Jurnal Informatika Ekonomi Bisnis

http://www.infeb.org

2025 Vol. 7 Iss. 2 Hal: 364-370 e-ISSN: 2714-8491

Artificial Intelligence in Financial Decision-Making: Opportunities and Challenges for Investment Strategies

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Abstract

This study conducts a systematic literature review to explore the integration of artificial intelligence into financial decision-making, particularly in the context of investment strategies. Drawing from 52 peer-reviewed journal articles published between 2018 and 2024, the review identifies key application areas of AI in finance, including portfolio optimization, risk management, algorithmic trading, robo-advisory services, and sentiment analysis. The findings highlight the strategic benefits of AI, such as enhanced decision accuracy, operational efficiency, and increased financial inclusivity. However, the study also underscores significant challenges, including lack of model explainability, algorithmic bias, data privacy concerns, and regulatory uncertainty. These dual dimensions emphasize the need for ethical governance, transparent model design, and interdisciplinary collaboration to maximize the benefits of AI in investment contexts. The study concludes by outlining future research directions, particularly the integration of ESG factors, adaptation to emerging markets, and long-term impact assessments of AI-driven strategies.

Keywords: Artificial Intelligence, Financial Decision-Making, Investment Strategies, Portfolio Optimization, Algorithmic Trading

1. Introduction

In recent years, the integration of artificial intelligence (AI) into financial decision-making has transformed the landscape of investment strategies, offering unprecedented capabilities in data processing, pattern recognition, and predictive analytics. The financial sector, known for its complexity and high-volume data, has increasingly adopted AI technologies to enhance decision accuracy, reduce human error, and optimize portfolio management [1]. AI-driven systems, including machine learning algorithms and deep neural networks, are now employed to detect market anomalies, forecast asset prices, and facilitate high-frequency trading [2] [3]. As such, AI has shifted from being a supplementary tool to a core element in financial operations, influencing both institutional and retail investors.

The adoption of AI in finance is largely motivated by its capacity to process vast datasets and deliver real-time insights, a significant advantage in markets characterized by volatility and rapid change [4]. Financial institutions utilize AI-powered models for credit scoring, fraud detection, and risk assessment, increasing operational efficiency and regulatory compliance [5] [6] Moreover, AI enables dynamic portfolio rebalancing by identifying optimal investment mixes based on changing market conditions and investor profiles [7]. Such innovations are revolutionizing investment advisory services, as robo-advisors provide personalized and automated recommendations with minimal human intervention. However, while AI offers significant opportunities, it also presents challenges in interpretability, data privacy, and algorithmic bias.

The reliability of AI systems in financial contexts is deeply tied to data quality and model transparency, two aspects that remain under scrutiny [8]. Despite their accuracy, many AI models operate as black boxes, limiting their explainability and raising ethical concerns about accountability in financial decisions [9]. Furthermore, biased training data can lead to skewed outcomes, which may disproportionately affect certain investor groups or misrepresent market realities [10]. These issues highlight the importance of regulatory frameworks and ethical guidelines to ensure that AI applications in finance remain fair, transparent, and aligned with investor protection goals [11] [12]. The trade-off between model complexity and interpretability continues to challenge researchers and practitioners alike.

Another area of active exploration is the role of AI in managing investment risks. Financial markets are susceptible to systemic shocks, and AI tools can be instrumental in detecting early warning signs and stress-testing investment portfolios [13] [14]. Through natural language processing (NLP), AI also analyzes unstructured data from news articles, earnings reports, and social media to assess market sentiment and anticipate investor behavior [15]. This multifaceted application underscores the strategic value of AI across diverse asset classes and investment horizons [16]. Nevertheless, the overreliance on AI systems without

Accepted: 03-05-2025 | Revision: 26-06-2025| Publication: 30-06-2025| doi: 10.37034/infeb.v7i2.1140

human oversight may expose investors to unforeseen risks, particularly in situations requiring judgment or contextual understanding [17].

The existing body of literature indicates a growing recognition of AI's transformative potential in the investment domain, yet comprehensive evaluations of its dual impact opportunities and challenges remain limited. Some studies emphasize the superior performance of AI-based portfolios over traditional models in terms of return and risk [18] [19], while others caution against the volatility induced by algorithmic trading and flash crashes [20] [21]. Moreover, the scalability of AI adoption across different financial markets, particularly in emerging economies, raises questions regarding infrastructure readiness and talent availability [22] [23]. As financial institutions navigate the digital transformation, understanding the strategic implementation of AI tools becomes increasingly crucial for sustainable and ethical investment practices.

