IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Quantum Enhancement Investment Recommendation

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Abstract: This research presents a Hybrid Classical-Quantum Investment Recommendation Framework aimed at improving retail investor profitability through flexible, multi-asset portfolio structuring. To avoid the processing limits and fractional-share restrictions found in traditional models like Modern Portfolio Theory, this new system uses a Two Phase Dynamic Market Screener. This tool assesses high-momentum stocks alongside safer capital assets, specifically Digital Gold and Fixed Deposits. For accurate short-term price prediction, the platform employs a combination of classical machine learning algorithms, such as ARIMA and LSTM. At the same time, it integrates Generative AI (Gemini) to evaluate real-time macroeconomic news sentiment, turning complex market information into clear and understandable investment reasons. A key feature of this system is an automated Risk Profiler that continuously adjusts asset allocation based on user demographics. One example is a mandatory "Capital Protection Mode" aimed at protecting the investments of senior citizens. To handle complex portfolio construction, the framework uses the Quantum Approximate Optimization Algorithm (QAOA). By framing the allocation task as a 0-1 Knapsack combinatorial problem, the system ensures mathematically superior and fully executable whole share distributions. Supported by an integrated Smart Tax Advisor focused on automated tax loss harvesting, this system acts as a responsive and investor-oriented model for future FinTech ecosystems.

Keywords: Portfolio Optimization, Quantum Computing, Risk Analysis, Behavioral Finance, Hybrid Classical-Quantum Algorithms, Financial Forecasting.

INTRODUCTION

Background: Successful wealth management relies on optimizing portfolios to balance potential returns with financial risks. Traditional frameworks, like Modern Portfolio Theory, used continuous variables that theoretically allowed for fractional-share buying. However, trading platforms need whole-share allocations. This situation makes portfolio generation a complex 0-1 Knapsack problem, which creates significant processing delays for classical computing systems. Moreover, standard algorithms do not consider real-time macroeconomic sentiment or specific demographic needs, such as capital protection for older investors. To address these issues, our architecture combines the Quantum Approximate Optimization Algorithm for precise whole-share distribution with Generative AI to create highly personalized, sentiment-aware risk profiles

Motivation: Today's retail investors face the constant challenge of pursuing aggressive capital appreciation while securing essential downside protection. Conventional financial platforms frequently overlook this dilemma, providing uniform advice that neglects demographic realities, such as a senior citizen's strict requirement for capital preservation. Moreover, classical portfolio optimization models inherently rely on fractional-share purchasing, making their theoretical allocations impossible to execute on typical retail markets. Consequently, there is a pressing demand for an adaptable, context-sensitive advisory architecture. By synergizing automated demographic risk-profiling, Generative AI for instantaneous market sentiment evaluation, and Quantum Computing (QAOA) to resolve the discrete whole-share allocation constraint, this framework successfully delivers mathematically precise and deeply individualized investment strategies.

Existing Work: The modern financial scene includes several automated investment systems, commonly called robo-advisors, such as Wealthfront, Betterment, and Q.ai. Betterment depends significantly on Exchange Traded Funds (ETFs) guided by fixed, rule-based algorithms. Similarly, Wealthfront creates client portfolios mainly from cash reserves and ETFs, using data gathered through regular risk-assessment surveys. In contrast, Q.ai runs an algorithmic trading system that uses artificial intelligence to assess market sentiment, influencing its short-term equity choices.

Drawbacks of Existing System: The current financial environment has many automated investment systems, commonly called robo-advisors. Some notable examples are Wealthfront, Betterment, and Q.ai. Betterment uses Exchange Traded Funds (ETFs) based on fixed, rule-based algorithms. Similarly, Wealthfront creates client portfolios mainly from cash reserves and ETFs, using data from standard risk-assessment surveys. In contrast, Q.ai employs an algorithmic trading structure that uses artificial intelligence to assess market sentiment, which influences its short-duration equity choices.

