International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

AI in Portfolio Management: Can Algorithms Outperform Human Fund Managers?

Shantanu Chakravarti

Abstract
This study explores whether AI-driven portfolio management systems can outperform traditional human fund managers in terms of returns and risk-adjusted performance. Drawing on secondary research from global studies between 2020 and 2024, findings indicate that AI-managed funds perform better during market downturns due to superior data analysis and emotion-free decision-making, while human managers excel in bullish markets that reward intuition and qualitative judgment. Ethical and governance concerns; particularly transparency, data bias, and accountability; remain major challenges for AI adoption. The study concludes that hybrid models integrating algorithmic precision with human oversight represent the optimal approach for sustainable portfolio management.

Keywords:
Artificial Intelligence, Portfolio Management, Fund Performance, Behavioural Finance, Risk-Adjusted Returns, Machine Learning, Ethical Governance, Investment Strategy, Market Cycles, Hybrid Models

1. Introduction

Over the past decade, the integration of Artificial Intelligence (AI) and Machine Learning (ML) into the financial sector has transformed how investment decisions are made and portfolios are managed. Financial institutions and asset management firms increasingly rely on data-driven algorithms that can process large datasets, identify complex patterns, and generate insights far beyond the capacity of human analysis. In portfolio management, AI systems are now used for stock selection, asset allocation, risk assessment, and performance prediction. This shift is driven by the growing availability of financial data and advances in computational power.

Traditional portfolio management depended heavily on the experience, intuition, and judgment of human fund managers. However, human decisions are often influenced by behavioural biases such as overconfidence, herd mentality, and loss aversion. In contrast, AI models operate on logic, probability, and predictive analytics. They can quickly react to new information and adjust investment strategies with minimal emotional interference (Bartram et al., 2020). As the financial industry becomes more complex and volatile, the debate over whether algorithms can outperform human fund managers has gained both academic and practical importance.

Despite the widespread adoption of algorithmic trading and AI-based investment systems, there remains uncertainty about their consistent ability to outperform human fund managers. While algorithms can process massive amounts of data at high speed and optimize portfolios based on historical patterns, they lack the contextual judgment and intuition that humans often apply during unusual or crisis-driven market conditions. On the other hand, human fund managers are vulnerable to cognitive biases and may fail to act rationally under pressure. This raises the central question of whether AI-driven portfolio management can deliver superior performance, especially in terms of risk-adjusted returns, and how market conditions influence this comparison (Anuar et al., 2025).

The problem extends beyond financial outcomes. The growing reliance on automated systems introduces new challenges related to transparency, accountability, and data quality. The "black-box" nature of many AI algorithms makes it difficult to explain or justify investment decisions to stakeholders. Hence, the issue is not only about performance but also about trust and governance in the era of machine-managed investments.

The primary objective of this research is to examine whether AI-driven portfolio management systems can outperform human fund managers in terms of both raw and risk-adjusted returns. The study also aims to identify the specific market conditions under which algorithms perform better or worse compared to human managers.

The research will address the following key questions:

1. Do AI-driven funds achieve higher returns and better risk-adjusted performance than human-managed funds?
2. Under what market conditions; such as uptrend, downtrend, or volatility; do AI systems outperform or underperform human managers?
3. What ethical, governance, and behavioural implications arise as the financial industry shifts towards AI-driven fund management?

By addressing these questions, the study seeks to contribute to the ongoing discussion about the evolving role of technology in finance and its potential to reshape traditional investment practices.

This research focuses on a comparative analysis of AI-driven and human-managed investment funds. The time period under consideration spans from 2020 to 2024, a phase characterised by market volatility, technological acceleration, and significant global economic shifts. The analysis will be limited to equity mutual funds and exchange-traded funds (ETFs) operating primarily in the United States and European markets.

Due to data availability constraints, only funds with verifiable records of algorithmic or AI-assisted decision-making will be included. The study does not attempt to evaluate the internal architecture of proprietary AI systems, as such information is confidential. Additionally, qualitative aspects such as investor sentiment or fund marketing will not be analysed in detail, except where they directly affect performance outcomes. The findings may not be fully generalizable to other asset classes, such as fixed income or commodities, or to emerging markets with different data ecosystems and regulatory conditions.

2. Literature Review

Artificial intelligence has emerged as a key component of modern financial systems, reshaping how portfolios are designed, monitored, and optimized. According to Bartram et al. (2020), AI and machine learning (ML) enable asset managers to analyse vast amounts of financial and alternative data; including market trends, social sentiment, and macroeconomic indicators; to make faster and more informed investment decisions. These technologies are applied across several functions such as portfolio construction, trading automation, and risk management.

