International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

AI-Driven Strategic Decision-Making: Integrating Machine Learning into Financial Modeling and Corporate Strategy

Naveen Srikakulam[1]
[1]*Emory University- Atlanta, GA*

Abstract

Machine learning (ML) and artificial intelligence (AI) will be substituting financial modeling and corporate strategy and will offer an opportunity to make data-driven, adaptive, and predictive decisions. This review examines the application of machine learning processes to financial analytics and strategic management by mentioning that AI has the potential to enhance the accuracy of forecasts, risk evaluation, and flexibility. In the work, a synthesis of the literature at hand is given to demonstrate that AI-based systems are of significant advantage over traditional econometric approaches, in particular, in the processing of nonlinear and high-frequency, large-scale financial data. Nevertheless, the concerns of problematic issues also encompass interpretability of models, concerns of data quality, governance, and complexity of integrating AI in business decision models, which were also characterized in the review. Furthermore, the article introduces a theoretical framework that connects the ability of AI, the quality of financial modeling, and the results of strategic decisions with the emphasis on the mediating and moderating variables, like explainability, organizational preparedness, and ethical governance. Additionally, the future research directions are also mentioned in the review and can be explained as explainable AI, hybrid modeling techniques, real-time analytics, and regulatory frameworks. On the whole, the present research can be added to the existing knowledge base as it offers a systematic insight into the ways AI can be successfully used to experience sustainable competitive advantage in finance and corporate strategy. The results apply to both academics and practitioners interested in the changing nature of AI in terms of strategic decision processes.

Keywords:*Financial Modeling, Strategic Decision-Making, Predictive Analytics, Risk Management, Explainable AI, Corporate Strategy.*

1. Introduction

The last decade has changed the paradigm of financial model and corporate strategy as the artificial intelligence (AI) and machine learning (ML) technologies have appeared. Previously, econometric models, interpretation of historical data and human experience were the most important factors in financial decision-making and predicting the trends in the market to drive the strategic planning. However, with access to big data becoming more commonplace, computing power, and new sophisticated algorithms started being developed, organizations started to expand beyond their customary practices to data-driven and AI-driven decision-making processes [1]. Specifically, machine-learning-grounded methods, such as machine-learning supervised learning models and deep neural networks, have shown impressive abilities to discover nonlinear and complex patterns in financial data and thereby boost predictive performance and strategic inferences [2]. The significance of strategic decision-making with use of AI is a phenomenon that is gaining momentum in the most dynamic and uncertain economic environment. The financial market industry is changing and becoming more volatile, globalized and technologically troubled, which is not necessarily conducive to the antique forecasting models. In this respect, AI has the ability to handle large volumes of

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

structured and unstructured data such as market indicators, news sentiment, and other forms of data in real time to empower organizations in making more decisions that are fast and superior [3]. Moreover, companies that effectively implement machine learning into their strategic plans may gain a competitive edge by enhancing risk management, better resource management, and detection of new opportunities more efficiently than other businesses [4]. In a broader sense, the intersection of machine learning and financial modelling and corporate strategy is an intersection of various fields, such as finance, data science, operations research and strategic management. This interdisciplinarity highlights the fact that it has become considerably more acceptable that traditional financial theory needs to be modified in order to include data-driven approaches. The aim of the review is to bridge the gap in the evolution of theories and their real-life application, to critically evaluate the existing methodologies, describe the key limitations and unveil the novelties of the sphere. In particular, the paper will focus on how machine learning can be used to improve financial forecasting, risk management, and strategic planning, as well as discuss the problems of model interpretability, data control, and adoption by the organization. One such area is behavioral finance and algorithmic trading that have already demonstrated the ways in which AI can challenge and extend classical decisions about market efficiency and rationality [5]. In a similar manner, predictive analytics and AI-driven insights are increasingly becoming a part of corporate strategy, enabling companies to shift to reactive decision-making paradigms and, instead, practice proactive decision-making. Although these developments have been achieved, there are a number of research gaps and challenges. One of the most important issues that may hinder the trust and adoption by decision-makers is the interpretability and transparency of machine learning models, also referred to as the black box problem [6]. The lack of accountability also may be an issue with regards to compliance and ethics in highly regulated industries such as finance. Moreover, data quality and data availability are also a significant problem and quality, representative and unbiased data is crucially important to machine learning models. The other loophole is the interface between AI models and the existing organizational processes and legacy systems which may prove to be a very expensive process and entail organizational change. In addition, there is still no consensus on the optimal practices in harmonizing AI-driven insights with strategic decision-making models, in particular, in complex and uncertain conditions [7]. With these concerns in mind, a critical review that will be able to draw a synthesis of the current literature regarding AI-based strategic decision-making and its application to financial modeling and corporate strategy is needed.shown as Table 1 Summary of Key Research Papers

