AI-Based Financial Health & Investment System

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Abstract- *The AI-Based Personal Finance besides Investment Planning System operates as a working prototype designed to enhance the detection of individual credit risk and support long-term solvency through an automated financial structure. While traditional credit models often fail to measure how a single person withstands financial stress, this system addresses that gap by processing raw user data including income, expenditures, savings, and risk appetite. The program generates a comprehensive Financial Health Score (0–100) and calculates the specific "FIRE" (Financial Independence, