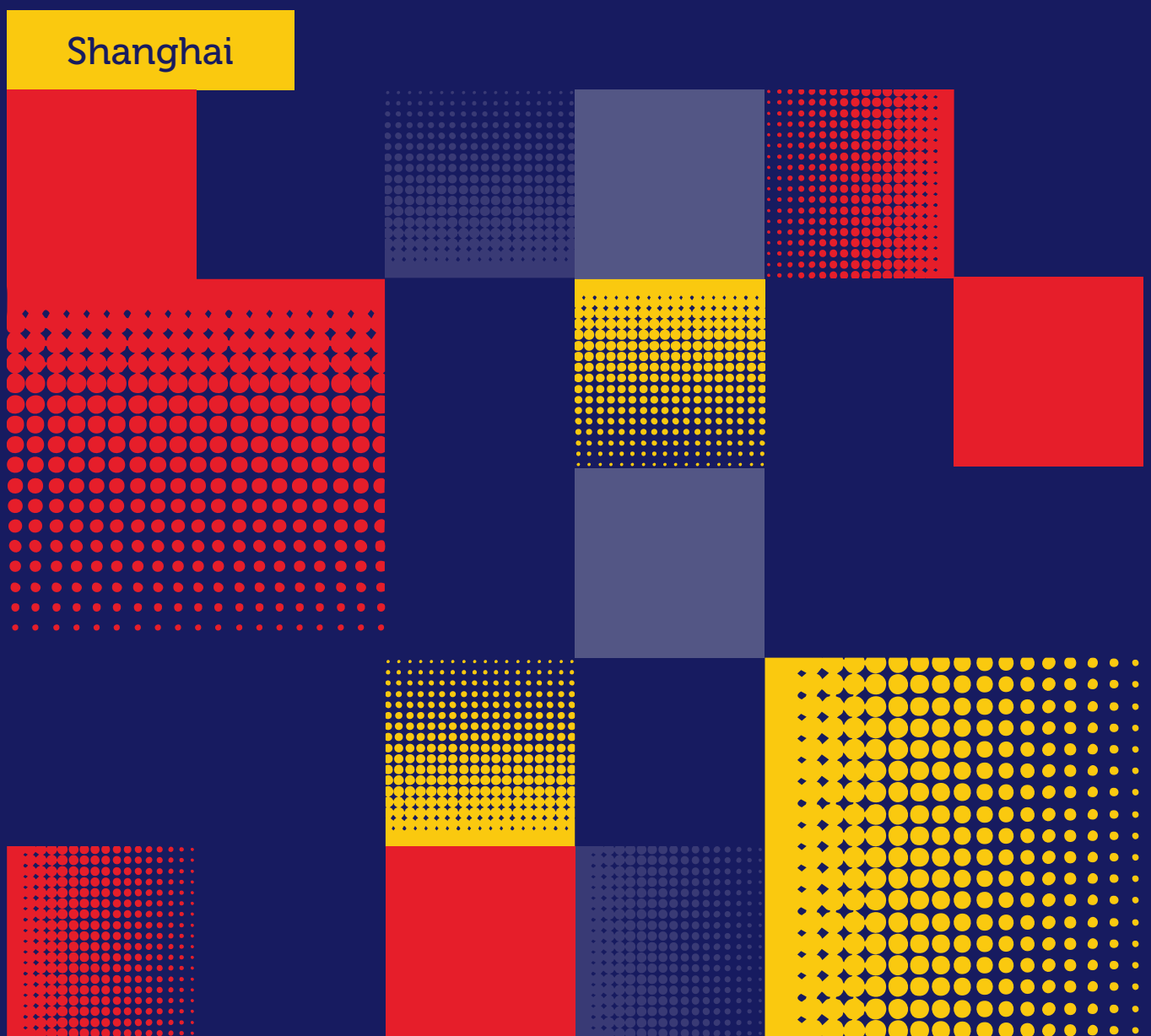


Future Ready Business Series 2025

The Future of AI-Powered Investing

Shanghai





About the series



Through the Future Ready Business Series, RMIT's College of Business and Law connects local business leaders with its growing Alumni community. The program provides a platform to network, exchange knowledge, and learn from global experts in business, technology, and social impact.

