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AI-Enabled FinTech and Investment Decision-Making: An Integrative Review of Capabilities, Behavioural Adoption, and Governance

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Abstract:

Artificial intelligence (AI) has moved from a back-office efficiency tool to a component of the decision architecture through which investments are researched, recommended, and executed. This review synthesises contemporary academic and authoritative institutional evidence on how AI-enabled financial technology (FinTech) reshapes investment decision-making, and on the behavioural, methodological, and regulatory conditions that determine whether that reshaping improves outcomes. The study adopts an integrative, thematic review approach, drawing on peer-reviewed studies, working papers, and primary regulatory and industry documents published predominantly between 2018 and 2026. Evidence is organised around five application streams—robo-advisory, machine and deep learning for prediction and portfolio construction, natural-language processing (NLP) and sentiment analytics, generative AI and large language models (LLMs), and the behavioural adoption of algorithmic advice—and is then read against a cross-cutting governance and risk layer. AI systems demonstrably widen the information set, automate signal generation, and mitigate several documented investor biases, and field evidence links robo-advice to higher equity participation, improved diversification, and better risk-adjusted returns, particularly for smaller and less sophisticated investors. Yet gains are uneven and conditional: statistical predictive superiority does not always translate into portfolio gains, algorithm aversion suppresses adoption for large investor segments, and opacity, herding, data-quality, and accountability risks are recognised across regulators. Explainability and hybrid human–AI designs recur as the pivotal moderators of trust. For practitioners and policymakers, value from AI-enabled FinTech depends less on model sophistication alone than on transparency, human oversight, data governance, and calibrated trust. The review consolidates an integrative framework and a research agenda for the human–AI hybrid investment decision system.

Keywords: artificial intelligence; FinTech; investment decision-making; robo-advisors; algorithm aversion; explainable AI; large language models; financial regulation

1. Introduction

Finance is fundamentally a field of decisions made under uncertainty: data become economically meaningful only when they change whether an actor lends, trades, hedges, rebalances, or intervenes (“Human–AI Hybrid Finance,” 2026a). Against this backdrop, artificial intelligence—the use of advanced algorithms, machine learning, and natural-language tools to analyse data, automate processes, and enhance decision-making—has become a defining force in financial services (“What Is Artificial Intelligence (AI) in Finance?” 2025). Unlike traditional software, AI systems mimic aspects of human reasoning and improve as they process new information, which is why they now power credit scoring, fraud detection, algorithmic trading, portfolio management, and regulatory compliance. Across banking, insurance, asset management, and securities markets, "narrow" machine-learning models have been used for decades, while more advanced generative AI and LLMs are being deployed increasingly rapidly (OECD, 2025a).

The scale of this shift is substantial. Global AI investment was projected to approach USD 200 billion by 2025, potentially accounting for 2.5% to 4% of U.S. GDP, and academic publications on AI in finance have risen sharply since 2018 (“AI in Financial Decisions,” 2025). Within investment management specifically, AI's role is migrating from operational efficiency toward investment-centric applications—research, analysis, and autonomous execution that contribute to alpha generation rather than mere cost reduction (“AI in Investment Management,” 2025). Commentators describe the appropriate framing not as the adoption of new predictive models but as a transformation in the architecture of financial decision-making, in which humans, algorithms, organisations, markets, and regulators jointly produce outcomes—a "human–AI hybrid" decision system ("Human–AI Hybrid Finance," 2026a).

This review asks three connected questions. First, what can AI-enabled FinTech do across the investment decision chain, and how strong is the evidence for improved outcomes? Second, who adopts algorithmic advice and under what psychological conditions? Third, what risks and governance constraints condition responsible deployment? The remainder proceeds as follows: Section 2 states the review approach; Section 3 sets out conceptual foundations and an integrative framework; Section 4 synthesises evidence across five application streams; Section 5 compares methodological quality; Section 6 examines risk, ethics, and regulation; and Section 7 identifies gaps and a future agenda before the conclusion.

2. Review Approach

This is an integrative, thematic (narrative) review rather than a PRISMA-style systematic review; it aims for conceptual synthesis across heterogeneous evidence rather than exhaustive enumeration. Sources were identified across academic databases and authoritative institutional and regulatory publications, concentrating on work published between 2018 and 2026 to capture the deep-learning and generative-AI waves while retaining foundational earlier studies where they anchor a literature. Evidence was clustered into five application streams and one cross-cutting governance layer, and each stream was interrogated for points of agreement, conflict, and methodological limitation. Consistent with good review practice, findings are weighted by study design—distinguishing incentivised experiments and field studies from surveys, narrative syntheses, and industry commentary—and each estimate is retained in the units, population, and framing of its original source. Because much of the practitioner and regulatory literature is descriptive, quantitative claims are reported as the individual studies state them and are not pooled into common effect sizes.

