A Comparative Analysis of Portfolio Construction Using LLM-Based Investment Models and Modern Portfolio Theory for Financially Inexperienced Users

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A Comparative Analysis of Portfolio Construction Using LLM-Based Investment Models and Modern Portfolio Theory for Financially Inexperienced Users

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Abstract

The investment landscape is changing with the rise of artificial intelligence tools, especially Large Language Models (LLMs) like ChatGPT, which aim to make financial investing more accessible. Yet, investors with little or no experience often face challenges building balanced portfolios, mainly due to limited knowledge of risk management and diversification. While Modern Portfolio Theory (MPT) has long been the standard, conversational AI is emerging as a simpler entry point for beginners.

This study compared portfolios built using a simple prompt, a technical prompt, and a Human approach using MPT, all portfolios were tested over the same period of time. Portfolios from simple prompts delivered strong results but came with high volatility and poor diversification, making them risky for novice investors. Technical prompts produced more stable outcomes, and MPT offered the lowest volatility overall. These findings suggest that LLM-based tools can help new investors if used with technical guidance and proper risk controls, while simple prompts may encourage risk-taking beyond a safe tolerance, underlining the need for built-in safeguards.

1 Introduction

The investment landscape in the financial world has been revolutionized through the democratization of financial markets and artificial intelligence as a decision support system for individual investors. Conventional portfolio building techniques, founded on mathematical theories like Modern Portfolio Theory (MPT), entail advanced financial knowledge and technical skills that are not possessed by most beginner investors Kim et al. (2024). In the meantime, the emergence of Large Language Models (LLMs) like ChatGPT has opened up new possibilities for financially inexperienced investors to obtain a better level of investment advice via natural language interactions Nie et al. (2024).

This intersection offers both unprecedented opportunity and significant risk deserving of structured deliberation. Though LLMs may potentially democratize access to advanced investment strategies such that anyone with a web connection can get individualised portfolio recommendations Schneider and Yilmaz (2025), whether, and to what degree, AI-derived investment counsel works in practice—especially for those who do not have the financial expertise to critically assess AI suggestions—is mostly untested Lee et al. (2024).

The recent investment volatility and social influence on investing trends have also coincided with the growing usage of AI-driven investment platforms among retail investors. Most novice investors, led by financial influencers and their desire for instant returns, are embracing AI tools as flawless consultants without realizing their inner workings and limitations Kotecha (2025). This trend prompts necessary questions regarding the efficiency of conversational AI for portfolio management and the risks of excessive dependence on machine-generated advice.

The timeliness of the study is highlighted by three issues evident in the recent literature. Firstly, as adoption increases, relatively little empirical research contrasts AI-generated portfolios against conventional approaches within real-market settings Biswas et al. (2023). Secondly, although AI platforms can democratize investment knowledge, their utility might also depend on the prompt engineering skills of the users, potentially introducing new obstacles for those that most need assistance Huang et al. (2024). Third, the general use of these AI recommendation systems could possibly drive up market correlations and minimize actual diversification gains Cao (2022).

In addition, Romanko et al. (2023) observes that the current research on AI portfolio construction is in its infancy stage, while Zhang (2024) highlights increased consumer interest in AI-powered financial products without corresponding research that exposes their performance to critique. Santos et al. (2024) conducted a systematic review of research on portfolio optimization and concluded that conventional methods increasingly fail to encapsulate dynamic market features, potentially leaving room for innovative AI-based solutions.

In light of these gaps, this study focuses on key variables that may influence portfolio performance and risk profile: the type of AI prompt used (vague vs. technical), the investor's financial expertise, diversification level, and volatility measures.

This study addresses the following primary research question:

To what extent can Large Language Model (LLM)-based investment tools support financially inexperienced investors in constructing diversified and risk-balanced stock portfolios, when using vague versus technical prompts, as compared to traditional portfolios based on Modern Portfolio Theory (MPT)?

To address the research question, the following specific sets of research objectives were derived:

1. To investigate the current approaches for portfolio construction using AI tools and how they compare to traditional methods
2. To design different prompting strategies (vague vs technical) for LLM-based portfolio creation
3. To implement these approaches alongside MPT-based portfolios using real market data over the same testing period
4. To evaluate which methods provide appropriate risk-return balance for inexperienced users

The main contribution of this research is to study how different prompt types, vague and technical, affect the portfolios created by LLM-based investment tools, with a special focus on new investors. Many previous studies have examined how AI can improve investment strategies or help professional investors, but there is little work about its use for people with no financial knowledge. In this study, we compare portfolios generated with vague prompts and technical prompts to portfolios created with the traditional Modern Portfolio Theory (MPT). The analysis was made using real-time portfolio creation on

May 16, 2025, and their performance was followed until July 18, 2025, instead of only working with past historical data. By doing this, the research gives practical evidence about how conversational AI can help or fail to help novice investors. It also shows both opportunities and limitations, especially in terms of risk management and diversification. The remainder of this paper is structured as follows: Section 2 reviews the relevant literature of this research. Section 3 describes the research design, data collection process, and portfolio implementation methods. Section 4 presents the comparative analysis of the LLM- and MPT-generated portfolios. Section 5 discusses the implications of the findings for financially inexperienced investors. Finally, Section 6 summarises the key contributions, limitations, and suggestions for future research.

2 Literature Review and Related Work

2.1 Modern Portfolio Theory: Foundations and Contemporary Challenges

Modern Portfolio Theory (MPT), developed by Markowitz (1952), remains a foundational framework for constructing diversified portfolios that optimise risk and returns. This framework, relies on quantitative optimisation using historical returns, variances, and covariances of assets and while MPT provides a rigorous mathematical structure, it assumes strong financial knowledge, rational investor behaviour and stable correlations, which may not hold in highly volatile or emergent market conditions.

Although MPT is theoretically sound, empirical research documents significant challenges in implementing MPT, particularly for novice investors who lack sophisticated financial expertise Kim et al. (2024). These investors often struggle to optimize risk-return trade-offs effectively. MPT relies on quantitative optimization using historical returns, variances, and covariances of assets.

Kim et al. (2024) provides an overview of portfolio optimization models, highlighting that base mean-variance models cannot capture real-world examples' complexities such as transaction costs, behavioral biases, and time-varying market conditions. The study observes that while theoretical foundations are accurate, practical application entails understanding high-level statistical measures and financial markets still out of reach for naive investors.

Similarly, Tavakkoli (2023) illustrates how widespread mathematical techniques employed for portfolio optimization, i.e., quadratic programming, are typically ahead of the dynamic speed of the market and typically require typical financial literacy experience beyond inexperienced investors. Such experience and computational hurdles significantly restrict the extent of MPT to increasing numbers of retail investors who need investment advice.

Santos et al. (2024) systematically evaluated 80 highly ranked portfolio optimization papers, which concluded that old-fashioned approaches are increasingly powerless to capture the dynamic characteristics of financial markets and they perform miserably in the case of one-shot market activity. Their observations suggest that despite the fact that MPT is theoretically sound, its inflexibility causes it to be less sensitive to users who need more dynamic and user-friendly investment instruments.