Table 1 Summary of Key Research Papers

Reference	Findings
[8]	Despite being initially designed to learn sequences, LSTM was subsequently found to be more useful in financial forecasting due to its ability to store useful historical patterns across time than typical recurrent networks. This was particularly useful in modeling time-series behavior, like stock prices, stock volatility, and macro-financial indicators.
[9]	The researchers demonstrated that feature extraction was enhanced by time learning in predicting financial time-series tasks. Its results gave credence to the notion that deep architectures are able to encapsulate nonlinear

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

	relationships as opposed to most of the traditional models in finance.
[10]	The article underscored how the quality of markets can be distorted by the speed-based algorithm systems and competition can be enhanced by the advantage of executing. Its further strategic implication is that the application of AI in finance may lead to both efficiency and systemic risks and needs careful governance and institution-level design.
[11]	The authors discovered that companies would benefit the most with AI when it is implemented to automate processes, generate insights, and interact with customers instead of when it is made wholesale in terms of managerial judgment. The paper is renowned in demonstrating that integration and not adoption brings about strategic value.
[12]	The researchers discovered that companies that embraced data-driven-based decision-making practices had improved productivity and performance results. It supported the strategic thesis that analytics and AI can become a competitive advantage, when incorporated into managerial routines.
[13]	The paper has highlighted that performance is not sufficient in high stakes environment such as finance. It claimed that interpretability is a key to trust, accountability, and regulatory compliance in particular situations when AI systems are involved in affecting lending, investment, or risk decisions.
[14]	The authors demonstrated that deep learning is able to reveal the complex latent structures in asset-pricing data that can be ignored by standard linear factor models. Their findings indicated that ML can significantly enhance prediction and portfolio model, and this has significant implications to strategic investment decisions.
[15]	The results of this survey were that machine learning was now playing a bigger role in the fields of forecasting, risk management, fraud detection, portfolio construction, and credit scoring. It also observed that there has been enduring challenges like overfitting, lack of transparency and difficulties in implementation in actual organizational environments.
[16]	The study argued that AI is no longer just an operational tool but a governance issue. Boards must understand AI-related risks, ethics, accountability, and strategic opportunities in order to guide firms responsibly in increasingly data-driven environments.
[17]	The paper discovered that explainability is the key to responsible AI adoption, particularly in those areas where the decisions to be made have to be explained to regulators, managers, investors, or customers. It endorses the perception that credible AI is more sustainable than the black-box optimization in the context of financial modeling and strategy.

2. Proposed Theoretical Model

To strengthen the review, it will be expedient to move outside the literature overview, and into an exposition of the conceptualization of how AI-driven strategic decision-making processes work in practice. The literature reviewed suggests that to date, machine learning has the potential to create value not only by producing predictions, but also by incorporating those predictions into organizational decision systems to bring together data, analytics, managerial interpretation, and strategic action [18], [19]. Finance and corporate strategy In finance and corporate strategy, it suggests that the feasibility of AI depends on how well companies integrate information

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

streams, predictive algorithms, systems of governance, and executive decisions into a single framework [20]. The main takeaway of recent studies is that financial modeling on the basis of AI should not be regarded as a technical endeavor that exists in a vacuum. Instead, it can be seen as part of the greater strategic cycle, in which machine learning systems absorb internal and external data, which are interpreted by decision-makers, and transformed into action, i.e. into capital allocation, risk mitigation, pricing, investment planning, or strategic repositioning [21]. This multi-faceted approach is particularly relevant since effectiveness of AI is not only limited to the accuracy of the models, but also to organizational abilities in the form of digital maturity, data governance, and managerial trust [22]. These block diagrams are some of those that can be implemented in the review article to give a graphic representation of this logic.

