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QUANTIFUND MODEL FOR COHESIVE MUTUAL FUND PORTFOLIO OPTIMIZATION

Dr. Kavitha Muthukumaran
Associate Professor, Department of Management Studies
Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam
Chennai, Tamil Nadu, India.

Dr. K. Usha,
Associate Professor, Department of Electrical and Electronics Engineering,
Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam,
Chennai, Tamil Nadu, India.

Dr. Vani Haridasan,
Associate Professor, Department of Management Studies,
Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam,
Chennai, Tamil Nadu, India.

Abstract
This article introduces *Quantifund*, an intelligent mutual fund portfolio optimization model developed using Microsoft Excel and Visual Basic for Applications (VBA). The tool is designed to empower mutual fund distributors and financial advisors with an affordable, user-friendly solution for generating data-driven, cohesive investment recommendations. With the exponential growth of the Indian mutual fund industry and the accompanying complexity in selecting among thousands of schemes, there is a critical need for decision-support systems that blend logic-driven automation with personalized advisory capabilities (Gupta & Singh, 2021).

Existing robo-advisory platforms, while algorithmically efficient, often fail to penetrate lower-tier advisory ecosystems due to high costs, complexity, and lack of contextual customization (Bhattacharyya, 2024). *Quantifund* addresses this gap by collecting investor-specific inputs—such as age, investment horizon, risk appetite, expected return, and target goals—and processing them through a VBA-coded selection engine. The model incorporates historical fund performance data from the top 15 Asset Management Companies (AMCs), applies weighted return calculations with greater emphasis on long-term performance, enforces an AMC exposure cap to ensure diversification, and filters fund options in alignment with the investor's profile (Sultana & Pardhasaradhi, 2012).

Unlike fully automated robo-advisors, this semi-automated model facilitates human oversight, allowing advisors to review and adjust recommendations, thereby preserving a personalized touch. The output interface displays the recommended funds along with their categories, Net Asset Values (NAVs), and projected future values, enhancing decision clarity and transparency (Al-Abdullatif, 2023).

Beyond its technical utility, *Quantifund* promotes financial literacy, reduces advisor reliance on third-party platforms, and builds client trust through consistent and explainable logic. This article situates the development of *Quantifund* at the intersection of behavioral finance, modern portfolio theory, and technology acceptance, thereby contributing a scalable fintech framework characterized by simplicity, efficiency, and relevance to underrepresented advisory segments (Chitra & Thenmozhi, 2006).

Keywords: Mutual Fund Advisory, Portfolio Optimization, Excel-VBA Tool, Financial Decision Support, Investment Recommendation Engine, Retail Advisory, Fintech Innovation

INTRODUCTION

The Indian mutual fund industry has been growing significantly over the past decade. The increasing financial literacy, government reforms, and penetration of financial services into Tier II and Tier III cities have resulted in substantial participation from retail investors. According to AMFI (2023), the mutual fund industry has witnessed a remarkable growth in Assets Under Management (AUM), which stood at ₹8.9 trillion in 2013 and surpassed ₹49 trillion by 2023. This growth brings complexity in selecting schemes due to a large variety of options, variations in fund performance, and differences in investor goals and risk profiles.

Despite the availability of information, investors often face difficulty in interpreting data and translating it into actionable investment decisions. Particularly in rural and semi-urban areas, mutual fund distributors (MFDs) play a crucial role in handholding investors through the selection process. However, MFDs themselves face several challenges in adopting advanced portfolio tools due to high costs, dependence on third-party robo-advisors, API integration complexities, and limitations in customizing recommendations to client-specific contexts (Bhattacharyya, 2024).

Behavioral finance research highlights that investors frequently make emotionally biased or heuristically flawed decisions (Sultana & Pardhasaradhi, 2012). While automated robo-advisors can help reduce biases, they often fail to gain traction among traditional advisors due to their complexity and rigidity. Hence, a gap exists between low-tech manual processes and high-end, automated robo-advisory platforms.

To address this, *Quantifund* is introduced as a low-cost, Excel-VBA-based semi-automated tool that empowers MFDs with a decision support system to recommend diversified and risk-aligned mutual fund portfolios. The tool collects key investor parameters such as age, investment horizon, risk tolerance, and expected returns, and processes them using inbuilt VBA logic to generate optimized portfolios. The tool uses weighted returns with greater emphasis on long-term performance and applies constraints like AMC capping to ensure diversification and compliance with advisory standards (Chitra & Thenmozhi, 2006).