Proposed Approach: The proposed system updates retail financial advisory by creating a hybrid classical-quantum structure. It moves beyond traditional, rule-based advisors. This platform works as a dynamic quantitative engine that evaluates equities, commodities, and fixed-income assets. It uses a Two-Phase Dynamic Screener that pulls live API data to filter high-momentum assets. Then, it carefully forecasts these using classical machine learning models like ARIMA and LSTM. At the same time, Generative AI combines live macroeconomic news to produce easy-to-understand sentiment analysis. One main innovation is the built-in demographic Risk Profiler. This tool adjusts market exposure and automatically directs capital into safe-haven assets for senior citizens. To complete the portfolio, whole-share allocation is set up mathematically as a 0-1 Knapsack combinatorial problem. The Quantum Approximate Optimization Algorithm (QAOA), using the Qiskit framework, solves this to ensure optimal capital distribution. With a secure, asynchronous backend that manages user profiles and activity logs, this hybrid framework effectively translates complex, multi-factor data into clear, personalized, and actionable financial advice.

FUNDAMENTALS OF PORTFOLIO MANAGEMENT AND QUANTUM COMPUTING

Basics of Portfolio Management Portfolio management is the process of selecting and overseeing a group of investments that meet the long-term financial goals and risk tolerance of a client, company, or institution. The main aim is to construct an "efficient frontier," which is a set of optimal portfolios that provide the highest expected return for a specific level of risk. Your project uses Modern Portfolio Theory (MPT) to achieve this through diversification. This involves spreading capital across uncorrelated asset classes like stocks, gold, real estate, fixed deposits, and cryptocurrencies to reduce unique risks. To ensure solid financial planning, the system includes classical risk analysis techniques. Value at Risk (VaR) is used to measure the maximum potential loss over a certain period with a specified confidence level. This provides a clear metric for downside risk. Additionally, Monte Carlo simulations help model the likelihood of different outcomes in unpredictable situations caused by random variables. This allows the system to stress-test portfolios against thousands of potential market scenarios. Moreover, predictive modelling relies on time series algorithms, including ARIMA, Prophet, and Long Short-Term Memory (LSTM) networks. These analyse historical data to predict future asset returns before optimization starts. Despite their usefulness, these traditional methods often struggle with the computational demands of large, high-dimensional datasets common in modern finance.

Basics of Quantum Algorithms: Quantum computing uses superposition and entanglement to solve combinatorial problems that classical methods cannot handle. This project combines two main hybrid protocols

Quantum Approximate Optimization Algorithm (QAOA): Quantum Approximate Optimization Algorithm (QAOA): This algorithm is meant for combinatorial tasks. It translates asset selection into a Quadratic Unconstrained Binary Optimization (QUBO) model. It explores large solution spaces to find nearly optimal configurations for portfolio construction.

Overview of Quantum Investment Concepts: Once encoded as a QUBO model, quantum protocols like QAOA find optimal configurations without getting stuck in local optima that often impact classical approaches. By using superposition, these algorithms explore large solution spaces at the same time, effectively handling complex constraints like liquidity, capital limits, and risk thresholds. This leads to a scalable system that can rebalance portfolios in real time as market conditions change rapidly

PROBLEM STSTEMENT

Where should I invest to get high returns?
How do I balance profit with safety?
Which assets will grow the most over time?
How can I plan my investments according to my financial goals?

METHODOLOGY

Data Acquisition and Preprocessing: The architecture uses a live data pipeline to gather market updates through a WebSocket link to the Angel One SmartAPI. This setup allows for the constant streaming of National Stock Exchange (NSE) securities. It also incorporates historical performance data and Exchange-Traded Fund (ETF) information for commodities like Gold and Silver through the yfinance library. Additionally, it collects macroeconomic indicators and global news using NewsAPI. All processed market data and user logs are stored in a local SQLite database, ensuring quick access and efficient data management.

Generative AI Fundamental and Sentiment Analysis: The predictive module includes a generative AI framework to analyze financial data and market news at the same time. By processing key company indicators and news headlines through Gemini, the system generates structured investment insights and categorizes market sentiment into three labels: Buy, Hold, or Sell. These sentiment metrics, along with expected returns, serve as the main input for the portfolio optimization phase.

Hybrid Quantum Optimization Framework: The allocation strategy is designed as a discrete optimization challenge, akin to a knapsack model, with the goal of maximizing anticipated returns within specified capital constraints. This optimization logic is developed using the Qiskit framework and resolved via the Quantum Approximate Optimization Algorithm (QAOA). To maintain system reliability and guarantee execution, a classical dynamic programming solver is integrated as a secondary fallback mechanism.

Backend Processing and Tax Analysis: To ensure real-world feasibility, the initial quantum results are processed by a Classical Feedback Optimizer. This component reviews the output to make sure that key limitations, like liquidity needs and overall capital allocation, are strictly met. The final portfolio is then sent to the application's backend through a FastAPI or Flask interface for smooth delivery

Presentation Layer and User Interaction: The front-end architecture uses server-side rendered templates along with Tailwind CSS to create a responsive and interactive dashboard. Real-time market visualization is achieved through Trading View widgets. Important user actions, such as ticker searches and portfolio optimization requests, are logged securely to support ongoing session tracking and personalized analytics.

SYSTEM ARCHITECTURE

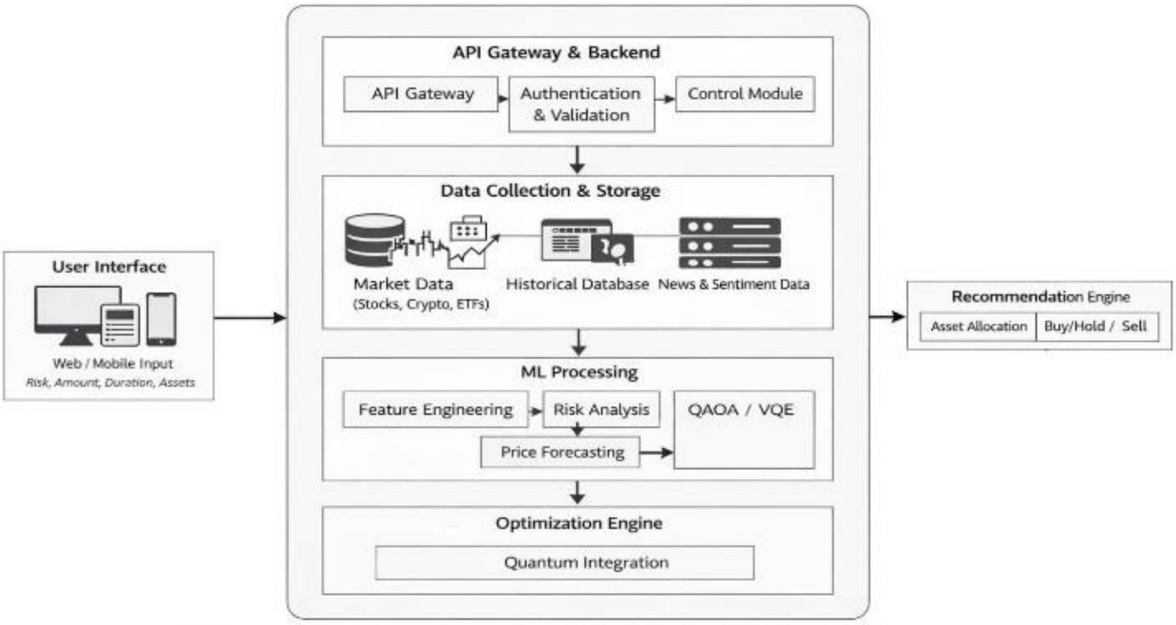


Figure 1 Architecture

The system's framework is designed to provide smart investment guidance using data pipelines and machine learning. The process starts at the user interface, where the system captures parameters like capital, risk tolerance, and investment horizon through a web or mobile dashboard. These inputs go through an API Gateway to the backend, which handles authentication, input validation, and process management. The data acquisition layer then collects market variables, including equities, crypto, and ETFs, along with news sentiment and historical logs for storage. In the machine learning layer, the system performs feature engineering and price forecasting, using QAOA and VQE to improve accuracy. An optimization engine combines these results to generate an ideal strategy using both quantum and classical methods. Finally, the recommendation engine provides specific asset allocations and Buy, Hold, or Sell signals to support informed financial decisions.

IMPLEMENTATION

The proposed hybrid classical-quantum investment architecture is built entirely in the Python ecosystem. It uses a high-performance backend managed by the FastAPI framework and the Uvicorn ASGI server. The system continuously pulls in real-time market data and historical datasets through the Angel One SmartAPI and Yahoo Finance. It also includes macroeconomic news streams through NewsAPI. Key financial indicators and statistical features are calculated with the Pandas and NumPy libraries. To assess market volatility and create high-quality investment strategies, the framework uses TextBlob for sentiment scoring and the Gemini large language model through the googlegenai SDK for advanced generative intelligence.

Component	**Library / Tool Used**
Web Framework	FastAPI 0.100+, Uvicorn (ASGI Server), Jinja2 Templates
Quantum Computing	Qiskit, qiskit-algorithms, qiskit-optimization (QAOA, Knapsack, MinimumEigenOptimizer, CO
Generative AI	Gemini via google-genai SDK

Machine Learning	TensorFlow/Keras (LSTM), statsmodels (ARIMA), scikit-learn (MinMaxScaler)
Market Data Sources	yfinance, SmartApi-Python (Angel One), NewsAPI (via requests)
Sentiment Analysis	TextBlob for polarity scoring of financial news
Authentication	bcrypt password hashing and HTTP-only session cookies
Database	SQLite3 database with SQLAlchemy Async ORM
Frontend	Tailwind CSS, Font Awesome 6, TradingView Widget JavaScript, Vanilla JavaScript WebSock

RESULTS AND DISCUSSION

Results: The Following the data synthesis phase, the primary portfolio allocation is mathematically structured as a 0-1 Knapsack problem. This combinatorial optimization is solved using the Quantum Approximate Optimization Algorithm (QAOA) via the IBM Qiskit framework to determine the ideal distribution of whole-share capital. The backend infrastructure maintains persistent data integrity through a local SQLite database, interfaced via the SQLAlchemy ORM. Security is prioritized through rigorous authentication mechanisms, including bcrypt hashing and the implementation of HTTP-only session cookies. The frontend is developed using Jinja2 templates and styled with Tailwind CSS, while interactive market visuals and live analytics are delivered via TradingView widgets. Finally, native JavaScript WebSockets facilitate asynchronous data streams for real-time price updates across the investment dashboard.

