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Development of a Portfolio Optimisation Tool Using Modern Portfolio Theory

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ABSTRACT

Portfolio optimisation remains a practical challenge for investors in emerging markets such as Nigeria, where market volatility, macroeconomic instability, and limited access to locally oriented analytical tools can constrain evidence-based investment decisions. Although Modern Portfolio Theory (MPT) provides established procedures for constructing portfolios according to expected return and risk, there is limited availability of accessible software that operationalises these procedures for Nigerian Exchange (NGX) equities. This study developed and evaluated a portfolio optimisation tool that applies MPT to selected NGX-listed equities through an accessible software interface. The tool was implemented as a Python-based client-server application using PyPortfolioOpt for portfolio optimisation, EODHD for historical market data, and Streamlit for the user interface. The implementation incorporated historical return estimation, covariance analysis, Efficient Frontier optimisation, maximum Sharpe ratio and minimum-volatility portfolio construction, and comparison with an equally weighted benchmark. System functionality was evaluated through unit, integration, functional, and user acceptance testing, while portfolio characteristics were examined using a six-asset test portfolio over June 2024–June 2025. Under the specified assumptions, the maximum-Sharpe portfolio produced an expected annualised return of 39.50%, annualised volatility of 19.84%, and Sharpe ratio of 1.041, compared with 25.50%, 15.50%, and 0.430, respectively, for the equally weighted benchmark. The minimum-volatility portfolio produced an expected annualised return of 22.80%, volatility of 13.50%, and Sharpe ratio of 0.293. These results demonstrate the feasibility of translating MPT optimisation procedures into an accessible tool for NGX equities and illustrate the risk–return differences among alternative portfolio constructions within the test period. The study contributes a locally deployable software artefact for portfolio analysis and provides a foundation for extending portfolio optimisation tools for Nigerian and other emerging-market investment contexts.

1. INTRODUCTION

Investment decisions in emerging financial markets are shaped by substantial uncertainty in asset prices, macroeconomic conditions, and the availability of reliable analytical information. In Nigeria, these challenges are particularly relevant because investors operate within an environment characterised by changing inflation, interest rates, exchange-rate conditions, and equity-market dynamics. The Nigerian Exchange (NGX) has experienced periods of substantial market movement, increasing the importance of

market movement, increasing the importance of systematic approaches to balancing investment return against portfolio risk. However, the availability of market information does not necessarily translate into accessible analytical tools through which individual and institutional investors can systematically construct and evaluate diversified portfolios.



Modern Portfolio Theory (MPT), introduced by Markowitz (1952), provides a foundational framework for addressing this problem by treating portfolio selection as an optimisation problem involving expected return and risk. Rather than evaluating securities independently, MPT considers the interaction among asset returns through their covariance and uses diversification to identify portfolios that offer efficient combinations of risk and expected return. The resulting Efficient Frontier represents portfolios that provide the highest expected return for a given level of risk or the lowest risk for a given expected return. Sharpe (1966) subsequently provided a risk-adjusted performance measure through the Sharpe ratio, which compares excess portfolio return with portfolio volatility and is widely used in portfolio evaluation.

The practical value of these concepts depends partly on the availability of computational tools capable of translating the underlying mathematical procedures into usable investment workflows. Modern Python-based portfolio analytics libraries, including PyPortfolioOpt, provide functions for estimating expected returns and covariance matrices and for constructing portfolios under different optimisation objectives. Such tools, however, do not by themselves constitute locally oriented investment applications. Their usefulness to Nigerian investors depends on the availability of relevant NGX market data, appropriate parameterisation, understandable interfaces, and outputs that can be interpreted by users without implementing the underlying optimisation procedures manually.

Existing portfolio optimisation research in Nigeria has largely focused on applying quantitative portfolio models to historical market data. While these studies provide evidence of the applicability of portfolio theory within the Nigerian market, comparatively less attention has been directed towards converting such optimisation procedures into an accessible software artefact for practical portfolio analysis. This creates a distinction between demonstrating that a

mathematical optimisation technique can be applied to Nigerian equities and providing an operational tool through which users can obtain and evaluate optimised portfolios. This study therefore focuses on the development and evaluation of a portfolio optimisation tool that operationalises selected MPT procedures for NGX-listed equities. The tool integrates historical market-data acquisition, return and covariance estimation, Efficient Frontier analysis, maximum-Sharpe and minimum-volatility optimisation, portfolio visualisation, and comparison with an equally weighted portfolio. The emphasis is consequently not on proposing a new portfolio optimisation theory, but on translating an established theoretical framework into a locally oriented and accessible software application.

1.2 Problem Statement

Despite the availability of established portfolio optimisation techniques, Nigerian investors may encounter practical difficulties in applying these techniques to NGX-listed securities. Constructing an efficient portfolio requires the estimation of asset returns and covariance relationships and the solution of an optimisation problem, processes that are not readily accessible to users without quantitative programming or financial modelling skills. Existing investment practices may therefore rely substantially on individual judgement, simple diversification rules, or general-purpose investment platforms that are not specifically configured around Nigerian equities.

The problem is consequently not the absence of portfolio optimisation theory, but the limited translation of that theory into an accessible tool tailored to the Nigerian investment context. Without such a tool, the practical application of Efficient Frontier and Sharpe-ratio optimisation to NGX securities remains dependent on specialised software skills or manual analytical procedures. This limits the accessibility of systematic portfolio construction for users seeking to examine the risk–return implications of alternative combinations of Nigerian equities.

