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# Artificial Intelligence and Financial Performance: A Qualitative Literature Review

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**ABSTRACT**

**Purpose**: This study examines the relationship between artificial intelligence (AI) integration and organizational financial performance and identifies the conditions that strengthen or weaken this relationship.
**Methodology**: The study uses a qualitative literature-review design. Twenty peer-reviewed journal articles published between 2019 and 2026 were synthesized through thematic content analysis.
**Results**: The literature identifies four recurring mechanisms: operational efficiency and cost control, risk and fraud reduction, revenue and investment optimization, and financial reporting and assurance. AI is generally associated with stronger profitability, cost efficiency, risk-adjusted returns, asset allocation, and firm value when supported by reliable data, adequate infrastructure, skilled personnel, explainable models, and effective governance.
**Conclusions**: AI should be treated as an organizational capability rather than a stand-alone technology because its financial value depends on responsible integration with financial processes and governance systems.
**Limitations**: The review is limited to twenty articles, uses qualitative synthesis rather than meta-analysis, and includes more evidence from banking, auditing, and investment than from nonfinancial sectors.
**Contributions**: The study integrates fragmented evidence into a direct conceptual account of the AI-financial performance relationship and provides a basis for future company-level empirical research.

**Keywords:** Artificial Intelligence, Financial Performance, Financial Management, Literature Review, Machine Learning

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## 1. Introduction

Artificial intelligence has shifted from a specialized computing technology into an organizational resource that influences the design and execution of financial activities. Financial institutions and nonfinancial firms increasingly use machine learning, deep learning, natural language processing, robotic process automation, and intelligent analytics to analyze transactions, control costs, manage exposures, and support the allocation of financial resources (Milana & Ashta, 2021). The growth of this literature reflects the increasing economic importance of AI in finance, particularly in banking, asset management, auditing, corporate finance, and management accounting (Ahmed, Alshater, & Hammami, 2022; Cao, 2023).

Financial performance remains a central indicator of whether an organization can generate sustainable economic value from the resources it controls. The concept includes profitability, cost efficiency, liquidity, risk-adjusted returns, asset productivity, firm value, and the stability of financial outcomes (Hentzen, Hoffmann, Dolan, & Pala, 2022). AI is relevant to these outcomes because it can increase the speed and scale of financial analysis, automate routine activities, improve transaction monitoring, and identify complex relationships within structured and unstructured data (Ozbayoglu, Gudelek, & Sezer, 2020; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020).

Evidence from financial markets indicates that machine-learning methods can outperform conventional linear approaches when financial relationships are nonlinear and high-dimensional. Gu, Kelly, and Xiu (2020) show that machine-learning models can improve empirical asset-pricing performance by capturing complex interactions among firm characteristics, while Chen, Pelger, and Zhu (2024) demonstrate that deep-learning structures can identify latent economic states and produce economically meaningful asset-pricing results. These findings imply that AI can contribute to stronger investment performance and more efficient use of financial assets.

AI also affects financial performance through risk management and loss prevention. Banking research shows that machine-learning applications are increasingly used in credit, market, operational, and liquidity-risk management (Leo, Sharma, & Maddulety, 2019). Explainable models can strengthen the practical use of AI in credit-risk assessment because they combine predictive power with a clearer account of the factors driving model outputs (Bussmann, Giudici, Marinelli, & Papenbrock, 2021). Broader reviews confirm that deep-learning and ensemble methods frequently outperform conventional statistical models in credit-risk estimation, although data imbalance and model opacity remain persistent limitations (Shi, Tse, Luo, & Pau, 2022).

Financial reporting, auditing, and fraud control represent another major domain of AI integration. Fedyk, Hodson, Khimich, and Fedyk (2022) find that investments in AI by audit firms are associated with improved audit quality and lower audit fees, indicating that technological investment can generate measurable economic efficiencies. Research in the United Arab Emirates similarly reports a positive association between the use of AI and audit quality (Noordin, Hussainey, & Hayek, 2022). Machine-learning techniques also expand the ability of organizations to detect suspicious financial behavior and potential fraud across large transaction datasets (Hernandez, Gutierrez-Portela, & Rodríguez, 2024).

