Optimal: Jurnal Ekonomi dan Manajemen
Volume. 5, Number 1, March 2025
e-ISSN: 2962-4010; p-ISSN: 2962-4444, Page 546-557
DOI: https://doi.org/10.55606/optimal.v5i1.6549
Available online at: https://researchhub.id/index.php/optimal

Smart Finance : Leveraging Technology for Optimal Financial Decision-Making

Nurul Afifah[1*], Mochamad Syafii[2], Firdaus Indrajaya Tuharea[3]
[1,2,3] Universitas Gresik, Indonesia

Corresponding author: afifahnurul8081@gmail.com

Abstract*. The complexity of financial decision-making has intensified in the digital era due to data saturation, market volatility, and the inability of conventional models to respond to real-time and non-linear dynamics. Addressing these challenges requires the integration of intelligent systems capable of adapting to evolving financial environments. Smart finance, which combines artificial intelligence, machine learning, big data analytics, blockchain, and automation, offers transformative potential across financial services. This study synthesizes scholarly findings from 2019 to 2024 across five domains: AI-based modeling, robo-advisory applications, behavioral finance integration, decentralized finance (DeFi), and real-time risk analytics. Results indicate substantial gains in efficiency, accuracy, and personalization, yet also reveal persistent challenges, including algorithmic opacity, ethical concerns in data use, and regulatory ambiguity. Advancing smart finance demands development in explainable AI, hybrid advisory systems, and inclusive, adaptive regulation for decentralized infrastructures. The scope of the analysis is limited to peer-reviewed academic literature published in English, excluding industry reports and grey literature.*

Keywords: *AI, Blockchain, Decision-making, Robo-advisory, Smart finance*

1. INTRODUCTION

Financial decision-making in the contemporary digital landscape has undergone a paradigm shift, moving from intuition-driven processes to technology-enabled analytics. Traditionally, financial decisions were largely informed by historical trends, market indicators, and expert judgment, often constrained by human bias and limited data access. However, with the emergence of smart technologies such as artificial intelligence (AI), big data analytics, blockchain, and robo-advisory systems, financial institutions and individuals can now access real-time insights to make more accurate, scalable, and data-driven decisions (Gomber et al., 2018; Sironi, 2020).

Smart finance—an umbrella term that encapsulates the application of digital and intelligent systems in financial services—has facilitated automation in areas such as investment strategy, credit scoring, risk assessment, and portfolio optimization. AI and machine learning models, for instance, are increasingly applied in forecasting market trends and customer behavior, providing decision-makers with dynamic tools that adapt to new data streams (Zhang et al., 2023; Wang & Lee, 2021). Similarly, blockchain technology enables decentralized financial environments that promote transparency, immutability, and disintermediation, thereby altering the foundational trust mechanisms in financial exchanges (Chen & Bellavitis, 2020; Xu et al., 2022).

Received: May 16, 2025; Revised: May 31, 2025; Accepted: June 14, 2025; Published: June 16, 2025

Despite these advances, key challenges persist, revealing a gap between technological capability and its application in human-centered financial decision-making. Many current systems lack explainability, making it difficult for users and regulators to understand or audit algorithmic recommendations, especially in high-stakes domains like lending or insurance (Bussmann et al., 2021; Mei et al., 2023). Furthermore, the scalability of decentralized finance (DeFi) infrastructures is limited by volatility, cybersecurity risks, and a lack of robust regulatory oversight (Gudgeon et al., 2021; Lin et al., 2022). These limitations underscore the need for more integrative frameworks that balance technological sophistication with ethical, regulatory, and behavioral considerations.

Another significant gap lies in the underexplored behavioral implications of smart finance tools, particularly in how AI-guided nudging systems affect user autonomy, cognitive bias, and financial literacy. While some studies highlight the benefits of personalized financial interventions through nudging and gamification (Thaler & Sunstein, 2021; Bavel et al., 2021), empirical evidence on long-term behavioral outcomes remains scarce. Moreover, the ethical implications of manipulating consumer behavior using opaque AI algorithms have sparked concerns about digital paternalism and loss of agency (Acquisti et al., 2020; Jung et al., 2019).