Figure 1 General Block Diagram for AI-Driven Strategic Decision-Making

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

This block diagram demonstrates the concept that AI can only result in the creation of organizational value when data, algorithms and strategic interpretation are related to feedback mechanisms. The research on information systems and strategy has consistently discovered that analytics capabilities improve performance within firms when combined with a set of complementary managerial and organization practices, but not when implemented as isolated technical systems [18], [23]. This implies that in the financial realm, the predictive outputs are expected to be constantly evaluated in terms of the market forces, business goals and regulatory provisions [24]. Shown as Figure 2 Block Diagram for AI Integration into Financial Modeling

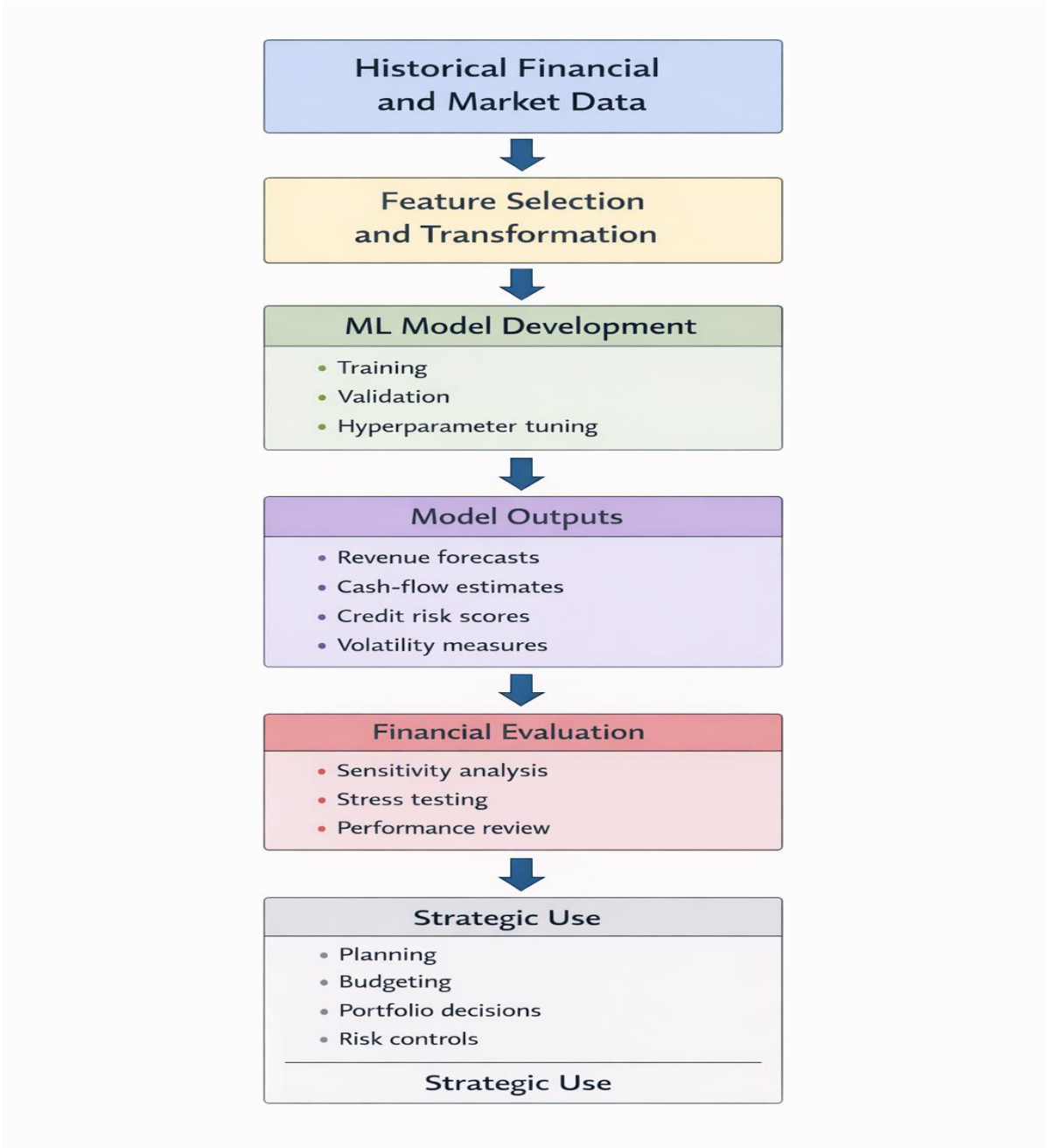

Figure 2 Block Diagram for AI Integration into Financial Modeling

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

The second diagram has more to do with financial modeling as such. It embodies the emerging agreement that machine learning enhances financial forecasting especially in cases where model development is