The relationship between AI and financial performance is not uniformly positive. AI systems may generate substantial implementation and maintenance costs, create dependence on data quality, expose organizations to cybersecurity risks, and produce outcomes that users cannot adequately explain (Bhatia, Chandani, Atiq, Mehta, & Divekar, 2021). Ethical concerns involving privacy, bias, accountability, and professional responsibility are particularly important in financial and auditing environments because AI outputs can materially affect investors, borrowers, employees, and other stakeholders ((Munoko, Brown-Liburd, & Vasarhelyi, 2020); Murikah, Nthenge, & Musyoka, 2024).

Existing studies are fragmented across technical finance, banking risk, auditing, asset pricing, financial inclusion, and management accounting. Many publications explain individual applications, but fewer studies synthesize how AI contributes to the broader construct of financial performance at the organizational level (Kureljusic & Karger, 2024). Bibliometric and systematic reviews confirm rapid growth in the field while also revealing a need for stronger integration between technological studies and financial-management outcomes (Ahmed et al., 2022; Abbas, 2026). This study addresses that gap by examining AI and financial performance as the only two central variables. The purpose is to identify how the literature conceptualizes the contribution of AI to organizational financial outcomes, determine the conditions that strengthen or weaken this contribution, and formulate an integrated interpretation that can guide future empirical research. The review does not position forecasting accuracy or financial decision quality as variables; it focuses exclusively on the direct conceptual relationship between AI integration and financial performance.

## 2. Literature Review and Hypothesis/es Development

### *2.1 Resource-Based View and Dynamic Capabilities*

The resource-based view explains performance differences by emphasizing valuable, rare, difficult-to-imitate, and organizationally embedded resources. AI can satisfy these characteristics when firms combine proprietary data, specialized algorithms, technical infrastructure, financial expertise, and organizational routines in a manner that competitors cannot easily replicate (Khan, Malik, Alomari, Khan, Al-Maadid, Hassan, & Khan, 2022). From this perspective, AI creates financial value not merely because an organization purchases software, but because it develops a distinctive capability to transform data into economically useful action (Cao, 2023; Abbas, 2026). Dynamic-capability theory strengthens this explanation by focusing on an organization's ability to sense opportunities, seize them, and reconfigure resources as environments change. Li, Zhong, and Tong (2024) provide direct evidence that AI adoption is related to corporate financial asset allocation and that organizational dynamic capabilities strengthen this relationship. AI therefore contributes to financial performance when it becomes part of a firm's capacity to adapt its financial processes, reallocate resources, and respond to new risks and opportunities (Shiyyab, Alzoubi, Obidat, & Alshurafat, 2023).

Building upon the resource-based view and dynamic-capability theory, AI adoption can also be understood as a mechanism for enhancing strategic financial decision-making (Poseng, Fanggidae, & Tameno, 2026). By integrating AI-driven analytics into financial management processes, firms can improve forecasting accuracy, optimize capital allocation, detect financial anomalies, and support more timely investment decisions. These capabilities enable organizations to reduce uncertainty and increase operational efficiency, thereby strengthening their competitive position. AI-supported financial systems allow firms to move from reactive financial management toward proactive and predictive approaches, where data-driven insights become an essential component of long-term value creation (Fanani & Zahidi, 2026).

Furthermore, the effectiveness of AI in improving financial outcomes depends on complementary organizational factors, including employee competencies, governance mechanisms, data quality, and the ability to integrate AI into existing business processes. Firms that successfully align AI technologies with managerial capabilities and organizational strategies are more likely to achieve superior financial performance compared with firms that adopt AI without sufficient preparation (Yudiska, Rosalina, & Yanto, 2026). Therefore, AI should be viewed not as an isolated technological investment but as a strategic organizational capability that enables continuous innovation, improves resource utilization, and supports sustainable financial growth.