1.3 Research Gap

The literature establishes MPT as a well-developed framework for portfolio selection and documents a range of extensions addressing its limitations, including downside-risk, robust, and data-driven optimisation approaches. Research involving Nigerian and other emerging-market equities has similarly demonstrated the application of quantitative portfolio techniques to local financial data. However, the existing evidence identified in this study is concentrated primarily on the analytical application of portfolio models, rather than on the development of an accessible software artefact that integrates the complete workflow from NGX data acquisition to portfolio optimisation and user-facing visualisation. A practical gap therefore exists between portfolio optimisation as a mathematical procedure and portfolio optimisation as an accessible software service for Nigerian investors. This study addresses that gap by developing a Python-based tool that integrates NGX-related historical data, MPT return and covariance estimation, Efficient Frontier analysis, maximum-Sharpe and minimum-volatility optimisation, and an interactive Streamlit interface. The contribution is thus primarily an applied software and methodological contribution: demonstrating how established MPT procedures can be assembled into a locally oriented portfolio optimisation workflow and evaluated using a Nigerian equity test portfolio.

1.4 Aim and Objectives

The aim of this study is to develop and evaluate a portfolio optimisation tool based on Modern Portfolio Theory to analyse selected Nigerian Exchange equities.

The specific objectives are to:

1. analyse the functional and non-functional requirements for a portfolio optimisation tool

designed for NGX-listed equities;

2. design and implement an MPT-based optimisation workflow that uses historical NGX equity data to estimate expected returns and covariance and construct Efficient Frontier portfolios;
3. implement maximum-Sharpe and minimum-volatility portfolio optimisation subject to the specified portfolio constraints;
4. develop an accessible interactive interface through which users can select assets, obtain portfolio optimisation results, and examine portfolio risk–return characteristics; and
5. evaluate the developed tool and its portfolio outputs through systematic software testing and comparison of the optimised portfolios with an equally weighted benchmark.

1.5 Significance of the Study

The study has both practical and academic significance. Practically, it provides a software artefact through which established portfolio optimisation procedures can be applied to selected NGX equities without requiring users to independently implement the underlying mathematical models. By integrating data acquisition, portfolio optimisation, performance measures, and visualisation within a single interface, the tool provides a more accessible workflow for examining portfolio risk and expected return. The study also contributes to the application of MPT within the Nigerian context. Rather than proposing a new optimisation theory, it demonstrates the practical translation of established MPT procedures into a locally oriented computational application. The resulting implementation provides an applied basis for examining the behaviour of maximum-Sharpe and minimum-volatility portfolios using Nigerian equity data and for comparing these portfolios with a simple equally weighted benchmark.

From a software-development perspective, the study

demonstrates how financial data services, portfolio optimisation libraries, and interactive web technologies can be integrated into a functional portfolio analytics application. The tool can also provide an educational resource for demonstrating concepts such as diversification, covariance, the Efficient Frontier, and risk-adjusted return. The significance of the findings is nevertheless bounded by the empirical design of the study. The portfolio results represent model-based estimates generated under the specified assumptions and a six-asset test portfolio over June 2024–June 2025; they do not establish that the optimised strategy will consistently outperform other strategies or generate superior returns for Nigerian investors generally. Within these boundaries, the study provides a foundation for subsequent extensions involving longer datasets, broader asset universes, transaction costs, rebalancing effects, and alternative risk and return estimation techniques.

1.6 Foundations of Modern Portfolio Theory

Modern Portfolio Theory (MPT), introduced by Markowitz (1952), provides a mathematical framework for selecting portfolios by considering the relationship between expected return and risk. In the mean-variance framework, risk is represented by the variance or standard deviation of portfolio returns, while portfolio selection involves identifying combinations of assets that provide desirable risk–return trade-offs. A central proposition of the theory is that diversification can reduce portfolio risk because assets do not generally exhibit perfect positive correlation. Consequently, the risk of a portfolio depends not only on the individual risk of its constituent securities but also on their interactions through covariance (Hoang, 2022; Iyobor *et al.*, 2025).

The relationship between portfolio risk and expected return is represented by the Efficient Frontier, which comprises portfolios offering the highest expected

return for a given level of risk or, equivalently, the lowest risk for a given expected return (Markowitz, 1952). This provides a systematic basis for comparing alternative portfolio compositions rather than evaluating securities independently. For practical portfolio selection, the Sharpe ratio provides a complementary risk-adjusted performance measure by relating a portfolio's excess return over the risk-free rate to its standard deviation (Sharpe, 1966). In the present study, these two concepts provide the principal analytical basis for constructing and evaluating maximum-Sharpe and minimum-volatility portfolios.

1.7 Limitations of Modern Portfolio Theory

Despite its continuing relevance, MPT has important limitations that are particularly pertinent when historical data from volatile emerging markets are used for portfolio optimisation. First, the classical framework relies on assumptions concerning investor rationality, information availability, and the behaviour of financial markets that may not fully reflect actual investment environments. Evidence from emerging markets, including Nigeria, indicates the presence of market inefficiencies, information asymmetries, and behavioural influences that can complicate the assumptions underlying conventional portfolio models (Iyobor *et al.*, 2025).

Second, the mean-variance framework does not fully capture the non-normal characteristics that may occur in financial return distributions. Skewness and fat tails can result in extreme gains or losses occurring more frequently than would be expected under a normal distribution, thereby limiting the adequacy of variance as the sole representation of investment risk (La & Rashif, 2024; Zhang, 2024). Third, expected returns and covariance matrices are typically estimated from historical observations. Such estimates are sensitive to the choice and length of the estimation period and can become particularly unstable in markets experiencing structural and macroeconomic changes (Iyobor *et al.*, 2025; Xu,

2025). A further limitation concerns the static nature of the classical single-period formulation. Conventional MPT does not, by itself, incorporate issues such as transaction costs, portfolio turnover, liquidity constraints, or changes in investor preferences over time. These considerations become important when a theoretical optimal portfolio is translated into an investment strategy that must be implemented and periodically rebalanced (PGIM, 2025).

These limitations do not invalidate MPT as the basis of the present study. Rather, they define the conditions under which its outputs need to be interpreted. The present study therefore treats MPT as an established portfolio-construction framework and evaluates its computational implementation within a specified Nigerian equity setting rather than presenting the resulting portfolios as universally optimal investment solutions.