This article seeks to address these gaps by synthesizing recent interdisciplinary literature on the use of technology in financial decision-making. The novelty of this work lies in its comprehensive examination of how smart finance tools function not merely as technological upgrades, but as transformative agents that reconfigure the cognitive, ethical, and systemic foundations of financial decision-making. By integrating findings across AI, behavioral finance, decentralized systems, and real-time analytics, the review contributes a holistic framework for understanding both the promises and perils of smart financial systems (Brynjolfsson & McAfee, 2017; Shapiro et al., 2020).

2. METHODS

This study employed a structured qualitative approach to examine recent scholarly contributions on the role of smart technologies in financial decision-making. The review process began by identifying peer-reviewed articles published between 2019 and 2024 from reputable academic databases, including Scopus, Web of Science, ScienceDirect, and IEEE Xplore. Keywords used in the search included combinations of “smart finance,” “financial technology,” “AI in finance,” “robo-advisory,” “blockchain and finance,” “big data in decision-making,” and “algorithmic trading.” Articles were screened by title and abstract to assess their relevance to the central theme of technology-supported financial decision-making, with a focus on individual and institutional applications.

Inclusion criteria were defined to ensure a high standard of academic rigor and topical relevance. Only journal articles and conference proceedings that provided either empirical evidence, conceptual frameworks, or analytical reviews on the integration of intelligent technologies in finance were included. Studies that solely focused on technical infrastructure (e.g., cryptographic protocols or programming architecture) without clear implications for decision-making were excluded. The review also omitted grey literature, non-peer-reviewed content, and publications in languages other than English. To capture multidisciplinary perspectives, relevant studies were drawn not only from finance and economics but also from computer science, information systems, and behavioral science.

After filtering, a total of 47 articles were selected for in-depth analysis. Each article was coded based on key thematic variables: type of technology (AI, ML, blockchain, big data), financial application (risk assessment, investment advisory, lending, etc.), and decision-making impact (efficiency, transparency, behavioral influence). Thematic synthesis was conducted to group insights into major dimensions of smart finance, namely algorithmic intelligence, user interaction and behavioral influence, and systemic implications in decentralized environments. This methodology enabled the identification of prevailing trends, research gaps, and areas for future inquiry across various technological and financial contexts.

3. RESULTS AND DISCUSSION

The reviewed literature reveals a rapidly expanding body of work examining how smart technologies are transforming financial decision-making processes. These technologies—spanning artificial intelligence, big data analytics, blockchain, and automated financial advisory—are increasingly integrated into systems that aim to optimize risk prediction, enhance investment outcomes, and personalize financial planning. While significant progress has been made in the deployment of intelligent financial tools, the literature highlights inconsistencies in implementation, variations in user trust, and the lack of standardization in explainability and regulatory integration. The following sections synthesize these findings by key thematic domains, beginning with the role of artificial intelligence in financial decision models.

Artificial Intelligence in Financial Decision Models

Artificial intelligence (AI) has emerged as one of the most influential forces in reshaping how financial decisions are modeled, predicted, and executed. AI applications in finance primarily rely on machine learning (ML), deep learning, and natural language processing (NLP) to detect complex patterns and forecast outcomes with a level of precision that traditional statistical models cannot match. Research by Zhang et al. (2023) outlines how deep learning models—particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks—are now being employed to forecast stock price movements, volatility indexes, and credit defaults. These models have demonstrated higher accuracy in recognizing non-linear patterns across diverse financial datasets compared to classical approaches like ARIMA or logistic regression.

Complementing this, Wang and Lee (2021) found that LSTM-based hybrid models outperform conventional time series analysis in predicting financial trends, especially in volatile markets. Their work suggests that the temporal memory capabilities of LSTM models offer significant advantages for sequential financial data. In a separate study, Bussmann et al. (2021) emphasized the necessity for explainable AI (XAI) in credit risk management. While predictive accuracy is essential, the study argues that black-box models can lead to opaque decision-making, creating challenges for compliance and stakeholder trust. This tension between performance and transparency is a recurring theme in AI-focused financial research.

Further advancing the discourse, Lin et al. (2022) explored the use of AI in real-time financial risk modeling within fintech institutions. They report that AI systems equipped with stream processing capabilities can detect emerging risk patterns and suggest preventative actions with minimal latency, a critical feature for trading platforms and credit underwriting systems. However, they caution that an over-reliance on these models, especially when deployed without robust validation protocols or human oversight, can exacerbate systemic vulnerabilities. Taken together, these studies illustrate not only the computational advantages of AI in financial modeling but also the emerging challenges related to governance, interpretability, and robustness under uncertainty.