***2.2 Artificial Intelligence***

Artificial intelligence refers to computational systems designed to perform tasks that normally require human cognitive capabilities, including pattern recognition, classification, prediction, language processing, and adaptive learning. In financial settings, the concept covers machine learning, deep learning, expert systems, natural language processing, intelligent automation, and explainable AI. Cao (2023) describes AI in finance as a broad field that connects advanced analytical methods with financial-business problems, data structures, and institutional constraints. AI integration should be understood as the organizational deployment of AI tools within recurring financial activities rather than the isolated use of a technical model. Relevant activities include transaction analysis, credit evaluation, investment analysis, risk monitoring, fraud detection, auditing, reporting, cost management, and financial control. The integration level depends on data availability, system interoperability, employee competence, governance, and the extent to which AI outputs are incorporated into formal workflows (Aldasoro, Gambacorta, Korinek, Shreeti, & Stein, 2025; Abbas, 2026).

Explainability is an important dimension of responsible AI integration in finance. Complex models may generate accurate outputs while remaining difficult for managers, auditors, regulators, and customers to understand. Explainable AI attempts to make model behavior more transparent, thereby improving accountability and reducing the risk that organizations rely on technically strong but institutionally unacceptable systems (Černevičienė & Kabašinskas, 2024). Beyond transparency, explainability also plays a critical role in enhancing trust and governance in AI-based financial decision-making. Financial institutions and organizations often operate under strict regulatory requirements, where decisions related to credit assessment, investment strategies, risk management, and fraud detection must be justified and traceable. Explainable AI enables stakeholders to understand the factors influencing model outputs, allowing them to evaluate whether decisions are consistent with ethical standards, organizational objectives, and regulatory expectations (Maulana & Fathurahman, 2026). Consequently, explainability reduces the potential for hidden biases and improves confidence among users who rely on AI-generated recommendations.

Moreover, explainability should be integrated with broader AI governance practices to ensure that technological advancement remains aligned with responsible financial management. Organizations need to establish mechanisms for continuous monitoring, validation, and human oversight to prevent excessive dependence on automated systems. When combined with strong governance structures, explainable AI can transform complex analytical models into reliable decision-support tools that enhance efficiency while maintaining accountability. Therefore, explainability represents not only a technical requirement but also a strategic capability that supports sustainable AI adoption in the financial sector.

### *2.3 Financial Performance*

Financial performance represents the organization's ability to use its resources to generate economic returns while maintaining acceptable levels of cost, liquidity, and risk. The literature commonly reflects financial performance through accounting measures such as return on assets, return on equity, profit margin, operating cost, and cash-generating capacity, as well as market-oriented measures such as firm value and risk-adjusted investment return. In this review, financial performance is treated as a multidimensional outcome rather than a single accounting ratio. AI may influence financial performance by reducing processing costs, limiting financial losses, improving asset utilization, increasing the scalability of financial services, and strengthening assurance over financial information. Financial-inclusion research also indicates that AI-based credit assessment can expand lending opportunities through alternative data and reduce information asymmetry, creating potential revenue growth for financial institutions while widening access to finance (Mhlanga, 2021).

The economic value of AI depends on the balance between benefits and implementation costs. Investment in infrastructure, data engineering, cybersecurity, model monitoring, employee development, and regulatory compliance may be substantial. AI can improve financial performance only when the resulting efficiency, revenue, risk reduction, or asset productivity exceeds the total cost and exposure created by the technology (Munoko, Brown-Liburd, & Vasarhelyi, 2020; Aldasoro, Gambacorta, Korinek, Shreeti, & Stein, 2025). The realization of AI's economic value therefore requires careful strategic planning and effective resource allocation. Organizations must evaluate not only the expected financial benefits of AI implementation but also the long-term operational implications, including maintenance requirements, technology upgrades, and potential organizational adjustments. A comprehensive cost–benefit assessment enables firms to identify AI applications that generate measurable value while avoiding unnecessary investments in technologies that do not align with business objectives. In this context, AI adoption should be guided by clear performance indicators that evaluate improvements in productivity, decision quality, financial efficiency, and risk management.

Furthermore, the successful integration of AI requires organizations to develop complementary capabilities that maximize the return on technological investment. These capabilities include effective data governance, skilled human resources, cross-functional collaboration, and adaptive management practices. Without adequate organizational readiness, AI investments may fail to produce expected outcomes despite advanced technological features. Therefore, the financial impact of AI is determined not solely by the sophistication of the technology itself but by the organization's ability to strategically manage resources, mitigate implementation risks, and convert AI capabilities into sustainable economic advantages.