succeeded by stringent validation, stress testing, and managerial interpretation [24], [25]. One of the key lessons of the literature is that companies must not consider algorithmic outputs as inherently objective. Unless well monitored and recalibrated, prediction systems may increase bias, long-term drift or not work in novel market environments [19], [26]. Shown as Figure 3 Block Diagram for Corporate Strategy Alignment

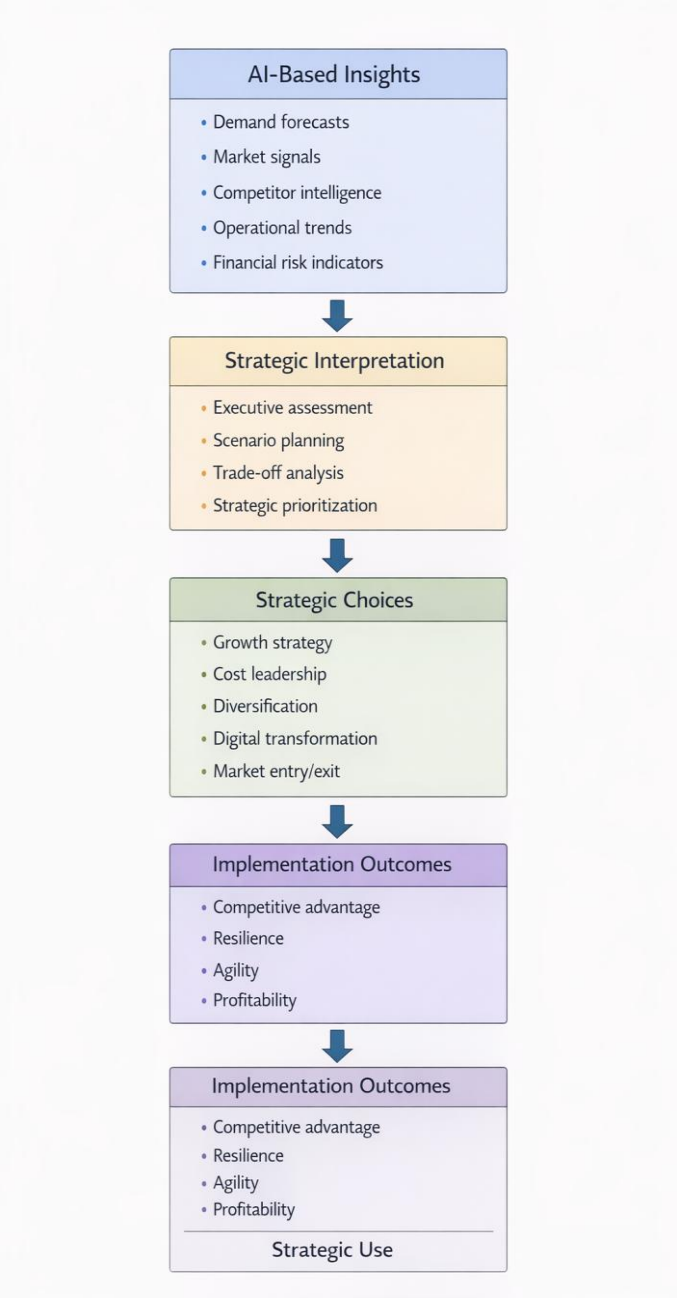

Figure 3 Block Diagram for Corporate Strategy Alignment

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

The point highlighted in this diagram is that AI does not substitute corporate strategy but augments strategic reasoning. The reason is that the literature is becoming more and more convinced that the most successful companies are adopting AI to assist with scenario assessment, spot signals sooner, and become more responsive when faced with uncertainty, while retaining managerial judgment in their ultimate decision-making [20], [21]. This is particularly critical in the strategic environment where long-term investment, organizational culture and environmental change cannot be simplified into a simple optimization of quantitative form [27].