This study aims to provide a comprehensive literature review on the integration of artificial intelligence into financial decision-making, focusing on its opportunities and challenges for investment strategies. By synthesizing insights from recent academic and industry research, this review will explore how AI reshapes investment decision-making, identify key barriers to adoption, and propose directions for future inquiry. Given the rapid evolution of AI and its growing influence on financial markets, this study contributes to the ongoing discourse on technology-driven finance and aims to inform both academic researchers and financial practitioners.

2. Research Method

This study adopts a systematic literature review (SLR) approach to synthesize and critically evaluate existing scholarly work on the integration of artificial intelligence (AI) in financial decision-making, particularly in the context of investment strategies. The SLR method is chosen due to its rigorous, transparent, and replicable structure, which enhances the credibility and academic contribution of the research [24]. The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure the comprehensiveness and validity of the study [25]. The key objective of this methodology is to identify, assess, and summarize peer-reviewed journal articles that explore the opportunities and challenges presented by AI technologies in financial investment contexts.

The literature search was conducted across four major academic databases: Scopus, Web of Science, ScienceDirect, and IEEE Xplore, given their extensive indexing of high-impact journals in both finance and technology domains. The search strategy utilized a combination of keywords such as Artificial Intelligence, AI, Financial Decision-Making, Investment Strategies, Machine Learning, Algorithmic Trading, and Robo-Advisors. Boolean operators (AND, OR) were applied to refine search results, and filters were set to include only peer-reviewed journal articles published in English between 2018 and 2024. The selection criteria were designed to capture contemporary discussions and insights that reflect the evolving nature of AI applications in finance.

The inclusion criteria for this review comprised empirical or conceptual studies that directly discuss AI methods and tools in the context of financial investments, including their implications for portfolio optimization, risk management, trading algorithms, and financial analytics. Studies that focused solely on general AI applications outside the financial context, pre-2018 publications, non-English articles, conference papers, and grey literature were excluded to maintain the relevance and academic rigor of the synthesis. A two-stage screening process was applied: title and abstract screening followed by full-text assessment. To reduce selection bias and improve reliability, two independent reviewers conducted the screening, and disagreements were resolved through discussion and consensus.

The literature selection process is summarized in Table 1, detailing the number of articles identified, screened, assessed for eligibility, and finally included in the review. The PRISMA flow technique enabled a transparent mapping of each filtering stage, ensuring that only the most relevant and high-quality studies formed the basis of the analysis. A total of 52 articles were ultimately included in the synthesis, representing a diverse range of AI methodologies, financial applications, and geographic contexts.

Table 1. Summary of the Literature Selection Process (PRISMA-Based)

Stage	Number of Articles
Initial database search	1,284
After removing duplicates	1,056
Title and abstract screened	1,056
Full-text articles assessed	115
Articles included in review	52

Each selected article was coded and analyzed using thematic content analysis to identify recurring themes, challenges, and opportunities. Themes were grouped based on AI applications (e.g., machine learning for prediction, NLP for sentiment analysis), financial domains (e.g., trading, portfolio management), and strategic implications (e.g., decision efficiency, ethical risks). This qualitative synthesis provides a structured understanding of how AI is reshaping financial decision-making and where critical gaps or limitations still exist. The results of this analysis form the foundation for the next section, which elaborates on the empirical and conceptual contributions of the reviewed literature.

3. Result and Discussion

The integration of artificial intelligence (AI) into financial decision-making has introduced a broad spectrum of applications, ranging from portfolio optimization to sentiment analysis and algorithmic trading. The review of 52 selected journal articles highlights the increasing role of AI in investment strategies, providing both practical benefits and theoretical advancements. This section synthesizes the findings from the reviewed studies by clustering them into major thematic domains: AI applications in investment decision-making and the strategic opportunities offered by AI in finance.

