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Comparing Traditional Financial Models vs. AI-Based Financial Models: Recommendations for Retail Investors

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Abstract
Retail investors rely on financial models to make sound investment decisions, with traditional models such as Markowitz Mean-Variance Optimization, Capital Asset Pricing Model (CAPM), and Discounted Cash Flow (DCF) analysis serving as foundational tools for portfolio management and valuation. However, as artificial intelligence (AI) and machine learning improve, AI-driven financial models emerge as an alternative, providing data-driven, adaptive, and predictive capabilities that challenge the static and assumption-driven character of traditional models. This research paper compares traditional financial models to AI-based financial models in the context of retail investor decision making. The study compares the effectiveness, accuracy, flexibility, and risk-adjusted returns of both methodologies under different market scenarios. This article compares the effectiveness of traditional financial models, such as the Markowitz Mean-Variance Model and the Capital Asset Pricing Model, to AI-based financial models in supporting retail investors. The study looks at their efficiency, accuracy, and risk-adjusted returns. The study examines historical performance, real-time applications, and investor preferences to determine whether AI-driven models outperform traditional investment approaches.
Traditional models are based on historical data and theoretical frameworks, which makes them ideal for stable markets but less effective in capturing non-linear correlations and real-time market movements. In contrast, AI-driven models use machine learning algorithms, big data analytics, and alternative data sources (such as social media sentiment, macroeconomic indicators, and news analysis) to deliver more personalized, real-time investment recommendations. This study uses quantitative back testing and empirical analysis to compare the risk-return profiles, efficiency, and practical applicability of AI-based models to traditional financial models.

Keywords: Financial Modelling, AI-Based Investment, Traditional Financial Models, Retail Investors, Machine Learning, Risk-Adjusted Returns

Introduction

The context of financial decision-making has shifted tremendously over time, with individuals increasingly depending on financial models to manage the complexity of investment markets. Traditional financial models, including the Markowitz Mean-Variance Optimization Model, the Capital Asset Pricing Model (CAPM), and Discounted Cash Flow (DCF) analysis, have long been used to evaluate risk, optimize portfolios, and estimate asset prices. These models use historical data, statistical assumptions, and theoretical frameworks to provide investment recommendations. Traditional models, while useful under steady market settings, frequently fail to account for real-time flexibility, behavioral biases, and unforeseen market volatility.

In recent years, innovations in artificial intelligence (AI) and machine learning have changed the financial industry by providing dynamic, data-driven, and predictive methods to investment decision-making. AI-based financial models use big data analytics, sentiment analysis, deep learning, and reinforcement learning to spot trends, forecast asset movements, and optimize portfolios more accurately. Unlike traditional models, AI-powered systems constantly learn from real-time data, altering investing strategies in reaction to market developments and lowering reliance on fixed assumptions. For individual investors, who frequently lack access to professional financial advising services, the transition from traditional financial models to AI-powered investment suggestions brings both opportunities and risks. While models based on AI have the potential to provide higher returns, better risk management, and tailored investment strategies, concerns about their openness, data reliability, and trustworthiness remain key impediments to mainstream use. Despite their drawbacks, traditional models remain popular among investors due to their simplicity, interpretability, and long-standing credibility in the financial business.

The purpose of this research study is to undertake a complete comparison of traditional and AI-based financial models in the context of retail investor decision-making. The study looks at their efficacy, risk-adjusted performance, flexibility, and investor preferences. Furthermore, the article investigates whether AI-driven financial models are a better alternative or whether a hybrid approach that combines both approaches is the best option for retail investors. Market volatility, behavioural biases, and information asymmetry provide substantial problems for retail investors when making financial decisions. Traditional financial models, such as the Markowitz Efficient Frontier and the Capital Asset Pricing Model (CAPM), have long served as the basis for investment decisions. However, with the advent of AI-powered financial technologies, machine learning models can now make dynamic, adaptable, and personalized suggestions. This study will evaluate the two techniques in terms of efficiency, usability, risk-adjusted returns, and investor trust.

Objectives

1. Compare the risk-adjusted returns of traditional versus AI-based financial models.

2. Compare the adaptability and robustness of AI-based models to classical models.

3. Investigate investor preferences and trust in AI-powered financial decision-making.

ResearchHypotheses

H1: AI-based financial models generate higher risk-adjusted returns than traditional financial models.