2.2 The Emergence of Large Language Models in Financial Decision-Making

The use of Large Language Models (LLMs) in finance is a qualitative shift from mathematical models to the more natural and conversational user interfaces. Nie et al. (2024) presents the most comprehensive survey of LLM use in finance with more than 150 papers being reviewed and concludes that portfolio management is one of the most promising uses. Their paper illustrates that LLMs have robust contextual understanding, transfer learning, and real-time scalability skills that make them ideally appropriate to support financially unsophisticated investors.

Liu et al. (2024) empirically tested ChatGPT-4o's financial analysis alongside human analysts for economic exercises. As per their results, ChatGPT can perform basic and moderately complex financial exercises adequately but is outperformed by human analysts for more analytical and upper-level reasoning exercises, particularly for technical realms of finance. More significantly, they emphasize that "integrating AI with human expertise is crucial for effective decision-making," highlighting the necessity of a hybrid approach of AI recommendations and traditional financial techniques Jangra et al. (2024).

The LLM investment competencies were rigorously tested in practical terms by Ko and Lee (2023) to examine ChatGPT portfolio management, i.e., asset diversification and asset allocation strategy. The quantitative test revealed that ChatGPT's asset picks were statistically significantly better in terms of diversification measures than the randomly chosen assets. Additionally, portfolios built based on ChatGPT's suggestions performed better than randomly developed portfolios, which experienced real value addition in portfolio building activity.

Jadhav and Mirza (2025) carefully surveys 84 2022-early 2025 papers that summarize the state of LLM application in equity investment. Their detailed survey covers prevalent research trends, where LLMs have vast potential for sentiment mining, data analysis, and integration with reinforcement learning for injecting market feedback. They do recognize, however, underlying gaps in scalability, interpretability, and real-world assessment that need to be filled prior to applied use.

2.3 Direct Comparative Studies: LLMs versus Traditional Portfolio Construction

Recent empirical work has comparatively few examples of having explicitly compared LLM-based portfolio construction with conventional methods, which is positive evidence regarding the efficacy of AI-based methods. Romanko et al. (2023) performed one of the early extensive studies comparing the portfolios produced by ChatGPT and the quantitative optimization models and widely known investment funds. Although their findings corroborate that ChatGPT is good at picking stocks, they may not be so efficient at deciding optimal weights to stocks in the portfolio.

Most importantly, Romanko et al. (2023) shows that the integration of ChatGPT stock picking and traditional portfolio optimization models results in better performance, with the implication that hybrid models result in stronger and more positive investment results. This confirms the fact that AI tools are meant to augment and not substitute traditional finance methods Ambuli et al. (2024).

Schneider and Yilmaz (2025) tested if large language models can create investment portfolios with varying risk profiles, and more specifically for retail investors in United

States and European equity markets. Their test with various ChatGPT models (GPT-4, GPT-4o) showed that portfolios with more risk have more return, and that portfolio risk and return measures can be well controlled by ChatGPT based on individual risk tolerance.

Furthermore, Schneider and Yilmaz (2025) discovered that private investors can utilize ChatGPT to automate investment decision-making, ratifying the LLM's potential for financially inexperienced users directly. However, they also suggest that model choice has to be made definitively in order to ensure compatibility with local market dynamics and individual risk appetite.

Huang et al. (2024) constructed a formalized prompt template for portfolio selection and tested the impact of prompt design on the output of the generative AI tool. They proved that very formalized prompts greatly improved the portfolio optimization solutions with respect to higher Sharpe Ratios and outcomes closer to the efficient frontier when constraints were set correctly. This result supports the hypothesis that prompt sophistication does indeed contribute materially to the quality of AI response.

2.4 User Experience and Technology Adoption in AI-Based Financial Services

Practical application of LLM-based financial services raises some very important user experience matters, especially for financially illiterate investors. Zhang (2024) conducted a survey of 259 participants to explore consumers' attitudes towards AI-facilitated financial advice, such as technology adoption, decision support systems, and perceived usefulness. Findings offer proof of how technological integration improves customers' attitudes and adoption, with critical concerns revolving around data security and compatibility.

K V et al. (2024) addressed new investors' requirements squarely through proposing a system with cutting-edge statistical analysis and portfolio recommendations. Their research highlights that emerging investors, keen to invest in multiple asset classes, end up suffering financially because they don't have the right guidance and because portfolio management is a complicated process. The research gives justification to the implementation of natural technologies in filling the gap between sophisticated financial analysis and ease.

Ahmed et al. (2024)researched the use of AI in education and gained a critical evaluation of user engagement with generative AI models. Their 200-student survey showed that 95% utilized AI to do homework and 53% reported it was very helpful. Nonetheless, 64% reported that they don't think AI can replace human intelligence altogether, resulting in the loss of balanced use of AI support and conventional methods.

2.5 Challenges and Limitations of AI-Driven Portfolio Management

While the application of LLMs for portfolio management is of monumental scale, research has revealed that there remain gigantic areas and gaps. Biswas et al. (2023) is giving an overview in the case of ChatGPT applications in investment decision-making since it asserts that research on potential applications of ChatGPT is still in its early stages and reiterates the need for empirical research in extensive elaboration for AI capability testing in finance.

Lee et al. (2024) had a real vision for finance generative AI under new topic modeling paradigms with emphasis on topical matters in terms of regulatory controls and proper verification requirements of proposals for AI. Their paper brings the disruptive impact of finance field LLMs into perspective and at the same time indicates the need for timely proper governance and inquiry in a manner to avoid possible perils.

Cao (2022) thoroughly covers AI issues in finance with particular focus on the major concerns like data privacy, algorithmic bias, and transparency of AI decisions. The research underscores that the solutions of such moral flaws are at the center of the financial system, particularly safeguarding individuals with low finance literacy.

Ranjan et al. (2024) is addressing the challenges of finance AI adoption and data security and privacy issues, regulation challenges, fairness and bias concerns, and ethical deployment of AI. The paper records case studies and addresses solution strategies in terms of AI-enabling encryption algorithms, privacy-preserving machine learning algorithms, and AI innovation testing regulation sandboxes.

2.6 Personalization, Ethics, and Strategic AI Use in Investment

K V et al. (2024) suggested personalized investment experiences with integrated platform development, whereas Alfzari et al. (2025) offers a classical economic theory-based framework for facilitating AI computation of ideal portfolio compositions. These models offer insightful views that identify user flexibility as the most important in supporting new classes of investors and augmenting theoretical underpinnings with technical analysis.

The application of AI for investments carries ethical implications of serious concern to this research. Ahmed et al. (2024) were adamant about the necessities for making machine-based models transparent, accountable, and fair. Hayat and Shoeb (2024) shared the same sentiments when they report on how such technologies are implemented in multicultural global contexts.

2.7 Research Positioning and Contribution

This research fills a clear gap by comparing, portfolios created with different prompt styles in LLM tools against those built with traditional MPT with a human approach and also focusing specifically on novice investors. Unlike studies that rely only on backtesting, this one also includes a real-time simulation period to capture how these portfolios behave as market conditions change.

The work is relevant because most research in this space is aimed at experienced investors with strong and technical financial or Technological knowledge. In this case, the main focus is on how a inexperienced user and without formal financial training can use conversational AI effectively. .

3 Methodology and Design Specification

This research uses a comparative simulation design to test whether novice investors can construct balanced and diversified portfolios with LLM-based investment products versus conventional Modern Portfolio Theory (MPT) products. The research design is quantitative, and there are three different methods of portfolio construction using the same simulated initial investment fund of EUR 1,000 for comparison testing purposes and simulating an investor profile starting out in the investment world. Answering the underlying research question with the controlled experiment design that holds market conditions and test horizons constant, thus separating the effect of different portfolio construction methods. The technique makes it possible to compare the designs suggested by AI with the canonical conditions of modern theory in a similar way.

3.1 Methodological Considerations and Justification

3.1.1 Alternative Approaches Considered

Historical Backtesting Approach
Traditional portfolio studies commonly employ historical backtesting methodologies, however this approach was discarded due toit does not address adequately the central research question. When financially inexperienced investors seek investment guidance from LLMs on a particular date (May 16, 2025), the AI system likely provides recommendations based on recent historical performance patterns. The crucial question that needs to be answered is: how do these recommendations perform going forward? Historical backtesting cannot provide this forward-looking performance evaluation, which is fundamental for assessing the real-world utility of LLMs for novice investors.

Social Trading Platforms (eToro, etc.)
Copy-trading and social investment platforms were also considered but ultimately rejected due to several reasons:

- These platforms allowed to primarily focus on returns rather than risk-balanced portfolio construction measures.
- The research focus lies on portfolio construction methodology rather than return optimization strategies

Alternative LLM Platforms
Other AI platforms such as TradeGPT were evaluated, but ChatGPT-4 was selected because research demonstrates it is the predominant AI language model for conversational applications Ray (2023). This widespread adoption makes it the most representative choice for examining financially inexperienced user behavior patterns.

3.2 Portfolio Construction Methodologies

3.2.1 Portfolio 1 – Vague Prompt (LLM-Based)

Portfolio 1 resulted from a natural language command given to ChatGPT-4 on May 16, 2025, without mention of investment horizon, risk attitudes, or financial theory. The command was: "I have €1,000 to invest, give me a portfolio." This method was a simulation of the standard interaction of a totally inexperienced investor seeking simple investment recommendations without technical expertise or specific demands.

This vague prompt strategy mirrors actual situations in which new investors ask AI for help with poorly specified financial goals or risk parameters, which compelled AI to generate reasonable default suggestions.

3.2.2 Portfolio 2 – Technical Prompt (LLM-Based)

Portfolio 2 was constructed using a more sophisticated and detailed, risk-conscious prompt submitted to ChatGPT-4 on the same date. The detailed prompt stated:

"As a finance professional, I'm looking to invest 1,000 EUR for the next 3 to 6 months specifically into individual common stocks, aiming for maximum capital appreciation with a moderately aggressive risk tolerance. I need a portfolio of highly liquid stocks that have strong short-term growth catalysts and a focused, strategic diversification to manage risk without diluting potential returns. Please provide the exact percentage allocation and ticker for each recommended stock."

The conditions and prompt given in the second portfolio were based on the results of the first portfolio, as for both to be comparable was needed to use horizon, risk tolerance and in this case, given that the first portfolio resulted in stocks only, the second portfolio was specified to also use stocks. This due to comparability purposes and taking into account that an experienced investor, as is the case with portfolio 2, would be more specific and detailed in these parameters.

3.2.3 Portfolio 3 – Human-Guided MPT Portfolio

Portfolio 3 was developed by applying the core principles of Modern Portfolio Theory (MPT). The process began with a careful selection of assets from those already included in Portfolio 1 and Portfolio 2. This selection was based on a review of their historical performance, correlation with each other, and their potential to improve diversification.

Once the assets were chosen, the efficient frontier was calculated using their expected returns, variances, and covariances. This step allowed you to visualize the set of possible portfolios and understand the trade-off between risk and return. From this analysis, was identified the point that met the objective of minimizing volatility while still achieving a specific target return.

This approach followed the logic of how a better-informed investor and how he would construct a portfolio in real life: using theoretical models to guide decisions, but also applying practical judgment when choosing the final allocation.

3.3 Data Collection and Tools

3.3.1 Data Sources and Implementation

All the analyses in this portfolio were carried out in Google Colab and Python environments. Historical prices of the assets in question were retrieved through the Yahoo Finance API by the yfinance Python package, offering standardized and uniform financial data for all the analyses.

Essential Python packages included:

- NumPy and pandas for data manipulation and mathematical calculations
- matplotlib and seaborn for visualization and statistical plotting
- scipy for optimization and statistical analysis
- yfinance for financial data retrieval
- plotly for interactive visualizations

3.3.2 Analysis Periods and Temporal Considerations

For Portfolios 1 and 2 given by the conversational LLM on May 16, 2025, they were tested from that date until July 20, 2025. This future strategy emulates actual circumstances in which investors make decisions based on AI-recommended ideas at reception without the taint of hindsight bias and in portfolios tested in the then-exists scenario.

Although this is a short evaluation period indeed (approximately two months), it is worth noting that measures on portfolio diversification, volatility, and risk exposure characteristics are of special use to financially inexperienced investors. The study is centered on risk-adjusted performance measures instead of absolute returns because of the brevity of the period.

The MPT portfolio selected the best historical stock data from portfolios 1 and 2, entirely manually and without IA advice, the best performers from different industries were selected, and in this case a period from May 15, 2018, to July 18, 2025 was used to plot efficient frontier and identify optimal risk-return alternatives, as the MPT does. After find and select the portfolio allocation, the same period of Mat 16 to July 20 was used to compare all portfolios under the same time frame.

3.4 Financial Metrics and Evaluation Framework

3.4.1 Core Performance Metrics

The evaluation framework includes multiple financial measures to provide a comprehensive portfolio assessment across the three approaches for the evaluation period (May 16 - July 20, 2025):

Return Calculations:

$$R_{period} = \frac{P_{final} - P_{initial}}{P_{initial}} \times 100 \quad \text{(Total Period Return)} \tag{1}$$

Risk Metrics:

$$\sigma_{daily} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(R_t - \bar{R})^2} \quad \text{(Daily Volatility for Period)} \tag{2}$$

Risk-Adjusted Performance:

$$\text{Sharpe Ratio} = \frac{\bar{R}_{daily} - R_f}{\sigma_{daily}} \tag{3}$$

$$\text{Jensen's Alpha} = R_p - [R_f + \beta_p(R_m - R_f)] \tag{4}$$

$$\text{Risk-Return Ratio} = \frac{\bar{R}_{daily}}{\sigma_{daily}} \tag{5}$$

3.4.2 Diversification Analysis

The diversification effectiveness was measured using correlation-based metrics following Modern Portfolio Theory principles:

$$\text{Average Correlation} = \frac{1}{n(n-1)/2}\sum_{i<j}\rho_{ij} \tag{6}$$

$$\text{Diversification Score} = (1 - \text{Average Correlation}) \times 100\% \tag{7}$$

Where ρ_{ij} represents the correlation coefficient between assets i and j.

3.4.3 Risk Management Metrics

Value at Risk (VaR) calculations were implemented using historical simulation methods to assess potential losses:

$$\text{VaR}_{95\%} = \text{5th Percentile of Historical Returns} \tag{8}$$

$$\text{VaR}_{99\%} = \text{1st Percentile of Historical Returns} \tag{9}$$

Portfolio Beta was calculated to measure market sensitivity:

$$\beta = \frac{\text{Cov}(R_p, R_m)}{\text{Var}(R_m)} \tag{10}$$

3.4.4 Modern Portfolio Theory and Monte Carlo Simulation

Portfolio 3 was evaluated using a combination of Monte Carlo Simulation and the Modern Portfolio Theory. The Monte Carlo Simulation generated 4,000 random weight allocations across the selected assets, producing a stochastic distribution of expected returns and volatilities. This provided a probabilistic view of the feasible set and visual identification of the efficient frontier.

In the MPT framework, the portfolio variance given by:

$$\sigma_p^2 = w^T \Sigma w \tag{11}$$

Where w is the vector of portfolio weights and Σ is the covariance matrix of asset returns

The optimization problem was:

$$\text{maximize} \quad SR = \frac{w^T \mu - r_f}{\sqrt{w^T \Sigma w}} \tag{12}$$

$$\text{subject to} \quad w^T \mathbf{1} = 1 \tag{13}$$

$$w_i \geq 0, \quad \forall i \tag{14}$$

Where μ is the vector of expected returns and r_f is the risk-free rate.

In this case, was selected a 40% target return to create a comparable benchmark with the LLM-generated portfolios (Portfolio 1 and 2), ensuring that this approach targeted similar return expectations rather than using conservative minimum-variance optimization that would not provide a fair comparison basis for evaluating the relative performance of the three portfolio construction methods.

4 Implementation

The final stage of the implementation was carried out using three notebooks structured in Jupyter, each corresponding to one of the portfolio construction methods: vague prompt with LLM, technical prompt with LLM and Modern Portfolio Theory (MPT). Each notebook was designed as a stand-alone module with standardised sections: data acquisition, return calculation, risk assessment and summary results.

All the key financial indicators mentioned above were implemented manually through Python code using the libraries mentioned in the previous section.

- Final portfolio weighting tables.
- Covariance and correlation matrices for assessing risk and diversification.
- Comparative risk-return visualisations and cumulative return charts.
- Consolidated data frames with all key metrics for cross-sectional comparison.

Each notebook also integrated a final comparison layer that allowed the three strategies to be quantitatively evaluated under the same market conditions and period of analysis. This implementation produced the results and information needed to answer the research question, focusing on the ability of the LLM-generated strategies to simulate the interaction of a new versus financially prepared investor using IA versus a financially prepared investor not using IA at all.

5 Evaluation

5.1 Portfolio Composition and Allocation Analysis

This section analyzes the internal structure of each portfolio, including asset allocation, level of diversification, and the relationships between them, exploring key metrics and visualizations such as correlation matrices and composition charts.

5.1.1 Portfolio 1 (Vague Prompt) - Composition and Characteristics

The figure 1 shows how the Portfolio is constructed, yielded a technology-skewed portfolio in terms of concentration risk. The portfolio contained 45% technology stocks, and NVIDIA was allocated the greatest individual position at €200 (20%). This would seem to be ChatGPT's seemingly systemic bias toward hip, flashy tech stocks featured in the news in May 2025.

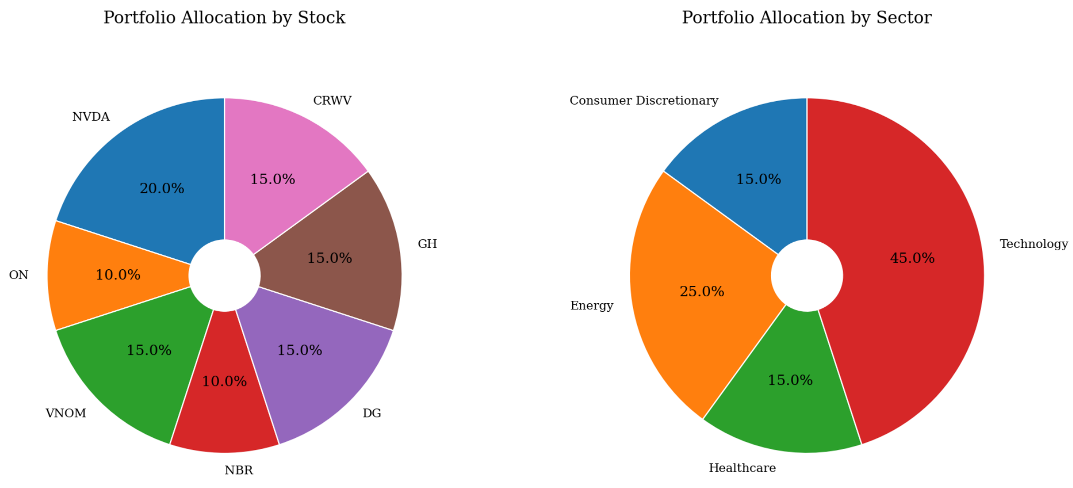

Figure 1: Portfolio 1 Allocation by Stock and Sector (Vague Prompt)

Table 1: Portfolio 1 Composition and Allocation

Ticker	Company	Sector	Allocation (EUR)	Allocation (%)
NVDA	NVIDIA	Technology	€200	20.0%
ON	ON Semiconductor	Technology	€100	10.0%
CRWV	CoreWeave	Technology	€150	15.0%
VNOM	Viper Energy	Energy	€150	15.0%
NBR	Nabors Industries	Energy	€100	10.0%
GH	Guardant Health	Healthcare	€150	15.0%
DG	Dollar General	Consumer Discretionary	€150	15.0%
Total			**€1,000**	**100.0%**

The table 1 shows an asset distribution that, while incorporating different sectors—technology, energy, healthcare, and consumer discretionary—presents a considerable concentration in the technology sector, which represents 45% of the total. Furthermore, a high concentration of 20% to a single asset (NVIDIA).

