

AI-Enabled Financial Strategy and Strategic Decision-Making

RISHI GUPTA
NMIMS Mumbai

Abstract- Artificial Intelligence (AI) is increasingly influencing how financial decisions are analyzed, evaluated, and executed. Traditionally, financial strategy has relied on managerial judgment, financial models, historical information, and established frameworks for decisions relating to capital allocation, investment, financing, liquidity, and risk. The emergence of machine learning, predictive analytics, natural language processing, and generative AI is expanding these capabilities by enabling financial professionals to process large volumes of information, identify patterns, generate forecasts, and evaluate alternative scenarios.

This paper examines the transformation of financial strategy through AI-enabled financial strategy, defined as the integration of AI-driven analytical capabilities into strategic financial decision-making while retaining human judgment and oversight. Rather than examining AI solely as an automation tool, the paper positions it as an emerging strategic capability that can influence forecasting, capital allocation, investment analysis, risk management, liquidity management, and financial intelligence.

Existing research documents AI applications across individual financial functions, but these applications are often examined separately. Limited attention has been given to how AI-enabled capabilities collectively influence strategic financial decision-making and under what organizational conditions they translate into measurable outcomes. The paper therefore develops a conceptual framework connecting AI capabilities, financial intelligence, strategic decision-making, and financial outcomes.

The paper further proposes AI Absorptive Capacity as an organizational capability that influences the extent to which AI-generated insights are assimilated and applied to financial decisions. Data quality, human expertise, AI literacy and trust, and governance are also identified as important conditions affecting value realization. The study concludes by identifying avenues for empirical research into the relationship between AI adoption, decision quality, organizational capability, and financial performance.

Index Terms- AI-Enabled Financial Strategy, Artificial Intelligence, Strategic Financial Decision-Making, Financial Strategy, Human-AI Complementarity, AI Absorptive Capacity, Value Creation

I. INTRODUCTION

A. Background and Context of Financial Strategy

Financial strategy determines how an organization acquires, allocates, and manages financial resources to achieve its strategic objectives and create long-term value. Key decisions include investment, financing, capital structure, liquidity, risk management, and resource allocation. Traditional corporate finance frameworks provide analytical foundations for these decisions through concepts such as capital budgeting, Free Cash Flow, WACC, and risk-return evaluation. However, modern financial decision-making has become increasingly information-intensive. Financial managers must evaluate historical performance alongside market conditions, macroeconomic developments, customer behavior, competitive dynamics, regulatory changes, and potential risks. As a result, the effectiveness of financial strategy increasingly depends on an organization's ability to collect, process, interpret, and apply large volumes of information.

The reference literature on Advisory Capital highlights a similar challenge: specialized knowledge can improve complex financial decisions, but its value ultimately depends upon the firm's ability to assimilate and apply that knowledge.

The emergence of Artificial Intelligence introduces a new dimension to this environment. AI can process large datasets, identify patterns, generate predictions, and support scenario analysis, thereby expanding the analytical capabilities available to financial decision-makers. This raises an important strategic question:

how does AI change the process through which financial strategy is formulated and executed?

B. Emergence of AI-Enabled Financial Strategy

The evolution of technology in finance can broadly be viewed as a progression from financial automation to data-driven analysis and, increasingly, AI-enabled decision support.

Earlier financial technologies primarily automated repetitive activities and improved transaction processing. Advanced analytics subsequently enabled organizations to analyze larger datasets and improve forecasting and performance monitoring. AI represents a further development by enabling systems to identify patterns, generate predictions, process unstructured information, and increasingly produce decision-support outputs.

These capabilities can be applied across financial activities such as forecasting, budgeting, investment analysis, capital allocation, treasury, risk management, and financial research. Existing research reviewed for this study indicates that AI adoption is expanding across FP&A, treasury, investment banking, wealth management, credit, and risk management. However, the literature remains relatively fragmented across individual applications and functions.

This distinction is important. AI in finance refers broadly to the application of AI to financial activities, whereas AI-enabled financial strategy focuses specifically on how AI-generated intelligence influences decisions concerning the allocation and management of financial resources.

Accordingly, this paper defines AI-enabled financial strategy as:

The integration of AI-driven analytical, predictive, and information-processing capabilities into strategic financial decision-making while retaining human judgment, oversight, and accountability.

The resulting decision process can therefore be conceptualized as:

Data → AI-Enabled Financial Intelligence → Human Interpretation → Strategic Financial Decision

Thus, the transformation is not simply about replacing human activities with technology. It concerns

expanding the information-processing and analytical capabilities available to financial decision-makers.