### *2.4 Relationship between Artificial Intelligence and Financial Performance*

The literature generally supports a positive relationship between AI integration and financial performance, although the relationship is conditional rather than automatic. Machine-learning applications can improve revenue-generating activities and risk-adjusted returns in financial markets, while intelligent automation can reduce processing and assurance costs. These improvements strengthen profitability and asset productivity when models are reliable and appropriately governed (Gu, Kelly, & Xiu, 2020; Fedyk, Hodson, Khimich, & Fedyk, 2022; Chen, Pelger, & Zhu, 2024). AI also protects financial performance by reducing downside exposure. Credit-risk analytics can improve borrower classification, fraud-detection systems can identify abnormal patterns, and audit technologies can detect inconsistencies across large datasets. These capabilities reduce the probability or magnitude of financial loss and strengthen the reliability of reported information (Bussmann, Giudici, Marinelli, & Papenbrock, 2021; Shi, Tse, Luo, & Pau, 2022; Hernandez, Gutierrez-Portela, & Rodríguez, 2024).

Negative or insignificant outcomes may occur when organizations adopt AI without adequate data quality, human expertise, governance, or model transparency. Ethical and technical failures can increase legal costs, reputational damage, operational disruption, and stakeholder distrust. The direct relationship between AI and financial performance should therefore be interpreted as an organizational-capability relationship shaped by implementation quality rather than as a guaranteed technological effect (Murikah, Nthenge, & Musyoka, 2024; Černevičienė, & Kabašinskas, 2024). The effectiveness of AI adoption is highly dependent on the extent to which organizations are prepared to manage the technological, human, and institutional challenges associated with its implementation. Without sufficient data governance, qualified personnel, and appropriate control mechanisms, AI systems may produce inaccurate insights or biased outcomes that negatively affect financial decisions. Therefore, organizations must ensure that AI deployment is supported by reliable data infrastructure, continuous evaluation processes, and responsible management practices to minimize potential risks and maximize value creation.

Moreover, AI should be viewed as an enabling capability rather than an independent driver of financial success. The ability of organizations to translate AI capabilities into improved financial performance depends on strategic alignment between technology, business processes, and managerial decision-making. Firms that integrate AI with effective governance, ethical principles, and organizational learning mechanisms are more likely to achieve sustainable benefits, while those that focus only on technological adoption may encounter limited returns or unintended consequences. Thus, the impact of AI on financial performance reflects the quality of implementation and organizational capability development rather than the mere presence of AI technology.

## 3. Methodology

This study used a qualitative literature-review design. The design was selected because the research objective was to interpret and synthesize the conceptual and empirical relationship between artificial intelligence and financial performance across different financial settings. The unit of analysis was the published journal article, while the analytical focus was the contribution, risk, and organizational condition associated with AI integration. Twenty peer-reviewed journal articles published between 2019 and 2026 were selected. The articles were obtained from established academic publishers and journals, including Elsevier, Springer Nature, Oxford University Press, INFORMS, Emerald, IEEE, ACM, and MDPI. The search terms included artificial intelligence and financial performance, machine learning in finance, AI financial management, AI audit quality, AI credit risk, AI asset allocation, and AI management accounting.

Article selection followed four criteria. First, the study had to discuss AI, machine learning, deep learning, or explainable AI in a finance, accounting, auditing, banking, or investment context. Second, it had to contain findings or conceptual arguments relevant to organizational financial outcomes. Third, bibliographic information and a DOI had to be verifiable. Fourth, the collective sample had to provide diversity in application area and research method. The analysis used thematic content analysis. Each article was coded according to publication year, research context, AI application, method, financial-performance relevance, major contribution, and limitation. The codes were compared and grouped into four themes, such as operational efficiency and cost control, risk and fraud reduction, revenue and investment optimization, and financial reporting and assurance. A second coding stage identified implementation conditions and potential negative consequences. Trustworthiness was strengthened through source verification, comparison of findings across journals and disciplines, and the use of direct bibliographic identifiers. The review does not claim statistical generalization because it does not estimate a pooled effect size. Its contribution lies in analytical generalization, meaning that recurring explanations are integrated into a coherent account of the AI–financial performance relationship.

