THE ROLE OF PREDICTIVE MODELLING IN ENHANCING CORPORATE FINANCIAL PERFORMANCE

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ABSTRACT
This article investigates the impact of predictive modelling on enhancing corporate financial performance. Drawing on conceptual and theoretical analysis, the study highlights the ways in which predictive analytics enables organisations to forecast market trends, optimise resource allocation, and mitigate financial risk. The findings underscore the critical role of data-driven decision-making in improving profitability, operational efficiency and strategic planning. By integrating advanced predictive technologies, corporations are able to anticipate financial challenges and opportunities, thereby supporting more informed investment and management decisions. The study further addresses implementation challenges, and identifies best practices for the effective application of predictive models in corporate finance. The research demonstrates that predictive modelling serves as a key tool for promoting sustainable financial growth and maintaining competitive advantage in today's dynamic business environment.
KEY WORDS: *predictive modelling, corporate finance, financial performance*.

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Introduction

The most important drivers of corporate growth and sustainability are concentrated in the ability of companies to ensure financial stability, profitability, competitiveness and resilience, to which several closely related aspects can be listed in detail: strategic planning, efficient resource allocation, effective management of uncertainties, technological adaptation, innovation, long-term investment security, operational efficiency, access to capital, human resource development, transparency, and compliance with governance standards. If one of these factors changes, or, conversely, does not evolve in line with market dynamics, the improvement of corporate financial outcomes may be constrained.

Corporate financial results are widely analysed in relation to both internal and external determinants, whether positive or negative, across the entirety of an organisation's activities at a specific point in time. Studies have shown that profitability, growth and stability are increasingly linked to the ability of firms to adopt data-driven strategies and advanced analytical tools (Mousa et al., 2022; Broby, 2022). Predictive modelling has emerged as a crucial element in this process, providing corporations with the capacity to project key indicators, anticipate risks and support sustainable development in a volatile business environment.

Approaches to predictive modelling in corporate finance range from traditional statistical techniques such as ARIMA, VAR and GARCH to advanced methods based on machine learning and artificial intelligence,

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including neural networks, deep learning and sentiment analysis (Awan, 2023; Vinoth et al., 2024). Traditional methods often fall short in capturing qualitative and industry-specific factors, while modern approaches integrate large and complex datasets to enhance accuracy. Successful applications are observed across multiple financial domains, including credit risk detection, loan underwriting, stock price projections, investment evaluation and long-term planning (Bartošová, 2017; Abdellatif et al., 2023).

The aim of the research: to investigate the impact of predictive modelling on enhancing corporate financial performance, focusing on its role in anticipating financial trajectories, mitigating exposure to uncertainties and guiding corporate strategy.

Tasks:

1) to analyse theoretical findings on predictive modelling methods and their applicability in corporate finance;
2) to investigate applications of predictive modelling in projecting corporate results, managing financial vulnerabilities, and strengthening managerial choices;
3) to identify challenges and best practices in implementing predictive models for corporate financial growth.

Research methods applied: conceptual and theoretical analysis of scientific publications, with an emphasis on comparative assessment of traditional statistical approaches and advanced machine learning techniques.

Data used in the research: academic studies, empirical evidence from industry-specific applications, and findings from recent investigations into predictive modelling in finance.