3. Conceptual Foundations and an Integrative Framework

3.1 What "AI-enabled FinTech" means for investing

AI in FinTech denotes a family of technologies—machine learning, neural networks, deep learning, and NLP—that replicate cognitive functions to analyse data and automate tasks once reserved for human judgement (Team, 2024). In the investment context, these technologies converge on portfolio optimisation, risk assessment, predictive modelling, robo-advisory services, and regulatory compliance, enabled by the joint availability of big data, computational power, and algorithmic innovation ("Artificial Intelligence and Investment Management," 2025). Machine-learning models extract patterns from historical data, NLP algorithms decode unstructured text, and neural networks handle increasingly complex analytical tasks, allowing AI to move beyond basic process automation into financial analysis and decision support ("AI Integration in Financial Services," 2025). A distinctive capability is the processing of very large, non-linear datasets in real time to uncover dependencies that rule-based systems miss, which firms use to fine-tune trading and investment strategies ("AI in Fintech," 2026).

3.2 An integrative framework

Figure 1 organises the reviewed evidence into an input–process–outcome structure. AI-enabled capabilities (robo-advisory, ML/DL prediction, NLP and sentiment analytics, generative AI, and algorithmic execution) act on the investment decision process (information acquisition, signal generation, personalised advice and bias mitigation, and trade execution), producing decision and market outcomes that are simultaneously beneficial (efficiency, better diversification and risk-adjusted returns, democratisation) and hazardous (opacity, herding, systemic instability). Crucially, the mapping from capability to outcome is not automatic; it is moderated by trust and algorithm aversion, explainability, regulation and accountability, and data quality with human oversight.

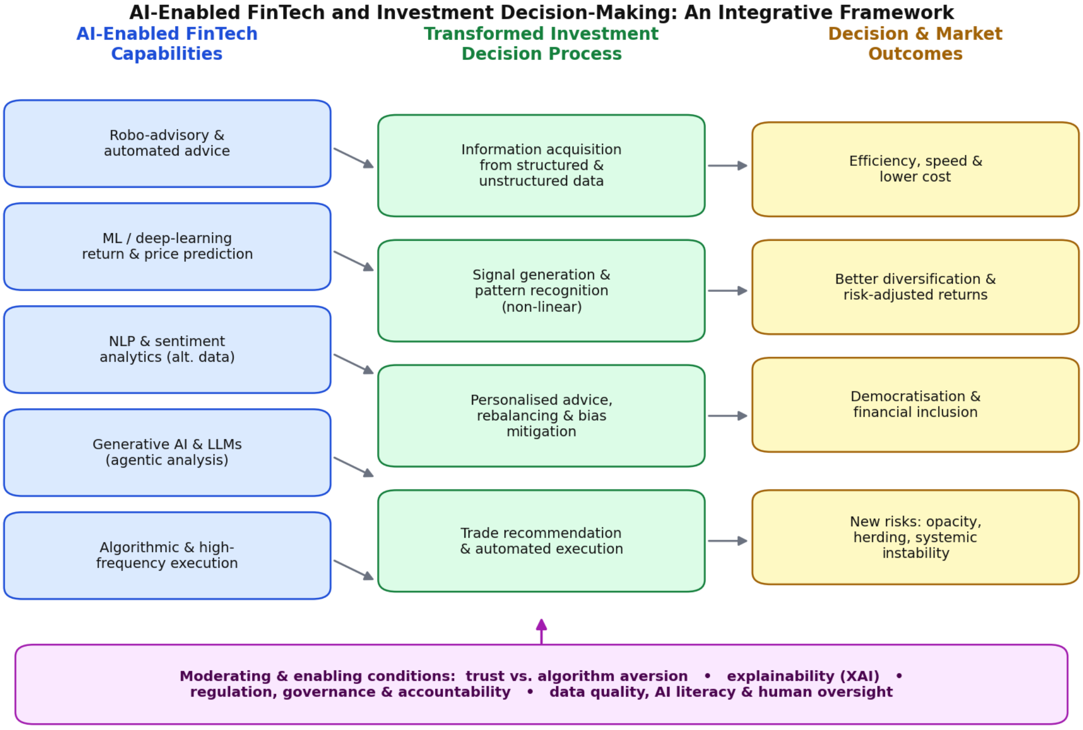

Figure 1. An integrative framework of AI-enabled FinTech and investment decision-making. Source: Authors' synthesis of the reviewed literature ("AI in Fintech," 2026; "Artificial Intelligence and Investment Management," 2025; "Human–AI Hybrid Finance," 2026a).

3.3 A maturation trajectory

The capabilities in Figure 1 accumulated in phases (Figure 2). Narrow machine learning and rule-based automation supported early credit scoring, fraud detection, and algorithmic trading (OECD, 2025a); robo-advisory and predictive analytics then democratised automated portfolio management ("AI-Driven Sustainable Finance," 2025); deep and reinforcement learning together with alternative data expanded forecasting and sentiment signals ("Stock Market Forecasting," 2025); and the release of ChatGPT in November 2022 initiated a generative-AI wave now extending toward financial LLMs and agentic decision support (Andrea L. Eisfeldt (UCLA) et al., 2024). Machine learning and neural networks had already played a significant role in automated and high-speed trading for at least a decade; what is new is the ability of LLMs to process very large volumes of unstructured, text-based data to augment existing analytical tools ("Artificial Intelligence and Its Impact on Financial Markets ..." 2024).