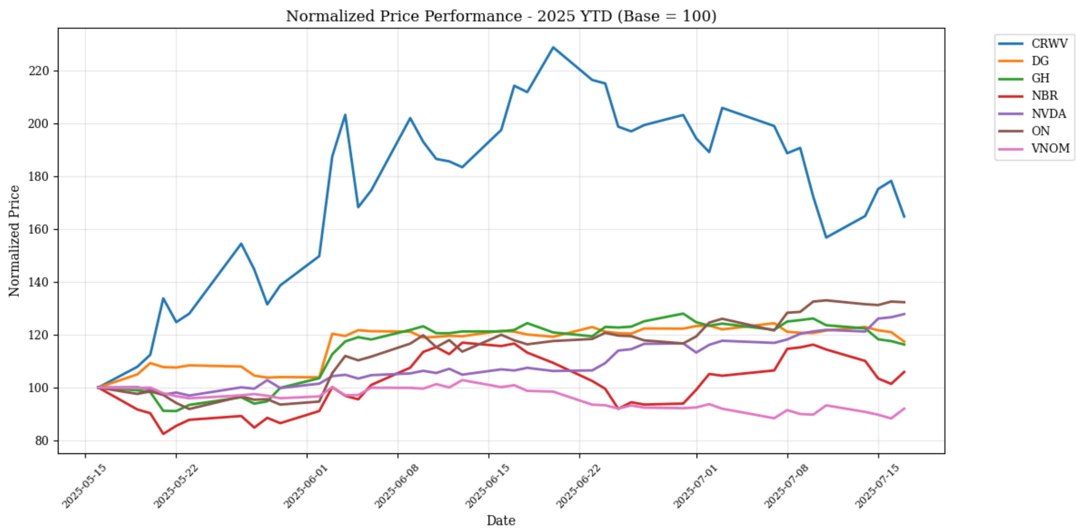

Figure 2: Portfolio 1. Period Historical Price

Figure 2 illustrates the historical performance of the portfolio's assets using normalized prices, which allows for a proportional comparison of each stock's trajectory over time, regardless of their original price levels. This chart is representative and serves illustrative purposes, showing the performance of the assets selected by the AI from the date that the prmpt was generated. While most assets show relatively stable behavior, it is important to note that CRWV also shows a period of accelerated growth during that time, likely due to a short-term momentum or trend. This historical outperformance does not necessarily imply that such growth will continue in the future, and it highlights the importance of distinguishing between sustained performance and speculative spikes.

5.1.2 Portfolio 2 (Technical Prompt) - Composition and Characteristics

The following figure 3 shows the results of the technical prompt used for the second portfolio:

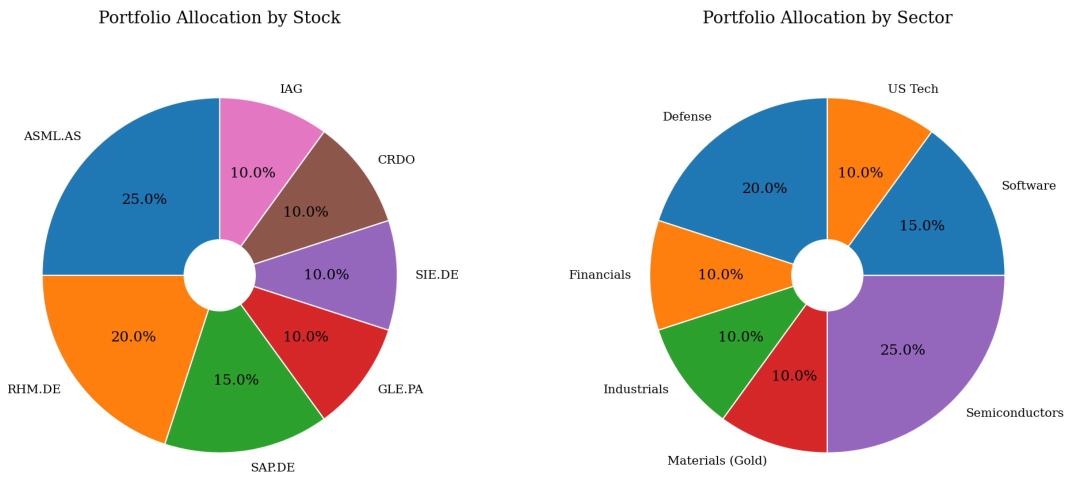

Figure 3: Portfolio 2 Allocation by Stock and Sector (Technical Prompt)

The left chart in 3 breaks down investments by individual stocks, with ATLAS holding the largest position at 25%, followed by DE at 20%, and SAP.DE at 15%, while IAG, CRDO, SIE.DE, and GLE.PA each represents 10% of the portfolio. The right chart shows the same portfolio organized by sector, with Semiconductors comprising the largest allocation at 25%, Defense at 20%, Software at 15%, and US Tech, Financials, Industrials, and Materials (Gold) each accounting for 10% of the total investment.

Table 2: Portfolio 2 Composition and Allocation

Ticker	**Company**	**Sector**	**Allocation (EUR)**	**Allocation (%)**
ASML.AS	ASML Holding	Semiconductors	€250	25.0%
RHM.DE	Rheinmetall AG	Defense	€200	20.0%
SAP.DE	SAP SE	Software	€150	15.0%
GLE.PA	Société Générale	Financials	€100	10.0%
SIE.DE	Siemens AG	Industrials	€100	10.0%
CRDO	Credo Tech	US Tech	€100	10.0%
IAG	IAMGOLD Corp	Materials (Gold)	€100	10.0%
Total			**€1,000**	**100.0%**

The table 2 also showsthe allocations and how this portfolio had high concentrations in ASML Holdings and Rheinmetall AG stocks, the portfolio's diversification encompassed more sectors and offered greater geographic coverage and area and industry cycle diversification.

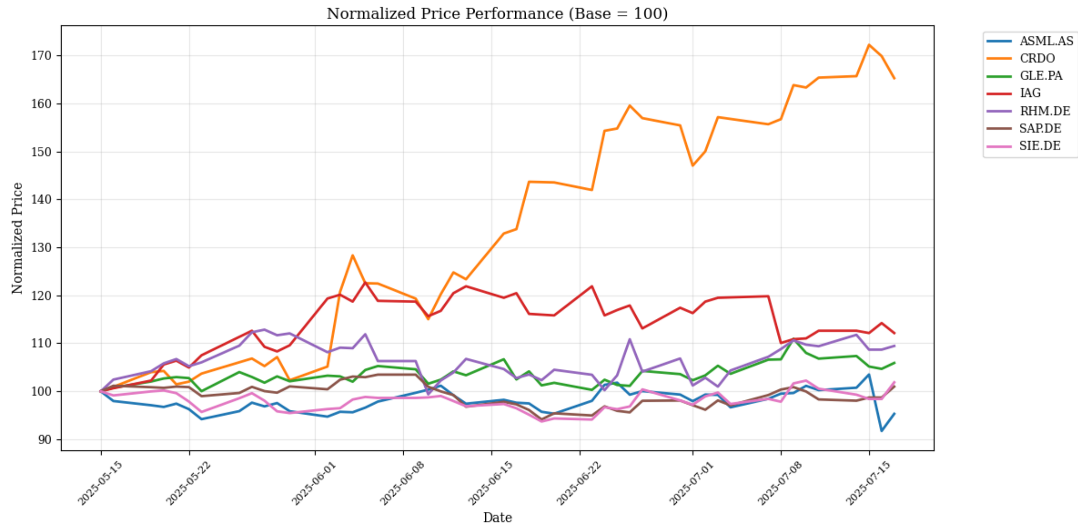

Figure 4: Portfolio 2. Period Historical Price

The figure 4 shows the normalized prices chart with the performance of the assets during the period analyzed. As done in the portfolio 1, for better visual comparability, all assets start from the same base (100), making it easier to compare their percentage performance regardless of their nominal price. Within the AI's selection, CRDO stands out with a solid upward trajectory, reaching levels close to 170 by mid-July. This performance suggests strong market momentum but the same considerations needs to be take into account as in portfolio 1.

