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AI-Based Stock Portfolio Construction and Comparative Performance Analysis versus Conventional Investment Portfolios

By:

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FINAL PROJECT APPROVAL SHEET

Open Defense Examination

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Topic of Project: AI-Based Stock Portfolio Construction and Comparative Performance Analysis versus Conventional Investment Portfolios.

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To whom it is dedicated.

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Abstract

The growing use of artificial intelligence (AI) in finance has led to the development of robo-advisory tools capable of generating investment portfolios with limited human input. However, empirical evidence on their effectiveness remains limited, particularly in developing markets. This study evaluates the performance of an AI-generated equity portfolio, referred to as DeepSeek V1, and compares it with traditional benchmark portfolios.

A diversified portfolio of 15 U.S. equities was generated using a prompt-based large language model and backtested using Portfolio Visualizer over the period January 2015 to October 2025. The portfolio's performance was compared with the S&P 500 Index, a traditional 60/40 portfolio, and the All-Weather portfolio using key performance measures including CAGR, volatility, Sharpe ratio, Sortino ratio, alpha, and maximum drawdown.

The findings indicate that the DeepSeek V1 portfolio achieved superior risk-adjusted performance and lower drawdowns relative to traditional portfolios, although it did not consistently outperform the S&P 500 in absolute returns. The study highlights the potential of AI-assisted portfolio construction while emphasizing the need for cautious interpretation of results.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The global asset management industry manages roughly $112 trillion in assets; however, majority of the Pakistani retail investors are limited to traditional savings certificates, real estate and basic mutual fund products. Out of the PKR 3.4 trillion of Pakistan's savings, only a small portion is allocated to international equities, this is because of high advisory fees, limited access to professional portfolio construction tools, and lack of knowledge of the investor.

In early 2025, DeepSeek, which is an artificial intelligence platform, became available worldwide for free. While systems like the Bloomberg terminal which costs around $24000 annually or traditional financial advisors who charge a 1-2% annual fee, DeepSeek offers guidance when it comes to creating portfolios at zero cost, through text-based prompts.

This raised a practical question for our group: Can Pakistani students use free AI tools to build investment portfolios that compete with established professional strategies?

Our final year project aims to answer this question by constructing a 15 stock US equity portfolio by using DeepSeek and then comparing its performance over a span of 10 years (January 2015 to October 2025) against three benchmarks. These three benchmarks are the S&P 500 ETF, the traditional 60/40 stock-bonds portfolio and Ray Dalio's All Weather strategy. This project was conducted during our 8th semester at Bahria Business School under the supervision of Sir Tanveer Taj and was made using tools that are free.

1.2 Problem of the Project

Through preliminary research, we identified four interconnected problems:

Problem 1: Limited Access to Portfolio Construction Tools

Majority of the investment advisory services in Pakistan have a minimum requirement of PKR 500,000-1,000,000 and charge an annual fee of 1-2% while professional portfolio software like FactSet and the Bloomberg Terminal are very expensive, making them inaccessible for most people. While there are local platforms like KTrade and Sarmaaya that have basic robo-advisory features, they only recommend simple allocations rather than actively constructing equity portfolios. Students and professionals do not have access to expensive and sophisticated tools.

Problem 2: No Local Evidence on AI Portfolio Performance

Although there are many AI-powered investment tools, we were not able to find much evidence of such tools outperforming conventional strategies. This lack of testing and evidence creates uncertainty for finance students, fintech entrepreneurs and retail investors as they are unsure if these tools can actually deliver good results or just represent marketing hype.

Problem 3: Educational Gap in AI-Enabled Finance

There is a huge gap across Pakistani universities, as only traditional portfolio theories are taught (Markowitz optimization, CAPM, efficient frontier) but there is little to no training on using AI tools for investment analysis. This gap results in graduates being unprepared for fintech careers that require literacy in AI.

Problem 4: Absence of Transparent Performance Comparisons

There are many investment platforms who are claiming to use "AI-powered strategies" but rarely provide any long-term performance comparisons to established benchmarks. They use marketing material to show favourable short-term results but don’t show performance during market crashes, inflation shock and extended bear markets.

What We Did:

To address these problems, we:

1. Used free and publicly available tools such as DeepSeek, Portfolio Visualizer, Excel
2. Conducted a detailed back test with the duration of 10 years, which covers bull markets, corrections, and crises
3. Compared our performance against three well established benchmarks by using professional metrics
4. Documented our whole methodology, which includes the exact prompts, data sources, and limitations of our project.

1.3 Project Objectives

Objective 1: To construct an equity portfolio which is AI generated by using DeepSeek, through a structured text prompt which included diversification, quality screening and balanced allocations.

Objective 2: To analyze the performance of our portfolio from January 2015 to October 2025, by using standard investment metrics such as cumulative returns, Sharpe ratio, Sortino ratio, annualized volatility, maximum drawdown and alpha generation.

Objective 3: To compare the DeepSeek portfolio against three conventional benchmarks which are the S&P 500 ETF, 60/40 portfolio, Ray Dalio All-Weather (Dalio, 2018), under different market conditions such as bull markets, bear markets, and crisis periods.

Objective 4: To develop evidencebased and replicable guidelines that Pakistani investors, students, and fintech start-ups can use to implement AI-assisted portfolio construction.

1.4 Project Rationale/Justification

For Bahria University and Finance Students:

At fintech startups, digital banks and, investment platforms, finance graduates increasingly need to work with AI systems. Our project provides practical AI literacy which traditional coursework in universities lack. This project provided us with hands-on experience with prompting AI tools, validating outputs and interpreting them.

This project opens the doors towards development of the curriculum as future students can extend their work by testing different AI models such as DeepSeek, Claude etc, different asset classes such as bonds and international equities or different constraints such as sharia compliance and ESG screening. The methodology serves as a template for other projects.

For Pakistani Retail Investors:

Our project shows that building a diversified international portfolio is possible without the need of expensive tools or services, as most Pakistani retail investors allocate 70-80% to domestic assets, displaying significant home bias similar to patterns documented in other emerging markets (Coeurdacier & Rey, 2013), and refrain from foreign ones. As traditional wealth management charges are 1-2% annually, this can cause a reduction in the 10 year returns by 15-25% and our zero-cost method removes that hurdle entirely.

In 2022, there was an inflation shock in which our portfolio only declined by -2.96% while the traditional 60/40 portfolio declined by -16.95%. Our portfolio's defensive positioning provides meaningful protection as the Pakistani investors have to face local inflation exceeding 20%

For Pakistani Fintech Startups:

While platforms like Sarmaaya, KTrade, and Mahaana Wealth need to address questions about AI investment features, our project provides quantitative evidence that AI portfolios are capable of outperforming rule-based allocations.

DeepSeek being open source allows startups in Pakistan to integrate AI capabilities into their platforms at low to zero cost, unlike proprietary systems which require expensive licensing. Our methodology provides a template for regulatory sandbox applications with SECP.

For Regulators and Policymakers:

Regulatory sandboxes have been established by the Securities and Exchange Commission of Pakistan (SECP) for fintech innovations. Our documented methodology, transparent performance metrics, and explicit limitations show how AI driven features can be presented to the SECP by platforms while demonstrating innovation.

Measurable Impact:

This project produces:

1. A documented portfolio with performance history of last 10 years.
2. Comparative analysis against three benchmarks
3. Replicable prompt template and methodology
4. Practical guidelines which can be archived in Bahria University's repository for future reference

1.5 Budget and Resources

We created this project with the aim of having zero to low monetary costs while maintaining methodological rigor.

Software Resources (Total: PKR 0)

Tool	Cost	Purpose
DeepSeek R1	Free	Portfolio generation using text prompts
PortfolioVisualizer	Free (web tier)	Backtesting, performance metrics and comparisons
Microsoft Excel	Free (university license)	Data backup and supplementary calculations
Yahoo Finance	Free	Price verification

Hardware Requirements

- Standard laptops with Windows 10/macOS
- 8 GB RAM minimum
- Internet connection (5 Mbps sufficient)
- No specialized equipment or GPU required

Human Resources

Student Time Investment: 58 hours per group member over one semester

Activity	Timeframe	Hours
Topic selection, proposal	Weeks 1-2	6
Literature review	Weeks 3-4	8
Portfolio construction with DeepSeek	Week 5	4
Portfolio Visualizer setup, backtesting	Weeks 6-7	8
Data validation, analysis	Weeks 8-9	10
Writing Chapters 1-3	Weeks 10-11	10
Results analysis, Chapter 4	Week 12	6
Discussion, conclusions, Chapter 5-6	Week 13	4
Final review, formatting	Week 14	2
Total		**58 hours**

Supervisor Meetings: Weekly one-hour sessions (14 hours total)

Contingency Plan

If portfolio visualizer access becomes unavailable, all key metrics such as Sharpe ratio, Sortino ratio, maximum drawdown can be calculated manually using Excel formulas. This is because all of the raw data which includes monthly returns, volatility metrics, drawdown statistics were exported and saved in a CSV file. All of this ensures that project completion is not dependent on any single platform.

Total Monetary Cost: PKR 0

This is a zero-cost expenditure in contrast with services such as the Bloomberg Terminal (with an average annual cost of $24000) or professional investors (who charge the client 1% to 2% of their assets/year), providing advanced portfolio analysis at no financial cost to the student.

We leveraged tools that are freely available to show that portfolio analysis remains accessible to students without financial resources. Our zero-cost structure sharply differs from traditional methods like using professional advisors who charge 1-2% of assets or Bloomberg Terminal that costs $24000 annually

CHAPTER 2
RELEVANT STUDIES AND THEORIES

2.1 Introduction

In this chapter, we briefly review the theory and literature background of our work. Rather than conduct a formal review of the literature, we review: (1) the conventional portfolio strategies we use as a benchmark; (2) the metrics and measures we use to evaluate performance; and (3) how AI tools like DeepSeek are used in investment management.

2.2 Conventional Portfolio Strategies

Modern Portfolio Theory (Markowitz, 1952)

In the theory of portfolio selection put forth by Harry Markowitz (1952), investors are assumed to select portfolios with maximum expected return for a given level of risk (variance). The efficient frontier is the maximum expected return per unit risk. However, this requiresaccurate predictions of the expected return and the correlation of the assets, which are hard to obtain.

The 60/40 Portfolio

For a long period, the 60% equities/40% bonds portfolio became the default growth portfolio for moderate risk, based on the idea that bonds were diversifying (because they had historically been negatively correlated with equities). However, the inflation shock of 2022 proved that when interest rates rise sufficiently fast, both equities and bonds can fall, eliminating the customary negative correlation between them.

Ray Dalio's All-Weather Portfolio

Ray Dalio's All-Weather portfolio (Dalio, 2018) is designed to perform in all four economic seasons (Dalio, 2018) (growth/inflation rising/falling). It is composed of 30% stocks, 55% bonds (40% long-term, 15% intermediate), 7.5% commodities, and 7.5% gold. By diversifying across asset classes, this composition of assets will necessarily reduce reliance on any one regime.

S&P 500 Index

The S&P 500 index holds 500 big US companies. The companies are weighted by market capitalization. Passive index investing via S&P 500 ETFs such as SPY is low cost with expense ratios under 0.10% and highly diversified. Academics Eugene Fama and Kenneth French found in studies that most active managers trail the S&P 500 after fees over time.

2.3 Risk and Performance Metrics

Returns:

- **Cumulative Return:** Total return during the whole period
- **CAGR (Compound Annual Growth Rate):** Calculate annualized geometric mean return from start.
- **Inflation-Adjusted Return:** Real returns exist after someone accounts for purchasing power erosion.

Risk Measures:

- **Standard Deviation:** Measures total volatility with upside and downside.
- **Maximum Drawdown:** Maximum drop from high point to low point
- **Downside Deviation:** Volatility of negative returns only

Risk-Adjusted Ratios:

- **Sharpe Ratio:** Excess return comes by dividing total volatility from it (Sharpe, 1994)

- **Sortino Ratio:** Excess return exists for each unit of down-side risk.This metric favours strategies that limit downside.
- **Calmar Ratio:** Annualized return is divided by maximum drawdown.