3. AI-Driven Financial Decision Models in Corporate Strategy

An AI-Driven Strategic Financial Decision Model is a useful theoretical model that can be utilized in this paper based on the reviewed literature. The model describes the process in which machine learning can be used to help the corporate strategy by a series of interconnected constructs.

3.1.Core idea of the model

The model suggested is that AI capability enhances the quality of financial modeling, which subsequently increases the quality of strategic decisions, and eventually results in the overall organizational performance. This is not however an automatic relationship. A combination of mediating and moderating factors, such as the quality of data, its interpretability, the readiness of the organization, and the governing mechanisms, strengthens or weakens it [18], [19], [22]. Shown as Figure 4 Proposed conceptual structure

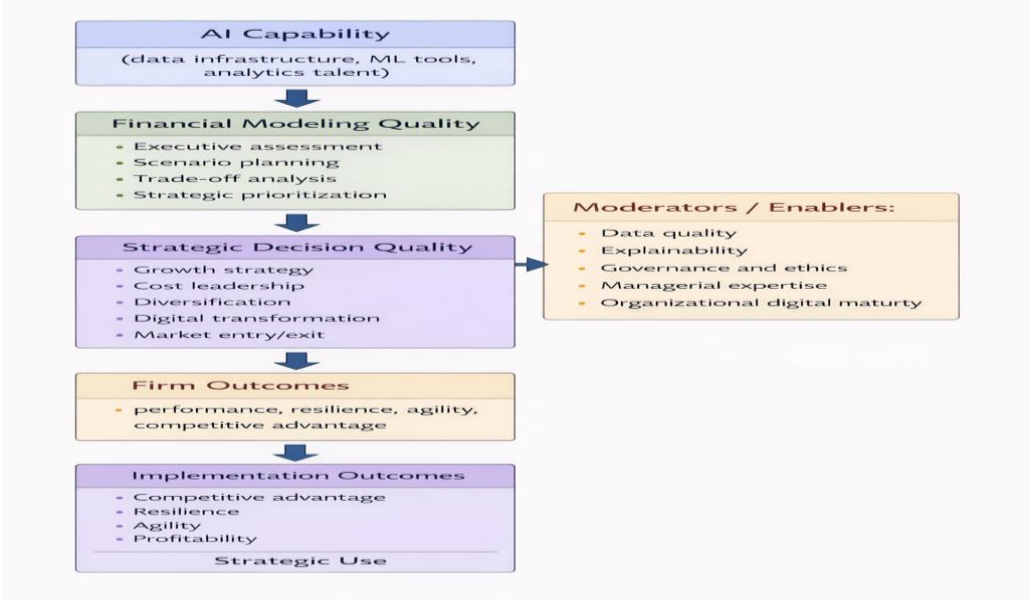

Figure 4 Proposed conceptual structure

3.2.AI Capability as the input layer

The initial element is AI capability, which is the capacity of the organization to collect, manipulate, and interpret data by employing machine learning applications, technical expertise, and digital hardware. Previous studies indicate that analytics capability is a strategic resource that can only be effective when companies have the complementary assets they need to make its use effective [18], [23]. That is, merely having access to algorithms does not suffice; companies require solid data structure, trained analysts, and management. In financial models, AI enables companies to analyze a greater amount of data which is also diverse as compared to

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

the traditional models. This includes both structured and unstructured financial reports, textual disclosure, market news and consumer sentiment [24]. Such abilities further augment the ability of a company in the face of detecting latent patterns, respond promptly to changes and produce more dynamic predictions.

3.3.Financial modeling quality as a mediating construct

The second one is the quality of financial modeling that serves as the initial key mediator in the model. Construct evaluates the degree to which AI improves technical and practical quality of financial models with regards to better prediction, better pattern recognition, faster processing and better fit to changing conditions [25], [28]. Literature also indicates that in certain activities like bankruptcy prediction, credit scoring, asset pricing, and volatility forecasting, ML-based models can outperform traditional linear models when the relationships are nonlinear or extremely complex [24], [28]. The advantage however lies in the discipline of models. Even highly precise models cannot become unstable or misleading without validation, transparency, and continual monitoring [19], [26]. As such, the financial modeling quality must not be determined solely in terms of predictive accuracy, but the quality of financial models must also be determined by their strength, interpretability and strategic utility.