1. Theoretical findings in predictive modelling in corporate finance and financial performance

Predictive modelling in corporate finance is a crucial tool for forecasting financial performance, aiding in strategic decision-making and enhancing profitability. Various approaches, including statistical methods, machine learning and artificial intelligence, have been employed to develop accurate predictive models. In most cases, approaches to predictive modelling are applied statistical methods: traditional statistical methods have been used to predict financial performance, but they often fail to capture complex relationships and qualitative information (Mousa, et al., 2022). Modern approaches were applied to machine learning and AI, such as neural networks and large language models, to improve prediction accuracy by incorporating extensive data, including textual information from financial reports (Mousa, et al., 2022; Awan, 2023; Vinoth, et al., 2024). There were different achievements for model development in several fields, for example, in the construction industry, and good examples are pointed out by researchers: A study on the construction industry used a three-stage mathematical modelling procedure to develop firm-specific financial performance forecasting models. The models explained 78.9% of the variation in performance data, with mean absolute percentage error (MAPE) values ranging from 9.54% to 19.69% (Salih, Hagras, 2019). The application of advanced AI techniques noted by researchers in integrating AI techniques like deep learning and sentiment analysis with traditional methods has shown significant improvements in predictive accuracy. For instance, combining recurrent neural networks with language models and noise filtering techniques resulted in greater accuracy for stock price predictions (Vinoth, et al., 2024). Applications were in corporate finance, especially in risk management, where AI-based predictive models helped in detecting and analysing credit risks, improving loan underwriting and minimising financial risk (Bartošová, 2017). Researchers have also indicated financial forecasting, where predictive models were used to forecast various financial metrics, aiding in strategic planning and resource allocation (Broby, 2022; Abdellatifet, et al., 2023). Applications in decision support were noted by researchers where financial models provided descriptive, explanatory and predictive insights, supporting decision-making processes in corporate finance (Broby, 2022). Researchers have indicated challenges and considerations, such as the necessary qualitative information, for traditional models often overlook qualitative information, which can be crucial for accurate predictions. Often incorporating data from annual reports and corporate governance can enhance model performance (Mousa, et al., 2022). It is important to take into account the industry-specific context: the relationship between financial performance and other variables can vary significantly across industries. Industry-specific models are necessary to capture these nuances (Valaskova, et al., 2020). Researchers have concluded that predictive modelling in corporate finance is evolving with the integration of advanced AI and machine learning techniques. These models offer significant improvements in accuracy, and provide valuable insights for financial decision-making. However, challenges remain in incorporating qualitative data and industry-specific factors to enhance model reliability and applicability. Multiple studies demonstrate the effectiveness of various predictive modelling approaches in different contexts. Predictive modelling has a significant impact on financial performance in corporate finance, with various techniques being used for financial performance analysis. Here is a breakdown of the key points, challenges and ethical considerations related to predictive modelling in corporate finance and key predictive modelling techniques in corporate finance. Financial modelling in corporate finance involves the comprehensive quantification of a company's operations, exhibiting descriptive, explanatory and predictive qualities (Mousa, et al., 2022). Traditional statistical models, such as ARIMA, VAR and GARCH, are used to forecast financial factors like stock market performance, interest rates and market changes (Awan, 2023). Machine learning techniques, including neural networks, are increasingly being used for financial forecasting, surpassing traditional statistical models in evaluation precision and enhancing business decision-making efficacy (Vinoth, et al., 2024). Predictive analytics and machine learning are utilised to develop forecasting models for financial performance, with a shift from statistical methods to artificial intelligence methods such as neural networks (Salih, Hagras, 2019). Supervised machine learning methods, such as linear discriminant analysis, quadratic discriminant analysis and random forest, are employed to predict corporate financial performance, incorporating sentiment analysis of disclosure tone in annual report narratives to improve predictive accuracy (Bartošová, 2017). Advanced machine learning techniques, including ARIMA, LSTM and Gradient Boosting Regression, are used to forecast key financial measures and evaluate a firm's long-term success (Broby, 2022). Researchers have indicated that the challenges and limitations of predictive modelling in corporate finance associated with predictive analytics include data quality, identification of correct variables, and the right methodology to experience maximum benefits (Abdellatif, et al., 2023). The limitations of predictive analytics in corporate finance are not limited to data quality, the identification of correct variables, and the right methodology to experience maximum benefits (Abdellatif, et al., 2023). The use of unsuitable models and incorrectly selected accounting data in internal analyses can lead to distorted results and the incorrect interpretation of results in management practice (Valaskova, et al., 2020). The predictive ability of bankruptcy models developed in specific economic sectors outperforms models developed in different economic sectors and countries, highlighting the importance of using models developed in the same economic conditions and industrial sector for accurate predictions (Mohamed, 2004). Researchers have underlined the integration of predictive modelling with financial data and decision-making: predictive modelling provides a way to increase profitability and customer satisfaction in the financial services sector, demonstrating successful use in marketing activities for credit cards (Lukić, 2017). Statistical and computational methodologies are integrated into decision support systems to aid management and help with strategic decisions, enabling financial managers and risk oversight professionals to achieve better outcomes (Tang, 2024). The use of predictive models in financial applications helps organisations enhance their service quality and productivity, and reduce financial risk, supporting strategic planning and risk management in today's fast-paced corporate climate (Ievsieieva, et al., 2020). Many other aspects are indicated and deeply analysed.

