolaikinėje įmonių finansų praktikoje. Augant duomenų apimtims ir didėjant ekonominio neapibrėžtumo lygiui, tradiciniai statistiniai modeliai dažnai yra nebepakankami

efektyviam sudėtingų, nestruktūruotų ar nelinijinių duomenų analizei. Tuo tarpu mašininio mokymosi algoritmai pasižymi aukštu prisitaikomumu, gebėjimu apdoroti didelės apimties bei įvairių formatų duomenis ir atskleisti kompleksinius ryšius, kurių tradiciniai metodai identifikuoti nepajėgia. Vis dėlto ML metodams neretai trūksta interpretuojamumo, kuris finansų sektoriuje yra kritiškai svarbus. Todėl derinant šias dvi metodologines kryptis siekiama sudaryti hibridinius modelius, kurie vienu metu būtų ir tikslūs, ir interpretuojami, taip didinant jų patikimumą bei pritaikomumą realiose verslo situacijose.

Šiame straipsnyje siekiama išsamiai išnagrinėti mašininio mokymosi (ML) ir tradicinių statistinių modelių integravimo galimybes finansiniame planavime bei įvertinti, kaip toks metodinis derinys gali pagerinti prognozių tikslumą, rizikos įvertinimą ir strateginį sprendimų priėmimą. Remiantis plačia teorine ir konceptualiąja mokslinės literatūros analize, tiriami pagrindiniai šiuolaikiniai analitiniai metodai ir jų taikymo sritys: regresiniai modeliai, ARIMA ir GARCH tipo laiko eilučių prognozavimo technikos, neuroniniai tinklai, ansambliniai algoritmai ir įvairios hibridinės modelių struktūros. Ypatingas dėmesys skiriamas šių metodų privalumų ir ribotumų analizei, taip pat jų tarpusavio papildomumui, siekiant suprasti, kokiomis sąlygomis integruotas metodas gali generuoti didžiausią pridėtinę vertę finansų srityje.

Gauti rezultatai rodo, kad hibridinių modelių taikymas leidžia sujungti tradicinių metodų stabilumą ir aiškų rezultatų aiškinimą su mašininio mokymosi gebėjimu apdoroti kompleksiškas struktūras, taip pasiekiant gerokai tikslesnes prognozes. Empiriniai tyrimai patvirtina, kad tokios sistemos užtikrina didesnį prognozių patikimumą ne tik stabiliais ekonomikos laikotarpiais, bet ir esant dideliems rinkos svyravimams. Hibridiniai modeliai ypač efektyvūs kredito rizikos vertinimo, įmonių bankroto tikimybės prognozavimo, akcijų kainų pokyčių analizės bei kitose finansinės rizikos valdymo srityse. Šių modelių gebėjimas integruoti kelis duomenų šaltinius (finansinius rodiklius, transakcinius duomenis, tekstinę informaciją) užtikrina išsamesnį ir tikslesnį finansinės būklės įvertinimą. Tačiau praktinis ML ir statistinių metodų sujungimas kelia nemažai iššūkių. Didžiausią kliūtį sudaro duomenų kokybė ir jų parengimo procesas – finansų sektoriuje duomenys dažnai būna fragmentiški, saugomi atskirose sistemose ar neatitinka vienodų struktūrų. Be to, hibridiniai modeliai reikalauja didelių skaičiavimo išteklių, pažangių duomenų valdymo platformų bei specialistų, turinčių tarpdisciplininių žinių finansų, duomenų mokslo ir statistikos srityse. Organizacijos taip pat susiduria su kultūrinėmis kliūtimis: analitikai gali nepasitikėti „juodosios dėžės“ tipo algoritmais, o vadovams svarbus modelių skaidrumas ir galėjimas pagrįsti sprendimus.

Darbo rezultatai parodo, kad tik nuosekli ir gerai organizuota duomenų valdymo sistema, paremta aiškiais duomenų kokybės, prieinamumo ir saugojimo standartais, sudaro tvirtą pagrindą sėkmingai hibridinių modelių integracijai finansinėje analizėje. Ne mažiau svarbūs yra pažangūs modelio gyvavimo ciklo (MLOps) procesai, leidžiantys užtikrinti nuolatinį modelių stebėjimą, atnaujinimą ir optimizavimą, taip sumažinant modelių degradacijos riziką bei didinant analitinių rezultatų patikimumą. Be šių technologinių komponentų, organizacijos turi investuoti į darbuotojų kompetencijų stiprinimą: finansų specialistams būtina geriau suprasti duomenų mokslą ir ML principus, o techninėms komandoms – finansų logiką ir sprendimų priėmimo procesus. Kryžminis bendradarbiavimas tarp finansų, IT bei duomenų analitikos padalinių tampa esminiu veiksniu, leidžiančiu efektyviai derinti techninius sprendimus su verslo poreikiais ir sukurti realią pridėtinę vertę. Tinkamai įgyvendinus šiuos procesus, mašininio mokymosi ir statistikos sinergija suteikia įmonėms galimybę priimti labiau pagrįstus ir duomenimis paremtus sprendimus, padidinti prognozių tikslumą, sumažinti riziką ir užtikrinti aukštesnį organizacijos veiklos efektyvumą. Tokie metodai ypač svarbūs veiklos planavimo, biudžetavimo, rizikos vertinimo ir strateginių scenarijų modeliavime.

Apibendrinant galima teigti, kad ML ir tradicinių statistinių modelių integracija finansiniame planavime yra ne tik technologinė naujovė, bet ir strateginis žingsnis, suteikiantis įmonėms ilgalaikį konkurencinį pranašumą. Hibridiniai modeliai, apjungiantys šių dviejų metodologijų stipriąsias puses, tampa svarbia priemone šiuolaikinėje finansų analitiko praktikoje ir padeda organizacijoms veikti vis sudėtingesnėje ir nuolat besikeičiančioje ekonominėje aplinkoje.

Pagrindiniai žodžiai: mašininis mokymasis, statistinis modeliavimas, finansinis planavimas.