1.8 Alternative and Extended Portfolio Optimisation Approaches

Several approaches have been developed to address specific limitations of classical MPT. Behavioural Portfolio Theory, for example, incorporates investor psychology and multiple objectives into portfolio construction and therefore moves beyond the conventional assumption of a single risk–return trade-off (Iyobor *et al.*, 2025; Poddar *et al.*, 2025). Downside-risk approaches, including Conditional Value-at-Risk (CVaR), semivariance, and Conditional Drawdown-at-Risk (CDaR), focus more directly on adverse outcomes than symmetric variance-based measures. CVaR optimisation, in particular, provides a framework for evaluating losses beyond a specified Value-at-Risk threshold (Rockafellar & Uryasev, 2000).

Other extensions address estimation instability and the statistical characteristics of financial returns. Mean-Variance-Skewness-Kurtosis models

incorporate higher-order moments, while robust optimisation seeks to reduce the sensitivity of portfolio weights to estimation errors and extreme observations (La & Rashif, 2024; Zhang, 2024). Hierarchical Risk Parity provides an alternative approach to diversification that does not depend on the same covariance-matrix optimisation procedure, while Black-Litterman combines market-implied information with investor views to generate portfolio allocations (Martin, 2021). Machine learning and artificial intelligence approaches have also increasingly been applied to return prediction and financial risk management, including work directed towards African financial markets (Liang, 2025; Hsiao, 2025; Oladuji *et al.*, 2022).

These approaches demonstrate that portfolio optimisation is an evolving field and that no single framework addresses all investment conditions. However, they are not implemented as the primary optimisation mechanisms in the present study. They are therefore considered primarily to position the selected MPT approach within the wider portfolio-optimisation literature rather than to suggest that the developed tool resolves all limitations associated with classical portfolio theory.

1.9 Portfolio Optimisation in the Nigerian and Emerging-Market Context

Empirical research applying portfolio optimisation to Nigerian equities remains relatively limited compared with the broader international literature. Nnanwa *et al.* (2016), for example, applied the Markowitz model to financial-services stocks in the Nigerian market and demonstrated the applicability of mean-variance optimisation to NGX-related equity data. This provides an important foundation for the present study because it establishes the analytical feasibility of applying classical portfolio theory to Nigerian securities.

Recent studies continues to highlight the importance of diversification and risk management while also drawing attention to the market characteristics that can complicate conventional portfolio assumptions. Iyobor *et al.* (2025) examined portfolio management and financial performance among listed industrial firms and emphasised the relevance of diversification and risk management within the Nigerian setting. Similarly, Oladuji *et al.* (2022) proposed an AI-oriented framework for financial risk forecasting in African markets, illustrating the broader movement towards computational approaches that account for local financial conditions. Evidence from other emerging markets provides additional context. Ahmar *et al.* (2025), using Value-at-Risk analysis in the Indonesian equity market, reported that diversification could reduce potential losses even within a relatively small portfolio. Satpute *et al.* (2025) demonstrated the use of computational decision-support techniques combining investment information with optimisation procedures, while Hoang (2022) highlighted the importance of appropriately calibrated forecasting methods for emerging and frontier markets.

Generally, these studies indicate that quantitative portfolio analysis is applicable to emerging markets but also that local market characteristics matter when financial models are operationalised. For Nigeria, the existing literature provides evidence of portfolio optimisation at the analytical level, but comparatively less attention has been given to developing an accessible application that integrates local market data, portfolio optimisation and user-facing visualisation within a single workflow. This distinction between demonstrating an optimisation model and deploying that model as an accessible software tool is central to the present study.

1.10 Software Implementation of Portfolio Optimisation

The practical application of portfolio theory

increasingly depends on computational tools capable of translating mathematical optimisation procedures into reproducible analytical workflows. PyPortfolioOpt is an open-source Python library that provides functions for expected-return estimation, covariance estimation, Efficient Frontier construction, Sharpe-ratio optimisation and several alternative portfolio-optimisation procedures (Martin, 2021). Its functionality provides a computational bridge between the mathematical formulation of MPT and software-based portfolio analysis. The use of a specialised optimisation library is particularly relevant to the present study because the objective is not to develop a new optimisation algorithm but to integrate established MPT procedures into an accessible application for Nigerian equities. The developed tool combines the optimisation capabilities provided by PyPortfolioOpt with historical market-data retrieval, data preprocessing, portfolio constraints and an interactive Streamlit interface. This integration shifts the focus from the mathematical availability of portfolio optimisation algorithms to their practical accessibility within a Nigerian investment context.

Downside-risk methods such as CVaR provide examples of functionality that can extend portfolio analysis beyond the variance-based approach used for the primary optimisation in this study (Rockafellar & Uryasev, 2000). Their availability within computational portfolio libraries also creates opportunities for future versions of the developed tool to incorporate alternative risk objectives without requiring a complete redesign of the software architecture.

1.11 Synthesis and Research Gap

The reviewed literature establishes three important points. First, MPT provides a well-established framework for portfolio construction through diversification, mean-variance analysis and Efficient Frontier optimisation, with the Sharpe ratio offering a

widely used measure of risk-adjusted performance (Markowitz, 1952; Sharpe, 1966). Second, the framework has recognised limitations relating to market assumptions, non-normal returns, estimation error, and the static treatment of portfolio implementation. These limitations have motivated the development of downside-risk, robust, behavioural, hierarchical and computationally intelligent alternatives. Third, existing Nigerian and emerging-market studies demonstrate the relevance of quantitative portfolio analysis to local and comparable markets, but much of this work remains focused on empirical model application rather than accessible software deployment.

The principal gap addressed by this study is therefore the limited translation of established portfolio optimisation procedures into an accessible, locally oriented software tool for Nigerian equities. While previous research demonstrates the applicability of Markowitz-based optimisation to Nigerian financial data, the present study integrates historical NGX-related data acquisition, return and covariance estimation, Efficient Frontier analysis, maximum-Sharpe and minimum-volatility optimisation, portfolio metrics, and interactive visualisation within a single application. The contribution is consequently not a new portfolio theory or optimisation algorithm. Rather, it is the development and evaluation of a practical software artefact that operationalises

established MPT procedures for selected NGX equities and makes the resulting analysis more accessible to users without requiring them to implement the underlying optimisation workflow manually. This gap provides the basis for the system requirements, architecture, optimisation procedures, and evaluation strategy presented in the following section.