Launched in 2020 to provide the RMIT alumni business community with practical advice to respond to the challenges created by the pandemic, the "Business Transformation in Challenging Times" webinar series attracted alumni from across the globe, including Australia, Spain, Vietnam, and Singapore.

The series was rebranded as the *Future Ready Business Series* in 2022 and provides the global alumni network, business leaders and local government bodies with valuable insights into emerging business trends and the evolving global marketplace through in-person events.

Since its inception, there have been 33 initiatives in this series, held in Australia, Vietnam, Singapore, India, China, and Indonesia.

As part of the Future Ready Business Series, RMIT's College of Business and Law convened leaders from academia, industry, and policy to examine a pivotal question:

How is artificial intelligence reshaping the future of investing?

Artificial Intelligence (AI) and Machine Learning (ML) are reshaping the foundations of modern finance. What began as a set of experimental models is now a powerful toolkit for forecasting risk, optimising portfolios, and holding companies accountable for their claims. From credit default prediction to Environment, Social and Governance (ESG) monitoring, AI-driven insights are influencing how capital is allocated and how markets respond.

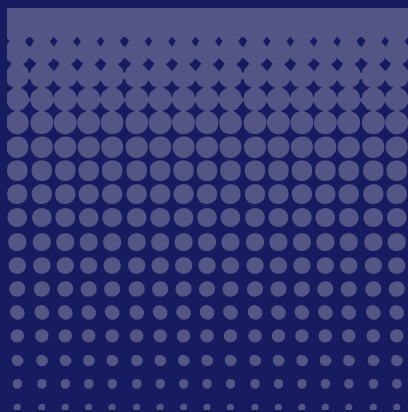
Yet the reality of its use showcases the complexities of adoption. On one hand, machine learning models can detect patterns across vast and complex datasets, offering investors unprecedented predictive power. On the other hand, the rise of opaque “black-box” systems, uneven access to advanced tools, and tightening data privacy regimes demand careful governance.

The financial sector sits at the centre of this transformation. As capital flows increasingly rely on algorithmic insights, questions of transparency, equity, and accountability grow more urgent. The future of investing will be defined by how businesses, regulators, and universities shape the principles and practices that govern its use.



Key Takeaways

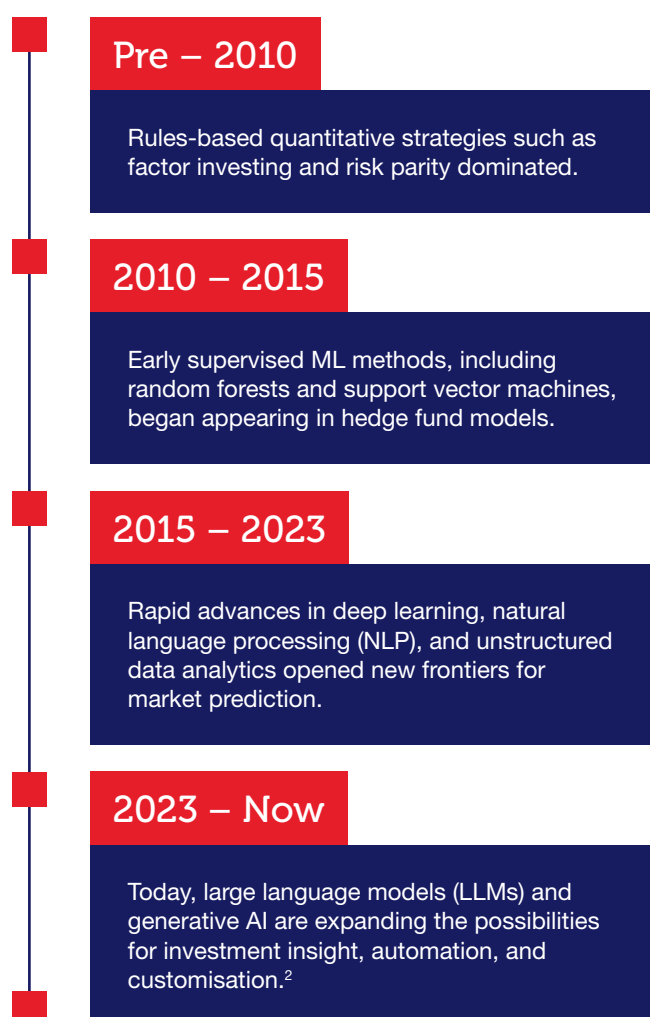
- AI is expanding the frontiers of financial insight. ML is moving beyond experiments to deliver robust forecasts, richer analysis, and more responsive decision-making across asset classes.
- New data sources are unlocking broader perspectives where AI enables investors to capture dimensions of market behaviour previously hidden from view.
- Far from only serving profit, AI is being applied to detect greenwashing, benchmark disclosures, and support more responsible corporate behaviour.
- Global standards are emerging to build trust. Policymakers, industry associations, and regulators are laying the foundations for explainability, fairness, and responsible innovation in financial AI.
- Businesses, universities, and governments each play a distinct role in ensuring that AI augments human judgment, enhances equity, and strengthens market confidence.