5.1.3 Portfolio 3 (MPT-Based) - Comprehensive Mathematical Optimization

The table 3 shows the optimal weights assigned to each asset in Portfolio 3 under four different allocation strategies, all derived using the principles of Modern Portfolio Theory (MPT). Each strategy represents a different approach depending on the investment objective and risk profile, and allows to observe how the portfolio composition varies depending on the imposed parameters.

Table 3: Portfolio 3 – Optimal Weights by Strategy

Asset	**Min Vol**	**Min Vol 40%**	**Max Sharpe**	**Sharpe Vol 0.28**
NVDA	0.00	17.85	37.82	19.60
PLTR	0.00	4.99	5.93	4.86
AMZN	28.08	10.89	0.00	8.18
VNOM	10.27	1.86	0.00	1.03
RHM.DE	25.10	44.62	56.24	45.18
SAP	36.56	19.79	0.00	21.15
Total	**100.00**	**100.00**	**100.00**	**100.00**

Min volatility: This strategy seeks exclusively to minimize portfolio volatility, without requiring a minimum return. As a result, it avoids highly volatile assets such as NVDA and PLTR, and concentrates the majority of the weights in more stable stocks such as SAP, AMZN, and RHM.DE. It is the most conservative option, ideal for low-risk profiles.

Min volatility return of 40% Unlike the previous strategy, this strategy imposes a target return restriction of 40% per year, simultaneously seeking to minimize volatility. To achieve this objective, it incorporates assets with higher return potential (such as NVDA), albeit in moderate proportions to maintain risk control. The result is a portfolio more balanced between return and stability. For comparison reason this portfolio is that it will be used to compare with the other two.

Max Sharpe ratio: This strategy optimizes the Sharpe ratio, that is, it maximizes risk-adjusted return. As a result, a high concentration in a few assets—mainly RHM.DE and NVDA—is generated due to their relative good performance during the analyzed period. While this strategy is theoretically efficient, it entails greater risk due to a lack of diversification.

Max Sharpe Ratio, volatility of 0.28: Similar to the previous strategy, this seeks to maximize the Sharpe ratio, but adds an additional restriction: the total volatility of the portfolio must not exceed 28%. This requires a more even distribution of weights among various assets to maintain a balance between efficiency and risk control. The strategy achieves a more diversified mix without completely sacrificing risk-adjusted returns.

5.2 Portfolios Comparison

In summary, the final allocations of the three portfolios analyzed are presented in the following table 4

Table 4: Portfolio Allocations (May 16 – July 20, 2025)

Portfolio 1 (Vague)		**Portfolio 2 (Technical)**		**Portfolio 3 (MPT)**	
Ticker	**%**	**Ticker**	**%**	**Ticker**	**%**
NVDA	20.0	ASML.AS	25.0	NVDA	17.85
ON	10.0	RHM.DE	20.0	PLTR	4.99
CRWV	15.0	SAP.DE	15.0	AMZN	10.89
VNOM	15.0	GLE.PA	10.0	VNOM	1.86
NBR	10.0	SIE.DE	10.0	RHM.DE	44.62
GH	15.0	CRDO	10.0	SAP	19.79
DG	15.0	IAG	10.0	–	–

The following table 5 offers a detailed comparison of all three portfolio metrics over the same time frame to make the metrics in all three Portfolios comparable over time, en selecting a risk and return similar to across them. The comparison presents a number of key observations to answer the main research question concerning the effectiveness of LLM among financially inexperienced investors.

Table 5: Performance Comparison Summary

Performance Metric	Portfolio 1 (Vague)	Portfolio 2 (Technical)	Portfolio 3 (MPT & Human)
Return Metrics			
Daily Average Return (%)	0.619	0.302	0.126
Maximum Daily Gain (%)	+25.19	+14.80	+7.73
Maximum Daily Loss (%)	-17.20	-11.37	-9.37
Total Period Return (%)	28.49	11.52	5.66
Risk Metrics			
Daily Volatility (%)	2.566	1.508	0.816
Annualized Volatility (%)	40.73	23.94	12.95
VaR 95% (%)	-2.194	-1.972	-1.021
VaR 99% (%)	-3.212	-2.747	-1.207
Portfolio Beta	1.280	0.703	0.885
Risk-Adjusted Performance			
Sharpe Ratio	1.857	1.195	0.896
Risk-Return Ratio	0.241	0.231	0.154
Jensen's Alpha (%)	+0.434	+0.014	+0.089
Diversification Metrics			
Number of Securities	7	7	6
Number of Sectors	4	7	6
Average Correlation	0.364	0.135	0.287
Diversification Score (%)	63.6	86.5	71.3
Diversification Benefit (%)	27.8	47.2	39.6

All metrics calculated for the same evaluation period (May 16 – July 20, 2025)

5.3 Return Metrics

5.3.1 Daily Average Return Performance Analysis

The daily returns show significant differences in performance among the three portfolios during the period analyzed. Portfolio 1 (Vague) achieved a notable daily return of 0.619%, but also it demonstrated a very aggressive approach, although this was accompanied by greater return. Portfolio 2 (Technical) got a more moderate return of 0.302%, reflecting a better and safe balance between profitability and risk management characteristic of strategies based on more technical knwledge. Portfolio 3 (MPT) recorded the most conservative return at 0.126%, demonstrating Markowitz's optimization philosophy, which prioritizes efficient risk-return ratios, looking the maximization of the returns.

5.3.2 Maximum Daily Gain Analysis

Portfolio 1 (Vague) demonstrated an explosive growth potential by reaching a peak of +25.19%, significantly outperforming the other portfolios. Portfolio 2 (Technical) achieved a maximum gain of +14.80%, displaying more controlled but still robust behavior on favorable market days. Portfolio 3 (MPT) exhibited the lowest upside volatility with a maximum gain of +7.73%, confirming its conservative design that sacrifices extreme growth potential for stability and predictability of returns.

5.3.3 Maximum Daily Loss Analysis

Revealed important insights for new investors that can be exposed to higher looses; Portfolio 1 (Vague) experienced the biggest loss at -17.20%, confirming that its high return potential comes with the more significant risk. Portfolio 2 (Technical) showed better loss control at -11.37%, suggesting that technical analysis techniques provide better exit signals and risk management. Portfolio 3 (MPT) demonstrated its defensive strength with the smallest loss of -9.37%. Total Period Return Analysis: As mentioned before, the window period is not long enough to predict returns, and it can be influenced by trendy peaks. However, as expected, the higher the risk, the higher the return, but also the greater the potential loss.