2. Material and Methods

2.1 Requirements Analysis

The development of the portfolio optimisation tool commenced with an analysis of its functional and non-functional requirements (Chung *et al.*, 2012). The functional requirements were defined around the complete workflow required to construct and evaluate an optimised portfolio of Nigerian equities. These requirements included user authentication, selection of Nigerian stock tickers, retrieval of historical market data, data cleaning and preparation, estimation of expected returns and covariance, Efficient Frontier generation, identification of optimal portfolios, calculation of portfolio performance metrics, interactive visualisation, and downloading of data and results. Table 1 summarises the functional requirements implemented in the system.

Table 1. Functional requirements of the portfolio optimisation tool

ID	Requirement	Description	Priority	Module
FR001	User authentication	Authenticate users before accessing the tool	High	User Interface
FR002	Stock selection	Input/select Nigerian stock tickers	High	User Interface
FR003	Historical data retrieval	Retrieve historical price data from EODHD	High	Data Acquisition
FR004	Data preparation	Clean and prepare retrieved market data	High	Data Processing
FR005	Expected-return estimation	Calculate expected asset returns	High	Portfolio Optimisation
FR006	Covariance estimation	Compute the asset-return covariance matrix	High	Portfolio Optimisation
FR007	Efficient Frontier	Generate and display the Efficient Frontier	High	Optimisation/Visualisation

	generation	Frontier			
FR008	Optimal portfolio identification	Identify and display optimised portfolios	High	Optimisation/Visualisation	
FR009	Performance metrics	Calculate and display portfolio performance measures	High	Optimisation/Visualisation	
FR010	Interactive visualisation	Provide interactive charts and graphical outputs	Medium	Visualisation	
FR011	Results download	Allow users to download data and results	Medium	User Output	Interface/Data

Non-functional requirements were defined in relation to system performance, security, reliability, scalability, usability, and maintainability. These requirements were intended to ensure that the application was not only computationally functional but also sufficiently accessible to users without specialist programming expertise.

Table 2. Non-functional requirements of the portfolio optimisation tool

Category	ID	Requirement	Measure/Acceptance Criterion	Priority
Performance	NFR001	Load charts and display results promptly	Maximum 5 seconds	High
Performance	NFR002	Optimise portfolios for larger asset universes	Maximum 30 seconds for 50 assets	High
Security	NFR003	Protect sensitive data	AES-256 and TLS/SSL	High
Security	NFR004	Protect user data and privacy	Data-privacy compliance	Medium
Reliability	NFR005	Maintain system availability	Minimum 99% uptime	High
Reliability	NFR006	Handle system errors appropriately	Clear and informative error messages	High
Scalability	NFR007	Support future functional expansion	Modular architecture	Medium
Scalability	NFR008	Accommodate increasing data volumes	Efficient data handling	Medium
Usability	NFR009	Provide an intuitive interface	Ease of navigation/minimal training	High
Usability	NFR010	Present outputs clearly	Clear labels and concise presentation	High
Usability	NFR011	Support different device sizes	Responsive interface	Medium
Maintainability	NFR012	Facilitate system maintenance	Documented and modular codebase	Medium

2.2 System Architecture and Design

The tool was implemented as a client-server application comprising a Python backend and a Streamlit-based web frontend. This modular design separates core functionality into distinct modules: a data loader for acquisition and pre-processing, a portfolio optimiser for MPT calculations, and a visualisations module for graphical output, orchestrated by a top-level application module serving as the Streamlit entry point. Figure 1 presents the resulting

architecture, showing the client layer, the data acquisition, processing, and optimisation modules, and the data storage layer.

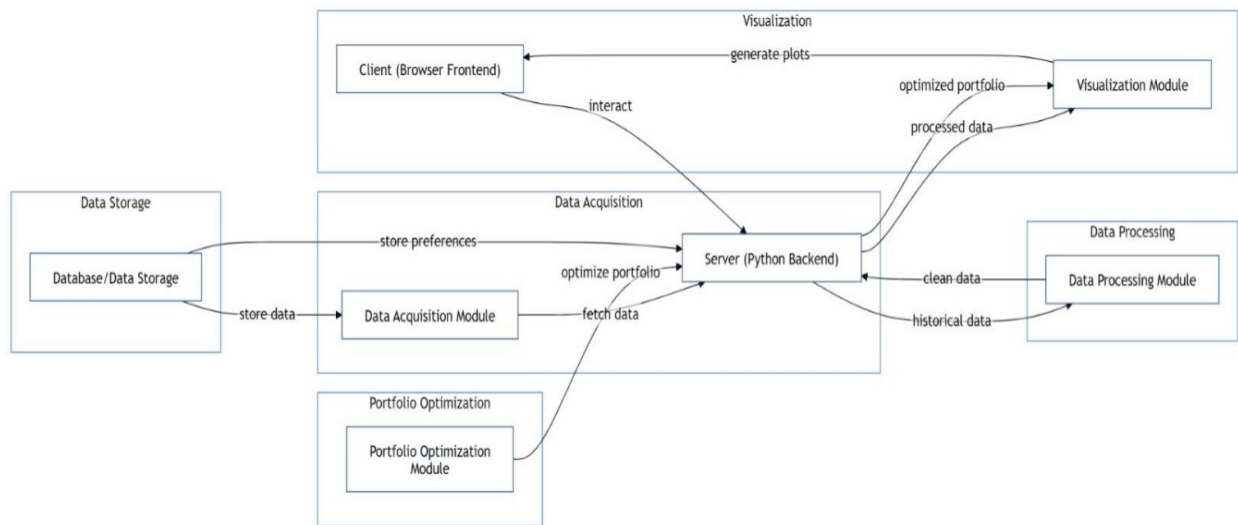


Figure 1. High-level system architecture diagram, showing the client (browser frontend), the Python backend server, the data acquisition, processing, and portfolio optimisation modules, and the data storage layer.