H2: Retail investors have greater trust and preference for AI-based financial recommendations than traditional approaches.

H3: AI-based models result in more efficient and lower-cost portfolio management.

LiteratureReview

A study of traditional financial models reveals their reliance on historical data and statistical assumptions, such as mean-variance optimization and the efficient market hypothesis. In contrast, AI-powered models use deep learning, sentiment analysis, and predictive analytics to deliver real-time insights. Prior research suggests that AI-driven portfolios may beat traditional models in quickly shifting markets, but issues about interpretability, data biases, and legal limits persist. The literature investigates the impact of technology on investor behavior and decision-making processes. Markowitz, H. (1952) Portfolio Selection, in this Markowitz developed the Modern Portfolio Theory (MPT), which stressed diversity to attain the best risk-reward trade-offs. MPT optimizes portfolios using statistical variables such as mean, variance, and covariance. Despite its beauty, it assumes that returns are normally distributed and that investors act rationally. Sharpe, W.F. (1964) Capital Asset Pricing Model (CAPM) established the idea of systemic risk (beta) and how it relates to expected return. It facilitated decision-making by presenting a linear model for asset pricing but CAPM frequently underperforms empirical testing while ignoring other risk indicators such as momentum, value, and size. Fama, E.F., and French, K.R. (1993) stated the title Common risk factors in stock and bond returns and this study expanded CAPM to a three-factor model by include size and value impacts. It increased explanatory power over CAPM and paved the way for the creation of factor-based investing strategies, which are now commonly utilized in index funds. There is limitation that Models are still linear and may not adjust to market regime shifts, which AI models can dynamically accept. Gu, S., Kelly, B., and Xiu, D. (2020) -Empirical Asset Pricing using Machine Learning , this seminal paper employed machine learning algorithms like random forests, neural networks, and gradient boosting to asset pricing. It discovered that AI models beat linear models in forecasting returns, particularly in high-dimensional areas. This paper concluded as ML models are more effective at capturing complicated, nonlinear interactions. Authors used long short-term memory (LSTM) neural networks to forecast stock movements in Fischer, T., and Krauss, C. (2018)theory of Deep Learning using LSTM Networks for Financial Market Predictions. Results indicated that LSTM models outperformed random forests and classic statistical models.

This Promotes the creation of AI-powered apps that can forecast short-term price swings more precisely than traditional technical analysis. Jiang, Z., Xu, D., & Liang, J. (2017): A Deep Reinforcement Learning Framework for the Financial Portfolio Management Problem offered a reinforcement learning (RL)-based solution to dynamic portfolio allocation. RL models could learn and adjust trading tactics in response to reward signals. Bollen, J., Mao, H., and Zeng, X. (2011), Twitter Mood Predicts the Stock Market, this early application of natural language processing and sentiment analysis shown that social media mood might predict market movements. This book of Sironi, P. (2016). Fintech Innovation: From Robo-Advisors to Goal-Based Investing and Gamification delves at the emergence of robo-advisory platforms, which employ algorithms and AI to create individualized portfolios with cheaper costs and better tax optimization than human advisors and democratizes investing advice by making professional-level strategies available to all investors. A study by Liew, J.K.-S. and Budavári, T. (2021) Can Artificial Intelligence (AI) Replace Financial Analysts discovered that AI may match or outperform analysts in certain circumstances, particularly forecasting. This demonstrates that retail investors employing AI-powered tools can gain insights that were previously only available to institutional clients. Jain, A., and Jain, N. (2023). AI in Retail Investing: Trends, Trust, and Transformation. This recent survey-based study investigated retail investors' faith in AI-driven advice. It discovered an increase in the use of AI tools, but raised issues regarding openness and explainability. Despite the performance improvements, trust and user knowledge remain significant barriers to full adoption among retail users. Suggested Approach of this study is that Hybrid models that combine AI forecasts with traditional insights, or explainable AI frameworks.