Predictive modelling in corporate finance is a crucial tool for forecasting financial performance, aiding in strategic decision-making and enhancing profitability. Various approaches, including statistical methods, machine learning and artificial intelligence, have been employed to develop accurate predictive models. The emergence of explainable AI (XAI) has addressed critical interpretability challenges associated with complex algorithms, making model outputs more transparent and actionable for financial decision-makers (Molnar, 2022; Arrieta et al., 2020). Modern approaches leverage machine learning and AI, such as neural networks and large language models, to improve prediction accuracy by incorporating extensive data, including textual information from financial reports (Mousa et al., 2022; Awan, 2023; Vinoth et al., 2024). Recent systematic reviews confirm the expanding application of machine learning across various corporate finance functions, while also highlighting persistent implementation challenges that require careful consideration (Fedorova, Lukianova, 2023).

Applications in risk management demonstrate how AI-based predictive models have significantly improved credit risk assessment capabilities. Advanced machine learning techniques now enable more accurate default prediction and enhanced credit scoring mechanisms, although these applications require robust validation frameworks to ensure reliability (Bussmann et al., 2021). The effectiveness of these models fundamentally depends on data quality and comprehensive governance frameworks, as inadequate data management can severely compromise model performance and decision-making outcomes (Dietrich et al., 2023). Furthermore, researchers have indicated that financial forecasting benefits substantially from predictive modelling, with applications ranging from strategic planning to resource allocation (Broby, 2022; Abdellatif et al., 2023). Researchers worldwide are addressing these complex challenges, contributing to a rapidly expanding body of scientific literature that continues to refine and advance the integration of machine learning and statistical modelling in financial planning.

2. Applications and practical implications of predictive modelling in corporate finance

Predictive modelling is increasingly applied in corporate finance to strengthen organisational resilience and improve long-term outcomes. By analysing historical and real-time data, companies are able to project key financial indicators, anticipate market fluctuations, and align their strategies with changing economic conditions. Traditional statistical approaches, such as ARIMA or VAR models, have historically been used to forecast revenues, interest rates and market behaviour, but they often struggle to account for complex, non-linear relationships and qualitative influences (Mousa et al., 2022; Awan, 2023). The growing integration of machine learning and artificial intelligence has therefore transformed predictive modelling into a more adaptive and accurate instrument for financial decision-making.

One of the most significant practical applications is in credit risk analysis and financial stability management. Advanced predictive algorithms allow institutions to detect early warning signals of loan default or liquidity shortages, thereby reducing exposure to potential losses. AI-based models have shown particular effectiveness in improving loan underwriting processes and minimising systemic financial risk, as is demonstrated in empirical studies on credit assessment (Bartošová, 2017). These tools not only mitigate uncertainty but also support more sustainable lending and investment practices, ensuring better resource allocation in volatile markets.

Another area of growing importance is performance projection and investment planning. Predictive models assist corporations in estimating future profitability, evaluating investment scenarios and identifying potential growth opportunities. Modern techniques, such as neural networks and deep learning, combined with sentiment analysis, have improved the precision of forecasts by incorporating textual data from financial reports and market narratives (Vinoth et al., 2024). Such integration enables managers to evaluate a broader range of variables and adjust strategies proactively, turning predictive modelling into a powerful enabler of evidence-based strategic planning.

Beyond the theoretical potential, the true value of predictive modelling is realised in its applications across corporate finance functions. These tools are increasingly embedded in core financial decision-making processes, transforming raw data into a strategic asset. The transition from traditional econometric models to AI-driven approaches has been particularly impactful in areas requiring the analysis of high-dimensional data or the capture of complex, non-linear relationships. To systematically illustrate this range and impact, the table below synthesises the primary application areas, the methodological evolution they embody, and the tangible organisational benefits they deliver.