Figure 2 shows the data flow diagram, tracing a request from ticker input through validation, acquisition, pre-processing, parameter estimation, optimisation, and output delivery.

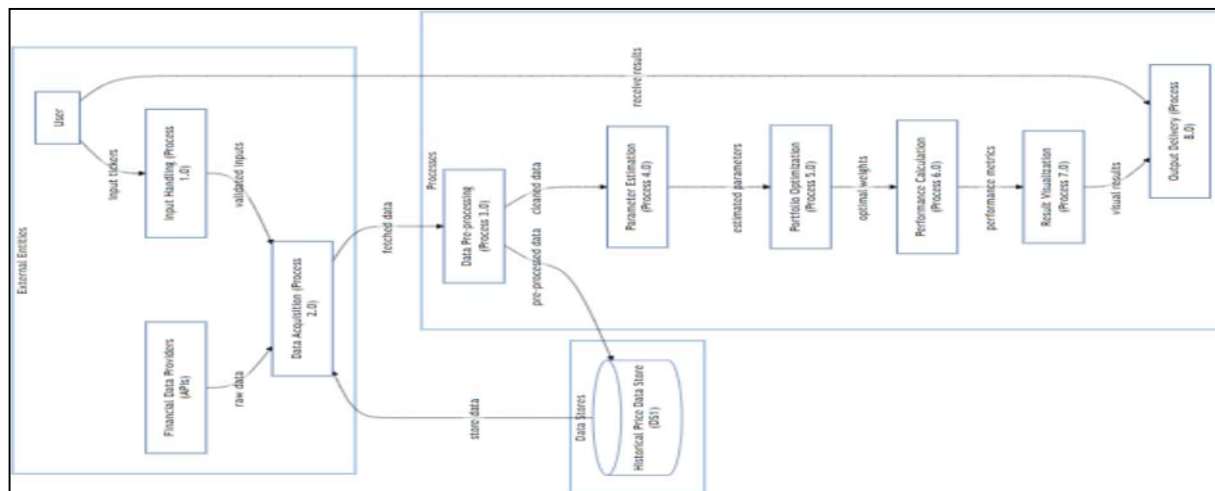


Figure 2. Data flow diagram (DFD), tracing the flow of ticker input, historical price data, pre-processed data, estimated parameters, optimal weights, and performance metrics through the system's eight constituent processes.

Figure 3 shows the use case diagram, summarising the eight interactions available to the user: selecting assets, fetching data, viewing performance, generating the Efficient Frontier, identifying the maximum Sharpe and minimum volatility portfolios, viewing metrics, and downloading data.

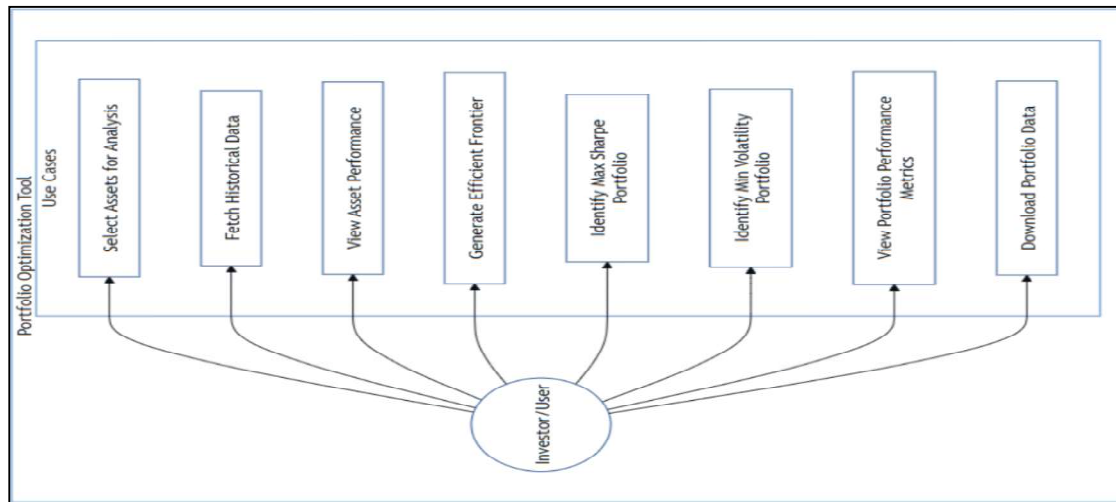


Figure 3. Use case diagram, summarising the eight core interactions available to the investor/user within the portfolio optimisation tool.

2.3 Development Environment and Tools

The tool was developed in Python using PyPortfolioOpt, Streamlit, Pandas and NumPy, and the EODHD API for historical Nigerian equity data (Martin, 2021). EODHD was selected as a budget-friendly financial data API provider that offers institutional-grade data to retail investors, developers, and small firms.

2.4 Data Acquisition and Pre-processing

Historical equity-price data were acquired through the EODHD API. The dataset was processed before portfolio optimisation to address missing observations, ensure consistent data types, and derive daily simple returns from adjusted closing prices. These preprocessing steps were necessary because the estimated expected returns and covariance matrix form the principal inputs to the MPT optimisation procedure. Several data-quality safeguards were incorporated into the processing workflow. Daily returns exceeding $\pm 20\%$ were clipped to those bounds, while annualised returns exceeding 50% were capped. Return series exhibiting zero variance or infinite values were flagged and excluded. The covariance matrix was checked for symmetry and

positive definiteness, with regularisation applied where necessary to facilitate stable optimisation.

Where fewer than 200 trading days were available, the manuscript specifies that the return series was bootstrapped and augmented to 500 observations to improve covariance-estimation stability. This procedure was incorporated as a data-sufficiency safeguard within the processing workflow. The risk-free rate used for the Sharpe-ratio calculation was set at 18.84%, corresponding, according to the study design, to the Nigerian Treasury Bill rate in June 2025. The rate was incorporated into the portfolio optimisation and risk-adjusted performance calculations.