The Evolution of Financial AI

AI mimics human intelligence to improve decision-making and prediction, while ML applies data-driven algorithms that learn and adapt over time. In practice, this means tools that can forecast defaults, detect fraud, optimise portfolios, or identify trading signals from data sources too vast or complex for human analysis alone.¹

Over the past two decades, AI adoption in investment has followed a clear trajectory.



Academic studies confirm this trajectory. ML models can outperform traditional methods in predicting U.S. stock returns, understanding the Chinese equity market, and even enhance short-term forecasts using high-frequency trading data. Together, these studies point to a consistent pattern: machine learning delivers higher predictive accuracy and stronger returns when compared to conventional approaches.

In large, liquid markets, non-linear algorithms have been shown to capture complex interactions among fundamental and market variables, delivering more accurate forecasts and stronger portfolio performance than traditional linear techniques.³ The flexibility of these models allows them to uncover predictive relationships that standard regression methods overlook, offering investors a competitive edge in building long-short strategies and risk-adjusted returns.

Evidence from emerging and high-frequency markets reinforces this advantage. In China, predictive signals rooted in liquidity and investor composition highlight how market microstructure can shape model performance.⁴ At the millisecond level, sparse modelling approaches demonstrate that even short-lived patterns in noisy trading data can be harnessed to improve out-of-sample fit and risk-adjusted gains.⁵

It is reasonable to believe that the degree of technical acceleration is not without its downsides. As regulatory frameworks are tightening, structural imbalances are evident. The significant investment needed to acquire proprietary datasets, build infrastructure, and attract specialised talent means that advanced AI capabilities remain concentrated among large institutions, require significant energy resourcing, and raise concerns about equity and access across markets.

1 Hu X (2025) Keynote address: In the new age of investment – The application of AI in finance. RMIT College of Business and Law. Transcript provided.

2 Ibid.

3 Gu S, Kelly B, Xiu D (2020) Empirical Asset Pricing via Machine Learning. *Review of Financial Studies* 33(5): 2223–2273. <https://academic.oup.com/rfs/article/33/5/2223/5758276>

4 Leippold M, Wang Q, Zhou W (2022) Machine-Learning in the Chinese Factor Zoo. *Journal of Financial Economics* 145(2): 64–82. https://www.researchgate.net/publication/349474718_Machine-Learning_in_the_Chinese_Factor_Zoo

5 Chincio A, Clark-Joseph AD, Ye M (2019) Sparse Signals in the Cross-Section of Returns. *Journal of Finance* 74(1): 449–492. <https://onlinelibrary.wiley.com/doi/10.1111/jofi.12733>



AI as a Market Intelligence Amplifier

From prediction to pattern recognition

AI is redefining how markets are analysed and investment opportunities are identified. In the Chinese corporate bond market, one of the world's most opaque and fragmented, ML models can significantly outperform traditional benchmarks in forecasting bond returns.⁶ By capturing subtle, nonlinear patterns in issuer and bond characteristics, these models reveal relationships that conventional approaches easily miss.

The rise of ML has shifted investment analysis from rule-based prediction toward sophisticated pattern recognition. Traditional quantitative models rely on linear relationships and predefined factors such as value, momentum, or volatility to forecast returns. While effective in stable environments, these approaches often miss the nonlinear interactions and subtle dynamics that shape markets under stress or in fragmented settings.