3.4.Strategic decision quality as the second mediating construct

The third element is the quality of strategic decisions. This is a measure of how far decision-makers go in utilizing AI-assisted financial information to enhance planning, prioritization, and execution. More timely, granular and scenario sensitive information is expected to yield better strategic decisions when it is received by the managers [20], [21]. As an illustration, AI may assist executives to analyze the time to invest, nonperforming business units, quantify downside risk, and model alternative strategy options. Nevertheless, the literature indicates clearly that the quality of decisions is not only determined by the availability of information, but also by the interpretation of information by managers. Human judgment has been critical to the formulation of strategic issues, the compromise of quantitative and qualitative factors, and decisions in the face of uncertainty [27]. Consequently, the model considers AI as an augmentation mechanism, as opposed to an executive reasoning substitute.

3.5.Firm outcomes as the dependent variable

The last dependent construct will be firm outcomes, such as profitability, operational resilience, strategic agility and competitive advantage. Analytics and strategy research indicates that companies that integrate data-driven decision systems into their organizational processes are in a better position to react to uncertainty and are better than their competitors [18], [23]. Financially, these firms can gain more effective capital allocation, good risk controls as well as long-term value creation. The correlation between AI and performance is, however, indirect. AI adds value when it enhances decision making and when such decisions are brought into action. That is why this model positions the quality of financial modeling and the quality of strategies between the ability of AI and organizational results.

4. Moderators and Enablers in the Model

4.1.Data quality

One of the most crucial enabling factors is the data quality. Models can be highly weakened by poor data completeness, inconsistency, bias, or timeliness and this can also cause misleading decision-making [24], [26]. Financial decisions are usually high stakes, and as such, data governance must be perceived as a strategic, not necessarily a technical, problem.

4.2.Explainability and interpretability

Interpretability determines the level of trust in AI outputs by the executives, regulators, and stakeholders. Finance In finance, black-box systems can perform good predictions, but when there is no explanation, an organization may not be willing to trust it to make strategic decisions [19], [29]. Explainability also facilitates accountability particularly in cases where decisions are made regarding credit issuance, investment, and adherence.

4.3.Organizational readiness

Organizational preparedness comprises digital culture, workforce skills, executive dedication, and procedures integration. The studies of AI adoption are always consistent that suggests that the more companies are oriented to workflows, decision rights, and strategic priorities, the greater benefits they enjoy [20], [22]. Not even the latest models are used

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

without preparation.

4.4.Governance and ethics

The responsible use of AI is influenced by governance mechanisms that take into consideration the issue of fairness, oversight, accountability, and compliance. This is particularly critical in strategic finance since algorithmic decisions may be legally, reputational, and societal in nature [29], [30]. The model should thus integrate governance as an ongoing control layer as opposed to a mention after thought.

4.5.Suggested Propositions for the Review

In order to render the theoretical model academically applicable, the propositions below may be made:

- P1. Higher AI capacity has a positive impact on financial modeling quality of firms [18], [24].
- P2. The quality of higher financial modeling has a positive impact on the quality of the strategic decision [20], [25].
- P3. The quality of strategic decisions has a positive impact on the performance and competition of firms [21], [23].
- P4. High quality of data and organizational preparedness enhances the correlation between AI potential and quality in financial modeling [22], [26].
- P5. Model explainability and governance mechanisms enhance the relationship between strategic decision quality and financial modeling quality [19], [29].

The suggested block diagrams and theoretical model indicate that AI-driven strategic decision-making should be viewed more as an organizational system, as opposed to a prophetic tool. Machine learning adds value when it enhances financial modeling, when the outputs of the modeling process are useful in making strategic decisions, and when the overall process is backed by quality data, understandability, governance, and management ability [18], [20], [30]. This framing also contributes to the discovery of where the future research needs to be directed: not merely at enhancing the performance of the algorithms, but the ways in which AI can be made responsibly integrated into the real-life processes of strategic and financial decision-making.

