

Artificial Intelligence and the Future of Financial Governance

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ABSTRACT: Artificial Intelligence (AI) is increasingly recognized as a transformative force in financial decision-making, with applications spanning risk prediction, portfolio optimization, fraud detection, corporate financial reporting, consumer finance, and market sentiment analysis. This narrative review aims to synthesize current knowledge on the opportunities and risks associated with AI adoption in the financial sector. Literature was collected from leading academic databases, including Scopus, Web of Science, and Google Scholar, using keywords such as “Artificial Intelligence,” “Financial Decision-Making,” “Risk Management,” and “Portfolio Optimization.” Inclusion criteria prioritized peer-reviewed studies published between 2010 and 2025. Findings reveal that AI consistently outperforms traditional approaches in risk prediction and credit assessment, with neural networks and hybrid models achieving predictive accuracies exceeding 85%. AI-driven robo-advisors provide higher investment returns and expand financial inclusion by reducing cost barriers. In fraud detection, adaptive algorithms achieve accuracy rates up to 90% and improve resilience against evolving threats. Corporate reporting benefits from AI-driven transparency, particularly when supported by high-quality auditing. Moreover, AI tools promote sustainable financial practices by aligning investment strategies with social and environmental objectives, while advanced models like GPT enhance market sentiment analysis. However, the review also identifies key challenges, including black-box opacity, algorithmic bias, systemic vulnerabilities, and regulatory uncertainties. Addressing these issues requires explainable AI, algorithmic audits, representative datasets, and collaborative governance mechanisms. This review concludes that while AI holds enormous potential to transform global financial systems, its sustainable and equitable integration depends on balancing innovation with regulatory adaptation, transparency, and fairness.

Keywords: Artificial Intelligence, Financial Decision-Making, Risk Management, Portfolio Optimization, Fraud Detection, Financial Reporting, Sustainable Finance.



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INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in the financial sector over the last decade, particularly in reshaping decision-making processes in areas

such as risk assessment (e.g., credit default prediction models), investment strategies (e.g., robo-advisors), and portfolio management (e.g., real-time algorithmic trading). The rapid advancements in machine learning (ML), deep learning, and natural language processing (NLP) have enabled the development of sophisticated tools capable of analyzing massive volumes of structured and unstructured data, thus providing more accurate predictive analytics and enhancing automated decision support systems in finance (Ghosn, 2025; Dote-Pardo et al., 2025; Yang, 2022). These technological innovations have altered the competitive landscape of financial institutions, pushing firms toward greater reliance on algorithmic models and data-driven insights.

The adoption of AI in financial decision-making reflects the broader digital transformation of global finance. Financial institutions now integrate AI into trading systems, fraud detection mechanisms, auditing processes, and investment advisory services, with the aim of optimizing efficiency and accuracy (Ghosn, 2025; Biju, 2025). AI-driven platforms are particularly notable in algorithmic trading, which leverages real-time data analysis for faster execution and improved precision, giving firms a distinct competitive advantage in volatile markets (Kuzior, 2024). This trend underscores how AI has shifted from being a supplementary tool to a central component of financial operations, fundamentally changing the way institutions interact with financial data and make strategic decisions.

Empirical evidence highlights the profound economic impact of AI adoption within financial services. Studies reveal that organizations employing AI report reduced operational costs, improved compliance mechanisms, and greater accuracy in financial reporting (Singh et al., 2024; Alhazmi et al., 2025). In the domain of risk management, AI models have proven effective in stabilizing markets by mitigating volatility through advanced risk assessment strategies (Kuzior, 2024; Manta et al., 2024). Moreover, recent surveys indicate that institutions leveraging AI achieve stronger performance metrics and better financial outcomes compared to their counterparts relying on traditional approaches (Manta et al., 2024; Alhazmi et al., 2025). This evidence suggests that AI adoption is not merely a technological upgrade but a driver of systemic improvements in financial practice.