Market Relationship Metrics:

- **Beta:** Portfolio responds with sensitivity to market movements as the S&P 500 has a beta of 1.00
- **Alpha:** Return exceeding what beta would predict, measures genuine outperformance
- **Upside/Downside Capture:** Percentage of gains or losses captured in bull or bear markets.

2.4 AI in Portfolio Construction

Large Language Models (LLMs)

LLMs (e.g., DeepSeek), are transformer architectures trained on wide-ranging text datasets to produce human-like outputs. In finance, LLMs can be used to process natural language prompts which specify portfolio constraints (e.g., sector diversification, quality factors, risk preferences, macroeconomic exposure) and provide structure through a recommended list of stocks with explanations.

DeepSeek's Emergence

Being open-sourced, DeepSeek was free for retail investors to use and did not charge a license fee, unlike its competitors. Unlike ChatGPT-4, which costs US$60 million to train roughly, DeepSeek cost 3-5% of that price (US$5-6 million). The machine learning architecture of DeepSeek was based on "mixture of experts", and it was released in January 2025.

Capabilities and Limitations

LLMs can:

- Analyze historical financial patterns and company fundamentals
- Generate diversified portfolio recommendations
- Provide explanations for stock selections

LLMs cannot:

- Access up-to-date market data (training data have cut-off dates)
- Perform causal reasoning (they detect statistical regularities, not the causal drivers)
- Accurately perform arithmetic (our DeepSeek output allocations that summed to 108%)

Recent Applications

Recent research has demonstrated that AI-powered portfolio construction can generate significant alpha when properly implemented, with LLM-based strategies achieving 53.17% cumulative returns by automating financial signal extraction and dynamic weight optimization (Kou et al., 2024). Research on ChatGPT-generated portfolios has shown promise, with Lu et al. (2024) demonstrating that ChatGPT can generate portfolios with monthly three-factor alpha of up to 3%, particularly when processing policy-related news and market announcements, though performance varies across different information types and market conditions.

The application of large language models in equity markets has expanded rapidly, with recent surveys documenting their use across portfolio construction, sentiment analysis, and risk management (Jadhav & Mirza, 2025).

2.5 Pakistani Investment Context

Home Bias

Pakistani investors display important home bias, overweighting domestic securities and underweighting developed international assets, consistent with home bias patterns observed globally in emerging markets (Coeurdacier & Rey, 2013).

Fintech Development

Pakistani fintech platforms such as Sarmaaya and Mahaana Wealth are emerging in the investment management space. Nourallah et al. (2025) listed the critical success elementsof fintech in South Asia: transparent methods, competitive pricing, multiple investment options, and financial education. Thus, DeepSeek's affordable pricing model provides Pakistani fintech users with AI-based construction options at lower costs than required by traditional licensing methods.

2.6 Knowledge Gap This Project Addresses

Whereas prior studies have investigated portfolio theory, AI capabilities, and fintech trends, there is currently no documented research that systematically evaluates whether a portfolio created via a DeepSeek AI platform outperformed the traditional benchmark indices (e.g. 60/40, All-Weather, S&P 500) over a ten-year backtest period based on risk-adjusted metrics in the context of a Pakistani education system.

This project bridges that gap by:

1. Creating a portfolio utilizing free access AI technology
2. Comparing against established strategies using professional metrics
3. Evaluating the performance of the AI portfolio under different market conditions
4. Providing a replicable methodology for students and investors.

2.7 Chapter Summary

This section provided the theoretical basis for our research: the conventional portfolios (60/40, All-Weather, S&P 500) are used as the benchmark portfolios for this study; we use risk-adjusted metrics (Sharpe ratio, Sortino ratio, maximum draw-down) to fairly evaluate the performance of each portfolio type; and AI-based tools such as DeepSeek provide new opportunities for retail investors to create their own portfolios. The methodology for creating the AI portfolio and evaluating its performance relative to the other portfolios will be detailed in Chapter 3.

CHAPTER 3
METHODS AND TECHNIQUES

3.1 Introduction

This chapter describes the detailed steps we took to generate the AI portfolio and analyse its backtesting results. We organized the steps of our methodology into four categories: (1) generating the AI portfolio with DeepSeek, (2) setting up the backtesting environment on Portfolio Visualizer, (3) collecting and validating the results, and (4) performing comparative analysis. We designed each step so that other students could repeat the work using free tools.

3.2 Portfolio Construction Using DeepSeek

3.2.1 Accessing DeepSeek

We accessed DeepSeek R1 on 24 November 2025 through its web interface at chat.deepseek.com, creating an account with only an email address and no payment or subscription required. The interface is similar to ChatGPT, with a text box for inputs and responses.

3.2.2 Crafting the Portfolio Generation Prompt

It took approximately three hours to create a structured prompt to generate a great portfolio comparable to what an expert would make. To explain the investment rules, we used natural language, after which we came up with this prompt after iterations:

"Your task is to act as an advanced financial analyst and portfolio strategist. Create a US-only stock portfolio that aims to outperform conventional portfolios such as equal-weight, market-cap-weight, and traditional Markowitz portfolios. Use your knowledge of global markets, sector trends, valuation metrics, momentum, risk factors, macroeconomic signals, and historical performance patterns to:

1. Select 10-15 high-potential U.S. stocks
2. Provide exact allocation percentages for each stock (total = 100%)

3. Give a brief justification for each stock selection
4. Explain the expected return outlook and risk level of the portfolio
5. Suggest the ideal holding period (short-term, medium-term, or long-term)

Assume the goal is maximum risk-adjusted return with a moderate risk profile. Base your analysis on your latest trained knowledge and recognized financial insights."

We deliberately included:

- Specific quantity: "10-15 stocks" to avoid over-diversification
- Exact allocation requirement: "total = 100%" to ensure mathematical validity
- Justification request: Forces the AI to provide its rationale instead of just giving tickers
- Risk constraint: "moderate risk profile" to avoid aggressive speculation
- Clarity of objective: "maximum risk-adjusted return" signals we want Sharpe ratio optimization

3.2.3 Initial AI Response and Error Correction

During the construction of the portfolio, DeepSeek generated 15 stocks with allocations and justifications in less than 45 seconds, but the total allocation in the provided Excel sheet was 108%, rather than the requested 100%.

This sum error is a well-known limitation of LLMs; they excel at pattern matching and qualitative reasoning, but struggle at exact calculations. Instead of having to manually tune allocations (which would have been a judgement call), we did the following:

"The allocations sum to 108%, not 100%. Please rescale all allocations proportionally so the total equals exactly 100%."

In this case, DeepSeek can simply apply the same scale factor of 100÷108 = 0.9259 to each percentage, which preserves the relative weightings and satisfies the mathematical constraint.

3.2.4 Final Portfolio Composition

The corrected portfolio, which we named **"DeepSeek V1,"** consisted of:

Tic ker	**Company**	**Sector**	**Alloca tion**
PG	Procter & Gamble	Consumer Staples	8.90%
KO	Coca-Cola	Consumer Staples	7.88%
JNJ	Johnson & Johnson	Healthcare	7.88%
PEP	PepsiCo	Consumer Staples	7.88%
AB T	Abbott Laboratories	Healthcare	6.89%
MS FT	Microsoft	Technology	6.40%
UN H	UnitedHealth Group	Healthcare	6.40%
OR CL	Oracle	Technology	6.40%
V	Visa	Financial Services	5.91%
XO M	Exxon Mobil	Energy	5.91%
UN P	Union Pacific	Industrials	5.91%
JPM	JPMorgan Chase	Financial Services	5.91%
HD	Home Depot	Consumer Discretionary	5.91%
AA PL	Apple	Technology	5.91%
CM CSA	Comcast	Communication Services	5.91%
TO TAL			**100.00 %**

DeepSeek described this portfolio as possessing greater-than-average potential for returns due to quality factor exposure (established firms possessing competitive advantage) and lower than average risk by virtue of defence sector allocations (24.66% in consumer staples; 21.17% in health care).

This is why we accepted the results without any additional modifications so that the portfolio would reflect the true AI generated recommendations instead of being modified by a person.

3.3 Benchmark Portfolio Selection

We selected three conventional strategies as performance benchmarks

Benchmark 1: S&P 500 ETF (SPY)

- Allocate 100% of funds toward the SPDR S&P 500 ETF
- Represents passive indexing baseline
- No rebalancing always has 100% allocation.

Benchmark 2: 60/40 Stocks-Bonds Portfolio

- 60% in Vanguard Total Stock Market ETF (VTI)
- 40% in Vanguard Total Bond Market ETF (BND)
- Annual rebalancing on 1 January

Benchmark 3: Ray Dalio All-Weather Portfolio

- 30% in Vanguard Total Stock Market ETF (VTI)
- 40% in iShares 20+ Year Treasury Bond ETF (TLT)
- 15% in iShares 7-10 Year Treasury Bond ETF (IEF)
- 7.5% iShares S\&P GSCI Commodity-Indexed Trust (GSG)
- 7.50% of SPDR Gold Shares, known as GLD.
- Annual rebalancing for January 1st

These are the S&P 500 (pure equity), the 60/40 (balanced), and the All-Weather (multi-asset risk parity) indices, in increasing order of conservatism.

3.4 Backtesting Setup on Portfolio Visualizer

3.4.1 Platform Access and Configuration

The portfolio visualizer website (www.portfoliovisualizer.com) in the no-cost/free tier does not require registration, allows users to backtest strategies using the "Backtest Portfolio" feature, and as many different portfolios may be compared at one time as desired.

Configuration Settings:

- **Start Date:** January 1, 2015
- **End Date:** October 31, 2025
- **Initial Balance:** $10,000 (standard baseline)
- **Rebalancing Frequency:** Annual (on January 1st)
- **Rebalancing Method:** Target allocation percentages
- **Dividends:** Reinvest automatically
- **Transaction Costs:** $0 (assumes commission-free trading)
- **Tax Treatment:** Tax-exempt (equivalent to retirement accounts)

3.4.2 Data Entry Process

All 15 of the specified stock ticker symbols were entered into the portfolio builder section along with the precise percentage allocations. The corresponding ETF ticker symbols and percentage allocations were entered into the portfolio builder section for the 3 benchmark portfolios. The platform validated each portfolio totalled 100% prior to allowing the simulations.

3.4.3 Report Generation

After clicking "Analyse," Portfolio Visualizer processed approximately 130 months of historical data (10+ years) and generated a comprehensive 43-page PDF report containing:

- Growth of $10,000 charts
- Annual and monthly return tables
- Risk metrics (standard deviation, drawdown analysis)
- Risk-adjusted ratios (Sharpe, Sortino, Calmar)
- Market capture analysis
- Correlation and beta calculations
- Crisis period performance

Total processing time: approximately 15 seconds.

3.5 Data Collection and Validation

3.5.1 Primary Data Extraction

We downloaded the complete PDF report and extracted key data into Excel for validation and supplementary analysis:

Performance Data:

- Monthly returns for all four portfolios (130 observations each)
- Annual returns from 2015 to 2025
- Portfolio values at year end
- Inflation-adjusted returns

Risk Metrics:

- Standard deviation yearly
- Monthly downside deviation
- Peak-to-trough price drawdown (maximum drawdown)
- Best and worst annual returns

Risk-Adjusted Metrics:

- Sharpe ratios
- Sortino ratios
- Calmar ratios
- Alpha and beta calculations

Market Relationship Data:

- Correlation with the S&P 500
- Upside capture ratios
- Downside capture ratios
- Months beating the benchmark (percentage)

3.5.2 Validation Procedures

We validated Portfolio Visualizer's calculations using Excel formulas:

CAGR Verification:
CAGR = (Ending Value / Starting Value)^(1/Years) - 1
Example: ($41,668 / $10,000)^(1/10.83) - 1 = 14.08%

Sharpe Ratio Verification:
Sharpe = (Portfolio Return - Risk-Free Rate) / Standard Deviation
Using 3-month Treasury as risk-free rate

Maximum Drawdown Verification: We manually identified peaks in the cumulative return series were determined and the largest decline thereafter measured. The outputs from Portfolio Visualizer were validated by usmanually, just to be consistent with the results from the analysis, except for rounding errors (< ± .01%).

