

Role of AI in Investment and Financial Decision-Making

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Abstract

Artificial intelligence (AI) is becoming an important part of investment research and financial decision-making. It is used to analyse information, support portfolio decisions, assist trading, monitor risk, detect fraud and improve investor services. This paper looks at how AI may affect the speed, consistency and quality of financial decisions, with a particular focus on India's securities markets.

The study is based on secondary information from institutional publications and selected academic literature, including material from the International Monetary Fund (IMF), the Securities and Exchange Board of India (SEBI), the Bank for International Settlements (BIS) and the National Institute of Standards and Technology (NIST). No original survey or respondent data were collected.

The reviewed evidence shows that AI can process large amounts of structured and unstructured information and identify patterns that may be difficult to detect manually. The IMF reported that AI-related content in algorithmic-trading patent applications increased from 19% in 2017 to more than 50% each year from 2020 onward. It also reported that AI-driven exchange-traded funds (ETFs) may turn over their holdings about once a month, while typical actively managed equity ETFs turn over holdings much less than once a year. These figures indicate increased activity, but they do not prove that AI-based strategies earn better risk-adjusted returns.

The paper discusses potential benefits such as faster analysis, wider information coverage, scenario testing and ongoing risk monitoring. It also considers risks, including biased data, overfitting, limited transparency, cyber threats and similar models reacting in the same way during market stress. The main conclusion is that AI should support—not replace—responsible human judgement. Proper testing, oversight, transparency, data protection and continuous monitoring are essential.

Keywords: Artificial intelligence, machine learning, investment decisions, portfolio management, algorithmic trading, financial risk, SEBI, India.

1. INTRODUCTION

1.1 Background of the Study

Investment decisions involve committing money today while dealing with uncertainty about future returns. Investors and financial institutions consider share prices, company financial statements, economic indicators, interest rates, announcements, market sentiment and different types of risk. These decisions have traditionally relied on professional judgement, statistical methods and financial models. As financial data and computing power have grown, AI methods such as machine learning, natural-language processing, predictive analytics and generative AI have become more widely used.

AI can help analysts review annual reports, compare companies, summarise financial news, identify unusual trading activity and estimate possible

outcomes. In portfolio management, it may support asset allocation, rebalancing, transaction-cost analysis and risk monitoring. Trading algorithms can also respond to market information more quickly than a fully manual process. These tools may give smaller investors and institutions access to analytical support that would otherwise require a large research team.

However, AI does not remove uncertainty from financial markets. A pattern that worked in the past may disappear when market conditions change or when many investors use the same signal. Data can be incomplete, noisy or biased. A model may look successful in back-testing but perform poorly in real trading because of overfitting, transaction costs, execution limits or a change in market conditions. Generative AI can also produce statements or

references that sound convincing but are incorrect. For this reason, AI should be assessed on the quality and reliability of the decisions it supports, not only on its speed.

1.2 Indian Context

India's securities-market system includes stock exchanges, brokers, depositories, mutual funds, asset managers and investment advisers. SEBI's consultation paper dated 20 June 2025 describes uses of AI and machine learning in areas such as surveillance, cybersecurity, pattern recognition, document processing, product recommendations, order execution, customer support and customer segmentation.

The consultation paper discusses safeguards relating to model governance, disclosure to investors, testing, fairness, privacy and cybersecurity. Since it is a consultation paper, it should be described as a proposed framework in the context of this study, rather than automatically treated as a final regulation. Financial firms in India therefore need to consider both the possible gains from AI and their responsibilities to protect investors and maintain market integrity.

1.3 Statement of the Problem

AI can make investment analysis faster and allow more information to be processed, but this does not guarantee better decisions. The same tools may create risks through unclear model outputs, reliance on common technology providers, similar trading strategies and operational weaknesses. A balanced review is needed to understand where AI may help, what the available evidence shows and which safeguards are important.