C. Problem Statement and Research Questions

Although AI adoption in finance is expanding, existing research provides a fragmented understanding of its strategic implications. Studies frequently examine individual applications such as trading, credit scoring, portfolio optimization, fraud detection, or financial forecasting, while industry research often focuses on adoption and productivity gains. Comparatively less attention has been given to integrating these applications into a broader framework of financial strategy.

A second gap concerns the relationship between AI-generated intelligence and human financial judgment. Strategic financial decisions involve uncertainty, trade-offs, organizational constraints, and accountability. Therefore, greater analytical capability does not automatically guarantee better strategic decisions. Human expertise, interpretation, trust, and oversight remain relevant to the realization of AI-generated insights.

A third gap concerns outcome measurement. Improvements in processing speed or analytical accuracy do not necessarily translate into financial value. It is therefore important to examine the pathway through which AI capabilities influence financial intelligence, decision quality, and ultimately measurable financial outcomes.

Based on these gaps, the study addresses the following research questions:

RQ1: What mechanisms enable AI to influence strategic financial decision-making across forecasting, capital allocation, investment, risk, and liquidity management?

RQ2: What evidence exists regarding the effect of AI-enabled financial strategy on decision quality, analytical efficiency, and financial outcomes?

RQ3: How does human expertise interact with AI-generated financial intelligence in strategic financial decision-making?

RQ4: Under what conditions do data quality, AI literacy, trust, governance, and organizational capability influence the effectiveness of AI-enabled financial strategy?

RQ5: How does AI Absorptive Capacity influence the conversion of AI-generated financial intelligence into realized strategic and financial value?

D. Contribution and Structure of the Study

This paper contributes to the emerging literature by positioning AI not merely as an automation technology but as an emerging strategic capability within financial decision-making. It integrates AI capabilities with established concepts of financial strategy and organizational capability.

The paper also incorporates human–AI complementarity, recognizing that AI can expand analytical capacity while finance professionals provide contextual interpretation, strategic judgment, and accountability.

Building on the concept of Absorptive Capacity in the reference study, the paper introduces AI Absorptive Capacity as the organization's ability to recognize, assimilate, evaluate, and apply AI-generated financial intelligence. The reference study demonstrates that access to specialized knowledge does not automatically produce value; realization depends on the organization's ability to implement that knowledge.

The conceptual framework proposed in this paper can therefore be represented as:

AI Capabilities → Financial Analysis & Intelligence
→ Strategic Financial Decision-Making → Financial
& Strategic Outcomes

The effectiveness of this relationship is influenced by:
Data Quality + Human Expertise & Trust + AI
Governance + AI Absorptive Capacity

II. LITERATURE REVIEW: THEORETICAL FRAMEWORK OF FINANCIAL STRATEGY

A. Financial Strategy and Firm Value

Financial strategy is fundamentally concerned with how firms allocate financial resources to create and sustain value. Core decisions include investment, financing, capital structure, liquidity, and risk management. Traditional corporate finance theory evaluates these decisions through expected cash flows,

risk, cost of capital, and the efficient allocation of resources.

Investment decisions seek to allocate capital toward opportunities that are expected to generate returns exceeding their required cost of capital. Financing decisions determine how these investments should be funded through debt, equity, or internally generated resources. Capital structure consequently represents a balance between the benefits and costs associated with alternative sources of financing.

These decisions are interdependent. The quality of an investment decision depends on the accuracy of forecasts and valuation assumptions, while financing choices influence the firm's cost of capital and financial flexibility. Financial strategy therefore requires the integration of multiple sources of information rather than isolated financial decisions.

This provides the theoretical foundation for examining AI in financial strategy. If financial strategy depends substantially on the quality, timeliness, and interpretation of information, technologies capable of improving information processing may influence the quality and efficiency of strategic financial decisions.

B. Strategic Financial Decision-Making

Strategic financial decision-making can be viewed as a process through which financial information is transformed into resource-allocation decisions.

A simplified decision process can be represented as:
Information → Analysis → Forecast → Evaluation →
Decision → Implementation

Historically, this process has relied heavily on financial models, historical data, managerial experience, and professional judgment. However, the increasing volume and complexity of available information creates challenges for purely human-driven analysis.

AI introduces an additional analytical layer into this process. Machine learning can identify patterns in historical data, predictive systems can generate forecasts, and natural language technologies can process large quantities of structured and unstructured financial information. AI therefore has the potential to strengthen the analysis and forecasting stages of financial decision-making.

Importantly, improved analysis does not automatically imply improved strategy. Financial decisions involve qualitative considerations, uncertainty, organizational objectives, and trade-offs that may not be completely captured by historical data. Consequently, AI-generated outputs must be interpreted within the broader strategic context.

This establishes the central distinction of the paper: AI can enhance the information and analytical foundation of financial strategy without independently replacing strategic financial judgment.

C. AI as a Strategic Financial Capability

The increasing use of AI suggests that its role in finance can be understood not only as a technological investment but also as an organizational capability.