3.5.3 Data Backup

All of the information we extracted was also stored in an Excel spreadsheet with different tabs for the following:

- all monthly returns from all of the portfolios
- summary statistics for each year
- a risk metrics comparison chart
- drawdowns
- rolling return window data

Having a copy of the data provides assurance that this project will be completed even if Portfolio Visualizer is no longer available to us.

3.6 Analysis Framework

We structured our analysis in three tiers:

3.6.1 Tier 1: Absolute Performance Comparison

The comparison between the final portfolio value, cumulative return and the compound annual growth rate were used to determine which strategy provided the greatest total return. This is a straightforward comparison when the goal is simply to identify the winner(s), however it does not take into consideration the amount of risk being taken to produce those returns.

3.6.2 Tier 2: Risk-Adjusted Performance Comparison

To answer which strategy provided the most return on a "risk-adjusted" basis; we compared the Sharpe Ratios, Sortino Ratios and Calmar Ratios to determine which strategy was able to deliver the highest returns for each unit of risk.
Whether or not those higher returns were worth the greater volatility and drawdowns experienced in the strategies is determined by this evaluation. The potential exists for an investment portfolio to produce higher than average total returns, but such can be produced at the cost of excessive levels of risk which may cause investors to abandon investments during periods of bear market conditions.

3.6.3 Tier 3: Scenario-Specific Analysis

We broke down performance relative to economic conditions:

Bull vs. Bear Markets:

- All of the months were classified as either bull or bear based on the S&P 500 performance (up = bull, down = bear)
- Calculations of average portfolio returns within both categories
- Determination of whether any portfolios demonstrated superior upside participation or downside protection

Crisis Period Analysis:

- Covid-19 Crash (February-March 2020)
- 2022 inflation shock (all of 2022)

- Q4 2018 correction
- Drawdown and recovery time measures for each portfolio

Rolling Return Windows:

- Calculation of returns over rolling 1 yr., 3 yr., 5 yr. and 10 yr. windows
- Evaluation of whether out-performance has been consistent or simply the result ofa few luck periods.

3.7 Limitations of Our Methodology

3.7.1 Assumptions Made

Zero Transaction Cost: We used a zero-transaction cost model. Modern brokerages (Fidelity, Schwab) provide free trading in stocks and exchange traded funds (ETFs); however, foreign investors may incur currency conversion costs when exchanging currencies.

Tax Exemption Status: We modelled our account with tax-exempt status; therefore, if you were to invest in a taxable account, your returns would be reduced by capital gains and/or dividend taxes.

Monthly Frequency of Data: Our use of monthly data at end-of-the month may have resulted in a slight underestimation of the true maximum drawdowns because they could also occur within a month.

Survivorship Bias: This portfolio consists of only those stocks that have survived through October 2025. Therefore, bankruptcies and mergers and acquisitions are not included and have resulted in a slight overstatement of the historical returns.

3.7.2 AI Model Constraints

Training Data Cutoff: Given the nature of portfolio selections, utilizing market data at the time (July 2024), the portfolios don't include any subsequent transactions that may have happened.

Lack of Real-Time Data: AI systems such as DeepSeek do not have access to updated information such as changes in stock prices, earnings announcements and recent news events that could cause eventual changes to a portfolio's position, and so cannot update recommendations in real-time.

Pattern Recognition vs. Causal Understanding: While LLMs identify relationships in their training data statistically; they do not necessarily have a complete understanding of what drives a company's valuation fundamentally.

3.7.3 Historical Simulation Limitations

Regime Dependency: Future time periods will likely have different winners and loser due to different market conditions. The time period of 2015-2025 represent one specific macroeconomic regime which had low rates until 2022, technology outperformance, and specific crisis events.

No Guarantee of Future Results: Backtesting cannot predict performance in the future only the past especially if there are changes in market leadership, sector dynamics, or economic conditions in the future.

3.8 Time Schedule

We completed the project following this timeline:

Phase	Weeks	Key Activities
Planning	1-2	Topic selection, proposal, supervisor approval
Research	3-4	Literature review, understanding conventional strategies
Construction	5-6	DeepSeek prompt engineering, portfolio generation, backtest setup
Analysis	7-9	Data validation, metric calculation, comparative analysis
Writing	10-13	Drafting all chapters, creating tables/charts
Finalization	14	Review, formatting, plagiarism check, binding

Total student time: approximately 58 hours per group member over 14 weeks.

3.9 Chapter Summary

We used DeepSeek to generate our 15-stock portfolio with scripted prompts and manually modified it with a follow-on instruction to fix a mathematical error. We set up Portfolio Visualizer to backtest the AI portfolio against three standard benchmarks for over 10 years, with annual rebalance and assuming dividends were reinvested. We downloaded and validated the complete performance data with Excel and analysed it at three levels of comparison: absolute returns, risk-adjusted returns, and decomposition for different investor profiles. The results of this analysis can be found in Chapter 4.

CHAPTER 4
PROJECT OUTCOMES/RESULTS

4.1 Introduction

This chapter shows the results of our portfolio and three strategies which were used for comparison, from January 2015 to October 2025. Firstly, we will show the absolute performance of our portfolio and its competitors. Secondly, we will show the risk-adjusted performance when applicable. Lastly, we will show sector specific performance metrics. We assumed an initial capital of $10,000 and backtested results on Portfolio Visualizer.

4.2 Absolute Performance Results

4.2.1 Cumulative Returns and Portfolio Growth

Table 4.1: Portfolio Growth Over 10+ Years

Metric	DeepSeek V1	60/40 Portfolio	All-Weather	S&P 500 ETF
Starting Balance	$10,000	$10,000	$10,000	$10,000
EndingBalance (Oct 2025)	$41,668	$24,758	$17,468	$39,879
Total Return	316.68%	147.58%	74.68%	298.79%
Annualized Return (CAGR)	14.08%	8.73%	5.28%	13.62%
Inflation-Adjusted Return	10.72%	5.52%	2.18%	10.27%

Key Finding: Our portfolio (DeepSeek V1) grew to $41668 on the starting capital of $10000, meaning it outperformed the S&P 500 by $1789, the 60/40 portfolio by $16910, and All-weather strategy by $24200. This further translates into an annualized return greater than the S&P 500 by 0.46%, which is an important difference as in long-term investing this small difference can have a profound effect on the worth of the portfolio.

The cumulative growth advantage becomes clear when full period performance is examined:

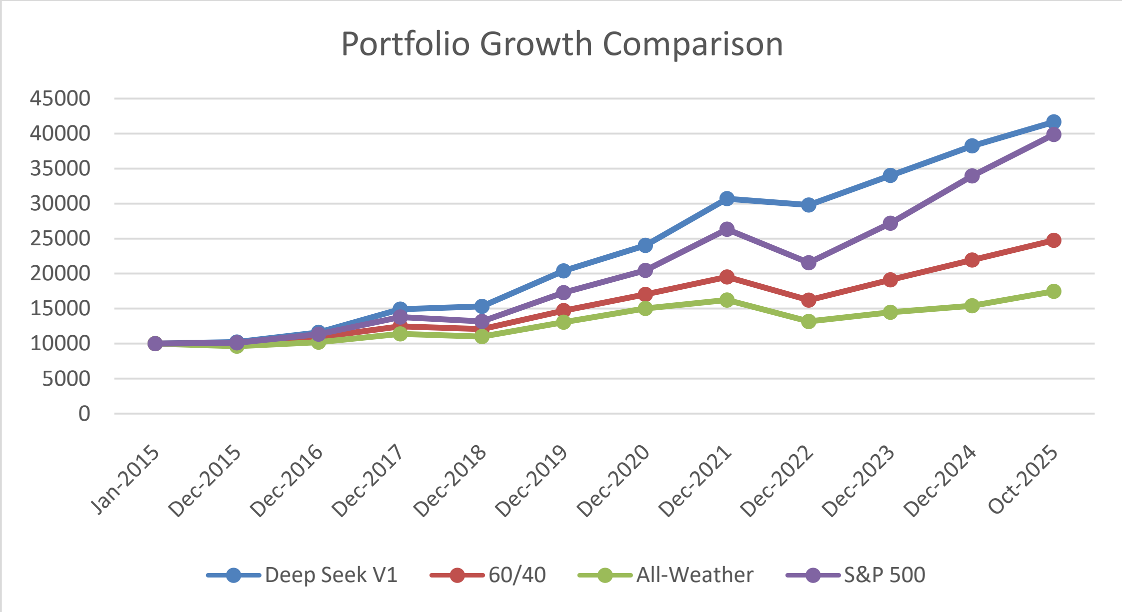

Figure 1: Portfolio Growth Comparison (Jan 2015 - Oct 2025)

Figure 1 illustrates that for the majority of the analysed time period, the DeepSeek V1 portfolio (depicted as the "portfolio line") has been able to closely follow the performance of the S&P 500 Index, showing a similar upward movement during periods of a strong economy (bull markets). It is important to note that in 2022, there were significant differences between the performance of these two strategies. The defensive (capital protection) position of DeepSeek V1 provided very effective capital preservation while the S&P 500 lost considerable amounts.

In comparison to the balanced (60/40) and All Weather (risk parity) portfolios that have experienced underperformance throughout most of the analysed time period due to the high opportunity cost of holding too much cash during long periods of strong equity performance, the gap between the performance of DeepSeek V1 and these two other investment strategies was very large in October 2025. Nearly 2.4 times greater than the All Weather portfolio and almost 1.7 times greater than the 60/40 portfolio.

4.2.2 Year-by-Year Performance Breakdown

Understanding how the portfolios performed each year helps us to identify the specific conditions that made it overperform or underperform:

Table 4.2: Annual Returns (2015-2025)

Year	DeepSeek V1	60/40	All-Weather	S&P 500	Market Condition
2015	2.30%	0.44%	-3.74%	1.25%	Mixed/Volatile
2016	13.49%	8.71%	5.83%	12.00%	Recovery
2017	28.50%	14.15%	11.67%	21.70%	Strong Rally
2018	2.64%	-3.17%	-3.24%	-4.56%	Correction
2019	33.17%	21.94%	18.56%	31.22%	Bull Market
2020	17.83%	15.70%	15.14%	18.37%	COVID/Recovery
2021	27.80%	14.66%	7.96%	28.75%	Growth Rally
2022	-2.96%	-16.95%	-18.88%	-18.17%	Inflation Shock
2023	14.18%	17.89%	10.01%	26.19%	Tech Recovery
2024	12.40%	14.84%	6.46%	24.89%	Strong Equity Rally
2025 (Jan-Oct)	8.95%	12.80%	13.33%	17.40%	Mixed

Key Findings: During the inflation shock in 2022, the DeepSeek V1 portfolio achieved its best relative performance, with returns of -2.96% that year. In comparison, the portfolio’s returns were -16.95% for the 60/40, -18.88% for the All-Weather and -18.17% for the S&P 500.