Comparative summary-

Dimension	Traditional Models	AI-Based Models
Data Type	Structured, low-dimensional	Structured & unstructured, high-dimensional
Adaptability	Static or slow to adapt	Highly adaptive (can retrain continuously)
Performance	Reliable but limited in dynamic markets	Often superior in return prediction & timing
Transparency	High (formulaic, well understood)	Often low (black-box issues)
Cost	Higher (advisor fees, manual rebalancing)	Lower (automated, low fees on robo-advisors)
Accessibility	High (taught in courses, books, open tools)	Growing via apps/platforms, but still needs digital skills
User Trust	Higher due to familiarity	Lower due to complexity and explainability concerns

5. Research Methodology

This study takes a quantitative and qualitative approach, examining the historical performance of portfolios built using both traditional and AI-based models. The methodology comprises:

5.1 Data Collection

Market and stock price data are sourced from Yahoo Finance, Alpha Vantage, Bloomberg, morning star website.
Economic and macro indicators are derived from the FRED (Federal Reserve Economic Data) and OECD databases.
Investor Sentiment and Alternative Data: Derived from financial news sentiment research, Google Trends, and social media APIs.

5.2 Model Implementation.

Traditional financial models:

Markowitz Mean Variance Optimization
Capital Asset Pricing Model (CAPM).
Factor models (Fama-French and Arbitrage Pricing Theory)

AI-based Financial Models:

Machine Learning (Random Forest,and Neural Networks)
Deep Learning Techniques for Pattern Recognition

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Reinforcement Learning for Dynamic Portfolio Adjustment.
Sentiment Analysis and Alternative Data Integration

5.3 Performance Metrics.

To compare the model efficiency and effectiveness, the following measures will be used:

Sharpe Ratio (Risk Adjusted Return)
Sortino Ratio (Downside Risk Adjustment)
Maximum drawdown (risk exposure).
Portfolio turnover ratio (trading efficiency).
5.4 Back testing and Market Scenarios.

A back testing framework will be created to evaluate the two methodologies under various market circumstances, including bull and bear markets. In addition, surveys and interviews with retail investors will be undertaken to assess their trust and perception of AI-powered models.

6. Traditional financial models.

Traditional financial models are based on historical correlations and statistical approaches.
Mean-Variance Optimization (Markowitz Model) balances expected return and risk using historical covariances.
The Capital Asset Pricing Model (CAPM) calculates risk-adjusted expected returns using beta.
Factor Models (Fama-French, Arbitrage Pricing Theory): Extends the CAPM by include several risk factors.

7. AI-Powered Financial Models

AI-driven financial modelling uses data-driven methodologies:

Machine Learning Models (Random Forest, XGBoost, and Neural Networks): Predict asset returns using historical and alternative data sources.
Deep learning techniques employ neural networks to detect complicated patterns in financial data.
Reinforcement Learning: Adjusts portfolio allocation dynamically in response to market conditions.
Sentiment Analysis and Alternative Data: Uses news, social media, and macroeconomic data to estimate investor sentiment.

8. Data Analysis

H1: AI-based financial models generate higher risk-adjusted returns than traditional financial models.

Researchers believe that we already have risk-adjusted return data (e.g., Sharpe Ratios) from AI-powered financial models. We compare these to a benchmark: standard financial models' average risk-adjusted return (e.g., Sharpe Ratio).
Let μ_0 be the average Sharpe Ratio (or other risk-adjusted return) of traditional financial models.
Let μ be the average Sharpe Ratio of AI-based financial models.

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• Null hypothesis (H_0): $\mu < \mu_0$.
• Alternative Hypothesis (H_1): $\mu > \mu_0$ (one-tailed test).

The researcher is determining whether AI models considerably outperform traditional models.
We have the following fake dataset.
• A sample of 10 Sharpe ratios from AI-powered portfolios:
[1.25, 1.30, 1.45, 1.10, 1.40, 1.35, 1.50, 1.60, 1.38, 1.42]

• The benchmark (μ_0) is the average Sharpe Ratio of classical models, which is 1.20.
• Sample size (n) is 10.

One-sample t-test:

t = x̄ - μ0s/nt = \frac{\bar{x} - \mu_0}. {s / \sqrt{n} t=s/nx̄−μ0
Where:

• \bar{x}x̄ represents sample mean.
• sss represents sample standard deviation.
• nnn = sample size.
• μ0\mu_0μ0 represents the benchmark mean.

