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Evaluating Short-Term Equity Portfolio Performance: A Comparative Study of AI-Driven and Human-Managed Strategies

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ABSTRACT

Despite recent developments in artificial intelligence (AI) for portfolio management, it is still unknown how free AI agents compare to human fund managers in constructing short-term, high-risk portfolios. This study uses an experimental design model with the aim of evaluating whether free AI tools can outperform human managers. Four professional human fund managers and three free AI agents (ChatGPT, Gemini, and Perplexity) created portfolios consisting of ten global stocks, with a starting portfolio value of SGD $10,000. Portfolios were assessed over a one-month period from November 17th to December 16th, 2025. To analyze the data, portfolio returns and risk were calculated using the percentage change in value and portfolio standard deviation through a covariance matrix, respectively. The results showed that human-managed portfolios (-3.33% return) slightly outperformed AI-managed portfolios (-3.46% return), with a lower average risk of 0.964% compared to AI portfolios' 1.603%; however, AI portfolios demonstrated better risk-adjusted performance as measured by Sharpe ratios (-2.010 versus -4.834). No clear relationship between risk and return was found for either group. AI-managed portfolios were volatile and concentrated in high-growth sectors, whereas human-managed portfolios tended to deliver more consistent returns across diverse sectors. These preliminary findings suggest the importance of human judgment while highlighting AI's potential to help with investment decisions, though further research with larger samples is needed to confirm these results.

1. Introduction

1.1. General Background

The recent trends in the use of artificial intelligence (AI) show that 91% of fund managers are using or planning to use AI for investments (Mercer, n.d.). Artificial intelligence has become increasingly popular in the field of portfolio management, currently accounting for a large portion of the global equity market volume through algorithmic trading, robo-advisory services, and machine learning tools (Allied Market Research, 2024). While humans working

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in mutual funds, hedge funds, and private wealth management have historically dominated portfolio management, recent research has shown its challenges. Humans often make investment decisions based on experience, intuition, and observation, but they also struggle to deal with the amount of real-time market data available today. Investment decision-making is meant to be a logical approach to choosing assets that maximize returns, but it becomes difficult due to human psychology, including cognitive biases and risk perception (Ahmad et al., 2025). Cognitive biases are ways humans think using mental shortcuts to simplify complex decisions, which can reduce effort and help one process information faster. However, under uncertainty or time pressure, it also leads to judgment errors and poor decision-making and investment choices (Ahmad et al., 2025).

Investment decision-making is also influenced by behavioral biases. These are availability bias, where decisions are affected by the latest or most memorable information; anchoring, where one makes excessive use of a single point of reference when making decisions; loss aversion, where one is focused more on avoiding losses than gaining profits; and overconfidence (Ahmad et al., 2025). Such biases and mental fallacies may constrain human portfolios due to the negative impact on decision-making skills (Hasan et al., 2023). Such problems have made technology be taken more seriously in investment management. AI has enhanced language processing and deep learning capabilities, allowing models to better analyze unstructured data, such as news sentiment, and alter their strategies; particularly with multi-agent AI systems, which are more likely to perform well on simple tasks compared to simple single-model systems (Han et al., 2024).

The general market contributes to this tendency, with studies worldwide indicating that in unstable market conditions, AI-controlled strategies can outperform human professionals (Anuar et al., 2025). Additionally, AI and generative AI have become more efficient, which has resulted in new methods of forming portfolios and defined AI as a significant component of the current investment management (Joshi, 2025; Usman, 2024). It has motivated fintech platforms to start offering an increasing number of AI-driven solutions to investors seeking low-cost, data-driven investment solutions. Consequently, an increasing number of companies are investing in AI-powered robo-advisors, which means that the size of the global robo-advisor market is expected to grow even more: the global market size will rise to USD 102.03 billion by 2034, compared to USD 14.08 billion in 2026 (Fortune Business Insights, 2026). This has been fuelled by growth in the financial sector, technological innovation, and emerging consumer tastes. Big financial institutions like The Vanguard Group and Betterment now have AI features in their systems to provide personalized advice; an example is JPMorgan releasing an AI-based investment advice system in May 2023 (Fortune Business Insights, 2026).

Nevertheless, AI is not very effective, particularly during periods of market uncertainty. Most of these models are based on past data and trends that, in many cases, do not capture the volatility of the stock market. Indicatively, there has been a recent war in the Middle East (2026), which has rendered financial markets very volatile and unpredictable. It implies that historical patterns adopted by AI become inapplicable anymore; therefore, these tools might become less efficient during such periods. Humans, on the other hand, can be more informative; human-managed strategies can be more effective in market recoveries as human managers can analyze macroeconomic trends, comprehend company-specifics, and apply qualitative judgment better (Anuar et al., 2025). Because of these varying views, investors would prefer to have a better understanding of how AI and human managers perform comparatively in practice. It is argued that AI can be better because it does not rely on emotions, and processes information faster, whereas some think that such systems may give bias and misunderstand information. This brings the question of whether AI does actually enhance the performance of investments, or whether it merely replaces the old human biases with new algorithmic biases.

1.2. Literature Review

There is a change in the field of portfolio management as traditional management steps towards AI-based management. Although the aim of both is to enhance returns, the literature notes disparities between AI and human investment performances to offer a subtle interpretation of this argument.

Anuar et al. (2025) conducted a study to examine the relative performance of AI-managed funds and human-managed funds in various market conditions. The paper utilized data on 80 equity funds in the period 2021-2024 to evaluate the performance of the funds using risk-adjusted performance measures such as the Sharpe ratio, Treynor ratio, Jensen alpha, and t-tests. The researchers discovered that human-managed funds are more effective during recoveries compared to AI-managed funds, which are more effective in markets that are in downtrends.

This can be attributed to the fact that human beings are dependent on qualitative judgment, whilst the AI can increase and decrease risk rapidly, which may explain the performance gap between AI and human-managed funds. This notion is furthered in another study, by Sutiene et al. (2024), which sought to gauge the effectiveness of AI systems in portfolio management.

Based on a literature review of AI portfolio systems, the research evaluated the performance of the algorithms in various applications, including both positive and transparency concerns. It was concluded that AI systems can give more consistent results because it is better at estimating risks and dynamically allocating, but it also raises the issue of transparency. Although AI might be able to deliver correct results, they do not always have clear reasoning, and it becomes more difficult to trust human investors to make decisions.

On a comparable plane, Hasan et al. (2023) sought to examine how AI can decrease behavioral biases in finance decision-making. The research conducted a comparison of AI and human-based decision-making behavior in risk and uncertainty situations, involving confirmation and hindsight bias, using simulations. They reiterate these biases in human management and that AI can mitigate these behavioral biases that influence human financial choices. The analysis found the AI systems to minimise emotional and cognitive biases, which results in more rational decision-making.