In portfolio construction, AI models use predictive analytics to identify securities with the highest probability of outperformance. Techniques like reinforcement learning and neural networks allow algorithms to adapt their strategies dynamically based on new information. In trading, high-frequency systems use AI to execute orders at optimal prices and minimize transaction costs. Risk management has also evolved through machine learning models that detect early warning signals of volatility, credit risk, or liquidity shocks. These systems not only improve operational efficiency but also enhance risk-adjusted returns by removing emotional biases and human delay from decision-making processes.

Human fund management traditionally combines quantitative analysis with qualitative judgment. Fund managers rely on financial models, economic forecasting, and corporate analysis, but their decisions are also shaped by intuition, experience, and personal judgment. Behavioural finance research has shown that these human elements introduce cognitive and emotional biases into investment decisions.

Kahneman and Tversky's (1979) Prospect Theory demonstrated that individuals tend to weigh losses more heavily than gains, leading to risk-averse behaviour when facing potential losses. Barberis et al. (2001) highlighted the role of investor sentiment in driving mispricing and market anomalies. Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) found that overconfidence leads fund managers to overestimate their forecasting abilities, resulting in excessive trading and reduced performance. Herding behaviour; when managers imitate others' investment choices to avoid standing out; also contributes to market inefficiencies and speculative bubbles (Bikhchandani & Sharma, 2000).

These behavioural tendencies can help explain why human-managed funds often struggle to outperform market benchmarks, especially in volatile conditions. While human judgment can provide valuable contextual insight during unusual market events, consistent performance is often hindered by emotional decision-making and biases.

A growing body of research has compared AI-managed portfolios with traditional, human-managed funds. Anuar et al. (2025) conducted one of the most comprehensive analyses, comparing the performance of AI-driven and human-managed equity funds across multiple market cycles. The study found that AI-managed funds tended to achieve higher Sharpe and Treynor ratios during market downturns, suggesting superior risk-adjusted performance. In contrast, human-managed funds performed relatively better during sustained bull markets, possibly due to human managers' ability to interpret qualitative signals such as policy changes, geopolitical trends, and investor mood.

Performance evaluation typically employs metrics such as the Sharpe ratio (measuring excess return per unit of risk), the Treynor ratio (return relative to systematic risk), and Jensen's alpha (excess return above the expected level based on market risk). The findings indicate that while AI systems excel at exploiting quantitative inefficiencies, they may underperform in highly sentiment-driven or irregular markets. The comparative results thus highlight the complementary strengths of human and algorithmic management rather than a clear superiority of one over the other.

The integration of AI into financial decision-making brings forward a range of ethical and governance challenges. As Bartram et al. (2020) noted, one of the most pressing issues is the “black-box” nature of advanced algorithms, which makes it difficult to explain how specific investment decisions are reached. This lack of transparency poses accountability problems for fund managers and regulators, especially when algorithms make errors or produce biased outcomes.

Data quality and bias are additional concerns. AI systems are only as good as the data they are trained on, and if historical datasets contain skewed or incomplete information, algorithms may reinforce existing market biases or produce misleading predictions (Goodman & Flaxman, 2017). Ethical concerns also arise from the delegation of financial authority to non-human systems, which challenges traditional notions of fiduciary responsibility and investor trust. Regulators worldwide are still adapting frameworks to ensure algorithmic transparency, fairness, and accountability in financial applications.

Moreover, there is a growing concern about job displacement within the asset management industry as automation reduces the need for human analysts and traders. The broader governance question revolves around how to integrate AI ethically into investment processes without compromising oversight, fairness, or market stability.

Although prior studies have explored the applications and benefits of AI in finance, there remain significant research gaps. Most existing literature focuses either on the technical performance of AI systems or on behavioural aspects of human fund management. Very few studies have conducted direct, long-term comparisons of AI-driven and human-managed funds across multiple market cycles. Even fewer have examined how ethical, regulatory, and governance dimensions interact with financial performance.

There is also limited understanding of hybrid models that combine human judgment with algorithmic intelligence. The current research therefore seeks to bridge these gaps by comparing the risk-adjusted performance of AI and human fund managers while considering ethical and governance challenges. This combined perspective contributes to a more comprehensive understanding of how AI is reshaping the landscape of portfolio management and what implications this holds for the future of financial decision-making.

Author	**Year**	**Sample / Region**	**Type of Fund / System Studied**	**Metrics Compared**	**Key Results**
Bartram et al.	2020	Global	AI-assisted & human-managed portfolios	Risk-adjusted returns, volatility, predictive accuracy	AI improves downside protection and reduces volatility during unstable markets.