5. Future Directions

Though AI-based financial modeling and strategic decision-making has been rapidly developed, there are several important research areas under-researched. These aspects should be taken into consideration as far as the ensuring of AI systems being not only technically feasible, but also strategically meaningful, ethically responsible, and organizationally feasible. One of the most important future research directions is the creation of explainable and interpretable AI systems that are specifically created to be implemented in the financial decision-making situations. Even though more predictive models such as deep neural networks outperform poorly on predictive performance, the non-transparency of these models is a limitation in the use of deep neural networks in high stakes environments. Further studies are needed to create hybrid models, which may find the optimal balance between predictive accuracy and interpretability to make sure that decision-makers can comprehend and interpret the results of AI-based models in a more appropriate way [31]. This may be more so the regulated industries where explainability is the most critical in compliance, auditing and trust to stakeholders. The second potential way is the development of hybrid models, which will involve machine learning techniques and the traditional financial and econometric models. Even though machine learning can effectively model nonlinear trends, classic models may be theoretically based and interpretable. Future research should understand the way these approaches could be put together to develop more powerful and theoretically consistent financial models [32]. This integration is capable of filling this gap between the data-driven prediction and the theory-driven explanation, which is one of the key weaknesses of the current studies. The introduction of real-time and streaming data analytics also provides a significant opportunity in creating AI-based strategy. Financial markets are becoming more and more real time and decision-making systems need to change as well. The future study should be aimed at how the machine learning models could be simplified by continually updating with streaming information to assist organizations to react dynamically to market, geopolitics, and new risks

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

[33]. This involves creation of adaptive algorithms that can deal with concept drift and high change of environment. Secondly, strategic scenario planning and uncertainty management are now a more topical sphere where AI is being talked about. Conventional strategic planning tends to be based on inflexible forecasting and narrow-minded scenario analysis. This can be enhanced using machine learning to provide more sophisticated simulations, probabilistic predictions, and stress testing under different conditions. Future studies need to be done on the ways AI can be used to facilitate long-term strategic thinking, especially in settings that are highly uncertain and complex [34]. The other significant line of future research is the legal and ethical ramifications and regulation of AI in finance. As the influence of the AI systems on the formulation of the corporate strategies and financial performance increases, the concerns of prejudice, equity, responsibility, and transparency become more prominent. Future studies need to come up with responsible AI governance frameworks that are compatible with regulatory and societal expectations, but which nonetheless allow innovation and competitive advantage [35]. Creating models of successful collaboration between humans and AI will be essential in making sure that AI complements, but not compromises the quality of strategic decisions. It includes thinking over how to audit AI systems, to make credit and investment decision-making fair, and to avoid the unintended consequences. Besides, the idea of AI preparedness and the ability to build on the organizational level deserves more consideration. Although AI technologies are considered the most expensive to use by numerous companies, not all are able to implement these systems within their strategies. Future research can consider the impact of organizational culture, leadership, skill development, and change management on the successful implementation of AI-based decision-making systems [36]. These factors are critical in translating technological capability to derive the actual business value. Lastly, the interplay between human judgment and AI systems in strategic decision-making needs to be investigated in future studies. Instead of considering AI as a substitute of human decision-makers, it is necessary to comprehend how human-AI cooperation may be streamlined. This involves researching the effect that cognitive biases, trust in AI, and decision-making heuristics have on applying AI-generated insights in practice [37]. Creating models of successful collaboration between humans and AI will be essential in making sure that AI complements, but not compromises the quality of strategic decisions[38].

Conclusion

This review has discussed how artificial intelligence and machine learning are increasingly becoming important in changing financial modeling and corporate strategy. As it was mentioned, AI-based solutions have considerable advantages over the old ones, in particular, predictive accuracy, scalability, and high-dimensional and complex data processing. With machine learning in the financial modeling, organizations are capable of conducting better forecasting, risk management and provide smarter and active strategic decisions. Simultaneously, the results also reflect the fact that the value of AI is also not absolute. It has several important parameters to its success such as the quality of data, model interpretability, preparedness and governance structures of an organization. The possibility to implement the AI systems into the decision-making and trust its results and use are predetermined by the availability of these aspects. In this regard, AI is not a technological resource per se, but a strategic competency, which would have to be aligned to organizational structures, processes, and goals. The proposed theoretical framework provides a methodical way of understanding the effect of the AI capability on the quality of financial modeling that, in later stages, has its influence on the strategic decision-making and performance of the organization. The model underlines the need to mediate and moderate variables and provides a more narrow-focused view of the relationship between the adoption of AI and the company performance. It also suggests the need to have a systems level approach, which will take into account both the technical and organizational direction. The future of AI-based strategic decision making will be founded on the ability to overcome the major challenges associated with explainability, ethical governance and human-AI interaction in the future. As the complexity and