5.4 Risk Metrics

5.4.1 Daily Volatility Analysis

The three portfolios show different levels of daily risk. Portfolio 1 (Vague) has the highest volatility at 2.566%, meaning its prices fluctuate significantly each day, both up and down. Portfolio 2 (Technical) is in the middle at 1.508%, showing moderate daily price changes. Portfolio 3 (MPT) is the most stable at only 0.816% volatility; its prices do not change much from day to day. Annualized Volatility Analysis: When looking at risk over a full year, the differences become greater. Portfolio 1 (Vague) has 40.73% annual volatility; highly risk. Portfolio 2 (Technical) has 23.94%, a medium risk. Portfolio 3 (MPT) with 12.95%, which was more safe.

5.4.2 Value at Risk (VaR) Analysis

VaR shows how much investors can lose on the worst days. With a 95% VaR, Portfolio 1 (Vague) can lose up to -2.194% on a bad day, Portfolio 2 (Technical) up to -1.972%, and Portfolio 3 (MPT) only up to -1.021%. On very bad days (99% VaR), losses can be greater: Portfolio 1 (-3.212%), Portfolio 2 (-2.747%), and Portfolio 3 (-1.207%). Portfolio 3 loses the least when things go wrong.

5.4.3 Portfolio Beta Analysis

Beta shows the way of each portfolio reacts when the market rises or falls. Portfolio 1 (Vague) has a beta of 1.280, which moves more than the market—when the market rises 10%, it can rise 12.8%. Portfolio 2 (Technical) has a beta of 0.703, which moves less than the market—if the market falls 10%, it falls only 7%. Portfolio 3 (MPT) has a beta of 0.885, which moves almost as much as the market, but slightly less.

5.5 Risk-Adjusted Performance

5.5.1 Sharpe Ratio Analysis

The Sharpe Ratio shows how well a portfolio compensates for risk with returns. Portfolio 1 (Vague) has the best Sharpe Ratio at 1.857, meaning it provides a good return for each unit of risk taken. Portfolio 2 (Technical) has 1.195, which is good but not as high as Portfolio 1. Portfolio 3 (MPT) has 0.896, the lowest.

5.5.2 Risk-Return Ratio Analysis

Comparing returns with risk in another way. Portfolio 1 (Vague) has 0.241, showing that it may generate more returns (but also major losses). Portfolio 2 (Technical) has 0.231, very similar to Portfolio 1, indicating that both manage the relationship between returns and risk well. Portfolio 3 (MPT) has 0.154, the lowest, confirming is more safe for long term investments.

5.5.3 Jensen's Alpha Analysis

Overall, all portfolios performed above the expected return for their respective risk levels. Notably, and logically, the portfolio with the highest risk, Portfolio 1, also exceeded expectations. However, the excess return does not offset the high risk and the unacceptable volatility of 40% associated with this portfolio.

5.6 Diversification Metrics

5.6.1 Number of Securities and sectors Analysis

The three portfolios have similar amounts of stocks but with slight differences. Portfolio 2 (Technical) is in 7 different sectors, which is excellent for reducing risk because it is highly diversified. Portfolio 3 (MPT) is in 6 sectors, which provides even better diversification. Portfolio 1 (Vague) is in only 4 sectors, which means it is more concentrated and therefore has more risk.

5.6.2 Average Correlation Analysis

Portfolio 2 (Technical) has the lowest correlation at 0.135, meaning its stocks move very independently, which is very good for reducing risk. Portfolio 3 (MPT) has 0.287, which is average—some stocks move together, but not all. Portfolio 1 (Vague) has 0.364, the highest correlation, meaning its stocks tend to move in the same direction, increasing risk.

5.6.3 Diversification Score Analysis

This score summarizes how well diversified each portfolio is. Portfolio 2 (Technical) has the best score at 86.5%, showing excellent diversification. Portfolio 3 (MPT) has 71.3%, which is good diversification. Portfolio 1 (Vague) has 63.6%, the lowest score, confirming that it is the least diversified of the three.

5.6.4 Diversification Benefit Analysis

Shows how much risk is reduced due to their diversification. Portfolio 2 (Technical) gets the most benefit at 47.2%, significantly reducing its risk due to its diversified nature and more stocks utilized. Portfolio 3 (MPT) reduces its risk by 39.6%, which is a good return. Portfolio 1 (Vague) only reduces its risk by 27.8%, the lowest return, because it is less diversified than the other two.

6 Conclusion and Future Work

6.0.1 Research Question and Objectives Restatement

This research answered the question: ”To what extent can investment tools based on Long Language Models (LLM) support financially inexperienced investors in constructing diversified and risk-balanced equity portfolios when using vague versus technical prompts, compared to traditional portfolios based on Modern Portfolio Theory (MPT)?”

The study had three main objectives: first, to see whether artificial intelligence tools can help individuals with no investment experience build stock portfolios; second, to compare how different the results are when using simple versus more technical questions; and third, to see how these AI portfolios compare to traditional methods used by experts.

To perform this, ChatGPT-4 (Large Language Model, OpenAI) was used on May 16, 2025, and created three different portfolios: one with simple questions (Portfolio 1), another with technical questions (Portfolio 2), and a third using more traditional optimization methods (Portfolio 3). The performance of these portfolios was tracked for two months to see how they performed in terms of profit, loss, and risk.

6.0.2 Addressing Research Objectives

The research successfully answered all the questions initially posed. Finding that AI can democratize investment portfolio creation for new investors. However, the quality of the results varies greatly depending on the technical knowledge. The results provide very useful information for individuals who are just starting out in investing, for companies developing these tools, and for regulators who want to better understand the impact of artificial intelligence on personal finance.

6.0.3 Key Findings

Portfolio Performance Results

The numbers showed a very clear story about the differences between the three approaches. Portfolio 1 (vague questions) yielded the highest returns with 28.49% total gain and 0.619% average daily gain, but it was also the riskiest with 40.73% annual volatility and a maximum loss of -17.20% in a single day. However, It is important to understand that these high returns were not the primary focus in this study, due to the timeframe limitation.

As mentioned, Portfolio 1 yielded high returns, However, such stocks selected by the LLM were heavily focused on trendy tech stocks, especially NVIDIA and semiconductor companies. Following an obvious market trend when no clear instructions are given.

The Impact of Better Built Prompts: An important finding was to evaluate the quality of the promot, which reflects the knowledge of the individual interacting with the LLM, for instance, Portfolio 2 (technical questions) achieved a much better balance with 11.52% total return and 23.94% volatility, showing better metrics when adjusted for risk. These results directly support the work of Huang et al. (2024), which mathematically confirmed the significant improvement in portfolio optimization outputs with formalized prompts.