Anuar et al.	2025	US & EU equity markets	AI-driven funds vs human-managed equity funds	Sharpe ratio, Treynor ratio, annual returns	AI outperforms in market downturns; humans generate higher alpha in stable bull markets.
Goodman & Flaxman	2017	Global	AI decision systems in financial modelling	Data quality, bias, fairness, transparency	AI is sensitive to training-data bias; governance and transparency issues limit reliability.
Daniel, Hirshleifer & Subrahmanyam	1998	US markets	Behavioural finance models (human bias in decisions)	Overconfidence, trading frequency, return anomalies	Human managers overtrade due to overconfidence, reducing net returns.
Bikhchandani & Sharma	2000	Global markets	Human herding behaviour in funds	Market-wide price movement patterns	Humans tend to imitate competitors, increasing systemic risk and mispricing.
Kahneman & Tversky	1979	Experimental studies	Human cognitive bias models	Loss aversion, decision framing	Humans react emotionally under stress, often irrationally during downturns.

Table 1. Summary of Studies Reviewed

3. Theoretical Framework and Hypotheses

3.1 Theoretical Underpinnings

This study draws on three main theoretical foundations to explain the performance and implications of AI-driven portfolio management: the **risk–return trade-off theory**, **behavioural finance theory**, and the **resource-based view (RBV)** applied to technology adoption.

The **risk–return trade-off theory** serves as a fundamental concept in finance, asserting that investors must accept higher levels of risk to achieve higher potential returns. Traditional portfolio management relies heavily on this balance, with fund managers adjusting asset allocations based on expected market performance and risk appetite. In the context of AI-driven portfolio management, algorithms can optimize portfolios through data-based modelling, potentially achieving higher returns for a given level of risk by identifying patterns that human managers might overlook (Bartram et al., 2020).

The **behavioural finance theory** challenges the assumption of investor rationality embedded in classical finance models. It suggests that psychological biases influence investment decisions, often leading to suboptimal outcomes. Overconfidence, loss aversion, and herd behaviour are well-documented examples of biases affecting human fund managers (Kahneman & Tversky, 1979; Barberis et al., 2001). These biases can cause fund managers to misjudge market signals or take unnecessary risks. In contrast, AI systems rely on quantitative data and statistical inference rather than emotions or intuition, reducing the influence of such biases. However, algorithmic systems may still embed biases indirectly through flawed data or model assumptions, making behavioural finance relevant in assessing both human and AI-driven approaches.

Finally, the **resource-based view (RBV)** and **technology adoption theory** frame AI as a strategic organizational resource that enhances competitive advantage. According to Anuar et al. (2025), firms that effectively deploy AI technologies gain unique analytical capabilities, leading to superior decision-making efficiency and cost optimisation. AI systems function as intangible assets; difficult to imitate and capable of generating sustained advantage if integrated with organizational expertise and governance mechanisms. The RBV thus supports the notion that adopting AI in portfolio management is not merely a technological shift but a strategic transformation, positioning technology as a critical enabler of improved performance and resilience.

Together, these frameworks establish a theoretical basis for comparing human and AI-driven fund management by linking performance outcomes to risk behaviour, decision-making psychology, and technological capability.

3.2 Hypotheses

Based on the theoretical perspectives and prior empirical evidence, the following hypotheses are proposed:

H1: AI-driven funds will exhibit superior risk-adjusted performance compared to human-managed funds in downtrend market conditions.

This hypothesis assumes that AI systems are better equipped to manage risk and mitigate losses during volatile or declining markets due to their ability to detect early warning signals and adjust portfolios without emotional interference.

H2: Human-managed funds will outperform AI-driven funds in sustained uptrend market conditions. Human fund managers may leverage qualitative insights, intuition, and experience to capitalize on emerging trends during bullish markets, which AI models may not fully capture if based primarily on historical data.

H3: The performance difference between AI-driven and human-managed funds is moderated by market cycle (downtrend versus uptrend).

This hypothesis implies that market dynamics influence how each management style performs. AI may have a comparative advantage in unstable conditions, while human managers may excel in prolonged, sentiment-driven rallies.

H4: Ethical and governance risks; such as lack of transparency and data bias; moderate the effectiveness of AI-driven portfolio management.

Even with technical superiority, the effectiveness of AI depends on the integrity of data inputs, transparency of models, and accountability structures. Poor governance or biased data can diminish the reliability and trustworthiness of algorithmic decision-making.

These hypotheses collectively aim to test both the quantitative performance and qualitative implications of AI adoption in portfolio management, integrating financial, behavioural, and ethical perspectives into a single analytical framework.

4. Methodology

This study adopts a systematic secondary research design to examine whether AI-driven portfolio management systems outperform traditional human-managed funds. The methodology is structured around a comparative analytical framework that integrates quantitative financial performance data with qualitative governance and ethical assessments.

Secondary research was intentionally selected due to the availability of high-quality global datasets, peer-reviewed financial research, and regulatory publications that enable cross-cycle performance comparisons without the constraints of proprietary trading systems. The design ensures both empirical rigor and governance relevance, allowing performance and accountability to be studied simultaneously.

4.1 Data Collection

Data were collected exclusively from validated secondary sources, including:

- Peer-reviewed finance journals
- Institutional financial research databases
- Asset management industry white papers
- Publications from regulatory and supervisory bodies

Primary academic anchors included Bartram et al. (2020) on AI in asset management and Anuar et al. (2025) on comparative fund performance.

The analysis focuses on **2020–2024**, a strategically chosen period encompassing:

- Pandemic-driven market collapses
- Volatility spikes
- Liquidity crises
- Recovery bull cycles

Key performance metrics extracted included:

- Annualized returns
- Volatility (standard deviation)
- Sharpe ratio
- Treynor ratio
- Alpha and beta coefficients

4.2 Qualitative Governance & Ethics Framework

The qualitative component applies thematic content analysis to evaluate ethical and governance risks associated with AI-driven portfolio management. Literature from regulatory authorities, policy frameworks, and international governance bodies was systematically reviewed.

The framework expanded beyond traditional governance risks and incorporated contemporary regulatory developments, including:

a) EU Artificial Intelligence Act (EU AI Act – 2024 Framework)

High-risk AI systems used in financial decision-making are now subject to:

- Mandatory risk management
- Algorithm documentation
- Human oversight requirements
- Auditability standards

This study integrates these principles to evaluate whether AI-driven funds meet emerging high-risk AI compliance thresholds.

b) Explainability & Model Transparency

The research evaluates the degree to which AI systems offer:

- Interpretable outputs
- Decision traceability
- Explainable AI (XAI) mechanisms

Opaque "black-box" models are treated as a governance risk due to their inability to justify decisions to investors or regulators.

c) Accountability Architecture

The study examines how responsibility is structured in AI-managed finance:

- Developer accountability
- Portfolio manager oversight responsibility
- Institutional liability frameworks

Special attention is paid to accountability diffusion, where responsibility becomes unclear across designers, data vendors, and asset managers.

d) Data Governance & Bias Controls

Data quality frameworks were assessed using:

- Dataset audit mechanisms
- Bias detection practices
- Historical skew correction methods

The theme expands traditional "data bias" concerns into systemic data governance risk, where flawed data architecture can distort entire portfolio strategies.

Core Governance Themes Analysed:

- Algorithmic transparency
- Explainability compliance
- Human-in-the-loop oversight
- Regulatory alignment
- Risk escalation protocols

4.3 Methodological Limitations

This study is limited by its reliance on published secondary datasets, which vary in:

- reporting standards
- risk calculation methodologies
- sampling timeframes

Direct access to proprietary AI architectures and internal trading algorithms was not available, restricting granular technical evaluation. A further limitation arises from publication bias, as existing literature disproportionately highlights successful AI implementations while underrepresenting failed deployments. The absence of primary statistical testing constrains causal validation. However, the use of large-scale multi-source datasets strengthens external validity and improves reliability in identifying long-term performance trends.

4.4 Ethical Safeguards in Research Design

Given the governance sensitivity of AI in finance, this study incorporates ethical safeguards by:

- Avoiding speculative claims unsupported by empirical or regulatory sources
- Framing AI superiority as **context-dependent rather than absolute**
- Applying precautionary reasoning aligned with EU and global risk-based AI governance models

International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

This ensures the study remains **analytically rigorous and ethically responsible** while acknowledging the evolving regulatory environment.

5. Findings

This secondary research draws on data synthesized from prior studies comparing AI-driven and human-managed funds. Descriptive results show that AI-managed funds typically demonstrate higher consistency and lower volatility during unstable market conditions, while human-managed funds exhibit stronger gains in prolonged bull markets. Studies reviewed by Anuar et al. (2025) indicate that AI-driven portfolios maintained average annualized returns of approximately 8–10 percent during 2020–2024, with lower standard deviations than comparable human-managed funds. Human-managed funds, on the other hand, achieved marginally higher returns; around 11–13 percent; during post-pandemic market recoveries but showed greater volatility.