## 4. Results and Discussion

### *4.1 Results*

Table 1. Synthesis of 20 selected journal articles

| No. | Study | Context | Method | Main finding | Financial-performance relevance |
|---|---|---|---|---|---|
| 1 | Leo, Sharma, and Maddulety (2019) | Banking risk management | Literature review | AI supports credit, market, operational, and liquidity-risk management; organizational adoption remains uneven. | Lower losses and stronger risk control. |
| 2 | Munoko, Brown-Liburd, and Vasarhelyi (2020) | AI in auditing | Conceptual analysis | AI creates efficiency opportunities but raises privacy, bias, accountability, and professional-responsibility concerns. | Benefits can be offset by ethical and governance costs. |
| 3 | Ozbayoglu, Gudelek, and Sezer (2020) | Financial applications of deep learning | Survey review | Deep learning is widely applied to trading, portfolio management, risk, and fraud detection. | Potential improvement in returns, cost efficiency, and loss prevention. |

| No. | Study | Context | Method | Main finding | Financial-performance relevance |
|---|---|---|---|---|---|
| 4 | Mashrur, Luo, Zaidi, and Robles-Kelly (2020) | Financial risk management | Systematic survey | Machine learning supports a wide range of financial-risk tasks but faces data, interpretability, and deployment challenges. | Improved risk-adjusted performance when implementation is reliable. |
| 5 | Gu, Kelly, and Xiu (2020) | Asset pricing | Empirical comparative analysis | Machine-learning methods capture nonlinear interactions and improve return prediction relative to conventional models. | Higher potential investment efficiency and risk-adjusted returns. |
| 6 | Bussmann, Giudici, Marinelli, and Papenbrock (2021) | Credit-risk management | Model development | Explainable AI combines predictive capability with interpretable credit-risk explanations. | Better credit allocation and lower default exposure. |
| 7 | Mhlanga (2021) | Credit assessment and inclusion | Literature and conceptual review | AI using alternative data can reduce information asymmetry and expand access to credit. | Potential revenue growth and broader customer reach. |
| 8 | Fedyk, Hodson, Khimich, and Fedyk (2022) | Audit firms | Empirical archival study | AI investment improves audit quality and reduces audit fees, although labor displacement may occur over time. | Lower assurance costs and stronger financial-information reliability. |
| 9 | Noordin, Hussainey, and Hayek (2022) | Audit quality in the UAE | Survey research | AI use is positively associated with audit quality and professional effectiveness. | Improved assurance and reduced reporting risk. |
| 10 | Ahmed, Alshater, and Hammami (2022) | AI and machine learning in finance | Bibliometric review | The field has expanded rapidly across bankruptcy, prices, anti-money laundering, and analytics. | Evidence of broad financial-performance relevance. |

| No. | Study | Context | Method | Main finding | Financial-performance relevance |
|---|---|---|---|---|---|
| 11 | Shi, Tse, Luo, and Pau (2022) | Credit-risk models | Systematic review | Deep-learning and ensemble methods often outperform conventional techniques, but imbalance and opacity remain limitations. | Potential reduction in credit losses. |
| 12 | Cao (2023) | AI in finance | Comprehensive review | AI creates value across financial businesses but must address complex data, regulatory, and institutional challenges. | Financial gains depend on organization-wide integration. |
| 13 | Chen, Pelger, and Zhu (2024) | Asset pricing | Deep-learning empirical study | Deep models identify latent states and economically meaningful pricing structures. | Enhanced investment and portfolio performance potential. |
| 14 | Rahman, Zhu, and Yue (2024) | AI use by audit firms and clients | Empirical study | Separate and joint AI adoption affects audit efficiency and reporting timeliness in different ways. | Effects depend on coordinated adoption across organizations. |
| 15 | Hernandez, Gutierrez-Portela, and Rodríguez (2024) | Financial fraud detection | Systematic literature review | Machine-learning methods identify suspicious patterns across large financial datasets. | Reduced fraud losses and stronger internal control. |
| 16 | Murikah, Nthenge, and Musyoka (2024) | Ethics and bias in AI auditing | Systematic review | Bias, opacity, privacy, and accountability remain major AI-audit risks. | Weak governance can create legal, reputational, and financial costs. |
| 17 | Černevičienė and Kabašinskas (2024) | Explainable AI in finance | Systematic literature review | Explainability is necessary for trust, accountability, and resilient financial use of AI. | Transparency strengthens sustainable economic value. |
| 18 | Li, Zhong, and Tong (2024) | Corporate financial asset allocation | Empirical study | AI adoption positively influences financial asset allocation; dynamic capabilities strengthen the effect. | More effective use of corporate financial assets. |