2.5 Portfolio Optimisation Algorithm Implementation

Portfolio optimisation was implemented using the Efficient Frontier functionality of PyPortfolioOpt. Expected returns were estimated using historical average returns, while the covariance matrix was estimated from the corresponding historical return series. Thus, the expected-return and covariance estimates used in optimisation were derived from the

same underlying return observations. The optimisation was constrained to long-only portfolios, with a maximum allocation of 50% to any individual stock. This constraint was intended to limit excessive concentration in a single security while allowing the optimisation procedure sufficient flexibility to identify portfolios with different risk–return characteristics.

Two optimisation objectives were evaluated. The first maximised the portfolio Sharpe ratio using the specified risk-free rate, while the second minimised portfolio volatility. The resulting allocations were processed using PyPortfolioOpt's weight-cleaning functionality to obtain feasible portfolio weights suitable for presentation to users.

The optimisation outputs represent model-estimated portfolio characteristics based on historical data and the specified assumptions. They are therefore interpreted as expected rather than guaranteed or realised investment outcomes.

2.6 User Interface Development

The interface placed portfolio parameters and ticker selection in a sidebar, with dynamic outputs in the main area, keeping complexity out of the user's immediate view. Figure 4 shows the resulting interface, branded the Nigerian Portfolio Wizard, through which a user filters stocks by sector and sets parameters such as rebalancing frequency, risk level, investment horizon, and the risk-free rate.

	Code	Name
0	ABBEYES	ABBEY MORTGAGE BANK PLC
1	ABCTRAVS	ABC TRANSPORT PLC
2	ACADEMY	ACADEMY PRESS PLC
3	ACCESSCORP	ACCESS HOLDINGS PLC
4	AFRINSURE	AFRICAN ALLIANCE INSURANCE PLC
5	AFRIPRUD	AFRICA PRUDENTIAL PLC
6	AFROMEDIA	AFROMEDIA PLC
7	AIICO	AIICO INSURANCE PLC
8	AFRIMOB	AFRIMOB

Figure 4. The tool's stock selection interface (Nigerian Portfolio Wizard), showing sector-based filtering of available NGX-listed stocks, portfolio parameter controls, and step-by-step usage guidance for the investor.

Interactive Plotly charts visualised the Efficient Frontier and asset performance, while summary panels and pie charts presented metrics and weights, a direct response to the usability requirements (NFR009 to NFR011).

2.7 System Testing and Validation

System validation comprised four complementary forms of software testing: unit testing, integration testing, functional testing, and user acceptance testing (UAT). Unit testing examined individual system functions, while integration testing assessed interactions among the data-acquisition, data-processing, and portfolio-optimisation modules. Functional testing examined the complete workflow from user input and market-data retrieval through parameter estimation, optimisation, and presentation of portfolio outputs. User Acceptance Testing (UAT) with non-specialist users was used to assess interface usability, navigation, and the clarity of the resulting outputs. Performance testing using the six-asset test portfolio confirmed that the system returned results within five seconds, satisfying NFR001. The 30-second optimisation requirement for a 50-asset portfolio (NFR002) remained a design target for larger asset universes and was not treated as a demonstrated result of the six-asset evaluation.

For portfolio evaluation, six Nigerian equities including SFSREIT, FIDSON, ACADEMY, TRANSPOWER, TRANSCORP, and UPL were selected from the available NGX-listed assets. The selection was guided principally by the availability of usable historical price observations required for return and covariance estimation and by the suitability of the securities for demonstrating diversification across different business sectors. Using a manageable six-asset universe also provided a transparent test case through which the operation of the optimisation procedure, portfolio weights, and risk–return characteristics could be examined without introducing unnecessary complexity into the system evaluation. The selected assets therefore served as a representative test portfolio for demonstrating the tool's optimisation workflow, rather than as a claim that they constitute the most liquid, largest, or otherwise optimal securities on the NGX.

Portfolio evaluation was treated separately from

software-system validation. Whereas the software tests examined whether the application operated according to its specified requirements, the portfolio evaluation examined the characteristics of the portfolios produced by the implemented MPT procedures. The maximum-Sharpe and minimum-volatility portfolios were compared with an equally weighted portfolio constructed from the same six candidate assets. The equally weighted portfolio was selected as a simple and transparent baseline because it applies the same asset universe without optimisation and therefore provides a straightforward reference point for examining the effect of the MPT allocation procedure. It was not treated as a comprehensive representation of alternative investment strategies.

The empirical portfolio evaluation covered the period June 2024 to June 2025. Portfolio expected returns, volatility, and Sharpe ratios were estimated using the MPT procedures described in Sections 3.4 and 3.5. Additional risk measures, including Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and maximum drawdown, were examined to provide supplementary information about downside and realised portfolio behaviour. The evaluation consequently distinguishes between two forms of evidence. First, software testing provides evidence concerning the functionality, integration, usability, and response performance of the developed application. Second, portfolio evaluation describes the risk–return characteristics generated by the implemented optimisation procedures within the selected six-asset universe, study period, and modelling assumptions. The comparison with the equally weighted portfolio is therefore interpreted as an **in-study benchmark comparison**, rather than evidence of persistent or generalised investment outperformance for Nigerian investors (Nnanwa *et al.*, 2016).

3. Results

3.1 Portfolio Allocation Output

The developed tool was evaluated using six Nigerian equities, SFSREIT, FIDSON, ACADEMY, TRANSPOWER, TRANSCORP, and UPL over the period June 2024 to June 2025. The six-asset portfolio was used as an illustrative test case for examining the optimisation workflow, allocation outputs, and associated risk–return characteristics. The maximum-Sharpe optimisation generated portfolio weights of 30.0% for SFSREIT, 26.1% for FIDSON, 16.4% for ACADEMY, 15.0% for TRANSPOWER, 10.6% for TRANSCORP, and 1.9% for UPL. The resulting portfolio had a model-estimated expected annualised return of 39.50% and annualised volatility of 19.84%.