Retail investors specifically have many of these biases. Vijaya (2014) named overconfidence, anchoring, loss aversion, and herd behavior as the main factors influencing retail investor decision-making, while Kuzminsky and Ziemtsov (2024) further showed that retail investors often underperform compared to institutional investors. They attributed this difference to limited access to analytical tools and a lack of investment goal-setting. Together, these findings suggest that retail investors face multiple decision-making challenges, which AI tools may be able to address.

This is consistent with the findings of Chen and Ren (2021), who studied whether AI-managed mutual funds perform better or worse compared to the traditional human-managed funds. The paper employed empirical fund performance data to determine annual returns based on comparative performance. Their results show that AI-managed funds outperform human-managed funds by about 5.8% annually, which is primarily due to their reduced transaction costs, better stock-picking abilities, and reduced behavioral biases. Nevertheless, they also point out that these funds underperform in comparison to the market, implying that the key advantages of AI managers are the decreased human bias.

Although numerous studies have demonstrated the advantages of AI, other scholars present alternative outcomes. The purpose of the study by Praxmarer and Simon (2024) was to compare the performance of funds run by AI and those run by humans. The research employed the data of the U.S. mutual funds being managed by AI to study fund performance. They discovered that AI-based mutual funds do not outperform the market, but are slightly better than the performance of human-managed funds, although AI fund performance declined recently. They also indicate that AI performs well when it comes to market timing and can help with tasks like analyzing a large number of stocks, but it fails in certain areas, like stock selection, which contradicts the belief that AI will always result in better performance. There are also numerous papers devoted to the cooperation of advanced AI systems. Han et al. (2024) aimed to evaluate how effective multi-agent AI systems are in financial decision-making. The study used a multi-agent AI system that could handle fundamentals, sentiment, and risk, and analyzed 10-K filings. Their system was able to dynamically adapt to various market conditions and optimize their strategy.

The study found that their model was able to outperform single-agent systems with better accuracy, efficiency, and adaptability. This demonstrates that the benefits of AI could be maximized when used in cooperation with several systems.

Beyond multi-agent systems, recent research has also looked at the specific role of large language models (LLMs) such as ChatGPT in portfolio decisions. Ko and Lee (2024) studied ChatGPT's capability in selecting assets and portfolio diversification across many asset classes, finding that ChatGPT's selections statistically improved diversification relative to randomly selected assets. This suggests that LLMs can be useful assistants in portfolio construction.

However, their study used ChatGPT as a supplementary tool instead of an independent manager, leaving open the question of how freely available LLMs perform when used independently to construct portfolios.

Chou and Chen (2024) have another point of view and attempt to investigate the efficiency of sequential decision systems in portfolio optimization. Portfolio efficiency and adaptability were the metrics used to compare the study with human-based portfolios using a sequential decision-aid expert system and optimization algorithms. The analysis found that AI models were more responsive and quicker in decision-making, resulting in more predictable portfolios as compared to human managers. Equally, Nagalaxmi et al. (2025) carried out a study to examine the implications of AI on portfolio management in terms of application, benefits, and challenges. The study, based on a mixed-method approach comprising a case study and a controlled experiment, concluded that AI enhances predictive accuracy, portfolio construction, and efficiency in decision-making. Nevertheless, they also note such issues as the problem of data quality and algorithm bias. They conclude that AI has influenced portfolio management and investment greatly, enabling new opportunities.

Also, Joshi (2025) strives to investigate the increasing role of AI in portfolio optimization and risk management in relation to predictive analytics, risk evaluation, and law adherence. Using a literature synthesis of over 50 sources, the study assessed the applications of AI in this field.

They discovered that AI lowers the number of errors and raises the predictive accuracy, yet it also introduces risks associated with transparency, bias, and regulatory compliance, which require robust governance. Lastly, Usman (2024) wanted to enhance portfolio diversification through machine learning methods. The study utilized different regression and classification models using historical stock data. They discovered that machine learning models, particularly linear regression with standardization, have the potential to enhance diversification, which assists investors in minimizing risk and overconcentration.

All in all, these studies demonstrate that, although AI is developing and shaping the future of the portfolio management industry, it is unlikely to be a complete replacement for human managers. The speed, efficiency, consistency, and minimization of bias offered by AI can be contrasted with human intervention, which adds value in the form of qualitative judgment and interpretation.

Nevertheless, even though there is increasing evidence regarding the application of AI in the management of portfolios, the current literature mainly addresses institutional AI systems in the long-term context, which does not clarify how AI tools that are publicly available perform compared to human fund managers in the short-term.

1.3. Literature Gap and Rationale of the Study

A large number of studies compare human and AI-managed funds by examining the long-term performance over several years; however, there are limited studies on the comparative short-term portfolio construction with the purpose of maximizing returns. Investors tend to make decisions in the short term, like weeks or months, and need to have the capacity to respond to changes in ¶the market. The existing literature primarily discusses historical data rather than decisions of the portfolio in real-time, leaving a gap in the comprehension of the performance of each portfolio during a short period.

In addition, the majority of available literature examines institutional AI systems like robo-advisors or hedge fund models, although more human retail investors would be able to access AI agents that are widely available and free, like ChatGPT-based applications. Therefore, there are few studies that compare the performance of these AI tools with that of human managers with the same data, which leaves a significant gap because millions of retail investors use these publicly available AI tools, yet it is unclear whether they generate better or worse portfolios than human managers.

Moreover, the majority of the studies that have compared AI and human portfolio management involve large amounts of data or simulated trading conditions rather than small studies that concentrate on the actual decision-making scenario that an individual investor is presented with when forming a portfolio. Consequently, there is a lack of comparative opportunity on the practical level between AI and humans when given the same conditions and constraints, which leaves it hard to comprehend how the two perform.

Retail investing is growing in popularity with artificial intelligence, with millions of users relying on free AI products to make financial choices. Nevertheless, a good portion of these investors still have confidence in their judgment or rely on the recommendation of professional fund managers. This begs the question of whether AI can be able to outperform human expertise in real-world investing scenarios. Even though it has grown swiftly, it remains unknown how well these popular AI tools work in comparison to experienced managers in creating short-term¶portfolios. The literature primarily examines either long-term or institutional AI systems, and a gap in knowledge pertains to whether public AI tools can deliver returns in actual market settings. The aim of the study is to compare portfolios generated by free AI agents and professional human-managed portfolios.