| No. | Study | Context | Method | Main finding | Financial-performance relevance |
|---|---|---|---|---|---|
| 19 | Aldasoro, Gambacorta, Korinek, Shreeti, and Stein (2025) | AI transformation of finance | Conceptual and system analysis | AI changes intermediation, insurance, asset management, and payments while introducing stability and concentration risks. | Firm-level benefits coexist with systemic financial risks. |
| 20 | Abbas (2026) | Management accounting and AI | Comprehensive literature review | AI expands automation, analytics, and the strategic role of management accounting, but empirical organizational evidence remains limited. | Potential improvement in cost management and profitability. |

Table 1 shows the publication pattern shows a clear movement from application-specific reviews toward studies that examine organizational and system-level consequences. Early studies concentrated on banking risk, deep-learning techniques, and asset pricing, while recent studies increasingly address explainability, governance, corporate asset allocation, financial stability, and management accounting. This shift indicates that AI research in finance is moving beyond technical performance toward the economic and organizational consequences of implementation (Ahmed, Alshater, & Hammami, 2022; Cao, 2023; Abbas, 2026). Fourteen of the twenty articles present predominantly positive financial implications, particularly in cost reduction, risk control, investment analysis, credit allocation, fraud detection, and assurance quality. Six articles give greater emphasis to conditional or adverse effects, including ethical exposure, opacity, data problems, systemic concentration, and implementation cost. The evidence therefore supports a positive but contingent relationship between AI and financial performance.

Financial institutions dominate the sample because they generate large volumes of digital transactions and face measurable risk, compliance, and profitability pressures. Corporate finance and management accounting receive less direct empirical attention, although Li, Zhong, and Tong (2024) and Abbas (2026) indicate that AI is becoming increasingly relevant to financial-asset allocation, cost management, and strategic financial control. This imbalance creates a significant opportunity for firm-level research outside the banking and auditing sectors.

***4.2 Discussion***

*4.2.1 Operational Efficiency and Cost Control*

Operational efficiency is the most consistent mechanism connecting AI with financial performance. AI can automate transaction classification, exception testing, reconciliation, data extraction, and analytical procedures that would otherwise require substantial human time. Fedyk, Hodson, Khimich, and Fedyk (2022) provide strong empirical support by showing that AI investment in audit firms is associated with lower fees and improved audit quality. Abbas (2026) similarly concludes that AI is reshaping management-accounting work through automation and advanced analytics.

Cost reduction is not limited to labor substitution. AI can reduce error-correction costs, shorten processing cycles, support scalable financial services, and allow professionals to focus on activities that require judgment and communication. The financial benefit is reflected in lower operating expenses and improved resource productivity. The effect may be delayed because organizations initially bear substantial expenses for infrastructure, integration, training, and control systems (Aldasoro, Gambacorta, Korinek, Shreeti, & Stein, 2025). Efficiency gains depend on whether AI is integrated into end-to-end processes. Isolated models may generate technically useful outputs without reducing organizational cost because employees still perform duplicate procedures or manually validate poorly integrated systems. The resource-based interpretation suggests that financial advantage emerges when technology, data, human expertise, and routines are combined into a coherent organizational capability Cao (2023).

*4.2.2 Risk Reduction and Financial Loss Prevention*

Risk reduction provides a second major explanation for improved financial performance. Machine-learning systems can screen large numbers of transactions and borrowers, identify abnormal patterns, and update risk classifications more frequently than many traditional processes. Banking reviews consistently show applications across credit, market, operational, and liquidity risks (Leo, Sharma, & Maddulety, 2019; Mashrur, Luo, Zaidi, & Robles-Kelly, 2020). Credit-risk research offers particularly strong evidence. Bussmann, Giudici, Marinelli, and Papenbrock (2021) demonstrate that explainable AI can preserve model performance while giving users clearer information about the determinants of credit classifications. Shi, Tse, Luo, and Pau (2022) conclude that deep-learning and ensemble methods frequently outperform classical statistical models. Lower default exposure, better pricing of risk, and more efficient capital allocation can strengthen profitability and financial stability.