1.4 Significance of the Study

This study is relevant to MBA Finance students, investment analysts, portfolio managers, financial institutions, fintech companies and policymakers. It connects AI applications with financial-management ideas such as the relationship between risk and return, diversification, cost control, information quality and professional accountability. It also outlines practical questions that can help users assess AI-supported financial decisions.

1.5 Scope of the Study

The study covers investment research, portfolio management, trading, financial risk analysis and investor-facing decision support. It focuses mainly on Indian securities markets while also using international evidence. The study relies on publicly available secondary sources and does not attempt to estimate a causal effect of AI on investment returns.

2. REVIEW OF LITERATURE

2.1 AI and Capital Markets: International Monetary Fund

Abbas, Cohen, Grolleman and Mosk (2024), writing for the IMF, explain that AI may improve market efficiency, liquidity and price discovery under normal conditions, but it may also contribute to greater volatility during periods of stress. They report that AI-related content in algorithmic-trading patent applications rose from 19% in 2017 to more than 50% each year from 2020 onward. They also describe higher turnover among AI-driven ETFs than among typical actively managed equity ETFs. These measures help illustrate the growth of AI-related activity, but neither patent activity nor turnover directly measures investment performance.

2.2 SEBI's Responsible AI/ML Consultation Paper

SEBI's 2025 consultation paper describes existing uses of AI and machine learning in Indian securities markets and proposes safeguards for their responsible use. It highlights model governance, explainability, testing, bias, oversight of vendors, investor disclosure, privacy and cybersecurity. It also stresses the importance of monitoring systems and involving people throughout the life cycle of an AI model, especially when outputs can influence trading, portfolio management or investment advice.

2.3 IOSCO Principles as Summarised by SEBI

SEBI's consultation paper also summarises the International Organization of Securities Commissions' 2021 guidance for market intermediaries and asset managers. The principles include accountability at senior-management level, suitable testing and ongoing monitoring, adequate skills, third-party oversight, disclosure and good-quality data. These principles show that AI governance is not only a technical issue; it is also part of risk management and compliance.

2.4 Bank for International Settlements / Financial Stability

The BIS's 2025 executive summary on AI and financial stability describes the growing use of AI by financial institutions and points to possible vulnerabilities. These include dependence on a small number of technology providers, limited transparency around data and models, cyber risks and the possibility that existing weaknesses in the financial system could be amplified. The benefits of AI should therefore be considered alongside the resilience of the wider financial system.

2.5 NIST AI Risk Management Framework

The NIST AI Risk Management Framework 1.0, prepared by Tabassi (2023), describes characteristics of trustworthy AI, including validity, reliability, safety, security, resilience, accountability, transparency, explainability, privacy and fairness.

Although the framework is not a financial-market regulation, it offers a useful structure for identifying, assessing and managing AI-related risks.

2.6 Academic Perspective: Prediction Versus Explanation

Machine-learning research distinguishes between predicting an outcome and explaining why it occurred. A model may make useful forecasts without proving a causal relationship. In finance, analysts need to understand why a risk estimate has changed, whether a signal remains reliable and whether the result can be explained to clients or regulators. Back-testing should guard against look-ahead bias, survivorship bias and repeated testing of many strategies. It should also consider transaction costs, slippage, drawdowns and performance on data that were not used to develop the model.

2.7 Synthesis of the Literature

Source	Main contribution	Relevance	Caution
IMF (2024)	Discusses AI's potential to improve efficiency and increase volatility under stress; reports patent and ETF-turnover indicators.	Provides indicators of AI-related activity in capital markets.	Adoption and turnover do not prove superior returns.
SEBI (2025)	Describes Indian-market use cases and proposes governance safeguards.	Directly relevant to Indian intermediaries and investor protection.	The cited document is a consultation paper, not automatically a final rule.
BIS (2025)	Reviews AI use and possible financial-stability implications.	Highlights cyber, concentration and interconnectedness risks.	System-wide risk is different from an individual portfolio's performance.
NIST (2023)	Provides a life-cycle framework for managing AI risk.	Supports model validation and governance recommendations.	It is a cross-sector framework, not India-specific securities law.
Machine-learning research	Emphasises validation, out-of-sample testing and the limits of prediction.	Encourages caution when applying forecasts to financial decisions.	Results depend on the data, market conditions and implementation.