AI capability refers broadly to an organization's ability to deploy AI technologies, integrate relevant data, generate useful analytical insights, and incorporate those insights into business processes. In financial strategy, this capability can support activities such as forecasting, scenario analysis, investment evaluation, risk assessment, liquidity planning, and financial intelligence.

The existing research reviewed for this study identifies AI applications across several financial functions but also highlights that much of the literature remains fragmented by application or function.

From a strategic perspective, the importance of AI therefore lies not simply in whether a firm possesses AI tools, but in whether those tools improve the organization's ability to make financial decisions.

The conceptual relationship can be expressed as:

AI Capability → Financial Intelligence → Decision Quality → Strategic Outcomes

Here, financial intelligence represents the insights generated through AI-enabled analysis, while decision quality reflects the relevance, accuracy, timeliness, and usefulness of those insights for strategic financial decisions.

D. Human–AI Complementarity

The relationship between AI and financial professionals is central to AI-enabled financial

strategy. AI can process large datasets and identify patterns at a scale and speed that may be difficult to achieve through conventional analysis. Financial professionals, however, contribute domain knowledge, contextual understanding, strategic judgment, and accountability.

The interaction can therefore be viewed as complementary rather than purely substitutive:

AI = Analytical Scale + Speed + Pattern Recognition
Human Expertise = Context + Judgment + Interpretation + Accountability

This complementarity is particularly relevant for strategic financial decisions because financial outcomes depend on assumptions about uncertain future conditions. An AI model may identify a potential risk or forecast a particular outcome, but management must determine its strategic significance and decide how to respond.

The existing research identifies the limited systematic treatment of this human–AI interaction as an important gap. While AI tools increasingly function as decision-support or “copilot” systems, the extent to which human expertise, trust, and interpretation affect the resulting decision remains an important area for further research.

Accordingly, this paper treats human expertise and AI capability as complementary resources within the financial decision-making process.

E. AI Absorptive Capacity

The concept of Absorptive Capacity (ACAP) provides the key organizational capability underlying this framework. The reference study defines ACAP as the ability of a firm to recognize the value of new external information, assimilate it, and apply it for business purposes. It distinguishes between potential ACAP, involving the acquisition and recognition of knowledge, and realized ACAP, involving its application and exploitation.

The same logic can be extended to AI-enabled financial strategy.

The availability of AI-generated information does not necessarily create financial value. An organization may have sophisticated AI systems but fail to realize

their benefits because employees cannot interpret the outputs, data systems are poorly integrated, decision-makers do not trust the results, or AI insights are not incorporated into actual decision processes.

This paper therefore proposes the concept of AI Absorptive Capacity:

AI Absorptive Capacity is an organization's ability to recognize, assimilate, evaluate, and apply AI-generated intelligence within strategic financial decision-making.

It can be understood through three stages:

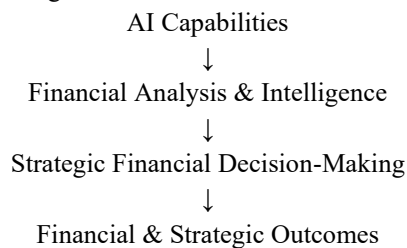
AI Access & Recognition → AI Assimilation & Evaluation → AI Application & Realization

This creates an important distinction:

AI Capability ≠ AI Value

Rather, value realization depends on the organization's ability to convert AI-generated intelligence into effective financial decisions.

The resulting theoretical framework is:



with the relationship influenced by:

Data Quality + Human Expertise & Trust + AI Governance + AI Absorptive Capacity

This framework provides the theoretical basis for examining, in the following section, the specific mechanisms through which AI can influence financial strategy.

III. MECHANISMS OF AI INFLUENCE ON FINANCIAL STRATEGY

Artificial Intelligence influences financial strategy primarily by strengthening the information, analytical, and decision-support capabilities available to finance professionals. Its impact can be observed across four interconnected mechanisms: AI-enabled forecasting and scenario analysis, capital allocation and

investment analysis, risk and liquidity management, and strategic financial intelligence.

The importance of these mechanisms lies not simply in the automation of individual tasks, but in their potential to improve the quality, speed, and breadth of information available during strategic financial decision-making.

A. AI-Enhanced Forecasting and Scenario Analysis

Forecasting is one of the most direct areas through which AI can influence financial strategy. Traditional forecasting relies heavily on historical trends, management assumptions, manually selected drivers, and periodic revisions. AI and machine-learning models can incorporate larger datasets and identify relationships between multiple variables, allowing forecasts to be updated more dynamically.