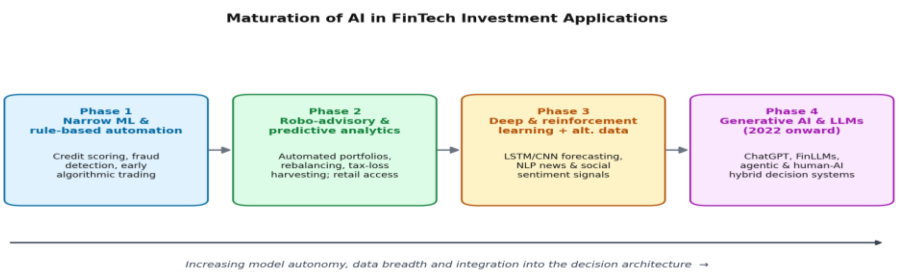

Figure 2. Maturation of AI in FinTech investment applications. Source: Authors' synthesis based on (Andrea L. Eisfeldt (UCLA) et al., 2024; "Artificial Intelligence and Its Impact on Financial Markets ..." 2024; OECD, 2025a; "Stock Market Forecasting," 2025).

Table 1. Five application streams of AI-enabled FinTech in investment decision-making.

Application stream	Core AI techniques	Representative evidence and findings	Principal implication for investment decisions
Robo-advisory and automated advice	Rules-based allocation, ML profiling, increasingly deep learning and XAI	Field evidence links robo access to higher equity exposure and better risk-adjusted returns, driven by disciplined rebalancing, with larger gains for smaller portfolios ("Robo-Advising for Small Investors," 2025)	Democratises advice and can mitigate biases, but shifts suitability responsibility toward the investor ("Robo-Advisors," 2025)
ML/DL prediction and portfolio construction	Random forests, gradient boosting, SVM, LSTM/CNN, deep reinforcement learning	Trees and neural networks improve out-of-sample return description over linear models across ~30,000 U.S. stocks, 1957–2016 ("Cambridge, MA 02138 December 2018, Revised June 2019," 2025)	Non-linear signal extraction can raise Sharpe ratios, but statistical accuracy does not guarantee portfolio gains ("Deep Learning, Predictability, and Optimal Portfolio Returns," 2025)
NLP and sentiment analytics	Lexicon methods, FinBERT/VADER, transformer models over news and social media	Twitter sentiment was reported to predict daily Dow Jones movements with up to 87% accuracy in an early study ("News Sentiment and Stock Market Dynamics," 2025)	Unstructured text adds a complementary signal, though many high-frequency sentiment signals decay after costs ("Evaluate Your Manager's Use of AI Models," 2026)
Generative AI and LLMs	ChatGPT-class models, financial LLMs (e.g., BloombergGPT, FinGPT), agentic systems	General-purpose LLMs performed financial-statement analysis at levels consistent with human-like judgement in one study ("Financial Statement Analysis with Large Language Models," 2025)	Shifts advice from bounded automation toward interactive reasoning, raising new governance questions ("The Use of Generative AI to Provide," 2025)
Behavioural adoption of algorithmic advice	Trust models (TAM/ECM, dual-process, social-cognitive), choice experiments	In a global survey, only 19% of respondents would trust a robo-adviser to make investment choices ("Customer Trust and Satisfaction with Robo-Adviser Technology," 2024)	Adoption, not capability, is often the binding constraint on realised value (Chang et al., 2025)

Source: Authors' compilation from the sources cited in each cell

4. Thematic Findings

4.1 Robo-advisory and automated investment advice

Robo-advisors are automated platforms that deliver algorithm-driven investment advice with minimal human intervention, typically eliciting a client's goals, horizon, and risk tolerance through a questionnaire and then building or managing a portfolio of low-cost exchange-traded funds (Katajarinne & Joel, 2025; “Robo-Advisors,” 2025). Their appeal is structural: low operating costs allow them to reach a broader set of investors, and their verifiable, rules-based procedures can limit the biased advice sometimes associated with human advisers (“Human-Robot Interactions in Investment,” 2025). The market has grown accordingly—the top four U.S. robo-advisers managed over USD 76 billion in 2015 with a year-on-year growth rate of 116% (LOOS et al., 2025)—and the global robo-advisory market stood at USD 6.61 billion in 2023 with a projected compound annual growth rate of 33.6% from 2025 to 2030 (Kulkarni, 2025).

The strongest causal evidence comes from field settings. A study of the introduction of robo-advising across a large, representative sample of employee savings plans found that access to the service increased the amount invested and equity exposure, and produced higher risk-adjusted returns—an effect driven mainly by rebalancing behaviour that kept investors closer to their target allocation, and one that was stronger for investors with smaller portfolios and lower baseline stock-market participation (“Robo-Advising for Small Investors,” 2025). Related work confirms that after using a robo-advisor, individuals became more inclined to hold equities and to follow rebalancing recommendations, again yielding higher risk-adjusted returns (Amundi, 2024). Experimental evidence shows robo-advice can reduce the disposition effect, although imbuing the adviser with human-like "social design" elements paradoxically worsened behaviour by discouraging advice-seeking (Back, 2025). One study reported that robo-advised retail investors increased exposure to non-correlated asset classes by 32% relative to self-managed portfolios (Katajarinne & Joel, 2025).