Within investment and portfolio management, AI has facilitated a deeper understanding of market dynamics and behavioral finance. Through predictive analytics and automated learning, financial institutions are now able to anticipate market trends, identify investment opportunities, and develop personalized strategies tailored to investor preferences (Biju, 2025; Ghosn, 2025). The introduction of robo-advisors exemplifies the democratization of financial planning, offering personalized, low-cost investment advice that was previously available only to high-net-worth individuals (Ibrahim et al., 2024; Jain, 2025). Such innovations have enhanced client engagement while broadening access to financial services.

The application of AI in portfolio management has significantly strengthened institutional capacity to assess risks and adjust strategies in real-time. Firms adopting AI-driven forecasting models report substantial improvements in investment returns, with models showing greater accuracy in predicting market movements and managing volatility (Yang, 2022; Ibrahim et al., 2024). Moreover, these models enhance the ability of organizations to adapt dynamically to economic shocks, thereby contributing to the resilience of both institutional and individual investment

strategies (Kuzior, 2024). As financial ecosystems continue to grow in complexity, such predictive capabilities are increasingly critical for maintaining stability and competitiveness.

Despite these opportunities, the adoption of AI in financial decision-making presents considerable challenges. A major issue lies in the transparency of AI systems. Deep learning algorithms, often described as “black boxes,” provide little interpretability of their decision-making processes. This opacity raises concerns about accountability and trust, as stakeholders—including regulators, investors, and consumers—struggle to understand how AI reaches its conclusions (Guerrero et al., 2024; Watkins et al., 2021). Lack of transparency not only hampers regulatory oversight but also undermines stakeholder confidence in financial systems that are increasingly reliant on opaque algorithms.

Another critical challenge is algorithmic bias. When AI systems are trained on biased or non-representative datasets, they may replicate or even amplify existing social and economic inequalities. For example, AI-based credit scoring systems risk disproportionately disadvantaging certain demographic groups, thereby perpetuating discrimination in lending practices (Issa et al., 2024; Draws et al., 2021). Beyond fairness, algorithmic bias can exacerbate systemic risks in financial markets when widely adopted biased models influence large-scale financial decisions (Akour et al., 2024; Buckmann et al., 2021). As a result, ensuring fairness and representativeness in data and algorithms remains an urgent research and policy priority.

Systemic risks further complicate AI adoption in finance. The widespread use of similar AI models across institutions can heighten interconnectedness, making financial systems more vulnerable to collective shocks. If multiple institutions simultaneously respond to market fluctuations using comparable algorithmic strategies, the likelihood of cascading failures increases, potentially triggering large-scale financial crises (Akour et al., 2024; Buckmann et al., 2021). This concern underscores the paradox of AI in finance: while it promises greater stability through improved risk assessment, it can simultaneously create new systemic vulnerabilities.

A notable gap in the literature concerns the long-term impact of AI adoption on global financial stability. Existing studies tend to emphasize the short-term efficiency gains and immediate performance improvements associated with AI (Mazur et al., 2015). However, relatively little research explores how increasing dependence on algorithmic decision-making influences systemic risk, inter-institutional dynamics, and the broader resilience of financial markets over time (Policepatil et al., 2024; Buckmann et al., 2021). This gap limits our ability to fully anticipate the macro-level implications of AI adoption, particularly in an era of growing financial interconnectedness.

Against this backdrop, the present review seeks to analyze the opportunities and risks of AI adoption in financial decision-making. The objective is to provide a comprehensive synthesis of the literature, examining how AI has influenced operational efficiency, risk management, portfolio optimization, and fraud detection, while also addressing the associated challenges of transparency, bias, and systemic vulnerability (Biju, 2025; Shiyyab et al., 2023; Barone et al., 2024). By mapping both the benefits and pitfalls of AI, the review aims to contribute to a balanced understanding of how these technologies are reshaping finance.