2. Materials and Methods

2.1. Research Aim and Objectives

This research aims to compare the short-term stock portfolios created by human fund managers and publicly available AI agents. To evaluate the same, the following objectives were considered:

- To calculate and compare the average short-term returns of the portfolios designed by human professionals and AI agents
- To assess the differences between the average risks of the portfolios created by the two groups
- To analyse the diversification of stocks proposed by human managers and AI agents

2.2. Research Design

This study follows an experimental research design. All the participants, including human professionals and AI agents, were given a hypothetical case study for an investor who expects to maximize profits in a span of one month from 17th November 2025 to 16th December 2025.

Participants were instructed to create a portfolio with 10 equity stocks or ETFs worth 10000 Singapore dollars. Moreover, there were several constraints on the portfolios prepared by the individuals. Firstly, one stock or ETF cannot comprise more than 30 percent of the portfolio value. Additionally, amendments in the portfolio cannot be made during the experiment period.

Hence, trading between the observation days was not allowed. Finally, short selling was not permitted during the experiment.

2.3. Sampling and Sample Characteristics

This study used a random sampling method to select 3 free AI agents: ChatGPT's GPT-5.1, Gemini 2.5, and Perplexity. On the contrary, the targeted and convenience sampling methods were applied to identify four human portfolio managers. Of the 4 human portfolio managers, 3 were aged between 40 and 47 years, while the fourth was over 70 years old. Subsequently, 75 percent of the human managers had more than 5 years of experience, while one of them had 3-5 years of experience. Finally, all of them hold a master's degree or more. Hence, these demographic characteristics of the portfolio managers indicate they are the best fit for this experiment.

2.4. Data Collection

During the first phase of experimentation, human portfolio managers were instructed to create the portfolio according to the case study in one week's time. The data around participants' demographics and the amount allocated to different stocks and ETFs in the portfolios were collected using a Google Form. Once this data was gathered, AI agents were prompted with the same case study. All the portfolios were from human portfolio managers, and AI agents were organised in a spreadsheet. Daily closing prices for all the equities were monitored and collected for one month to calculate the average return and risk.

2.5. AI Agent Prompting Protocol

To ensure reproducibility, the exact prompts provided to each AI agent are documented below. All three AI agents were prompted on 17th November 2025. Each agent received the following standardized prompt without modification:

Background

You are acting as a portfolio manager tasked with designing a short-term, high-risk equity portfolio for an individual investor, Mr. Adrian Lee. The primary objective is to maximize returns over a one-month investment horizon, accepting elevated volatility and downside risk in pursuit of superior short-term gains. Mr. Lee intends to invest SGD 10,000 for a period of one month, during which no trading or rebalancing will be allowed — the portfolio must remain static throughout the investment horizon. The performance will be evaluated strictly at the end of this one month. Mr. Lee is a 35-year-old Senior Technology Consultant at a multinational firm in Singapore, with an annual income of SGD 180,000 and moderate investing experience, including five years of managing ETFs and blue-chip stocks. He and his spouse, Rachel Tan (33), are expecting their first child in six months, which creates an underlying need to balance liquidity for upcoming family-related expenses while aggressively pursuing short-term capital appreciation. Their current financial landscape includes SGD 50,000 in ETFs, SGD 30,000 in cash savings, and a recently purchased 3-bedroom condo in central Singapore. They maintain a mortgage, plan for childcare costs, and allocate funds for occasional family holidays. Mr. Lee's risk tolerance is aggressive, reflecting his willingness to accept significant fluctuations in portfolio value to capture potential upside over the one-month investment horizon. There are no liquidity constraints during this period, allowing full exposure to high-risk positions. The investment universe includes global equities and ETFs across any international exchange, enabling exposure to a broad range of sectors and markets, including technology, financials, energy, and other high-growth industries.

Investor Profile

- Name: Mr. Adrian Lee
- Age: 35
- Occupation: Senior Technology Consultant at a multinational firm
- Annual Income: SGD 180,000
- Investment Experience: Moderate (5 years investing in ETFs and blue-chip stocks)
- Investment Objective: Short-term capital appreciation over a one-month horizon
- Risk Tolerance: Aggressive — willing to accept high volatility and drawdown for potentially superior returns
- Liquidity Needs: None during the investment period
- Investment Universe: Global equities and ETFs across any international exchange Financial Goals for the SGD 10,000 Investment
- Primary Goal: Achieve short-term capital appreciation within one month, targeting above-market returns through high-risk, high-growth equity exposure.
- Secondary Goal: Leverage market momentum in sectors such as technology, renewable energy, and financials to capture short-term price surges.
- Tertiary Goal: Test short-term tactical equity allocation strategies to inform future high-risk investments without compromising long-term financial stability.

Task

- Construct a portfolio of 10 securities (stocks and/or ETFs) for Mr. Lee's SGD 10,000 investment.
- You may allocate funds across the 10 instruments as you see fit, but:
  - No single position may exceed 30% of the total portfolio value.
  - Short selling, derivatives, and leverage are not permitted.
  - Trading or portfolio adjustments during the one-month period are not allowed.
- The investment will be evaluated strictly over a one-month period from the date of construction.

No follow-up prompts or clarifying instructions were provided after the initial submission. The AI-generated portfolios were recorded directly from each agent's response without modification.

2.6. Data Analysis Method

The data collected for the portfolios were analysed on Microsoft Excel by estimating the average returns and risk.

- Portfolio Returns: The initial value of all the portfolios was 10,000 Singaporean dollars each. Portfolio returns were calculated by subtracting the initial portfolio value from the portfolio value at the end of the period.

Portfolio Return = Portfolio Value (as on 16th December)- $10000 SGD After calculating individual portfolio returns, the average returns for humans and AI agents were compared.

- Portfolio Risk: The risk of each portfolio was measured using portfolio-level standard deviation, calculated using a variance-covariance matrix approach that accounts for both individual stock volatility and the correlations between stocks within each portfolio. First, daily returns for each stock were calculated over the investment period using the following formula:

Daily Return = (Current Price − Previous Price) ÷ Previous Price

Second, a 10×10 variance-covariance matrix was constructed for each portfolio using the COVARIANCE.S function in Microsoft Excel, where each cell represents the covariance between the daily returns of two stocks in the portfolio. Third, portfolio variance was calculated using the following matrix formula:

Portfolio Variance $= w^T \Sigma w$

Where w represents the vector of portfolio weights for each stock, calculated as the proportion of total portfolio value allocated to each stock, and Σ represents the 10×10 variance-covariance matrix of daily returns.

Finally, portfolio standard deviation was calculated by taking the square root of portfolio variance and multiplying by 100 to express risk as a percentage:

Portfolio Risk (%) $= \sqrt{(w^T \Sigma w)} \times 100$

Average risk for human managers and AI agents was then calculated separately and compared.