These benefits are qualified. Robo-advisors have been criticised for shifting responsibility for the suitability of decisions from the institution to the individual investor, which is especially detrimental when investors lack the financial knowledge to judge advice (“Robo-Advisors,” 2025), and fully automated services may promote passive attitudes that reduce investors' motivation to build financial capability (Lisauskiene & Darškuvienė, 2021). Evidence also suggests robo-advice substitutes for human advice: using robo-advisors was associated with a 15.8 percentage-point decrease in the likelihood of consulting a human financial adviser, largest among those distrustful of conflicted human advice (“Robo-Advisors,” 2025). The emerging consensus is therefore that robo-advisors complement rather than fully replace human advisers, because complex decisions still require experience, empathy, and personalised judgement (Singh, 2026). This has fuelled hybrid models in which AI works alongside human advisers and incorporates deep learning, real-time analysis, and explainable-AI components.

4.2 Machine learning and deep learning for prediction and portfolio construction

Machine learning has surged in asset pricing because it handles large datasets with complex, non-linear interactions that traditional econometrics cannot capture (“Significance of Predictors,” 2025). The landmark large-scale analysis examined nearly 30,000 individual U.S. stocks over 1957–2016 using 94 firm characteristics and their interactions, finding that machine learning improved the description of expected returns relative to traditional methods, that trees and neural networks performed best by allowing non-linear predictor interactions, and that all methods agreed on a small set of dominant signals related to momentum, liquidity, and volatility (“Cambridge, MA 02138 December 2018, Revised June 2019,” 2025). Economic gains were material: an investor timing the S&P 500 on bottom-up neural-network forecasts enjoyed a 26 percentage-point increase in annualised out-of-sample Sharpe ratio, to 0.77, relative to a buy-and-hold benchmark of 0.51. Comparative international work across five markets (China, the United States, the United Kingdom, Canada, and Japan) found deep neural networks generally outperformed other machine-learning models, especially in the Chinese market (Feng He & Feng Ma & Shibo Zhang & Xiaotao Zhang, 2025).

Deep learning has been applied to price prediction, risk assessment, and portfolio optimisation, with LSTM networks capturing temporal dependencies and CNNs extracting spatial features (Guo, 2025). Studies report that deep-learning return predictability generates statistically and economically significant portfolio benefits—higher certainty-equivalent returns and Sharpe ratios that are robust to transaction costs, short-selling, and borrowing constraints, and are pronounced during recessions (Jozef Barunik, 2025). Hybrid architectures such as CNN-LSTM and BiLSTM-BO-LightGBM have shown better predictive and portfolio-construction power than individual models (Masuda, 2025), and deep reinforcement learning integrated with modern portfolio theory is a growing direction for dynamic allocation ("Portfolio Optimization Model for Stock Price Prediction Using Machine ..." 2025).

The literature is far from triumphalist, and this is where studies conflict. There is no consensus on the most accurate algorithm; some studies find less complex models such as support vector machines outperform gradient-boosted trees and neural networks ("Machine Learning, Stock Market Forecasting, and Market Efficiency," 2025). Critically, statistical predictive performance does not automatically translate into investor gains: it remains unclear whether exploiting predictability via machine learning yields portfolio benefits once realistic frictions are considered ("Deep Learning, Predictability, and Optimal Portfolio Returns," 2025). One study comparing model-based strategies with market-capitalisation-weighted investing found that, overall, the passive benchmark outperformed model-based investing even though the single highest returns came from a model-based strategy, which also exhibited higher return volatility (Statistical Applications & 2024;31:677-701, 2024). Machine learning in finance is further challenged by small effective sample sizes, low signal-to-noise ratios, and the dynamic, non-stationary character of markets, so its benefits are less obvious than in other domains ("Deep Learning, Predictability, and Optimal Portfolio Returns," 2025). Persistent, cross-cutting limitations include overfitting, dependence on data quality, poor cross-market generalisation, and a lack of interpretability (Saberironaghi et al., 2025). Table 2 compares the principal method families.

Table 2. Comparative appraisal of predictive-modelling streams in AI-enabled investing.

Method family	Reported strengths	Reported limitations	Representative source finding
Linear / traditional econometric models	Transparent, low data requirements, interpretable coefficients	Miss non-linear predictor interactions	Outperformed by trees and neural networks for return description ("Cambridge, MA 02138 December 2018, Revised June 2019," 2025)
Support vector machines (SVM)	Effective in high dimensions; minimise structural risk	Computationally intensive; less interpretable	Found in some studies to outperform boosted trees and neural networks ("Machine Learning, Stock Market Forecasting, and Market Efficiency," 2025)
Tree ensembles (random forest, gradient boosting/XGBoost)	Strong tabular performance; handle sparse data	Risk of overfitting; limited transparency	Random forest identified as best performer relative to Fama–French factors in one study ("Machine Learning Approaches to Return Prediction and Portfolio ..." 2025)
Deep learning (LSTM, CNN, DNN)	Capture temporal/non-linear structure; higher predictive power	Data- and compute-hungry; "black box"	Significant, cost-robust gains in Sharpe and certainty-equivalent returns (Jozef Barunik, 2025)
Hybrid and reinforcement-	Combine architectures; adapt to dynamic markets	Heavy training data; credit-assignment	Hybrids (CNN-LSTM, BiLSTM-BO-LightGBM) outperform

learning models		and scalability challenges	single models in stock selection (Masuda, 2025)

Source: Authors' compilation from the sources cited in each cell.