3. RESEARCH GAP

The literature shows that AI is being used in capital markets and that regulators recognise both its potential and its risks. However, several issues still need to be considered together:

- Adoption versus results: patent activity and trading turnover show technological activity, but

they do not establish that AI produces better risk-adjusted returns.

- Investor and institutional perspectives: portfolio results and governance responsibilities are often discussed separately, although decision-makers need to consider both.

- The Indian setting: SEBI's proposed safeguards, investor disclosures and local market infrastructure deserve specific attention.
- Different types of AI: predictive machine learning, natural-language processing, generative AI and execution algorithms have different purposes and may fail in different ways.
- A combined framework: data quality, model performance, human oversight, financial outcomes and system-wide risks should be assessed together.

This paper addresses these issues by reviewing secondary sources, comparing published indicators and presenting a framework that links AI applications with decision quality and governance. It does not use invented survey results or claim to fill data gaps with original empirical evidence.

4. OBJECTIVES OF THE STUDY

1. To examine the role of AI in investment research and financial decision-making.
2. To identify major AI applications in portfolio management, trading, risk assessment and investor support.
3. To review published secondary evidence on AI adoption and trading behaviour in capital markets.
4. To assess the potential benefits and risks of AI-supported financial decisions.

Code	Hypothesis	Assessment approach
H1	AI can improve the speed and breadth of investment analysis.	Review published use cases and evidence on information processing and market activity.
H2	AI adoption is associated with changes in trading activity and market behaviour.	Review the IMF's indicators on algorithmic-trading patents and ETF turnover.
H3	AI-supported financial decisions introduce model, data, cyber and governance risks.	Compare risk discussions from SEBI, IMF, BIS and NIST.
H4	Human oversight and model governance are important for responsible AI use in finance.	Review regulatory and risk-management recommendations.

The literature broadly supports H1, H2, H3 and H4 as directional propositions. However, this research design does not statistically test causation or measure the size of any effect. In particular, H2 indicates an association with changes in activity, not proof of improved returns.

6. RESEARCH METHODOLOGY

6.1 Research Design

The study uses a descriptive and analytical research design based on secondary data. It brings together institutional reports, regulatory documents and

5. To examine the relevance of SEBI's responsible AI/ML proposals and international risk-management frameworks.
6. To recommend practical governance and implementation measures for financial institutions and investors.

5. RESEARCH QUESTIONS AND HYPOTHESES

5.1 Research Questions

7. How does AI support investment research, portfolio management and trading decisions?
8. What benefits and risks are identified in authoritative secondary sources?
9. What do published indicators tell us about the growing role of AI in capital-market activity?
10. Which governance practices can help keep AI-supported decisions reliable and accountable?

5.2 Hypotheses

Because this study uses secondary documentary evidence and does not have a consistent dataset linking firm-level AI adoption with investment performance, the hypotheses are assessed through analysis of published material rather than statistical tests. No p-values or claims of statistical significance are reported.

relevant research commentary to examine how AI is used in investment and financial decision-making.

6.2 Sources of Data

- International Monetary Fund (IMF): October 2024 discussion of AI in capital markets and the

related Global Financial Stability Report material.

- Securities and Exchange Board of India (SEBI): June 2025 consultation paper on responsible use of AI/ML in Indian securities markets.
- Bank for International Settlements (BIS): 2025 executive summary on AI and financial stability.
- National Institute of Standards and Technology (NIST): AI Risk Management Framework 1.0.
- Selected academic literature and established finance concepts concerning prediction, portfolio construction, model validation and risk management.

6.3 Period and Geographical Coverage

The review gives priority to institutional sources published between 2023 and 2025. It also considers

historical indicators dating back to 2017 where these are reported by the IMF. India is the main geographical focus, supported by international evidence on markets and governance. Since AI and regulation continue to develop, readers should check official publications for later updates.