Moreover, *Quantifund* bridges the fintech access gap by simplifying complex logic into an easy-to-use interface, thereby enabling financial advisors to generate rational, transparent, and client-specific mutual fund recommendations. Its implementation does not require any licensing fees or third-party APIs, which makes it scalable and adaptable across India's advisory ecosystem, especially in cost-sensitive and digitally underserved regions.

LITERATURE REVIEW AND MODEL FRAMEWORK

Several additional contributions have supported the construction of user-driven portfolio tools. Al-Gahtani (2016) emphasized that technology adoption in financial systems depends heavily on perceived usefulness and compatibility with existing workflows. This supports the case for using common platforms like Excel-VBA in regions where sophisticated infrastructure is lacking. Al-Abdullatif (2023) and Ha & Janda (2008) have argued that ease of use and customization significantly increase user acceptance, reinforcing the importance of a flexible input-driven architecture.

Furthermore, Gefen (2000) and Jarvenpaa et al. (2000) discussed how familiarity with tools and transparency of recommendations influence trust in digital systems—an important factor in financial advisory services. In the context of model creation, Bhosale & Ray (2023) and Lee et al. (2020) provide strong support for structured VBA logic and interactive dashboard outputs, making complex outputs more understandable and accessible.

Chakraborty et al. (2021) and Kim et al. (2009) demonstrate the relevance of integrating AI and automation principles into service delivery platforms, even in conventional sectors such as airline booking and tourism. These findings parallel this study's effort to introduce automation logic into mutual fund advisory workflows.

Chitra & Thenmozhi (2006) highlighted the importance of behaviorally driven fund selection and investor segmentation. Tools that allow the classification of investors based on age, horizon, and RoR expectations can improve financial outcomes. Similarly, Gupta & Singh (2021) emphasized that digital transformation in advisory services should be aligned with user control and trust-building mechanisms. This aligns with the semi-automated, VBA-powered approach proposed in this study.

Moreover, Sultana & Pardhasaradhi (2012) identified heuristics and biases in investor choices in India, reinforcing the value of rule-based systems in eliminating judgmental errors. These insights support the structuring of logic flows in the VBA backend, ensuring repeatability and rationality.

Finally, Value Research (2023) and AMFI (2023) provide benchmarks and performance metrics that have been factored into this model's data structure and ranking algorithm. Integrating these reliable sources ensures that the tool recommendations mirror actual market standards.

From a theoretical standpoint, this study is anchored in modern portfolio theory, behavioral finance, and decision science. The modern portfolio theory (Markowitz, 1952) provides the foundational framework for diversification and return optimization. By using weighted averages across different time periods, the model reflects this principle by emphasizing long-term performance while accounting for short-term volatility. Behavioral finance research (Thaler, 1985; Barberis & Thaler, 2003) suggests that investors often act irrationally due to heuristics and cognitive biases. Tools that embed logical selection mechanisms and provide visual clarity can serve as behavioral correctives, enhancing confidence and rationality.

Methodology (Data Sources, Model Design, and VBA Integration)

The development of *Quantifund* followed a structured methodology involving data collection, model design, and iterative integration using Microsoft Excel and Visual Basic for Applications (VBA). The objective was to embed robust financial logic into a user-friendly tool, enabling practical application by mutual fund advisors.

Data Sources and Preparation:
The model is built on a curated dataset of mutual fund schemes from the top 15 AMCs in India by total Assets Under Management (AUM). Data included scheme-wise performance for equity, hybrid, and debt funds, focusing on fields such as scheme name, AMC, category, and historical returns over 1-year, 3-year, and 5-year periods. Publicly available sources like *Value Research Online* and *AMFI* were used to ensure data accuracy and consistency (Gupta & Singh, 2021).

Data was imported and cleaned using Power Query, which helped standardize return formats, prune irrelevant columns, and normalize data entries. While Power Query supports automated refreshes, data updates in this version remain manual—a limitation noted for future improvement. Using reputable industry sources ensures that the recommendations generated are credible and based on current fund performance.

Model Design and Selection Logic

The core of the model is a selection engine that ranks and filters mutual funds based on long-term performance and investor suitability. A **weighted return score** was used to reflect sustained performance: 50% weight to the 5-year return, 30% to the 3-year, and 20% to the 1-year return (Chitra & Thenmozhi, 2006). This ensures that long-term stability is prioritized without ignoring short-term trends.

Investor-specific inputs such as age, investment horizon, expected return, risk tolerance, and investment amount are entered through a custom Excel form. Based on these, the VBA backend filters funds by category (aligned to risk), sorts them by the weighted score, and applies a diversification rule: **no single AMC is allowed to dominate more than 40% of the portfolio** (Sultana & Pardhasaradhi, 2012).

The **Output Layer** then presents the top five recommended funds with attributes like scheme name, category, AMC, current NAV, and projected future value—computed either using historical averages or the investor's expected return. This dual-projection feature enhances transparency and supports meaningful client discussions.

The overall model logic and layered structure were mapped using the **Technology Acceptance Model (TAM)** to ensure that the tool is easy to adopt, traceable in its logic, and effective in practical usage (Davis, 1989).

Investor-specific input variables such as age, investment horizon, risk level, and expected rate of return were captured through a user input form. Based on these inputs, the tool automatically filtered appropriate schemes and selected a combination of five top-ranked mutual funds. To maintain diversification and avoid bias, the logic was coded to ensure that no single AMC contributes more than 40% of the recommended portfolio. Further, fund category restrictions were applied based on investor risk profile—low-risk users received conservative debt-oriented suggestions while high-risk users were offered aggressive equity schemes.

The output interface was designed to display the selected scheme names, categories, NAVs, and projected future value based on user-entered expected return and tenure. A VBA-driven button was programmed to refresh the portfolio recommendations instantly. In addition, validation scripts ensured that blank fields or inconsistent inputs were flagged, enhancing usability.

The model was subjected to rigorous scenario testing using profiles of different investor types, and the recommendations were compared with general advisory benchmarks. Across most scenarios, the model delivered diversified, risk-aligned, and data-consistent portfolios. Its ability to respond in real-time to changing investor input parameters and automate the logic-driven filtering process makes it a practical asset for mutual fund advisors, particularly in resource-constrained environments.

MODEL MAPPING

To provide a structured foundation for the design of the mutual fund advisory tool, a conceptual model was mapped that aligns user characteristics, tool functions, and expected outcomes. The model was designed to ensure that key decision-making constructs—such as perceived usefulness, ease of use, and behavioral risk alignment—are embedded at each stage of tool interaction. This model mapping provides clarity to how various components such as user input, back-end logic, and portfolio output interact with each other.

The conceptual framework builds upon the TAM (Technology Acceptance Model) and integrates elements of portfolio theory and behavioral segmentation. The stages include:

1. **User Input Layer** – Captures current age, investment horizon, risk appetite, expected return, and investment amount.
2. **Processing Layer** – Applies weighted return calculation, risk filtering, AMC allocation rules, and logic constraints coded in VBA.
3. **Output Layer** – Generates scheme list, future value calculation, fund diversification, and visual display.

Conceptual Model Mapping for Mutual Fund Optimization Tool

This layered model ensures traceability of logic from input to output, thereby increasing user trust and interface transparency. Moreover, it establishes a link between investor behavior theories and computational output structures, strengthening the tool's usability.

VBA MODULE DEVELOPMENT ACROSS SIX PHASES

The backend development of the tool is structured into six distinct VBA-driven modules, each aligned to a critical user journey phase. This modular structure enhances both maintainability and functional clarity.

1. **Input Initialization Module** – This phase initializes the data input form, allowing the user to enter variables such as current age, years to goal, and investment amount. The form is validated using VBA to ensure that all mandatory fields are correctly filled.
2. **Horizon & Risk Profile Mapping Module** – Once the user inputs age and years to goal, the tool computes the investment horizon automatically. Based on this horizon, the corresponding risk profile (low, moderate, or high) is mapped using a lookup table and drop-down selections populated through VBA.

3. **RoR Recommendation Logic** – This module uses conditional logic to guide the user in selecting a realistic expected rate of return (RoR) based on their risk profile. If the user enters an RoR inconsistent with the risk type, an alert prompts correction.
4. **Fund Filtering Engine** – This is the core algorithm that filters mutual fund schemes based on the selected risk profile. It sorts and ranks funds by their weighted average return. This step also applies AMC exposure constraints (max 40%) to ensure diversification.
5. **Output Presentation Layer** – After filtering, the recommended five funds are populated in the output sheet with scheme name, AMC, category, and expected future value. Formatting tools are invoked using VBA to highlight top schemes and add borders or shading for visual clarity.
6. **Reset and Update Function** – The final module allows users to clear inputs or refresh the recommendation with updated values. It also includes validation error handling, ensuring inputs remain consistent throughout multiple iterations.

Together, these six modules comprise the comprehensive VBA framework that powers the mutual fund optimization tool, ensuring logical consistency, user engagement, and advisory relevance.