A prominent area of AI application lies in portfolio optimization, where machine learning models are deployed to manage asset allocations dynamically in response to shifting market conditions. As highlighted by Chen et al. [18] AI-based portfolio optimization techniques outperform traditional models by learning non-linear relationships between macroeconomic indicators and asset returns. These models can continuously adjust portfolios to align with investor goals while minimizing risk exposure. Similarly, Gupta and Jain [7] demonstrated that reinforcement learning algorithms could learn optimal trading policies through reward maximization, enabling more adaptive strategies than static models. The benefit of such methods lies in their ability to consider vast multidimensional datasets that traditional approaches often fail to integrate. These models can continuously adjust portfolios to align with investor goals while minimizing risk exposure [7] [18]. Recent work by Kraus and Feuerriegel [26] also confirms the value of explainable AI in optimizing portfolios, particularly when incorporating ESG data, macroeconomic trends, and investor sentiment into the decision loop.

In addition, risk management represents a critical application domain where AI technologies offer substantial advantages. Financial markets are inherently uncertain, and risk mitigation remains a core component of sound investment strategy. Dastile et al. [1] argued that machine learning algorithms such as support vector machines (SVM) and random forests are particularly effective in credit risk modeling due to their ability to detect complex patterns in borrower behavior. Yang et al. [14] further emphasized the role of AI in systemic risk analysis, whereby algorithms can simulate the propagation of financial shocks across markets. The ability of AI to run simulations under multiple scenarios enables firms to anticipate and prepare for adverse market conditions more robustly. These findings are supported by Zhang and Zhou [27], who demonstrated that ensemble learning models improve predictive power in multi-asset risk simulations during market turbulence.

Moreover, the deployment of robo-advisors has democratized access to sophisticated investment advice, offering automated, algorithm-driven financial planning services. AI-driven robo-advisors are transforming client interactions by providing low-cost, personalized portfolios based on client risk preferences and financial goals. Arora and Dhar [4] found that AI enhances user experience through natural language processing interfaces that allow users to interact with investment platforms more intuitively [5]. While the automation of advice delivery significantly reduces cost, it also challenges the traditional role of human advisors in terms of trust and personalization. Ghosh et al. [28] found that AI-based robo-advisory platforms also drive financial inclusion by offering risk profiling in regional languages, which is crucial for developing markets.

Another rapidly expanding domain is algorithmic trading, which leverages AI to execute trades at high frequency and with minimal latency. Kirilenko et al. [21] provided early insights into the role of AI in flash crashes, where autonomous trading algorithms contribute to market volatility due to their speed and feedback loops. Nonetheless, more recent studies by Krauss et al. [13] indicate that ensemble models-such as combinations of neural networks, gradient-boosted trees, and logistic regression-can generate predictive signals that improve trading performance over time. AI allows for faster signal processing, continuous market scanning, and real-time execution, which are essential for short-term investors and hedge funds.

In addition to structured financial data, AI technologies are increasingly applied to unstructured data analysis, particularly in extracting market sentiment from textual sources. Through natural language processing (NLP), algorithms analyze financial news, analyst reports, and social media content to gauge investor sentiment and forecast market movements. Gao et al. [15] demonstrated that sentiment scores derived from financial news significantly improve the accuracy of short-term stock price predictions. Nassirtoussi et al. [16] further validated that NLP-driven sentiment analysis complements traditional technical indicators and can be integrated into hybrid trading systems. These tools provide investors with timely insights into behavioral dynamics that influence price movements, bridging the gap between fundamental and behavioral finance. Mao et al. [29], contributed to this area by applying transformer-based NLP models that outperformed traditional sentiment classifiers in predicting short-term returns on emerging market equities. To illustrate the prominence of these application areas, Table 2 provides a classification of the 52 reviewed studies by domain.

Table 2. Classification of Reviewed Studies Based on AI Application Area

AI Application Area	Number of Studies	Sample References
Portfolio Optimization	14	Chen et al. (2021); Gupta & Jain (2020)
Risk Management	10	Dastile et al. (2020); Yang et al. (2021)
Robo-Advisory	8	Sironi (2020); Arora & Dhar (2021)
Algorithmic Trading	12	Krauss et al. (2017); Kirilenko et al. (2017)
NLP and Sentiment Analysis	8	Gao et al. (2022); Nassirtoussi et al. (2020)

These findings suggest that AI is not limited to one aspect of financial decision-making but serves as an overarching enabler of innovation across investment domains. AI technologies offer strategic opportunities that extend beyond efficiency gains, enabling firms to create differentiated investment products, personalize client experiences, and access real-time market intelligence. For example, AI contributes to better regulatory compliance by automating reporting processes and anomaly detection, which also improves investor confidence.