The scope of this review includes an examination of both developed and developing economies, as the dynamics of AI adoption vary significantly across contexts. In developed economies, research often focuses on advanced technological integration and its role in enhancing global competitiveness and innovation (Buckmann et al., 2021). Conversely, studies in developing economies highlight infrastructural and educational barriers to adoption, as well as the potential of AI to promote financial inclusion by extending access to underserved populations (Akour et al., 2024; Trincanato & Vagnoni, 2024; Maheshwari & Samantaray, 2025). This comparative perspective allows for a nuanced exploration of AI's role in global financial transformation, highlighting both opportunities for growth and challenges in equitable implementation.

METHOD

The methodology of this review was designed to ensure a systematic and comprehensive identification of scholarly works on Artificial Intelligence (AI) in financial decision-making, following a stepwise process involving database selection, keyword strategy, and rigorous screening to enhance clarity and replicability. Given the breadth of the subject matter and the cross-disciplinary nature of AI applications in finance, a multi-stage approach was adopted. This involved careful selection of databases, strategic use of keywords, well-defined inclusion and exclusion criteria, and a rigorous process for screening and evaluating relevant studies. By employing these procedures, the study sought to maximize both the breadth and depth of coverage while maintaining high academic standards.

The initial step of the methodology involved the identification of appropriate academic databases that provide comprehensive and reliable access to peer-reviewed research. Scopus and Web of Science were chosen as the primary sources due to their extensive indexing of high-quality scholarly journals in economics, finance, computer science, and interdisciplinary fields. These databases are widely recognized in bibliometric research for their ability to capture citation trends, co-authorship patterns, and emerging themes across diverse domains (Barone et al., 2024; Dote-Pardo et al., 2025). Their inclusion ensured that the review would be anchored in well-established, peer-reviewed contributions. To supplement these resources, Google Scholar was also utilized, owing to its broader coverage and ease of access. While it includes a wide range of academic articles, conference papers, and working papers, Google Scholar's open indexing system introduces variability in quality. Thus, the database was employed mainly to capture grey literature and studies that might not be fully indexed in Scopus or Web of Science, with careful scrutiny applied to maintain credibility (Barone et al., 2024).

In constructing the search strategy, specific keywords and Boolean operators were employed to maximize retrieval of relevant literature while reducing irrelevant results. The core keywords included "Artificial Intelligence," "Financial Decision-Making," "Risk Management," "Portfolio Optimization," and "Fraud Detection." These terms were selected based on their frequent appearance in prior reviews and their centrality to the intersection of AI and finance (Abrokwah-Larbi & Awuku-Larbi, 2023; Darji et al., 2025). To further refine the searches, combinations such as "AI AND financial analysis," "AI AND investment strategies," and "machine learning AND

credit risk” were employed. The inclusion of these variations allowed for the capture of nuanced perspectives within subfields, ensuring that the review covered diverse approaches ranging from algorithmic trading systems to AI-enhanced auditing processes (Mauro et al., 2022).

To maintain rigor, clear inclusion and exclusion criteria were established. Studies were included if they were peer-reviewed, published between 2010 and 2025, and directly addressed the application of AI in financial decision-making. Eligible studies encompassed empirical research, systematic reviews, and conceptual papers that explored AI technologies such as machine learning, deep learning, natural language processing, and robo-advisory systems within financial contexts. Publications focusing exclusively on computer science without financial applications, or those centered on financial decision-making without AI integration, were excluded. Non-English articles were also excluded to maintain consistency and accessibility, though abstracts in English were occasionally reviewed to ensure no critical works were overlooked.

The review incorporated a diverse range of study designs to capture the multifaceted role of AI in finance. Randomized controlled trials (RCTs) were included when available, although such designs were rare in this context. More commonly, cohort studies, case studies, econometric analyses, and simulation-based research were encountered. These studies provided valuable insights into the operationalization of AI in various financial domains, from predictive risk modeling to market sentiment analysis. Case studies and industry reports were particularly useful in contextualizing AI adoption across different geographical and institutional settings, offering practical insights into implementation challenges and benefits.

The literature selection process involved a multi-step filtering procedure. Initial searches across the selected databases yielded a large corpus of studies, which were then screened by title and abstract to assess relevance. Articles that explicitly mentioned AI and financial decision-making in their titles or abstracts were shortlisted. The full texts of these articles were subsequently reviewed to ensure compliance with the inclusion criteria. Duplicate entries across databases were identified and removed. In total, the final selection represented a diverse set of studies spanning multiple methodologies, disciplines, and regions.