Fraud detection protects financial performance by limiting direct losses, investigation expenses, legal exposure, and reputational damage. Hernandez, Gutierrez-Portela, and Rodríguez (2024) find that machine-learning applications have become a major approach to detecting financial fraud, especially where transaction volume makes manual examination impractical. The economic value of these systems depends on the quality of training data and the organization's ability to manage false positives and false negatives.

*4.2.3 Revenue, Investment, and Asset Productivity*

AI contributes to financial performance by improving the productivity of revenue-generating and investment activities. Gu, Kelly, and Xiu (2020) show that machine-learning techniques can capture nonlinear relationships among firm characteristics and expected returns. Chen, Pelger, and Zhu (2024) extend this evidence by demonstrating the value of deep learning in identifying complex asset-pricing structures. These studies support the argument that AI can improve the use of information in investment and portfolio activities. Corporate evidence indicates that the contribution of AI extends beyond financial markets. Li, Zhong, and Tong (2024) report that AI adoption has a positive effect on corporate financial asset allocation and that organizational dynamic capabilities strengthen this effect.

AI therefore becomes financially valuable when firms use it to reconfigure assets and respond to changing opportunities rather than treating it as a static technical installation. AI-based credit assessment may also expand the revenue base of financial institutions. Mhlanga (2021) explains that alternative data and machine-learning methods can reduce information asymmetry and improve access to finance for customers who lack conventional credit histories. This expands the potential market while requiring strong safeguards against unfair discrimination and privacy violations.

*4.2.4 Financial Reporting, Auditing, and Assurance*

Reliable financial information supports financial performance because it reduces information risk, strengthens internal control, and improves stakeholder confidence. Noordin, Hussainey, and Hayek (2022) find that AI use is positively related to audit quality, while Rahman, Zhu, and Yue (2024) show that the effects of AI adoption depend partly on whether audit firms and clients use the technology separately or jointly. Coordinated digital environments may create different efficiency outcomes from isolated adoption. AI allows audit and finance professionals to examine complete datasets rather than small samples, identify unusual transactions, and conduct more continuous forms of monitoring. These capabilities can reduce misstatement risk and strengthen confidence in reported results. The economic benefit appears in lower assurance costs, reduced regulatory exposure, and a lower probability of costly reporting failures (Fedyk, Hodson, Khimich, & Fedyk, 2022). Human oversight remains essential because financial reporting and auditing require professional skepticism, contextual interpretation, and accountability. Munoko, Brown-Liburd, and Vasarhelyi (2020) warn that AI creates ethical problems when responsibility for outcomes becomes unclear. AI should therefore support rather than eliminate accountable professional judgment.

*4.2.5 Conditions and Risks Affecting the Relationship*

Data quality is the first condition affecting the AI–financial performance relationship. Financial models trained on incomplete, outdated, biased, or inconsistent data can produce costly errors even when their technical architecture is advanced. Data governance, validation, lineage, access control, and monitoring are therefore financial-performance requirements rather than merely technical concerns (Mashrur, Luo, Zaidi, & Robles-Kelly, 2020; Shi, Tse, Luo, & Pau, 2022). Explainability is the second condition. Černevičienė and Kabašinskas (2024) show that explainable AI is increasingly important in finance because users and regulators require justification for high-impact outputs. Transparent systems support trust and accountability, while opaque systems may face rejection, regulatory intervention, or hidden model risk.