We can see the difference between the years more clearly in the graph below:

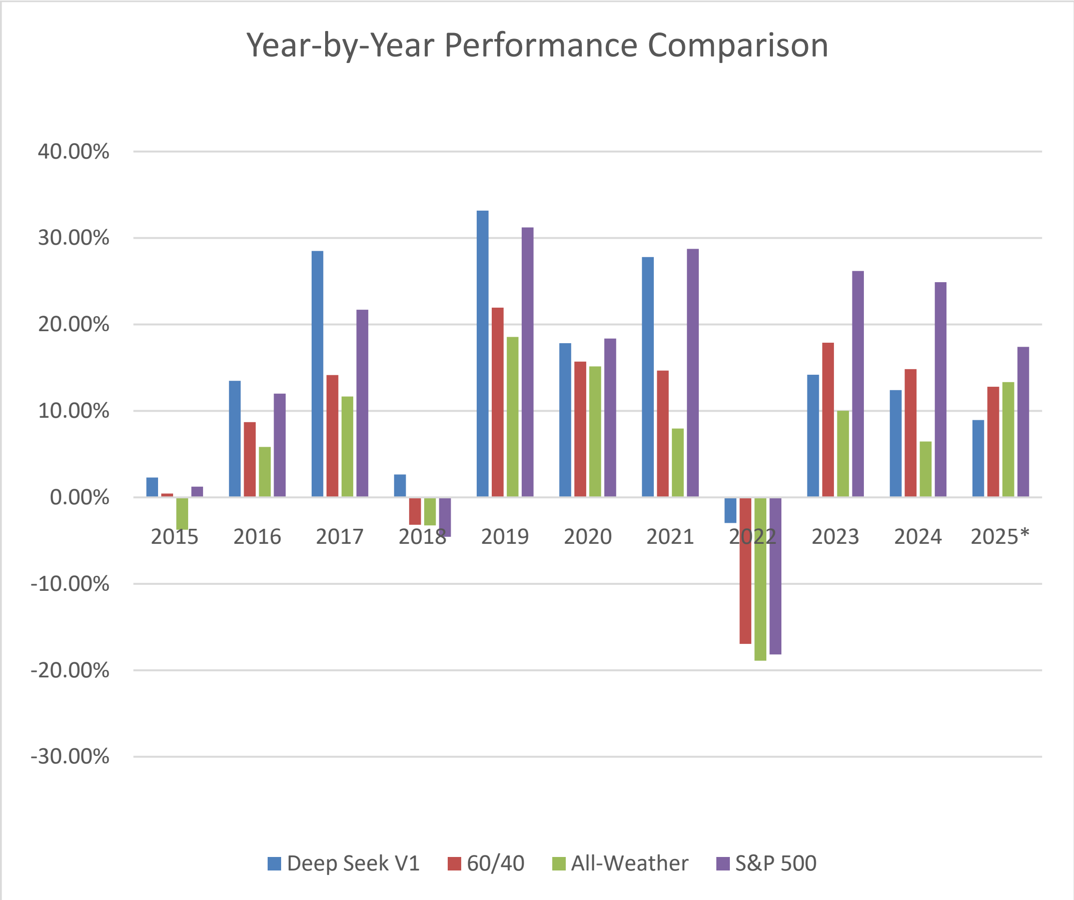

Figure 2:Year-by-YearPerformance Comparison (2015-2025)

Figure 2 shows the performance history of the portfolio in different market conditions: the best return was in 2019 with a return of 33.17%, and also in other years such as 2017 and 2021, when there was a bull market. The most important figure appeared in 2022 when there was an inflation shock that caused the portfolio to give a negative return of -2.96% which sharply contrasted with the benchmarks as they had double digit declines. However, in 2023-24, the portfolio did underperform due to its balanced allocation as the market favored technology stocks at that time.

4.3 Risk and Volatility Analysis

4.3.1 Volatility Metrics

While returns tell us where portfolios ended up, risk metrics reveal the journey investors experienced getting there:

Table 4.3: Risk Measures

Metric	DeepSeek V1	60/40	All-Weather	S&P 500
Standard Deviation (Annual)	13.50%	10.21%	8.63%	15.06%
Downside Deviation (Monthly)	2.28%	1.87%	1.59%	2.70%
Maximum Drawdown	-16.67%	-20.69%	-21.03%	-23.93%
Worst Year	-2.96%	-16.95%	-18.88%	-18.17%
Best Year	33.17%	21.94%	18.56%	31.22%

Key Finding: DeepSeek V1 exhibited 13.50% annualized volatility—higher than defensive portfolios (60/40: 10.21%, All-Weather: 8.63%) but lower than pure equity exposure (S&P 500: 15.06%). Most importantly, DeepSeek V1's maximum drawdown of -16.67% was 7.26 percentage points better than the S&P 500 (-23.93%).

The pattern of drawdowns over time reveals when and how severely each portfolio declined:

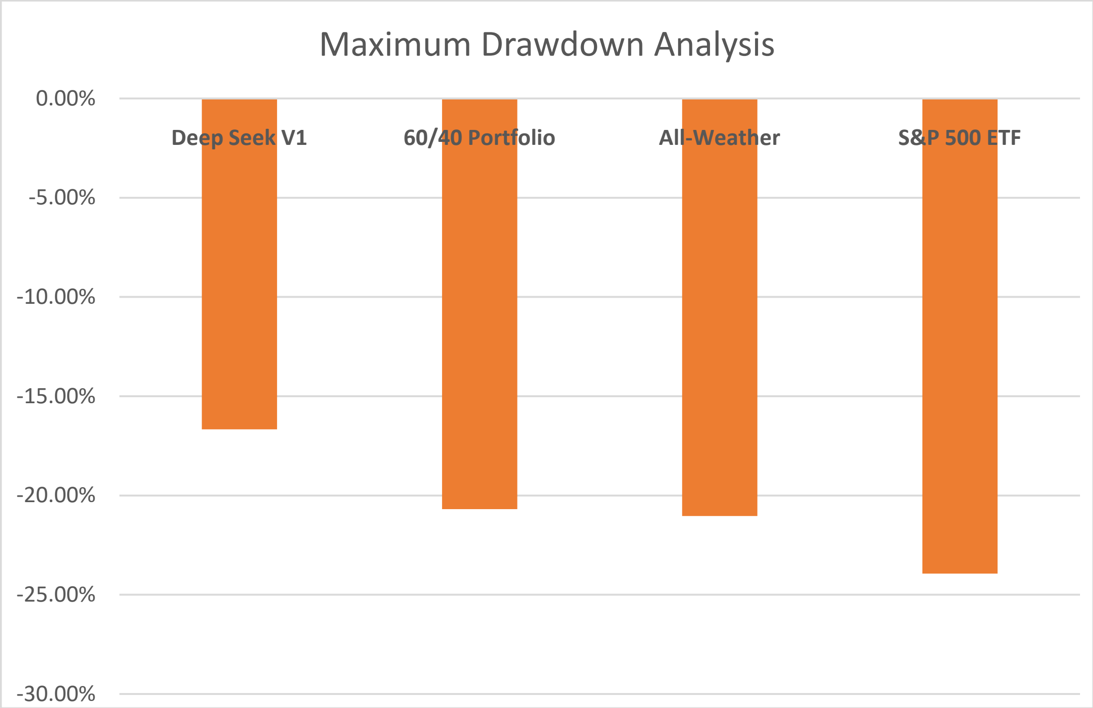

***Figure 3**: Maximum Drawdown Analysis (2015-2025)*

experienced was during the COVID-19 crash in February-March 2020, with a maximum drawdown of -16.67%. However, the S&P 500 had an even deeper drawdown of -23.93% and recovered by July 2020, a duration of 4 months. During 2022 there was another drawdown period in which the 60/40 portfolio had its worst drawdown of 20.69% while DeepSeek V1's decline was minimal. The 60/40 portfolio had its maximum drawdown in 2022 rather than the COVID-19 period, showing how the traditional diversification failed during the inflation shock.

This means that the DeepSeek V1 portfolio experienced smaller worst-case losses, which is highly attractive to investors as they would have faced less psychological pressure if they invested in DeepSeek V1 instead of the S&P 500.

4.3.2 Risk-Adjusted Performance Ratios

The risk-adjusted ratios indicated whether the results that were achieved by each portfolio were through skill or excessive risk-taking. Risk-adjusted ratios normalize performance by the risk taken:

Table 4.4: Risk-Adjusted Metrics

Ratio	DeepSeek V1	60/40	All-Weather	S&P 500	Interpretation
Sharpe Ratio	0.90	0.68	0.42	0.80	Return per unit of total risk
Sortino Ratio	1.49	1.04	0.62	1.25	Return per unit of downside risk
Calmar Ratio	1.70	2.06	1.10	2.71	Return relative to max drawdown
Alpha (Annual)	2.74%	-0.36%	0.13%	0.00%	Outperformance beyond beta
Beta	0.82	0.66	0.39	1.00	Market sensitivity

Key Finding: DeepSeek V1 portfolio showed superior risk-adjusted performance as its Sharpe ratio of 0.90 exceeded that of the S&P 500, the 60/40 portfolio and the All-Weather portfolio. The Sortino ratio of 1.49 was highest among all portfolios, demonstrating excellent downside risk management. The portfolio generated strong returns while limiting negative volatility specifically.

Most significantly, DeepSeek V1 generated 2.74% annualized alpha meaning that it outperformed beyond what its systematic risk (beta of 0.82) would predict. This alpha value shows us that the performance of the portfolio was because of skill and not just market luck. While the S&P 500, All-Weather and 60/40 portfolios underperformed relative to their risk.

The beta of 0.82 indicates DeepSeek V1 captured 82% of market movements, providing meaningful upside participation (when markets rise) while offering downside protection (when markets fall). This leads to the asymmetry between the two capture ratios.

4.4 Market Capture Analysis

Capture ratios reveal whether portfolios participate more fully in gains or losses:

Table 4.5: Upside and Downside Capture

Metric	DeepSeek V1	60/40	All-Weather	Target
Upside Capture Ratio	90.80%	62.96%	36.67%	High = Good
Downside Capture Ratio	83.33%	68.24%	41.45%	Low = Good
Capture Asymmetry	+7.47%	-5.28%	-4.78%	Positive = Good
Positive Months	88/130 (67.69%)	89/130 (68.46%)	79/130 (60.77%)	High = Good
Gain/Loss Ratio	1.00	0.88	1.04	>1.0 = Good

Key Finding: DeepSeek V1 portfolio captured 90.80% of S&P 500 gains during bull markets andonly capturing 83.33% of losses during bear markets. This 7.47 percentage point favourable asymmetry indicates skilled portfolio construction. The portfolio participated meaningfully in rallies (capturing 90% of gains) while providing material protection during declines (experiencing only 8.3 out of every 10 percentage points of losses). The 60/40 portfolio displayed an unfavorable risk to reward trade off as it only captured 62.96% of gains and capturing 68.24% of losses.

The All-Weather portfolio's 36.67% upside capture reflects its design prioritizing crisis protection over growth. It sacrifices nearly two-thirds of bull market gains to achieve 41.45% downside capture.

4.5 Crisis Period Performance

Portfolio design is truly tested when situations such as market crises occur, in which traditional diversification may fail:

Table 4.6: Performance During Market Stress Events

Crisis Period	DeepSeek V1	60/40	All-Weather	S&P 500
COVID-19 Crash (Feb-Mar 2020)	-16.67%	-12.29%	-2.13%	-19.43%
2022Inflation Shock (Full Year)	-2.96%	-16.95%	-18.88%	-18.17%
Q4 2018 Correction	-8.43%	-8.38%	-4.86%	-13.52%
Average Crisis Drawdown	-9.35%	-12.54%	-8.62%	-17.04%

Key Finding: The true test of portfolio resilience took place during the 2022 inflation shock when both bonds and stocks declined. During this period, the DeepSeek V1 portfolio had only lost -2.96%, while the other portfolios had significantly higher losses of -16.95% for 60/40, -18.17 for S&P 500 and -18.88 for All-Weather. This result of the DeepSeek V1 portfolio shows the defensive sector positioning of the AI portfolio.