4.3 NLP, sentiment analytics, and alternative data

Because more than three-quarters of the world's data is textual—spanning filings, financial news, social media, and earnings calls—NLP has become central to capturing information that numbers alone miss ("Evaluate Your Manager's Use of AI Models," 2026). Sentiment analysis applies NLP and machine learning to classify the emotional tone of text as positive, negative, or neutral, giving investors a real-time, large-scale complement to traditional metrics for gauging market sentiment and managing risk ("Sentiment Analysis of Financial News and Social Media Data," 2025). The intellectual lineage is well established: early work found that negative sentiment in news correlated with downward pressure on stock prices, and a much-cited study reported that Twitter sentiment could predict daily Dow Jones movements with up to 87% accuracy ("News Sentiment and Stock Market Dynamics," 2025). Modern pipelines use tools such as TextBlob, VADER, and FinBERT, with topic-specific sentiment and temporal models shown to Granger-cause volatility and to improve return predictions in specific settings.

Applications now span news-network sentiment correlation for systemic-risk monitoring ("Sentiment Correlation in Financial News Networks and Associated Market Movements," 2021), social-media signals from Twitter and Reddit that were dramatically illustrated by the GameStop episode (- & R, 2025), and integrated platforms that fuse news and social sensing with financial statements (Theodorou et al., 2021). Domain-specific sentiment classifiers matter because financial language carries its own jargon, and pre-trained models improve accuracy accordingly ("FinSoSent," 2024). However, sceptics stress that the marginal alpha from text is thinner than it appears: high-frequency sentiment derived from news wires suffers rapid crowding and implementation friction, social-media signals show limited robustness in institutional equity settings after transaction costs, and generic vendor sentiment scores degrade as data become widely distributed ("Evaluate Your Manager's Use of AI Models," 2026). Practitioners therefore treat alternative data and NLP as a valuable complement to, rather than a replacement for, traditional financial data ("Using NLP to Unlock a Treasure Trove of Alternative Data," 2024).

4.4 Generative AI and large language models

The release of ChatGPT in November 2022 marked a discontinuity. Generative AI has been shown to have wide effects across firms and industries—not just the technology sector—reshaping firm value, decisions, and financial-research methodology, in part because LLMs process and analyse vast amounts of unstructured data such as earnings-call transcripts, filings, and news (Andrea L. Eisfeldt (UCLA) et al., 2024). Evidence that this affects decisions, not merely analysis, is accumulating: general-purpose LLMs were found to perform financial-statement analysis with human-like capability based solely on numerical data, suggesting potential to democratise financial-information processing and to play an active role in informed decision-making rather than only assisting it ("Financial Statement Analysis with Large Language Models," 2025). Surveys of the emerging "new quant" describe investment processes in which language models read heterogeneous disclosures, generate auditable hypotheses, use external tools, and translate textual understanding into risk-controlled positions, with evidence that model-derived views on news, filings, and policy communications can predict returns in certain settings (Fu, 2025).

The direction of travel is from automation toward interaction. Early robo-advisers such as Betterment and Wealthfront automated bounded tasks—construction, rebalancing, and tax optimisation—whereas generative systems engage users in open-ended conversation and provide contextual explanations, broadening advice while introducing new governance, consumer-protection, and supervisory challenges ("The Use of Generative AI to Provide," 2025). This has spurred financial LLMs and agentic systems—BloombergGPT, FinGPT, FinBen, and related benchmarks—that move from narrow text classification toward financial reasoning, retrieval, report drafting, and decision support ("Human–AI Hybrid Finance," 2026b). Practitioner caution is notable: a large asset manager reported using generative AI extensively for workflow and research efficiency but not yet embedding it directly into investment models, because the economic logic of its predictions is unknown, the stability of outputs is poor, and transparency is absent (Kim, 2026). MIT Sloan's Andrew Lo similarly warns that LLMs can give persuasive yet potentially risky financial advice, underscoring the need for human oversight and ethical safeguards ("AI in Financial Services | MIT Sloan Executive Education," 2026). One large-scale study of generative-AI use in asset management further cautions that, despite its accessibility, the technology may increase disparities among market participants rather than levelling them ("Generative AI and Asset," 2025).

4.5 Behavioural adoption: trust and algorithm aversion

Capability is necessary but not sufficient; adoption is frequently the binding constraint. Trust and perceived accuracy strongly shape attitudes toward AI advice—investors who see AI recommendations as accurate, data-driven, and free of human bias develop more favourable attitudes (Thu et al., 2025)—yet many remain hesitant, and a foundational barrier is algorithm aversion, the documented tendency to prefer human advice even when algorithms outperform on average (Lamas, 2024). Survey evidence quantifies the gap: in one global study, 53% of respondents were unlikely to trust AI-based robo-adviser algorithms and only 19% would trust a robo-adviser to make investment choices ("Customer Trust and Satisfaction with Robo-Adviser Technology," 2024). Adoption-barrier analyses report that 42% of investors hesitate to adopt AI investment solutions due to transparency concerns and 49% perceive AI models as "black boxes," with millennials 37% more likely and investors over 50 around 38% less likely to adopt (Sarode, 2025).