ML models can map hidden connections among credit quality, liquidity, and pricing anomalies that may elude human analysts. Similar advances have been demonstrated in equity markets, where models trained on financial fundamentals, momentum indicators, and risk exposures identify predictive signals overlooked or oversimplified by standard factor models.⁷ The advantage lies in ML's flexibility in accommodating complexity. In practice, this

means they can capture shifts in investor sentiment, detect fleeting arbitrage opportunities, or flag risks building under the surface.

Crucially, this does not imply that algorithms replace the need for financial expertise. Forecasts derived from ML remain probabilistic and require interpretation in context. What these tools provide is an extension of analytical vision, surfacing weak, nonlinear, or short-lived signals that would otherwise remain hidden. By augmenting rather than substituting human judgment, ML offers investors the possibility of more robust forecasts, better risk control, and a more nuanced understanding of market drivers.⁸

6 Hu X (2025) Keynote address: In the new age of investment – The application of AI in finance. RMIT College of Business and Law. Transcript provided.

7 Ibid.

8 Gu S, Kelly B, Xiu D (2020) Empirical Asset Pricing via Machine Learning. *Review of Financial Studies* 33(5): 2223–2273.



Scaling market intelligence in practice

The momentum behind AI in finance is already reshaping how some of the world's largest institutions operate. Leading asset managers and hedge funds are embedding machine learning and alternative data into their core systems, demonstrating what large-scale adoption looks like in practice. The following examples highlight how different players are applying AI to portfolio optimisation, sentiment analysis, and the integration of alternative data.

Case Study 1:

BlackRock – The Aladdin Platform

Aladdin, BlackRock's flagship investment management system, operates as a comprehensive "operating system" for asset managers, integrating portfolio construction, risk management, and scenario analysis across asset classes. It handles over US \$21 trillion in assets and is continuously enhanced with AI capabilities, most recently through the "Aladdin Copilot," a generative-AI assistant that surfaces insights instantly within the platform.⁹

Case Study 2:

JPMorgan – AI-Driven Sentiment & LLM Tools

JPMorgan has embedded AI deeply into its investment workflows. Its Spectrum platform includes tools like Smart Monitor, which scans data to surface insights, and Moneyball, which flags behavioural biases. Across 200,000 employees, the firm operates over 400 AI use cases, saving research time by 83% and delivering nearly US \$1.5 billion in benefits. Generative AI tools are also being embedded in email drafting and document summarisation, demonstrating a systemic transformation.¹⁰

Case Study 3:

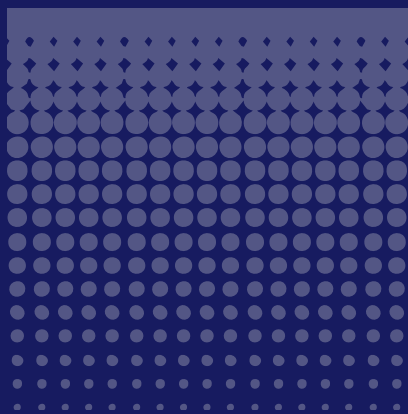
Two Sigma – Alternative Data at Scale

Two Sigma has built its reputation on treating data science as the foundation of its investment strategy. The firm's investment management process systematically draws on more than 10,000 structured and unstructured datasets, spanning traditional market indicators as well as alternative sources such as satellite imagery, consumer transactions, and web activity. These diverse inputs are transformed into predictive features through rigorous modelling pipelines, giving portfolio managers signals that conventional analysis often misses. Two Sigma demonstrates how scale, scientific rigour, and technology can be combined to create a durable competitive advantage in financial markets.¹¹