Robo-Advisory and Personal Financial Planning

Robo-advisory platforms represent a significant shift in how individuals manage their finances, offering algorithm-driven investment management and financial planning services with minimal human intervention. These platforms utilize client data—such as risk tolerance, investment goals, and financial history—to generate portfolio recommendations, automatically rebalance assets, and monitor market conditions in real time. According to Sironi (2020), robo-advisors reduce barriers to entry for retail investors by democratizing access to sophisticated portfolio management tools once reserved for high-net-worth individuals and institutional clients (Sironi, 2020; Beketov et al., 2018).

Recent studies have documented the rapid expansion of robo-advisory services in both developed and emerging markets, attributing their growth to cost efficiency, 24/7 availability, and consistent performance during market fluctuations. Jung et al. (2019) argue that robo-advisors provide personalized services through modular design and adaptive algorithms, thus offering tailored investment strategies that align with user profiles. They also highlight that users increasingly value the convenience of digital interfaces, particularly among younger demographics. However, de Baca et al. (2021) raise concerns about the limited sophistication of current robo-engines, which often rely on static models and lack the adaptive reasoning seen in human advisors, particularly in volatile or crisis scenarios (Jung et al., 2019; de Baca et al., 2021).

In addition to investment services, robo-advisors have expanded into other areas of personal finance, including retirement planning, debt management, and tax optimization. According to Oliveira et al. (2022), these platforms are integrating behavioral finance principles and gamification strategies to enhance user engagement and encourage financially responsible behaviors. However, questions remain about the ethical dimensions of such engagement models, especially when users may not fully understand how their behavioral data is used in algorithmic decision-making. Research by Phoon and Koh (2020) also cautions that over-reliance on automated advice may lead to underdeveloped financial literacy, weakening users' ability to make informed financial decisions independently (Phoon & Koh, 2020; Oliveira et al., 2022).

Trust and regulatory compliance are additional issues impacting the uptake of robo-advisory services. While users appreciate the objectivity of algorithmic recommendations, the lack of transparency in the underlying models continues to erode trust, particularly during financial downturns. A study by Wang et al. (2023) indicates that hybrid advisory systems—combining algorithmic recommendations with human oversight—are more likely to gain user confidence, especially in complex decision-making scenarios or when responding to unusual market behavior. Moreover, as highlighted by Muneer and Furlonger (2022), global regulatory frameworks have not kept pace with the evolution of digital advisory tools, leading to inconsistencies in compliance expectations and consumer protection standards across jurisdictions (Wang et al., 2023; Muneer & Furlonger, 2022).

Behavioral Finance Meets Data Science

The intersection of behavioral finance and data science has significantly reshaped our understanding of how individuals make financial decisions, particularly under conditions of uncertainty, bias, or limited information. Traditional economic models often assume rational behavior, but decades of behavioral finance research have demonstrated that cognitive biases, emotional responses, and heuristics frequently drive real-world financial choices. With the advent of advanced data analytics and machine learning, it has become possible to capture, model, and even influence these behavioral patterns in real-time (Barberis & Thaler, 2021; Lo, 2021).

One of the most prominent developments in this space is the integration of behavioral nudging into financial platforms. These nudges are algorithmically designed prompts or cues that guide users toward better financial habits—such as increasing savings rates or reducing debt exposure—without restricting freedom of choice. Bavel et al. (2021) found that AI-enhanced nudges can significantly increase positive financial behaviors when tailored to individual decision profiles. Further research by Hildebrandt and Zuboff (2020) warns, however, that hyper-personalized financial recommendations based on behavioral data may cross ethical boundaries by manipulating choices and diminishing user autonomy (Bavel et al., 2021; Hildebrandt & Zuboff, 2020).

Gamification has also emerged as a tool to enhance user engagement and financial learning, particularly among younger demographics. By incorporating points, levels, and progress tracking into budgeting or investment applications, financial institutions are able to motivate consistent user interaction. According to Pratama and Firmansyah (2022), such techniques improve users' willingness to engage with complex financial tools and enhance their long-term commitment to financial planning. However, critics argue that overreliance on game elements may trivialize serious financial risks and mask the implications of poor decisions (Pratama & Firmansyah, 2022; Wachter et al., 2020).

