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DEVELOPMENT OF ADAPTIVE FINANCIAL STRATEGIES BASED ON SCENARIO ANALYSIS AND MACHINE LEARNING IN DYNAMICALLY CHANGING MARKETS

Bordusenko Dmytro[i]
Senior Finance Associate,
American Bureau of Shipping (ABS),
Spring, USA
orcid.org/0009-0007-4643-2457

Abstract:
The article examines adaptive financial strategies in volatile markets, focusing on the timing of managerial response and decision latency in financial decision-making. The role of scenario analysis as a tool for structuring uncertainty and assessing the resilience of financial indicators under alternative macroeconomic and industry trajectories is analyzed. The importance of machine learning methods for improving forecasting accuracy, identifying nonlinear relationships, and dynamically updating model parameters is emphasized. It is concluded that the integration of scenario analysis and machine learning forms a predictive financial control framework that enhances cash flow stability, optimizes capital structure, and strengthens the long-term competitiveness of companies. The study further introduces a temporal decision-making dimension by incorporating early operational signal detection, reducing decision latency between economic events and managerial response.

JEL: G32, C53, G31

Keywords: adaptive financial strategies, scenario analysis, machine learning, strategic financial planning, forecasting, corporate resilience

1. Introduction

Modern financial markets are marked by high volatility and increasing macroeconomic uncertainty, which reduces the effectiveness of traditional static financial strategies. Recurrent shocks – including financial crises, pandemics, and geopolitical and logistical disruptions – require companies to adopt more flexible and dynamic approaches to financial management, with a strong emphasis on rapid adaptation and continuous updating of strategic priorities.

[i] Correspondence: email dbordusenko84@rambler.ru

However, the principal limitation of existing adaptive financial frameworks lies not in forecasting accuracy but in the temporal gap between the emergence of economic signals and managerial response.

Even highly accurate predictive models do not eliminate the delay between operational deviations and their recognition within financial reporting systems. As a result, organizations frequently react to already materialized financial outcomes rather than to early operational indicators, which constrains the effectiveness of adaptive decision-making under volatility.

Therefore, improving financial strategy adaptability requires not only enhanced prediction methods but also a reduction in decision latency – the time interval between signal detection and managerial action.

In this context, the integration of scenario analysis and machine learning (ML) represents a promising basis for developing adaptive financial strategies. Scenario modeling supports the construction of alternative macroeconomic and industry trajectories, while ML methods improve the accuracy of forecasting cash flows, cost of capital, and investment outcomes.

However, the effectiveness of these tools depends on their ability to support timely managerial response. Therefore, this study aims not only to examine the combined use of scenario analysis and ML, but to develop a methodological framework that links predictive analytics with early signal detection and reduces decision latency in financial management, thereby enhancing corporate resilience and long-term viability.

2. Main part. Theoretical foundations of adaptive financial strategies

Adaptive financial strategies view the firm as an open system operating under incomplete information and multidimensional uncertainty. Rather than a set of fixed long-term guidelines, strategy in a volatile environment is interpreted as a managed process of continuous revision of decisions and model parameters as new information becomes available [1].

Contemporary theoretical frameworks explain the sources of such adaptability from different perspectives, whose synthesis forms the methodological foundation of adaptive financial strategies (Table 1).

As shown in Table 1, adaptive financial strategy arises at the intersection of several theoretical perspectives and rejects performance as a static optimum. Instead, performance is viewed as achieving stable outcomes across multiple market states under risk and operational constraints, while strategy functions as a predictive financial control framework in which decisions are continuously updated through predefined, rule-based adjustments rather than frequent discretionary shifts.

Table 1: Theoretical approaches to adaptive financial strategy formation [2, 3]

Theoretical approach	Core idea	Interpretation in financial strategy	Practical implications
Dynamic capabilities theory	Competitive advantage depends on the ability to reconfigure resources.	Flexible adjustment of capital structure, investment parameters, and liquidity sources.	Regular revision of financial priorities.
Risk-oriented and robust methods	Preference for solutions resilient to adverse scenarios.	Use of worst-case and min–max optimization.	Selection of resilient financing structures.
Tail risk measures (VaR, ES)	Focus on extreme losses.	Emphasis on downside risk control.	Enhanced stress testing.
Real options theory	Investments as managerial rights.	Staged financing and review gates.	Reduced irreversibility of errors.
Antifragility concept	Systems may improve under stress.	Portfolio of asymmetries: limited downside, preserved upside.	Liquidity buffers, barbell strategies.
Digital economy perspective	Finance depends on digital infrastructure.	Consideration of cyber risk and data reliability.	Integration of digital metrics.

3. Temporal dimension of financial decision-making

Existing theoretical approaches to adaptive financial strategies primarily focus on the selection and optimization of financial decisions under uncertainty. However, they implicitly assume that managerial response occurs immediately after relevant information becomes available. In practice, corporate financial systems operate through accounting recognition procedures that introduce a structural delay between operational events and their financial interpretation.

This delay creates a distinct analytical category – decision latency – representing the time interval between the emergence of an economically meaningful signal and the moment of managerial action.

The temporal gap may be formally expressed as:

$$DT = Tr - Td, \quad (1)$$

Where:
Td – moment of detection of an operational economic signal,
Tr – moment of its recognition within financial reporting and decision processes.

Traditional financial management relies predominantly on recognized financial outcomes (Tr), meaning that decisions are frequently made after the economic impact has already materialized. As a result, adaptive strategies operate reactively rather than preventively.

Incorporating early operational indicators shifts financial management from retrospective control toward predictive control, in which managerial action is triggered by signal detection rather than accounting recognition. Consequently, adaptability becomes a function not only of forecast accuracy but also of response timing.

This temporal perspective extends adaptive financial strategy theory by introducing decision timing as an independent determinant of financial resilience, complementing risk, return, and information dimensions.

4. Scenario analysis as a tool of strategic financial planning

Under high external uncertainty, this approach is widely used in long-term financial decision-making to construct alternative trajectories of macroeconomic, industry, and firm-level parameters and assess their impact on financial performance [4]. According to a global Deloitte survey of 1,326 finance leaders, 30 % of companies plan to strengthen advanced scenario-planning capabilities by 2026 as a key instrument for managing uncertainty (Figure 1).

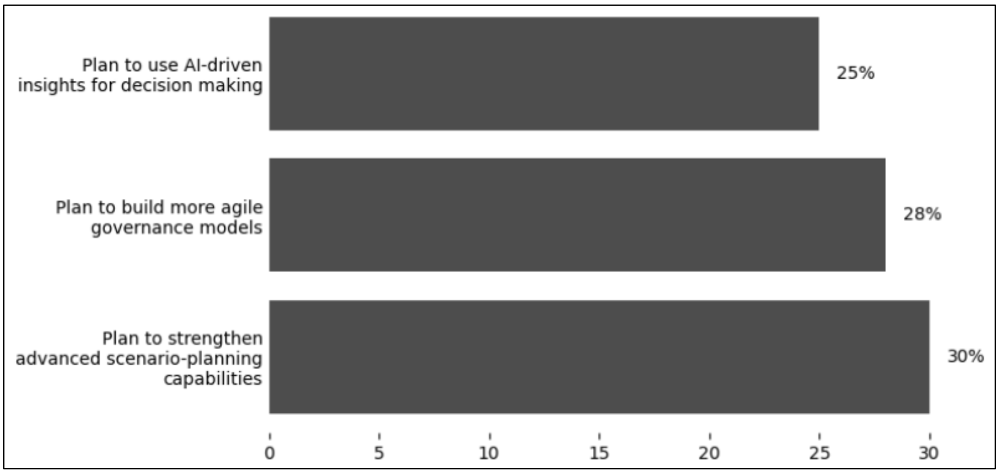

Figure 1: Priority areas for the development of financial functions [5]

The obtained results indicate the limitations of static planning approaches and the need for more flexible analytical instruments. In this context, scenario analysis represents a logical extension of strategic financial analysis. Unlike traditional forecasting based on a single baseline scenario, this approach allows for the consideration of multiple possible market states, including adverse and extreme developments (Table 2).