Evidence from the FP&A Trends Survey 2024 illustrates this potential. Across the surveyed organizations, 42% rated their forecasts as “good” or “great”; among organizations using AI or machine learning, this figure increased to 65%. However, only 18% of organizations were able to produce a forecast within two days, while 53% required more than five days.

These figures suggest that AI adoption may be associated with improvements in perceived forecast quality, although they should not be interpreted as proof of a causal relationship because the survey compares organizations rather than randomly assigned AI and non-AI users.

AI also expands forecasting beyond a single expected outcome. Financial managers can use AI-enabled systems to generate multiple scenarios based on changes in variables such as revenue growth, interest rates, commodity prices, exchange rates, operating costs, or liquidity requirements.

This changes the role of forecasting within financial strategy:

Traditional approach:

Historical Data → Forecast → Budget

AI-enabled

approach:

Historical + Real-Time Data → AI Forecast → Multiple Scenarios → Strategic Response

The strategic benefit therefore lies not only in potentially improving forecast accuracy but also in enabling finance teams to evaluate alternative future conditions more rapidly.

B. AI-Enabled Capital Allocation and Investment Analysis

Capital allocation represents one of the most consequential areas of financial strategy because firms must determine where scarce financial resources should be deployed. Decisions may involve acquisitions, capital expenditure, portfolio investments, new business opportunities, or restructuring.

AI can support this process by rapidly processing financial statements, market information, transaction documents, valuation inputs, and other relevant information. Machine-learning models can identify patterns and anomalies, while natural language processing can extract relevant information from large volumes of unstructured documents.

This is particularly relevant in M&A and investment analysis, where the volume of information involved in due diligence can be substantial. AI can assist in identifying financial inconsistencies, extracting contractual information, comparing targets, and highlighting potential risks.

The importance of speed can be illustrated through JPMorgan's COiN (Contract Intelligence) system. The system was designed to analyze commercial-credit agreements and extract contractual information. JPMorgan reported that the targeted workflow represented as many as 360,000 hours of annual manual review across approximately 12,000 agreements, while the software could analyze documents in seconds. Importantly, this figure represents an estimated annual manual workload for a specific document-review process, rather than 360,000 hours of general financial decision-making being independently replaced by AI.

The strategic implication is that AI can reduce the time required to transform large quantities of financial information into usable intelligence. This can allow financial professionals to spend relatively more time on valuation assumptions, strategic fit, negotiation,

and decision-making rather than information extraction.

The mechanism can therefore be represented as:

Large Information Set → AI Screening & Analysis → Relevant Insights → Human Evaluation → Capital Allocation Decision

AI consequently functions as an analytical accelerator rather than an autonomous capital allocator.

C. AI-Driven Risk and Liquidity Management

Risk and liquidity management require continuous monitoring of financial conditions. Conventional approaches often depend on predefined thresholds, historical information, periodic reporting, and manual monitoring. AI can strengthen these processes by identifying patterns and anomalies across large datasets and generating more frequent predictions.

In risk management, AI can support areas such as credit assessment, fraud detection, anomaly identification, market-risk monitoring, and scenario analysis. The value of these systems is closely related to their ability to identify signals that may not be immediately visible through conventional analysis.

Liquidity management provides another important application. Cash-flow forecasting requires organizations to estimate future inflows and outflows while accounting for uncertainty in customer payments, operating expenses, financing requirements, and market conditions. AI-enabled forecasting can incorporate multiple variables and continuously update expected liquidity positions.

The strategic importance of AI in this area is therefore linked to the relationship between forecasting accuracy and financial flexibility. More accurate liquidity forecasts can potentially allow firms to maintain sufficient liquidity while avoiding unnecessarily large cash buffers.

However, AI-based risk management also illustrates why human oversight remains important. Model outputs depend on historical data and model assumptions, while unexpected market conditions can reduce predictive reliability. Consequently, AI should support rather than eliminate financial risk judgment.

This produces a two-stage process:

AI: Detect → Predict → Flag

Finance Professional: Validate → Interpret → Respond

The effectiveness of AI-enabled risk management therefore depends not only on predictive capability but also on governance, data quality, and the ability of financial professionals to interpret model outputs.

D. AI-Enabled Strategic Financial Intelligence

Beyond specific forecasting and risk applications, AI can influence financial strategy by improving the generation and communication of strategic financial intelligence.

Financial professionals frequently spend substantial time collecting information from financial reports, market research, portfolio data, company disclosures, internal systems, and other sources before strategic analysis can begin. Generative AI and natural language processing can reduce this information-processing burden by summarizing documents, identifying relevant information, generating analytical narratives, and connecting information across different sources.

A practical example is BlackRock's Aladdin Wealth Auto Commentary. The system combines portfolio risk analytics, a firm's investment outlook, and individual client portfolio information. It processes hundreds of data points and converts them into concise insights for financial advisors. The tool was initially implemented through Morgan Stanley Wealth Management's Portfolio Risk Platform.

