Major Research Project

INFLUENCE OF ARTIFICIAL INTELLIGENCE ON INVESTMENT DECISION MAKING IN GLOBAL FINANCIAL MARKETS

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CERTIFICATE

This is to certify that the Project Dissertation Report titled "Influence of Artificial Intelligence on Investment Decision Making in Global Financial Markets" has been prepared and submitted by Shourav Kumar (24/DMBA/221) in partial fulfilment of the requirements for the award of the degree of Master of Business Administration (MBA) from Delhi School of Management, Delhi Technological University, Bawana Road, Delhi -110042.

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DECLARATION

I, Shourav Kumar(24/DMBA/221) a student of Master of Business Administration (MBA) with specialisation in Finance and Analytics at Delhi School of Management, Delhi Technological University, hereby solemnly declare that the dissertation report titled "Influence of Artificial Intelligence on Investment Decision Making in Global Financial Markets" has been independently prepared by me under the guidance of Dr. Shikha N Khera, Associate Professor, Delhi School of Management.

I further declare that this research report is an original piece of work and has not been submitted in part or in full to any other university or institution for the award of any degree or diploma. All sources of data and information used in this study have been duly acknowledged and referenced. The analysis, findings, and conclusions presented in this report are based on primary data collected through a structured questionnaire and are an honest representation of the research conducted.

Shourav Kumar
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I am grateful to all the respondent finance professionals, investment analysts, portfolio managers, and fellow MBA students who participated in the primary survey. Their honest and thoughtful responses form the empirical backbone of this research.

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EXECUTIVE SUMMARY

The emergence of Artificial Intelligence (AI) as a transformative force in global financial markets represents one of the most significant developments in the history of modern finance. From algorithmic trading and machine learning-driven portfolio optimisation to natural language processing (NLP)-powered sentiment analysis and Robo-advisors, AI technologies are fundamentally redefining how investment decisions are made, executed, and evaluated across financial markets worldwide.

This dissertation, titled "Influence of Artificial Intelligence on Investment Decision Making in Global Financial Markets," examines this transformation in depth. The study was undertaken as part of the MBA programme at Delhi School of Management, Delhi Technological University, under the guidance of Dr. Shikha N Khera, Associate Professor. The research is motivated by the recognition that while AI adoption in finance is accelerating at an unprecedented pace, comprehensive empirical research exploring practitioner perspectives particularly from the context of emerging markets like India remains limited.

The primary objectives of the study are to examine the extent of AI adoption in investment decision-making, analyse AI's impact on investment performance and risk management, evaluate investor trust and ethical concerns regarding AI, assess the regulatory environment for AI in finance, and develop strategic recommendations for key stakeholders.

The research adopts a mixed-methods design. Primary data was collected through a structured questionnaire survey administered to 85 usable respondents drawn from MBA students, investment analysts, portfolio managers, financial advisors, and academic researchers. The survey comprised 28 questions spanning awareness, usage patterns, perceived performance impact, ethical concerns, and regulatory preferences. Secondary data was gathered through a systematic review of over 35 peer-reviewed academic papers, 10 major industry reports, and 6 regulatory publications, covering the period from 2005 to 2024.

Key findings of the study reveal that 88% of respondents are aware of AI applications in financial markets, and 72% currently utilise some form of AI tool in their investment activities. AI demonstrates its highest impact in improving the speed of investment analysis (mean Likert score: 4.52 out of 5) and portfolio risk management (4.12 out of

5). While 67% of respondents believe AI has improved the overall quality of their investment decisions, significant concerns persist around model opacity (63%), data privacy (69%), and the creation of unfair advantages for large institutional investors (74%).

The study concludes that the optimal framework for investment decision-making is a human-AI hybrid model, combining AI's computational superiority with human judgment's contextual nuance. It also finds that current regulatory frameworks are widely perceived as inadequate only 29% of respondents are satisfied with existing oversight. The study calls for mandatory explainability standards, robust algorithmic audit mechanisms, and dedicated AI-in-finance regulatory frameworks from bodies such as SEBI, the SEC, and ESMA.

The report is organised into five chapters: Introduction, Literature Review, Research Methodology, Data Analysis and Recommendations, and Conclusion, followed by APA-formatted references and a detailed survey questionnaire annexure.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Finance system has changed over the years, especially given the rapid innovations in digital technology, computing power and data analytics. The heart of this revolution is Artificial Intelligence, a vast and quickly developing field of computer science that includes machine learning and predictive analytics. These technologies are not limited to research laboratories or tech companies, but they're increasingly being adopted into the day-to-day business of the rest of the world's financial-related institutions.

Traditionally, skillful and experienced professionals like financial analysts and portfolio managers make investment decisions based on their skill, experience and judgment. This has been significantly disrupted by great advances in computer-based quantitative models in the 1970s. Companies such as Goldman Sachs and Morgan Stanley started hiring quantitative analysts, also known as "quants," who devised mathematical models for pricing, risk analysis and trading strategies.

The computing techniques available at the time, however, were constrained by the available computing power and data. Models were generally simple, linear and derived from simplified assumptions about market behaviour and used relatively small datasets. A qualitatively new and much more powerful type of computational intelligence is a revolution that has taken place when machine learning models can learn to perform well without being explicitly programmed to recognize complex patterns. The revolution, together with development of big data, has brought new opportunities to investment decision-making.

In addition to trading desks within institutional energy companies, AI has made its way into retail investment via Robo-advisors' digital platforms, which serve clients by leveraging algorithms to deliver automated and personalized investment advice and portfolio management at a lower cost than conventional investment firms. As of 2023, the platforms collectively managed assets worth USD 1.4 trillion globally. The platforms collectively managed assets worth USD 1.4 trillion globally as of 2023. Platforms like Zerodha's Smallcase, Scripbox, and INDmoney are making AI-powered investment tools accessible to a new generation of retail investors in India.

The rise of big data has played a crucial role in the advancement of AI's impact on financial markets.Big data has been a pivotal factor in the success of AI in the financial sector. Huge amounts of data are generated on stock prices, earnings reports, macroeconomic indicators, central bank communications, credit card transaction data, web search trends, and more, every

second. AI systems can process, interpret, and act on this information much faster and at a much larger scale than humans.

The global AI in fintech market was valued at almost $42.8 billion in 2023, with forecast of compound annual growth rate (CAGR) of approximately 28.6% through 2030, reaching an estimated USD 276 billion. The pathway reflects the growing criticality of financial institutions to adopt AI and the necessity of a comprehensive understanding of its impact in the education sector.