Another strategic benefit lies in enhanced decision-making accuracy, particularly when facing information overload. As Gomber et al. [8] noted, financial markets generate massive volumes of data that exceed human processing capacity. AI filters, structures, and interprets this data to identify actionable signals, reducing cognitive bias and reaction delays. This enhancement is particularly vital in volatile or crisis periods, where traditional decision models may underperform. Holmlund et al. [9] added that AI-enabled dashboards provide multi-layered visualizations that support real-time decision-making in asset management and financial planning.

Furthermore, AI technologies facilitate financial inclusivity by lowering entry barriers for retail investors and underserved market segments. Robo-advisory platforms, in particular, offer professional-grade portfolio management at a fraction of the cost of traditional advisory services. This inclusivity also fosters greater participation in capital markets and promotes a culture of data-driven financial literacy. Alhassan and Asare [19] argued that the accessibility of AI-driven tools allows smaller investors to engage in sophisticated investment decisions, which historically have been reserved for institutional players.

In addition to operational benefits, AI introduces competitive advantages for firms that successfully adopt and integrate these technologies. Shrestha et al. [22] pointed out that early adopters of AI in emerging markets gain a first-mover advantage by offering more agile, adaptive, and responsive investment services. However, the extent of benefit often depends on organizational readiness, data infrastructure, and regulatory environment. Firms with well-established digital ecosystems are better positioned to leverage AI for strategic transformation.

While artificial intelligence offers transformative benefits for investment decision-making, the reviewed literature also reveals substantial challenges and limitations that must be critically examined. These include issues of algorithmic bias, lack of transparency, ethical ambiguity, data dependency, and uneven regulatory adaptation. The overreliance on opaque AI systems in high-stakes financial environments introduces risks that are both technical and socio-economic in nature, and these limitations warrant as much attention as the strategic advantages previously discussed.

One of the most pressing concerns identified in the literature is the lack of explainability in AI models used for financial decision-making. Many AI techniques, particularly deep learning architectures, function as black boxes, producing outputs that cannot be easily interpreted by humans [11]. In financial contexts, where regulatory compliance and fiduciary accountability are critical, the inability to explain how a model reaches its conclusion can undermine investor trust and complicate oversight. Explainability is not just a technical requirement, but a legal and ethical imperative when automated decisions affect asset allocation and investor outcomes. This aligns with Martínez-García et al. [30] who noted that financial regulators increasingly require traceable decision paths in AI tools used for client-facing financial services.

Compounding this issue is the presence of algorithmic bias. AI systems are only as fair and accurate as the data they are trained on, and financial data often reflects historical inequalities and market inefficiencies. Biased training data can result in discriminatory outcomes, a risk that is particularly acute when models are used in credit scoring, wealth management, or financial inclusion initiatives. If AI perpetuates biased recommendations, it could lead to systemic discrimination against certain investor groups, exacerbating social and economic disparities. These findings highlight the importance of data auditing and algorithmic fairness frameworks in financial AI deployment. Similarly, Agarwal & Nayak [33] showed how gender and geographic location disparities emerge in AI-driven loan assessments, especially when models are not subject to fairness constraints.

Data dependency further complicates the reliability of AI systems. Unlike human analysts who can rely on domain knowledge and contextual cues, AI systems require vast amounts of structured and unstructured data to function effectively. Real-world data in finance is often noisy, incomplete, or manipulated, which poses challenges to model training and accuracy. Moreover, proprietary data used by financial institutions is not always standardized or shared, creating information silos that hinder collaborative advancements in AI-driven decision-making. Lee and Tan [31] highlighted that data sparsity and structural missingness in developing countries' financial data inhibit AI training and increase risk of overfitting.

Another significant challenge pertains to data privacy and security. The growing reliance on customer data for personalized investment advice raises concerns about how such sensitive information is collected, stored, and used. Holmlund et al. [9] underline the tension between personalization and privacy in robo-advisory systems. Unauthorized access or breaches of financial data can not only lead to financial losses but also damage firm reputation and erode public trust. With regulations such as GDPR and emerging AI Acts, firms must navigate complex compliance landscapes while ensuring that their AI models remain effective. According to Schmidt and Hamacher [34], a global regulatory taxonomy for AI in finance is still missing, creating difficulties in multinational AI deployments.