- Sharpe Ratio: To assess risk-adjusted performance, the Sharpe ratio was calculated for each portfolio, which measures the return earned per unit of risk taken. It was calculated using the following formula:

Sharpe Ratio = (Portfolio Return − Risk-Free Rate) ÷ Portfolio Standard Deviation Where portfolio return is the percentage return over the investment period, portfolio standard deviation is the covariance-based risk figure calculated for each portfolio, and the risk-free rate is the monthly equivalent of the average annualized 1-month US Treasury bill rate over the investment period. Daily 1-month T-bill rates from November 17 to December 16, 2025, were obtained from the US Treasury Department and averaged to derive an annualized rate of 3.912%, which was converted to a monthly rate of 0.326% (3.912% ÷ 12) for use in the calculation. Average Sharpe ratios for human managers and AI agents were then calculated separately and compared.

- T-Test: An independent samples t-test (Welch's) was used to determine whether the difference in returns between human-managed and AI-managed portfolios was statistically significant. A two-tailed test was used with a significance threshold of $p < 0.05$.

2.7. Ethical Considerations

Ethical considerations were ensured in the form of anonymity, confidentiality, and informed consent throughout the study. Anonymity was maintained in the experiment as the individuals didn't reveal any identifiable information. Moreover, all the participants were well informed about the experiment and the objectives of the study. Along with this, the individuals can withdraw from the experiment at any point in time. Finally, all the data points remained confidential. The data is solely used for research purposes and not disclosed to any third party.

3. Results

3.1. Human Portfolios

Table 1: Portfolio Performance Summary – Human Manager 1 Total Initial Investment: $10,000 SGD | Total Final Value: $9,795.46 SGD | Overall Return: -2.045%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
KraneShares CSI China Internet ETF	Communication Services	2000	40.53	49.35	46.79	1896.25	1.315	-5.187
¶SPDR S&P 500 ETF Trust	Broad Market	2000	2.31	867.31	878.36	2025.48	0.724	1.274
iShares MSCI India ETF	Broad Market	1000	14.18	70.52	68.54	971.92	0.659	-2.808
HDFC Bank Ltd.	Financials	1000	21.08	47.44	46.45	979.13	1.270	-2.087
TCW Transform Systems ETF	Technology	1000	8.10	123.4	124.05	1005.27	1.542	0.527
Vanguard FTSE Emerging Markets ETF	Broad Market	1000	14.12	70.81	69.41	980.23	0.559	-1.977
Vanguard FTSE Developed Markets ETF	Broad Market	500	6.40	78.08	81.08	519.21	0.694	3.842
NVIDIA Corporation	Technology	500	2.02	247.58	227.47	459.39	1.895	-8.123
Amazon.com, Inc.	Consumer Discretionary	500	1.66	300.41	287.15	477.93	1.419	-4.414
ICICI Bank Limited	Financials	500	12.33	40.56	38.99	480.65	0.722	-3.871

Table 2: Portfolio Performance Summary – Human Manager 2
Total Initial Investment: $10,000 SGD | Total Final Value: $9579.89 SGD | Percent Change: -4.201%

Stock Name	**Sector**	**Amount Invested (SGD)**	**Number of Shares**	**Closing Price SGD (17th November)**	**Closing Price SGD (16th December)**	**End Total (SGD)**	**Risk (%)**	**Returns (%)**
ICICI Bank Limited	Financials	1000	24.65	40.56	38.99	961.29	0.722	-3.871
HDFC Bank Ltd.	Financials	1000	21.08	47.44	46.45	979.13	1.270	-2.087
Sea Limited	Consumer Discretionary	2000	10.91	183.36	156.9	1711.39	2.998	-14.431
XP Inc.	Financials	1000	41.17	24.29	22.7	934.54	3.572	-6.546
¶Localiza Rent a Car SA	Consumer Discretionary	1000	92.42	10.82	11.39	1052.68	2.775	5.268
Novo Nordisk A/S	Healthcare	500	7.96	62.84	65	517.19	2.837	3.437
Exxon Mobil Corporation	Energy	1000	6.44	155.3	151.99	978.69	1.042	-2.131
Visa Inc.	Financials	500	1.16	429.65	447.72	521.03	1.630	4.206
Microsoft Corporation	Technology	1000	1.51	664.38	612.82	922.39	1.391	-7.761
Taiwan Semiconductor Manufacturing Company Limited	Technology	1000	2.70	370.79	371.37	1001.56	1.905	0.156

Table 3: Portfolio Performance Summary – Human Manager 3
Total Initial Investment: $10,000 SGD | Total Final Value: $9897.01 SGD | Percent Change = -1.030%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
Nu Holdings Ltd.	Financials	2500	121.36	20.6	21.48	2606.80	2.289	4.272
HDFC Bank Ltd.	Financials	1000	21.08	47.44	46.45	979.13	1.270	-2.087
MercadoLibre, Inc.	Consumer Discretionary	500	0.19	2667.65	2537.81	475.66	3.036	-4.867
Sea Limited	Consumer Discretionary	1500	8.18	183.36	156.9	1283.54	2.998	-14.431
AngloGold Ashanti plc	Materials	1000	9.87	101.3	108.79	1073.94	2.972	7.394
iShares MSCI India ETF	Broad Market	1000	14.18	70.52	68.54	971.92	0.659	-2.808
¶iShares MSCI Brazil ETF	Broad Market	1000	23.15	43.2	43.33	1003.01	1.911	0.301
ICICI Bank Limited	Financials	500	12.33	40.56	38.99	480.65	0.722	-3.871
Accenture plc	Technology	500	1.57	319.22	354.39	555.09	1.969	11.017
XP Inc.	Financials	500	20.58	24.29	22.7	467.27	3.572	-6.546

Table 4: Portfolio Performance Summary – Human Manager 4
Total Initial Investment: $10,000 SGD | Total Final Value: $9397.20 SGD | Percent Change = -6.028%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
Hindustan Unilever Limited	Consumer Staples	1000	28.05	35.65	32.42	909.40	1.411	-9.060
Nestle India Ltd.	Consumer Staples	1200	64.27	18.67	17.65	1134.44	0.961	-5.463
DLF Limited	Real Estate	700	61.89	11.31	9.79	605.92	1.439	-13.439
Dr. Reddy's Laboratories Limited	Healthcar e	800	43.76	18.28	18.15	794.31	0.876	-0.711
	Technolog							

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
Infosys Ltd.	y	1800	81.30	22.14	22.6	1837.40	0.807	2.078
United Breweries Ltd.	Consumer Staples	1100	41.95	26.22	23	964.91	0.964	-12.281
Asian Paints Ltd.	Materials	700	16.51	42.4	39.57	653.28	1.430	-6.675
Tata Motors Limited	Consumer Discretion a ry	800	145.99	5.48	4.89	713.87	1.055	-10.766
Hindalco Industries Limited	Materials	600	50.55	11.87	11.83	597.98	1.461	-0.337
Aarti Industries	Materials	1300	224.14	5.8	5.29	1185.69	1.596	-8.793
Limited								