Evaluation of the included literature was guided by both qualitative and quantitative considerations. Each study was assessed for methodological rigor, clarity of research design, and the robustness of findings. For empirical studies, attention was given to sample size, data sources, and the validity of analytical techniques. For conceptual papers and reviews, the comprehensiveness of arguments, theoretical grounding, and contribution to existing literature were considered. Particular emphasis was placed on the extent to which studies addressed key issues of transparency, bias, and systemic risk in AI adoption. This evaluation process ensured that only high-quality and relevant works informed the synthesis presented in this review.

Overall, the methodological approach employed in this review ensured a systematic, transparent, and replicable process of literature selection and evaluation. By combining multiple databases, strategic keyword usage, explicit inclusion and exclusion criteria, and rigorous evaluation, the review captures a comprehensive picture of current knowledge on the role of AI in financial

decision-making. This methodological foundation not only strengthens the validity of the review but also enhances its contribution to ongoing scholarly and policy debates in this evolving field.

RESULT AND DISCUSSION

The findings of this narrative review are organized into six thematic areas that reflect the most prominent domains of AI application in financial decision-making. These include risk prediction and management, portfolio management and wealth optimization, fraud detection and credit risk, corporate financial reporting and auditing, consumer finance and sustainable practices, and market insights and sentiment analysis. Each theme synthesizes existing literature, highlights empirical evidence, and incorporates global perspectives on the role of AI in reshaping financial processes.

Risk prediction and management has been one of the most intensively studied areas in the application of AI within finance. Algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks have consistently demonstrated superior predictive accuracy compared to traditional statistical models. Froese et al. and Biju (2025) provided evidence that Neural Networks achieved higher levels of accuracy in predicting market risk than regression-based models, reflecting the adaptability of AI to nonlinear and complex financial datasets. Similarly, Kuzior (2024) found that AI-based methodologies contributed to reducing volatility in financial markets, fostering greater stability in trading environments. Empirical data supports these observations, with Alhazmi et al. (2025) reporting that institutions employing AI for credit risk assessment reduced default rates by approximately 15–20% compared with those using conventional approaches. Complementing this, Huang and Lin (2025) demonstrated that AI-driven models predicted financial failure with accuracy exceeding 85%, reinforcing the idea that AI systems not only enhance predictive power but also provide actionable insights for strategic decision-making in risk management.

The role of AI in portfolio management and wealth optimization has similarly grown in prominence, with robo-advisors emerging as a transformative tool. These platforms leverage AI algorithms to process large datasets and adjust portfolios dynamically in response to market conditions, such as reallocating assets during sudden stock market downturns or optimizing bond-equity ratios in volatile interest rate environments. Research by Škare and Vlahović and Ding et al. (2024) indicated that investors utilizing robo-advisors achieved annual investment returns on average 3% higher than those relying on human managers. This improvement was attributed to the ability of AI to analyze market signals more efficiently and optimize asset allocations in real-time. Moreover, AI-driven robo-advisors have broadened access to financial services. Leocádio et al. (2025) found that algorithm-based investment platforms lowered barriers to entry for individuals with lower incomes by reducing costs and enabling investment with smaller amounts of capital. Such applications contribute to greater financial inclusion, particularly in developing regions where access to traditional financial advisory services is limited.

AI has also proven effective in fraud detection and credit risk analysis. Machine learning models excel in identifying irregular patterns of behavior that indicate fraudulent activity. Yaseen and Al-Amarneh (2025) demonstrated that AI systems could detect unusual transaction patterns with

accuracy rates reaching 90%, outperforming conventional fraud detection methods that often suffer from high false positive rates. Importantly, the adaptive nature of AI systems allows them to evolve continuously by learning from emerging fraud patterns, thereby increasing resilience against novel threats. Beyond fraud detection, integrating textual data such as loan application notes with structured numerical datasets has improved predictions of credit default. Hilal et al. (2022) showed that hybrid models combining text and numeric inputs yielded more accurate forecasts of credit delinquency than models relying solely on quantitative data, underscoring the value of multimodal approaches in financial risk analysis.