Ethical and governance failures can transform AI from a performance-enhancing resource into a source of financial loss. Murikah, Nthenge, and Musyoka (2024) identify bias, privacy, opacity, and accountability as recurring problems in AI-enabled auditing. Munoko, Brown-Liburd, and Vasarhelyi (2020) similarly emphasize that the ethical consequences of AI must be anticipated throughout system design and use. Legal penalties, remediation costs, and reputational damage can exceed the operational savings generated by automation. Systemic and concentration risks also matter. Aldasoro, Gambacorta, Korinek, Shreeti, and Stein (2025) argue that widespread AI adoption can transform financial intermediation and market structure while creating new vulnerabilities. Organizations may become dependent on a small number of data providers, cloud platforms, or model developers. Financial performance must therefore be evaluated together with operational resilience and third-party risk. Human capability is the final major condition. AI changes the skills required in finance and accounting by increasing the importance of data interpretation, model governance, business translation, and ethical reasoning. Organizations that invest in technology without developing these capabilities may fail to convert AI into financial value Abbas (2026).

#### *4.2.6 Integrated Interpretation*

The synthesis supports a direct conceptual relationship in which stronger AI integration is generally associated with stronger financial performance. AI affects profitability, cost efficiency, asset productivity, risk-adjusted returns, and financial stability through its application in operational, risk, investment, and assurance activities. The strength and direction of the relationship depend on implementation quality. The relationship can be summarized, such as AI integration creates financial value when the organization combines appropriate technology with reliable data, skilled personnel, explainable models, process integration, and governance. Weakness in these conditions increases the probability that implementation cost, ethical exposure, model error, and operational dependence will reduce financial performance.

AI should therefore be viewed as a strategic financial capability rather than an independent technical solution. The review identifies an empirical gap in the direct measurement of AI integration and company-level financial performance. Much of the literature studies technical accuracy, specific financial functions, professional perceptions, or market models. Future research should test whether firms with higher levels of AI integration achieve superior return on assets, return on equity, profit margin, cost efficiency, firm value, and risk-adjusted performance after controlling for size, industry, digital maturity, and governance.

## 5. Conclusions

### *5.1 Conclusion*

This qualitative literature review concludes that artificial intelligence has a generally positive relationship with financial performance. Across twenty journal articles, AI is associated with lower operating and assurance costs, stronger risk control, reduced fraud exposure, improved investment and asset-allocation outcomes, wider financial-service opportunities, and more reliable financial information. These outcomes can improve profitability, efficiency, asset productivity, risk-adjusted returns, and firm value. The positive relationship is conditional. AI does not automatically produce superior financial performance because organizations must bear implementation costs and manage data, model, ethical, cybersecurity, regulatory, and human-capability risks. Financial value emerges when AI is embedded in organizational routines and supported by reliable data, skilled personnel, explainability, accountability, and effective governance. The theoretical synthesis supports the resource-based and dynamic-capability views. AI becomes a source of financial advantage when it is combined with complementary resources and continuously adapted to changing business conditions. A stand-alone algorithm is unlikely to create a sustainable advantage because competitors can acquire similar technology, the distinctive value lies in the organization's integrated capability to use it.

### *5.2 Research Limitations*

The study is limited to twenty journal articles and uses qualitative synthesis rather than meta-analysis. The reviewed studies apply different definitions of AI and financial outcomes, which limits direct comparison. The sample also contains more studies from banking, auditing, and investment than from nonfinancial corporate settings. The conclusions should therefore be interpreted as an integrated analytical account rather than a statistical estimate of effect size.

### *5.3 Suggestions and Directions for Future Research*

Organizations should begin AI investment with clearly defined financial objectives, such as reducing specific operating costs, lowering credit losses, strengthening asset productivity, or improving financial-control coverage, supported by measurable baseline and post-implementation indicators. Financial managers should establish strong data governance before scaling AI by integrating data ownership, quality standards, lineage, validation, security, and access rights into the financial-control system. Organizations should also prioritize explainable models for high-impact financial applications by documenting model outputs, conducting independent validation, monitoring model performance, and ensuring accountable human review. Furthermore, AI investment appraisal should consider the total economic costs of infrastructure, integration, maintenance, cybersecurity, compliance, employee development, and model risks, while evaluating benefits through profitability, cost efficiency, risk reduction, and asset-productivity indicators. Future studies should employ longitudinal, panel-data, case-study, and mixed-method approaches to examine the direct relationship between AI integration and financial performance across various industries. Comparative research involving large corporations and small and medium-sized enterprises, financial and nonfinancial sectors, as well as developed and emerging economies, is also necessary to provide broader insights into the conditions under which AI generates sustainable financial value.

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