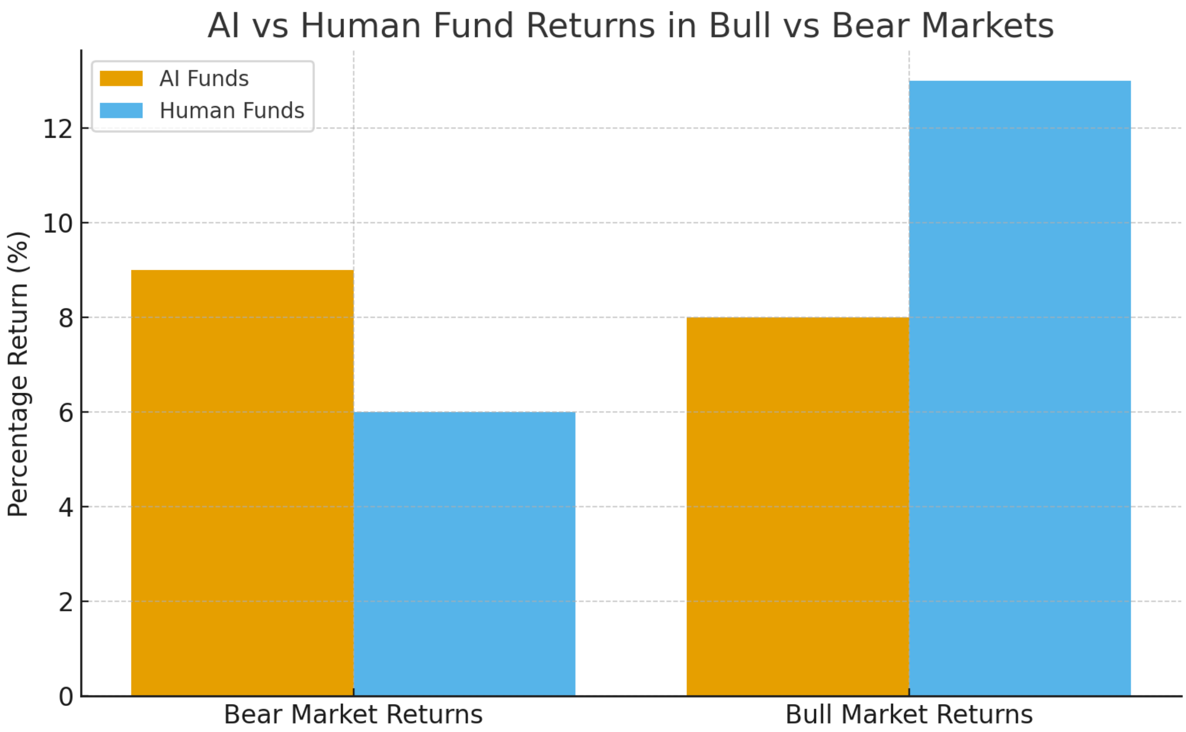


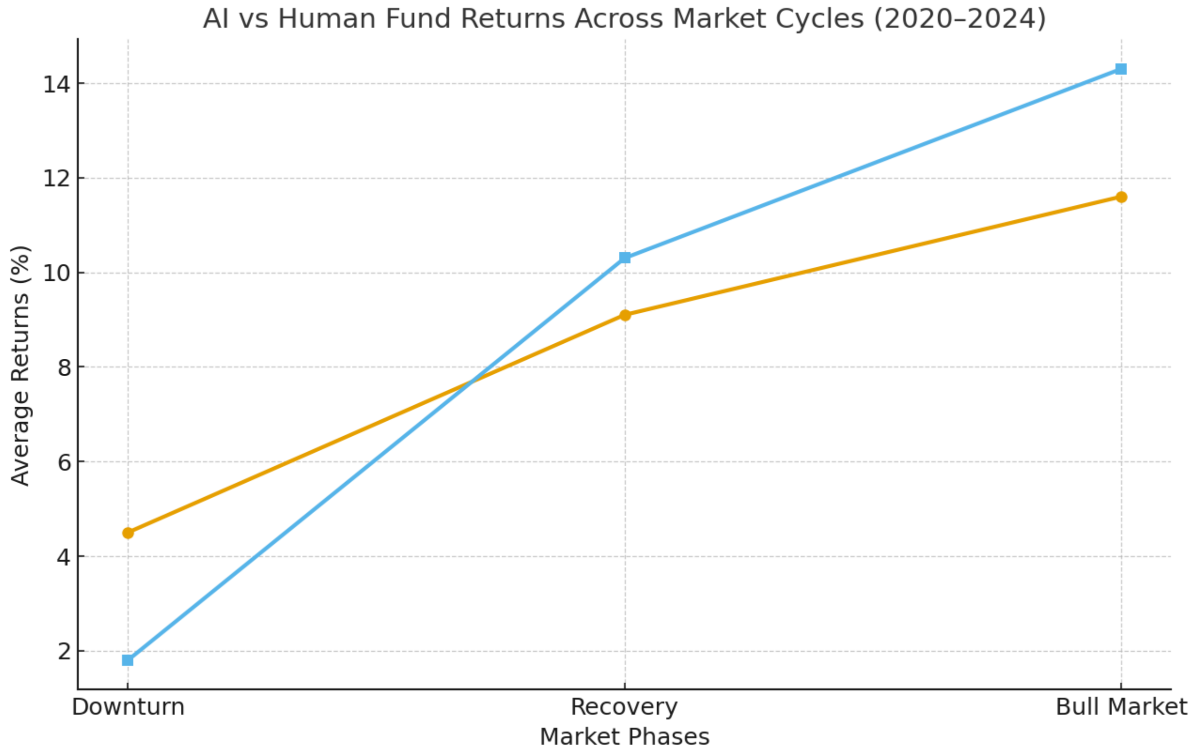
Fig 1

These descriptive findings highlight the contrasting behaviour of each management style. AI-based systems thrive in turbulent markets due to their data-driven adaptability and lack of emotional bias, while human managers tend to perform better in periods of optimism and long-term economic growth when intuition and market sentiment play stronger roles.