Methodologically, scenario analysis starts with identifying key exogenous factors and developing consistent changes to those factors to measure financial implications to firms. Baseline, optimistic, and stress scenarios are typically developed, followed by sensitivity analysis of NPV, IRR, EBITDA, FCF, and stability ratios using tools such as factor analysis, decision trees, and Monte Carlo simulation.

Table 2: Comparison of traditional forecasting and scenario analysis in strategic financial planning

Criterion	Traditional forecasting	Scenario analysis
Methodological basis	Single baseline forecast based on average expectations and fixed parameters (discount rate, growth, inflation).	Development of a set of consistent alternative trajectories (baseline, optimistic, stress) reflecting different combinations of key drivers.
Treatment of uncertainty	Considered mainly as deviation from the baseline; extreme values are often ignored.	Formalized through parameter ranges and probabilistic assessments, including adverse and crisis scenarios.
Analysis of factor impact	Limited sensitivity testing with respect to individual variables.	Integrated assessment of multi-factor changes (GDP, rates, exchange, demand) on NPV, IRR, EBITDA, and FCF.
Risk perspective	Focus on expected average outcome.	Evaluation of distributions of possible outcomes, probability of breaching critical thresholds, and downside losses under stress.
Integration with management	Primarily used for budget approval and investment justification.	Used to define leverage limits, liquidity buffers, and trigger points for strategy revision.
Flexibility of decisions	Decisions are relatively fixed and revised periodically.	Decisions are structured with pre-defined review points and adaptive adjustment mechanisms.
Strategic resilience	Vulnerable to regime shifts and sudden shocks.	Enhances resilience by preparing for alternative development paths.

The practical relevance of scenario analysis is supported by international FP&A benchmarking results. According to the 2026 AFP FP&A Benchmarking Survey (332 FP&A and finance professionals from 54 countries), teams that apply structured scenario planning complete budget preparation in an average of 8.1 weeks, whereas organizations without this approach require 9.2 weeks (approximately 11 % faster) [6]. In addition to this, structured scenario analysis results in higher strategic alignment. This includes strategic alignment being 14 % higher among top-performing teams, and 13 % higher in terms of consideration of external factors while making plans, compared to other teams not making use of this strategy. However, there is a maturity gap identified as well, where only 38 % of finance teams made use of structured scenario-based planning.

Therefore, scenario analysis takes the role of an important tool of strategic financial planning, allowing formalizing the uncertainty and enhancing the robustness of management decisions in the context of the changing market. At the same time, the growing complexity of economic interdependencies and the increasing volume of available data create prerequisites for further enhancement of this approach through the integration of ML techniques, capable of refining scenario probabilities and uncovering nonlinear relationships between financial variables.

5. Application of ML methods for the analysis of macroeconomic and industry changes

The growing volume of available economic data and the increasing speed of their updates create strong prerequisites for the active use of ML methods in strategic financial management. Modern markets are characterized by frequent structural shifts, nonlinear relationships between macroeconomic indicators, and a rising influence of behavioral factors, which limit the effectiveness of exclusively traditional econometric models [7]. ML algorithms make it possible to process large volumes of heterogeneous information – ranging from GDP, inflation, and interest rate statistics to industry indices, corporate disclosures, and market volatility measures – thereby uncovering latent relationships and generating more accurate forecasts of financial performance.

Quantitative evidence supporting the practical value of ML for monitoring macroeconomic and industry dynamics is provided by both surveys of finance executives and applied studies. In particular, a Gartner survey (2025; 183 CFOs and senior finance leaders) reports that 59% of respondents already use artificial intelligence within the finance function, indicating a broad organizational shift toward data-driven decision support, in which ML constitutes a core analytical component for interpreting macroeconomic indicators and market signals (Figure 2).