Results & Analysis

Expected Annual Return

39.50%

↑ 395,012 NGN

Investment Horizon: 1 - Returns and risk metrics are calculated based on this time period. Longer horizons

Portfolio Allocation

Portfolio Allocation: Shows the percentage of your investment allocated to each selected stock.

Portfolio Allocation



Figure 5. Results and analysis dashboard showing the expected annual return (39.50%) and portfolio volatility (19.84%) for the maximum Sharpe ratio portfolio, together with its resulting six-asset allocation.

The allocation demonstrates how the optimisation procedure incorporates the joint risk–return characteristics of the selected securities rather than allocating capital solely according to individual asset returns. No single security received more than the imposed 50% allocation constraint, and capital was distributed across all six assets. The relatively small allocation to UPL also illustrates that the optimisation does not require equal participation by every security when the estimated return and covariance structure favours alternative allocations. The 39.50% figure represents an expected annualised return estimated by the MPT model from the historical return data; it is not a realised return observed over June 2024–June 2025 and should not be interpreted as a forecast or guarantee of future performance. The result therefore demonstrates the output of the estimation and optimisation process rather than evidence that an investor actually earned 39.50% during the evaluation period (Ahmar *et al.*, 2025) documented in an analogous market.

3.2 Risk Metrics and Sharpe Ratio

Figure 6 presents the risk-analysis output for the maximum-Sharpe portfolio. The portfolio produced a Sharpe ratio of 1.041, while the historical return distribution generated an approximate annualised 95% Value-at-Risk (VaR) of 23%, Conditional Value-at-Risk (CVaR) of 31%, and maximum drawdown of approximately 8%.

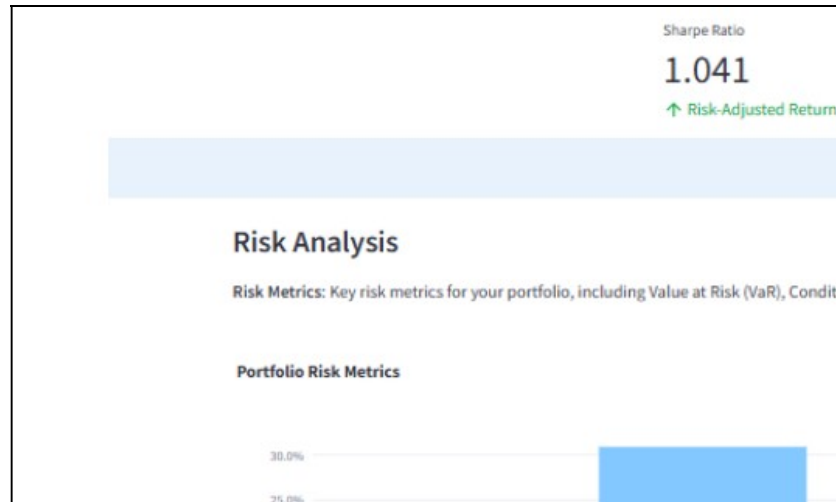


Figure 6. Risk-analysis output for the maximum-Sharpe portfolio, showing the Sharpe ratio, Value-at-Risk (95%), Conditional Value-at-Risk (95%), maximum drawdown, and volatility.

The VaR and CVaR measures were calculated empirically from the realised daily portfolio-return distribution rather than from a parametric normality assumption. This provides supplementary information about the historical downside characteristics of the portfolio, particularly because mean–variance optimisation does not explicitly optimise tail risk. The maximum drawdown similarly provides a historical measure of the largest observed decline from a previous portfolio peak during the evaluation period. A distinction is important between the risk measures reported in Figure 6 and the annualised volatility used within the optimisation. The 19.84% volatility associated with the maximum-Sharpe portfolio is derived from the estimated covariance matrix used by the MPT procedure, whereas the VaR, CVaR, and maximum drawdown are calculated from the realised portfolio-return series. Consequently, these measures describe different aspects of portfolio risk and should not be treated as interchangeable.

The Sharpe ratio of 1.041 indicates that, under the return and covariance estimates used by the model and the specified risk-free rate, the maximum-Sharpe portfolio generated a higher estimated excess return per unit of estimated volatility than the equally weighted benchmark. The finding is meaningful within the selected test portfolio, but the Sharpe ratio should not be interpreted as evidence of persistent or generalised superior performance for Nigerian investors. Rather, it demonstrates that the implemented optimisation procedure identified a more favourable estimated risk–return combination than the simple benchmark under the

conditions examined. The inclusion of VaR, CVaR, and maximum drawdown alongside the Sharpe ratio also improves the informational value of the tool. Although the optimisation remains fundamentally mean–variance based, users are presented with additional historical downside indicators that standard deviation alone does not capture. This is particularly relevant given the limitations of relying exclusively on mean and variance when return distributions exhibit non-normal characteristics (Rockafellar & Uryasev, 2000; Zhang, 2024).

3.3 Comparative Portfolio Performance

Table 3 compares the maximum-Sharpe portfolio, minimum-volatility portfolio, and equally weighted benchmark constructed from the same six assets. The equally weighted portfolio provides a simple and transparent baseline against which the effect of optimisation can be examined. It is not intended to represent the full range of alternative portfolio-construction strategies available to investors.

Table 3. Portfolio performance metrics for the maximum-Sharpe portfolio, minimum-volatility portfolio, and equally weighted benchmark, June 2024–June 2025

Portfolio type	Expected annualised return (%)	Annual volatility (%)	Sharpe ratio	Key asset weights: SFSREIT / FIDSON / ACADEMY / TRANSPOWER / TRANSCORP / UPL
Maximum-Sharpe portfolio	39.50	19.84	1.041	30.0% / 26.1% / 16.4% / 15.0% / 10.6% / 1.9%
Minimum-volatility portfolio	22.80	13.50	0.293	50.0% / 18.0% / 12.5% / 10.0% / 8.0% / 1.5%
Equally weighted benchmark	25.50	15.50	0.430	16.67% / 16.67% / 16.67% / 16.67% / 16.67% / 16.67%

The maximum-Sharpe portfolio produced the highest model-estimated expected annualised return (39.50%) and the highest Sharpe ratio (1.041) among the three portfolios. Its estimated annualised volatility was 19.84%, compared with 15.50% for the equally weighted benchmark. Thus, the optimisation produced a higher estimated return and higher estimated volatility than the benchmark, but the increase in estimated return was proportionally larger than the increase in estimated risk, resulting in the higher Sharpe ratio.