Portfolio 2 was particularly interesting because it provided a balanced approach among the three portfolios, reinforcing what previous studies had already found: AI can help us and empower us, but it does not replace the knowledge of an experienced investor who knows exactly the desired investment profile and portfolio motivations. Portfolio 2's diversification strategy proved more resilient to rapid market changes, suggesting that certain types of prompts can reduce time bias in AI recommendations. Using terms like "strategic diversification" and "risk management" in technical questions seems to encourage more thoughtful analysis than simply following current trends. Stability and Financial Knowledge

Portfolio 3 (MPT) demonstrated the most stable performance, achieving a 5.66% total return with only 12.95% volatility and optimal diversification characteristics. This portfolio was constructed using MPT principles and Monte Carlo Simulation where 4,000 portfolio simulations were generated to identify the optimal risk-return combinations. It is important to note that this particular portfolio represents just one point on the efficient frontier, selected to demonstrate moderate risk preferences. The efficient frontier methodology allows investors to identify portfolios that maximize expected returns for any given level of risk tolerance. Therefore, if an investor desired higher returns and was willing to accept greater risk, the same optimization framework could generate portfolios that might potentially exceed Portfolio 1 performance, following the fundamental investment principle that higher expected returns typically require accepting higher risk.

However, the critical distinction lies in the systematic approach to risk management. Even when targeting higher returns, a portfolio constructed using efficient frontier optimization would maintain proper diversification principles and avoid the concentrated exposure observed in Portfolio 1, which allocated substantial weight to trending technology stocks. Experienced investors who understand portfolio construction will always seek to optimize the risk-return trade-off through systematic diversification rather than relying on concentrated bets, regardless of their risk appetite. This disciplined approach to balancing risk and return is precisely what Portfolio 3 exemplified.

6.0.4 Market Context and Temporal Analysis

May 2025 Market Environment: The analysis period happened at the same time as some important events that explain why ChatGPT selected so many trending technology stocks. For instnce, on May 11, 2025, a trade agreement between United States and China was announced that reduced tariffs significantly, which made technology stocks go up a lot because it removed the uncertainty about a possible recession[1]. Also, the semiconductor industry reported record growth of 19.8% in May 2025, with global sales of 59.0 billion, mainly driven by the demand for AI chips[2]. These events could explain why the AI chose these "trendy" stocks, that were in all the financial news, Showing that the LLM model has bias towards recent market trends when it is not given more specific instructions. However, this market sentiment is an important bias to consider when investing using AI advise.
The bias towards recent trends in AI suggestions when analyzed which stocks it selected. The concentration in popular AI stocks like CoreWeave and NVIDIA in Portfolio 1 showed that ChatGPT's training and response patterns reflected the recent market mania in these areas. This is very significant for retail investors who use AI tools, because it shows that making more sophisticated questions can reduce this bias of following market sentiment

[1]`https://www.newsweek.com/china-us-agree-drop-tariffs-115-90-days-2070769`
[2]`https://www.semiconductors.org/global-semiconductor-sales-increase-27-0-year-to-year-in-may/`

in AI-based recommendations. As investors without knowledge, just as they can be lucky and win, they can also lose all their investments.

6.0.5 Research Implications and Efficacy

The results show that AI can make investors to have more access to sophisticated financial tools that before were only available for experts. The access advantage proves the argument of Nie et al. (2024) that LLMs will bring democratization of access to sophisticated financial instruments. The research also supports the result of Liu et al. (2024) that AI tools would perform better when they are used together with traditional financial knowledge instead of replacing it completely.

The results also suggested that AI can democratize the learning and testing of investments for individuals that do not know how to build classic investment models. This is especially valuable because traditionally, someone needed years of financial education or pay an expensive advisor to access diversified investment strategies. However, this study also showed that although AI can be a powerful tool, it does not completely replace the need to have basic financial knowledge. People who understand investment principles will always make better decisions about the balance between risk and return.

6.0.6 Limitations and Analytical Constraints

The analysis has several important limitations that affect how results should be interpreted. The period selected (May 16 to July 18, 2025) only covers approximately two months of market data, and this is not enough to capture complete market cycles or seasonal effects. The short evaluation horizon limits conclusions about long-term portfolio performance, but it does give valuable information about risk characteristics, diversification success, and short-term volatility behavior that is important for investors who avoid risk and for portfolio risk management in general.
Another important limitation is have used only one LLM tool, different versions or AI models could give completely different recommendations. The fact that all the prompts were performed on May 16, 2025 means we captured specific market conditions that might not represent other moments. However, this limitation also reflects real-world scenarios where individual investors would normally ask for AI advice, which makes our results more applicable to real situations. These limitations are balanced with the study's strengths in providing real-time and forward-looking perspectives that are free from retrospective bias and that capture optimally the real decision-making conditions that face common investors who seek AI-based investment guidance.

6.1 Future Work

For future it would be valuable to test more different AI platforms to see if the results we found are specific to ChatGPT or if they apply to other AI tools. Second, to develop and test a wider variety of specialized prompts to understand better what types of questions produce the best results. Third, and perhaps more important, perform a much longer temporal analysis. For instance, as asked on May 2025, what results would be seen for 2030, for example. It is important to mention that, many times portfolios that have less volatility are more stable and end up generating better long-term returns, as probably could be the case of Portfolio 3.

Proposals for Research Extensions A follow-up research project could explore better how LLMs behave in different market conditions. What happens with AI recommendations during bear markets, high volatility, or financial crises? It would also be valuable to develop more sophisticated prompt frameworks that incorporate multiple risk factors and study how well AI recommendations can adapt to specific investor risk profiles. Another important area for future research is studying user learning behavior. How do the questions that people ask change as they learn more about investments? And how can AI adapt better to users who are in different stages of their financial learning journey? Commercialization Potential The findings suggest significant opportunities to develop commercial tools that combine LLM accessibility with robust traditional financial principles. There is a clear market to create interfaces that guide novice users toward more effective prompts and hybrid systems that integrate AI recommendations with traditional quantitative optimization. Commercial applications could include educational tools that teach people how to make better questions about investments, platforms that combine AI with human advisory for different levels of user sophistication, and systems that adapt automatically to the complexity level of recommendations based on the experience of the investor.

6.1.1 Implications for the Financial Industry

The research demonstrates that although LLMs can democratize access to investment strategies, their greatest value lies in their use as complementary tools that require supervision and appropriate financial context to maximize their effectiveness and minimize risks. This suggests that the future of investments is not in completely replacing financial advisors, but in creating hybrid tools that make quality financial advisory more accessible and affordable and accesible for more people. For regulators, this research findings suggest the need to develop frameworks that protect novice investors from potential biases of AI tools while allowing innovation that can democratize access to quality financial services.

Disclaimer: The study is conducted for academic purposes only and should not be utilized as an investment guide. The outcome should not be considered as executing AI-driven investment directives without proper caution and expert opinion. Investors should always remember their financial status, risk-bearing ability, and investment objective before investing.

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