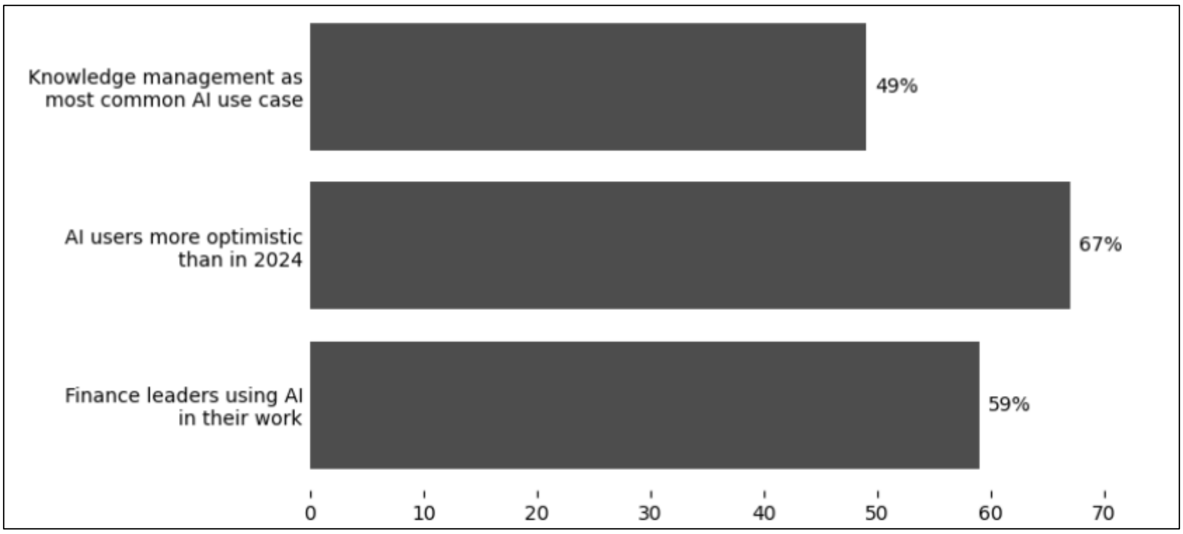

Figure 2: Adoption of AI in finance and key usage patterns [8]

A survey by Wolters Kluwer (2025, North America) reports that currently, 86 % of finance organizations operate at the explore or pilot stages of AI adoption (53 % exploring and 33 % piloting ML), underlining the strong pace of ML adoption for FP&A and external environment analysis [9]. This is an additional piece of information that supports the idea that ML assists in increasing the information content carried by macroeconomic and industry indicators by leveraging information contained in high-frequency and unstructured data. The increasing utilization of ML techniques to support time series forecasting, nonlinear patterns' detection, and regime identification improves the quality of financial projections and scenario planning (Table 3).

Table 3: Main types of ML methods and their applications in strategic financial planning

Class of ML methods	Example algorithms	Primary purpose	Practical application in financial planning
Regularized regression models	Ridge, LASSO, Elastic Net.	Time series forecasting under the impact of noise and multicollinearity.	Forecast of cash flows, revenues, costs of operations.
Ensemble methods	Random Forest, Gradient Boosting (XGBoost, LightGBM).	Detection of nonlinear relationships and factor interactions.	Improving the accuracy of short-term forecasts. Stress assessment.
Recurrent neural networks	LSTM, GRU.	Modeling sequential and temporal dependencies.	Forecasting revenue, demand, and input prices.
Clustering methods	k-means, hierarchical clustering.	Grouping economic states into regimes.	Construction of macroeconomic scenarios.
Dimensionality reduction methods	PCA, autoencoders.	Feature extraction from high-dimensional data.	Data preparation for scenario modeling.

A key advantage of ML is the ability to refine forecasts and support decision-making after early operational signals have been detected, improving the quality of response rather than eliminating the initial decision delay. The usefulness of such models is also dependent, apart from prediction accuracy, on the visualization of the data and how user interaction is presented, which can have an effect on investment decisions, such as decentralized finance [10]. However, AI-based methods have a need for precise control of data quality and risk of interpretation. In conclusion, the use of ML models has a positive effect on strategic analysis forecasts.

6. Integration of scenario analysis and ML into a unified adaptive model

The integration of scenario analysis and ML enables a comprehensive financial model that captures multiple external trajectories and dynamically updates their probabilities using incoming data. Scenario analysis structures alternative macroeconomic and industry states, while ML calibrates parameters, forecasts key indicators, and estimates regime transition probabilities, allowing financial strategy development to be represented as a sequential algorithm (Figure 3).