In the area of corporate financial reporting and auditing, AI adoption has been linked to improvements in transparency, timeliness, and accuracy. Alhazmi et al. (2025) found that firms integrating AI into financial reporting systems enhanced both the precision of disclosures and the efficiency of compliance processes, thereby strengthening governance and reducing uncertainty. This enhanced reliability was particularly significant in emerging markets, where consistent and accurate reporting is critical for attracting foreign investment and building investor confidence. Supporting this, Awad et al. (2025) emphasized that AI automation facilitated compliance and reduced the incidence of reporting errors. Khan et al. (2024) explored the moderating role of audit quality in this relationship, noting that high-quality audits amplified the transparency benefits of AI adoption. Their findings suggest that when AI and rigorous audit practices operate in tandem, they reinforce one another, improving the overall credibility of corporate disclosures and contributing to better-informed decision-making by stakeholders.

AI's contribution to consumer finance and sustainable practices is also noteworthy, particularly in contexts where financial literacy remains limited. AI-powered financial planning applications have made budgeting, saving, and investment management more accessible, empowering consumers to make better financial decisions despite limited expertise. Sarin and Sharma (2024) highlighted how AI tools support the achievement of Sustainable Development Goals (SDGs) by enabling sustainable finance practices. Their study showed that AI-based systems provided enhanced analysis of the social and environmental impacts of investments, thereby guiding consumers and institutions toward more sustainable options. This dual benefit—improved financial performance coupled with alignment to sustainability objectives—illustrates the broader societal impact of AI adoption in finance.

Finally, the use of AI in market insights and sentiment analysis has redefined how financial actors interpret unstructured data from social media and online forums. Traditional sentiment analysis models often struggled with nuance, leading to oversimplification of market sentiment. Wang and Chen (2024) demonstrated that GPT-based models surpassed conventional approaches by capturing subtle linguistic cues and context, thereby producing more accurate sentiment assessments. These improvements translated into better stock price predictions and more effective investment strategies. The global relevance of these findings is evident, as financial institutions in diverse regions increasingly adopt sentiment analysis tools to supplement traditional market intelligence. By analyzing sentiment in real-time, AI systems provide actionable insights that enhance decision-making under conditions of uncertainty.

Taken together, these results highlight the multifaceted contributions of AI to financial decision-making across domains. Risk prediction has been enhanced through improved accuracy and

reduced volatility; portfolio management has become more inclusive and efficient; fraud detection and credit risk analysis have been strengthened through adaptive and multimodal systems; corporate reporting has become more transparent with the integration of AI and high-quality audits; consumer finance has gained tools for sustainability and accessibility; and market insights have been enriched through advanced sentiment analysis models. The comparative evidence from developed and developing economies illustrates both the opportunities and disparities in AI adoption. While advanced economies focus on leveraging AI for competitiveness and innovation, developing economies emphasize inclusivity and accessibility, highlighting the varied yet convergent pathways through which AI is reshaping global financial systems.

The findings presented in this review confirm that Artificial Intelligence (AI) is reshaping financial decision-making across diverse domains, yet they also reveal significant challenges that align with broader global debates on regulation, systemic risk, and ethical implementation. The integration of AI into financial markets, credit systems, and auditing practices highlights the dual role of technology as both an enabler of efficiency and a source of new vulnerabilities. In examining these results against existing literature, it becomes evident that the benefits of AI are tightly coupled with systemic and regulatory conditions that influence its implementation.

The intersection between AI adoption in finance and regulatory policy has been a focal point in recent scholarly work. As Darji et al. (2025), Dote-Pardo et al. (2025), and Aysan et al. (2024) note, the proliferation of AI technologies in financial institutions has placed increasing pressure on regulators to adapt existing frameworks to safeguard transparency and accountability. The study by Khan et al. (2024) emphasized how AI adoption improved the quality of financial reporting, yet simultaneously underscored the urgency of developing regulatory mechanisms capable of addressing algorithmic bias and black-box opacity. Without such safeguards, the efficiency gains promised by AI may come at the expense of fairness and trust. This tension mirrors earlier concerns identified by Guerrero et al. (2024) and Watkins et al. (2021), who stressed that the lack of interpretability in deep learning models undermines accountability in high-stakes financial decision-making. The results of this review, which identified improvements in risk prediction and reporting accuracy, must therefore be contextualized within the broader literature that cautions against overreliance on opaque systems.

Systemic factors remain decisive in determining how effectively AI can be adopted in financial ecosystems. A recurrent barrier highlighted in both this review and prior literature is the disparity in digital infrastructure, particularly between developed and developing economies. Kuzior (2024) and Akour et al. (2024) found that while advanced economies focus on leveraging AI for competitiveness and innovation, developing economies grapple with infrastructural deficits, data security risks, and limited regulatory clarity. These structural weaknesses restrict the full realization of AI's benefits in emerging markets, despite evidence that algorithmic investment platforms and robo-advisors contribute significantly to financial inclusion (Leocádio et al., 2025). Furthermore, concerns about systemic risk amplify these challenges. Buckmann et al. (2021) demonstrated how widespread reliance on similar algorithmic models could create tightly coupled financial systems prone to cascading failures, a concern echoed by Akour et al. (2024). The findings of this review regarding improved predictive accuracy and stability must therefore be understood within the paradox that systemic risk may simultaneously increase as institutions converge on standardized AI solutions.

Addressing these challenges has become a central theme in the literature, with proposed solutions focusing on enhancing algorithmic transparency and mitigating bias. The concept of explainable AI (XAI) has been advanced as a practical approach to ensuring stakeholders can interpret the decisions made by complex models (Bandara et al., 2025). This approach emphasizes interpretability as a regulatory and ethical imperative, particularly in credit scoring and risk management where opaque decisions can have profound social and economic consequences. Bandara et al. (2025) further highlighted the utility of algorithmic auditing and bias testing, proposing that such mechanisms should become standard practice in financial AI systems. Sharma et al. (2025) and Watkins et al. (2021) extend this perspective by advocating for collaborative frameworks involving regulators, academics, and industry practitioners to design oversight mechanisms that combine technical expertise with normative accountability. The empirical evidence on credit risk reduction (Alhazmi et al., 2025) and predictive success rates above 85% (Huang & Lin, 2025) reinforces the need to align technical performance with transparent governance mechanisms.

A further line of debate concerns the role of representativeness in training data and the importance of continuous learning systems. Pria et al. (2024) emphasized the risks of training models on biased or incomplete datasets, a concern directly relevant to findings in this review regarding algorithmic bias in lending and investment. Incorporating diverse, representative datasets is essential to ensuring equitable decision-making and avoiding discriminatory practices. The dynamic nature of financial markets also necessitates continuous model updates and adaptive learning, as highlighted in studies of fraud detection systems that improved accuracy over time by learning from novel transaction patterns (Yaseen & Al-Amarneh, 2025). These findings suggest that beyond initial model design, long-term sustainability in AI-driven finance depends on mechanisms for ongoing learning, monitoring, and correction.

The global comparison of AI adoption provides further insights into the systemic challenges shaping its role in finance. In developed markets, AI integration into auditing, fraud detection, and robo-advisory services is often framed as a competitive strategy to enhance global market positions (Škare & Vlahović; Ding et al., 2024). By contrast, in developing economies, the emphasis is on accessibility and inclusion, with studies highlighting the role of AI in reducing entry barriers for low-income investors and expanding financial literacy (Maheshwari & Samantaray, 2025). However, the infrastructural and regulatory limitations in these contexts highlight a need for targeted capacity building to ensure that AI adoption does not exacerbate inequality between markets. Comparative evidence suggests that the transformative potential of AI will remain unevenly distributed unless systemic disparities in infrastructure, regulatory capacity, and digital literacy are addressed.