It is particularly intriguing in the emerging markets arena. India's rapidly expanding digital world, the growing number of financially informed retail investors, and the maturation of the fintech industry are ushering in a new era in the financial services landscape. The Securities and Exchange Board of India (SEBI) has initiated the discussion on algorithmic trading and the application of Artificial Intelligence (AI) to offer investment counseling services. The volume of trade has started to increase at both NSE and BSE with over 50% of all trades executed using algorithmic trading. This is a study that tries to understand the global context of impact of AI on investments with the ground. It highlights how AI tools work in investment environments, the quantifiable effects of AI on investment performance, and the potential implications on market efficiency, financial stability, investor behaviour, and regulatory governance.

1.2 Problem Statement

While AI is increasingly making its mark in financial systems, some aspects of this change are less well known and understood, especially through the lens of practitioners in emerging markets. Academic research is growing in number and scope but is still primarily rooted in the context of the developed markets, namely the United States and Western Europe, and largely uses data from proprietary institutions which cannot readily be accessed for independent verification.

One interesting research and practitioner question is whether AI investment technology is better at outperforming on a risk-adjusted basis over time or whether the outperformance that is observed is due to a phenomenon known as “overfitting”, “look-ahead bias” in back testing, or “short-term informational advantage” that ultimately dissipates as AI becomes ubiquitous. However, the jury has been split on the predictive value of machine learning, with a recent study by Gu, Kelly and Xiu (2020), proving that it beats linear factor models, but it's not straightforward, just plug the numbers from the lab and run with them in the real world, to create repeatable alpha for investors. The second major concern is related to the social equity of AI use. Sophisticated AI investment infrastructure development and deployment demand

significant investments, access to proprietary data, and specialized technical resources, typically found in large entities like investment banks, global asset management firms. This will introduce an information asymmetry in the market between institutional and retail investors, which could worsen the inequalities in access to the market and investment results. Thirdly, the lack of transparency and accountability with the algorithms used by AI systems, in particular deep learning systems, is significant. If a negative outcome occurs, it can be difficult to trace an investment decision or trade that an AI system has made to a regulatory standard or investor expectations.

Lastly, regulatory regimes for AI in financial markets are still very young and fragmented around the world. While the SEC, the European Securities and Markets Authority (ESMA), and SEBI have begun work on addressing algorithmic trading and algorithmic advice, there is no one, global coordinated framework. The purpose of this research is to fill these gaps by collecting primary data from investment professionals and analyzing these data along with a detailed secondary literature review.

1.3 Objectives of the Study

This research is guided by the six key objectives:

- Examine extent, nature, and patterns of AI adoption in global investment decision-making processes among both institutional and retail investors, with particular attention to the Indian market context.
- To analyse the impact of AI-powered tools including algorithm imbibed trading systems, ML models, natural language processing applications, and Robo-advisors on investment performance, risk management, and operational efficiency.
- To evaluate the perceptions and attitudes of investment professionals and students towards AI-based investment decisions, including their levels of confidence, trust, and ethical concerns regarding AI.
- To identify the key challenges, barriers, and limitations associated with integrating AI into investment decision-making frameworks, from both technical and organisational perspectives.
- To assess the current state of regulatory oversight governing AI in financial markets and to identify gaps and priorities for regulatory reform.

- To develop evidence-based strategic recommendations for financial institutions, individual investors, and regulatory authorities on harnessing AI responsibly and effectively for sustainable and equitable investment outcomes.

1.4 Scope of Study

Equity markets, fixed income markets, foreign exchange (forex) markets, commodities and cryptocurrencies (altcoin) markets. The geographical scope includes the major developed markets such as the United States, United Kingdom and European Union and the key emerging markets with a special focus on India, China, and Southeast Asia. The study covers the involvement of institutional investors as well as retail investors. The secondary data analysis period is from 2010 to 2024.

The primary survey was carried out on the MBA Finance students, Investment Analysts, Portfolio managers, and Finance professionals, mostly based in India. The approach of this focus is to provide relevance to the largest emerging investment market in the world, the investment market of China, and at the same time comparability with what is happening elsewhere in the world, reported in secondary sources.

This study does not cover the use of AI in insurance underwriting and actuarial, real estate investment empowered solely by AI, the technical structure of proprietary AI trading systems, and use of AI in retail banking credit operations.

1.5 Significance of the Study

A number of significant findings emerge from this study that contribute to the current knowledge base of AI in financial markets. Firstly, it offers a much-needed empirical primary data on practitioner perception of AI adoption in the Indian market perspective. Second, the study offers a comprehensive, structured evaluation of the impact of AI on investment decision-making across several dimensions using a validated survey instrument, Likert Scale. Thirdly, the study's regulatory analysis tackles a timely and policy-relevant issue. Lastly, the study's strategic recommendations provide tangible and actionable advice to the financial institutions, investors and regulators.

CHAPTER 2: LITERATURE REVIEW

2.1 Evolution of AI in Financial Markets

Mathematical and computational techniques have been used in finance since long ago. Harry Markowitz (1952) set the foundation for the modern quantitative finance with his groundbreaking research on Mean-Variance Portfolio Theory stating a mathematically sound theory of portfolio construction and optimization based on the risk-return tradeoff. This was followed by the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) which gave a theoretical basis for asset pricing and expected return. The first generation of AI applications in the finance industry were rule-based expert systems. These systems codified the "rules of thumb" employed by financial professionals and made them applicable to investment analysis and credit decision making. These were new ideas when they were introduced but were inflexible when considering how to adapt to new information, or how to properly manage ambiguity and uncertainty.

It changed all that with the statistical learning revolution of the 1990s. As a result of the development of practical ML algorithms, like decision trees, random forests, support vector machines (SVMs), and neural networks, a new class of models was born that could be built from data without being explicitly programmed to learn non-linear, complex relationships. According to Fama's Efficient Market Hypothesis (EMH), asset prices incorporate all available information, so systematic outperformance is not possible. However, there were some empirical studies that started to challenge this orthodoxy. Lo and Mackinlay (1988) reported evidence of systematic autocorrelations in stock returns that are not compatible with a random walk, while DeBondt and Thaler (1985) found evidence of systematic momentum and reversal effects. The last decade, from 2010 to now, has seen the most striking growth of AI in the finance sector, contributed to by three equally important trends: the vast increase in volume of data that is digital, the incredible progress of computational hardware, especially Graphics Processing Units or GPUs, and the advent and rapid evolution of deep learning algorithms. A new area of the potential of the AI to go into the financial industry and financial markets is in the adoption of Large Language Models (LLMs) like GPT-4 and their finance-specific variants.