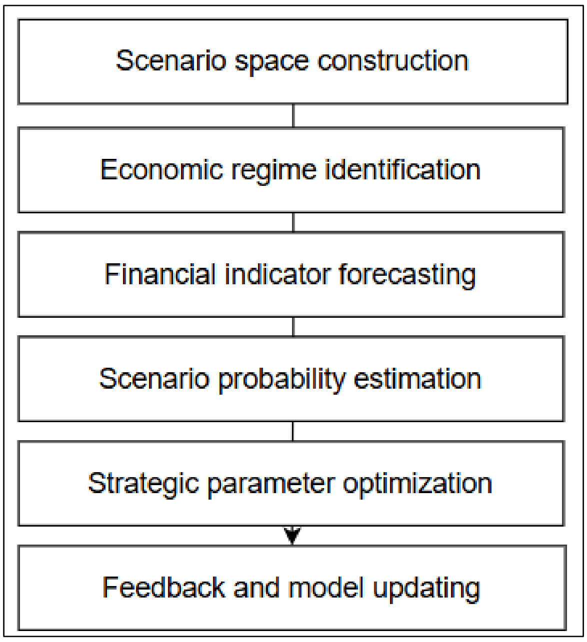

Figure 3: Algorithm of an integrated adaptive model for financial strategy development based on scenario analysis, machine learning, and operational signal detection

7. Signal detection layer in the adaptive financial model

The traditional integrated adaptive model described above assumes that scenario construction begins with the analysis of external macroeconomic conditions. However, such an approach still relies on information that has already been aggregated and interpreted, preserving the temporal gap between operational deviations and managerial response.

To address this limitation, the adaptive framework is extended with an initial signal detection layer based on operational indicators. Instead of initiating the strategic cycle from macroeconomic interpretation, the model begins with the identification of early economic signals emerging within operational processes, such as deviations in execution rates, resource consumption patterns, order dynamics, or working-capital behavior.

These signals precede financial recognition and, therefore, allow the strategy revision process to be triggered prior to the materialization of financial outcomes. Consequently, the adaptive model transforms from a reaction to financial results into a predictive financial control framework.

Within the integrated adaptive model, the first stage involves **scenario space construction**, which consists of forming a structured set of alternative external environment states reflecting possible combinations of changes in macroeconomic and industry parameters, including GDP growth, inflation, policy interest rates, exchange rates, and industry demand. This stage provides the foundation for organizing uncertainty and defining the initial set of development trajectories. The second stage focuses on **economic regime identification** using classification and clustering techniques that group observations into relatively stable economic states, such as expansion, overheating, recession, and recovery, thereby moving from isolated scenarios toward generalized regime representations.

At the third stage, **financial indicator forecasting** is carried out through the use of various ML algorithms, such as the use of "ensemble methods and neural networks," to forecast the expected values of revenue, profitability, free cash flow, and leverage ratios for each scenario or regime. The fourth stage involves **scenario probability estimation,** where the probability of the realization of the scenarios is dynamically updated on the basis of new releases of statistical data, market indicators, and high-frequency signals with the objective of capturing changes in the macro environment in near real time. The fifth step is **strategic parameter optimization**, in which forecasted figures and scenario probability are used to arrive at the optimum capital, investments, liquidity, or risks in accordance with the returns, resiliency, and compliance constraints. The sixth stage sets up a **feedback loop and updates the model** such that the real performance of the company is weighed against forecasted results. The objective of the adaptive framework is therefore to minimize decision latency (DT), shifting managerial action from financial recognition (Tr) toward early signal detection (Td). The model parameters, features, and scenario assumptions are then adjusted to decrease modeling risk and allow continuous change.

By introducing the signal detection stage, adaptability is achieved not only through better forecasts but through earlier intervention. The effectiveness of financial strategy, therefore, becomes dependent on reducing decision latency rather than solely improving predictive accuracy.

Taken together, these stages form a closed-loop framework for financial strategy development in which scenario analysis provides structural coherence, while ML supplies data-driven calibration and dynamic updating. This integration transforms uncertainty from an external constraint into a manageable factor, enhancing forecast reliability, accelerating strategic decision-making, and supporting long-term financial resilience in volatile and rapidly evolving markets.