In addition to infrastructural and regulatory challenges, ethical and social considerations must be integrated into the discourse on AI in finance. Studies of algorithmic discrimination in lending (Issa et al., 2024; Draws et al., 2021) underscore the risk of exacerbating social inequalities if AI systems replicate existing biases. This concern is particularly acute given findings that AI credit systems reduced default rates significantly (Alhazmi et al., 2025), suggesting that even highly effective systems may mask inequities in distributional outcomes. The literature therefore points to the importance of embedding fairness as a principle of AI design and deployment. Solutions

such as regulatory audits, bias-sensitive training data, and explainable models represent pathways to balancing efficiency with justice.

Despite the breadth of evidence reviewed, limitations in the existing body of research remain apparent. A consistent gap lies in the lack of long-term studies on how AI adoption influences systemic stability. Mazur et al. (2015) noted that most studies emphasize immediate efficiency gains while neglecting to analyze broader impacts on global financial resilience. This review corroborates that observation, finding limited exploration of how widespread AI adoption might alter inter-institutional dependencies or systemic risk profiles over extended periods. Similarly, while empirical studies provide valuable insights into model performance in specific contexts, they often lack generalizability across diverse regulatory and infrastructural environments. These limitations point to the need for longitudinal, cross-national studies that examine AI adoption holistically, integrating technical, regulatory, and socio-economic perspectives.

Another limitation arises from the methodological diversity of existing studies, which complicates direct comparison of findings. While some rely on simulation-based experiments (Yang, 2022; Ibrahim et al., 2024), others adopt case study or econometric designs, creating heterogeneity in both scope and results. This variability suggests that future research would benefit from methodological standardization to enable meta-analyses and broader synthesis of findings. Moreover, as emerging technologies such as GPT-based sentiment analysis (Wang & Chen, 2024) expand the scope of AI in finance, research must continue to interrogate the implications of such tools not only for predictive accuracy but also for governance and ethical accountability.

The insights from this discussion highlight the interdependence of technological, systemic, and regulatory factors in shaping AI's role in financial decision-making. The evidence suggests that while AI offers unprecedented opportunities for predictive accuracy, efficiency, and inclusivity, its successful adoption is contingent on addressing systemic barriers, mitigating algorithmic bias, and ensuring robust regulatory oversight. These findings underscore the imperative for multi-stakeholder collaboration in shaping the trajectory of AI in global finance, balancing the demands of innovation with the principles of fairness, transparency, and long-term stability.

CONCLUSION

This review suggests that Artificial Intelligence (AI) has the potential to reshape financial decision-making by enhancing predictive accuracy, streamlining portfolio management, improving fraud detection, strengthening corporate reporting, supporting sustainable consumer finance, and refining market sentiment analysis. Across these domains, empirical evidence highlights substantial benefits, such as reduced credit default rates, improved investment returns, greater transparency in financial reporting, and expanded financial inclusion. At the same time, significant challenges persist, particularly related to transparency, algorithmic bias, systemic risk, and regulatory gaps. These challenges emphasize the need for interventions that balance technological innovation with fairness, accountability, and long-term stability.

The findings underscore the urgency of developing adaptive regulatory frameworks that can ensure explainability, enforce auditability, and safeguard consumer protection. The adoption of

explainable AI, algorithmic audits, and representative data use are highlighted as strategies that can mitigate bias and strengthen stakeholder trust. Furthermore, collaborative efforts between regulators, industry, and academia are critical to designing governance mechanisms that align technological advancement with public accountability. Given the disparities between developed and developing economies in infrastructure and digital capacity, tailored policies are necessary to ensure equitable adoption and to prevent widening inequalities.

Future research should prioritize longitudinal and cross-national studies to explore the long-term systemic implications of AI adoption in finance. Methodological standardization would also support stronger evidence synthesis, enabling policymakers and practitioners to make more informed decisions. By advancing both technological and governance strategies, AI can deliver on its promise of driving innovation while fostering stability, inclusivity, and sustainability in global financial systems.

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