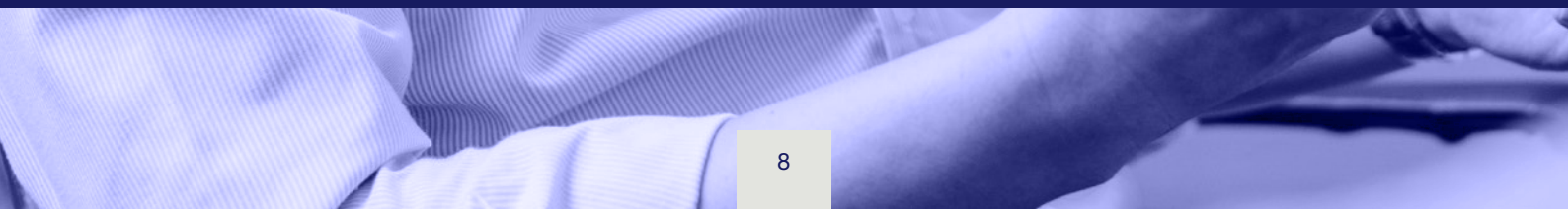
9 Microsoft (2024) Elevating investment management tech: AI-powered leadership from BlackRock and Microsoft. Microsoft Industry Blogs, 30 September 2024, accessed 25 August 2025, <https://www.microsoft.com/en-us/industry/blog/financial-services/2024/09/30/elevating-investment-management-tech-ai-powered-leadership-from-blackrock-and-microsoft/>

10 Reuters (2025) JPMorgan says AI helped boost sales, add clients in market turmoil. 5 May 2025, accessed 25 August 2025, <https://www.reuters.com/business/finance/jpmorgan-says-ai-helped-boost-sales-add-clients-market-turmoil-2025-05-05/>

11 Two Sigma (n.d.) Investment Management. Accessed 25 August 2025, <https://www.twosigma.com/businesses/investment-management>



Perception as a Market Driver



Measuring market sentiment

Financial markets are shaped as much by perception as by fundamentals. Investor sentiment, often shaped by perception and narrative, plays a decisive role in how prices move. Traditional methods of capturing sentiment, such as surveys or textual analysis of news reports, have long been used by behavioural economists. But AI is extending this frontier by quantifying the subtler cues that influence human decision-making.

Recent advances in computer vision illustrate the scale of this shift. By applying convolutional neural networks (CNNs) to thousands of financial news images, researchers have demonstrated that the emotional tone conveyed in photographs — fear, optimism, and uncertainty — can have a measurable impact on subsequent stock returns.¹² This suggests that market participants are influenced not just by what they read but also by what they see, even when those visual cues are processed subconsciously. When aggregated, these micro-level reactions compound into patterns visible in asset pricing and volatility.

The importance of this lies in its corrective potential. Whereas fundamentals-based models may fail to explain price swings during periods of heightened uncertainty, sentiment models offer additional explanatory power. They make visible the non-rational drivers of markets and provide investors with new tools to anticipate behaviour-driven dislocations. In practice, this enables more resilient portfolio management, as models that incorporate sentiment can capture shifts earlier than those reliant solely on financial metrics.

Broader applications of perception analysis

The use of image-based AI in finance is part of a broader movement toward extracting insights from unconventional data. CNNs were initially developed for tasks such as photo recognition and classification.¹³ They are now applied far beyond finance: to map rooftop solar installations, locate slave camps in conflict zones, and estimate poverty levels in underdeveloped regions using satellite imagery. These examples demonstrate the power of AI to decode visual information at scale, turning images into structured signals that can inform decision-making.

In capital markets, the implications are significant. Satellite images tracking retail car parks, shipping lanes, or crop growth can be used to predict company earnings or commodity price movements. Public images of climate events or infrastructure projects can become inputs for models assessing ESG risk. When combined with textual sentiment analysis, image recognition offers a multidimensional view of perception and behaviour.

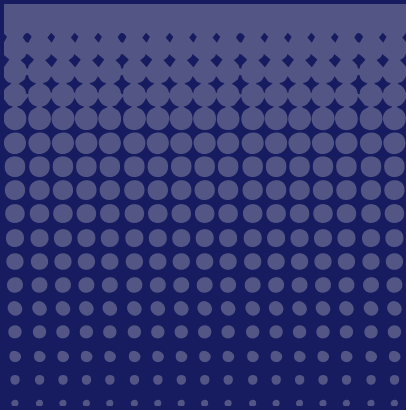
The private sector is already experimenting with this fusion. Retail companies apply machine learning to customer behaviour data, reviews, purchase histories, and social media engagement to predict demand shifts.¹⁴ Translated into finance, these analytics can serve as early warning indicators of consumer confidence and market trends. Investors who incorporate both textual and visual sentiment signals stand to gain an informational advantage over those who rely solely on fundamentals.