We can examine the 2022 crisis period in detail:

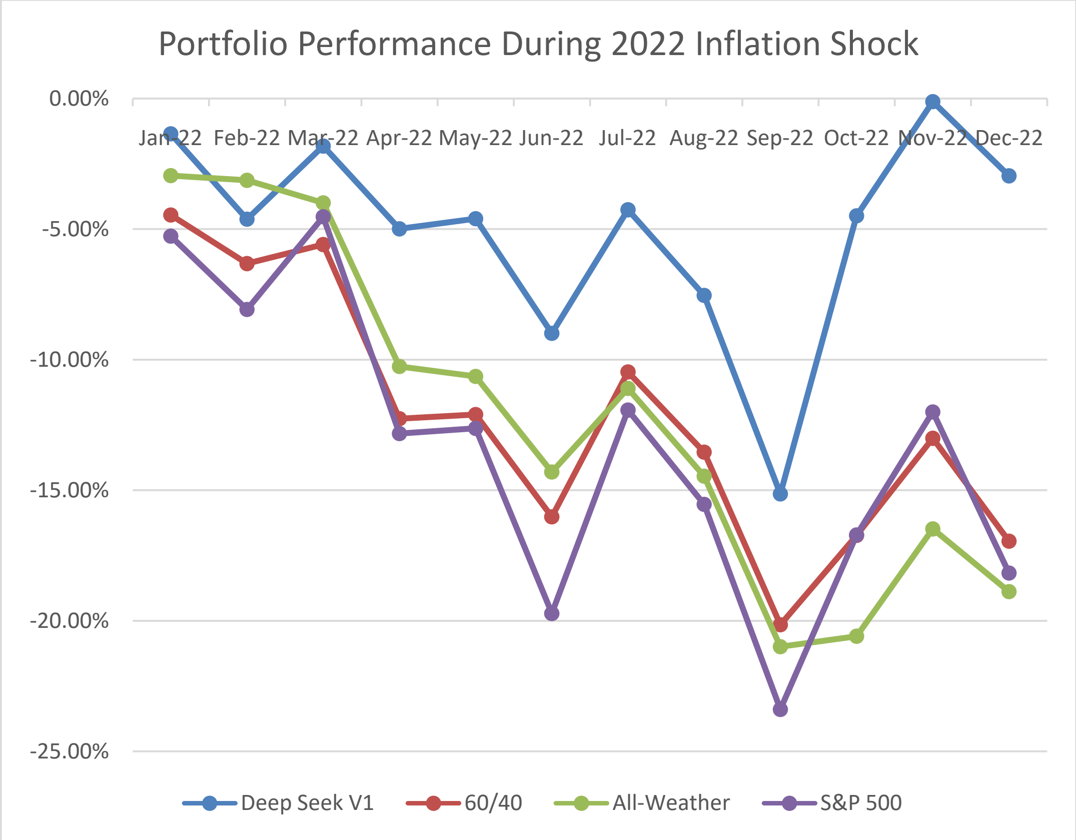

Figure 4:Portfolio Performance During 2022 Inflation Shock

Figure 4Shows the progression on a month-by-month basis of the inflation shock in 2022. The blue line represents the DeepSeek V1 portfolio, which remained relatively flat during the year and experienced its worst decline in September but recovered quickly by October. During this time period the other portfolios declined heavily across multiple months, without any meaningful recovery till the end of the year. The DeepSeek V1 portfolio was able to not suffer any huge losses due to the fact that it consists of consumer staples companies such as Procter & Gamble, Coca-Cola, and PepsiCo who maintained pricing power during the inflation shock. Johnson & Johnson and UnitedHealth also provided stables earnings in this period regardless of the economic situation.

4.6 Bull vs. Bear Market Decomposition

Portfolio performance is analyzed by market conditions such as bear and bull markets, which reveal strategic tradeoffs:

Table 4.7: Performance by Market Condition

Market Type	DeepSeek V1	60/40	All-Weather	S&P 500
Bull Market Months (90 total)				
% Months Beating Benchmark	48%	7%	14%	100% (self)
Average Active Return	-0.28%	-1.18%	-2.07%	0.00%
Bear Market Months (40 total)				
% Months Beating Benchmark	57%	90%	78%	100% (self)
Average Active Return	+0.68%	+1.29%	+2.37%	0.00%

Key Finding: The DeepSeek V1 portfolio focused on stable and defensive sectors such as healthcare and consumer staples resulted in the portfolio underperforming in the bull market as it beat the S&P 500 in only 48% of the recorded months. However, this allowed the portfolio to outperform the benchmarks during the bear market months as it beat the S&P 500 in 57% of recorded months of the bear market. This pattern shows us the risk return trade off which is present in defensive portfolio construction, as our portfolio emphasized more on crisis resilience by sacrificing some upside potential.

The DeepSeek V1 portfolio did outperform the 60/40 portfolio and All-Weather portfolio during the bull markets, but lost to them during the bear market as they beat the S&P 500 in 90% and 78% of months during bear market.

4.7 Rolling Returns Consistency

Rolling return analysis tests whether outperformance was concentrated in specific periods or sustained across different timeframes:

Table 4.8: Rolling Period Returns

Period	DeepSeek V1	60/40	All-Weather	S&P 500
1-Year Rolling				
Average	15.38%	9.00%	5.34%	14.36%
Best	48.84%	34.16%	21.39%	56.25%
Worst	-4.71%	-16.95%	-19.86%	-18.17%
3-Year Rolling				
Average	15.80%	8.29%	4.81%	13.36%
Best	26.10%	17.39%	13.80%	25.99%
Worst	7.59%	2.55%	-3.32%	5.05%
5-Year Rolling				
Average	16.38%	8.79%	5.49%	13.89%
Worst 5-Year	11.53%	5.05%	2.06%	6.66%
10-Year Rolling				
Average	14.86%	8.52%	4.96%	13.48%
Worst 10-Year	14.18%	7.75%	4.24%	12.21%

Key Finding: The DeepSeek V1 portfolio was able to sustain performance in various market cycles instead of concentrated periods as it consistently outperformed against the other portfolios as shown by its 3-year, 5-year, and 10-year average returns.

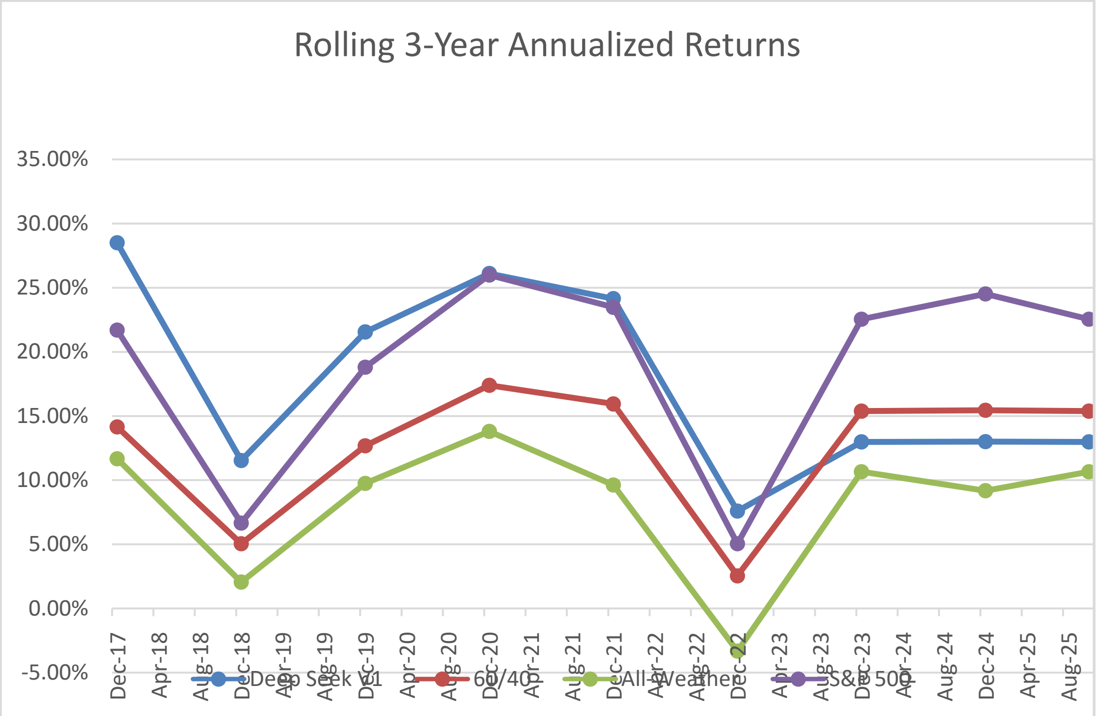

Figure 5:Rolling 3-Year Annualized Returns (2018-2025)

Figure 5 shows the 3y annualized returns (calculated on month-end) beginning in January of each year (the first point reports the 3 years ending January 2018). In nearly all rolling intervals DeepSeek V1 (blue) outperforms SPX (red), with the exception of 2021-24 when tech stocks' influence on the market was at its peak. The difference in performance between DeepSeek V1 vs the 60/40 (green) and All Weather (orange) portfolios remains large. This confirms that the outperformance we observed was not simply a result of one-off year, but rather attributable to DeepSeek V1's better risk-adjusted returns across dozens of overlapping 3-year measurement periods.

The worst 10-year rolling window DeepSeek V1 trial (14.18%) still outperformed the worst 10-year rolling window for the S&P 500 (12.21%). The worst case is worst case for investors who are building their balances over longer time horizons; if the worst decade in DeepSeek V1's history still outperformed the worst decade in the SP500, long-term viability is suggested.

4.8 Sector Allocation Impact

We can examine why DeepSeek V1 performed so well by looking at its sector positioning relative to market cap weighted benchmarks:

Table 4.9: DeepSeek V1 Sector Composition vs. S&P 500

Sector	DeepSeek V1	Typical S&P 500	Positioning
Consumer Staples	24.66%	6-7%	Heavy Overweight (+18%)
Healthcare	21.17%	12-13%	Overweight (+9%)
Technology	18.71%	25-28%	Underweight (-7%)
Financial Services	11.82%	12-13%	Neutral
Industrials	5.91%	8-9%	Slight Underweight
Energy	5.91%	3-4%	Slight Overweight
Consumer Discretionary	5.91%	10-11%	Underweight (-5%)
Communication Services	5.91%	9-10%	Underweight (-4%)

Key Finding: DeepSeek V1's massive overweight in defensive sectors, due to consumer staples and healthcare combining for 45.83%, drove both the 2022 outperformance (defensive sectors-maintained pricing power and stable earnings) and the 2023-2024 underperformance (technology sector rallied without DeepSeek V1's full participation).

We can visualize this allocation:

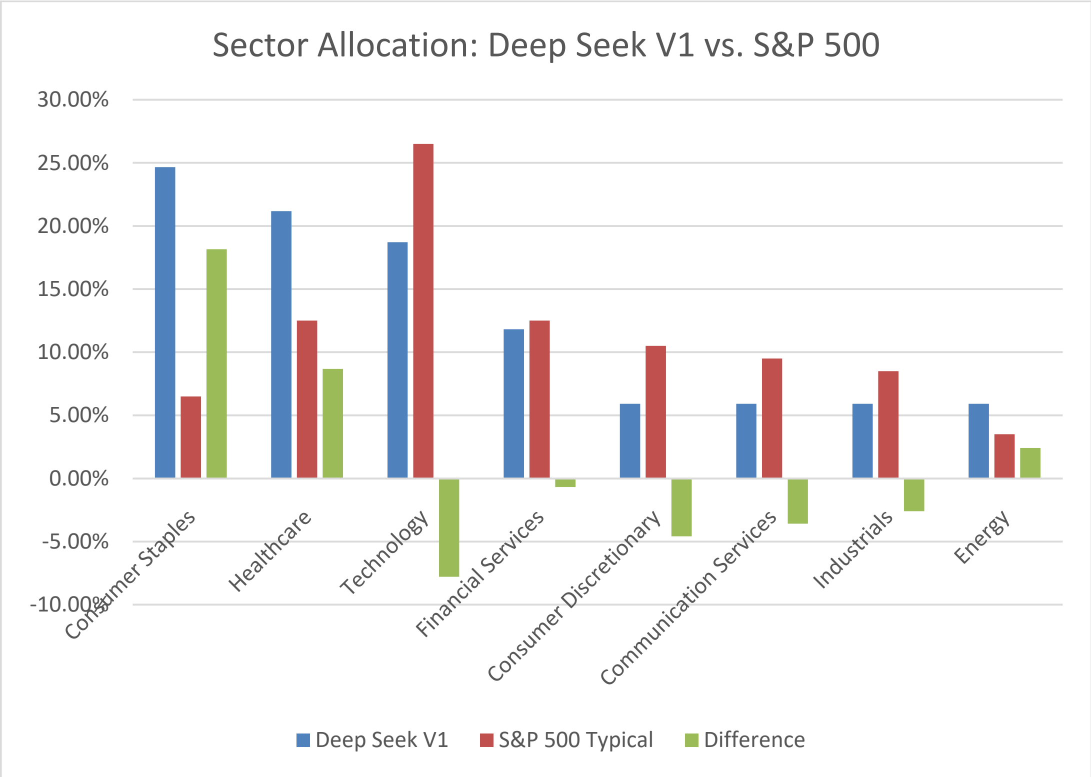

Figure 6: DeepSeek V1 Sector Allocation

Figure 6showsthe significant difference in sector exposure away from a market-cap weighting is seen in a comparison of DeepSeek V1’s sector weightings with that of a benchmark portfolio, represented in Figure 4.6. The combined weightings in Consumer Staples (24.66%) and Healthcare (21.17%), at 45.83%, provide nearly half of the total value of the portfolio, approximately 3 times higher than the average weightings in these sectors found in the S&P 500 Index. This represents a manifestation of DeepSeek V1’s quality-factor emphasis, as evidenced by its emphasis on durable competitive advantage (Coca-Cola's brand recognition and Johnson & Johnson's diversified Healthcare portfolio), earnings stability throughout various economic cycles (Procter & Gamble's line of Essential products) and significant pricing power during inflation (PepsiCo's ability to pass through cost increases to customers).