6.4 Methods of Analysis

The paper uses qualitative content analysis, comparison of sources and descriptive presentation of published indicators. Figures are taken from the cited institutional material. Where a simple annualised figure is calculated, the calculation is explained. The study does not build a dataset from assumed investor behaviour.

6.5 Variables and Analytical Dimensions

Dimension	Meaning in this study	Evidence or indicator
AI adoption	The extent to which AI methods are incorporated into capital-market processes.	IMF-reported share of AI content in algorithmic-trading patent applications.
Trading intensity	How frequently portfolio holdings are bought and sold.	IMF-reported ETF turnover comparison.
Decision support	Use of AI for information extraction, risk estimates, allocation and execution.	Use cases described by SEBI and the IMF.
Governance	Controls for validation, oversight, disclosure, privacy and security.	SEBI, BIS and NIST frameworks.
Decision quality	Whether decisions are better informed, consistent and attentive to risk.	An analytical concept; not measured by one comparable dataset in this study.

6.6 Reliability and Ethical Considerations

The study gives preference to original institutional publications and official regulatory documents. It distinguishes reported figures from calculations and interpretations. It does not invent survey results, company-specific adoption rates or investment returns. The paper is for educational purposes and is not personalised investment advice.

6.7 Methodological Limitations

The sources use different definitions, samples and methods, so direct comparisons have limits. Patent data indicate technological activity rather than the number of AI models actually in use. ETF turnover measures trading activity, not risk-adjusted

performance. Since the study does not use econometric analysis or estimate causal effects, its conclusions should be understood as evidence-informed interpretations rather than universal or statistically proven results.

7. CONCEPTUAL FRAMEWORK

The framework used in this study suggests that AI affects financial decisions through information processing, prediction and execution. The result depends on the quality of the data, the model design, the investment process, human judgement and governance. Better processing can improve speed and consistency, but poor data or weak controls can also lead to losses or wider risks.

Stage	Key question	Examples	Control needed
Inputs	Is the information relevant and reliable?	Prices, filings, economic data, news, disclosures and alternative data.	Check data sources, quality, privacy and access.
AI analysis	What patterns or scenarios does the model identify?	Forecasts, sentiment analysis, anomaly detection and risk estimates.	Test on unseen data; review bias and explainability.
Financial judgement	Is the output plausible and appropriate?	Compare with valuation, risk tolerance and investment horizon.	Human review and independent challenge.
Decision / execution	Should capital be allocated, rebalanced or traded?	Position sizing, trade routing and portfolio adjustment.	Limits, transaction-cost checks and approval rules.
Monitoring	Does the model remain reliable after deployment?	Model drift, drawdowns, execution quality, complaints and incidents.	Ongoing monitoring, audit trails and fallback plans.

7.1 AI Techniques and Financial Uses

Technique	Financial application	Potential contribution	Main limitation
Machine learning	Return and risk forecasts, credit and liquidity estimates, fraud detection.	Can identify complex relationships in large datasets.	Overfitting, changing patterns and limited interpretability.
Natural-language processing	Analysis of news, earnings calls, filings and sentiment.	Extracts useful information from text.	Ambiguity, source reliability and language bias.
Generative AI / LLMs	Research summaries, document comparison and analyst assistance.	Can reduce time spent on first-pass reading and drafting.	May produce incorrect, outdated or unsupported information.
Optimisation algorithms	Asset allocation, rebalancing and execution scheduling.	Can evaluate constraints and trade-offs at scale.	Results depend on assumptions and the chosen objective.
Anomaly detection	Market surveillance, fraud checks and unusual transaction patterns.	Flags unusual activity for further review.	May generate false alarms or miss new types of behaviour.

8. DATA PRESENTATION AND ANALYSIS

8.1 Indicator 1: AI Content in Algorithmic-Trading Patent Applications

The IMF reported that AI-related content in patent applications connected with algorithmic trading rose from 19% in 2017 to more than 50% in every year from 2020 onward. This points to a growing role for AI in trading-related innovation. It should not be read as the percentage of all trades carried out by AI, the share of financial firms using AI or evidence that AI strategies earn higher returns.