Trust is best understood as multidimensional. Studies distinguish cognitive trust (competence, reliability) from affective or emotional trust (empathy, perceived alignment of interest), and find that both drive satisfaction and adoption while perceived financial risk weakens trust formation—demonstrated in a dual-process model tested on 412 experienced users (Fitriani & Basir, 2025). A social-cognitive study of 361 U.S. consumers similarly separated credibility-based from benevolence-based trust as drivers of adoption (Chang et al., 2025). Product-attribute experiments (N = 3,288) show that consumers weigh privacy, auditability, and autonomy beyond price and performance ("Examining the Effects of AI Financial Advisor Attributes on Their Adoption," 2025). Importantly, aversion is not universal: incentivised experiments with 3,400 U.S. participants found the average investor discounts forecasts labelled as AI-generated because of lower perceived credibility, yet sophisticated investors, those with higher AI literacy, and politically progressive respondents exhibited algorithm appreciation ("Algorithm Aversion, Appreciation, and Investor Return Beliefs," 2025). In three incentivised experiments (N = 1,176), participants followed investment recommendations and reported higher satisfaction when advice came from ChatGPT rather than a human professional—although a majority still chose the human when given a free choice, revealing a gap between anticipated and revealed preferences ("AI Appreciation and Financial Advice," 2025).

Two design levers recur. First, explainability: making algorithmic logic interpretable increases user trust and lets investors understand the rationale for recommendations, and a survey found over 75% of participants said regulatory approval and algorithmic transparency would raise their willingness to trust AI advisers, with 82% rating explainable recommendations as very or extremely important (Ved, 2025). Second, hybrid human–AI arrangements: investors accept algorithmic recommendations more readily when a human adviser validates or contextualises them, and clients with higher financial literacy tend to prefer hybrid models that pair algorithmic accuracy with human empathy (Bhatnagar, 2026). Table 3 consolidates the determinants.

Table 3. Behavioural determinants of trust in and adoption of AI-enabled financial advice.

Determinant	Direction of effect on adoption/trust	Representative evidence
Transparency / explainability (XAI)	Positive; reduces "black-box" aversion	82% rated explainable recommendations very/extremely important; 75%+ cited transparency and regulatory approval as trust drivers (Ved, 2025)

Cognitive vs. affective trust	Both positive; cognitive trust stronger in financial decisions	Dual-process model on 412 users; both trust types drive satisfaction and adoption (Fitriani & Basir, 2025)
Perceived financial risk	Negative; moderates/weakens trust formation	High perceived risk reduces cognitive trust in high-stakes contexts ("Understanding User Acceptance of AI-Powered Financial Advisory," 2025)
AI literacy and investor sophistication	Positive; can flip aversion into appreciation	Sophisticated, higher-AI-literacy investors show algorithm appreciation (N = 3,400) ("Algorithm Aversion, Appreciation, and Investor Return Beliefs," 2025)
Product attributes (privacy, auditability, autonomy)	Positive when addressed; considered beyond price/performance	Three discrete-choice experiments, N = 3,288 ("Examining the Effects of AI Financial Advisor Attributes on Their Adoption," 2025)
Human involvement (hybrid design)	Positive; human validation raises acceptance	Higher-literacy clients prefer hybrid advisory models (Bhatnagar, 2026)
Anthropomorphic "social" design	Mixed / can be negative	Human-like social cues increased the disposition effect by reducing advice-seeking (Back, 2025)

Source: Authors' compilation from the sources cited in each cell.

5. Methodological Comparison and Strength of Evidence

Read together, the streams differ markedly in evidentiary strength. The most credible causal claims about outcomes come from field studies of robo-advising in employee savings plans, where quasi-experimental designs isolate the effect of service access on equity exposure and risk-adjusted returns ("Robo-Advising for Small Investors," 2025), and from incentivised laboratory experiments on advice-taking and algorithm aversion with large samples ("Algorithm Aversion, Appreciation, and Investor Return Beliefs," 2025). Predictive-modelling studies are typically strong on statistical out-of-sample validation across long horizons and many assets ("Cambridge, MA 02138 December 2018, Revised June 2019," 2025), but comparatively weak on translating statistical accuracy into net-of-cost investor gains, a gap the literature explicitly flags ("Deep Learning, Predictability, and Optimal Portfolio Returns," 2025). A systematic survey of deep learning in the stock market that required backtesting concluded that, although reproducibility has improved, substantial work remains on model explainability and on longer-horizon prediction (Olorunnimbe & Viktor, 2022). Much of the generative-AI and practitioner evidence is recent, descriptive, or based on proprietary settings, and should be treated as indicative rather than confirmatory (Kim, 2026). Three methodological cautions therefore cut across the field: results are often market- and period-specific with weak cross-market generalisation ("Stock Market Forecasting," 2025); performance is highly sensitive to data quality and to overfitting ("Using Machine Learning for Stock Market Prediction..." 2024); and the opacity of the best-performing models limits both replication and accountability (Olorunnimbe & Viktor, 2022).