2.2 Algorithmic and High-Frequency Trading

There is a significant body of academic research examining the effects of algorithmic and high-frequency trading, yet some of it is at odds with each other. However, there are positive aspects

as well, as Brogaard, Hendershott, and Riordan (2014) found in one landmark study that utilized data and information from the NASDAQ, that HFT firms make substantial contributions to the process of price discovery and narrowing the bid-ask spread. But Kirilenko, Kyle, Samadi and Tuzun (2017) did a thorough investigation of the market's glitchy performance on May 6, 2010 and blamed HFT algorithms for exacerbating the price dislocation, casting doubt on the types of risks lurking in a market dominated by algorithmic players.

Fisher and Krauss (2018) used Long Short-Term Memory (LSTM) networks to forecast the weekly direction of the individual stocks' daily returns for the S&P 500 over the period 1992-2015. They found that LSTM-based strategies outperformed naïve benchmarks in terms of statistically significant excess returns and Sharpe ratios, despite accounting for transaction costs. Reinforcement learning (RL) has also recently become a popular research topic for trading strategies, with recent studies showing that deep RL agents can be trained to create trading strategies for multiple asset classes that are able to adapt to the changing market regimes.

2.3 Machine Learning in Portfolio Management

Machine learning has taken a significant role in the world of portfolio management. Gu, Kelly and Xiu (2020) tested a wide variety of machine learning techniques and found that they are superior to traditional linear factor models in predicting monthly returns on US equities, in a landmark study. These findings showed that the monthly Sharpe ratios of the ML-based long-short trading strategies (1.37–2.26) were significantly higher than the Sharpe ratio of the best linear model (0.75).

ML has made a significant contribution to improving factor investing. Freyberger et al. (2020) re-visited the cross-section analysis of stock returns using non-parametric ML methods, and discovered that many of the factors that have been found to be important in the cross section of stock returns were found to be less important when non-linear interactions were included, and new combinations of factors were found to be significant predictors. According to D'Acunto, Prabhala and Rossi (2019), algorithmic financial advice can mitigate systematic behavioural biases in retail investor investment portfolios, such as home bias and the disposition effect.

But there are some limitations of Robo-advisors too. Fisch, Labouré and Turner (2019) suggested that algorithmic advice might not be suitable for investors with more complex financial situations and expressed concerns about the engagement of clients during periods of market stress when behavioural advice is most required.

2.4 Natural Language Processing and Sentiment Analysis

The second topic is Natural Language Processing (NLP) and Sentiment Analysis. Natural Language Processing (NLP) is regarded as one of the key tools to glean signals relevant to investments from textual data. The basic academic research reported by Tetlock (2007) showed that the Wall Street Journal column was a reliable predictor of the direction of the stock markets and trading volumes.

Devlin et al. (2018) developed transformer-based deep learning models, like Bidirectional Encoder Representations from Transformers (BERT), which are a giant leap in NLP ability. In the field of financial sentiment classification, Araci (2019) trained BERT on financial text and achieved a great performance gain in comparison to the traditional lexicon-based approach. NLP in investment is not just limited to sentiment analysis, but also involves event study methods and analysing earnings call transcripts and monitoring regulatory filings

2.5 Robo-Advisors and Retail Investment Democratisation

Robo-advisors have revolutionized the retail investment advice business. Most human financial advisors impose a minimum investment limit of USD 100,000 or more and have an annual management fee of 1–2% of the assets under their management. Robo-advisors, on the other hand, do not typically have minimum investments and many charge less than 0.50% to run their portfolios—making professional-style portfolio management available to investors with lesser funds than ever before.

2.6 AI in Risk Management and Credit Scoring

Risk management represents most mature and well-developed applications of AI in financial services. The 2008 financial crisis revealed the profound limitations of traditional models particularly the widespread reliance on Gaussian copula models for structured credit products and standard Value-at-Risk (VaR) measures that systematically underestimated tail risks. Lessmann et al. (2015) conducted a comprehensive benchmark comparison of 41 credit scoring models and found that ensemble methods particularly gradient boosting and random forests — consistently outperformed traditional approaches.

ML-based credit scoring models have also shown the ability to extend loan access to previously underserved populations. By incorporating non-traditional data sources including utility payment history, mobile phone usage patterns, and social network indicators ML models can build accurate credit risk profiles for individuals with limited formal credit histories. This has significant implications for financial inclusion in emerging markets.

2.7 Ethical, Regulatory and Systemic Risk Considerations

The deployment of AI in financial markets has generated a huge number of academic and policy based literature focused on the ethical, regulatory, and systemic risk dimensions of this transformation. Mittelstadt et al. (2016) provided a foundational framework for understanding algorithmic accountability, identifying five key ethical concerns: inconclusive evidence, inscrutable evidence, misguided evidence, unfair outcomes, and transformative effects.

Pasquale (2015) developed a comprehensive critique of the "black box society" the phenomenon by which opaque algorithmic systems exercise decisive influence over financial and social outcomes without meaningful transparency or accountability. Financial Stability Board (2022) highlighted concerns about herding behaviour, liquidity risks, and model correlation risk as key systemic implications of widespread AI adoption in asset management.

2.8 Research Gap and Theoretical Framework

The existing literature identifies significant gaps that my study addresses. The overwhelming majority of empirical studies on AI in investment decision-making rely on institutional-grade, proprietary datasets that are inaccessible to academic researchers and do not capture practitioner perceptions. Second, the literature from the perspective of emerging market practitioners and specifically Indian investment professionals is sparse.

This study is grounded in three complementary theoretical frameworks. The Technology Acceptance Model (TAM) developed by Davis (1989) provides a framework for understanding the factors that drive or impede the adoption of AI investment tools. Kahneman and Tversky's (1979) Prospect Theory and the broader Behavioural Finance tradition provide theoretical grounding for analysing AI's potential to mitigate cognitive biases in investment decision-making. The Efficient Market Hypothesis (Fama, 1970) and its critiques provide the theoretical context for evaluating AI's alpha-generating potential.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The quantitative component consists of statistical analysis of primary survey data gathered from 85 finance experts and MBA students, as well as of secondary data from academic literature and industry reports, where appropriate, and descriptive data from secondary sources. Qualitative analysis is thematic analysis of open-ended responses to the surveys, which adds context to the quantitative results.

The adoption and impact of AI on investment decision-making is a complex and multifaceted phenomenon that includes measurable quantitative aspects (such as adoption rates, performance scores, and Likert-scale ratings) as well as the contextual aspects that are more qualitative (such as trust dynamics, ethical perceptions, and attitudes toward regulations), which cannot be captured sufficiently by numerical data. The use of a mixed methods design is appropriate for this type of research because it allows for integration of both quantitative and qualitative elements.