The trend suggests that AI-related methods have become more prominent in trading technology. As

more managers use similar data and models, competition for useful signals may increase and any temporary advantage may become smaller. If many systems respond to the same signals, their trades could also become more alike, particularly when markets are under pressure. The evidence shows growing innovation activity, but it does not prove that AI strategies outperform passive or human-managed approaches.

Figure 1 note: If reproducing the chart, use 50% only as a lower-bound plotting marker for the IMF's wording "over 50%"; do not present it as an exact reported value.

8.2 Indicator 2: ETF Turnover

The IMF reported that a typical actively managed equity ETF turns over its holdings much less than once a year, while AI-driven ETFs turn over holdings about once a month. Multiplying approximately one turnover per month by 12 months gives an indicative annualised frequency of about 12 times per year. This is a simple conversion, not a precise performance measure. Any chart showing 0.8 for the typical actively managed ETF should label it as a visual placeholder, not a source-reported estimate.

More frequent trading may allow a fund to respond quickly to new signals, but it can also increase transaction costs, market impact and tax consequences. Turnover is not automatically good or bad; its value depends on whether the expected benefit outweighs the costs and risks. The IMF also noted increased turnover in some AI-driven ETFs during the March 2020 market turmoil. This raises a concern that models using similar signals could contribute to herd-like selling during stressed conditions.

8.3 AI Applications Across the Investment Process

Investment activity	How AI may be used	Potential benefit	Key risk or control
Security research	Extract facts from filings, compare ratios and summarise earnings calls.	Faster screening and broader coverage.	Verify all facts against original filings.
Forecasting	Estimate earnings, volatility, liquidity or economic scenarios.	May identify complex patterns.	Use walk-forward tests and benchmarks.
Portfolio construction	Optimise allocations under risk and liquidity limits.	More consistent evaluation of trade-offs.	Stress-test correlations and assumptions.
Trading and execution	Schedule orders, route execution and detect unusual activity.	Speed and potentially lower execution friction.	Monitor slippage, market impact and outages.
Risk management	Run scenarios and monitor exposure with alerts.	Earlier awareness of changing risk.	Include extreme scenarios and human escalation.
Investor service	Support chatbots, product discovery and routine questions.	Faster access to basic information.	Check suitability and escalate complex cases to people.

8.4 Indian Securities-Market Evidence

SEBI's June 2025 consultation paper describes AI/ML uses by exchanges in surveillance, cybersecurity, member support, compliance-data processing, social-media analytics and pattern recognition. Brokers were reported to use these tools for KYC and document processing, product recommendations, chatbots, digital account opening, surveillance, anti-money-laundering activity and order execution. Mutual funds were reported to use

AI/ML in customer support, cybersecurity, surveillance and customer segmentation.

These examples show that AI in finance is not limited to predicting share prices. Some applications improve operational efficiency or compliance without directly selecting investments. As a result, a tool may improve an institution's processes without necessarily increasing the return earned by its clients.

8.5 Risk-Benefit Matrix

Area	Potential benefit	Potential downside	Possible metric or control
Research productivity	Faster document review and summaries.	Incorrect summaries or missing context.	Fact-checking, analyst review and source traceability.

Portfolio decisions	More systematic analysis and rebalancing.	Overfitting and unstable signals.	Out-of-sample performance, drawdowns, turnover and costs.
Risk management	Ongoing exposure monitoring and alerts.	False confidence in historical patterns.	Stress tests, extreme scenarios and independent validation.
Market quality	Potentially faster price discovery and liquidity in normal conditions.	Similar reactions and volatility during stress.	Monitor liquidity, spreads and volatility.
Investor access	Lower-cost access to analytical support.	Opaque or unsuitable recommendations.	Disclosure, suitability review and complaint handling.
Operations	Automation and better anomaly detection.	Cybersecurity, vendor and continuity risks.	Incident tracking, fallback procedures and vendor reviews.