TOOL OUTPUT AND INTERFACE

The effectiveness of the developed tool is best illustrated by demonstrating how the interface functions through a sample use case. The tool begins by prompting the advisor or user to input core variables required to construct a suitable portfolio. These include current age, investment horizon, years to financial goal, expected rate of return (RoR), risk tolerance, and investment amount. These inputs determine how the filtering logic classifies and selects funds from the master database.

The key variables and their role are summarized visually in the following table - Input variables used in the model design.

Assumptions	
Current age	
Years to goal	
Investment horizon	
Risk Profile	
Minimum RoR	
Investment amount	
Future Value based on your minimum RoR	
Future Value based on Funds RoR	

Upon entering the values, the tool executes a VBA script that filters the mutual fund data table and returns a list of five recommended schemes. The user interface includes sections for fund name, AMC, category, current NAV, and a projected future value based on both user-entered RoR and fund's historical RoR. These dual projections provide a range of expectations, promoting informed decision-making.

The tool also features:

- Auto-refresh capability triggered by an “Update Portfolio” button
- Alerts for incomplete or inconsistent input entries
- Conditional formatting to highlight the best-performing scheme

This design ensures real-time responsiveness, usability, and data integrity while eliminating manual filtering errors. Future iterations may include more dynamic visuals such as fund comparison charts and historical return graphs.

Results and Analysis

The Quantifund model was tested using a dataset comprising mutual fund schemes from 15 leading Asset Management Companies (AMCs) in India. The tool was built to simulate a real advisory environment where a mutual fund distributor or advisor receives investment preferences from a client and then uses the Excel-VBA powered model to recommend an optimized mutual fund portfolio.

Input Parameters

The tool accepts the following investor-specific inputs:

- Name of the investor
- Age
- Expected return (%)
- Investment time horizon (in years)
- Risk profile (selected from a dropdown menu with options such as Conservative, Moderate, Aggressive)
- Investment amount

These parameters are entered into an input form in Excel. Once the data is entered, the advisor can click a button to generate the optimized portfolio.

Output Display and Interpretation

After processing the input, the model generates an output sheet with five recommended mutual fund schemes. These schemes are selected based on risk profile compatibility, long-term performance, and AMC diversification limits. Each recommended scheme displays:

- Scheme Name
- Fund Category (e.g., Large Cap, Mid Cap, Hybrid)
- AMC Name
- Current NAV
- Projected Future Value after investment horizon
- Average Weighted Return

The **Weighted Return** is calculated using the following formula to prioritize long-term performance:

$$\text{Weighted Return} = (0.5 \times \text{5-year return}) + (0.3 \times \text{3-year return}) + (0.2 \times \text{1-year return})$$

This formula ensures that schemes with sustained long-term performance are ranked higher than those with only short-term gains.

AMC Diversification Constraint

To avoid over-concentration in any single AMC, the model restricts the number of schemes from one AMC to a maximum of two (i.e., not more than 40% of the total portfolio). This logic is implemented in VBA using the following code logic:
This constraint ensures regulatory diversification and reduces institutional risk.

```
If WorksheetFunction.CountIfs(Range("B2:B100"), selectedAMC) > 2 Then
    'Skip adding this fund to output
End If
```

Output Screenshot

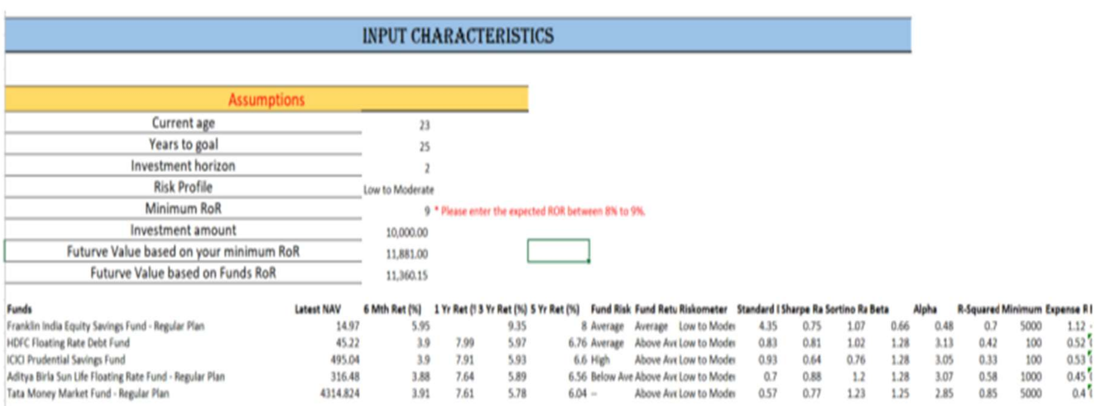
The output screen shows an example of the model output for a moderate-risk investor with a 10-year investment horizon. It displays:

- The top 5 mutual funds selected by the tool
- Current NAV values
- Expected future values
- Scheme types and AMCs

The model output is automatically refreshed every time the advisor changes the input parameters and presses the “Update Portfolio” button. This makes it easy to compare various investment scenarios in real-time.