What unites these diverse applications is the recognition that perception matters. By quantifying the signals that shape how people feel and react, AI provides investors with sharper tools to navigate the behavioural dynamics of markets. As with other uses of machine learning, the objective is not to replace fundamentals but to complement them, creating a more comprehensive lens through which to understand and anticipate market movement.

¹² Hu X (2025) Keynote address: In the new age of investment – The application of AI in finance. RMIT College of Business and Law. Transcript provided.

¹³ Krizhevsky A, Sutskever I, Hinton GE (2012) ImageNet Classification with Deep Convolutional Neural Networks. *Advances in Neural Information Processing Systems*, 25: 1097–1105.

¹⁴ Shopify (2025) How Machine Learning Transforms Retail: Benefits & Use Cases. Shopify Industry Blogs, 30 January 2025, accessed 25 August 2025, <https://www.shopify.com/au/retail/machine-learning-in-retail>



AI for Transparency and Accountability

Detecting greenwashing and false narratives

One of the most promising applications of artificial intelligence in finance lies not in predicting returns but in strengthening transparency. Corporate reporting, particularly on ESG matters, has expanded rapidly in recent years. Yet as disclosure volume grows, so too does the risk of inconsistency, selective presentation, or outright misrepresentation, commonly described as “greenwashing.” Traditional analysis often struggles to keep pace with the scale and complexity of sustainability reporting, leaving investors and regulators vulnerable to incomplete or misleading claims.

Machine learning and natural language processing (NLP) offer a corrective. By analysing corporate sustainability reports and comparing their language with objective performance indicators, AI systems can flag discrepancies between what companies claim and what they deliver.¹⁵ Early research shows that these models can detect subtle shifts in tone, changes in the frequency of ESG keywords, and the relationship between reported commitments and financial outcomes. Applied at scale, they give stakeholders sharper tools to interrogate corporate accountability, moving beyond surface-level commitments to evidence-based assessment of impact.

Broader studies of corporate social responsibility (CSR) reporting reinforce this view. Analyses of U.S. companies, for example, show that competitive pressures influence disclosure style: as product-market competition increases, firms differentiate their reporting rather than converge, and when peers’ disclosures become more complex, focal firms often respond by making their reports more readable.¹⁶ These behavioural dynamics highlight the importance of comparative analysis: patterns invisible in a single report become clear when thousands are examined side by side. AI enables precisely this kind of large-scale benchmarking, supporting more rigorous oversight by investors, regulators, and the public.

Compliance, oversight, and governance

The same analytical capabilities that strengthen corporate accountability are now being embedded into compliance and governance systems. Enterprise platforms increasingly combine textual analysis with regulatory frameworks to help firms meet disclosure requirements and manage risk exposure. Financial institutions are adopting AI-enabled compliance tools to automate parts of the monitoring process, but industry leaders emphasise that automation must be balanced with oversight. Systems must remain explainable to be credible, especially in high-stakes sectors where compliance failures carry reputational and financial penalties.

For global institutions, this is becoming a strategic imperative. The European Union’s Corporate Sustainability Reporting Directive and the proposed Corporate Sustainability Due Diligence Directive demand a level of consistency and comparability that is difficult to achieve manually.¹⁷ In parallel, regulatory regimes in Asia, including China’s Personal Information Protection Law, impose strict standards on how data can be collected and processed.¹⁸ AI can help firms manage these requirements by sifting through large volumes of disclosures, checking them against evolving rules, and flagging anomalies for human review.

However, it is the industry perspectives that reinforce this balance. Technology providers, for example, stress the importance of explainable AI in compliance systems; algorithms must not only detect anomalies but also justify their reasoning in ways auditors and regulators can understand. In practice, this means embedding features such as transparent model documentation, audit trails, and scenario testing into compliance platforms. Far from removing human judgment, these systems can elevate it. AI in compliance applications can be involved in routine scanning and anomaly detection, while interpretation, escalation, and enforcement remain the domain of compliance officers and boards.