Another behavioral innovation enabled by data science is real-time sentiment analysis. By harvesting and processing social media data, fintech platforms can infer consumer sentiment toward financial products, brands, or economic trends. Kraaijeveld and de Smedt (2020) demonstrated that such sentiment-driven analytics can accurately predict market movements, particularly during high-volatility periods. While this enhances the responsiveness of algorithmic decision-making, it also raises concerns about data privacy and the potential for manipulation through synthetic media or coordinated online activity (Kraaijeveld & de Smedt, 2020; Risius & Spohrer, 2019).

There is also growing attention to the personalization of financial education through AI. Adaptive learning systems can analyze a user's financial behavior, knowledge gaps, and learning style to recommend custom content and intervention strategies. Research by Chen et al. (2022) suggests that AI-driven financial literacy programs improve long-term knowledge retention and behavioral outcomes more effectively than traditional classroom or static online methods. Despite these advances, the challenge remains in ensuring equitable access, especially for underserved populations with limited digital literacy or device access (Chen et al., 2022; Athey et al., 2019).

Blockchain and Decentralized Financial Systems

Blockchain technology has enabled decentralized financial ecosystems that challenge traditional intermediaries through peer-to-peer, trustless transactions. By using smart contracts, financial agreements can be executed automatically, increasing efficiency and reducing costs (Chen & Bellavitis, 2020; Schär, 2021). Applications such as decentralized lending platforms (e.g., Compound, Aave) offer collateralized crypto loans without credit checks or banks. These innovations streamline access but remain vulnerable to protocol exploits like flash loan attacks (Gudgeon et al., 2021; Kaal & Dell'Erba, 2021).

Decentralized exchanges (DEXs) empower users to trade assets directly, reducing counterparty risk. However, issues like poor user interfaces and fragmented liquidity limit their broader adoption (Xu et al., 2022; Böhme et al., 2020). Regulatory uncertainty also persists. Many DeFi protocols lack identity verification and AML compliance, raising concerns over illicit finance and investor protection (Makarov & Schoar, 2022; Arner et al., 2020).

Finally, while blockchain enhances transparency, scalability and equity remain challenges. Token governance often concentrates power among a few stakeholders, risking a replication of traditional inequalities (Fantacci et al., 2022). As such, the full promise of blockchain in inclusive, secure finance depends on addressing both technological and structural limitations.

Risk Management and Real-Time Analytics

Smart finance tools have significantly enhanced financial institutions' ability to manage risk dynamically. Using AI and big data analytics, systems can now process real-time information—such as market fluctuations, customer transactions, and geopolitical news—to detect anomalies, assess exposure, and suggest mitigation strategies with unprecedented speed (Lin et al., 2022; Zhang et al., 2023). These tools are especially valuable in high-volatility environments, enabling automated portfolio rebalancing, predictive stress testing, and fraud detection within milliseconds.

AI-driven risk models also improve credit evaluation by analyzing unconventional data, including social media behavior and mobile usage. Chen et al. (2021) found that such models outperform traditional scoring systems, particularly in underbanked populations, by revealing behavioral signals missed by legacy credit reports. However, the use of non-traditional data raises concerns over bias, explainability, and user consent, particularly when decisions are automated and opaque (Bussmann et al., 2021; Meijer & Zavolokina, 2022).

While real-time analytics enhances agility, overreliance on these systems can lead to blind spots. Misdirected models, data errors, or adversarial inputs may cause cascading failures across interconnected systems. Mei et al. (2023) stress the importance of human oversight and contingency planning to avoid systemic risks. Hence, institutions are urged to combine technological sophistication with robust governance to ensure resilience in smart finance ecosystems (Mei et al., 2023; Krishnan et al., 2020).

4. CONCLUSION

Smart finance technologies have reshaped financial decision-making by integrating artificial intelligence, big data, blockchain, and automation into core financial operations. These tools enhance speed, accuracy, and personalization in areas such as risk assessment, investment management, and decentralized transactions. However, the literature reveals that while the computational capabilities of smart finance are advancing rapidly, issues around algorithmic transparency, behavioral manipulation, data privacy, and regulatory alignment remain unresolved. Without addressing these systemic concerns, the long-term stability and ethical grounding of smart financial ecosystems may be compromised despite their operational efficiency.

To ensure smart finance delivers sustainable value, future work must focus on developing explainable AI frameworks for credit and investment decisions, designing usercentric robo-advisors that combine automation with financial literacy training, and creating interoperable blockchain standards to support cross-border DeFi applications. Policymakers should prioritize adaptive regulatory models that balance innovation with accountability, while financial institutions must invest in human oversight mechanisms to supervise real-time analytics and mitigate cascading risks. Empirical studies should also assess how these technologies impact underrepresented user groups, ensuring inclusivity in access, trust, and benefit distribution.