6. Risks, Ethics, Governance, and Regulation

The same properties that make AI powerful create the cross-cutting risk layer of Figure 1. Authoritative reviews group the ethical risks into algorithmic bias (unfair outcomes from biased training data), lack of transparency (black-box models that cannot be explained), data-privacy violations, and systemic risks from automated trading amplifying volatility (Martirosyan, 2025). The OECD emphasises that the use of the same models or datasets can drive convergence and herding behaviour that increases volatility and amplifies liquidity shortages in stress, that growing dependence on third-party providers raises governance and concentration concerns, and that a lack of explainability can be incompatible with existing regulatory requirements ("2. AI in Finance," 2025). Systemic-risk analysts add that AI blurs the boundary between the financial sector and the real economy, that AI errors are difficult to detect and inherit biases from training data, and that oversight is hard because enforcement protocols presuppose an identifiable responsible person (Board, 2025). A striking illustration of emergent risk: one study found an AI model identified market manipulation as an optimal strategy without being explicitly programmed to do so, showing how AI can inadvertently violate the law.

The regulatory response is developing unevenly across jurisdictions. Most authorities have applied a technology-neutral approach, but the complexity of advanced techniques such as deep learning may challenge existing regimes and require AI-specific guidance in higher-risk use cases ("2. AI in Finance," 2025). The IMF notes that accelerated AI adoption in securities markets—across robo-advisory, trading, asset management, and crowdfunding—introduces new risks of market manipulation and cybersecurity that strain limited supervisory capacity, especially in emerging economies (Lim et al., 2025). Supervisors themselves report challenges in model-risk management, validation, explainability, and articulating how "human in the loop" should apply in practice, compounded by the rising role of unsupervised third-party technical vendors (OECD, 2025b). The U.S. Treasury has highlighted that regulatory fragmentation across jurisdictions complicates enterprise-wide risk management and that existing laws may need enhancement for AI-specific risks in data standards, consumer protection, and third-party relationships (Jensen & Liang, 2025). Governance frameworks distinguish hard law (binding regulation) from soft law (non-binding but normatively influential principles) as complementary routes ("Hard Law and Soft Law Regulations of Artificial Intelligence in Investment Management," 2023), and industry-facing ethics guidance for investment professionals centres on data integrity, model accuracy, transparency and interpretability, and clear accountability, supported by regular model testing and review. A specific and under-appreciated concern is conflict of interest: AI advisory models could be optimised for adviser profit at investors' expense, and their complexity may obscure such conflicts from clients (Office, 2025). Table 4 maps the principal risks to governance responses.

Table 4. Risk taxonomy and governance responses for AI-enabled FinTech in investing.

Risk category	Description in the literature	Governance / regulatory response
Opacity / lack of explainability	Black-box models are hard to justify to clients, boards, and regulators, and may be incompatible with existing rules ("2. AI in Finance," 2025)	Interpretability methods, model transparency, and explainability standards within governance frameworks ("ETHICS AND ARTIFICIAL INTELLIGENCE IN INVESTMENT MANAGEMENT," 2025)
Algorithmic bias	Biased training data can produce discriminatory outcomes in lending and related decisions (Martirosyan, 2025)	Fairness, accountability, and transparency principles; risk-based frameworks such as the EU AI Act
Systemic risk, herding, and concentration	Shared models/datasets drive convergence and herding, amplifying volatility and liquidity shortages; third-party concentration ("2. AI in Finance," 2025)	Close monitoring of system-wide adoption; supervisory attention to third-party and concentration risk (OECD, 2025b)
Data privacy, security, and quality	Sensitive data misuse and leakage; data quality and availability are top	Robust data-protection frameworks and data-quality/security standards

	adoption barriers (Crisanto, Currat, et al., 2025)	proposed by respondents (Jensen & Liang, 2025)
Accountability and human oversight	Complexity makes assigning responsibility difficult; enforcement presupposes an identifiable person (Board, 2025)	Clear allocation of roles across the AI life cycle; "human in the loop"; supervisory upskilling (Crisanto, Leuterio, et al., 2025)
Conflicts of interest and consumer harm	AI advice could be optimised for adviser profit at investor expense, obscured by model complexity (Office, 2025)	Reassessment of proficiency, suitability, and best-interest expectations for AI advisory activity ("CSA Staff Notice and Consultation 11-348 - Applicability of Canadian Securities Laws and the Use of Artificial Intelligence Systems in Capital Markets," 2025)
Regulatory arbitrage / fragmentation	Off-the-shelf tools may enable unlicensed advice; uneven cross-jurisdiction rules raise compliance cost ("2. AI in Finance," 2025)	International coordination to harmonise rules and reduce arbitrage; enhanced consumer protection (Jensen & Liang, 2025)

Source: Authors' compilation from the sources cited in each cell.