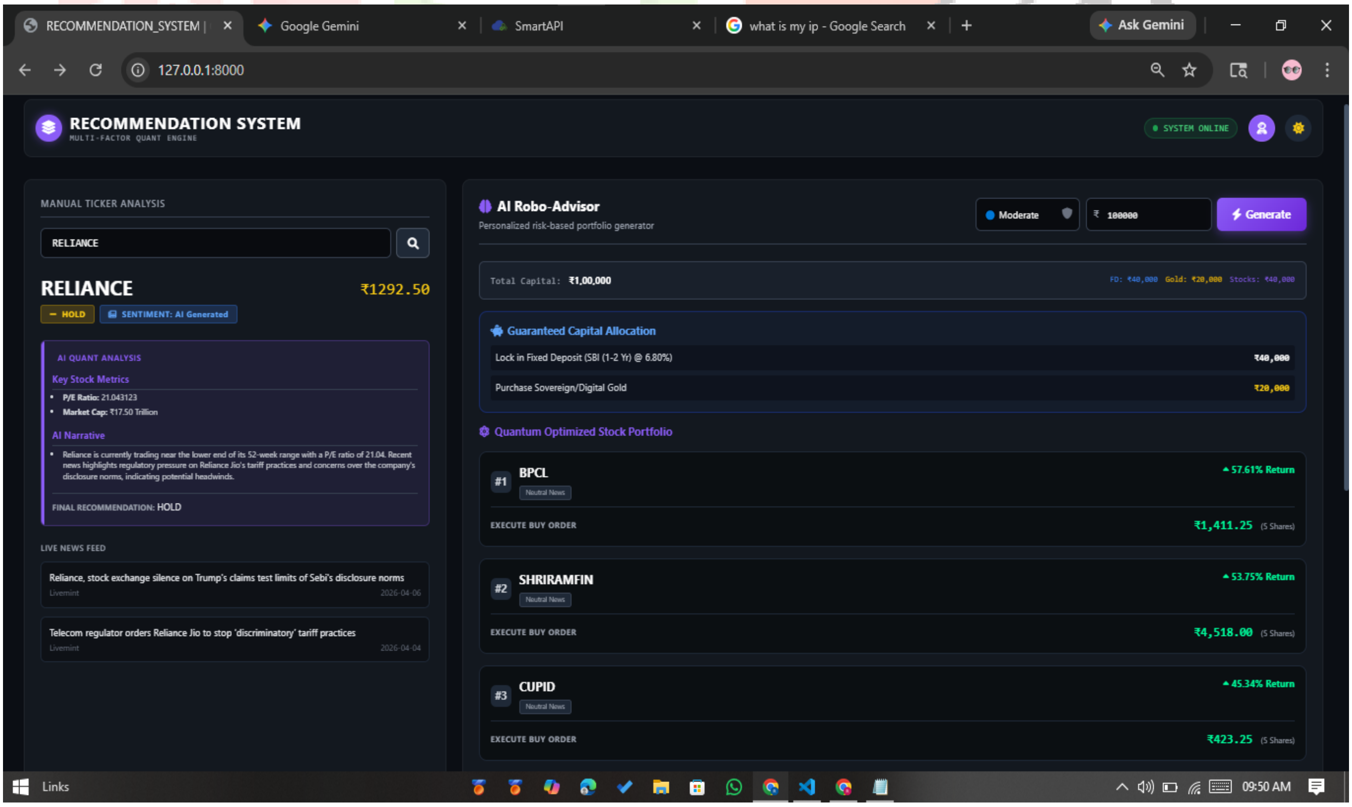


Figure 2: An AI-based dashboard recommending alternative stocks based on analysis of TCS

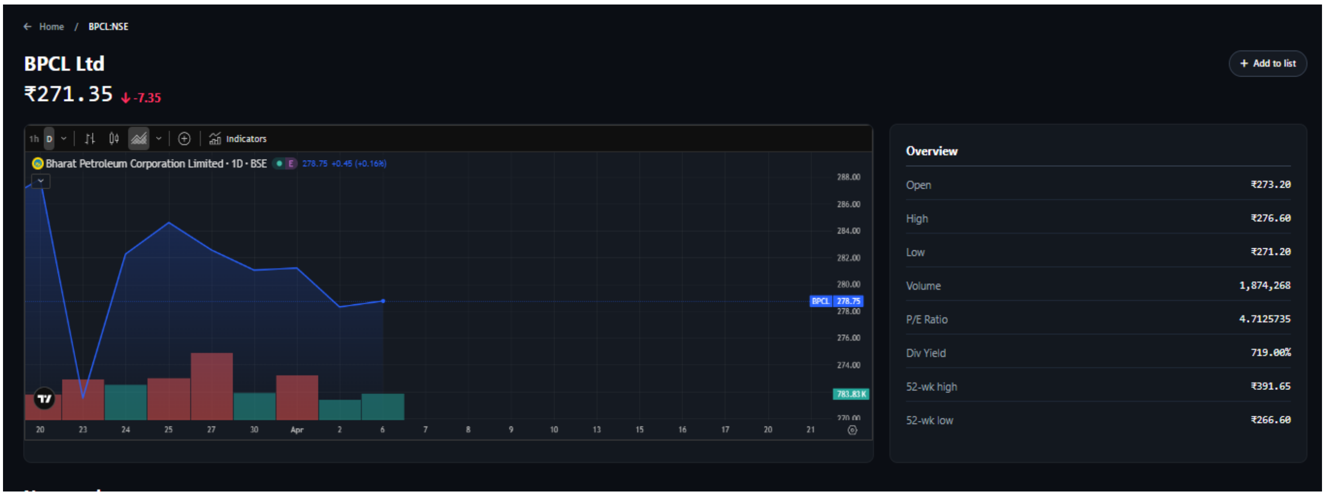
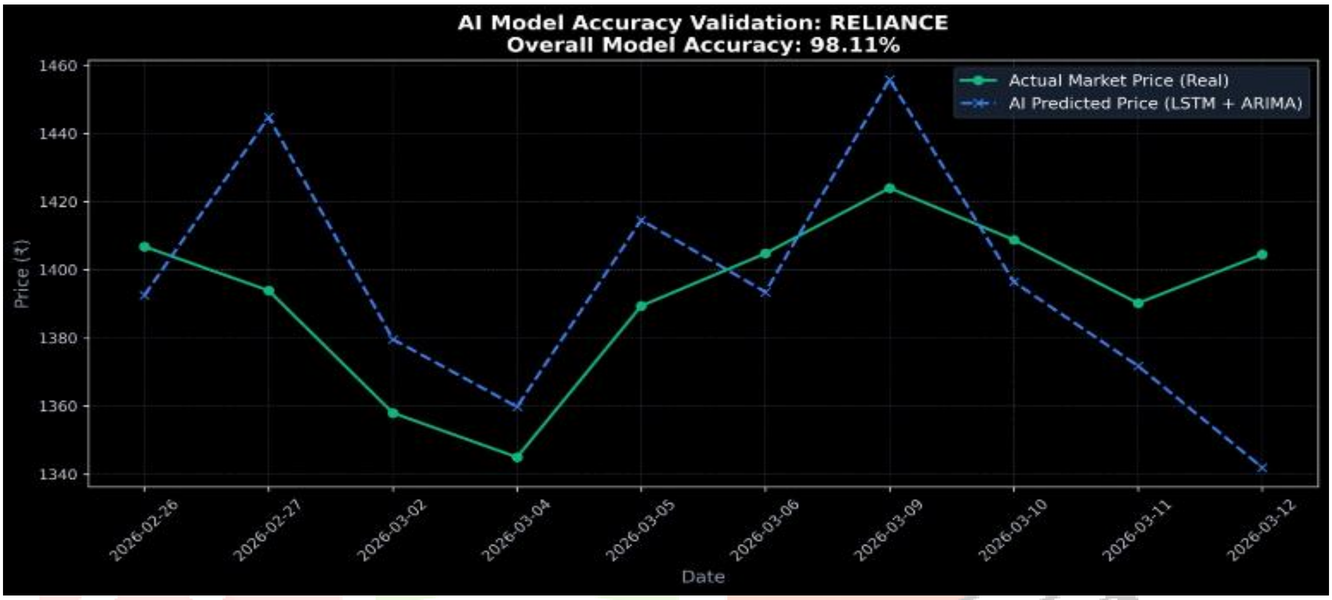


Figure 3 This figure displays the ONGC Ltd stock price chart with key market statistics and trading



performance

Figure 4These figures compare actual vs AI-predicted stock prices for Reliance Industries Ltd showing model validation accuracy of about 98.11%

Discussion: Empirical findings show that combining classical machine learning with quantum optimization creates a strong and effective framework for investment advisory systems. Legacy portfolio strategies often lead to fractional asset weights. In contrast, the discrete optimization method used here produces practical, whole-share recommendations for retail investors. The high-precision results from classical forecasting offered stable parameters for the quantum optimization layer. This enables efficient evaluation of asset pairings within specific capital limits. However, due to hardware limitations, we ran the quantum processes on a simulator instead of actual quantum processors. Additionally, the system relies on third-party market APIs and external AI engines, which could introduce latency or inconsistent accuracy during times of extreme market volatility. Despite these challenges, the combined classical-quantum architecture shows significant promise for the future of fintech solutions.

CHALLENGES

Scalability of Quantum Algorithm: A main challenge in using quantum technologies for finance is the ongoing issue of scalability. Research shows that while protocols like QAOA have great potential, they hit performance limits when dealing with large asset universes. As the number of securities increases, the complexity of fitting constraints into a Quantum Unconstrained Binary Optimization (QUBO) model rises sharply. This creates a major hurdle for current quantum hardware, which has trouble efficiently optimizing high-dimensional portfolios under these growing computational demands.

Integration of Complex Risk Metrics: Current frameworks often struggle to incorporate complex financial risk indicators directly into their optimization structures. Many modern QAOA implementations do not effectively include important measures such as Value at Risk (VaR) or Conditional Value at Risk (CVaR).

Without these metrics, the optimization models can generate portfolios that seem mathematically sound but do not provide a solid grasp of downside risk exposure. This can lead to inadequate capital protection in volatile markets.

Adaptability to Dynamic Market Conditions: Traditional optimization methods and many modern AI-driven models often perform poorly in uncertain and changing market conditions. Many existing frameworks rely on fixed rules or past data, lacking the necessary tools for real-time adjustments. This lack of immediate insight makes it very difficult to maintain portfolio stability when market conditions change suddenly or unexpectedly, ultimately undermining the effectiveness of long-term investment strategies.

Limitations in Asset Diversity: A key shortcoming of past quantum portfolio structures is their limited focus on binary asset classes or overly simplified investment sets. Evidence suggests that these earlier frameworks did not have the computing power to handle complex diversification across multi-category portfolios. Similarly, major commercial platforms like Betterment and Wealthfront often restrict users to ETF-centric strategies. This approach inadvertently limits asset variety by excluding alternative investments such as real estate or cryptocurrencies.

Absence of Behavioral Analysis: A critical shortcoming in contemporary financial advisory architectures is the persistent lack of behavioral tracking capabilities. Popular platforms like Betterment and Q.ai are defined by an absolute deficiency in emotional bias detection mechanisms. These systems rely exclusively on algorithmic or static rule-based logic that presumes purely rational investor conduct, thereby neglecting psychological variables such as panic selling which fundamentally alter long-term wealth outcomes and overall financial success.

Lack of Explain ability (Black-box Model): Trust is essential in financial advising, yet many existing platforms use "black-box" investment methods. For instance, Wealthfront and Q.ai do not provide any explanations for their investment decisions, making the portfolios unclear to the user. This lack of transparency limits the user’s ability to understand why certain assets were chosen or how risk is being managed.

FUTURE SCOPE

The trajectory for quantum-enhanced financial advisory offers several compelling avenues for advancement. As quantum hardware matures, a primary objective will be the engineering of fully scalable algorithms designed to manage substantially larger asset universes. While this framework successfully validates a hybrid classical-quantum approach, subsequent iterations could investigate sophisticated ansatz configurations, such as the Dicke State Ansatz, to refine diversification logic within multi-category portfolios.

Another pivotal area for growth involves transitioning from advisory modeling to active execution. While the current scope is limited to computation and optimization deliberately omitting trading and regulatory frameworks future developments could integrate direct brokerage APIs. This would facilitate automated trade execution while embedding real-time compliance modules to ensure strict adherence to evolving financial legislation.

Furthermore, there is immense potential to advance the platform’s personalization engine. The "Adaptive Learning" module could be evolved to evaluate long-term behavioral trends, sharpening the precision of future guidance. Additionally, the "Smart Tax and Timing Advisor" could be scaled to manage intricate tax-loss harvesting and jurisdictional tax codes, offering granular insights into optimal entry and exit points. Finally, incorporating deeper sentiment analysis from diverse news and social media streams would further sensitize the risk profiling mechanism to global macroeconomic shifts.

CONCLUSION

Quantum-augmented investment optimization is a groundbreaking area where financial technology meets advanced computational mathematics. Recent breakthroughs in hybrid classical-quantum architectures, particularly the use of the Quantum Approximate Optimization Algorithm (QAOA), have effectively addressed the high-dimensional challenges of discrete asset allocation. By treating portfolio generation as a 0-1 Knapsack problem, the system can calculate optimal, executable whole-share distributions that classical computing methods find hard to process efficiently.

This intelligent advisory platform lays a solid foundation for overcoming the theoretical limits of traditional models, like Modern Portfolio Theory, which depend on fractional shares that cannot be executed. Additionally, by replacing generic algorithms with a dynamic, 3-tier Risk Profiler (Safe, Moderate, Aggressive) and implementing automated capital protection for vulnerable groups such as senior citizens, the system fits well with the realities of individual investors. The combination of Generative AI (Gemini) and a Smart Tax Advisor ensures that mathematical precision is coupled with understandable market sentiment and regulatory efficiency.

Overall, the findings show that this hybrid framework provides unmatched accuracy, flexibility, and execution capability compared to standard, rule-based robo-advisors. By enabling real-time portfolio adjustments across live NSE equities, fixed deposits, and digital gold, the system ensures data-driven decisions that align with personalized financial goals. This research confirms that merging quantum optimization with generative artificial intelligence has transformative potential, offering a highly scalable, user-friendly model for the future of automated wealth management.

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