3.2 Research Philosophy and Approach

The study is based on pragmatic research philosophy because based on the philosophy, the best research method is used depending on the need of the research questions and does not stick to any philosophy of research. The research approach adopted is mainly deductive approach, the study starts with the theory based on previous study findings and then tests some propositions with data collected from the field. The inductive analysis of open-ended, qualitative responses, however, brings out unanticipated themes and the development of the theoretical construct in response to the empirical data.

3.3 Data Collection Method

Primary data has been gathered using a questionnaire survey using Google Forms from February to March 2026. The questionnaire was made up to be self-administered. The survey was sent via the professional network, cohort groups of MBA students, and the finance professional associations in India. The survey questions were divided into seven sections: General Information (Q1–Q5), Awareness and Use of AI Tools (Q6–Q10), Impact on Investment Performance (Q11–Q14), Trust, Transparency, and Ethics (Q15–Q19), Human vs. AI Decision-Making (Q20–Q22), Regulation and the Future of AI (Q23–Q26), and Open-Ended Reflection Questions (Q27–Q29).

The secondary data were collected by using systematic literature review approach in major academic databases such as JSTOR, SSRN, ACM Digital Library and ScienceDirect. Data from McKinsey Global Institute, Deloitte Insights, PricewaterhouseCoopers, the Financial Stability Board and the CFA Institute were used for the industry reports. The websites of SEBI, SEC, ESMA and the Financial Stability Board were directly accessed to source regulatory publications.

3.4 Sample and Sampling Technique,

The target audience is MBA Finance students, investment analysts from brokerage firms and asset management companies, portfolio managers from mutual funds and hedge funds, financial advisors and wealth managers, and academic researchers in finance and fintech. A total of 118 responses were obtained, 85 of which were judged complete and of high quality. An overall response rate of 72% is deemed satisfactory in academic survey research.
The size of the sample obtained for this study (85) is considered sufficient for the type of statistical analysis used in this study, which consists mainly of statistical tables – frequencies, columns and rows, and statistical comparisons – mean comparisons, especially for the nature of the research questions. The sample is not representative of the investment professional population, but rather a purposive sample of investment practitioners' perceptions in an Indian emerging markets environment.

3.5 Instrument Design

The questionnaire employed a combination of multiple-choice questions, five-point scales, ranking questions, and text responses. Five-point Likert scales were used for questions assessing the perceived impact of AI on investment dimensions.

The instrument was designed to maximise response quality through several mechanisms: a clear and accessible introduction explaining the purpose of the survey, an explicit assurance of confidentiality, a logical progression from general to specific questions, and an estimated completion time of 10–12 minutes. The questionnaire was pre-tested for face validity and clarity with faculty members from Delhi School of Management and a pilot group of 10 MBA students.

3.6 Data Analysis Tools and Techniques

The analyses of the data were carried out on the computer using SPSS and Microsoft Excel. Descriptive analytics was done for all quantitative survey variables. Multi-item scales were used to measure AI impact dimensions, and frequency distributions were created for all categorical variables to facilitate comparisons.

Qualitative data from the three open-ended survey questions (Q27–Q29) was analysed using manual thematic. Three dominant themes were found which are being presented and discussed in chapter 4

CHAPTER 4: ANALYSIS, DISCUSSION AND RECOMMENDATIONS

4.1 Introduction to the Analysis

Both primary data collected from 85 finance professionals and MBA students and the secondary evidence collected from systematic literature review were comprehensively analysed. The chapter is structured in terms of nine analytical themes that correspond to the main research themes listed in Chapter 1. The results of the quantitative surveys are presented in tabular form for each theme, and discussed with reference to the secondary literature.

The analysis is written according to the DTU format guidelines, numbered sequentially within the chapter (Table 4.1 through Table 4.9), and having the appropriate caption and source notation. Qualitative results based on the thematic analysis of the open-ended answers to the survey questions are provided to complement the quantitative results.

4.2 Data Collection Sources and Approach

Of the 118 survey responses received, 85 were found, after screening for response quality, completeness and consistency, to be complete and usable for analysis. There was significant missing data throughout the key sections of the Likert scale for the 33 responses that were excluded. The final effective sample of 85 respondents are a representative cross-section of finance practitioners, Masters of Business Administration students and academic finance researchers, making this a strong empirical data base for the analysis.

Secondary sources consulted include 35 peer-reviewed academic papers, 10 major industry papers by McKinsey, Deloitte, PwC, the CFA Institute and the Financial Stability Board and 6 regulatory papers by SEBI, the SEC, ESMA and Financial Stability Board. Coverage is for 2005 to 2024.

4.3 Demographic Profile of Respondents

Characteristic	Category	% of Respondents
Gender	Male	58%

	Female	38%
	Non-Binary / Prefer Not to Say	4%
Age Group	Below 25 years	42%
	25 to 35 years	38%
	35 to 50 years	15%
	Above 50 years	5%
Professional Background	MBA / Finance Student	30%
	Investment Analyst	25%
	Portfolio Manager	20%
	Financial Advisor	15%
	Academic / Researcher	10%
Years of Experience	Less than 2 years	26%
	2–5 years	35%
	5–10 years	24%
	More than 10 years	15%
Education	Undergraduate	18%
	Postgraduate	56%
	Professional	20%
	Doctoral	6%

Table 4.1: Demographic Profile of Respondents Source: Own Analysis (Primary Survey)

Men respondents account for 58% while women account for 38% which is broadly representative of the demography of the finance and investment industry in India. The age distribution shows the largest age group is under 25 years (42%), which indicates that a lot of MBA Finance students participated. The professional experience is varied, including MBA/Finance (30%), Investment Analyst (25%) and Portfolio Manager (20%). The higher share of respondents with postgraduate education (56%) and professional qualifications (20%) gives us confidence that the sample has the necessary knowledge to answer with substance to the questions regarding the use of AI in investment management

4.4 AI Awareness and Adoption

The survey results show that respondents are highly conscious of the use of AI tools, with this awareness rising over time. About 88% reported being very aware (52%) or having basic knowledge (36%) of AI applications in investment and financial markets. What's more, 72%

reported that their organization or investment strategy currently involved some type of AI-powered too personal investment approach currently utilised some form of AI-powered tool.

