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Navigating Finance Transition: A Thematic Review of AI Revolution and its Implications

Sofiane AKHKHA
Laboratory of Innovation in Finance, Governance, and Artificial Intelligence, National School of Business and Management (ENCG Settat), Hassan First University of Settat, Morocco.

Abstract. Artificial intelligence is increasingly embedded in financial activity, yet the literature remains divided between technical studies of algorithmic capability and application-based studies on specific financial functions. This fragmentation limits the understanding of how AI is changing finance as an integrated decision environment. This article provides a thematic review of AI in finance, focusing on how AI alters information handling, decision support, automation, governance and accountability across financial domains. The review draws on a structured corpus of 70 sources, including peer-reviewed articles and institutional reports, selected through a staged screening process covering academic databases and targeted regulatory and institutional sources. The findings indicate that AI does not simply provide novel instruments to established financial practices, it reorganises the chain through which financial decisions are prepared, assessed, justified and controlled. Across corporate finance, capital markets and international finance, AI expands operational capacity while shifting pressure towards validation, explainability, human oversight and institutional responsibility. The review also identifies persistent constraints regarding data quality, model opacity, cyber exposure, third-party dependence, regulatory fragmentation and uneven evidence maturity. The article argues that the future value of AI in finance will depend less on technological sophistication alone than on the capacity of firms, investors, regulators and researchers to maintain accountability, resilience and trust within machine-assisted financial decision structures. Future research should therefore examine AI under actual institutional constraints, focusing more on governance performance, human intervention, systemic effects and decision accuracy.

Keywords: Finance; Artificial intelligence; Machine learning; Financial markets; Corporate finance; Capital markets; International finance; Algorithmic risk; Governance; Generative AI.

1. Introduction

Finance operates as an information processing domain because financial activities convert dispersed and heterogeneous information into price signals, risks assessment, liquidity decisions, quality judgements, and coordination mechanisms (Bahoo et al., 2024 ; Aldasoro et al., 2024b). This conversion process is altered by artificial intelligence (AI), which deploys algorithmic models that utilise large datasets and machine learning (ML) to generate predictions, analysis, recommendations, or decisions. These computational frameworks classify data, forecast outcomes, and detect patterns without exclusive reliance on predefined rules (Aldasoro et al., 2024b ; OECD, 2021 ; Belhaj & Hachaïchi, 2021). This capability expands the categories of data available for analysis by combining structured market and accounting data with news text, corporate reports, social media signals, sentiment indicators, and visual chart information (Nie et al., 2024 ; Kudelić et al., 2025 ; Bartram et al., 2021). Further studies extend this perspective documenting that AI technology is fundamentally integrated into the finance domain through data processing and computational abilities. These instruments facilitate the exploration of complex and large datasets resolving analytical inquiries that would otherwise require unsustainable allocations of time, workforce, operational cost, and further could presumably exceed the limits of manual or conventional evaluation methods (Gao et al., 2024 ; Ranta et al., 2023 ; Wasserbacher & Spindler, 2022). Consequently, the wider data baseline and technical capacity alter how market and corporate inputs are evaluated across operations including forecasting, classification, fraud detection, asset pricing, credit scoring, portfolio allocation, risk management, and automated decision support (Alami et al., 2025 ; Vuković et al., 2025 ; Aldasoro et al., 2024b ; Nazareth & Reddy, 2023). The transition in finance domain therefore reflects a movement from predefined, rule-bound numerical processing toward faster, broader, and context-aware synthesis of diverse financial information. Moreover, the diversity of these AI applications in finance domain renders a global assessment of literature difficult, as identical AI models execute distinct functions across various fields such as asset trading, credit assessment, risk analysis, and client interactions. The analytical requirements change depending on whether research evaluates technological capacity, operational constraints, governance structures, or institutional decision-making (Mirishli, 2025 ; Theodorakopoulos et al., 2025 ; IOSCO, 2025 ; Fritz-Morgenthal et al., 2022). Hence, academic research captures this transition of finance practices by matching specific computational methods to the precise functional demands of each finance subfield. Consequently, distinct branches of enquiry were established, the first dominant trajectory of literature focuses on algorithmic advancements, mapping the technical evolution of AI frameworks applied to the finance domain. These reviews primarily assess the architecture of ML and deep learning (DL) models, evaluating how effectively these instruments process heterogeneous data for predictive accuracy and pattern recognition (Golec & Alabduljalil, 2025 ; Gao et al., 2024 ; Ye et al., 2024 ; Nazareth & Reddy, 2023). Conversely, the second research stream evaluates functional use cases rather than technical architectures. It tracks how AI models perform when deployed across specific operational tasks, such as portfolio management, algorithmic trading, and fraud detection (Chen et al., 2025a ; George et al., 2025 ; Bahoo et al., 2024 ; Nazareth & Reddy, 2023). Thus, research covering the finance transition in the AI era remains structurally fragmented. With the field broadly divided into technical and deployment dimensions, current syntheses dominantly focus on opportunities, algorithmic capabilities, and ML applications to finance. As a result, existing literature offers a rigorous examination of discrete applications; however, it often falls short of providing a comprehensive articulation of the evolution of finance practices driven by the utilisation of AI technology, leaving critical aspects such as limitations, risks, governance and regulatory compliance, relatively underexplored.

The research gap is therefore essentially an integration gap: resolving this fragmentation requires a thematic review that draws together technical capabilities, financial applications, structural limits, and governance frameworks. More precisely, the distinct contribution of this review lies in positioning AI in finance beyond the existing technical and application-centred literature streams. Prior reviews have largely focused on mapping machine learning methods, bibliometric structures, or specific financial tasks such as credit scoring, fraud detection, portfolio management, and algorithmic trading (Chen et al., 2025a ; Bahoo et al., 2024 ; Gao et al., 2024 ; Nazareth & Reddy, 2023). In contrast, the present review examines AI as a broader transition in the financial decision environment itself, where data expansion, algorithmic prediction, automation, human validation, explainability, accountability, and regulatory control operate as interdependent elements of the same transformation. This synthesis is particularly necessary today because recent developments in generative AI, financial-domain language models, explainability expectations, and supervisory frameworks have fundamentally shifted the core question. The primary issue is no longer simply whether AI can improve technical performance, but whether machine-assisted financial decisions can remain reliable, auditable, accountable, and institutionally governable across corporate finance, capital markets, and international finance.

To address this gap, the current review provides an integrated thematic synthesis of how AI is reshaping finance domain. To navigate this transition, the article addresses three core research questions: first, what foundational capabilities and inherent constraints define AI in financial information processing; second, how do these applications transform decision-making across corporate finance, capital markets, and international finance; and third, how do emerging governance frameworks attempt to balance algorithmic innovation with compliance obligations?

This study makes three contributions to literature. First, it develops a perspective of finance transition that interprets AI not as a set of isolated technologies applied to finance, but as a change in how financial information is collected, processed, predicted, automated and governed. Second, it integrates research streams that are usually examined separately, including algorithmic capability, financial application, data and model limitation, regulatory control and decision-making consequences. Third, it provides a thematic basis for future AI-finance research by clarifying where existing evidence explains financial transformation, where it remains fragmented, and where stronger attention to reliability, accountability and governance is required. This study may benefit also industry practitioners and regulatory bodies navigating the finance transition. For corporates, risk managers, and technology providers, it offers an operational framework to evaluate model reliability, explainability, data governance, and control safeguards prior to deployment. For regulators and supervisors, it isolates the specific channels through which algorithmic adoption drives innovation while creating distinct challenges for accountability, compliance, consumer protection, and systemic risk.

The remainder of this article is organised into five sections. Section 2 outlines the methodology of review, detailing the design, database selection, search strategy, and screening criteria. Section 3 evaluates AI capabilities and explores data constraints, limitations, governance obligations, and algorithmic risks. Section 4 maps these dynamics across three operational domains: corporate finance, capital markets, and international finance. Section 5 synthesises the findings by assessing shifts in financial decision-making, implications for stakeholders, and the tension between innovation and control requirements. Finally, Section 6 concludes the article, underlines limitations, and suggests future research directions.

2. Methodology

a. Review design and database selection

This study employs a structured thematic literature review design to examine how AI influences finance domain by restructuring information collection, processing, prediction, automation, governance, and application across financial functions. This approach is suited to a research field currently fragmented, and appropriate when the primary analytical task is to collect, organise, and synthesise an expansive, multi-disciplinary body of knowledge (Snyder, 2019 ; Zupic & Čater, 2015 ; Braun & Clarke, 2006). Source identification combined academic database extraction with targeted institutional document harvesting. Academic records were compiled from Scopus, Web of Science, Google Scholar, and OpenAlex. To capture critical governance, regulatory and supervisory developments, targeted institutional sources were gathered from the Bank for International Settlements (BIS), the Organisation for Economic Co-operation and Development (OECD), the International Monetary Fund (IMF), the European Central Bank (ECB), the Financial Stability Board (FSB), and the International Organization of Securities Commissions (IOSCO).

The preliminary results cover an initial sample of 547 records, comprising 364 academic database entries and 183 institutional documents. Incorporating both streams was essential because the operational, stability, and governance implications of AI are evaluated just as rigorously in institutional reports as they are in academic field.

The substantive literature coverage was delimited to sources published between 2020 and 2026. This period was selected because it captures the acceleration of AI adoption in finance following the expansion of machine learning, big data analytics, and generative AI applications (Rasheed et al., 2026), while remaining recent enough to reflect current regulatory and institutional concerns. The primary literature collection phase was executed between 1 February 2026 and 13 March 2026. This initial extraction was succeeded by an analytical processing phase conducted between 17 March 2026 and 10 May 2026. Finally, an update and verification search was performed continuously until 18 May 2026 to identify highly relevant, recent publications, with a specific focus on 2026 studies addressing generative AI, agentic systems, financial-domain language models, and AI supervisory mechanisms in finance.

b. Search strategy, keywords, and screening criteria

The search strategy deployed combined finance-related and AI-specific keyword strings. The finance block comprised terms such as 'finance', 'financial markets', 'corporate finance', 'capital markets', 'risk management', 'asset pricing', 'credit scoring', 'portfolio management', 'algorithmic trading', and 'international finance'. Concurrently, the AI block integrated expressions including 'artificial intelligence', 'machine learning', 'deep learning', 'natural language processing', 'big data analytics', 'generative AI', 'large language models', 'algorithmic decision-making', 'explainable AI', and 'AI governance'. These terms were operationalised using Boolean operators and calibrated to the syntax requirements of each respective database.

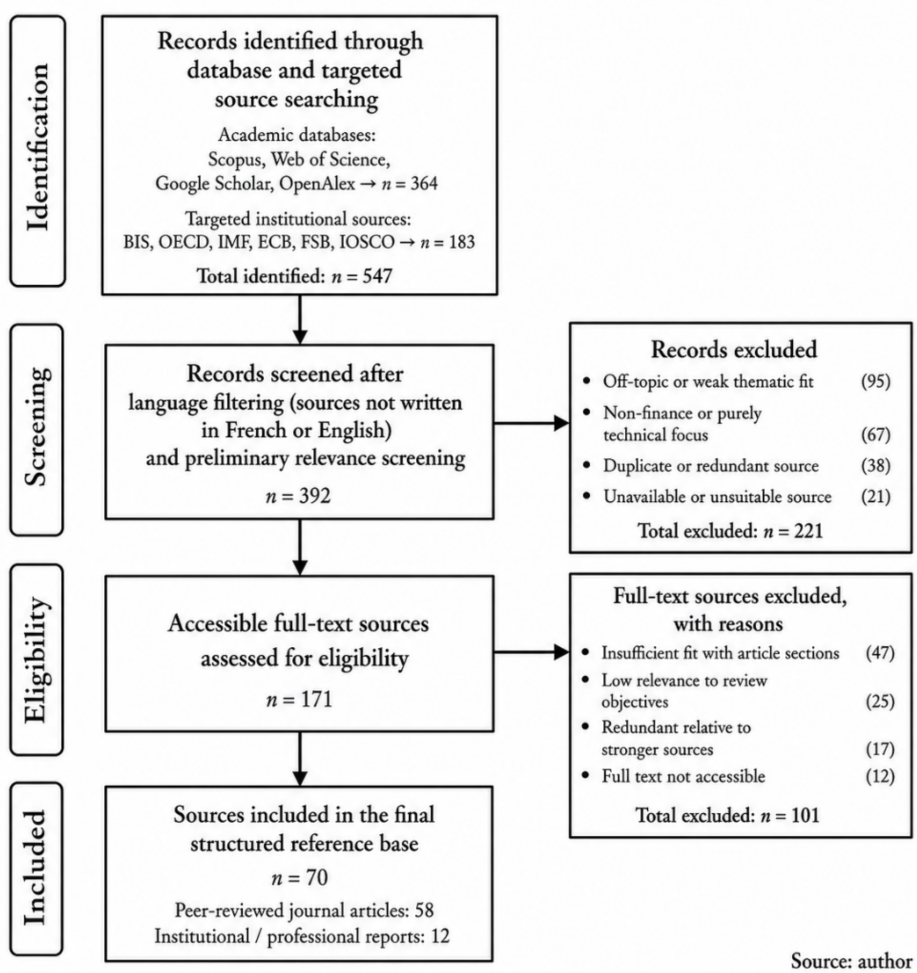
The workflow was organised to maintain transparency across source identification, screening, eligibility assessment, and thematic synthesis. The reporting discipline was informed by the PRISMA protocol framework, which requires a transparent accounting of study identification, selection criteria, and structural synthesis (Page et al., 2021). The preliminary search identified 547 records, comprising 364 academic database entries and 183 institutional documents. Following language filtering and preliminary relevance screening, 392 records remained in the initial selection pool. At the screening stage, 221 records were excluded: 95 due to off-topic or weak thematic fit, 67 for a non-finance or purely technical computational focus, 38 because they constituted duplicate or redundant entries, and 21 due to non-availability or unsuitability.

The subsequent eligibility stage evaluated 171 accessible full-text documents. As summarised in Table 1, the eligibility assessment applied explicit inclusion and exclusion criteria to ensure that retained sources were thematically relevant, analytically usable, and sufficiently aligned with the review objectives. At this stage, 101 full-text sources were excluded: 47 for insufficient fit with article sections, 25 for low relevance to the review objectives, 17 due to redundancy relative to stronger sources, and 12 because the full text was not accessible. The resulting structured reference base comprises 70 unique sources, partitioned into 58 peer-reviewed journal articles and 12 institutional or professional reports. The screening framework also distinguished sources used for methodological grounding from those used for substantive synthesis, preventing procedural references from being treated as evidence for empirical or thematic findings.

Table 1. Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
a) Directly addressed AI, ML, or related algorithmic approaches in explicit relation to corporate finance, capital markets, financial decision-making, international finance, or regulatory and governance issues in finance.	a) Exhibited an off-topic, weak thematic fit, or low relevance to the review objectives and article sections.
b) Provided conceptual, empirical, or review-based evidence capable of supporting at least one objective or thematic component of this review.	b) Focused on non-financial contexts or on purely technical and computational issues without meaningful financial relevance.
c) Presented sufficient analytical or structural detail to allow reliable interpretation and thematic integration into the review.	c) Represented duplicate, redundant, or less complete records relative to methodologically stronger retained sources.
d) Retrieved from academic databases or targeted institutional sources, including peer-reviewed journals and institutional or professional reports directly relevant to the review objectives.	d) Were unavailable, unsuitable, or inaccessible in full-text format. e) Were written in languages other than English or French.

Figure 1: PRISMA flow diagram of the literature collection process



Source: author

3. The AI Revolution: Capabilities, Opportunities, Risks, and Limitations

a. The algorithmic engine: capabilities and opportunities

Earlier computational tools automated calculations based on operational rules explicitly defined by programmers. In contrast, the current algorithmic engine relies on ML models that infer classificatory and predictive relations directly from data, while DL extends this mechanism to detect systematic patterns across high dimensional and complex inputs (Alami et al., 2025 ; Aldasoro et al., 2024b ; OECD, 2021). This architecture redefines how quantitative and qualitative financial data is extracted, evaluated, and converted into decisions. According to Alami et al. (2025), ML and DL demonstrate a stronger capacity to capture nonlinear dependencies and improve predictive accuracy than traditional modelling approaches. Consequently, this predictive capacity has become central to forecasting, classification, anomaly detection, and automated decision support across the financial system. Moving from prediction to concurrent execution, these models vastly accelerate the system's ability to evaluate large amounts of raw data, instantly calculate predictive probabilities, and generate content (Aldasoro et al., 2024b). This operational capability is primarily driven by generative artificial intelligence (GenAI), which refers to computational architectures of AI systems capable of producing novel textual, numerical, visual, or code-based outputs from learned data patterns, rather than merely classifying or predicting predefined outcomes. Within this broader category, large language models (LLMs), a by-product of GenAI, utilise DL trained on extensive data inputs to interpret, summarise, and reason over natural language. The extension of these instruments in finance domain is reflected through specialised financial-domain language models (FinLLMs), which adapt this underlying architecture to finance domain terminology, regulatory disclosures, market narratives, and accounting statements. By integrating text, tables, and unstructured images into a unified analytical workflow, FinLLMs establish robust foundation models capable of understanding complex financial context and generating valuable insights (Chen et al., 2025b ; Lee et al., 2024 ; Nie et al., 2024).

b. Data constraints and inherent limitations

The predictive and generative capacity described in the previous subsection depends on the conditions under which financial data are collected, selected, processed, and evaluated. AI systems do not transform raw financial data into reliable decisions by default; their outputs remain exposed to weaknesses in data quality. Essentially, big data enlarge the informational basis of financial analysis, but unreliable sources, unsuitable datasets, biased collection systems, and insufficient representation of relevant subpopulations undermine the veracity of model outputs and could lead to hallucination or inaccurate outcomes. The generic AI models also do not automatically satisfy specific requirements of finance, because financial applications often require legal compliance, multimodal document processing, long horizon time series analysis, and strict privacy safeguards (Chen et al., 2025b; FSB, 2024b ; OECD, 2021).

Data abundance also creates a second limitation: larger volume of data increases potential signals but simultaneously multiplies potential distortions. Combining heterogeneous datasets can improve pattern detection, but it frequently introduces confounding effects, selection bias, and spurious correlations. These issues are particularly critical in financial decision support such as credit risk assessment, fraud detection, assets rating, and market analysis where datasets often reflect historical institutional practices, reporting gaps, or particular market imbalances. Therefore, AI can mitigate certain forms of discretionary human bias, however it risks reproducing or intensifying unfair treatment when flawed data or biased labels are incorporated in the training process (Yang et al., 2026; Chawla et al., 2025 ; Deprez et al., 2025 ; Schmitt, 2024 ; FSB, 2024b). Furthermore, the reliability of models is also limited by drift and weak generalisation due to the non-stationary nature of financial data, where volatility regimes, crises, stakeholders behaviour, and macroeconomic relationships change continuously over time. Hence, static validation sets frequently understate model fragility, and financial ML applications remain vulnerable to training materials drift. These limitations do not render AI unusable; rather, they demonstrate that technical performance on historical data is not equivalent to real world operational reliability. Transitioning safely from raw algorithmic capability to systematic financial deployment therefore demands continuous validation, monitoring, and robust governance mechanisms to verify that outputs remain accurate and fit for purpose under continuous changing conditions (Baviskar, 2025a, 2025b; OECD, 2021).

c. Governance obligations and algorithmic risks

The limitations do not render AI technology unsuitable for finance domain, but they shape the conditions for responsible deployment. Once algorithmic outputs actively influence financial decisions, the historical data defects, opacity, model drift, and underlying biases can no longer be evaluated as isolated software errors; instead, they transition into binding institutional governance obligations that demand compliance and accountability frameworks. Consequently, supervision institutions must actively translate the rules regarding prudence, data privacy, cybersecurity, and operational resilience into dynamic control structures capable of monitoring opaque or outsourced AI models (BCBS, 2024). This objective is documented for instance in the European Union AI Act, which imposes explicit pre-deployment conformity assessments, mandatory performance logging, and structured registration protocols on high impact algorithmic profiling and outsourced AI systems (OECD, 2026, 2024; Mirishli, 2025 ; Crisanto et al., 2024). Moreover, the regulatory oversight framework is fundamentally challenged by the black-box architecture of deep neural networks, which generates severe information asymmetry that threaten consumer protection, data privacy, operational trust, and external auditing standards (Crisanto et al., 2026). Within this context, the capacity to understand the fabric of the model and explain its behaviour is central to this control structure, because AI instruments influence decision-making while relying on models that are difficult to uncover. This opaque nature explains the increasing relevance of Explainable AI (XAI), which refers to methodologies designed to render algorithmic outputs more understandable to users, auditors, and regulators by clarifying the precise factors driving a given prediction, classification, or recommendation. Within this domain, Shapley Additive Explanations (SHAP) estimate the marginal contribution of each input variable to a model output by relying on cooperative game-theory logic, while Local Interpretable Model-agnostic Explanations (LIME) approximate complex model behaviour locally by constructing a simpler surrogate model around a specific prediction instance. Although these analytical tools are valuable for diagnostic interpretation, they do not automatically render the underlying models fully transparent or institutionally accountable. Indeed, popular post-hoc explanation metrics such as LIME and SHAP exhibit inherent instability under dynamic market conditions. These operational failures produce unreliable approximations rather than true structural transparency; hence, the mere deployment of XAI instruments cannot, by itself, satisfy broader institutional governance obligations and regulatory compliance. The responsibility therefore remains to explicitly define the necessary depth of explanation, disclosure eligibility rules, verification protocols, and whether the framework permits meaningful human intervention (Mohsin & Nasim, 2025; Mirishli, 2025 ; Pérez-Cruz et al., 2025 ; Crisanto et al., 2024). From this perspective, comprehensive AI governance mandates dynamic, continuous monitoring and lifecycle-based model risk management to counter performance degradation and limit human oversight failures such as automation bias (OECD, 2026; Bengio et al., 2025 ; Manheim et al., 2024)

4. AI implication across financial domains

a. AI and corporate finance

Corporate finance structures the broader finance transition by embedding AI directly into core organisational routines (Zhang & Wang, 2024). This technology alters how finance departments generate forecasts, prepare reports, allocate resources, and monitor liquidity. Empirical evidence indicates that adoption is no longer limited to basic financial reporting. A global survey of 2,900 finance executives across 23 markets tracks AI deployment in areas such as financial reporting, risk, generative AI, treasury, accounting, FP&A, and tax. Within these tracks, the study groups organisations into clear implementation stages: beginners, implementers, and leaders (KPMG International, 2024). The data reveals that 71% of surveyed companies deploy AI within their finance functions. Among these applications, accounting and FP&A exhibit the highest adoption rates, while treasury and risk departments primarily pilot or use the technologies on a smaller scale. These metrics reflect widespread technological diffusion rather than absolute proof that AI automatically improves financial outcomes across all firms.

These findings demonstrate that corporate departments adopt AI at entirely different paces, based on functional demands, infrastructure readiness, and internal control practices. The initial layer of organisational maturity adopting AI systems involves analytical workflows. Within this domain, FP&A teams support management and boards by evaluating projects, preparing financial plans, and aligning corporate resources with strategic priorities. ML extends this analytical capacity by building predictive models from complex, multidimensional datasets. This allows systems to isolate underlying patterns that traditional spreadsheet-based routines frequently miss (Wasserbacher & Spindler, 2022). Management accounting evidence highlights a secondary data channel, where ML converts qualitative and unstructured materials into measurable variables. This conversion refines forecasting accuracy and utilises explainable AI to help decision makers interpret non-linear outputs (Ranta et al., 2023). Furthermore, LLMs expand the corporate analytical interface. Advanced financial question-answering systems execute reasoning tasks over structured reports, corporate earnings statements, tabular disclosures, ratio analyses, trend analyses, and variance attributions (Liu et al., 2026). Consequently, analytical maturity in corporate finance goes beyond larger data capture; it requires direct integration with operational forecasting, corporate planning, and human strategic interpretation. The second layer concerns operational maturity which materialises when AI modifies recurring finance workflows rather than isolated analytical tasks. In corporate treasury, automated cash-flow forecasting platforms optimise liquidity management through precise predictions, real-time variance analyses, and continuous scenario simulations. This operational environment requires explicit collaboration between machine intelligence and human treasury expertise (J.P. Morgan, 2024). Within accounting operations, the integration of AI and ML automates transaction tracking, ledger entry, financial statement generation, and real-time reporting while accelerating internal audit tracks (Wang et al., 2025; Estep et al., 2023). This shift moves the accounting function away from passive historical record storage toward instantaneous processing and continuous anomaly detection (Kanaparthi, 2024). Financial reporting and conversational question-answering systems introduce an additional operational layer. These tools support automated natural language reporting, decision support, and contextual reasoning over integrated corporate financial statements (Liu et al., 2026). This technological transition does not displace corporate finance professionals. Instead, it reconfigures the specific information they must validate, explain, and transform into strategic decisions.

The adoption of AI in corporate finance remains nevertheless subject to critical structural dependencies. Operational barriers include high implementation costs, data inconsistencies, human capital deficits, and data security liabilities, alongside integration difficulties and organisational resistance. Similarly, baseline data quality and structured human-machine collaboration operate as vital prerequisites for deploying AI within treasury frameworks. For smaller organisations, severe infrastructure constraints emerge. Deploying advanced financial question-answering pipelines frequently requires cloud-based graphics processing unit (GPU) capacity, dedicated technical teams, and high-volume inference infrastructure that small and medium enterprises (SMEs) cannot easily maintain (Liu et al., 2026). Within FP&A workflows, a distinct analytical boundary persists. While a predictive model can optimise expected outcome estimations, effective corporate planning and corrective actions require causal insights regarding intervention effects. Consequently, statistical predictive accuracy cannot be equated with structural causal understanding (Wasserbacher & Spindler, 2022). Model validation represents a vital internal control in this case because FinLLMs can misinterpret professional terminology or misreport numerical values. These hallucinated or inaccurate outputs can propagate rapidly through automated reporting or analytical pipelines if firms fail to validate model results against domain specific evidence (Zhang et al., 2025). Corporate finance adoption of AI is therefore an ongoing maturity problem. Algorithmic value depends on embedding models directly into planning, accounting, treasury, and reporting workflows while strictly maintaining data quality, human judgment, validation, and assurance. The next financial domain shifts the level of analysis from internal corporate processes to capital markets, where AI is incorporated in asset pricing, market trading, portfolio construction, and investor information processing.

b. AI and capital markets

In corporate finance, AI is embedded mainly in internal functions: forecasting, treasury, accounting, reporting, planning, and validation. In capital market, the mechanism is different. AI affects the competitive process through which dispersed information becomes tradable signals, asset prices, market orders, portfolios and investor advice. Its role is therefore not only to automate financial analysis, but to alter the pace, scope and technical structure of price discovery, trading execution and investment allocation. IOSCO (2025) identifies AI use across diverse capital market fields such as investment research, sentiment analysis, algorithmic trading, robo-advising, asset management, and client interaction. Thus, the influence of AI within capital markets essentially centers on information; it expands what can be observed, how signals are extracted, how rapidly they are converted into trades, and how investment decisions are distributed to market participants. Regarding signal extraction, capital market reacts to price history, corporate disclosures, macroeconomic news, analyst commentary, investor sentiment and other relevant miscellaneous information. Within this context, AI adoption expands the informational perimeter as ML systems can infer predictive relations from data (Aldasoro et al., 2024b). NLP and LLMs extend this logic by processing news, reports, social-media signals, market commentaries, conference call transcripts and visual chart information as inputs to market forecasting. Sentiment analysis has therefore moved from lexicon scoring toward ML and LLMs grounded approach that can process context dependent language and convert market mood into predictions (Nie et al., 2024 ; Lee et al., 2024). This transition contributes presumably to enhance the accuracy rather than providing market related outcomes that are mechanically reliable. Thus, AI systems operate within tradable signals environment and translate what can enter the market prediction process, for instance: text, tone, narratives, visual patterns and high frequency information flows (Chen et al., 2025b). Moreover, asset pricing reflects this transformation. The traditional modeling remains important, yet insufficient when return dynamics are non-linear, and the set of candidate predictors expands. Conversely, ML methods respond to these conditions by estimating unknown return functions through flexible models such as tree-based methods, random forests, gradient boosting, neural networks, graph neural networks and dimensionality-reduction techniques (Ye et al., 2024). These models construct predictive structures from multidimensional data, cross asset relations, sparse dependencies and time varying interactions. Hence, the contribution underscored is not merely computational speed, AI systems alter the modelling problem itself. From this perspective, empirical asset pricing is less dependent on predefined linear factor structures and rely more on data-driven identification of unstable, dynamic, non-linear and heterogeneous return patterns. This market prediction advantage remains conditional nonetheless because market data contain noise, structural breaks and undermined by shifts in conditions. Consequently, AI models that demonstrate high accuracy during back testing may underperform when applied to real markets as they lack the interpretability needed to validate their economic logic. (Alami et al., 2025 ; Ye et al., 2024 ; ESMA, 2023).

The incorporation of AI technology in portfolio management activities is documented as well. AI systems support the investment chain and optimisation objective through signal generation, financial asset selection, expected return estimation, risk assessment, portfolio construction, rebalancing and transaction cost modelling. Asset management evidence nevertheless requires restraint as AI branded investment products do not automatically imply superior performance, lower fees or replacement of investment judgement. The stronger supported claim is that AI automates repetitive analytical work, identifies patterns in large and unstructured datasets, supports dynamic rebalancing and contributes to modeling trading costs and market impact (Bartram et al., 2021, 2020). The portfolio manager's intervention perimeter evolved therefore from producing every signal manually to validating data sources, model assumptions, optimisation constraints, economic interpretation and the stability of algorithmic recommendations.

Trading and robo-advising are fields that benefit as well from AI technology integration in capital market domain. Regarding trading, AI models are embedded in pipelines that include pre-trade analysis, outcomes generation, strategy design, back testing, order routing, execution optimisation, sensitivity tests, and post trade processing (IOSCO, 2025 ; ESMA, 2023). LLMs add a further technical layer by supporting code generation for financial computational purposes, while multimodal and agent-based systems can combine textual, numerical and visual inputs formulating presumably adequate trading strategies (Chen et al., 2025b ; Nie et al., 2024). Therefore, AI technology is not merely a prediction instrument in the trading domain; it is part of the infrastructure through which market decisions are converted into orders under speed, liquidity and cost constraints. Meanwhile, studies exploring the impact of AI in robo-advising service underline a shift in practices from standard professional investment workflows to investor-facing advice. It translates algorithmic portfolio construction into customised recommendations, automated rebalancing, risk management and lower-cost access to financial analysis (Feng et al., 2025 ; Bartram et al., 2020). This access remains conditional because complete integration depends on trust, digital competence, financial confidence, risk propensity and the continuing need for human interaction, especially when investors face anxiety or complex decisions (Aristei & Gallo, 2025). Automated risk profiling also develops investor protection concerns when irrelevant attributes alter risk scores, making explanation, consistency and human escalation essential (Chawla et al., 2025).

Ultimately, AI creates a distinct capital market risk because model outputs interact through markets rather than remaining inside one organisation. When many participants rely on similar datasets, models or execution rules, AI can align interpretations, concentrate trades and affect price discovery, liquidity and market stability, creating risks of herding, crowded positions, distorted prices and liquidity stress (FSB, 2024b ; Leitner et al., 2024). Agentic and multi-agent trading systems deepen this concern because individual profitability does not prove market level resilience. Their evaluation must therefore include market impact, stress behaviour, liquidity, market depth and systemic effects, not only prediction accuracy or trading returns (Aldridge et al., 2026).

c. AI and international finance

International finance differs from the previous domains because its problems arise across borders. Currency conversion, payment chain opacity, sovereign exposure, local political events, and jurisdictional differences make financial relations harder to compare and monitor. AI is therefore most useful when it helps harmonise, adapt and convert particular cross border inputs into usable financial assessments. In currency markets, this includes separating the relevant exchange rate text from news that refers simultaneously to both countries in a currency pair (Abouzaid & Boussedra, 2025 ; Meng et al., 2024 ; Ayitey Junior et al., 2023). According to Ding et al. (2024a, 2024b), LLMs can filter such material, score sentiment, and connect it with market indicators. The value of this approach is not that it adds another technical model to finance. Its contribution lies in handling cross border ambiguity. Earlier dictionary-based sentiment methods struggle with static vocabularies, domain specific expressions, and numerical meanings in financial language. By contrast, language model pipelines can isolate the relevant part of a currency-related text before it enters the analytical system. This distinction matters because exchange-rate language often carries mixed references: one statement may concern both economies, both currencies, and both policy environments at once.

Another contribution of AI to international finance appears in sovereign risk analysis. Recent studies on geopolitical and geoeconomic shocks separates sovereign credit default swap reactions into direct repricing, global financial cycle effects, uncertainty, and domestic amplification (Belly et al., 2023). This moves the analysis beyond a single market reaction and identifies which channel responds first in each crisis episode (Ortiz et al., 2025). The result is closer to a diagnostic map of international risk transmission than to a simple country risk rating. From this perspective, AI systems contribute to distinguish exposure type, transmission channel, and country sensitivity. Cross border payments extend the same logic from risk assessment to infrastructure. International payments remain slow, costly, and opaque because they pass through intermediaries, currency conversion layers, compliance checks, and fragmented messaging standards (Cerutti et al., 2025 ; FSB, 2024a). Smart contract architectures and ISO 20022 compatible message parsing can make transaction states more visible, auditable, and interoperable, although legacy system compatibility remains a practical constraint (Mridul et al., 2024). The international finance implication is precise: digital systems do not merely accelerate transfers; they make payment chains more legible. Transaction monitoring gives this infrastructure argument a supervisory edge. Cross border anti money laundering systems face complex transaction patterns because globalised finance enables sophisticated laundering techniques across jurisdictions. Within this context, ML and DL systems can support anomaly detection, while adaptive monitoring is presented as necessary for financial fraud control in a globalised economy (Yu et al., 2024 ; Chen et al., 2025a ; Mousavian & Miah, 2025 ; FSB, 2024a).

5. Discussion

a. Synthesis of major findings

The reviewed evidence suggests that the AI-finance transition should not be interpreted as the mere diffusion of advanced AI tools across financial domains. Its more profound consequence is a fundamental structural shift within the decision-making chain itself. While AI expands the range of tasks that can be delegated to computational systems, it simultaneously intensifies the operational necessity for rigorous validation, contextual interpretation, and control. The central finding is therefore not simply that finance has become more technologically dense, but that financial judgement increasingly relies upon systems whose outputs must be systematically verified, explained, and governed. This transition introduces a distinct operational bottleneck. Whereas legacy technological advancements primarily targeted the processing speed and transactional costs of data handling, contemporary AI frameworks present a more complex trade-off. While they successfully alleviate specific operational frictions , they simultaneously introduce systemic fragilities stemming from shared technical infrastructures, convergent model behaviour, heightened cyber exposure, and the deficient governance of highly intricate computational outputs. Consequently, the ultimate value of AI within the financial domain remains strictly conditional; it depends far less on raw computational capacity than on the capacity of institutions to harmonise human accountability, market integrity, and supervisory visibility with machine-assisted decision-making processes (Aldasoro et al., 2024a ; Aldasoro et al., 2024b ; Gao et al., 2024 ; FSB, 2024b ; Leitner et al., 2024). Furthermore, the synthesis demonstrates that AI does not influence financial domains in isolation. Although corporate finance, capital markets, and international finance are characterised by distinct operational challenges, they converge upon a singular pivotal shift: AI relocates the core of financial workflows away from the manual production of information towards evaluating whether AI generated outputs are sufficiently reliable to justify strategic action. It is precisely this convergence that provides this review with its integrated analytical framework. Ultimately, the true significance of AI technology lies not in the mere addition of an extra technical layer to existing financial practices, but in how fundamentally it reorganises the relationship between information, professional judgement, and institutional responsibility.

b. How AI changes financial decision-making

AI alters financial decision-making by fundamentally decoupling the generation of algorithmic outputs from the ultimate authority to act upon them. Within corporate planning and forecasting, model driven estimations continue to necessitate strategic business interpretation, corrective human judgement, and deeply contextual organisational knowledge. Similarly, within the sphere of retail investment and robo-advisory services, digital channels serve primarily to complement independent professional consultation, rather than suggesting a total displacement of standard advisory pathways. Consequently, the overarching implication of this transition is not the wholesale substitution of human expertise, but rather a structural redistribution of workforce and analytical responsibilities between advanced computational systems and accountable decision-makers. This realignment profoundly changes the definition of professional expertise within the financial domain. Practitioners are no longer primarily tasked with routine calculation, data classification, or preliminary screening; instead, their core responsibility shifts to assessing the plausibility of algorithmic insights, identifying when outputs must be challenged, and determining precisely when human escalation is required. Consequently, AI establishes a hybrid decision making architecture characterised by a mutual interdependence between technical capacity and professional judgement. Paradoxically, as the financial domain grows increasingly reliant upon automated models, the human component becomes markedly more critical in executing rigorous post model validation, managing operational exceptions, and maintaining clear lines of institutional accountability (Aristei & Gallo, 2025; Feng et al., 2025 ; Wasserbacher & Spindler, 2022). The primary operational risk within this framework is the misallocation of authority, where black-box architectures or LLMs generate a superficially plausible result that lacks true structural transparency or verifiable grounds for trust. This dynamic frequently induces human oversight failures such as automation bias, wherein practitioners endorse automated outputs simply because they appear technically rigorous rather than objectively justified. This vulnerability underscores why the transition cannot be evaluated purely through the lens of operational efficiency, cost reductions, or processing speed. Ultimately, the critical challenge is whether financial actors can clearly distinguish between computational assistance and fully autonomous delegated judgement, ensuring that institutions preserve the capacity for meaningful human intervention as automated outputs become deeply embedded in routine workflows.

c. Implications for firms, investors, regulators, and researchers

For firms, the primary implication of the finance-AI transition is organisational rather than technological. The deployment of these advanced frameworks necessitates the establishment of rigorous model validation routines, dedicated data governance teams, specialised human capital, and explicit protocols for human escalation.

For investors, the integration of AI reconfigures the conditions of institutional trust. While automated wealth management and robo-advisory channels significantly lower transactional barriers and broaden access to standardised portfolio analysis, their practical utility remains strictly contingent upon the user's digital competence, and awareness of personal data exposure. Furthermore, because automated risk profiling can undermine investor protection when flawed or irrelevant parameters distort algorithmic scores, human escalation is essential for clients navigating high stakes or anxiety-inducing financial choices. Consequently, regulatory frameworks and educational initiatives must expand their scope beyond merely promoting AI-market access; they must actively cultivate the capacity of retail participants to recognise structural risk, systemic model uncertainty, and the psychological perils of overconfidence or automation bias within algorithmic trading environments.

For regulators, the central implication manifests in tracking and monitoring problems. AI architectures are rapidly becoming integrated across market infrastructures, internal corporate activities, and retail financial services well before supervisory mechanisms can fully capture or quantify their aggregate effects. Consequently, regulatory work must transition faster from passive observation to defining explicit, enforceable expectations regarding algorithmic explainability, lifecycle model governance, operational resilience, and the systemic risks of third-party vendor concentration. Given the frictionless nature of algorithmic execution, this monitoring mandate also demands robust cross border coordination to harmonise oversight across fragmented jurisdictions.

For researchers, the corresponding task is to shift scholarly attention away from isolated, controlled settings and instead evaluate whether AI genuinely improves financial outcomes under real institutional constraints. Future empirical inquiry must prioritise investigating model performance amidst non-stationary data drift, real market stress conditions, and complex validation intersecting human and algorithms workflows.

d. Tensions between innovation and control

The core tension inherent in the AI-finance transition lies in the paradox that the exact characteristics driving its adoption are those that fundamentally complicate institutional control. While rapid computational processing minimises operational delays and transactional friction, it simultaneously compresses or eliminates the analytical window required for thorough human review and pre-execution validation. Similarly, while the vast scale of automated architectures allows institutions to expand their service provision, it concurrently risks systematically replicating flawed training data, historical biases, or uniform model assumptions across thousands of automated decisions. Furthermore, while outsourcing development to external software vendors accelerates technological integration, it introduces critical fragilities by concentrating market wide dependence on a highly restricted cluster of third-party technology providers. Consequently, technological innovation mechanically engenders sophisticated compliance and governance obligations at the exact moment it delivers operational efficiencies (Crisanto et al., 2024; Leitner et al., 2024 ; FSB, 2024b ; ESMA, 2023 ; Saha et al., 2025).

This conflict is most acute where algorithmic architectures directly influence systemic market behaviour. Indeed, reliance upon identical underlying technical infrastructures, concentrated third-party vendors, and convergent model outputs can rapidly transmit localised operational vulnerabilities into widespread market stresses, such as crowded positions and liquidity drops. Cybersecurity introduces a further dual use paradox: the very computational instruments deployed to enhance fraud detection, transaction monitoring, and anomaly tracking can concurrently strengthen fraud, impersonation or automated manipulation (Karaosman et al., 2026). Ultimately, these systemic dynamics do not imply that AI originates entirely unprecedented categories of financial risk; rather, its deployment heavily intensifies long standing, familiar vulnerabilities by amplifying execution speed, compounding structural opacity, and deepening institutional interconnection.

Regulatory control is also constrained by the fragmented maturity of international oversight. While certain jurisdictions rely strictly on legacy, technology-neutral rules, others issue non-binding guidance, and some move decisively towards explicit, AI-specific frameworks. Although this asymmetric regulatory landscape provides local flexibility, it leaves fundamental operational questions unresolved: what structural level of explanation is legally sufficient, who assumes the validation burden when verifying opaque third-party systems, and precisely when existing rules require formal reinterpretation. Consequently, the innovation-control tension cannot be reduced to a binary choice between technological adoption and legislative restriction; it represents an institutional design problem centred on allocating responsibility, establishing standardized audit evidence, and executing enforceable supervisory oversight (Crisanto et al., 2024; OECD, 2024 ; Leitner et al., 2024 ; FSB, 2024b)

6. Conclusion

Concluding this review, the ongoing integration of AI technology within the financial domain should not dominantly be evaluated through the lens of diffusion of novel algorithmic tools across conventionally established financial activities. A more comprehensive interpretation reveals that AI essentially restructures the analytical chain through which financial decisions are framed, evaluated, justified, and controlled. Across the reviewed literature, this transition does not eradicate human agency or subtract decision-making from the financial ecosystem; instead, it displaces professional judgement towards the critical spheres of validation, context-aware interpretation, human escalation, and governance accountability. Consequently, the central challenge for modern finance is not whether market participants can successfully adopt AI technology, but whether institutions can rigorously govern the operational conditions under which automated outputs become actionable. This thematic review addresses a historically fragmented literature base by integrating technical computational capabilities, financial use cases, structural data limitations, and regulatory governance requirements into a unified thematic framework. The resulting synthesis demonstrates that AI alters the financial domain most distinctly when it reconfigures the structural relationship linking information processing with institutional responsibility. Corporates, market participants, and supervisory bodies are no longer confronted simply with accelerated analytical software. They are interacting with complex decision-making infrastructures that require verifiable evidence of model reliability, explicit boundaries of human responsibility, continuous oversight, and the active capacity to intervene when automated recommendations diverge from economic reality. Ultimately, the long-term success of the AI-finance transition relies more on the maturity of institutional control frameworks rather than the pure sophistication of the underlying algorithmic engines. Future progress cannot be evaluated solely on the basis of technological integration rates, baseline model performance, or the expansion of commercial use cases. Instead, it must be assessed by its capacity to safeguard explainability, regulatory compliance, systemic robustness, and market trust within hybrid decision structures.

This review is primarily constrained by the underlying source base that reflects an uneven evidence maturity across financial domain; while certain fields exhibit advanced technical data, others remain reliant on preliminary institutional reports or early-stage applications. Moreover, because rapid technological acceleration continually outpaces academic publication cycles, these findings risk capturing transitional arrangements rather than stable operational conclusions. Consequently, this synthesis serves as a cautious interpretive framework rather than definitive stance regarding market wide implementation outcomes, failure cases, or long-term institutional adaptation.

Future research should move beyond technical performance and examine financial usefulness. The central question is whether AI-supported decisions improve economic outcomes, reduce avoidable losses, strengthen risk control and remain defensible under stress. A second research priority concerns accountability in hybrid and autonomous decision environments. As AI systems become more embedded in consulting, trading, compliance, cyber defence and institutional workflows, accountability becomes harder to attribute. Future studies should examine traceability records, human override, liability sharing, audit trails, incident reporting and progressive deployment. These topics are central because governance failure may arise even when the underlying system performs well under technical evaluation.

7. References

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