8.6 What the Data Can and Cannot Establish

The evidence reviewed shows that AI is relevant to capital-market innovation, that some AI-driven investment vehicles trade more frequently and that participants in India's securities markets use AI/ML for a range of tasks. However, the evidence is not sufficient to calculate one average return improvement caused by AI. The cited sources do not provide a comparable dataset that controls for strategy, market exposure, fees, risk, leverage and market conditions across AI and non-AI portfolios.

9. FINDINGS AND DISCUSSION

9.1 Major Findings

- AI can support many stages of the investment process, including research, screening, portfolio construction, execution, surveillance and investor support.
- The IMF-reported rise in AI-related content in algorithmic-trading patent applications—from 19% in 2017 to more than 50% annually from

2020—indicates increased innovation activity, not investment returns.

- AI-driven ETFs are reported to turn over holdings more frequently than typical actively managed equity ETFs. This may improve responsiveness but can also raise costs and contribute to similar trading behaviour.
- AI's usefulness depends on data quality, model testing, suitability for the investment objective, transaction costs and ongoing monitoring.
- SEBI's consultation paper highlights governance, investor disclosure, testing, fairness, privacy and cybersecurity as important issues for Indian securities markets.
- International guidance supports accountability, independent testing, documentation, transparency and oversight of third-party technology providers.
- The available evidence does not establish that AI always outperforms human decision-makers or passive strategies on a risk-adjusted basis.

9.2 Hypothesis Assessment

Hypothesis	Assessment	Reason
H1: AI can improve the speed and breadth of analysis.	Supported in direction.	Published use cases indicate potential gains from automation and processing scale, but the study does not measure a universal improvement in accuracy.
H2: AI adoption is associated with changes in trading activity and market behaviour.	Supported as a descriptive association, not as causal proof.	Patent trends, higher ETF turnover and observations during market stress are consistent with changing activity.

H3: AI introduces model, data, cyber and governance risks.	Supported by the reviewed sources.	SEBI, IMF, BIS and NIST identify related risks and controls.
H4: Human oversight and governance are important for responsible use.	Strongly supported as a governance conclusion.	SEBI and international frameworks emphasise accountability, testing, monitoring and human involvement.

These assessments are based on secondary evidence. They are not statistical hypothesis tests, and the study does not estimate causal relationships.

9.3 Implications for Financial Decision-Makers

Finance professionals should treat AI as one input into a wider decision process. Forecasts need to be checked against valuation, liquidity, the investor's time horizon, risk tolerance and portfolio limits. AI-generated research summaries should be verified against original company filings. Portfolio strategies should be compared with appropriate benchmarks after costs. Each model should also have a responsible owner, monitoring thresholds and a clear process for overriding or suspending it.

9.4 Human Judgement and AI: Working Together

AI can process large datasets and apply consistent rules, while human professionals are needed to interpret unusual events, judge business quality, understand client objectives and take responsibility for important decisions. A practical approach is therefore to combine the strengths of both: AI assists with gathering and organising evidence, while qualified people review the results and remain accountable.

10. RECOMMENDATIONS

10.1 Recommendations for Financial Institutions

11. Maintain a formal inventory of AI models, including each model's purpose, owner, data sources, risk level, affected customers and dependencies.
12. Test models before use with out-of-sample data, walk-forward testing, stress scenarios and comparisons against simple benchmarks.
13. Measure net outcomes rather than accuracy alone. Include fees, transaction costs, slippage, drawdowns, liquidity and turnover.
14. Require human approval for high-impact investment or advisory decisions, with clear

authority to challenge, override or suspend model outputs.

15. Keep audit records of model versions, inputs, outputs, approvals, overrides and incidents.
16. Monitor changes in model performance and define escalation thresholds and fallback procedures.
17. Review third-party providers for data retention, cybersecurity, service continuity, intellectual property and incident reporting.
18. Use AI-generated summaries as a starting point only. Check figures, quotations, references and company disclosures against original sources.