This illustrates a broader transformation in financial strategy:

Raw Financial Information → AI Synthesis → Decision-Relevant Intelligence → Human Interpretation → Strategic Action

The objective is not simply to produce more information. It is to convert information into a form that can be incorporated into financial decisions.

This distinction becomes particularly important as AI moves from traditional analytics toward generative AI. In September 2026, for example, Anthropic launched

Claude for Financial Advisors, integrating its AI system with investment analytics and wealth-management platforms to assist with activities such as meeting preparation, portfolio reviews, and follow-up tasks.

These developments indicate a shift from AI being used primarily as a back-end analytical tool toward AI becoming an interactive decision-support layer within financial workflows.

E. Integrated Mechanism of AI Influence

The four mechanisms identified above are interconnected rather than independent.

AI-enabled forecasting provides better estimates of future financial conditions. Investment and capital-allocation tools use financial intelligence to evaluate opportunities. Risk and liquidity systems identify potential threats and financial constraints. Strategic intelligence systems integrate information from these activities and make it more accessible to decision-makers.

The evidence also suggests that the magnitude of these benefits should not be assumed to be uniform. For example, the FP&A survey shows a 23-percentage-point difference in the share of organizations rating forecasts as good or great between AI/ML users and the overall sample (65% versus 42%). At the same time, KPMG's 2026 survey of 1,013 senior finance leaders across 20 countries and 13 sectors reported that 75% of respondents were actively using AI in the finance function, compared with 30% in 2024. The survey also reported improvements in decision-making quality (70%), decision speed (71%), and forecast accuracy (64%).

These figures demonstrate the growing organizational adoption and reported benefits of AI in finance, but they should be interpreted as reported associations and survey perceptions rather than universal causal effects. Consequently, the central implication of this section is that AI influences financial strategy through multiple analytical and informational mechanisms, but the realization of those benefits depends on what organizations do with AI-generated intelligence. This leads directly to the next section, which examines whether these mechanisms translate into quantifiable financial outcomes.

IV. EMPIRICAL EVIDENCE AND QUANTIFIABLE FINANCIAL OUTCOMES

The preceding section identified the principal mechanisms through which AI can influence financial strategy. The next question is whether these mechanisms translate into measurable improvements in financial decision-making and organizational outcomes. Available evidence indicates improvements in forecasting, decision quality, decision speed, risk management, and economic returns. However, much of the current evidence is based on surveys and organization-reported outcomes rather than controlled causal studies. The distinction is therefore important when interpreting the results.

A. AI and Forecasting Performance

Forecasting provides one of the clearest areas in which AI-enabled financial strategy can be evaluated quantitatively. Forecast quality can be assessed through forecast error, accuracy, scenario coverage, and the time required to generate forecasts.

The FP&A Trends Survey 2024 found that 42% of organizations rated their forecasts as “good” or “great,” while this proportion increased to 65% among organizations using AI or machine learning. This represents a 23-percentage-point difference between the overall sample and AI/ML users. However, only 18% of organizations were able to produce a forecast within two days, while 53% required more than five days.

The survey therefore provides two important observations. First, AI/ML adoption is associated with a higher proportion of organizations reporting strong forecast quality. Second, forecasting speed remains a challenge even where analytical capabilities have improved.

More recent evidence from KPMG's 2026 Global AI in Finance survey, covering 1,013 senior finance leaders across 20 countries and 13 sectors, provides a broader picture. 64% of organizations reported improved forecasting accuracy over the previous year. The figure was particularly notable in banking, where 71% of respondents reported moderate or significant improvements, compared with 44% in healthcare.

The 27-percentage-point difference between these sectors suggests that AI performance is influenced by the underlying data environment. Financial institutions often possess highly structured and extensive datasets, while fragmented data environments can limit the effectiveness of AI models. This provides empirical support for the argument developed in Section II that AI capability alone does not determine financial outcomes.

B. AI and Financial Decision Quality

Beyond forecasting, AI can influence the broader quality and speed of financial decision-making. KPMG's 2026 survey reports that 70% of organizations experienced improvements in financial decision-making quality and 71% reported faster decision-making following AI adoption. At the same time, 71% of respondents stated that AI was meeting or exceeding their expectations regarding economic benefits or ROI.

These results are significant because they indicate that the reported benefits of AI extend beyond operational automation into activities involving financial judgment.

However, the evidence should be interpreted carefully. These figures represent self-reported organizational outcomes, meaning they demonstrate an association between AI adoption and perceived improvements rather than establishing that AI independently caused the improvements.