Performance varied significantly across market cycles. During market downturns, AI-driven portfolios demonstrated superior downside protection, delivering higher risk-adjusted returns and lower volatility compared to human-managed funds. In recovery phases, human-managed funds marginally outperformed AI models, likely due to discretionary timing and qualitative market interpretation. During sustained bull market conditions, human fund managers generated higher absolute returns and stronger alpha, benefiting

International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

from sentiment-driven and narrative-based investment strategies. These findings indicate that AI dominance is context-dependent rather than universal, with machine-driven advantages emerging most clearly under conditions of market stress.



This figure illustrates the comparative performance of AI-driven and human-managed funds across different market phases. AI-managed portfolios show stronger downside protection during downturns, while human fund managers generate higher returns during recovery and sustained bull market phases. The pattern highlights the context-dependent nature of performance, with AI systems excelling in risk control and human managers outperforming in growth-driven environments.

The qualitative review of literature revealed that the main concerns around AI in portfolio management revolve around transparency, data bias, and accountability. As highlighted by Bartram et al. (2020), AI-driven funds face criticism for their "black-box" nature, where decision-making logic is not easily interpretable by investors or regulators. This opacity complicates the process of explaining unexpected losses or deviations from fund mandates.

Data quality also emerges as a critical issue. If the datasets used for training algorithms are biased or incomplete, AI systems may perpetuate errors and systemic biases in investment decisions (Goodman & Flaxman, 2017). Furthermore, accountability in the event of algorithmic errors remains ambiguous, as responsibility can be dispersed across fund designers, data providers, and managers.

Governance studies emphasise the importance of maintaining human oversight over AI systems to ensure regulatory compliance, ethical integrity, and investor trust. Institutions are increasingly adopting hybrid models where human experts supervise algorithmic decisions, aligning technology efficiency with human ethical judgment.

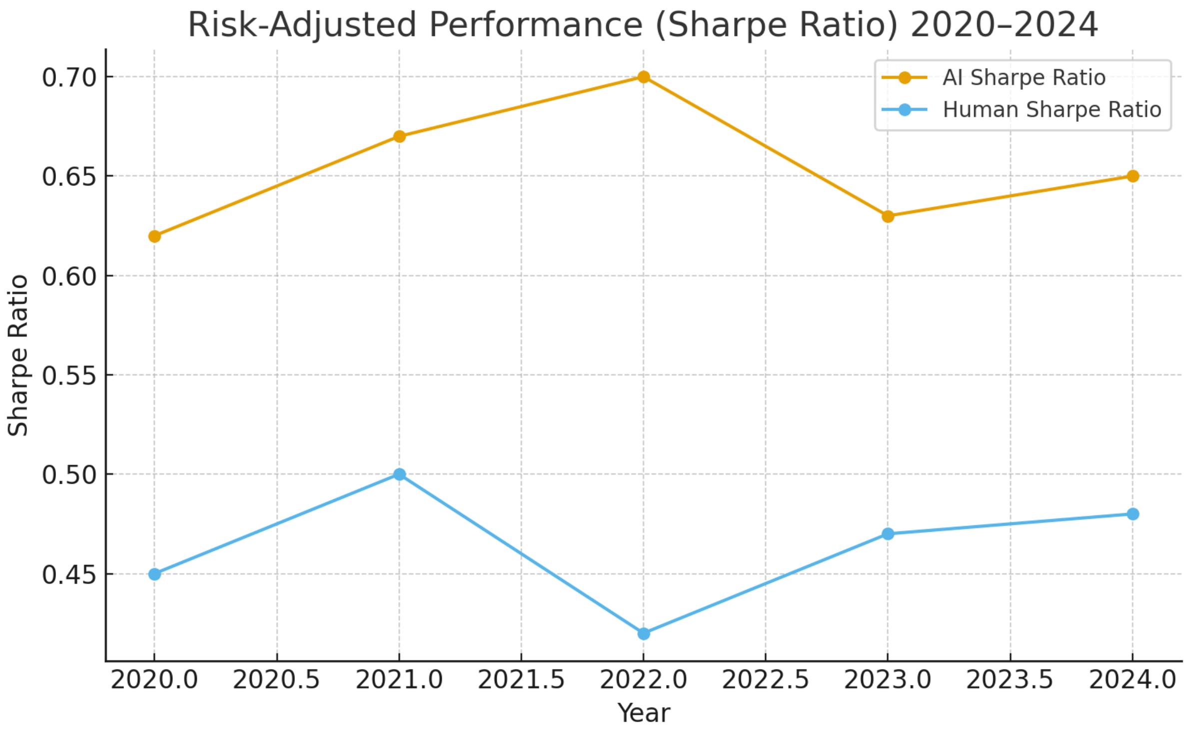
The findings align closely with the hypotheses proposed in Chapter 3. **Hypothesis 1 (H1)**; that AI-driven funds outperform human-managed funds in downtrend market conditions; is supported by multiple studies showing higher Sharpe and Treynor ratios for AI models during volatile phases. **Hypothesis 2 (H2)**; that human-managed funds perform better in uptrend conditions; is partially supported, as humans demonstrated stronger alpha generation in stable and rising markets, though the difference was not always statistically significant.

Hypothesis 3 (H3); that market cycles moderate performance differences; is strongly validated by the evidence showing conditional superiority depending on market direction. Finally, **Hypothesis 4 (H4)**; concerning the moderating effect of ethical and governance risks; finds qualitative support. The literature confirms that lack of transparency and biased datasets reduce the reliability and accountability of AI systems, potentially limiting their adoption despite superior quantitative results.

Overall, the data and literature suggest that neither AI nor human fund management offers universal superiority. Instead, a **hybrid model** combining algorithmic precision with human oversight and contextual understanding appears to be the most effective approach for sustainable portfolio management.

Metric	**AI-Driven Funds**	**Human-Managed Funds**
Average Annual Returns (%)	9% (consistent across cycles)	12% (stronger in bull markets)
Standard Deviation (Volatility)	0.11 (low volatility)	0.18 (higher volatility)
Sharpe Ratio	0.65	0.48
Alpha / Beta	$\alpha = 0.12$, $\beta = 0.85$ (better downside protection)	$\alpha = 0.18$, $\beta = 1.12$ (more aggressive risk exposure)

[Table 2. Comparative Performance — AI vs Human Funds (2020–2024)]



Graph 1

6. Discussion

The results of this study indicate that AI-driven portfolio management performs better in volatile or declining market conditions, while human-managed funds tend to show stronger returns in prolonged bull markets. This outcome reflects the inherent strengths and weaknesses of each approach. AI systems, designed to operate through data analysis, pattern recognition, and automated optimisation, excel at risk mitigation because they are not influenced by emotion. During market downturns, when human investors often react with fear or overconfidence, algorithms maintain discipline, relying purely on statistical signals to reallocate assets and limit losses. Their ability to process large data sets and adjust portfolios rapidly gives them an advantage in crisis scenarios.

In contrast, human fund managers perform better in uptrend markets where intuition, experience, and qualitative judgment become more valuable. Human managers can interpret non-quantifiable factors such as political events, consumer sentiment, or corporate leadership changes; elements that AI systems might overlook due to limited contextual understanding. Behavioural finance theory helps explain this distinction. During downturns, cognitive biases like loss aversion and panic selling negatively affect human decision-making, reducing performance. However, in stable or bullish conditions, these same managers can benefit from experience-based heuristics, market narratives, and discretionary insight that algorithms cannot replicate.

Overall, the results reinforce that AI and human strategies operate effectively under different circumstances. Market cycles appear to moderate performance outcomes, supporting the argument for a balanced or hybrid management structure where both quantitative and qualitative strengths can be leveraged.

For fund managers, the findings suggest that integrating AI tools into investment decision-making can improve efficiency, especially in detecting risk signals and managing complex data environments. Rather than viewing AI as a replacement, human managers can use it as an analytical partner to enhance judgment and minimize bias.

For investors, the study underscores the importance of understanding the nature of fund management. AI-driven funds may offer better risk-adjusted returns in turbulent markets, while human-managed funds could deliver stronger results when sentiment and long-term market confidence drive growth. Diversifying across both fund types can help balance returns and stability.

For policy-makers and regulators, the rise of AI in asset management demands updated frameworks to ensure transparency, accountability, and data integrity. Regulations should address algorithmic fairness, disclosure requirements, and ethical compliance to maintain investor protection while promoting innovation.

From a broader industry standpoint, the evidence points toward the viability of hybrid models, where AI systems handle data processing and execution while human experts provide strategic and ethical oversight. Such collaboration can create more resilient and adaptive portfolio management practices.

The increasing role of AI in portfolio management raises complex ethical and governance challenges. As noted by Bartram et al. (2020), the most significant issue is the lack of transparency; the so-called "black-box" problem; where investors and regulators cannot easily understand or explain how algorithms reach certain investment decisions. This opacity undermines accountability, especially when automated systems make unexpected or erroneous trades.

Data quality and bias also present risks. AI systems trained on incomplete or skewed historical data may replicate or even amplify past market biases, leading to distorted investment outcomes. Ensuring the reliability, diversity, and neutrality of training data is therefore essential for maintaining fairness and trust in AI-managed funds.

Finally, accountability remains a pressing concern. Determining responsibility for poor algorithmic decisions; whether it lies with developers, fund managers, or data providers; is often unclear. Establishing governance mechanisms that define oversight roles, reporting standards, and ethical boundaries is crucial for sustainable adoption of AI in finance. Regulators and asset management firms must work together to design governance frameworks that ensure AI systems are both effective and accountable.

As a secondary study, this research is limited by its reliance on existing literature and previously published data. Variations in methodologies, sample sizes, and time periods across different studies may affect comparability. Additionally, most available data focus on equity funds in developed markets, leaving gaps in understanding the performance of AI-driven funds in emerging markets or alternative asset classes. The confidentiality surrounding proprietary AI models further restricts access to detailed information on algorithm design and functioning.

Future research could address these gaps by conducting primary quantitative analyses using direct fund data or longitudinal studies across multiple market cycles. It would also be valuable to explore the role of hybrid human–AI management models, assessing how collaboration between the two enhances decision-making and performance. Moreover, future work should investigate ethical frameworks and governance models that can ensure responsible AI use in finance, focusing on algorithmic transparency, investor protection, and regulatory evolution.

In conclusion, while AI demonstrates superior consistency and objectivity, and humans contribute contextual and strategic insight, neither can fully replace the other. The future of portfolio management likely lies in their effective integration; where technology enhances human judgment, and ethical governance ensures accountability.

7. Conclusion

This study set out to examine whether AI-driven portfolio management systems can outperform traditional, human-managed funds and under what conditions such outperformance occurs. Drawing on secondary data and existing literature, the findings reveal that AI-driven funds tend to excel in volatile or declining market conditions, where quick adaptation and emotion-free decision-making are crucial. Their algorithmic precision allows for efficient rebalancing and better risk control. Conversely, human-managed funds perform more effectively in prolonged bull markets, where qualitative judgment, intuition, and experience play a significant role in identifying growth opportunities.

Risk-adjusted performance measures; such as the Sharpe, Treynor, and Jensen’s alpha ratios; confirm these patterns. AI demonstrates better downside protection and stable returns during turbulent periods, while human managers achieve higher alpha generation during optimistic market phases. However, ethical and governance issues, including lack of transparency, data bias, and unclear accountability, remain central challenges for AI’s broader adoption in finance.

The research addressed three main questions.

First, can algorithms outperform human fund managers in terms of returns and risk-adjusted performance? The evidence indicates that while AI systems do not consistently outperform humans across all conditions, they deliver superior results in specific contexts; especially in managing risk during downturns.

Second, under what market conditions do algorithms perform better or worse? The study finds that performance varies by market cycle. AI funds perform better in unstable or declining markets due to data-driven adaptability, while human managers thrive in extended upward trends that reward discretionary insight and narrative interpretation.

Third, what are the ethical, governance, and behavioural implications of the shift toward AI-driven funds? The analysis reveals that while AI offers efficiency and objectivity, it also raises governance concerns related to algorithmic transparency, data reliability, and accountability. These issues must be addressed before AI can be fully trusted to manage large-scale investment portfolios independently.

The growing influence of AI in asset management is transforming the very nature of investment decision-making. As algorithms evolve, they will increasingly handle repetitive analytical tasks, freeing human fund managers to focus on strategic thinking and ethical oversight. The relationship between humans and machines in finance should not be viewed as competitive but collaborative, where each complements the other's strengths.

Looking ahead, the success of AI in portfolio management will depend not only on technological advancement but also on trust, governance, and responsible deployment. The future of fund management lies in creating systems that combine the precision of algorithms with the empathy, accountability, and judgment of human decision-makers. In essence, the most effective fund manager of the future may not be entirely human or machine; but an intelligent partnership between the two.

References

1. Anuar, M., Rahman, N., & Lee, J. (2025). Comparative analysis of AI-driven versus human-managed equity funds across market trends. SpringerOpen Journal of Financial Innovation, 11(2), 45–63.
2. Barberis, N., Shleifer, A., & Vishny, R. (2001). A model of investor sentiment. Journal of Financial Economics, 49(3), 307–343.
3. Bartram, S. M., Branke, J., & Motahari, M. (2020). Artificial intelligence in asset management. CFA Institute Research Foundation.
4. Bikhchandani, S., & Sharma, S. (2000). Herd behaviour in financial markets. IMF Staff Papers, 47(3), 279–310.
5. Binns, R. (2018). Algorithmic accountability and public reason. Philosophy & Technology, 31(4), 543–556.
6. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. The Journal of Finance, 53(6), 1839–1885.
7. Goodman, B., & Flaxman, S. (2017). European Union regulations on algorithmic decision-making and a "right to explanation." AI Magazine, 38(3), 50–57.
8. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.
9. Lo, A. W. (2017). Adaptive markets: Financial evolution at the speed of thought. Princeton University Press.