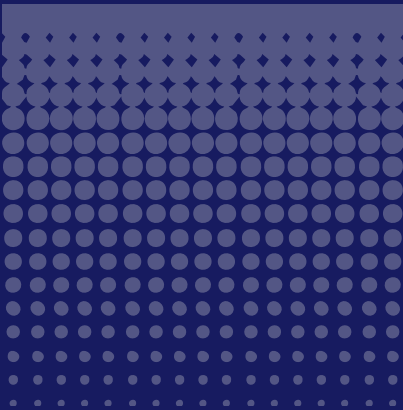
This convergence of AI and governance suggests a broader shift in how financial markets are regulated. Regulators and investors may increasingly operate with near-real-time visibility into corporate practices. If adopted responsibly, AI can reduce information asymmetries, strengthen accountability, and help build the trust on which sustainable capital markets depend.

15 Hu X (2025) Keynote address: In the new age of investment – The application of AI in finance. RMIT College of Business and Law. Transcript provided.

16 Khanna M, Vachhani R (2018) Product market competition and corporate social responsibility activities: Perspectives from an emerging economy. *Journal of International Financial Markets, Institutions and Money* 55: 30–46. Accessed 25 August 2025, <https://www.sciencedirect.com/science/article/abs/pii/S0927538X17302251>

17 European Union (2023) Corporate Sustainability Reporting Directive (EU) 2022/2464. Official Journal of the European Union.

18 Standing Committee of the National People’s Congress (2021) Personal Information Protection Law of the People’s Republic of China. Beijing: NPC.



Ethics, Equity, and Trust in AI-Led Finance

Unequal access and the risks of opacity

Artificial intelligence is often described as a democratising force, but in financial markets, the pattern is moving in the opposite direction. The institutions that gain the most from advanced machine learning are those with the scale to invest heavily in infrastructure, secure proprietary datasets, and recruit scarce technical expertise. Smaller firms, even when highly innovative, often find the barriers to entry insurmountable. The risk is that AI compounds existing hierarchies, concentrating informational advantages and reinforcing the dominance of incumbents rather than levelling the playing field.¹⁹

Opacity compounds this challenge. Many of the most accurate models operate as “black boxes,” producing results without any interpretable logic. While this may be acceptable in consumer applications, it becomes a governance risk in finance, where billions of dollars are at stake and systemic stability depends on confidence. Predictions that cannot be explained, audited, or justified undermine trust. Beyond accuracy, investors need confidence in robustness, regulators require verifiability, and institutions themselves must be able to defend their processes.²⁰

These two dynamics; 1) concentration of access and 2) lack of transparency, raise pressing ethical concerns. If the most sophisticated tools remain monopolised by a handful of firms and their outputs cannot be interrogated, AI risks eroding fairness and accountability in markets. Left unchecked, the technology designed to create efficiency could instead harden inequality and destabilise trust.

Guardrails and social licence

Earning trust in AI will depend on more than national legislation. While domestic rules are important, the global nature of financial markets requires common standards that transcend borders. Over the past five years, international bodies have begun to articulate such principles. The OECD AI Principles, endorsed by more than 40 countries, set out commitments to fairness, transparency, accountability, and human-centred values in the design and deployment of AI.²¹ Though not binding, they provide a baseline for ethical expectations across jurisdictions.

We are also starting to see sector-specific regulators engaging. The Basel Committee on Banking Supervision has flagged the need for robust model risk management as financial institutions adopt AI and ML for credit scoring, trading, and compliance. It warns that complexity and opacity can magnify risks if governance frameworks lag behind technological adoption.²² For global banks, these discussions signal that AI is moving firmly into the remit of prudential supervision.

The Global Financial Markets Association (GFMA) has proposed principles for responsible AI in capital markets, including requirements for explainability, robust testing, data integrity, and human oversight.²³ While voluntary, such initiatives demonstrate a recognition that maintaining a social licence to operate requires proactive standards-setting, not simply waiting for regulators to catch up.

Building trust in AI is therefore a core condition for sustainable adoption. It is important to note that even the best frameworks will falter if institutions treat them as box-ticking exercises rather than as foundations of trust. Embedding transparency, fairness, and accountability into everyday practice is essential. Markets ultimately run on confidence, which is a social resource; once depleted, it is difficult to restore.