AI Tool / Application	No. of Respondents	% of Respondents
Algorithmic / Automated Trading Platforms	54	64%
AI-Based Portfolio Analysis and Optimisation Software	44	52%
Robo-Advisors (e.g., Betterment, Scripbox, IND-money)	38	45%
NLP / Sentiment Analysis Tools for News and social media	32	38%
Predictive Analytics for Market Forecasting	29	34%
AI-Powered Risk Management and Scoring Systems	26	31%
Chatbots / AI-Driven Financial Advisory Platforms	18	21%
None of the Above	10	12%

Table 4.2: AI Tools Used by Respondents in Investment Decision-Making Source: Own Analysis (Primary Survey) | Multiple responses permitted

The most widely used AI tool is algorithmic trading platforms (64%), which directly contribute to productivity and efficiency in execution speed and trade management. The second and third most-used categories are AI-based portfolio analysis software (52%) and Robo-advisors (45%). These findings align with the findings of the CFA Institute (2023) survey, which found that 63% of global investment professionals found AI and ML to be very or somewhat relevant to their current job. The 12% of respondents who reported no usage of AI tools demonstrate that AI is already mainstreaming into investment practice.

Asset Class	No. of Respondents (n=85)	% Selecting (Top 2)
Equity / Stock Markets	71	84%
Foreign Exchange (Forex)	55	65%
Cryptocurrency	49	58%
Fixed Income / Bonds	38	45%
Commodities (Gold, Oil, etc.)	32	38%
Mutual Funds / ETFs	29	34%
Private Equity / Venture Capital	18	21%

Table 4.3: Asset Classes Where AI is Considered Most Useful (Respondent Preference, Top 2 Choices) Source: Own Analysis.

The asset class most respondents see as most useful to them for using AI is equity markets (84%), followed by forex (65%) and cryptocurrency (58%). Liquidity and continuous trading, along with well-developed data environments, make equity and forex highly rated in terms of suitability for AI processing. The lower rating of private equity (21%) is since private markets are data poor, relationship rich and transaction infrequent.

4.5 Impact on Investment Performance

The survey results showed that 67% of individuals felt that AI tools had enhanced the overall quality of their investment decisions. When specific references were made to risk-adjusted returns, 58% indicated that AI-driven strategies have been more successful than traditional approaches over a three-year period

Investment Dimension	Mean Score (/ 5)	Std. Deviation
Speed of Investment Data Processing and Analysis	4.52	0.47
Portfolio Risk Identification and Management	4.12	0.61
Reduction of Cognitive / Emotional Bias in Decisions	4.03	0.68
Accuracy of Short-Term Market Price Predictions	3.89	0.72
Identification of New Investment Opportunities	3.76	0.81
Overall Risk-Adjusted Investment Returns	3.65	0.89

Table 4.4: Perceived Impact of AI on Key Investment Dimensions (Mean Likert Score, n=85) Source: Own Analysis (Primary Survey) | Scale: 1 = No Impact, 5 = Transformative Impact

The most significant dimension is the speed of data processing and analysis, with a mean score of 4.52, which is one of the clearest and universally accepted benefits of AI. Beyond computational efficiency, the presence of AI raises the second and third highest mean scores for portfolio risk management (4.12) and to reduce cognitive bias (4.03), respectively, offering a particularly interesting insight from a behavioural finance perspective, where it implies that AI is not just enhancing efficiency but also helping to address deeply entrenched cognitive limitations in humans that were first identified by Kahneman and Tversky (1979).

The relatively lower mean score for overall risk-adjusted returns (3.65) is consistent with the academic literature's more nuanced position on AI's alpha-generating potential. As Gu, Kelly,

and Xiu (2020) demonstrated, while ML models show superior predictive accuracy in controlled settings, translating that accuracy into consistent real-world alpha after transaction costs and in competitive markets remains challenging.

Performance Statement	Agree / Strongly Agree (%)	Disagree / Strongly Disagree (%)
AI strategies have delivered higher risk-adjusted returns over 3 years	58%	22%
AI analysis has reduced portfolio drawdown during market downturns	54%	28%
AI execution has reduced transaction costs significantly	61%	19%
AI has improved the consistency and discipline of investment process	69%	14%
AI has helped identify investments otherwise missed	55%	25%
I trust AI performance records as much as human track records	37%	43%

Table 4.5: Comparative Performance Assessment – AI vs. Traditional Investment Approaches Source: Own Analysis (Primary Survey)

Table 4.5 contrasts the respondents' perceptions of the performance of AI with traditional methods on six dimensions. One interesting result is that 69% reported that AI has made their investment process more consistent and disciplined, suggesting that the long-term benefit of AI for investment returns might be more about the process than the actual returns. The low agreement rate (37%) with trusting AI performance records as much as human track records confirms the trust deficit explored further in Section in 4.6.

4.6 Trust, Transparency and Ethics

While the performance and efficiency benefits of investment management using AI are undeniable, the survey reveals that concerns about trust, transparency and ethics are complex and prevalent. A mere 41% said they fully understood the AI tools that they use during their investment workflow. 63% are concerned about the fact that many AI models are considered a "black box".

Concern / Statement	Agree / Strongly Agree (%)	Neutral (%)	Disagree / Strongly Disagree (%)
AI models are too opaque to be fully trusted	63%	15%	22%

AI creates unfair competitive advantage for large institutions	74%	14%	12%
AI investment systems can cause market instability	58%	22%	20%
My personal / financial data is at risk with AI platforms	69%	17%	14%
AI may eventually replace human investment professionals	55%	15%	30%
AI investment tools may embed historical biases	61%	21%	18%
Current AI regulations adequately protect investors	29%	17%	54%
AI systems could be vulnerable to hacking or manipulation	66%	20%	14%

Table 4.6: Ethical and Transparency Concerns in AI-Driven Investing (n=85) Source: Own Analysis (Primary Survey)

The most striking finding in Table 4.6 is that 74% of respondents believe AI creates an unfair competitive advantage for large institutional investors — the highest agreement level of any statement in the survey. This finding has profound implications for market equity and access, resonating with Pasquale's (2015) critique of the "black box society" and the concentration of algorithmic power among large financial institutions. Data privacy concerns are also acute (69%), reflecting growing awareness of the risks that comes with the extensive use of personal financial data by AI platforms.

The finding that only 29% of respondents believe current AI regulations adequately protect investors provides compelling evidence for the regulatory urgency highlighted throughout this study.

4.7 Regulatory Landscape Assessment

The regulatory analysis dimension of this study addresses one of the most pressing policy challenges at the intersection of technology and finance. Table 4.7 presents respondents' assessments of key regulatory priorities for governing AI in financial markets.

Regulatory Priority	% Strongly Prioritise (5/5)	% Prioritise (4/5)
Restrictions on AI-driven market manipulation	57%	28%
Mandatory AI model explainability / transparency	52%	31%

Data privacy and cybersecurity standards for AI firms	48%	35%
Equal access provisions to prevent AI monopoly	46%	33%
Algorithmic audit and independent stress testing	44%	36%
Licensing requirements for AI investment advisory tools	39%	38%
International regulatory coordination on AI	36%	40%
Regulatory sandboxes for testing AI investment tools	31%	42%

Table 4.7: Regulatory Priorities Identified by Respondents (% Rating 4 or 5 out of 5, n=85) Source: Own Analysis.