Table 1. Overview of key applications and implications of predictive modelling in corporate finance

Application area	Methods applied	Key outcomes and practical implications
Financial performance and profitability projection	Hybrid models (e.g. ARIMA, LSTM, Gradient Boosting) (Salih, Hagras, 2019; Broby, 2022)	Greater accuracy in forecasting firm-specific financial metrics, supporting strategic budgeting and long-term investment planning
Customer-centric product development	Predictive analytics (e.g. for marketing) (Lukić, 2017)	Increased profitability and customer satisfaction through personalised financial products and targeted marketing campaigns
Strategic planning and resource allocation	Predictive analytics, statistical and AI hybrid models (Tang, 2024; Broby, 2022)	Data-driven scenario analysis, optimised capital allocation, and enhanced strategic decision-making under uncertainty
Credit risk assessment and loan underwriting	Machine learning (e.g. neural networks, discriminant analysis) (Bartošová, 2017)	Enhanced default prediction, more accurate credit scoring, reduction in non-performing loans, and improved stability of lending portfolios
Stock price and market behaviour forecasting	RNNs, sentiment analysis, noise filtering (Vinoth et al., 2024)	More precise price forecasts by integrating quantitative data with qualitative insights from news and financial reports, aiding investment strategies

Source: Dariia Drozd, based on scientific publications studies.

The synthesised evidence confirms that predictive modelling is not a monolithic solution but a versatile toolkit adaptable to various financial challenges. Its practical implication lies in shifting managerial paradigms from reactive to proactive, and ultimately to prescriptive strategies. For instance, in credit risk management, models do not just predict defaults, but actively reshape underwriting processes, leading to more robust and sustainable lending practices. Similarly, in strategic planning, the integration of predictive analytics provides a data-driven foundation for scenario planning and resource allocation, moving beyond intuition-based decisions.

However, successful implementation hinges on addressing key challenges. The effectiveness of models in areas like stock price forecasting is critically dependent on data quality and the ability to filter market 'noise'. Furthermore, the choice of model must align with the specific problem context; an LSTM network might be superb for sequential data like time series, but a simpler model could be more efficient and interpretable for other tasks. Thus, the practical implication extends beyond mere application, to include the development of internal expertise (data literacy among financial managers and effective collaboration between data scientists and finance professionals) to ensure models are not just deployed, but are truly embedded and trusted within the organisation's decision-making fabric.

Ultimately, the adoption of predictive modelling is a strategic imperative that enhances resilience. By enabling firms to anticipate market shifts, optimise investments, and manage risks with greater confidence, these technologies contribute directly to improved financial performance and long-term competitive advantage.

Despite these advancements, the widespread implementation of predictive modelling is not without its obstacles. The efficacy of any model is intrinsically tied to the quality, completeness and granularity of the underlying data. Inconsistent data governance, siloed information systems and the inherent noisiness of financial markets can significantly impair forecasting accuracy and lead to misguided conclusions. Furthermore, the increasing complexity of state-of-the-art algorithms, particularly deep learning models, often results in a 'black box' problem, where the rationale behind a specific prediction is opaque. This lack of interpretability and explainability poses a serious challenge for financial managers and regulators who require clear audit trails and justifications for critical decisions involving risk, investments and compliance.

These very challenges, however, are actively shaping future research and development agenda in the field. The next frontier for predictive modelling in finance lies not only in improving algorithmic precision but also in enhancing model transparency, robustness and accessibility. Emerging trends include the development of explainable AI (XAI) techniques designed to make complex models' outputs understandable to human experts, the integration of alternative data sources (e.g. satellite imagery, social media sentiment, supply chain information) to provide a more holistic view of corporate health, and the rise of automated machine learning (AutoML) platforms that aim to democratise advanced analytics for smaller finance teams without extensive data science resources.