The distinction can be represented as:

AI Adoption → Reported Improvement

rather than automatically assuming:

AI Adoption → Causal Financial Performance Improvement

This distinction is particularly important when measuring strategic financial outcomes because organizational performance is simultaneously affected by economic conditions, management quality, capital structure, market conditions, and other strategic initiatives.

C. AI and Economic Returns

A more direct measure of AI's contribution is its economic return. KPMG's 2026 survey found that

71% of finance leaders reported that AI was meeting or exceeding their expectations for economic benefits, while approximately 29% did not report that level of performance.

The same study found that organizations with stronger AI governance and assurance capabilities reported substantially better outcomes. Organizations capable of producing AI audit evidence efficiently reported significant error reduction at a rate of 33%, compared with only 6% among organizations without the same level of assurance readiness. Similarly, confidence in scaling AI was reported by 42% of assurance-ready organizations compared with 14% among the comparison group.

The first difference represents more than a fivefold relative rate of reported error reduction, while confidence in scaling was three times higher.

These findings support an important proposition of this paper: AI value is not determined solely by the sophistication of the technology. Governance, controls, data quality, and organizational capability influence the extent to which AI produces measurable results.

D. AI, Data Quality and Financial Outcomes

The relationship between AI and financial outcomes is strongly dependent on the quality of the underlying data.

KPMG's 2026 study found that 36% of organizations identified data quality, integration, and system interoperability as both a major barrier and a major opportunity for extracting additional value from AI in finance. In addition, 38% of organizations were focusing on upskilling existing finance and internal audit teams, while 28% were building new capabilities through hiring.

These findings demonstrate that the technology-performance relationship is not linear.

A simplified relationship would be:

AI Investment → Financial Outcome

However, empirical evidence suggests a more realistic pathway:

AI Investment + Data Quality + Governance + Human Capability → Decision Improvement → Financial Outcome.

The banking-versus-healthcare comparison discussed earlier provides an illustration. While 71% of banking respondents reported improvements in forecast accuracy, the corresponding figure for healthcare was 44%. KPMG attributes this difference partly to differences in data foundations.

Therefore, data quality should not be considered merely a technical requirement. Within AI-enabled financial strategy, it becomes a strategic resource that influences the quality of information available for financial decision-making.

E. AI and Operational Efficiency

Although the central focus of this paper is strategic financial decision-making, operational efficiency provides an important supporting measure of AI value. AI can reduce the time required to collect, process, reconcile, and interpret financial information. The resulting time savings can create an indirect strategic benefit by allowing finance professionals to devote more attention to forecasting, analysis, risk evaluation, and strategic planning.

The FP&A evidence illustrates this limitation clearly. Only 18% of organizations in the 2024 survey could generate forecasts within two days, while 53% required more than five days.

This represents an important research opportunity. Future empirical research should move beyond measuring whether organizations use AI and examine whether improvements in AI-enabled financial decision-making ultimately translate into higher capital-allocation efficiency, lower financial risk, improved profitability, and sustainable firm value.

The evidence also reinforces the central proposition of this paper: The quality of data, governance mechanisms, human expertise, and organizational ability to assimilate AI-generated intelligence determine whether technological capability becomes realized financial value. This leads to the next section, which examines AI Absorptive Capacity as a potential moderating mechanism between AI capability and financial outcomes.

V. THE MODERATING ROLE OF AI ABSORPTIVE CAPACITY

The preceding sections establish that Artificial Intelligence can strengthen forecasting, investment analysis, capital allocation, risk management, liquidity planning, and financial intelligence. However, the evidence also indicates that the presence of AI capability does not automatically translate into superior financial outcomes. Differences in data quality, governance, employee capabilities, trust, and organizational integration can determine whether AI-generated insights are actually incorporated into financial decisions.

This creates an important distinction between having access to AI and realizing value from AI.

The reference study on Advisory Capital makes a similar distinction through the concept of Absorptive Capacity (ACAP). It defines ACAP as the firm's ability to recognize the value of external information, assimilate it, and apply it for business purposes. The study distinguishes between potential ACAP, associated with acquiring and recognizing external knowledge, and realized ACAP, associated with applying that knowledge operationally. It argues that external expertise may fail to generate value when firms lack the commitment, skills, incentives, or capabilities required for implementation.

This logic can be extended to AI-enabled financial strategy.

A. From AI Capability to AI Absorptive Capacity

AI capability refers to an organization's technological ability to deploy AI systems and generate analytical insights. However, AI-generated information becomes strategically valuable only when financial professionals can understand, evaluate, and incorporate those insights into actual decisions.

This paper therefore proposes AI Absorptive Capacity as:

The organization's ability to recognize the relevance of AI-generated financial intelligence, assimilate and evaluate it, and apply it effectively within strategic financial decision-making.