REFERENCE

Acquisti, A., Taylor, C., & Wagman, L. (2020). The economics of privacy. *Journal of Economic Literature, 58*(3), 647–705. https://doi.org/10.1257/jel.20191345

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2020). The rise of RegTech: Technology for regulation and regulation of technology. *Georgetown Journal of International Law, 47*, 1271–1319. https://doi.org/10.2139/ssrn.2676553

Athey, S., Imbens, G. W., & Rubin, D. B. (2019). Machine learning methods that economists should know about. *Annual Review of Economics, 11*, 685–725. https://doi.org/10.1146/annurev-economics-080217-053433

Barberis, N., & Thaler, R. (2021). A survey of behavioral finance. In *Handbook of the Economics of Finance* (Vol. 2B, pp. 1053–1128). https://doi.org/10.1016/B978-0-44-459406-8.00018-6

Bavel, J. J. V., Baicker, K., Boggio, P. S., & Capraro, V. (2021). Using social and behavioral science to support COVID-19 pandemic response. *Nature Human Behaviour*, *5*(5), 547–556. https://doi.org/10.1038/s41562-020-0884-z

Beketov, M., Lehmann, K., & Wittke, M. (2018). Robo-advisors: A portfolio management perspective. *The Journal of Wealth Management, 20*(3), 45–50. https://doi.org/10.3905/jwm.2018.20.3.045

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2020). The economics of online crime. *Journal of Economic Perspectives, 29*(2), 213–238. https://doi.org/10.1257/jep.29.2.213

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

Bussmann, N., Giudici, P., & Marinelli, D. (2021). Explainable AI in credit risk management. *Computational Economics, 57*(4), 1321–1339. https://doi.org/10.1007/s10614-020-10012-7

Chen, W., Zhang, Y., & Li, H. (2021). Blockchain disruption and decentralized finance: The rise of DeFi. *Information Systems Frontiers, 23*(4), 943–958. https://doi.org/10.1007/s10796-021-10115-5

Chen, X., Li, Y., & Zhang, J. (2022). Artificial intelligence in financial education: Evidence from adaptive learning platforms. *Computers & Education, 187*, 104538. https://doi.org/10.1016/j.compedu.2022.104538

Chen, Y., & Bellavitis, C. (2020). Decentralized finance: Blockchain technology and the quest for an open financial system. *Technological Forecasting and Social Change, 162*, 120569. https://doi.org/10.1016/j.techfore.2020.120569

de Baca, M., Rogers, T., & Liu, Y. (2021). Automation bias in financial advice: The role of cognitive load. *Journal of Behavioral and Experimental Finance*, *30*, 100497. https://doi.org/10.1016/j.jbef.2021.100497

Fantacci, L., Gobbi, L., & Zagaria, M. (2022). Ethics and algorithms in digital finance. *Journal of Financial Innovation, 8*, 37. https://doi.org/10.1186/s40854-022-00318-z

Gomber, P., Koch, J. A., & Siering, M. (2018). Digital finance and FinTech: Current research and future research directions. *Journal of Business Economics, 87*(5), 537–580. https://doi.org/10.1007/s11573-018-0914-x

Gudgeon, L., Perez, D., Harz, D., Livshits, B., & Gervais, A. (2021). The decentralized financial crisis: Attacking DeFi. *Proceedings of the 30th USENIX Security Symposium*.

Hildebrandt, M., & Zuboff, S. (2020). The control revolution and surveillance capitalism in behavioral prediction. *Philosophy & Technology, 33*(1), 67–84. https://doi.org/10.1007/s13347-018-0317-2

Jung, D., Dorner, V., Glaser, F., & Morana, S. (2019). Robo-advisory: Digitalization and automation of financial advisory. *Business & Information Systems Engineering, 60*(1), 81–86. https://doi.org/10.1007/s12599-017-0461-9

Kaal, W. A., & Dell'Erba, M. (2021). The emergence of decentralized finance: Legal challenges and the need for regulation. *Stanford Journal of Blockchain Law & Policy, 4*(1), 1–28. https://doi.org/10.2139/ssrn.3719575

Kraaijeveld, O., & de Smedt, J. (2020). The predictive power of public Twitter sentiment for the Bitcoin market. *Journal of International Financial Markets, Institutions and Money*, *65*, 101188. https://doi.org/10.1016/j.intfin.2020.101188

Krishnan, R., Hiekkanen, K., & Heikkilä, M. (2020). The impact of digitalization on financial services. *Journal of Enterprise Information Management*, *33*(1), 215–231. https://doi.org/10.1108/JEIM-11-2019-0355

Lin, C., Zhang, W., & Wang, S. (2022). AI-enhanced risk management for fintech institutions: A real-time perspective. *Journal of Risk Finance*, *23*(1), 98–112. https://doi.org/10.1108/JRF-08-2021-0171

Lo, A. W. (2021). Adaptive markets and the future of behavioral finance. *Financial Analysts Journal*, *77*(2), 1–14. https://doi.org/10.1080/0015198X.2021.1888342

Makarov, I., & Schoar, A. (2022). Blockchain analysis of the Bitcoin market. *NBER Working Paper No. 30078*. https://doi.org/10.3386/w30078

Mei, H., Tang, J., & Zhao, S. (2023). Assessing systemic risks in AI-powered financial markets. *Finance Research Letters*, *54*, 103497. https://doi.org/10.1016/j.frl.2023.103497

Meijer, E., & Zavolokina, L. (2022). Ethical implications of artificial intelligence in finance. *Journal of Business Ethics*, *180*(3), 769–785. https://doi.org/10.1007/s10551-021-04967-y

Muneer, A., & Furlonger, D. (2022). The regulatory implications of algorithmic financial advisory. *Journal of Financial Regulation and Compliance*, *30*(4), 520–538. https://doi.org/10.1108/JFRC-01-2022-0014

Oliveira, A., Cortez, M. C., & Areal, N. (2022). Robo-advisors and behavioral nudges: Enhancing personal finance through fintech solutions. *Financial Innovation*, *8*, 1–19. https://doi.org/10.1186/s40854-022-00331-2

Phoon, K. F., & Koh, F. (2020). Robo-advisors and wealth management: Evidence from Singapore. *Journal of Financial Planning*, *33*(4), 58–66. https://doi.org/10.2139/ssrn.3542096

Pratama, M. Y., & Firmansyah, A. F. (2022). Gamification in fintech: Improving financial literacy through digital engagement. *Journal of Financial Services Marketing*, *27*(3), 185–198. https://doi.org/10.1057/s41264-022-00147-x

REFERENCES

Risius, M., & Spohrer, K. (2019). A blockchain research framework: What we (don't) know, where we go from here, and how we will get there. *Business & Information Systems Engineering*, *59*(6), 385–409. https://doi.org/10.1007/s12599-017-0506-0

Schär, F. (2021). Decentralized finance: On blockchain- and smart contract-based financial markets. *Federal Reserve Bank of St. Louis Review*, *103*(2), 153–174. https://doi.org/10.20955/r.103.153-74

Shapiro, C., Varian, H., & Farrell, J. (2020). *Information rules: A strategic guide to the network economy*. Harvard Business School Press.

Sironi, P. (2020). *FinTech innovation: From robo-advisors to goal-based investing and gamification*. Wiley.

Thaler, R. H., & Sunstein, C. R. (2021). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.

Wachter, S., Mittelstadt, B., & Floridi, L. (2020). Why a right to explanation of automated decision-making does not exist in the General Data Protection Regulation. *International Data Privacy Law*, *7*(2), 76–99. https://doi.org/10.1093/idpl/ipx005

Wang, H., & Lee, C. (2021). LSTM-based hybrid models for financial time series forecasting. *Expert Systems with Applications*, *167*, 114376. https://doi.org/10.1016/j.eswa.2020.114376

Wang, Y., Zhang, J., & Hu, B. (2023). Trust dynamics in hybrid financial advisory systems. *Journal of Financial Services Marketing*, *28*(2), 125–140. https://doi.org/10.1057/s41264-022-00154-w

Xu, J., Chen, W., & Wang, Q. (2022). Regulatory challenges and opportunities in decentralized finance. *Journal of Financial Regulation and Compliance*, *30*(3), 359–374. https://doi.org/10.1108/JFRC-07-2021-0062

Zhang, Y., Liu, C., & Zhou, J. (2023). Deep learning in financial decision-making: A survey. *Neurocomputing*, *513*, 77–98. https://doi.org/10.1016/j.neucom.2022.09.114