3. Challenges, limitations and future directions of predictive modelling in finance

Despite its transformative potential, the integration of predictive modelling into corporate finance is not without significant challenges and limitations. These hurdles often stem from the inherent complexity of financial systems, the methodological nuances of model construction, and the practical realities of organisational implementation. A primary constraint lies in data quality and availability; models are highly sensitive to the accuracy, completeness and granularity of input data. Inconsistent data governance, siloed information systems and the inability to effectively capture qualitative factors, such as management expertise or corporate governance quality, can severely limit model reliability and lead to skewed outcomes (Mousa et al., 2022; Valaskova et al., 2020). Furthermore, the quest for methodological appropriateness remains critical. The selection of an unsuitable model for a given financial context, whether an oversimplified statistical approach or an excessively complex neural network, can distort results and provoke misguided strategic decisions (Abdellatif et al., 2023).

A further layer of complexity arises from the interpretability dilemma associated with advanced algorithms. While machine learning and deep learning techniques often achieve superior predictive accuracy, their 'black-box' nature obscures the rationale behind decisions. This lack of transparency poses a profound challenge for financial managers who require explainable insights to justify decisions in areas like risk management and investment allocation, ultimately eroding trust and hindering accountability. Moreover, overreliance on automated outputs can inadvertently perpetuate and amplify inherent biases present in historical data, leading to discriminatory lending practices or flawed risk assessments with serious ethical and financial repercussions (Abdellatif et al., 2023).

To synthesise these complex interdependencies between the technical, organisational and ethical dimensions of predictive modelling, Figure 1 provides a structured conceptual framework. It maps the primary challenges and limitations to emerging future directions, illustrating how innovations in technology and methodology are directly responding to current barriers.

As illustrated in Figure 1, the path forwards is defined by a targeted response to these constraints. The challenge of interpretability and bias is addressed by the rise of explainable AI (XAI) and ethical AI frameworks, designed to open the 'black box' and ensure fairness. The limitation of poor data quality is countered by the integration of alternative data sources (e.g. ESG metrics, satellite imagery) and advanced data governance techniques. Finally, the issue of methodological rigidity is overcome through the development of adaptive and sector-specific models that offer greater contextual relevance and resilience. This framework stresses that the evolution of predictive modelling is not merely technical but a holistic endeavour. It is through the simultaneous advancement of transparent algorithms, robust data practices and ethically-aware implementation that predictive modelling will fully solidify its role as a cornerstone of robust, resilient and responsible corporate financial management.

The cumulative effect of these challenges extends beyond technical limitations to fundamentally influence strategic decision-making and organisational trust. When predictive models lack transparency, or are fed with biased or incomplete data, they can erode confidence in data-driven initiatives and lead to costly misallocations of capital. This is particularly critical in areas such as long-term investment planning and risk management, where the consequences of erroneous predictions can impact market competitiveness and financial stability. Consequently, the ability to critically evaluate and interpret model outputs becomes as

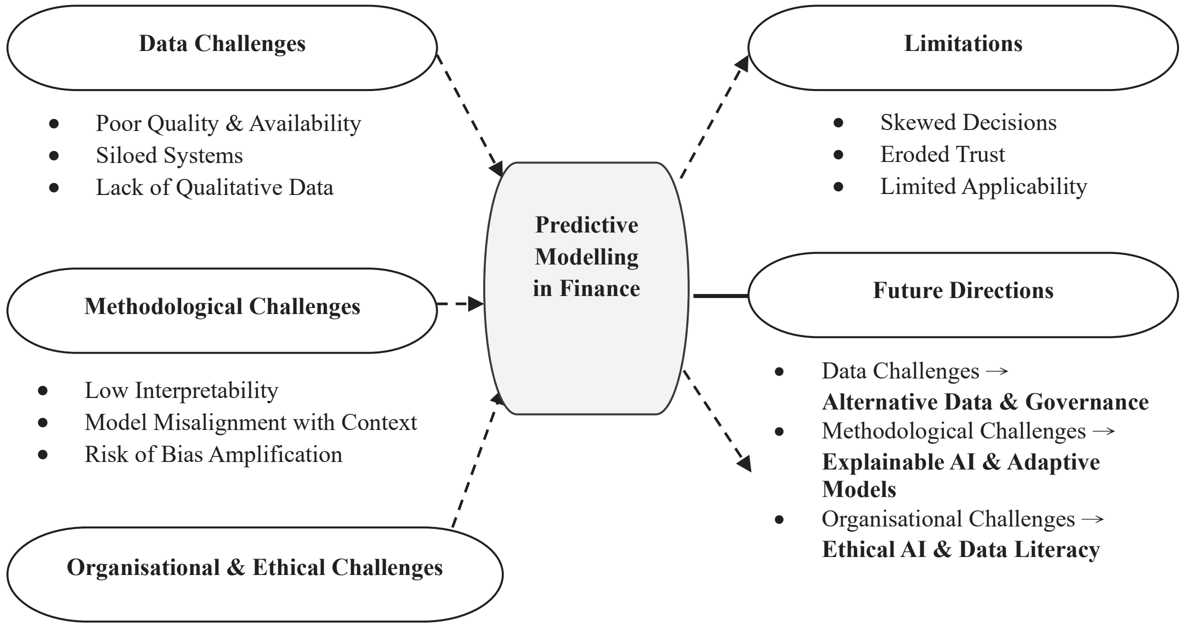

Figure 1. A framework of challenges, limitations and future directions in predictive modelling for finance

Source: Dariia Drozd, based on scientific publications studies.

important as the ability to develop the models themselves, necessitating a shift in how financial professionals are trained and how decisions are institutionalised.

Addressing these barriers requires a coordinated effort that spans technology, governance and human expertise. Organisations must invest not only in advanced modelling technologies but also in robust data governance frameworks that ensure quality, accessibility and ethical compliance. Equally important is fostering cross-functional collaboration between data scientists, financial analysts and strategic decision-makers. This ensures that models are not developed in isolation but are tailored to specific business contexts and objectives, whether it is optimising credit portfolios, evaluating merger opportunities, or anticipating macroeconomic shifts.

Moreover, the regulatory landscape is increasingly shaping how predictive models can be deployed responsibly. As financial authorities worldwide pay closer attention to algorithmic fairness and accountability, firms are encouraged, and in some cases required, to adopt practices such as model auditing, bias mitigation and explainability standards. This regulatory pressure, while initially perceived as a constraint, may ultimately serve as a catalyst for the adoption of more robust and transparent modelling practices, reinforcing the shift towards explainable AI (XAI) and ethical frameworks highlighted in this research.

In summary, the evolution of predictive modelling in finance is marked by a dual narrative of groundbreaking potential and significant implementation hurdles. This analysis has detailed a complex landscape where challenges related to data quality, algorithmic interpretability and ethical risks pose substantial barriers to adoption. Yet, as the framework (Figure 1) illustrates, each challenge is met with a targeted innovative response, be it explainable AI (XAI) for transparency, alternative data for richness, or ethical frameworks for accountability. Therefore, the future trajectory of predictive modelling will not be determined by algorithmic advances alone, but by a holistic, multi-disciplinary endeavour that integrates technological innovation with robust data governance, sector-specific adaptation, and unwavering ethical oversight. It is through this integrated approach that predictive modelling can truly solidify its role as a cornerstone of resilient and responsible corporate finance, capable of navigating the complexities of modern financial markets.

Based on a comprehensive analysis of challenges and future directions, this study proposes several key recommendations for the successful implementation of predictive modelling in corporate finance. First, organisations should develop integrated data governance frameworks that establish comprehensive data quality protocols and unified data architecture to ensure consistency, completeness and reliability of input data across organisational silos. Second, the implementation of explainable AI (XAI) solutions should be prioritised through the adoption of interpretable machine learning techniques that provide a transparent decision-making rationale while maintaining predictive accuracy. Third, enhanced model validation practices must be introduced, including rigorous stress-testing, back-testing and sensitivity analysis to ensure model robustness across diverse market conditions. Fourth, fostering cross-functional collaboration through structured mechanisms between data scientists, financial analysts and business stakeholders is essential for ensuring model alignment with business objectives and regulatory requirements. Fifth, investment in continuous education programmes is needed to develop specialised training that enhances financial professionals' understanding of predictive modelling capabilities, limitations and interpretation techniques. Sixth, the establishment of ethical AI governance committees comprising multidisciplinary oversight groups will help monitor model fairness, bias mitigation and ethical compliance throughout the model lifecycle. Finally, the adoption of sector-specific modelling approaches should be encouraged through the development of customised frameworks that account for industry-specific characteristics, regulatory environments and business model peculiarities. The implementation of these recommendations requires coordinated efforts across technological, organisational and regulatory dimensions, ensuring that predictive modelling evolves as both scientifically robust and practically applicable in corporate financial contexts.

Conclusion

This study systematically investigated the interdisciplinary domain of predictive modelling, examining its integration across corporate finance functions, data science methodologies and organisational leadership frameworks. The research achieves its stated objectives through the comprehensive analysis of theoretical foundations, empirical applications and implementation methodologies within corporate financial environments.

The findings establish that predictive modelling represents a paradigm shift in financial analytics, facilitating the transition from traditional statistical approaches to advanced machine learning and artificial intelligence frameworks. Methodological analysis demonstrates the superior capability of neural networks, deep learning architectures and ensemble methods in capturing complex financial patterns and non-linear relationships compared to conventional econometric models. Practical implementation studies reveal significant impacts across multiple domains: credit risk assessment systems have achieved enhanced default prediction accuracy, investment forecasting models have improved strategic allocation efficiency, and real-time market analytics have optimised trading strategies.

The research identifies critical implementation challenges requiring attention. Data quality management emerges as a fundamental constraint, necessitating robust governance frameworks for ensuring input integrity and feature reliability. Model interpretability limitations present substantial adoption barriers, particularly regarding regulatory compliance and managerial decision-making transparency. Furthermore, organisational integration challenges highlight the necessity for cross-functional collaboration protocols between quantitative analysts and financial domain experts.

Based on these findings, the study recommends the prioritised development of explainable AI (XAI) frameworks to enhance model interpretability while maintaining predictive performance. The implementation of comprehensive data governance ecosystems is essential for ensuring input quality and feature stability. Organisations should establish structured collaboration mechanisms between technical and financial departments to ensure model alignment with business objectives. Future research directions should focus on sector-specific model development, the integration of alternative data sources, and the standardisation of ethical AI implementation frameworks.

The study concludes that predictive modelling constitutes a transformative capability for corporate finance, enabling enhanced decision-making precision, improved risk management and strategic competitive advantage. However, realising its full potential requires addressing the identified challenges through integrated technological, organisational and methodological advancements.

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PROGNOZAVIMO MODELIAVIMAS, JO VAIDMUO STIPRINANT ĮMONĖS FINANSINĘ VEIKLĄ

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Santrauka

Šiame straipsnyje atliekama išsami prognozuojamojo modeliavimo poveikio įmonių finansinei veiklai tyrimo analizė. Remiantis konceptualia teorine analize, dėmesys kreipiamas į tai, kaip prognozuojamoji analitika gali padėti organizacijoms sistemingai prognozuoti rinkos tendencijas, optimizuoti turimų išteklių paskirstymą ir efektyviai mažinti finansinius rizikos veiksnius. Gauti rezultatai akcentuoja esminį duomenų pagrindu priimamų sprendimų vaidmenį gerinant įmonių pelningumą, operacinį efektyvumą ir strateginį planavimą.

Integravusios pažangias prognozuojamojo modeliavimo technologijas, korporacijos įgyja galimybę proaktyviai numatyti galimas finansines grėsmes bei išnaudoti esamas galimybes, tai ilgainiui lems tikslesnių investicinių ir valdymo sprendimų priėmimą. Taigi pagrindinė šio tyrimo išvada – prognozuojamasis modeliavimas veikia ne tik kaip rizikų valdymo metodas, bet ir kaip kertinis tvarų finansinį augimą bei konkurencinį pranašumą užtikrinantis elementas šiuolaikinėje dinamiškai besikeičiančioje verslo aplinkoje.

Straipsnyje aptariami pagrindiniai iššūkiai – nuo duomenų kokybės ir modelių metodologinio sudėtingumo iki organizacinės struktūros adaptacijos klausimų, be to, pasiūlytos gerosios praktikos gairės leiss veiksmingai taikyti prognozuojamuosius modelius korporatyvinių finansų kontekste.

RAKTINIAI ŽODŽIAI: *prognozuojamasis modeliavimas, įmonės finansai, finansiniai rezultatai.*

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