The portfolio optimization tool was tested using diverse investor scenarios to evaluate its adaptability, accuracy, and consistency in delivering appropriate recommendations. Output screens were generated by varying inputs such as age, investment horizon, expected RoR, and risk profile.

The following figure displays the outcome for a typical investor profile:



INPUT CHARACTERISTICS

Assumptions	
Current age	23
Years to goal	25
Investment horizon	2
Risk Profile	Low to Moderate
Minimum RoR	9 * Please enter the expected ROR between 8% to 9%.
Investment amount	10,000.00
Futurve Value based on your minimum RoR	11,881.00
Futurve Value based on Funds RoR	11,360.15

Funds	Latest NAV	6 Mth Ret (%)	1 Yr Ret (%	3 Yr Ret (%)	5 Yr Ret (%)	Fund Risk	Fund Retu	Riskometer	Standard I	Sharpe Ra	Sortino Ra	Beta	Alpha	R-Squared	Minimum	Expense R
Franklin India Equity Savings Fund - Regular Plan	14.97	5.95		9.35	8	Average	Average	Low to Mode	4.35	0.75	1.07	0.66	0.48	0.7	5000	1.12
HDFC Floating Rate Debt Fund	45.22	3.9	7.99	5.97	6.76	Average	Above Ave	Low to Mode	0.83	0.81	1.02	1.28	3.13	0.42	100	0.52
ICICI Prudential Savings Fund	495.04	3.9	7.91	5.93	6.6	High	Above Ave	Low to Mode	0.93	0.64	0.76	1.28	3.05	0.33	100	0.53
Aditya Birla Sun Life Floating Rate Fund - Regular Plan	316.48	3.88	7.64	5.89	6.56	Below Ave	Above Ave	Low to Mode	0.7	0.88	1.2	1.28	3.07	0.58	1000	0.45
Tata Money Market Fund - Regular Plan	4314.824	3.91	7.61	5.78	6.04	--	Above Ave	Low to Mode	0.57	0.77	1.23	1.25	2.85	0.85	5000	0.4

Model Output: Tool-generated recommendation based on user inputs

In one typical case, a 23-year-old investor with a 2-year goal, moderate risk preference, and a minimum expected return of 8.5% was offered a diversified selection of hybrid and balanced advantage schemes. The VBA module displayed the fund names, categories, NAVs, and projected future values in a structured format. The tool’s automatic application of AMC capping (40%) ensured distribution across fund houses, avoiding overexposure.

Table 1. Example output from Quantifund for a low-to-moderate risk investor.

Scheme (Fund Name)	Category	AMC (Fund House)	Current NAV (₹)	Projected Value (2 yrs @ 8.5%)
HDFC Balanced Advantage Fund	Hybrid – Bal. Advantage	HDFC Mutual Fund	50.2	11,770
SBI Equity Hybrid Fund (Growth)	Hybrid – Aggressive	SBI Mutual Fund	152.5	11,770
ICICI Prudential Corporate Bond Fund	Debt – Corporate Bond	ICICI Prudential AMC	24.8	11,770
Aditya Birla Sun Life Balanced Adv Fund	Hybrid – Bal. Advantage	Aditya Birla Sun Life AMC	32.1	11,770
Nippon India Short Term Fund	Debt – Short Duration	Nippon India Mutual Fund	40.3	11,770

These outputs validate the model's ability to dynamically adjust to user conditions while complying with investment best practices. The user interface further enhances decision clarity by visually distinguishing top-performing funds. The structured format of the tool output, combined with the backend logic, promotes transparency in the advisory process.

From a discussion standpoint, the tool offers multiple advantages over traditional advisory methods. First, it reduces the scope for human error and biases in fund selection. Second, it provides consistent logic irrespective of the advisor's financial expertise. Third, by allowing user-defined customization, it aligns better with client preferences compared to rigid robo-advisory systems. These features position the tool as a practical intermediary solution suited for semi-digital advisory models.