Table 5: Portfolio Performance Summary representing average returns and risks – Human Managers

Human Manager	Risk	Returns	Sharpe Ratio
Human Manager 1	0.661%	-2.045%	-3.587
Human Manager 2	1.197%	-4.201%	-3.781
Human Manager 3	1.420%	-1.030%	-0.955
Human Manager 4	0.577%	-6.028%	-11.016
Average	0.964%	-3.326%	-4.834

From the above tables, it can be depicted that over one month, all four human-managed portfolios experienced losses. The average return for these managers was -3.326%, with individual returns ranging from -1.030% to -6.028%. Human Manager 3 had the smallest loss at -1.030%, while Human Manager 4 had the largest loss at -6.028%. In terms of risk-adjusted performance, Human Manager 3 achieved the highest Sharpe ratio of -0.955, which is the most efficient return per unit of risk among human managers, while Human Manager 4 had the lowest Sharpe ratio of -11.016, showing poor returns relative to the risk taken.

In terms of risk, the average risk value for human managers was 0.964%, with individual risk levels ranging from 0.577% to 1.420%. While there was a slight variation among participants, the overall trend showed low risk. Notably, higher risk did not always lead to better performance; for example, portfolios with relatively higher risk did not yield better results than low-risk portfolios, suggesting that risk levels did not strongly affect the portfolio's short-term returns.

Furthermore, there was a clear difference in how the human participants constructed their portfolios. They were exposed to multiple sectors but tended to prefer traditional and established industries, such as the Financials sector, as many human managers invested in banks and other financial institutions. Technology and consumer-focused sectors, such as consumer discretionary and consumer staples, were also common but more balanced. Most human participants also put larger parts of their portfolios into popular blue-chip stocks and ETFs. Geographically, some portfolios were diversified across different geographic markets and asset types, while others concentrated on a single region. Generally, portfolios with investments in a wider range of markets performed better than those focused on a single domestic market. Overall, the results highlight varied portfolio outcomes due to differences in structure, risk, and stock selection.

3.2. AI Portfolios

Table 6: Portfolio Performance Summary – AI Agent 1 (ChatGPT)
Total Initial Investment: $10,000 SGD | Total Final Value: $9955.40 SGD | Percent Change = -0.446%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
NVIDIA Corporation	Technology	2,700	10.91	247.58	227.47	2480.69	1.895	-8.123
Palantir Technologie s Inc.	Technology	1,500	6.62	226.55	236.42	1565.35	2.353	4.357
First Solar , Inc.	Energy	1,200	3.64	329.48	330.14	1202.40	2.837	0.200
Enphase Energy, Inc.	Energy	900	24.10	37.34	40.47	975.44	2.424	8.382
Quanta Services Inc.	Industrials	900	1.61	559	562.3	905.31	2.248	0.590
ARK Innovation ETF	Technology	700	6.99	100.14	102.19	714.33	2.133	2.047
Invesco Solar ETF	Energy	600	9.31	64.45	61.37	571.33	1.812	-4.779
iShares Global Clean Energy ETF	Energy	600	27.08	22.16	21.39	579.15	1.548	-3.475
Plug Power Inc.	Energy	450	154.11	2.92	2.86	440.75	4.601	-2.055
Accton Technology Corporation	Technology	450	10.95	41.09	47.54	520.64	2.133	15.697

Table 7: Portfolio Performance Summary – AI Agent 2 (Gemini)
Total Initial Investment: $10,000 SGD | Total Final Value: $9137.18 SGD | Percent Change = -8.628%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
Advanced Micro Devices, Inc.	Technology	3,000	9.34	321.28	267.75	2500.16	3.137	-16.661
Palantir Technologies Inc.	Technology	1,500	6.62	226.55	236.42	1565.35	2.353	4.357
Sea Limited	Consumer Discretionary	1,000	5.45	183.52	156.9	854.95	2.998	-14.505
First Solar, Inc.	Energy	1,000	3.04	329.48	330.14	1002.00	2.837	0.200
iShares Global Clean Energy ETF	Energy	700	31.59	22.16	21.39	675.68	1.548	-3.475
UP Fintech Holding Ltd.	Financials	700	55.96	12.51	11.38	636.77	3.592	-9.033
Affirm Holdings, Inc.	Financials	600	6.54	91.78	84.69	553.65	2.729	-7.725
ARK Innovation ETF	Technology	500	4.99	100.14	102.19	510.24	2.133	2.047
Coinbase Global, Inc.	Financials	500	1.35	369.68	323.02	436.89	3.705	-12.622
NIO Inc.	Consumer Discretionary	500	62.34	8.02	6.44	401.50	3.200	-19.701

Table 8: Portfolio Performance Summary – AI Agent 3 (Perplexity)
Total Initial Investment: $10,000 SGD | Total Final Value: $9868.77 SGD | Percent Change = -1.312%

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
NVIDIA Corporation	Technology	1,000	4.04	248	227.47	918.70	1.895	-8.130
Tesla, Inc.	Consumer Discretionary	1,000	1.91	523.63	613.07	1170.81	2.370	17.081
	Consumer							

Stock Name	Sector	Amount Invested (SGD)	Number of Shares	Closing Price SGD (17th November)	Closing Price SGD (16th December)	End Total (SGD)	Risk (%)	Returns (%)
Sea Limited	Discretionary	1,000	5.45	183.42	156.9	855.41	2.998	-14.459
Singapore Technologie s Engineering Ltd	Industrials	1,000	115.34	8.67	8.23	949.25	1.037	-5.075
Invesco QQQ Trust	Technology	1,000	1.26	791.73	787.54	994.71	1.078	-0.529
DBS Group Holdings Ltd	Financials	1,000	18.51	54.03	55.58	1028.69	0.492	2.869
Jardine Matheson Holdings	Conglomerate	1,000	11.77	84.99	87.58	1030.47	2.896	3.047
Ltd								
iShares Global Clean Energy ETF	Energy	1,000	45.13	22.16	21.39	965.25	1.548	-3.475
BYD Company Limited	Consumer Discretionary	1,000	59.63	16.77	15.68	935.00	1.732	-6.500
ARK Innovation ETF	Technology	1,000	9.99	100.14	102.19	1020.47	2.133	2.047

Table 9: Portfolio Performance Summary representing average returns and risks – AI Agents

AI Manager	Risk	Returns	Sharpe Ratio
ChatGPT	1.478%	-0.446%	-0.522
Gemini	2.218%	-8.628%	-4.037
Perplexity	1.114%	-1.312%	-1.470
Average	1.603%	-3.462%	-2.010

Tables 6-9 represent the results of portfolios created by AI agents. The portfolios generated by AI recorded negative returns on average, and the mean portfolio was -3.462% over the one-month period. The individual AI portfolios' returns ranged between -0.446% and -8.628%, indicating that they recorded a greater range of results than the human portfolios. The ChatGPT portfolio experienced the least loss at -0.446%, and the largest loss was experienced by the Gemini portfolio at -8.628%. In terms of risk-adjusted performance, ChatGPT had the highest Sharpe ratio of -0.522, outperforming all portfolios in the study, while Gemini had the lowest Sharpe ratio of -4.037.

Compared to traditional portfolios, AI-managed portfolios were found to have a higher average risk of 1.603% and an individual risk of 1.114% up to 2.218%. Yet, these higher risks were not reflected in higher returns; the ChatGPT portfolio not only had a comparatively high risk but also smaller losses, whereas other AI portfolios with comparable or higher risk outperformed significantly worse. This indicates that AI-generated portfolios have a weak and inconsistent correlation between risk and return.

The AI agents were also more inclined to invest more of their portfolios in the US-listed stocks and ETFs in the growth sectors, particularly technology and energy. Most portfolios focused on technology and made major investments in semiconductor companies, software companies, and innovation ETFs. Investment in energy was also high in stocks and ETFs that invest in clean energy. Although both ChatGPT and Gemini exhibited comparable investment trends of concentrating on high-growth stocks, Perplexity developed a more diversified portfolio to incorporate a Singapore-based stock. Overall, the results of AI-managed portfolios varied widely during the month.

Upon comparison of the two groups, the average return of the human-managed portfolios was slightly higher at -3.326% than that of the AI-generated portfolios at -3.462%. The top performing AI portfolio (-0.446%) did better than the top human portfolio (-1.030%), and the worst performing AI portfolio lagged behind all human-run portfolios. Human portfolios had a smaller range of results, indicating more consistency among the participants, whereas AI portfolios were more varied, with small to huge losses.

Moreover, AI agents generated more risky portfolios than human managers did, and the average risk was much higher. The average Sharpe ratio for AI portfolios (-2.010) was also notably better than for human portfolios (-4.834). This greater risk did not, however, lead to higher returns.

Human portfolios were less risky but with a more consistent volatility than the worst cases of AI portfolios. This points out that the increased exposure to risk was not sufficient to enhance performance. The AI portfolios also under-invested in traditional financial institutions and consumer staples and over-invested in the technology and energy sectors, and focused on

high-growth equities. Human managers, on the other hand, invested in a much broader spectrum. Overall, both strategies led to different outcomes, as human-managed portfolios outperformed AI-managed portfolios slightly.

A Welch's independent samples t-test comparing human and AI portfolio returns yielded a p-value of 0.965. This value significantly exceeds the 0.05 significance threshold, so the difference in returns between human and AI portfolios was not statistically significant. This finding should be interpreted carefully given the small sample sizes (n=4 human managers, n=3 AI agents), which limit the statistical power of the test.

4. Discussion

4.1. Market-Wide Conditions During the Investment Period

The overall market environment at the time of conducting the study was one of the key factors that influenced the performance of both AI and human managers because the global markets encountered more volatility in the face of uncertainty in the economy. The interest rate policies, AI valuations, and tariffs were the issues of concern, and investors shifted to less risky investments, such as healthcare and consumer staples, rather than high-growth stocks (Global Content Team, 2025). This led to underperformance of both the AI and the human portfolios that concentrated on high-growth areas. Global trade conflicts and tariffs also affect high-growth sectors more because they put a strain on supply chains and decrease profits (Choudary, 2023). In addition, unpredictable interest rate policies are hurting high-growth businesses that are sensitive to future cash flows, which is helpful in explaining why big tech stocks such as Nvidia, Microsoft, and Sea Limited have performed poorly over the period (Weis et al., 2021).

4.2. Human-Managed Portfolios

Portfolios run by humans tended to be more diversified in terms of sector and geography. The distribution of investments by many participants was in financial, consumer staples, healthcare, materials, and ETFs, indicating a more prudent investment approach with human investors tending to invest in familiar industries and companies. Commonly used financial institutions included HDFC Bank, ICICI Bank, Visa, and DBS, and this indicated that human investors had faith in conventional banking and financial services.

Nonetheless, the financial sector had problems during this period because of interest rate conflicts, effects of the U.S. government shutdown, and poor performance of the U.S. dollar (Global Content Team, 2025). These are the reasons why most banking stocks in different human portfolios have negative returns. For instance, ICICI Bank and HDFC Bank suffered losses of approximately 2 percent and 4 percent, respectively.

Loss aversion and other behavioral factors could have also led to the performance of the portfolio. The reason why investors tend to sell stocks early is to gain profit and not to lose any profit; some investors make an immediate gain through leverage (Ahmad et al., 2025). This shows how, although human portfolios were diversified, this may have influenced investment decision-making based on an emotional response to stock movements, which favored short-term gains.

Further, the risk of human portfolios was rather low, and the average risk was 0.964 percent, which demonstrates that the human investors did not take much volatility. Nevertheless, greater risk was not necessarily accompanied by greater returns, with Human Manager 3 having the most risk and returns of the human participants, and Human Manager 2 with an equivalent degree of risk but significantly lower returns. This loose relationship between risk and return can be observed in the short term of investments, where minor shifts in market activity can lead to a dramatic effect on the prices of stocks (Hirota et al., 2015). Hence, in these short periods, contrary to the conventional thought, volatility does not ensure increased returns.

The least loss was experienced by Human Manager 3; this can be attributed to geographic and sector diversification, where the company invested in materials such as AngloGold Ashanti and technology consulting firms such as Accenture, which made 7.4 percent and 11 percent, respectively. These shares enjoyed an increase in demand and economic insecurity, which hinted that diversification of strategy in various regions and industries could have been beneficial in minimizing losses. Gold companies such as AngloGold Ashanti, the primary beneficiaries of the surging gold prices in late 2025, experienced success largely due to investor demand for safe-haven assets in economic uncertainty.

Human Manager 4, conversely, incurred the biggest loss, which was largely due to being heavily concentrated in Indian consumer and real estate stocks. Indicatively, HINDUNILVR, DLF, and TATAMOTORS, the consumer and real estate stocks that Human Manager 4 selected, all performed dismally, with a loss of 9 percent, 13.4 percent, and 10.8 percent, respectively.

Valuation concerns and the lack of rapid growth in demand did not favour consumer staples and discretionary stocks over this period, and a lack of diversification in international markets also increased the losses, illustrating the dangers of concentration in a single geographic location (Global Content Team, 2025).

4.3. AI-Managed Portfolios

AI-based portfolios laid more emphasis on high-growth stocks, which were concentrated on technology and clean energy sectors. The reason is that AI models rely on the past growth trend to forecast the future economic growth, yet these sectors were highly volatile during the investment period (Wang et al., 2024). Prices of benchmark products like Brent crude oil plummeted as a result of oversupply and lack of certainty on demand for energy products, affecting the revenue forecast of the energy companies and lowering stock prices (Crude Oil Prices Fell in 2025 amid Oversupply, 2026). Geopolitical tensions between key markets, like the United States and China, also put pressure on semiconductor stocks; these tariffs and trade barriers have the potential to increase the cost of production, which adversely affects future growth, hence resulting in losses in all the portfolios (The Effects of Tariffs on the Semiconductor Industry, 2025).

The average risk of AI-managed portfolios was higher at 1.603% than that of human portfolios, and this implies that AI-managed portfolios had more exposure to volatile stocks. Nonetheless, this higher risk was not associated with higher returns since the ChatGPT portfolio had high risk and low losses, whereas the Gemini portfolio had high risk and significantly lower returns. The Perplexity portfolio demonstrated that, given low risk, the amount of losses can decrease by marginal amounts, and this may be due to the fact that the portfolio with higher risk may be more likely to contain stocks with higher volatility. Such stocks might enhance performance, yet might result in greater losses during uncertain times (Yaman & Tuncel, 2025).

The portfolio of ChatGPT overall did the best, and it had the smallest loss among all AI and human-managed portfolios. It was primarily caused by significant gains in the stock values of individual companies, including Enphase Energy and Accton Technology, as they rose by 8.4 percent and 15.7 percent, respectively. The diversification in other sectors, such as technology, energy, and industrial, also contributed to enhancing the performance of ChatGPT. Although these areas have fallen, the careful choice of profitable stocks has allowed ChatGPT to reduce its losses since the stocks were doing better than the industry. Nevertheless, the concentration in particular industries is high, which indicates that this performance is more likely to be a consequence of stock-specific changes, as opposed to a more effective approach.

At the same time, the portfolio created by Gemini had the poorest overall performance due to the heavy exposure to risky technology and consumer discretionary stocks like AMD, NIO, and SE, which had negative returns of -16.7 percent, -19.7 percent, and -14.5 percent, respectively.

Despite some outperformance of stocks in these regions, these industries felt the pressure of decreased consumer demand and AI valuation worries, underscoring the danger of overconcentration in certain markets during turbulent times (Peytavin, 2026).

This discrepancy points out that AI strategies tend to turn to historical trends and growth indicators, and thus, it was hard to adapt to short-term fluctuations, which were particularly widespread during the time of investment. Consequently, it had too much confidence in high-growth industries, which ultimately translated to poor returns.

4.4. Human vs AI Portfolio Behavior

When the two groups are compared, preliminary results suggest that human investors concentrated on diversification in both sectors and geography, and invested in traditional sectors, which has resulted in fewer returns in portfolios. AI portfolios, on the other hand, were more concentrated and volatile, resulting in a large variation in returns. The most successful

AI portfolio outperformed all human portfolios; however, the poorest AI portfolio underperformed all human portfolios.

Sharpe ratio analysis added further nuance to these findings. Although human managers had a slightly better average return of -3.326% compared to AI's -3.462%, AI portfolios had significantly better risk-adjusted performance, with an average Sharpe ratio of -2.010 compared to -4.834 for human portfolios. ChatGPT achieved the best Sharpe ratio across all portfolios at -0.522, thereby outperforming all human managers when adjusted for risk. This suggests that while human managers were more conservative in their investments, their lower returns relative to the risk they took were overall less efficient than those of AI portfolios. The main exception was Human Manager 4, whose Sharpe ratio of -11.013 significantly pulled down the human average, likely due to the geographically overconcentrated portfolio. These risk-adjusted figures help provide a larger picture of investment efficiency beyond the scope of raw returns.

The trend shows that although AI strategies may have potential upside, they are also more susceptible to losses and downside risk. Instead, human strategies are more likely to be stable in turbulent times. Interestingly, there was no correlation in terms of risk and return in the portfolio of each group, and that point supports the importance of external economic factors to the short-term returns of investment portfolios rather than portfolio construction.

5. Conclusion

This paper examined the performance of publicly available AI agents against human fund managers in constructing short-term, high-risk stock portfolios to evaluate performance, risk, and returns under the same market conditions over one month. The study employed an experimental design in which four human managers and three free AI agents developed a portfolio of ten global stocks, with an initial portfolio of SGD $10,000. Portfolios were all evaluated using real market closing prices between November 17 and December 16, 2025, and the same rules were applied to all portfolios. The performance of portfolios was determined by calculating the percentage returns, and risk was determined using a covariance matrix, which was done in Excel.

The findings revealed that none of the portfolios made huge profits in the period. The human-managed portfolios performed a bit better with a -3.326% return against the AI-managed portfolios with a -3.462% return. The average risk of human portfolios was also lower at 0.964%, and AI portfolios had an average risk of 1.603%. However, Sharpe ratio analysis indicated that AI portfolios had better risk-adjusted returns on average (-2.010) compared to human portfolios (-4.834), suggesting more return efficiency per unit of risk despite slightly worse raw returns. Nevertheless, the overall best AI portfolio performed better than all the human portfolios, whereas the worst AI portfolio performed worse than all the human portfolios.

Moreover, human portfolios presented the more consistent results and the more investment in the traditional industry, whereas AI portfolios were more varied and invested more in high-growth stocks. The risk and returns in either group did not show any relationship. The main reasons why these results are the case are that there was much economic uncertainty at the time of investment, such as tariffs, trade tensions, interest rate concerns, geopolitical conflicts, and weak growth in demand. The agents of AI mainly concentrated on sensitive high-growth sectors, whereas human managers enjoyed more diversification and defensive sector investment. Finally, the preliminary findings indicate that AI may generate competitive short-term portfolios, but with increased risk, it is important to diversify and apply human judgment during turbulent times.

6. Policy Implications and Limitations

The research has implications for investors, fund managers, and researchers. The free AI tools should be viewed by retail investors as a guide to AI-generated portfolios rather than a substitute. The AI has growth opportunities, and before investing in the AI, users have to ensure that they are diversified and analyze the existing economic risk. Besides, AI may be useful in assisting professional fund managers in their financial decision-making, as AI models may aid in large-dataset analysis and stock screening, which are complementary to the qualitative insights and the speed of human managers to act on market fluctuations. To the researchers, this research shows that it is essential to conduct research on short-term investments rather than concentrating on long-term investments. Future financial regulations might consider informing retail investors about the boundaries of AI tools and caution against excessive reliance on AI tools in unstable times.