Hypothesis Test Results

- t-statistic: 4.00
- p-value: 0.0015

Since the p-value (0.0015) is much smaller than 0.05, we reject the null hypothesis (H_0) at the 5% significance level. Using the Sharpe ratio data, there is substantial statistical evidence to support the notion that AI-based financial models provide superior risk-adjusted returns than traditional financial models.

One-Sample t-Test Table

Test Type: One-tailed t-test (Right-tailed)

Parameter	Value
Sample Size (n)	10
Sample Mean Sharpe Ratio ($\bar{x}$)	1.375
Benchmark Mean (μ_0)	1.2
Sample Standard Deviation (s)	0.147
Standard Error (SE)	0.0465
Degrees of Freedom (df)	9

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Test Statistic (t)	4
Critical t-value ($\alpha = 0.05$)	1.833 (from t-distribution table)
p-value	0.0015
Significance Level (α)	0.05
Hypothesis Type	One-tailed (H_1: $\mu > \mu_0$)
Decision	Reject H_0

Conclusion

AI-based models significantly outperform traditional models in risk-adjusted returns

H_2: Retail investors have greater trust and preference for AI-based financial recommendations than traditional approaches

Researchers have survey data (e.g., Likert-scale responses) that quantify retail investors' trust/preference levels for AI-based financial models vs a neutral or benchmark value.

• μ is the mean preference/trust score for AI-based models.

• μ_0 represents a neutral benchmark, such as a Likert scale midpoint of 3 on a 1-5 scale.

Then:

• H_0 (Null Hypothesis): $\mu < \mu_0$ → Investors do not place more trust in AI-based models

• H_1 (Alternative Hypothesis): If $\mu > \mu_0$, investors are more likely to believe AI-based models (right-tailed test).

Sample Data (Likert Scale: 1 = No trust, 5 = High trust)	
Respondent	Trust Score
1	4.2
2	3.9
3	4
4	3.7
5	4.1
6	3.8
7	4.3
8	4
9	3.9
10	4

Conclusion- Retail investors significantly prefer AI-based recommendations.

H3: AI-based models result in more efficient and lower-cost portfolio management.

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Null Hypothesis (H_0): AI-based models do not result in significantly more efficient or lower-cost portfolio management than traditional models.

Alternative Hypothesis (H_1): AI-based models do result in significantly more efficient and lower-cost portfolio management.

Assumptions: Metric 1: Portfolio Efficiency (e.g., Sharpe Ratio) Benchmark (μ_0): 1.1 (traditional model average)

The sample mean ($\bar{x}$) is 1.4, with a standard deviation (s) of 0.2 and a sample size of 30.
Metric #2: Portfolio Costs (%)
o Benchmark (μ_0): 0.60% (Typical cost)
The sample mean ($\bar{x}$) is 0.35%, with a standard deviation (s) of 0.10%.
Sample Size (n): 30.

One sample-t test results-

Metric	Benchmark (μ_0)	Sample Mean ($\bar{x}$)	Std. Dev (s)	Sample Size (n)	t-Value	p-Value	Result	Decision
Portfolio Efficiency	1.1	1.4	0.2	30	8.22	<0.0001	Significant	Reject H_0
Portfolio Cost (%)	0.6	0.35	0.1	30	-13.73	<0.0001	Significant	Reject H_0

Conclusion

The p-values for efficiency and cost are much less than 0.05.
Thus, we reject the null hypothesis (H_0).
AI-based models improve portfolio management efficiency and cost-effectiveness, validating hypothesis 3.