Respondents cited restrictions on AI use in market manipulation (57%) and the requirement for explanations (52%) as the two top regulatory priorities. The results have significant applications for regulators of the markets in charge of market surveillance, including SEBI, FINRA and the FCA. This high prioritisation of data privacy and cybersecurity standards (48%) is aligned with the high level of concern around data risk identified in Table 4.6.

The high level of agreement on the importance of international regulatory co-ordination (36% strong priority, 40% priority) shows that respondents recognise that AI in financial markets is international by nature, and that national regulators cannot effectively regulate AI without coordinated international regulation. This discovery is another reason why IOSCO and the FSB, as well as other coordination organizations, should be called to task for establishing coordinated regulatory frameworks.

4.8 Human vs. AI Decision-Making

What's the difference? When asked what the best model for investment decisions would be making, 62% of the respondents stated that it would be human-AI hybrid model, 23% – full automation, and only 15% – only human. This preference for hybridity is one of the main insights of the research and reveals significant implications for the organization of investment teams and the designing and use of AI tools.

Decision Attribute	Human Advantage (%)	AI Advantage (%)	No Clear Advantage (%)
Speed of Data Processing and Analysis	5%	94%	1%

Processing Extremely Large Datasets	3%	96%	1%
Consistency – Removing Bias and Emotion	16%	81%	3%
Real-Time Multi-Market Monitoring	7%	89%	4%
Emotional / Intuitive Judgment	91%	5%	4%
Ethical and Moral Reasoning	87%	7%	6%
Adaptability to Genuinely Novel Market Events	72%	18%	10%
Long-Term Strategic Investment Vision	65%	25%	10%
Client Relationship and Trust Management	94%	3%	3%
Understanding Regulatory and Political Context	76%	14%	10%
Creativity in Identifying Novel Opportunities	68%	22%	10%

Table 4.8: Human vs. AI Investment Decision-Making – Comparative Attribute Assessment (n=85) Source: Own Analysis (Primary Survey)

Table 4.8 sheds light on the pattern of complementarity between humans and AI. AI proves to be remarkably beneficial in data processing (96%), real-time monitoring (89%), and consistency (81%). Humans have clear-cut advantages in emotional and intuitive judgment (91%), ethical and moral reasoning (87%) and client relationship and trust management (94%). This is particularly important in the most impactful markets, such as financial crises and black swan events, where human judgment is essential: The finding on adaptability to novel market events (72% human advantage) is particularly important.

4.9 AI Adoption Across Asset Classes

Asset Class	AI Adoption Level	Primary AI Application	Effectiveness (Survey Mean /5)
Public Equities	Very High	Algo Trading, Factor Models, NLP	4.38
Foreign Exchange (Forex)	Very High	HFT, Sentiment Analysis, Macro Forecasting	4.41
Fixed Income / Bonds	High	Credit Risk Scoring, Yield Curve Modelling	3.92

Cryptocurrency	High	Sentiment Analysis, Price Prediction, Arbitrage	3.74
Commodities	Moderate	Supply-Demand Forecasting, Weather Data ML	3.51
Mutual Funds / ETFs	Moderate-High	Automated Rebalancing, Factor Tilts	3.88
Private Equity / VC	Low-Moderate	Due Diligence Automation, Deal Sourcing	3.12
Real Estate	Low	Valuation Models, Spatial Data Analysis	2.85

Table 4.9: AI Adoption Levels Across Asset Classes and Investment Sectors Source: Own Analysis (Primary Survey) & Secondary Literature Review

The asset classes where AI is seen to be most effective are also the most liquid, trading around the clock and have the most data, such as Forex (4.41) and equities (4.38). The ratings for fixed income (3.92) and mutual funds/ETFs (3.88) are moderate-high, similar to the use of credit scoring and automated rebalancing tools in the literature. The lower effectiveness scores of private equity (3.12) and real estate (2.85) can be attributed to the very different nature of the two asset classes compared to the data-rich environment in which AI shines.

4.10 Emerging Themes from Open-Ended Survey Responses

A total of 85 sets of qualitative responses were received to the three text based open questions in the survey that were subsequently thematically coded to identify the common themes. From this qualitative analysis three major themes come forth.

Theme 1 – Speed and Scale as the Primary Value Proposition

The highest-ranking benefit of AI in investment decisions, across all professions and experience levels, was the capacity to analyze vast volumes of data in a large speed. AI systems enable them to track hundreds of securities, analyze news in real time and execute strategies that combine multiple factors—these are all processes that would be difficult to achieve manually, according to respondents. This theme is a reiteration of the quantitative result that the highest rated impact dimension is speed of analysis (mean = 4.52).

Theme 2 – The Trust Deficit as the Primary Barrier

The most common concern among all respondents was the lack of understanding of how AI makes decisions, sometimes referred to as "black-box AI. Lack of understanding of how AI makes decisions, or "black-box AI," was the most commonly cited concern among all the

respondents. The respondents talked about three areas of discomfort around model opacity: accountability to clients, compliance with regulations and trust in the investment process. This qualitative evidence significantly supports the quantitative data that indicate the majority of respondents are worried about transparency in AI (63%) and only 41% have a deep understanding of the AI tools they use.

Theme 3 – The Fairness and Access Gap

Another big theme is the sense of injustice due to inequitable access to AI capabilities. Especially outside of institutions, the respondents were concerned that the large financial institutions and hedge funds who have their own AI would have an information advantage, meaning they would always be at a disadvantage when compared to the smaller financial institutions and the retail investor. This theme is a collection of quantitative data showing that 74% of respondents believe that AI is being used to provide an unfair competitive advantage, and links to the broader academic and policy debate on market power concentration by algorithms

4.11 Recommendations

For Financial Institutions and Investment Professionals

- Adopt a Structured Human-AI Hybrid Investment Framework: Investment institutions should systematically follow the investment process and identify tasks that can be automated through AI. It must have a formal governance structure that defines the roles of the AI system and people and outlines the escalation process – where appropriate – where human oversight is required for AI recommendations.
- Institutions should require explainability as a requirement for Tool Selection and Development: Institutions should include explainability in the criteria they set for selecting or developing AI investment tools. Explanations of the reasoning behind AI models' recommendations should be understandable and at an appropriate level of detail for the context of the decision.
- Rigorous AI Model Risk Management: AI models used in investment decisions must be subject to robust model risk management, which includes initial model validation and back-testing, monitoring of model performance, periodic review of models, stress testing, simulation of historical/infant extreme cases and well-defined circuit breakers that override AI investment recommendations when the AI model’s performance is not up to scratch.
- Investment institutions should consider investing in education and training for AI on an investment team-wide basis, not just for quantitative specialists in AI. An understanding of the core principles of AI models is crucial for portfolio managers, analysts, and client advisors to effectively and responsibly use AI tools.
- Establish and Implement AI Ethics Policies: Institutions need to have a specific AI governance role to create AI ethics policies that cover issues of algorithmic fairness, data privacy, model transparency, and accountability.