8. The importance of financial model adaptability for corporate resilience

Financial resilience in its contemporary interpretation goes beyond maintaining regulatory liquidity ratios and capital adequacy levels. It implies an organization's ability to preserve solvency, investment capacity, and operational efficiency under sharp changes in the external environment. Similar principles can be observed at the macroeconomic level: for example, diversification of energy and raw material sources as a tool for enhancing energy independence demonstrates that reducing concentration in critical supply sources lowers systemic risks and increases resistance to external shocks [11]. Within the corporate financial system, the same logic is implemented through diversification of funding sources, flexible cost structures, and the development of stress-testing instruments.

Notably, finance executives in North America increasingly prioritize technological transformation and the manageability of uncertainty. According to Deloitte CFO Signals (survey of 200 CFOs from companies with revenues above $1 billion, November–December 2025), 50 % of CFOs identify digital transformation of the finance function as a priority for 2026, while 87 % consider artificial intelligence extremely or very important for finance operations, indirectly confirming demand for more adaptive planning and risk-control models [12].

An adaptive financial model reduces the sensitivity of cash flows to adverse shocks through dynamic management of capital structure, liquidity, and the investment portfolio. In this regard, the existence of committed credit facilities, flexible dividend policies, currency and interest rate hedging instruments, and options for budget revision is key to minimizing the risk of liquidity shortages and covenant breaches. This assumption has been proved true by the practices of large publicly listed corporations in the U.S., where, for instance, **Walmart** announced in April 2025 the renewal and extension of credit facilities, where as of October 31, 2025, the company had $15.0 billion of committed credit facilities in the U.S., which were fully undrawn and therefore acted as a buffer for any potential shocks.

At the same time, empirical evidence from corporate treasury functions indicates a persistent confidence gap in preparedness for financial risks. According to the EY Global DNA of the Treasurer Survey (2025), only 27 % of treasurers are "very confident" that their financial risk management strategies improve decision quality at the organizational level [13]. This finding strengthens the argument for formalized adaptive mechanisms based on scenario modeling, stress testing, and dynamic calibration of assumptions.

From a strategic perspective, adaptability also positively affects a firm's investment attractiveness, as it increases the predictability of obligation fulfillment and reduces the risk premium embedded in the cost of capital. U.S. issuer practice shows that disciplined adaptive financial policies directly support investor confidence. For instance, **GE Aerospace** states in its 2025 annual report that the objective is to maintain an investment-grade credit rating within a disciplined capital allocation and liquidity management framework. In 2025, the company produced $7.7 billion of free cash flow while sustaining access to reserve liquidity. This includes an unsecured revolving credit facility of $3.0 billion due 2029 that remains undrawn, which diminishes liquidity risk and undergirds the stability of its financial profile.

In general, these cases suggest that adaptability of the financial model serves as both a short-run shock-absorbing device and a long-run structural driver of corporate resilience and competitiveness in turbulent markets.

9. Conclusion

The formulation of adaptive financial strategies in an ever-changing market necessitates the evolution of management models from static planning paradigms toward probabilistic management models facilitated by the role of technology. The scenario analysis helps in structuring market uncertainties, evaluating the robustness of financial indicators in relation to alternative macrofinancial scenarios, while ML plays an important role in improving the accuracy of financial predictions by focusing on nonlinear dynamics.

In addition, the results indicate that the effectiveness of adaptive financial strategies is determined not only by the quality of forecasting but also by the timing of managerial response. The proposed framework introduces a temporal dimension of financial decision-making by formalizing decision latency – the interval between economic signal detection and financial recognition.

Incorporating an operational signal detection layer shifts the adaptive strategy from a reactive planning process toward a predictive financial control framework. Within this perspective, scenario analysis structures uncertainty, and ML refines probabilistic expectations, while their practical value depends on the ability to trigger managerial actions before financial outcomes materialize. Thus, corporate resilience can be enhanced not solely through improved prediction accuracy, but through earlier intervention in the decision process. Accordingly, the study extends adaptive financial strategy models by linking predictive analytics with managerial control through a decision-timing component, enhancing cash-flow stability and responsiveness to external shocks.