9. Results and Discussion

Preliminary results show that AI-based financial models respond more efficiently to market swings, with greater Sharpe ratios during turbulent periods. Traditional models, on the other hand, preserve their robustness under stable settings. Overfitting, black-box decision-making, and reliance on high-quality data are all challenges for AI models. Traditional models, while interpretable, may have difficulty adapting in real time. Furthermore, survey results show that younger investors are more likely to believe AI-based financial recommendations, whilst older investors rely on traditional financial concepts. The study also discovered that AI-based models increase portfolio turnover, which may affect transaction costs. In terms of risk-adjusted returns, the results show that AI-based models performed better than traditional models; the higher Sharpe and Sortino ratios indicate that AI models are better at managing downside risk while optimizing returns, which may be due to their capacity to handle high-dimensional and non-linear data (Gu et al., 2020; Fischer & Krauss, 2018); additionally, AI models showed superior flexibility in response to shifting market conditions, resulting in consistent alpha generation; however, it is crucial to remember that overfitting and data quality are still potential hazards in the use of AI. Retail investors were surveyed to find out their preferences and level of confidence in financial advice. Important conclusions include: For daily financial decisions, 67% of respondents favored AI-powered tools (such as robo-advisors). 59% said they had a lot of faith in AI-powered systems. Traditional advisor-based or formula-driven models were selected by 41%. Tech-savvy investors under 35 were more trusting, but investors over 50 favoured more conventional methods. According to the research, investors who are younger and more tech-savvy appear to be increasingly trusting and favouring AI-based recommendations. This preference is influenced by perceived AI system speed, personalization, and ease of use. Many retail investors expressed satisfaction with AI-powered platforms like Wealth front and Betterment, despite worries about transparency. Explainability and regulatory supervision are still essential for wider acceptability, though, especially with older or risk-averse investors. AI-based models reduced advising and transaction fees through automation, resulting in more economical portfolio management. Furthermore, AI-enabled platforms provided real-time changes, improved tax-loss harvesting, and dynamic rebalancing—all of which are challenging to accomplish in conventional setups. For individual investors, this means more cost reductions and operational efficiency. The results support Sironi's (2016) claim that robo-advisors powered by AI democratize access to complex investing strategies for a fraction of the price.

10. Conclusion

AI-based financial models have promise for improving retail investors' decision-making by dynamically adapting to market changes. However, careful implementation is required to reduce biases and overfitting. Traditional models remain significant due to their openness and theoretical validity. A hybrid technique that combines the benefits of both methodologies could be the best option for individual investors. However, AI-based models offer clear advantages in terms of adaptability, performance, and personalization—especially beneficial for retail investors when embedded in user-friendly platforms. However, the shift toward AI is not without its challenges: trust, explainability, and digital literacy are crucial obstacles. A hybrid approach—combining the fundamental insights of traditional models with the predictive power of AI—may offer the best course of action for retail investors. The literature demonstrates that traditional financial models remain relevant due to their simplicity, transparency, and theoretical rigor, especially for baseline analysis and educational purposes.By demonstrating that AI not only improves performance indicators but also conforms to changing investor expectations, this study adds to the expanding body of research on the adoption of financial technology. The findings imply that practitioners might enhance user engagement and outcomes by incorporating AI techniques into retail investment platforms. The study's limitations include its reliance on past financial data, which might not adequately reflect future market dynamics or black swan events, and the survey portion's small sample size, despite the encouraging results. Concerns about complete investor transparency are also raised by the "black box" nature of some AI models. This study sought to investigate and compare the performance, efficiency, and investor perceptions of tra1ditional and AI-based financial models, with a special emphasis on their suitability for retail investors. The study, which employs empirical analysis, investor surveys, and model comparisons, provides persuasive evidence that AI-based models have a major edge in today's dynamic and data-driven financial environment.

The results show that AI-based financial models routinely beat traditional models in terms of risk-adjusted returns, cost efficiency, and portfolio adaptability. Furthermore, the study found that retail investors are increasingly trusting and preferring AI-powered products, particularly those that provide automation, personalization, and ease of use. While classic models like Modern Portfolio Theory and CAPM are still useful for understanding fundamental investment principles, they frequently lack the responsiveness and complexity-handling capabilities needed in today's fast-moving markets. This research emphasizes the importance of taking a balanced approach. Instead of completely replacing traditional models, AI can be used to improve existing frameworks, giving investors hybrid methods that combine transparency and predictive capacity. Retail investors will now have unprecedented access to sophisticated, algorithm-driven financial advice that was previously only available to institutional clients. However, the use of AI in retail finance is not without obstacles. Model explainability, data integrity, and ethical automation use are all ongoing concerns. As such, investor education and regulatory monitoring will be vital to ensure appropriate adoption. To summarize, the shift from traditional to AI-based financial models is more than just a tool change; it signals a fundamental shift in how retail investors approach financial decision-making. As artificial intelligence advances, its careful integration into financial systems has the ability to democratize investing, maximize outcomes, and reshape the future of personal finance.

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