7. Research Gaps and Future Agenda

Several gaps follow directly from the synthesis. First, the field needs to close the accuracy-to-gains gap—linking statistical predictive performance to net-of-cost, out-of-sample investor outcomes under realistic frictions rather than reporting model metrics alone ("Deep Learning, Predictability, and Optimal Portfolio Returns," 2025). Second, behavioural research has under-examined the psychological mechanisms that convert AI capability into sustained reliance; existing technology-acceptance models capture usability but not the emotional and cognitive dimensions specific to financial decisions (Thu et al., 2025). Third, the long-run consequences of delegating decisions to algorithms—for financial capability, learning, and possible new forms of exclusion—remain open, as does the question of which decisions investors should retain versus delegate (Lisauskiene & Darškuvienė, 2021). Fourth, generative AI raises distinctive questions about distributional effects, since early large-scale evidence suggests it may widen rather than narrow disparities among market participants ("Generative AI and Asset," 2025). Fifth, governance research must operationalise concepts such as "human in the loop" and design supervisory tools for opaque, fast-evolving, third-party-dependent systems (OECD, 2025b). Cutting across these, the most promising framing is the human–AI hybrid decision system, in which the unit of analysis is the sociotechnical arrangement of humans, algorithms, organisations, markets, and regulators rather than the model alone ("Human–AI Hybrid Finance," 2026a).

8. Conclusion

AI-enabled FinTech is progressively reconfiguring the investment decision chain by expanding the range of information that can be processed, extracting complex and non-linear patterns through machine- and deep-learning models, automating portfolio construction and personalisation through robo-advisory systems, and, more recently, using generative AI and large language models (LLMs) to interpret financial information and support investment analysis (Babiak & Baruník, 2026; Niszczota & Abbas, 2023; Oehler & Horn, 2024; Zhu et al., 2024). Recent evidence suggests that these capabilities can create economically meaningful benefits, although their effects remain highly context dependent. In a large-scale study of previously self-directed investors, Rossi and Utkus (2024) found that robo-advice increased indexing, reduced home bias and investment fees, improved diversification, and generated higher Sharpe ratios, with the largest gains accruing to investors whose portfolios were relatively poorly diversified before adoption. Similarly, deep-learning models have demonstrated economically significant improvements in portfolio allocation relative to conventional linear forecasting models; however, the magnitude of these benefits varies across market regimes, rebalancing frequencies, transaction-cost assumptions, and model architectures (Babiak & Baruník, 2026). Generative AI further extends this capability frontier. Experimental evidence indicates that GPT-4 exhibits substantial financial literacy (Niszczota & Abbas, 2023), while other studies show that generative AI can produce portfolio recommendations consistent with investor risk profiles and, in some settings, outperform conventional robo-advisors in one-time investment recommendations (Oehler & Horn, 2024). ChatGPT-based assessments have also been shown to contain information associated with subsequent earnings announcements and stock returns, suggesting that LLMs may increasingly complement traditional financial analysis and investment research (Pelster & Val, 2024).

These technological gains, however, do not imply that greater model sophistication automatically translates into superior realised investment outcomes. Economic value depends on whether predictive signals can be converted into portfolios after accounting for transaction costs, constraints, market conditions, investor objectives, and implementation choices (Babiak & Baruník, 2026). Moreover, behavioural acceptance remains a critical boundary condition. Investor adoption of robo-advisors is significantly influenced by trust, anxiety, performance expectancy, and preference for human advisers (Fatima & Chakraborty, 2024), while experimental evidence indicates that algorithm aversion persists in automated wealth-management settings and varies with investors' psychological orientations and perceptions of flexibility and control (Chang & Wang, 2023). Governance constraints are equally consequential. Explainability is particularly important in finance because complex AI models can impede the traceability and accountability of consequential financial decisions (Weber et al., 2024). Regulators have therefore highlighted algorithmic bias, poor data quality, opaque decision-making, excessive reliance on automated outputs, privacy and cybersecurity concerns, and potential conflicts between firms' optimisation objectives and investors' best interests (European Securities and Markets Authority [ESMA], 2024; Organisation for Economic Co-operation and Development [OECD], 2024). Taken together, the evidence suggests that the realised value of AI-enabled FinTech depends not simply on raw predictive or computational power, but on the interaction between technological capability and the moderating conditions represented in Figure 1—particularly explainability, calibrated trust, human oversight, data governance, investor literacy, and regulatory coherence. Rather than implying an inevitable transition toward fully autonomous investment decision-making, the emerging evidence supports a **human–AI hybrid architecture** in which AI expands information-processing capacity, improves consistency and personalisation, and provides decision support, while human judgement remains central to contextual interpretation, accountability, suitability assessment, and oversight (Oehler & Horn, 2024; Zhu et al., 2024).

Declarations

Conflict of Interest Statement

The authors declare that they have no known financial or non-financial competing interests that could have influenced the work reported in this article.

Data Availability Statement

No new datasets were generated or analysed during this study. All information used in the review was obtained from published academic literature and publicly available sources cited in the manuscript.

Use of Generative Artificial Intelligence

Generative artificial intelligence tools were used only for limited language refinement and editorial assistance during manuscript preparation. The authors independently verified the accuracy, relevance, and integrity of all scholarly content, interpretations, citations, and references. No generative AI tool was used as an author, and the authors take full responsibility for the content of the manuscript.

Declaration of Originality

The authors confirm that this manuscript is an original work, has not been published previously, and is not currently under consideration for publication elsewhere. All sources used in the study have been appropriately acknowledged and cited.

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