However, limitations remain. The model currently depends on static data sets and lacks real-time fund updates. Future versions should consider API integration with platforms like Value Research or AMFI to ensure data freshness. The addition of graphical fund comparisons and scenario analysis modules can further elevate user engagement.

Overall, the tool's logic, design, and usability establish it as a scalable prototype for mutual fund distributors and small advisors, especially in Tier II and III cities where fintech infrastructure is limited.

The output results clearly demonstrate that all stated objectives of the study have been achieved. The tool enables accurate fund recommendation by combining user-defined inputs with a structured ranking system. The risk-based filtering logic, AMC diversification rule, and future value projections align with portfolio construction principles and investor-specific financial planning. Moreover, the VBA-based interface ensures that even non-technical users—especially mutual fund distributors in Tier II and III markets—can operate the tool efficiently, meeting the study's practical aims.

This study successfully applies practical concepts like diversification, weighted return calculation, and personalized filtering through an Excel-VBA-based tool. It meets the expected goals by helping advisors generate consistent and relevant portfolio recommendations. The tool also shows how familiar tools like Excel can be used effectively without the need for complex or expensive software. It demonstrates that even a independently developed tool, when built with clear logic and user understanding, can support meaningful investment decisions.

In addition to meeting technical expectations, the tool contributes to the broader agenda of financial literacy and accessibility. By simplifying fund selection and presenting results in a visual, user-friendly format, it promotes confident decision-making among first-time investors. The tool also supports advisors in building trust with clients by ensuring recommendations are based on consistent, explainable logic rather than subjective opinion.

Furthermore, the inclusion of return-based risk metrics, fund categorization, and diversification constraints aligns with practical financial planning practices recommended by AMFI and SEBI. In real advisory scenarios, these features ensure not only alignment with client needs but also regulatory compliance. Advisors who adopt such structured approaches are better positioned to maintain transparency, track investment suitability, and enhance service quality over time.

Finally, the tool acts as a teaching aid in environments, helping students bridge the gap between financial theory and applied modeling. It serves as a working example of how business problems can be solved using analytical tools without requiring coding expertise, making it a potential asset in management education.

Conclusion, Managerial Implications, and Future Scope

The Quantifund model represents a pragmatic response to the challenges faced by mutual fund advisors in India’s dynamic investment landscape. By integrating portfolio logic, investor profiling, and VBA-based automation into a single Excel tool, it offers a low-cost, high-impact solution for mutual fund distributors (MFDs), especially those in Tier II and Tier III markets.

One of the key managerial implications of this tool lies in its ability to empower local advisors who lack access to premium robo-advisory platforms. With minimal training, these professionals can deliver personalized, data-backed portfolio suggestions that are not only transparent but also compliant with regulatory diversification norms. The visual clarity of the output enhances client communication, building trust and increasing adoption of structured investment strategies.

From an operational standpoint, Quantifund helps reduce human error, improves advisory efficiency, and provides repeatable logic that can be customized for various client scenarios. Its affordability removes entry barriers for independent advisors and small firms, while its structured interface makes it highly usable even for those with limited technical experience. By automating fund filtering, ranking, and future value calculations, it adds a layer of professionalism to grassroots financial advisory services, aligning well with India's larger goals of financial inclusion and digital transformation in personal finance.

However, the current model is not without limitations. The most prominent constraint is its reliance on static fund data; without API integration, fund performance must be updated manually, which limits scalability and real-time adaptability. Additionally, while the tool incorporates a basic risk assessment framework, it does not yet support advanced financial metrics such as Sharpe ratio, standard deviation, or alpha-beta analytics. Its Excel-VBA structure, while accessible, may also limit adoption in environments requiring mobile or cloud-based advisory systems. Furthermore, the model does not incorporate investor feedback loops, performance tracking, or rebalancing logic, which are important components of full-scale portfolio advisory platforms.

Despite these limitations, the future scope for Quantifund is considerable. Enhancements can include automated data syncing via APIs, integration with mobile devices or cloud platforms, support for regional languages, and even machine learning components to adapt to investor behavior over time. Adding modules for SIP (Systematic Investment Plan) recommendations, tax-efficiency analysis, and periodic portfolio rebalancing can further enrich the tool's capabilities. As fintech adoption accelerates across India, simplified, customizable tools like Quantifund can serve as a bridge between manual advisory practices and digital financial planning ecosystems—making them highly relevant not only for current market conditions but also for future growth.

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