This work has certain limitations to be taken into consideration. To begin with, the sample was small, consisting of four human managers and three AI agents. Although this enabled a detailed study of individual portfolios, it restricts the scope of generalizing the results. Second, the investment duration was only one month, and this might overstate the impact of short-term market volatility and poor correlation between risk and returns. Increased investment time might have varied results, particularly when it comes to growth strategies employed by AI agents.

Third, the research was done on portfolios in various markets in the world, and this also brought in elements of currency, exchange rate, and regional economic variations that could have influenced performance. The SGD/USD exchange rate moved approximately 1.09% during the investment period, from 0.7674 to 0.7758. While returns were not fully FX-hedged, this movement was considered insufficient to significantly affect the findings. Lastly, the implemented AI agents were free and publicly available ones, which may not reflect the potential of institutional-level AI systems. Therefore, the results can be primarily generalized to readily available AI tools, but not sophisticated models.

References

Ahmad, U., Van Keulen, M., Briassouli, A., & Saad, M. (2025). Cognitive biases, Robo advisor and investment decision psychology: An investor's perspective from New York stock exchange. *Acta Psychologica*, *256*, 105048. https://doi.org/10.1016/j.actpsy.2025.105048

Allied Market Research. (2024, September). *Algorithmic Trading Market (2024 - 2032)*. https://www.alliedmarketresearch.com/algorithmic-trading-market

Anuar, A. A., Sulaiman, A. a. B., & Mohamad, M. T. B. (2025). Comparative analysis of AI-driven versus human-managed equity funds across market trends. *Future Business Journal*, *11*(1). https://doi.org/10.1186/s43093-025-00540-8

Chen, R., & Ren, J. (2021). Do AI-powered mutual funds perform better? *Finance Research Letters*, *47*, 102616. https://doi.org/10.1016/j.frl.2021.102616

Chou, J., & Chen, K. (2024). Optimizing investment portfolios with a sequential ensemble of decision tree-based models and the FBI algorithm for efficient financial analysis. *Applied Soft Computing*, *158*, 111550. https://doi.org/10.1016/j.asoc.2024.111550

Choudary, E. (2023). US-China trade rivalry: Ramifications on global economic politics. *Journal of Development and Social Sciences*, *4*(III). https://doi.org/10.47205/jdss.2023(4-iii)39

Crude oil prices fell in 2025 amid oversupply. (2026, January 5). U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=66944&#

Fortune Business Insights. (2026, March 9). *Robo advisory market size, share, trends*. Fortune Business Insights. https://www.fortunebusinessinsights.com/robo-advisory-market-109986

Global Content Team. (2025, December 5). *Monthly markets review - November 2025*. Schroders. https://www.schroders.com/en-sg/sg/individual/insights/monthly-markets-review/

Han, X., Wang, N., Che, S., Yang, H., Zhang, K., & Xu, S. X. (2024, November). Enhancing investment analysis: Optimizing AI-Agent collaboration in financial research. In Proceedings of the 5th ACM International Conference on AI in Finance (pp. 538-546).

Hasan, Z., Vaz, D., Athota, V. S., Désiré, S. S. M., & Pereira, V. (2023). Can artificial intelligence (AI) manage behavioural biases among financial planners? *Journal of Global Information Management*, *31*(2), 1–18. https://doi.org/10.4018/jgim.321728

Hirota, S., Huber, J., Stock, T., & Sunder, S. (2015). Investment horizons and price indeterminacy in financial markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2613945

Joshi, S. (2025). Generative AI in Investment and Portfolio Management: Comprehensive review of current applications and future directions. *International Journal of Innovative Research in Engineering & Management*, *12*(2), 1–12. https://doi.org/10.55524/ijirem.2025.12.3.1

Ko, H., & Lee, J. (2024). Can ChatGPT improve investment decisions? From a portfolio management perspective. *Finance Research Letters*, *64*, 105433. https://doi.org/10.1016/j.frl.2024.105433

Kuzminsky, V., & Ziemtsov, S. (2024). Economic Assessment of the Activity of Retail Investors on the Stock Market. *Economics, Finance and Management Review*, *3(19)*, 45–53. https://doi.org/10.36690/2674-5208-2024-3-45-53

Mercer. (n.d.). *AI in investment management survey*. https://www.mercer.com/insights/investments/portfolio-strategies/ai-in-investment-management-survey/

Nagalaxmi, K., Paparao, M., Manoja, P., & Akhil, C. (2025). AI-Powered Portfolio Management: Implications and Innovations [Journal-article]. *International Journal of Current Science (IJCSPUB)*, *15*(2), 28–30. https://www.rjpn.org/ijcspub/papers/IJCSP25B1004.pdf

Peytavin, L. (2026, February 2). *Market review - Review of markets over January*. J.P. Morgan Asset Management. https://am.jpmorgan.com/gb/en/asset-management/per/insights/market-insights/market-u pdates/monthly-market-review/

Praxmarer, M., & Simon, I. (2024). Assessing the performance of AI-Managed portfolios. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5037553

Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., Kabasinskas, A., Tidjani, C., Ozturkkal, B., & Cerneviciene, J. (2024). Enhancing portfolio management using artificial intelligence: literature review. *Frontiers in Artificial Intelligence*, *7*, 1371502. https://doi.org/10.3389/frai.2024.1371502

Usman, A. (2024). Algorithmic Alpha: A comparative analysis of machine learning and classical approaches for stock portfolio optimisation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4994831

Vijaya, E. (2014). An empirical analysis of influential factors on investment behaviour of retail investors' in Indian stock market: A behavioural perspective. *International Journal in Management & Social Science*, *2*(12), 296–308.

Wang, X., Zhu, X., Anwar, M. K., Meng, Q., & Zhong, N. (2024). Evaluating the role of AI and empirical models for predicting regional economic growth and transportation dynamics: ¶an application of advanced AI approaches. *International Journal of Transportation Science and Technology*, *19*, 156–174. https://doi.org/10.1016/j.ijtst.2024.08.007

Weis, C., Woltering, R., & Sebastian, S. (2021). Which stocks are driven by which interest rates? *Journal of Property Research*, *38*(3), 175–197. https://doi.org/10.1080/09599916.2021.1903531

Yaman, S., & Tuncel, M. B. (2025). The benefits of sectoral diversification for investors with different risk perceptions. *Borsa Istanbul Review*, *25*(3), 597–616. https://doi.org/10.1016/j.bir.2025.02.008