The minimum-volatility portfolio provides a contrasting optimisation objective. Its estimated annualised volatility of 13.50% was the lowest among the three portfolios, but its expected annualised return of 22.80% was also lower than the 25.50% estimated for the equally weighted benchmark. Its Sharpe ratio of 0.293 was consequently below the benchmark value of 0.430. This result illustrates an important distinction between minimising volatility and maximising risk-adjusted return: reducing estimated variance does not necessarily produce the highest estimated excess return per unit of risk. The allocation patterns further demonstrate this trade-off. The minimum-volatility solution assigned the maximum permitted 50.0% to SFSREIT, compared with 30.0% under the maximum-Sharpe solution.

The concentration reflects the optimisation constraint and the covariance structure estimated from the available historical observations. It also highlights a practical consideration for users of the tool: an allocation that minimises estimated volatility can produce greater concentration in particular securities and may therefore warrant additional consideration beyond the volatility objective itself.

Within this specific six-asset experiment, the maximum-Sharpe portfolio therefore had a higher estimated Sharpe ratio than the equally weighted benchmark (1.041 versus 0.430). This finding is consistent with the underlying purpose of MPT optimisation, which seeks an allocation that improves the estimated risk–return trade-off relative to an unconstrained or non-optimised allocation. It is also broadly consistent with evidence from Nigerian portfolio studies showing the potential usefulness of Markowitz-based allocation techniques (Nnanwa *et al.*, 2016). However, the present result extends that analytical idea into an interactive software implementation rather than establishing that the optimised strategy will consistently outperform alternative strategies across Nigerian market conditions.

4. Discussion

4.1 Discussion of System Testing, Validation, and Practical Challenges

The software evaluation provided evidence that the principal components of the application operated as intended. Unit testing examined individual functions, integration testing examined interactions among the data-acquisition, data-processing, and optimisation components, and functional testing assessed the complete workflow from user input to portfolio-output generation. User Acceptance Testing (UAT) indicated that the interface controls and dashboard outputs were navigable and understandable to non-specialist users. Performance testing using the six-asset test portfolio produced response times below

five seconds, satisfying the NFR001 requirement. The NFR002 requirement of optimisation of up to 50 assets within 30 seconds remained a design target for larger asset universes and was not treated as a demonstrated performance result of the present six-asset evaluation. This distinction is important because successful operation with six assets does not by itself establish that the same response time will be achieved for substantially larger portfolios.

Two practical challenges were particularly relevant to the development of the tool. First, inconsistencies in the quality of financial data retrieved for Nigerian equities required additional preprocessing and data-quality safeguards before the optimisation procedure could be applied. This reinforces the importance of data preparation when historical observations are used to estimate expected returns and covariance matrices. The issue is consistent with the broader concern that portfolio optimisation results can be sensitive to the quality and characteristics of historical financial data (Iyobor *et al.*, 2025; Xu, 2025). Secondly, generating the Efficient Frontier and estimating the covariance structure introduced computational demands that required engineering trade-offs to maintain the responsiveness expected of an interactive application. The finding demonstrates that translating a mathematical optimisation procedure into a usable software application involves not only implementing the underlying financial model but also managing data processing, computational efficiency, interface responsiveness, and error handling.

Taken together, the results provide two distinct forms of validation. The software testing demonstrates that the developed application can execute the specified portfolio-analysis workflow and provide interactive outputs within the demonstrated performance conditions. The portfolio evaluation demonstrates that the implemented MPT procedures can generate differentiated allocations corresponding to maximum-Sharpe and minimum-volatility objectives and that,

within the selected six-asset universe and study period, the maximum-Sharpe solution produced a higher estimated Sharpe ratio than the equally weighted benchmark.

The findings therefore support the feasibility of using an accessible software implementation of MPT for portfolio analysis in the Nigerian market. They do not, however, establish universal investment superiority. The portfolio estimates remain dependent on the selected securities, historical observations, expected-return estimation method, covariance matrix, risk-free rate, optimisation constraints, and evaluation period. These dependencies are consistent with the known sensitivity of classical MPT to estimation error and historical-data assumptions and define the appropriate boundaries for interpreting the present findings.

5. Conclusion

This study developed an interactive portfolio optimisation tool for Nigerian Exchange (NGX)-listed equities using Modern Portfolio Theory. The tool integrates historical market data, portfolio optimisation, Efficient Frontier analysis, and visualisation. Within the six-asset portfolio evaluated from June 2024 to June 2025, the maximum-Sharpe portfolio achieved a higher estimated Sharpe ratio than the equally weighted benchmark, while the minimum-volatility portfolio recorded the lowest volatility. These findings demonstrate the practical value of the tool while remaining specific to the selected assets, study period, and model assumptions. Future work should incorporate broader asset selections, longer datasets, transaction costs, and alternative risk measures.

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Conflict of Interest Declaration

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The historical market data used in this study were obtained from EODHD through their API. The data are available from the corresponding author upon reasonable request, subject to any restrictions imposed by the data provider. The source code for the portfolio optimisation tool is available from the corresponding author upon reasonable request.

Authors' Contributions

Mohammed Lawal: Conceptualisation, methodology, software development, data analysis, writing—original draft, writing—review and editing. Abdulquadri O. Oyeku: Methodology, validation, writing—review and editing. Jamiu O. Ibrahim: Data analysis, validation, writing—review and editing. Alli O. Abdurrazaq: Supervision, methodology, validation, writing—review and editing.

All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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