Moreover, the regulatory environment surrounding AI in finance remains fragmented and nascent. While some jurisdictions have introduced guidelines for responsible AI use, many financial authorities lack concrete frameworks to monitor and govern AI-driven investment tools. As a result, innovation often outpaces regulation, leaving critical gaps in investor protection. Gomber et al. [8] note that without standardized benchmarks for performance and transparency, it becomes difficult to compare the reliability of AI solutions across institutions. This regulatory uncertainty discourages adoption among more risk-averse firms and impedes the development of interoperable systems.

These challenges are compounded by organizational and human factors, including resistance to change, lack of technical expertise, and insufficient infrastructure. Many emerging markets, the absence of skilled personnel and weak digital infrastructure limit the effective adoption of AI tools. Even in developed economies, financial professionals often express skepticism toward replacing human judgment with machine-driven processes, particularly in areas like fiduciary advising or wealth planning. Hence, successful implementation of AI in finance requires not only technical readiness but also cultural transformation and workforce reskilling. To illustrate the frequency and distribution of challenges addressed in the reviewed literature, Table 3 presents a categorization of limitations identified across the 52 selected articles.

Table 3. Challenges of AI in Financial Decision-Making Identified in the Literature

Challenge Category	Frequency in Studies	Key References
Lack of Explainability	21	Holmlund et al. (2020); Jobst & Sole (2020)
Algorithmic Bias	17	Dastin (2018); Sun et al. (2022)
Data Dependency	14	Pereira et al. (2022); Gomber et al. (2022)
Privacy and Data Security	11	Holmlund et al. (2020); Bruckner (2021)
Regulatory Uncertainty	15	Gomber et al. (2022); Jobst & Sole (2020)
Infrastructure and Skills	12	Shrestha et al. (2022); Sironi (2020)

Despite these challenges, many researchers propose strategic solutions and governance frameworks to enhance the responsible use of AI in financial contexts. For example, Holmlund et al. [9] recommend integrating explainable AI (XAI) techniques such as attention visualization and rule extraction into financial models to improve transparency. Meanwhile, Nasiri et al. [6] argue for co-regulatory approaches, where firms collaborate with regulators to develop context-specific AI guidelines. Ethical AI development practices-such as fairness audits, human-in-the-loop systems, and algorithmic accountability structures-are increasingly being advocated as part of industry best practices.

The review also identifies several research gaps that future studies should address. One such gap is the lack of longitudinal analysis on the long-term impact of AI-driven investment strategies on market stability and investor behavior. Most current studies evaluate short-term performance but do not explore how continued reliance on AI might affect market dynamics over decades. Another gap lies in the geographical concentration of research: the majority of empirical work is based on data from developed markets such as the U.S. and Western Europe, with limited insights from Asia, Africa, or Latin America [23] [22]. This skews understanding and limits the generalizability of findings.

In addition, while AI excels at processing quantifiable data, it struggles with qualitative investment factors, such as environmental, social, and governance (ESG) considerations. Given the growing importance of sustainable finance, future research should explore how AI can be adapted to incorporate ESG metrics, stakeholder sentiment, and social responsibility signals into decision models [7]. Lastly, the integration of AI with other emerging technologies such as blockchain, quantum computing, and edge AI remains an underexplored frontier with vast potential for reshaping investment ecosystems. In line with this, Rahman et al. [32], proposed a hybrid AI framework combining NLP and ESG rating data to generate sustainability-aware investment signals, paving the way for more responsible finance.

Taken together, the second session of findings emphasizes that while AI holds transformative promise in finance, its deployment must be tempered with critical reflection on ethical, technical, and regulatory dimensions. Financial institutions must balance the pursuit of innovation with the imperative to uphold trust, fairness, and responsibility. This requires a multi-stakeholder effort involving technologists, regulators, financial professionals, and academic researchers to co-create resilient and inclusive AI systems for investment decision-making.

4. Conclusion

This study has critically examined the integration of artificial intelligence (AI) into financial decision-making through a systematic literature review, revealing that while AI offers transformative opportunities-such as enhanced portfolio optimization, real-time risk assessment, algorithmic trading efficiency, and democratized financial advisory services-it also introduces substantial challenges including algorithmic bias, lack of model transparency, data dependency, and regulatory ambiguity. The findings underscore that the successful application of AI in investment strategies requires not only technical innovation but also ethical governance, regulatory alignment, and interdisciplinary collaboration. As the financial sector continues to evolve with emerging technologies, future research must address current gaps-particularly the long-term effects of AI on market behavior, inclusion of ESG factors, and the global scalability of AI models-to ensure that AI-driven finance remains both effective and equitable across diverse contexts.

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