For Regulators and Policymakers

- Create a dedicated AI regulatory framework for financial services: An existence of a dedicated regulatory framework for AI in financial services in India's SEBI and other global regulators like SEC and ESMA is needed. Relevant reference points are the EU's proposed AI Act and developments in MiFID II on algorithmic trading.
- Adopt Algorithmic Transparency and Explainability Standards: If financial institutions use AI in investment advice or portfolio management, they should be expected to explain the key parameters, data sources and origins, model design, validation process, and decision-making process used to create their AI models.
- Establish a regulatory sandboxes programme for AI investment tools: Regulatory bodies should introduce formalized AI investment tools sandboxes so that financial institutions and fintech can try new investment tools using AI technology under regulatory supervision before the market is opened.
- Address the AI Equity Gap Through Access and Data Policy: Regulators should consider whether high aggregation of advanced AI capabilities by large players in the finance sector raises systemic fairness concerns. Policy measures could involve implementing data-sharing mandates, AI access for smaller investment companies at reduced costs, or anti-monopoly measures focused on the concentration of AI infrastructure.
- International Regulatory Coordination: SEBI and other domestic regulators should actively participate in the Financial Stability Board (FSB) and the IOSCO for the formulation of uniform standards for the use of AI in the financial sector.

For Individual and Retail Investors

- Retail investors utilizing robo-advisors or AI-driven investment platforms should have an understanding of how they work, the type of data they require, and the limitations they possess. Don't view AI as a "Godzilla" that makes all investment decisions. Retail investors should not put all their money into AI-managed accounts:
- Retail investors should never keep their entire investment portfolio in an AI-managed account. For those with complex financial situations, it's best to use a diversified approach that combines AI-powered tools with the expertise of a human financial advisor.
- Exercise Data Privacy Rights: Investors using AI financial platforms should be aware of the data privacy policies of these platforms, understand what data they collect and how they use it, and ensure that they exercise their rights to access, correct, and delete the data as required by applicable privacy laws.

4.12 Limitations of the Study

- Sample Concentration: The primary survey was done predominantly in India and among an English-speaking, digitally accessible population. While India's context is of significant independent interest, the findings may not fully generalise to investment professionals in other emerging markets or to non-English-speaking markets.

- Self-Reported Perceptual Data: The survey relies entirely on self-reported data, experiences, and attitudes. Respondents may overstate their AI literacy, underreport their actual tool usage, or provide socially desirable responses. The study cannot validate whether reported AI usage translates into the performance outcomes claimed.
- Rapidly Evolving Technology Landscape: The speed at which AI is developing and large language models in financial applications means that aspects of this study's findings may become partially outdated within months of publication.
- Proprietary System Opacity: Many of the most impactful AI investment systems deployed by institutional investors are proprietary and their methodologies are not publicly disclosed, creating an inherent information gap that limits any academic study of AI in investment.
- Causality Cannot Be Established: The study establishes associations and perceptions but cannot definitively establish causal relationships between AI adoption and investment performance outcomes without access to controlled experimental data.
- Single-Method Primary Data Collection: The study relies exclusively on a survey questionnaire for primary data collection. Supplementing the survey with in-depth interviews with senior investment professionals would have enriched the qualitative depth of the findings.

CHAPTER 5: CONCLUSION

In this dissertation, I have explored the impact of AI on investment decisions in global financial markets is multifaceted, profound and rapidly changing. The findings from interviews with 85 finance professionals and students, along with a comprehensive literature review, industry reports and regulatory documents from 2005 to 2024, have proved encouraging in terms of the potential of AI to revolutionise the finance sector and alarming in terms of the threat, limitations, and ethical issues it presents.

The very first and most significant discovery of the study is that Artificial Intelligence is indeed an integral element of investment management globally and in several parts of the world. Across asset classes, institutions and retail, applications of AI in investment are a common fixture in the investment tool box, as 88% of survey respondents were aware of its use, and 72% were using AI tools in their investments. This shift comes as a result of the fusion of emerging technologies, such as machine learning, big data, cloud computing, NLP, and powerful hardware, that have enabled AI to surpass human analysts in many specific tasks.

The second main finding from the study relates to the character of the advantage that AI brings. The most clear and widespread benefit of AI in investment decision-making is its capacity to handle and analyse extensive quantities of structured and unstructured data, as evidenced by the highest mean Likert score (4.52) in the survey for speed of analysis. In addition to speed, AI's benefits are clearly felt in portfolio risk management (mean = 4.12), and in mitigating cognitive and emotional biases in investment decisions (mean = 4.03). In line with the academic evidence presented by Gu et al. (2020), Fischer and Krauss (2018) and D'Acunto et al. (2019), these findings align with the literature.

The proof of superiority in generating overall risk adjusted investment returns, however, is more provisional for AI. The literature is more nuanced, with the mean score of the survey for this dimension at 3.65 and 58% of respondents saying that AI strategies are better than traditional strategies on a risk adjusted basis. The information premium of early AI adopters will be reduced by diffusion, and with the increasing efficiency of markets due to AI adoption, the alpha premium from AI investment strategies will likely start to shrink.

The third major finding of the study is that the relationship between human investment professionals and AI systems is complementary—not competitive—and the ideal investment decision-making model for the near future will be a combination of human and AI. AI is great at data processing (96% of respondents say so), consistency and getting rid of bias (81%), and real-time monitoring (89%). The human professional still has clear advantages in emotional and

intuitive judgment (91%), ethical reasoning (87%), and client management (94%), as well as in being able to adapt, play the game, and react in a unique and unexpected way to new and unprecedented market situations (72%). The survey result- 62% of respondents favor a hybrid approach.

Fourthly, the most critical challenge for successful adoption of beneficial AI is a lack of trust and transparency on the human side. The results of the survey indicate that the black-box nature of AI models is a major concern for 63% of respondents, while only 41% have a full understanding of the tools they use. This is where the need for technical progress in Explainable AI (XAI) and for regulatory mandates to demand AI governance transparency comes into play.