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3906-3917
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0511

dynamism of financial surroundings constantly increase, the organizations that incorporate AI in their strategic processes will be at the advantage that is more likely to attain sustainable competitive advantage. Simultaneously, researchers should also keep on experimenting with new methodology, frameworks and interdisciplinary approaches so that AI is utilized in a responsible and efficient manner. To sum up, AI-powered financial modeling and corporate policy represents a completely different way of corporate operations and rivalry. Even though it has done a tremendous leap, it still has a long way to go and be innovative. To help address the existing constraints and find the new opportunities that a new AI can bring, scholars, and practitioners can join forces and work towards the development of more powerful, transparent, and strategically oriented AI systems.

References

[1]. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260.
[2]. Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: Data mining, inference, and prediction. Springer.
[3]. Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165–1188.
[4]. Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. American Economic Review, 106(5), 133–139.
[5]. Lo, A. W. (2017). Adaptive markets: Financial evolution at the speed of thought. Princeton University Press.
[6]. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206–215.
[7]. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.
[8]. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.
[9]. Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. PLOS ONE, 12(7), e0180944.
[10]. Budish, E., Cramton, P., & Shim, J. (2019). The high-frequency trading arms race: Frequent batch auctions as a market design response. Quarterly Journal of Economics, 130(4), 1547-1621.
[11]. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.
[12]. Brynjolfsson, E., & McElheran, K. (2016). The rise of data-driven decision making in business. NBER Working Paper Series.
[13]. Rudin, C. (2020). Interpretable machine learning: Fundamental principles and 10 grand challenges. Statistics Surveys, 16, 1-85.
[14]. Gu, S., Kelly, B., & Xiu, D. (2020). Deep learning in asset pricing. Journal of Financial Econometrics, 18(4), 690-742.
[15]. Ozbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2021). Machine learning in finance: A survey. Financial Innovation, 7(1), 1-38.
[16]. Wrede, M., & Velamuri, V. K. (2021). Corporate governance and artificial intelligence: The role of the board in the era of AI. California Management Review, 63(4), 5-26.
[17]. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82-115.
[18]. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California Management Review, 61(4), 66-83.
[19]. Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning.
[20]. Rai, A. (2020). Explainable AI: From black

box to glass box. Journal of the Academy of Marketing Science, 48(1), 137-141.

[21]. Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. In The Economics of Artificial Intelligence: An Agenda (pp. 115-146). University of Chicago Press.

[22]. Adner, R., Puranam, P., & Zhu, F. (2019). What is different about digital strategy? From quantitative to qualitative change. Strategy Science, 4(4), 253-261.

[23]. Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. A. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management, 57(2), 103169.

[24]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365.

[25]. Cheng, M., & Lu, Y. (2021). Machine learning methods for financial forecasting: A review. Artificial Intelligence Review, 54(1), 459-489.

[26]. Fisher, T., Rudin, C., & Dominici, F. (2019). All models are wrong, but many are useful: Learning a variable's importance by studying an entire class of prediction models simultaneously. Journal of Machine Learning Research, 20(177), 1-81.

[27]. Bertsimas, D., Kallus, N., Hussain, R., & Kuhn, D. (2016). Data-driven robust optimization. Mathematical Programming, 167(2), 235-292.

[28]. Kaplan, S., & Orlikowski, W. J. (2013). Temporal work in strategy making. Organization Science, 24(4), 965-995.

[29]. Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124-136.

[30]. Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable AI in credit risk management. Computational Economics, 57(1), 203-216.

[31]. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689-707.

[32]. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. ACM Computing Surveys, 51(5), 1–42.

[33]. Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. Journal of Economic Perspectives, 31(2), 87–106.

[34]. Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., & Bouchachia, A. (2014). A survey on concept drift adaptation. ACM Computing Surveys, 46(4), 1–37.

[35]. Schoemaker, P. J. H. (1995). Scenario planning: A tool for strategic thinking. Sloan Management Review, 36(2), 25–40.

[36]. Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the 'good society': The US, EU, and UK approach. Science and Engineering Ethics, 24(2), 505–528.

[37]. Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2015). Strategy, not technology, drives digital transformation. MIT Sloan Management Review, 14(1), 1–25.

[38]. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126.