AI Absorptive Capacity can be viewed as a progression:

AI Access → Recognition → Assimilation → Evaluation → Application → Value Realization

The first stages represent the organization's ability to obtain and understand AI-generated information, while the latter stages determine whether that information actually influences financial decisions.

This distinction is important because an organization may possess sophisticated AI technology but still have low AI Absorptive Capacity. For example, a firm may implement an advanced forecasting system but continue relying primarily on manually generated forecasts because finance professionals do not trust the model, do not understand its outputs, or lack the processes required to incorporate those outputs into budgeting decisions.

Consequently:

AI Capability $\neq$ AI Absorptive Capacity $\neq$ AI-Generated Financial Value

AI capability represents technological potential, whereas AI Absorptive Capacity represents the organizational ability to convert that potential into practical financial outcomes.

B. Potential AI Absorptive Capacity

The first dimension concerns the organization's ability to recognize and acquire AI-enabled knowledge.

Potential AI Absorptive Capacity includes:

- Access to appropriate AI technologies and analytical systems
- Availability of relevant and reliable financial data
- Management awareness of AI capabilities
- Employee AI literacy and training
- Ability to identify financial problems where AI can add value

At this stage, the organization determines where and how AI should be used.

For example, a finance function may identify cash-flow forecasting as an area where AI could improve prediction accuracy. However, recognizing this opportunity does not guarantee that the resulting AI system will improve liquidity management.

This distinction mirrors the reference paper's argument that the acquisition of external knowledge represents only the initial stage of ACAP.

C. Realized AI Absorptive Capacity

The second dimension concerns the organization's ability to assimilate and apply AI-generated knowledge.

Realized AI Absorptive Capacity includes:

- Ability to interpret AI outputs
- Validation of model-generated recommendations
- Integration of AI insights into financial workflows
- Human oversight and decision accountability
- Ability to modify decisions based on AI-generated intelligence
- Continuous learning from AI implementation

This stage is particularly important for strategic financial decisions because AI outputs may contain uncertainty, model limitations, or assumptions that require professional interpretation.

For instance, an AI model may forecast a decline in future cash flows. The finance professional must determine whether the decline reflects a genuine deterioration in business conditions, a temporary market event, or a limitation in the underlying data. The strategic decision therefore emerges from the interaction between AI analysis and human interpretation, rather than from the AI output alone.

D. Factors Influencing AI Value Realization

Four organizational factors are particularly relevant to the conversion of AI capability into financial value.

1. Data Quality

AI systems depend on the quality, completeness, consistency, and accessibility of the underlying data. Poorly integrated or inaccurate financial data can reduce the reliability of AI-generated forecasts and recommendations.

Evidence discussed in Section IV supports this relationship. KPMG's 2026 survey found that 36% of organizations identified data quality, integration, and system interoperability as both a significant barrier and an opportunity for generating additional value from AI in finance.

Thus:

Better Data → Better AI Intelligence → Greater Decision Potential

2. Human Expertise and AI Literacy

Financial professionals remain responsible for interpreting AI outputs and applying them within specific business contexts. Employees therefore require not only traditional financial expertise but also sufficient AI literacy to understand model limitations, evaluate outputs, and identify inappropriate recommendations.

The objective is not to transform every finance professional into a data scientist. Rather, finance professionals need sufficient understanding to question, validate, and appropriately use AI-generated intelligence.

3. Trust and Governance

Trust influences whether AI-generated information is actually used in financial decisions. Excessive distrust can lead to underutilization, while excessive reliance can create risks associated with automation bias and insufficient human oversight.

Governance mechanisms therefore become essential. Financial institutions must establish appropriate controls concerning model validation, data privacy, explainability, accountability, and monitoring.

This is particularly important because financial decisions can have significant consequences for capital allocation, risk exposure, regulatory compliance, and shareholder value.

4. Organizational Integration

AI creates greater strategic value when its outputs are integrated into existing financial processes rather than operating as isolated analytical tools.

For example:

AI Forecast → Budgeting Process → Resource Allocation → Performance Monitoring
is strategically more meaningful than:
AI Forecast → Standalone Report

Organizational integration therefore determines whether AI-generated intelligence becomes part of the firm's actual decision architecture.

E. AI Absorptive Capacity as a Moderator

Based on the preceding discussion, AI Absorptive Capacity can be conceptualized as a moderating capability between AI capability and financial outcomes.

The relationship can be represented as:

AI Capability → Financial Intelligence → Decision Quality → Financial Outcomes

with: AI Absorptive Capacity

strengthening or weakening the relationship between AI-generated intelligence and actual financial decisions.

A simplified conceptual model is:



This framework explains why organizations with similar AI technologies may achieve different outcomes.

The reference paper makes an analogous argument for Advisory Capital: the value of external expertise depends substantially on whether the organization possesses the capability to implement and exploit that knowledge.

The same principle can therefore be extended to AI:

The strategic value of AI depends not only on what AI can produce, but on what the organization can absorb, interpret, and implement.

F. Implications for Financial Strategy

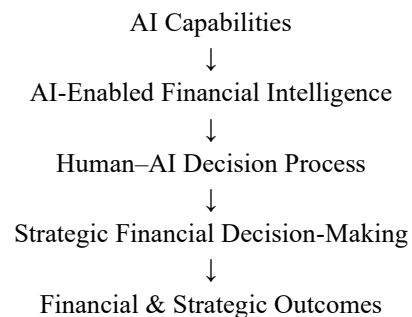
The concept of AI Absorptive Capacity shifts the focus of AI adoption from technology acquisition to organizational capability development.

A firm seeking to improve AI-enabled financial strategy therefore needs more than sophisticated models. It requires:

Technology + Data + Financial Expertise + AI Literacy + Governance + Organizational Integration

This also provides a more balanced interpretation of AI's role in financial strategy. AI should neither be viewed simply as an automation technology nor as an independent substitute for financial professionals. Its strategic value emerges when technological capabilities and human capabilities are effectively combined.

The framework developed in this paper can therefore be summarized as:



AI Absorptive Capacity, Data Quality, Human Expertise, Trust and Governance influence the strength of this relationship.

This provides the central theoretical proposition of the study:

AI-enabled financial strategy is most likely to generate measurable financial value when organizations possess the absorptive capacity required to convert AI-generated intelligence into informed, governed, and actionable financial decisions.

VI. CONCLUSION AND FUTURE TRAJECTORIES

Artificial Intelligence is increasingly changing the way financial strategy is formulated, analyzed, and executed. This paper examined AI not merely as a tool for automating financial activities, but as an emerging strategic capability that can strengthen forecasting, scenario analysis, capital allocation, investment evaluation, risk management, liquidity planning, and financial intelligence. Across these mechanisms, AI can improve the speed, scale, and analytical depth of financial decision-making while allowing finance professionals to retain strategic judgment and accountability.

The analysis indicates that the strongest evidence currently relates to intermediate decision outcomes, including improvements in forecasting, decision speed, analytical efficiency, and risk identification. However, evidence directly linking AI adoption to long-term measures such as ROE, shareholder returns, firm value, or sustainable profitability remains comparatively limited. Existing industry evidence is also frequently based on surveys and self-reported improvements, making it difficult to establish direct causal relationships between AI adoption and financial performance.

A central contribution of this paper is the introduction of AI Absorptive Capacity as a moderating factor in the AI–financial value relationship. AI capability alone does not guarantee financial value. Organizations must be capable of recognizing relevant AI-generated insights, evaluating their reliability, integrating them into existing financial processes, and translating them into actionable decisions. Consequently, the relationship can be represented as: AI Capabilities → AI-Enabled Financial Intelligence → Human–AI Decision Process → Strategic Financial Decisions → Financial & Strategic Outcomes with AI Absorptive Capacity, Data Quality, Human Expertise, Trust, and Governance influencing the strength of this relationship.

The findings therefore support a view of AI-enabled financial strategy based on human–AI complementarity rather than complete substitution. AI provides analytical scale, speed, pattern recognition,

and predictive capabilities, while financial professionals contribute contextual understanding, judgment, interpretation, and accountability. The effectiveness of AI-enabled financial strategy is consequently dependent not only on technological capability but also on organizational readiness to absorb and apply that capability.

Future Research Directions

Future research can strengthen this framework in several ways. First, researchers can develop measurable indicators of AI Absorptive Capacity and distinguish between organizations that merely adopt AI and those that successfully integrate it into strategic financial processes. Second, longitudinal and econometric studies can examine whether improvements in decision quality and efficiency translate into measurable changes in profitability, capital allocation efficiency, risk-adjusted returns, and firm value.

Third, future studies can examine differences across industries and financial functions, as the value of AI may depend on data availability, regulatory requirements, decision complexity, and the degree of human judgment involved. Research can also investigate how AI governance, employee expertise, trust, and organizational learning influence the realization of AI-generated financial value.

Finally, greater attention should be given to the evolution of AI-enhanced financial decision-making, including AI-supported due diligence, predictive risk modelling, scenario generation, and technology-mediated advisory services. As AI becomes increasingly embedded in financial processes, the key research question may shift from whether organizations use AI to how effectively they integrate AI-generated intelligence with human financial judgment.

Overall, AI-enabled financial strategy represents a shift from traditional information-driven decision-making toward a more intelligent, adaptive, and technology-supported financial decision process. Its long-term strategic value will depend not simply on the sophistication of AI systems, but on the ability of organizations to convert AI-generated intelligence into

informed, governed, and actionable financial decisions.

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