19 MIT Digital Currency Initiative (n.d.) MIT Digital Currency Initiative website, accessed 25 August 2025, <https://www.dci.mit.edu/>

20 Doshi-Velez F, Kim B (2017) Towards a rigorous science of interpretable machine learning. arXiv preprint 1702.08608. Accessed 25 August 2025, <https://arxiv.org/abs/1702.08608>

21 OECD (2019) OECD principles on artificial intelligence. OECD: Paris. Accessed 25 August 2025, <https://oecd.ai/en/ai-principles>

22 Basel Committee on Banking Supervision (2024) Regulating AI in the financial sector: recent developments and main challenges. Accessed 25 August 2025, <https://www.bis.org/fsi/publ/insights63.htm>

23 Global Financial Markets Association (2022) Principles for the responsible use of artificial intelligence in financial markets. GFMA. Accessed 25 August 2025, <https://gfma.org>

Recommendations

The future of AI in investment will be shaped as much by governance, skills, and trust as by technical innovation. To ensure AI delivers on its potential for transparency, inclusivity, and insight, the following priorities emerged:

For Business Leaders

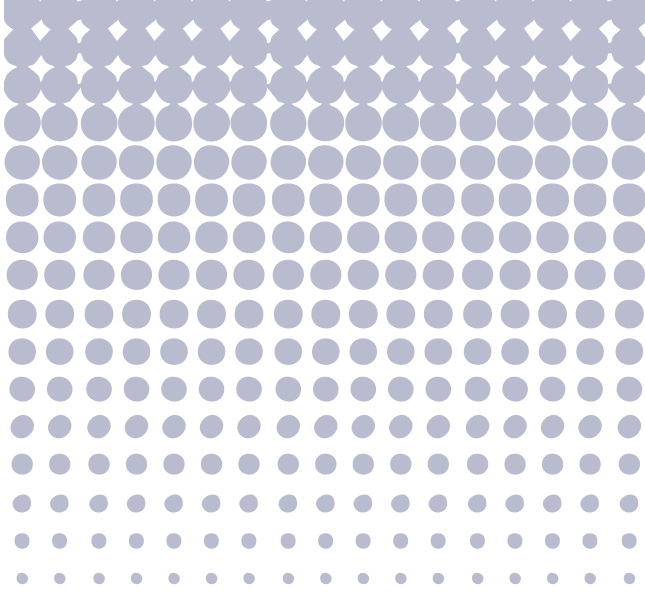
1. Establish clear governance frameworks for AI adoption, with defined accountability and oversight mechanisms.
2. Strengthen data governance practices to ensure quality, diversity, and ethical sourcing of datasets.
3. Implement systematic processes for model validation, monitoring, and recalibration to guard against performance decay.
4. Integrate AI tools into ESG monitoring and corporate disclosure analysis to reinforce transparency and accountability.



For Universities

1. Embed AI and data ethics within core finance and business curricula.
2. Advance research into explainable and interpretable AI, particularly in high-stakes financial contexts.
3. Foster cross-disciplinary collaboration between finance, computer science, law, and ethics faculties.
4. Strengthen industry partnerships to connect research outputs with practical applications in financial markets.





For Government and Ecosystem Partners

1. Establish harmonised regulatory frameworks for AI in finance that align with international standards.
2. Support the development of a shared, privacy-compliant data infrastructure to broaden access beyond large institutions.
3. Invest in AI talent pipelines by funding education, research centres, and reskilling programs.
4. Convene cross-sector forums to build consensus on standards for fairness, transparency, and accountability.



AI is becoming a central driver of change in finance. Across bonds, equities, sentiment, and disclosure, the evidence shows that ML equips decision-makers with sharper tools to anticipate risks and opportunities.

It is this momentum that creates an equally important responsibility. Businesses can govern AI to enhance accountability, universities can prepare graduates to use these tools critically and ethically, and governments can design frameworks that align innovation with public trust. Taken together, these efforts point toward a financial system that is both more efficient and more transparent.

The future of finance will be defined by the sophistication of algorithms and by the values that guide their use. Done well, AI will augment human judgment and strengthen trust at the core of global markets.