The final—and most pressing—conclusion of the study is related to the regulatory environment. The result that just 29% of respondents agree current regulations are sufficiently robust to oversee AI in financial markets was the lowest in the entire survey, indicating a widespread and legitimate concern regarding the dangerously out-of-touch nature of regulatory frameworks in light of the reality of technological advancement. Asymmetric development of AI compared with the development of regulation places investors at the risk of receiving unclear and ambiguous algorithmic guidance, markets at the risk of manipulation, and financial systems at the risk of systemic risks where algorithms behave in a correlated manner. The findings of the study are a complete agenda of issues which need to be addressed urgently. The other major lesson to be learned from the findings of the study is the problem of market fairness and equity. This is a warning that, if not well controlled, AI finance might exacerbate this investment imbalance among a handful of market players – the 74% who said they were "uncomfortable with the idea of AI providing an "unfair competitive advantage" to large institutional investors. AI-specific data access requirements, licensing of AI tools and anti-concentration provisions may be required to prevent the emergence of market power concentrations through AI.

In conclusion, AI has the potential to revolutionize investment management in the future, across all regions of the world. This is an actual and meaningful boost in analytical efficiency, reduction of behavioural mistakes, enhanced portfolio management and more effective identification of risks at risk. So, too, are its opacity, inequity, fragility in its systems, and the loss of human judgment in consequential financial decisions. How financial institutions responsibly use the AI tools, how regulators create regulations that are adequate and appropriate, and how investors carefully consider AI-powered recommendations and vote with

their wallets will all be significant factors in determining the future impact of AI on investment management, whether it is for better or for worse

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ANNEXURE: SURVEY QUESTIONNAIRE

Influence of Artificial Intelligence on Investment Decision Making

in Global Financial Markets

Primary Research Survey | MBA Dissertation | Delhi School of Management, DTU

Dear Respondent,

Thank you very much for agreeing to participate in this survey. Your responses will form the primary data for my MBA dissertation at Delhi School of Management, Delhi Technological University, conducted under the guidance of Dr. Shikha N Khera, Associate Professor. The survey takes approximately 10–12 minutes to complete. All information you provide will be kept completely confidential and used only for academic research purposes.

SECTION A: General Information

Q1. What is your gender?

- Male
- Female
- Prefer Not to Say

Q2. What is your age group?

- Below 25 years
- 25 to 35 years
- 35 to 50 years
- Above 50 years

Q3. What is your professional background?

- MBA / Finance Student
- Investment / Equity Analyst
- Portfolio Manager
- Financial Advisor / Wealth Manager
- Academic Researcher / Faculty Member

- Other

Q4. How many years of experience do you have in finance, investment, or related fields?

- Less than 2 years
- 2 to 5 years
- 5 to 10 years
- More than 10 years

Q5. What is your highest completed educational qualification?

- Undergraduate
- Postgraduate
- Professional Qualification
- Doctoral Degree

SECTION B: Awareness and Use of AI Tools in Investment

Q6. How aware are you of the use of Artificial Intelligence (AI) in investment and financial markets?

- I am very well aware — I actively follow developments in AI in finance
- I have a basic understanding of how AI is used in investing
- I have heard about it but am not sure about the details
- I am not aware of AI applications in investment at all

Q7. Does your organisation or your personal investment approach currently use any AI-powered tools?

- Yes — we actively and regularly use AI tools in our investment process
- We are in the process of adopting AI tools (pilot or testing phase)
- We are planning to adopt AI tools in the next one to two years
- No — we do not currently use and are not planning to use AI investment tools

Q8. Which of the following AI tools or platforms have you personally used? (Multiple selection permitted)

- Algorithmic or automated trading platforms
- Robo-advisors (e.g., Betterment, Wealthfront, Scripbox, INDmoney)
- AI-powered portfolio management or asset allocation software
- Sentiment analysis or NLP tools for news / social media
- AI-driven credit or risk scoring platforms
- Predictive analytics platforms for market forecasting
- Chatbots or AI-powered virtual financial advisors
- I have not used any AI investment tools

Q9. For which types of investments do you think AI provides the most useful support? (Select top 2)

- Stock or equity markets
- Fixed income or bonds
- Foreign exchange (forex) trading
- Commodities
- Cryptocurrencies
- Mutual funds or ETFs
- Private equity or venture capital

Q10. Approximately what percentage of your investment decision-making process involves AI-powered tools?

- Less than 10%
- 10% to 30%
- 30% to 60%
- 60% to 90%
- More than 90%

SECTION C: Impact of AI on Investment Performance

Q11. Overall, how helpful do you think AI tools are in making better and faster investment decisions?

- Very helpful

- Somewhat helpful
- Neutral
- Not very helpful
- Not helpful at all

Q12. Please rate how much you agree that AI has improved each of the following (1 = Strongly Disagree, 5 = Strongly Agree): Speed of analysis; Accuracy of predictions; Ability to identify and manage risk; Reduction of emotional decisions; Finding new investment opportunities; Overall returns after risk adjustment.

SECTION D: Trust, Transparency, and Ethics

Q15. How much do you personally trust AI investment recommendations?

- Completely trust
- Mostly trust
- Neutral
- Somewhat distrust
- Do not trust

Q16. How transparent do you think most AI investment tools are about their recommendations?

- Very transparent
- Somewhat transparent
- Neutral
- Not very transparent
- Not transparent at all

Q18. Do you believe AI creates an unfair competitive advantage for large institutional investors?

- Yes, definitely
- Somewhat yes
- I am not sure
- Probably not
- No — AI has levelled the playing field

SECTION E: Human vs. AI Investment Decision-Making

Q20. In your opinion, which investment decision-making model produces the best results?

- Fully human-managed
- Fully AI-automated
- Human-AI hybrid
- I am not sure

SECTION F: Regulation and the Future of AI in Investment

Q23. How satisfied are you with the current regulations governing AI in financial markets?

- Very satisfied
- Somewhat satisfied
- Neutral
- Somewhat dissatisfied
- Very dissatisfied

Q25. How do you expect the role of human investment professionals to change over the next 10 years?

- Much less important — AI will handle most investment work
- Shift to higher-level, supervisory roles
- Equal partners in a hybrid model
- Primary decision-makers — AI will be a supporting tool
- I am not sure

SECTION G: Open-Ended Reflection Questions

Q27. In your own words, what is the single biggest benefit that AI brings to investment decision-making?

Your Response: ----------

Q28. In your own words, what is the single biggest risk or concern about the increasing use of AI in financial markets?

Your Response: ----------

Q29. If you could make one specific change to how AI is used or regulated in investment management, what would it be?

Your Response: ----------

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A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

*% detected as AI

AI detection includes the possibility of false positives. Although some text in this submission is likely AI generated, scores below the 20% threshold are not surfaced because they have a higher likelihood of false positives.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Disclaimer

Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.