The practical relevance of this approach lies in strengthening cash flow stability, optimizing capital structure, and reducing corporate vulnerability to crises. An adaptive financial model may enhance investment attractiveness, improve transparency of managerial decisions, and support long-term competitiveness. Future research should focus on developing interpretable AI algorithms, advancing model risk management techniques, and expanding the use of digital tools in strategic financial planning.

Conflict of Interest Statement

The authors declare no conflicts of interest.

About the Author

Bordusenko Dmytro, Senior Finance Associate, American Bureau of Shipping (ABS), Spring, TX, USA.
ORCID: https://orcid.org/0009-0007-4643-2457
Email: dbordusenko84@rambler.ru

References

Margiutomo SAS, 2025. Integrating Financial Planning with Business Strategy to Achieve Long-Term Competitive Advantage. The Journal of Academic Science 2(5): 1411-1420. Retrieved from http://thejoas.com/index.php/thejoas/article/view/360

Levinthal DA, Wu B, 2025. Resource redeployment and the pursuit of the new best use: Economic logic and organizational challenges. Strategy Science 10(1): 32-47. https://doi.org/10.1287/stsc.2022.0105

Basiru JO, Ejiofor CL, Onukwulu EC, Attah RU, 2023. Financial management strategies in emerging markets: A review of theoretical models and practical applications. Magna Scientia Advanced Research and Reviews 7(2): 123-140. https://doi.org/10.30574/msarr.2023.7.2.0054

Al-hadrawi RH, Alasadi AAA, Atiyah SM, 2024. An analytical study of the impact of strategic scenario planning on competitive financial performance. Multidisciplinary Science Journal 6(12): 2024261-2024261. https://doi.org/10.31893/multiscience.2024261

Deloitte, 2026. Finance Trends 2026: Navigating the expanded scope of finance. Retrieved from https://www.deloitte.com/us/en/insights/topics/leadership/finance-trends-leadership.html. Accessed 6 February 2026

The Association for Financial Professionals, 2026. 2026 AFP FP&A Benchmarking Survey Report: Integrated Planning. Retrieved from https://www.financialprofessionals.org/training-resources/resources/survey-research-economic-data/Details/afp-fpabenchmarking-survey-report-integrated-planning. Accessed 6 February 2026

Khan MA, Abbas K, Su'ud MM, Salameh AA, Alam MM, Aman N, Aziz RC, 2022. Application of ML algorithms for sustainable business management based on macro-economic data: supervised learning techniques approach. Sustainability 14(16): 9964. Retrieved from https://doi.org/10.3390/su14169964?urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle

Gartner, 2025. Gartner Survey Shows Finance AI Adoption Remains Steady in 2025. Retrieved from https://www.gartner.com/en/newsroom/press-releases/2025-11-18-gartner-survey-shows-finance-ai-adoption-remains-steady-in-2025. Accessed 6 February 2026

Wolters Kluwer, 2025. New Wolters Kluwer survey finds 86% of North American finance teams in the early stages of AI adoption. Retrieved from https://www.wolterskluwer.com/en/news/pr-2025-north-america-cch-tagetik-intouch25-survey. Accessed 7 February 2026.

Ulyanov V, 2025. Impact of interface data visualization on investment decisions in decentralized finance. Journal of Advanced Research in Technical Science 51: 71-79. Retrieved from https://www.researchgate.net/publication/387364589_The_Impact_of_Data_Visualization_on_Investment_Decisions

Kukula I, 2025. Diversification of energy and raw material sources as a tool for enhancing the energy independence of the USA. ISJ Theoretical & Applied Science 146(6): 40-44. https://doi.org/10.15863/TAS.2025.06.146.8

Deloitte, 2025. Technology Transformation Emerges as a Top Priority for CFOs in 2026: Deloitte Q4 2025 CFO Signals Survey. Retrieved from https://www.deloitte.com/us/en/about/press-room/deloitte-q4-2025-cfo-signals-survey.html. Accessed 8 February 2026.

EY, 2025. How can treasurers transform to realize new value in a world of uncertainty? Retrieved from https://www.ey.com/content/dam/ey-unified-site/ey-com/en-gl/campaigns/cfo-agenda/documents/ey-gl-dna-of-the-treasurer-survey-09-2025.pdf. Accessed 8 February 2026