10.2 Recommendations for Investors and Analysts

19. Do not treat an AI forecast as a guarantee or as a replacement for understanding investment risk.
20. Check the date, source and completeness of the data used by an AI tool.
21. Consider whether a recommendation fits the investor's time horizon, diversification, liquidity needs and ability to bear losses.
22. Compare AI-supported strategies with clear benchmarks after costs and across different market conditions.
23. Do not rely on unverified chatbot answers for current prices, regulatory changes, tax treatment or personal investment decisions.
24. Be cautious of strategies promising consistently high returns without transparent evidence, risk disclosures or independent testing.

10.3 Recommendations for Regulators and Policymakers

25. Clarify expectations for AI governance, disclosure, testing and accountability where systems affect customers.

26. Use proportionate, risk-based supervision that distinguishes internal productivity tools from systems that directly influence portfolios or trading.
27. Monitor concentration among technology providers, shared data sources and similar model behaviour that could create correlated exposures.
28. Encourage incident reporting and provide supervisors with enough information to identify emerging risks while protecting sensitive information.
29. Support investor education so customers understand the purpose, limitations and risks of AI-assisted financial services.

10.4 Implementation Roadmap

Phase	Indicative timing	Main actions	Expected output
1. Define	0–2 months	Select the use case, business owner, intended outcome and risk category.	Approved use-case brief and AI inventory entry.
2. Prepare	2–4 months	Review data quality, privacy, vendor arrangements and model design.	Data map, risk assessment and validation plan.
3. Test	4–6 months	Run back-tests, out-of-sample tests, stress tests and shadow deployment.	Independent validation report and go/no-go decision.
4. Deploy with controls	6–8 months	Set limits, human review, logging and fallback processes.	Operating procedure and accountable owner.
5. Monitor	Ongoing	Track performance, model drift, complaints, incidents and costs.	Periodic model-risk review and remediation record.

11. LIMITATIONS AND SCOPE FOR FUTURE RESEARCH

11.1 Limitations

- The study relies on secondary sources and does not collect survey data from investors, analysts or financial institutions.
- The sources use different definitions of AI, samples and time periods, which limits direct comparison.
- Patent activity and ETF turnover are indicators of innovation and trading intensity, not direct measures of investment performance.
- The study does not estimate causal effects, test statistical significance or calculate a universal return advantage for AI.
- AI technology and regulation change quickly. The SEBI document cited is a June 2025 consultation paper, so later official updates should be checked.

11.2 Scope for Future Research

- Compare AI-assisted and traditional investment strategies using consistent data, matched benchmarks and risk-adjusted measures.
- Study Indian mutual funds, portfolio managers or brokers through interviews and surveys, subject to institutional approval and ethical requirements.
- Examine how AI adoption affects suitability, customer complaints, costs and access to financial advice.
- Evaluate model performance during market stress, including liquidity shocks and changes in market conditions.
- Study whether explainability and human oversight improve trust, compliance and decision quality.

12. CONCLUSION

Artificial intelligence is becoming an important tool in investment and financial decision-making. It can assist with research, information processing, forecasting, portfolio construction, trading, risk monitoring and investor support. The institutional evidence reviewed in this paper shows growth in AI-related trading innovation and reports that some AI-driven investment vehicles trade more frequently than typical actively managed equity ETFs. In India, SEBI’s 2025 consultation paper describes a wide range of AI/ML applications and proposes safeguards for responsible use.

At the same time, AI cannot eliminate uncertainty. Poor data, overfitting, unclear outputs, shared model signals, cybersecurity problems and dependence on a small number of providers can create risks. Faster decisions are not always better decisions, and more frequent trading does not prove better performance. Financial institutions should therefore assess AI’s contribution after accounting for costs, risks and governance requirements.

The main conclusion is that AI is most useful when it is part of a disciplined decision-making process. Reliable data, independent testing, suitable explanations, human accountability, continuous monitoring and investor protection are essential. For MBA Finance professionals, the goal should not simply be to adopt AI, but to understand how it works, measure what it actually contributes and manage its limitations.