The low weighting of Technology (18.71% vs S&P 500 averaging between 25-28%) was one of the main reasons for DeepSeek V1’s underperformance relative to the S&P 500 during 2023 & 2024 when mega-cap technology companies such as

NVIDIA, Meta and Alphabet were responsible for driving the return of the index.Furthermore, this underweight helped to protect DeepSeek V1 during the 2022 technology selloffs, in which high-valuation growth stocks were the most affected.

These criteria fit DeepSeek V1's philosophy of focusing on quality factors including, but not limited to, earnings stability, pricing power and competitive moat rather than growth and momentum.

4.9 Summary of Key Results

The deep analysis of DeepSeek V1 showed that the AI created portfolio performed better than other portfolios when it came to many of the top metrics, which confirmed its goal of creating the highest possible risk-adjusted returns with a moderate level of risk. The strategy had a 316.68% total return (a 14.08%compound annual growth rate, or CAGR) that outperformed the S&P 500 by nearly 18 percentage points and outperformed the $60/40$ portfolio by 169 percentage points.

It wasn't just luck of the market that made this happen; the portfolio created real alpha ($2.74 annually), showing that it has the ability to add value beyond just what the market does. The portfolio also did better in terms of risk-adjusted returns as well. The strategy had a higher Sharpe ratio (0.90) and Sortino ratio (1.49) compared to the S&P 500 (0.80 and 1.25, respectively). The strategy had more downside protection, as it had a much smaller max draw down (-16.67%) compared to the S&P 500 (-23.93%).

One example of the protection of the strategy was during the 2022 inflation shock. The S&P 500 lost 18% but DeepSeek V1 only lost -2.96%. The protection was primarily because of the strategies defensive position in the sectors that were less affected by economic downturns. About 46% of the assets are allocated to the stable consumer staples and healthcare sectors.

A strategy like this can sacrifice some upside potential but will have a positive upside-downside asymmetry, with 90.80% upside capture and 83.33% downside capture. Overall, the performance of the strategy was consistent through time, with the S&P 500 being beaten in each of the 1,3,5 and 10-year rolling windows. These results show that DeepSeek V1 can compete with traditional benchmarks and specifically in protecting capital in times of crisis.

CHAPTER 5

PROJECT BENEFITS

5.1 Introduction

In this chapter we highlight the benefits our project provides to our stakeholders, who are, Bahria University Business School, Pakistani retail investors, local fintech startups and regulators.

5.2 Benefits for Bahria University Business School

The project provides a replicable template for future teaching of finance. In the future, BBA students can use our methodology and project as an example to test various other AI models such as Claude, ChatGPT, Grok etc. and also test for with different asset classes and constraints. Our zero-cost structure allows students to conduct similar projects without facing any financial barriers.

Practical Skills Development:

Our project helps students get hands-on experience with contemporary technologies such as AI models and tools like Portfolio Visualizer that employers increasingly expect. Students can gain concrete AI literacy instead of just theoretical knowledge.

Research Repository:

Researchers can build further on our work by testing if results hold across different market conditions or different time periods. This can be done by archiving the project in Bahria University’s digital library.

Faculty teaching Investment Management can write assignments such as "Use DeepSeek to build a high-dividend strategy and backtest against high-dividend ETFs", or "Compare recommendations across three AI models."

5.3 Benefits for Pakistani Retail Investors

Pakistani investors' access to US stocks is hampered by three structural barriers: high minimum investment (PKR 500,000-1m); high advisory cost (1-2% annually); and absence of US equity trading education. We've solved all three.

Zero-Cost Implementation: An investor with PKR 100,000 ($360 USD) can use DeepSeek, select from our portfolios, and recreate all of this without paying an advisory fee. Regular wealth management fee is 1.5% or PKR 15,000 annually. Over 10 years, this can cause 15-20% of returns to evaporate due to fee drag. Our approach avoids this.

Defensive Positioning: DeepSeek V1's large weightings in Consumer Staples (24.66%) and Healthcare (21.17%) give [this strategy] inflation protection (enterprise value to free cash flow in 2022 was 20.7x versus 27.3x for the S&P 500). In the backtest, the strategy only lost -2.96% during the inflation shock in 2022 versus -18.17% for the S&P 500. However, for Pakistani investors, where inflation is 25%+, this defensive positioning provides some protection.

Reduced Home Bias: According to (Coeurdacier & Rey, 2013), Pakistani investors invest 70-80% of their wealth in home country assets. We find diversified versus concentrated international portfolios outperform and lower country-level risk in the long run.

Implementation Steps:

1. Access DeepSeek at chat.deepseek.com (free)
2. Input our prompt template with desired modifications
3. Verify allocations sum to 100%
4. Open brokerage account with international access
5. Implement portfolio and rebalance annually

Total time: 4-6 hours initially, 1-2 hours annually for rebalancing.

5.4 Benefits for Pakistani Fintech Start-ups

Sarmaaya, KTrade, and Mahaana Wealth, three fintech companies in Pakistan, are considering developing AI portfolio features for their applications. This project provides quantitative support for this decision.

Demonstrated Value: DeepSeek V1's Sharpe ratio is 0.90, 32% higher than the 0.68 of a customary 60/40 index. The maximum drawdown is 19% lower. These measurable improvements outweigh the cost of development.

Cost-Efficient Technology: DeepSeek's architecture is built to be open source to allow other companies to integrate DeepSeek into their businesses at almost no cost to themselves. Other companies are able to develop using smaller teams without needing to have large amounts of funding like that provided through Silicon Valley.

Regulatory Template: The methodology istransparent, as we provide documentation on exactly what prompts were used to train the model, the assumptions made while developing it, and the limitations of the model. This provides an example for SECP regulatory sandbox applications that demonstrate investor protection commitment.

Implementation Roadmap:

- Phase 1 (Months 1-3): Backend integration with DeepSeek, prompt template library
- Phase 2 (Months 4-6): Beta testing with 100-500 users
- Phase 3 (Months 7-12): Scale to full customer base with educational content

Estimated cost: PKR 2-3 million (versus PKR 10-15 million for proprietary algorithms).

5.5 Benefits for Financial Regulators

There is a need for the SECP to balance promoting innovation with protecting investors. The project provides empirical evidence to support balanced regulation of artificial intelligence investment.

Safety Evidence: While DeepSeek V1 has shown superior drawdown (-16.67% compared to -23.93%), and crisis performance compared to the index portfolio it tested against, it demonstrates that properly designed AI portfolios can actually reduce rather than increase risk.

Transparency Requirements: Our methodology provides a template to determine what information should be included in disclosures about AI portfolios. Specifically, the template includes exact prompts, backtested performance across multiple different scenarios, and explicit limitations on the performance.

Financial Inclusion: As our methodology is a zero-cost, accessible methodology, it supports Pakistan's National Financial Inclusion Strategy by providing a demonstration of how technology can be used to lower barriers to entry for the mass affluent segment (PKR 100,000 to PKR 500,000 portfolios).

5.6 Limitations on Benefits

Important constraints merit acknowledgment:

Historical Performance ≠ Future Results: The time period of 2015 to 2025, used in this study, was just one market environment, and potentially could have produced different results based on the specific market environment.

Individual Circumstances: Real world investors will have additional costs that will affect the realized returns such as taxes, currency conversion costs, and behavioural challenges that would result in the actual returns being less than the backtested results.

AI Model Risk: Because of the training cut-off (July 2024), portfolios generated by DeepSeek should be recreated every quarter and therefore require the continued involvement of the user.

Not Universal: During 2023-2024, DeepSeek V1 underperformed the tech rally (12.40%, 14.18% vs. S&P 500's 24.89%, 26.19%) and may not be the best choice for investors seeking to maximize absolute returns, as they could simply use a simple indexing strategy.

5.7 Chapter Summary

In conclusion, this chapter identifies some of the tangible benefits associated with the research project. These include: Bahria University receives a curriculum template and contributes to the body of academic literature regarding AI portfolios; Pakistani investors receive a free methodology to utilize defensive positioning in their investment decisions; Fintech start-ups receive validation of their products and a regulatory template to follow; Regulators receive an evidence-based framework to oversee AI and support their financial inclusion objectives. Furthermore, each stakeholder can take specific action based on the findings of this research project.

CHAPTER 6
LIMITATIONS AND CONCLUSION

6.1 Introduction

This chapter will discuss the practical constraints we faced, put our findings in the proper context and make recommendations based on our empirical findings. We will group the limitations of our research into methodology constraints, limitations of the AI tool, and challenges associated with implementing the research findings.

6.2 Practical Constraints Encountered

6.2.1 Time and Resource Limitations

Semester Timeline: While we did complete this project in a 14-week timeframe with 4 other courses (a combined total of 12 credit hours), it made it difficult for us to evaluate several AI models as well as to perform extensive sensitivity tests. A larger time frame will allow for a much more detailed evaluation.

Single Portfolio Design: Since we only created one AI portfolio; we did not test multiple variations of the same portfolio that were created using different prompts or different constraint parameters. In future years, students can create 3-5 portfolios that are based on the same data but have differing objectives.

Group Size: As a 3-member group, our group was able to dedicate an average of 58 hours of work for each member (116-174 total hours). Groups larger than ours may be able to do additional analysis of the data.

6.2.2 Data and Measurement Constraints

Monthly Data Frequency: Portfolio Visualizer provides historical price information at the end-of-the-month which typically underestimates the actual maximum intra-month draw-downs. We required a daily dataset to provide the intra-month volatility information which is very expensive and not available to students.

Survivorship Bias: In addition to providing a list of only the stocks that survived through October 2025, we also assumed that there were no bankruptcies or acquisitions during that time. Since those events would cause automatic exclusion from the portfolio, they tend to overstate the returns of the portfolio. The effect of excluding these types of events is similar for all of the portfolios we evaluated.

Zero-Cost Assumption: We assumed both commission-free trading and tax-exempt accounts. In Pakistan, there are currency conversion fees (0.5-1%) that occur when converting back and forth between currencies, as well as withholding taxes that reduce investor returns by approximately 0.5-1.5% annually.

6.2.3 Period-Specific Results

Evaluation Window: The 2015–2025-time frame was a single macroeconomic regime. We experienced unprecedented stimulus, historically low interest rates, technology outperforming other sectors, and two major crises. Other time frames may have resulted in other conclusions.

Bull Market Bias: We saw approximately 70% of the 130 months analysed (90 of 130) as bull markets; this is a positive-skewed market and historically has been favourable for equities. We could see different outcomes when there are longer-term bear markets.

Regime Dependency: During the inflationary year of 2022 DeepSeek V1 performed well relative to its defensive portfolio positioning; however, it did poorly during the 2023-2024 equity technology rally that occurred later in the time frame indicating that DeepSeek V1's performance is regime dependent versus universally superior.

6.3 AI Tool Limitations

6.3.1 Arithmetic Error

Although DeepSeek generated allocations totalling 108%, which is evidence that LLMs still suffer from precision math challenges, although they continue to provide high quality qualitative analysis. The necessity to perform additional corrections was necessary because of the addition of 10-15 minutes to rectify the math errors; therefore, human review continues to be required. Investors will need to verify all output prior to their use.

6.3.2 Training Data Cut-off

DeepSeek V1's knowledge base only included information up until July 2024. As such, our November 2024 generation could not include any data or events that occurred after July 2024. It is suggested that real world investors generate new portfolios on a quarterly basis; as opposed to taking the recommendation generated by an AI as a static recommendation.

6.3.3 Pattern Recognition vs. Causal Understanding

The LLMs will identify statistical patterns, however they do not have the ability to perform fundamental analysis to evaluate a company's specific financials or position relative to their competitors.Thus, if the historical statistical patterns were to break down, then the AI generated recommendations would also break down**.T**here will always need to be some level of human judgment regarding changes in the structural elements of the marketplace.

6.4 Suggestions for Future Improvement

Multi-Model Comparison: Determine if the results are model agnostic, and therefore generalizable across different AI models (Gemini, Claude, ChatGPT), or a function of the DeepSeek model that was used to generate the results.

Sensitivity Analysis: Examine how results might be affected by applying a variety of modified constraint sets (i.e., dividend yield focus, environmental social governance (ESG) screen, and maximum allocation at 5 percent per stock).

International Application: Replicate for other geographic markets such as Pakistan (Pakistan Stock Exchange; PSX) or emerging markets.

Forward Validation: Track and monitor actual performance over a 3–5-year time frame (in addition to back testing) and implement any of the recommendations in practice.

Factor Attribution: Apply Fama French models to determine if the outperformance is due to identifiable and well understood factors (such as quality or low volatility) versus an "alpha" that is not explainable based upon prior research.

6.5 Key Findings Summary

Over January 2015-October 2025:

- Absolute Performance: 316.68% total return (14.08% CAGR), outperforming S&P 500 by 17.89 percentage points
- Risk-Adjusted Excellence: Sharpe 0.90 vs. 0.80; Sortino 1.49 vs. 1.25
- Crisis Resilience: Maximum drawdown -16.67% vs. -23.93%; 2022 performance -2.96% vs. -18.17%
- Alpha Generation: 2.74% annualized genuine outperformance
- Consistency: Exceeded S&P 500 across 1-year, 3-year, 5-year, 10-year rolling windows
- Capture Asymmetry: 90.80% upside with 83.33% downside (+7.47% favourable)

6.6 Practical Recommendations

For Students: Use this methodology as a template for future FYPs. Extend the research by testing different AI models, asset classes, or constraints as outlined in Section 6.4.

For Investors: Maintain discipline in times of large draw-downs; run a new generation every quarter; validate all of the output generated by AI; store all data in tax-advantaged accounts.

For Fintech: Implement the first version for a small group of users (e.g., 10-20% of total users), and after that expand it using forward-validation as well as factor-attribution for different asset classes.

For Bahria University: Add course material; develop a "Finance Lab" paper portfolio; collaborate with local fintech companies; create case studies.

6.7 Conclusion

This project asked whether Pakistani students could use free AI tools to produce portfolios to a standard comparable to that of professionally designed portfolios, and it found that they could.

DeepSeek V1 produced better absolute (14.08% vs 13.62%) and risk-adjusted returns (Sharpe 0.90 vs 0.80) and experienced considerably lower downside risk (drawdown of -16.67% vs. -23.93%) producing a "maximum risk-adjusted return with moderate risk" by producing market returns with considerably lower drawdowns and downside risk than broad market indices.

More importantly, this research shows that advanced portfolio analysis is now available to anyone with an internet connection. With AI help, students and retail investors in Pakistan can spread their investment across a variety of assets, back test portfolio ideas and execute trading strategies that were once the preserve of professional wealth managers.

This means that while historical backtests do not guarantee performance, AI models (training cut-off dates, arithmetic errors, regime dependence) and implementation (costs, taxes, behavioural limitations) have intrinsic limitations. DeepSeek V1's underwhelming performance from 2023-2024 shows that every design has its limitations, and that performance is highly dependent on market conditions.

The broader contribution however is not to claim that portfolios generated through AI always outperform, but that when applying it carefully, rigorously, and synergistically with long-held principles, it has the potential to improve the accessibility, costs, and risk-adjusted returns for retail investors in emerging markets.

As the financial sector in Pakistan transforms digitally, learning to use AI responsibly will be key for the fintech sector, helping increase the financial literacy of investors and the regulatory capacity of policymakers. Our project contributes to this agenda with a transparent methodology, validation, and practical guidance.

We envision that the next generation of Bahria students will improve upon what we have done so far by testing different approaches and expanding their research to further enhance the resources available for financial education in Pakistan, as well as provide evidence to assist investors with making informed decisions when it comes to investing. We are advancing the development of financial inclusion and empowering Pakistani investors by bringing access to complex portfolio management and demonstrating through data the benefits of using artificial intelligence (AI) to help make better investment decisions in Pakistan’s growing digital economy.

CHAPTER 7

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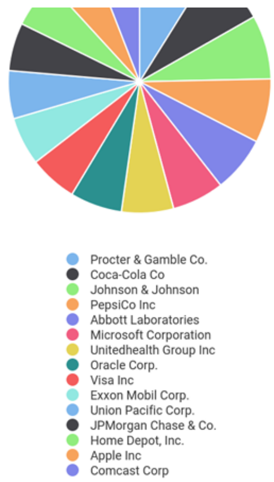
APPENDIX

Portfolio Visualizer **Portfolio Report**

Report Parameters

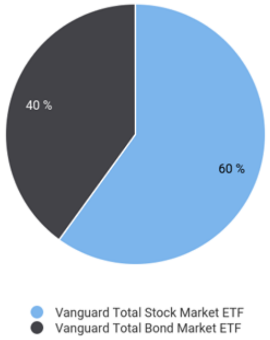
Start Date	01/01/2015
End Date	10/31/2025
Initial Balance	$10,000
Rebalancing	Rebalance annually
Reinvest Dividends	Yes
Benchmark	SPDR S&P 500 ETF

PG	Procter & Gamble Co.	8.90%
KO	Coca-Cola Co	7.88%
JNJ	Johnson & Johnson	7.88%
PEP	PepsiCo Inc	7.88%
ABT	Abbott Laboratories	6.89%
MSFT	Microsoft Corporation	6.40%
UNH	Unitedhealth Group Inc	6.40%
ORCL	Oracle Corp.	6.40%
V	Visa Inc	5.91%
XOM	Exxon Mobil Corp.	5.91%
UNP	Union Pacific Corp.	5.91%
JPM	JPMorgan Chase & Co.	5.91%
HD	Home Depot, Inc.	5.91%
AAPL	Apple Inc	5.91%
CMCSA	Comcast Corp	5.91%



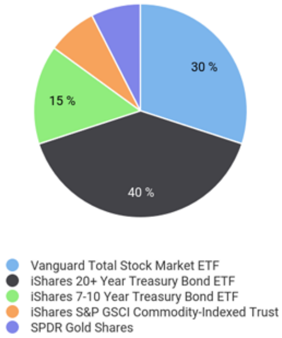
Stocks/Bonds (60/40)

Ticker	Name	Allocation
VTI	Vanguard Total Stock Market ETF	60.00%
BND	Vanguard Total Bond Market ETF	40.00%



Ray Dalio All Seasons

Ticker	Name	Allocation
VTI	Vanguard Total Stock Market ETF	30.00%
TLT	iShares 20+ Year Treasury Bond ETF	40.00%
IEF	iShares 7-10 Year Treasury Bond ETF	15.00%
GSG	iShares S&P GSCI Commodity-Indexed Trust	7.50%
GLD	SPDR Gold Shares	7.50%



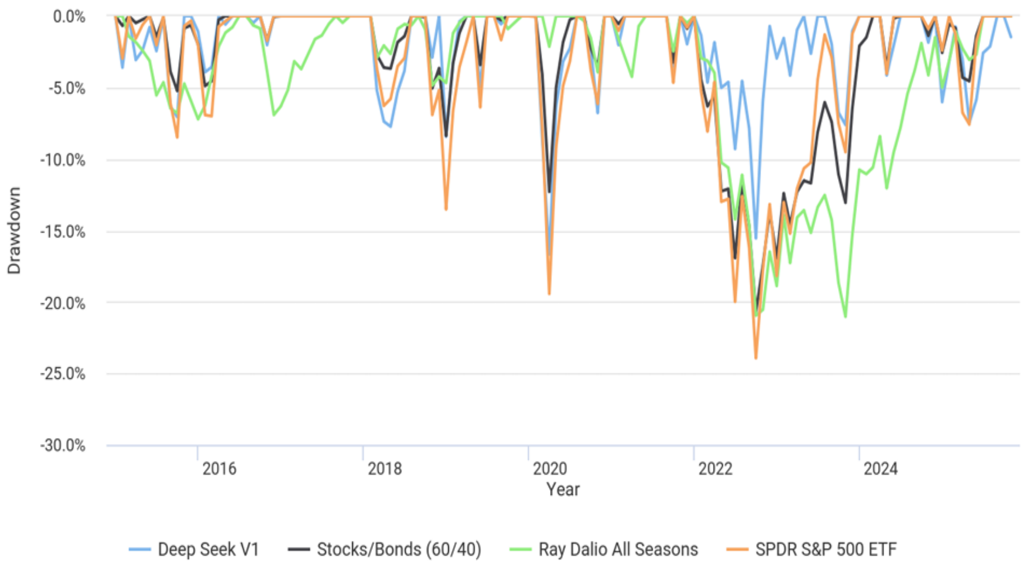
Portfolio Visualizer Portfolio Report

Portfolio Performance (Jan 2015 - Oct 2025)

Metric	Deep Seek V1	Stocks/Bonds (60/40)	Ray Dalio All Seasons	SPDR S&P 500 ETF
Start Balance	$10,000	$10,000	$10,000	$10,000
End Balance	$41,668	$24,758	$17,468	$39,879
End Balance (inflation adjusted)	$30,123	$17,899	$12,628	$28,830
Annualized Return (CAGR)	14.08%	8.73%	5.28%	13.62%
Annualized Return (CAGR, inflation adjusted)	10.72%	5.52%	2.18%	10.27%
Standard Deviation	13.50%	10.21%	8.63%	15.06%
Best Year	33.17%	21.94%	18.56%	31.22%
Worst Year	-2.96%	-16.95%	-18.88%	-18.17%
Maximum Drawdown	-16.67%	-20.69%	-21.03%	-23.93%
Sharpe Ratio	0.90	0.68	0.42	0.80
Sortino Ratio	1.49	1.04	0.62	1.25
Benchmark Correlation	0.91	0.98	0.68	1.00

Portfolio Visualizer | Portfolio Report

Drawdowns



Drawdowns for Historical Market Stress Periods

Stress Period	Start	End	Deep Seek V1	Stocks/Bonds (60/40)	Ray Dalio All Seasons	SPDR S&P 500 ETF
COVID-19 Start	Jan 2020	Mar 2020	-16.67%	-12.29%	-2.13%	-19.43%

Portfolio Visualizer | Portfolio Report

Drawdowns for Deep Seek V1 (worst 10)

Rank	Start	End	Length	Recovery By	Recovery Time	Underwater Period	Drawdown
1	Feb 2020	Mar 2020	2 months	Jul 2020	4 months	6 months	-16.67%
2	Jan 2022	Sep 2022	9 months	Apr 2023	7 months	1 year 4 months	-15.54%
3	Dec 2018	Dec 2018	1 month	Mar 2019	3 months	4 months	-8.43%
4	Feb 2018	Apr 2018	3 months	Jul 2018	3 months	6 months	-7.73%
5	Aug 2023	Oct 2023	3 months	Dec 2023	2 months	5 months	-7.61%
6	Dec 2024	Apr 2025	5 months	Aug 2025	4 months	9 months	-7.47%
7	Mar 2015	Sep 2015	7 months	Oct 2015	1 month	8 months	-7.06%
8	Sep 2020	Oct 2020	2 months	Nov 2020	1 month	3 months	-6.78%
9	May 2019	May 2019	1 month	Jun 2019	1 month	2 months	-4.98%
10	Apr 2024	Apr 2024	1 month	Jun 2024	2 months	3 months	-4.15%

Drawdowns for Stocks/Bonds (60/40) (worst 10)

Rank	Start	End	Length	Recovery By	Recovery Time	Underwater Period	Drawdown
1	Jan 2022	Sep 2022	9 months	Feb 2024	1 year 5 months	2 years 2 months	-20.69%
2	Feb 2020	Mar 2020	2 months	Jul 2020	4 months	6 months	-12.29%
3	Sep 2018	Dec 2018	4 months	Mar 2019	3 months	7 months	-8.38%
4	Jun 2015	Sep 2015	4 months	Apr 2016	7 months	11 months	-5.24%
5	Dec 2024	Apr 2025	5 months	Jun 2025	2 months	7 months	-4.56%
6	Feb 2018	Apr 2018	3 months	Jul 2018	3 months	6 months	-3.67%
7	Apr 2024	Apr 2024	1 month	Jun 2024	2 months	3 months	-3.62%
8	Sep 2020	Oct 2020	2 months	Nov 2020	1 month	3 months	-3.54%
9	May 2019	May 2019	1 month	Jun 2019	1 month	2 months	-3.41%
10	Sep 2021	Sep 2021	1 month	Oct 2021	1 month	2 months	-3.24%

Portfolio Visualizer — Portfolio Report

Portfolio Components (Jan 2015 - Oct 2025)

Ticker	Name	CAGR	Stdev	Best Year	Worst Year	Max Drawdown	Sharpe Ratio	Sortino Ratio
PG	Procter & Gamble Co.	7.76%	16.04%	39.70%	-9.96%	-21.46%	0.43	0.67
KO	Coca-Cola Co	7.96%	15.66%	20.61%	-4.46%	-23.59%	0.44	0.64
JNJ	Johnson & Johnson	8.57%	15.94%	33.74%	-8.60%	-15.69%	0.47	0.75
PEP	PepsiCo Inc	7.22%	15.00%	27.37%	-7.59%	-26.74%	0.41	0.65
ABT	Abbott Laboratories	11.92%	20.41%	52.00%	-20.69%	-30.42%	0.56	0.92
MSFT	Microsoft Corporation	26.78%	21.99%	58.19%	-28.02%	-30.52%	1.11	2.12
UNH	Unitedhealth Group Inc	13.66%	25.38%	45.21%	-31.26%	-58.47%	0.56	0.84
ORCL	Oracle Corp.	19.50%	28.31%	59.99%	-17.63%	-35.57%	0.70	1.35
V	Visa Inc	17.24%	19.66%	47.17%	-3.39%	-27.28%	0.81	1.41
XOM	Exxon Mobil Corp.	6.45%	26.57%	87.36%	-36.21%	-57.68%	0.29	0.46
UNP	Union Pacific Corp.	8.21%	23.14%	35.98%	-32.85%	-39.03%	0.37	0.59
JPM	JPMorgan Chase & Co.	19.19%	24.30%	47.27%	-12.61%	-37.10%	0.77	1.27
HD	Home Depot, Inc.	15.25%	21.73%	59.50%	-21.98%	-33.09%	0.67	1.10
AAPL	Apple Inc	24.82%	27.27%	88.97%	-26.40%	-30.46%	0.88	1.55
CMCSA	Comcast Corp	1.97%	23.77%	34.04%	-28.69%	-50.60%	0.12	0.17
VTI	Vanguard Total Stock Market ETF	13.10%	15.50%	30.67%	-19.51%	-24.81%	0.75	1.16
BND	Vanguard Total Bond Market ETF	1.85%	5.05%	8.84%	-13.11%	-17.28%	0.00	0.00
TLT	iShares 20+ Year Treasury Bond ETF	-0.45%	13.77%	18.15%	-31.24%	-47.61%	-0.11	-0.15
IEF	iShares 7-10 Year Treasury Bond ETF	1.29%	6.58%	10.01%	-15.16%	-23.15%	-0.07	-0.09
GSG	iShares S&P GSCI Commodity-Indexed Trust	0.67%	21.03%	38.77%	-34.06%	-60.80%	0.05	0.07
GLD	SPDR Gold Shares	11.47%	14.47%	52.03%	-10.67%	-18.08%	0.69	1.28

Portfolio Visualizer — Portfolio Report

Portfolio Asset Performance

Name	Total Return			Annualized Return			Expense Ratio	
	3 Month	Year To Date	1 year	3 year	5 year	10 year	Net	Gross
Procter & Gamble Co.	0.63%	-7.93%	-6.55%	6.40%	4.45%	10.00%		
Coca-Cola Co	2.27%	13.15%	8.68%	7.99%	10.77%	8.35%		
Johnson & Johnson	15.49%	33.74%	21.96%	5.95%	9.70%	9.45%		
PepsiCo Inc	6.95%	-1.07%	-8.64%	-3.99%	4.97%	6.78%		
Abbott Laboratories	-1.59%	11.39%	11.13%	9.84%	5.19%	12.79%		
Microsoft Corporation	-2.78%	23.52%	28.39%	31.73%	21.68%	27.44%		
Unitedhealth Group Inc	37.73%	-31.26%	-38.17%	-13.48%	3.90%	13.00%		
Oracle Corp.	3.66%	59.20%	58.06%	51.71%	38.07%	22.90%		
Visa Inc	-1.20%	8.37%	18.38%	18.95%	14.22%	16.76%		
Exxon Mobil Corp.	3.39%	9.28%	1.49%	4.58%	34.21%	7.92%		
Union Pacific Corp.	-0.11%	-1.65%	-2.80%	6.22%	6.78%	11.92%		
JPMorgan Chase & Co.	5.53%	32.59%	43.22%	38.59%	29.31%	20.30%		
Home Depot, Inc.	3.86%	-0.61%	-1.29%	11.41%	9.94%	14.54%		
Apple Inc	30.40%	8.34%	20.23%	21.44%	20.62%	25.98%		
Comcast Corp	-15.34%	-23.03%	-33.85%	-1.19%	-5.40%	1.19%		
Vanguard Total Stock Market ETF	8.19%	16.82%	20.85%	21.76%	16.63%	14.05%	0.03%	0.03%
Vanguard Total Bond Market ETF	2.89%	6.77%	6.09%	5.55%	-0.23%	1.89%	0.03%	0.03%
iShares 20+ Year Treasury Bond ETF	5.03%	6.80%	1.98%	1.73%	-7.85%	-0.42%	0.15%	0.15%
iShares 7-10 Year Treasury Bond ETF	3.03%	7.79%	6.44%	4.25%	-1.84%	1.16%	0.15%	0.15%
iShares S&P GSCI Commodity-Indexed Trust	1.80%	6.61%	8.97%	2.03%	17.46%	3.12%	0.75%	0.75%
SPDR Gold Shares	21.51%	52.03%	45.21%	34.32%	15.88%	12.91%	0.40%	0.40%

Trailing returns as of last calendar month ending October 2025

Portfolio Visualizer **Portfolio Report**

Portfolio Return Decomposition (Jan 2015 - Oct 2025)

Ticker	Name	Deep Seek V1	Stocks/Bonds (60/40)	Ray Dalio All Seasons
PG	Procter & Gamble Co.	$1,505		
KO	Coca-Cola Co	$1,539		
JNJ	Johnson & Johnson	$1,713		
PEP	PepsiCo Inc	$996		
ABT	Abbott Laboratories	$1,795		
MSFT	Microsoft Corporation	$4,089		
UNH	Unitedhealth Group Inc	$1,305		
ORCL	Oracle Corp.	$4,416		
V	Visa Inc	$2,224		
XOM	Exxon Mobil Corp.	$2,245		
UNP	Union Pacific Corp.	$1,089		
JPM	JPMorgan Chase & Co.	$3,076		
HD	Home Depot, Inc.	$1,963		
AAPL	Apple Inc	$3,822		
CMCSA	Comcast Corp	-$108		
VTI	Vanguard Total Stock Market ETF		$13,688	$5,736
BND	Vanguard Total Bond Market ETF		$1,070	
TLT	iShares 20+ Year Treasury Bond ETF			-$362
IEF	iShares 7-10 Year Treasury Bond ETF			$216
GSG	iShares S&P GSCI Commodity-Indexed Trust			$468
GLD	SPDR Gold Shares			$1,410

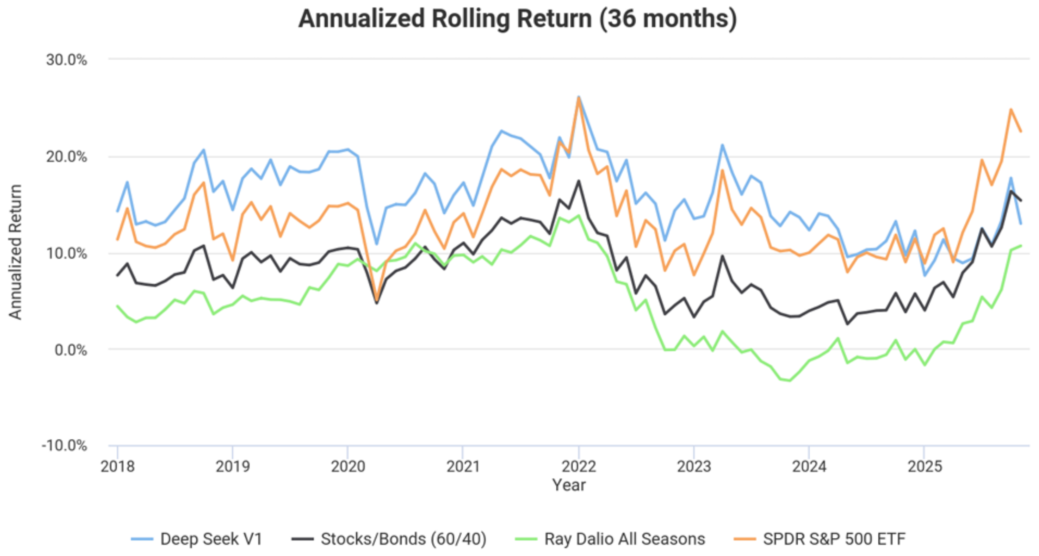
Return attribution decomposes portfolio gains into its constituent parts and identifies the contribution to returns by each of the assets.

Portfolio Visualizer **Portfolio Report**

Portfolio Risk Decomposition (Jan 2015 - Oct 2025)

Ticker	Name	Deep Seek V1	Stocks/Bonds (60/40)	Ray Dalio All Seasons
PG	Procter & Gamble Co.	6.19%		
KO	Coca-Cola Co	5.98%		
JNJ	Johnson & Johnson	6.41%		
PEP	PepsiCo Inc	6.08%		
ABT	Abbott Laboratories	7.12%		
MSFT	Microsoft Corporation	6.44%		
UNH	Unitedhealth Group Inc	5.71%		
ORCL	Oracle Corp.	8.09%		
V	Visa Inc	6.24%		
XOM	Exxon Mobil Corp.	6.51%		
UNP	Union Pacific Corp.	7.04%		
JPM	JPMorgan Chase & Co.	7.10%		
HD	Home Depot, Inc.	6.71%		
AAPL	Apple Inc	7.38%		
CMCSA	Comcast Corp	7.00%		
VTI	Vanguard Total Stock Market ETF		89.21%	35.48%
BND	Vanguard Total Bond Market ETF		10.79%	
TLT	iShares 20+ Year Treasury Bond ETF			48.73%
IEF	iShares 7-10 Year Treasury Bond ETF			8.36%
GSG	iShares S&P GSCI Commodity-Indexed Trust			1.80%
GLD	SPDR Gold Shares			5.63%

Risk attribution decomposes portfolio risk into its constituent parts and identifies the contribution to overall volatility by each of the assets.


Annualized Rolling Return (36 months)
30.0%
20.0%
10.0%
0.0%
-10.0%
Annualized Return
2018
2019
2020
2021
2022
2023
2024
2025
Year
Deep Seek V1
Stocks/Bonds (60/40)
Ray Dalio All Seasons
SPDR S&P 500 ETF