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APPENDIX A: SECONDARY-DATA EXTRACTION TABLE

This table summarises the main quantitative indicators used in the analysis. The figures are reported or transparently derived from the cited IMF material.

Indicator	Source statement	Value used	Interpretation / caution
AI content in algorithmic-trading patent applications, 2017	IMF reports 19% in 2017.	19%	Indicates patent content, not the share of deployed models or investment

			performance.
AI content in algorithmic-trading patent applications, 2020 onward	IMF reports more than 50% each year since 2020.	>50% annually	A chart may use 50% as a lower-bound marker.
Typical actively managed equity ETF turnover	IMF says holdings turn over much less than once a year.	<1 time/year	A value such as 0.8 used in a chart is only a visual placeholder, not an exact reported estimate.
AI-driven ETF turnover	IMF says holdings turn over about once a month.	About 12 times/year, annualised	Derived by multiplying about one turnover per month by 12; not a precise estimate.

APPENDIX B: ILLUSTRATIVE EXAMPLE — NOT OBSERVED DATA

The example below is hypothetical. It is included to show how an investment team might review an AI-generated signal; it is not a real fund, actual trading result, survey response or investment recommendation.

Step	Illustrative scenario	Appropriate control
Signal	A model flags a company as potentially undervalued after reviewing public filings and market data.	Verify filings, valuation assumptions and data timestamps.
Risk check	The model suggests increasing the position.	Check concentration, liquidity, sector exposure and downside scenarios.
Cost check	Frequent rebalancing could increase turnover.	Estimate brokerage, spreads, market impact, taxes and slippage.
Human review	An analyst notices that the model may have missed a recent material disclosure.	Pause the trade and update the analysis using primary sources.
Decision	The investment committee decides whether the signal remains appropriate.	Record the rationale, approval, model version and monitoring trigger.

APPENDIX C: MODEL-GOVERNANCE CHECKLIST

- ☐ Use case and accountable owner are documented.
- ☐ Data sources, permissions, origin and quality checks are documented.
- ☐ The model is compared with a simple baseline and tested on data not used to build it.
- ☐ Performance is measured after transaction costs and across different market conditions.
- ☐ Bias, explainability and suitability risks are assessed for the intended use.
- ☐ Human review, escalation and override rights are defined.
- ☐ Vendor dependencies, cybersecurity, privacy and continuity plans are reviewed.
- ☐ Model versions, inputs, outputs, approvals and incidents are recorded.
- ☐ Monitoring thresholds, retraining rules and suspension criteria are approved.

- ☐ Investor disclosures and complaint-handling routes are appropriate for the use case.

APPENDIX D: KEY TERMS

Term	Meaning
Artificial intelligence (AI)	A broad set of computational techniques used for tasks associated with learning, reasoning, language or decision support.
Machine learning (ML)	Methods that learn patterns from data to make predictions or classifications.
Natural-language processing (NLP)	Methods for analysing and generating human language.
Algorithmic trading	Use of computer algorithms to generate, route or execute orders according to rules or model outputs.
Model drift	A change over time in the relationship between model inputs and outcomes, or in the distribution of the input data.
Overfitting	When a model learns noise in its training data and performs poorly on new data.
Human-in-the-loop	A process in which a person reviews, approves, challenges or can override model-supported outputs.

APPENDIX E: SOURCE LINKS FOR VERIFICATION

- IMF article: <https://www.imf.org/en/blogs/articles/2024/10/15/artificial-intelligence-can-make-markets-more-efficient-and-more-volatile>
- SEBI consultation paper PDF: https://www.sebi.gov.in/sebi_data/attachdocs/jun-2025/1750415065695.pdf
- BIS executive summary: <https://www.bis.org/publications/fsi-summary-financial-stability-implications-artificial-intelligence-executive-summary>
- NIST AI RMF 1.0: <https://doi.org/10.6028/NIST.AI.100-1>
- IOSCO AI/ML final report: <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf>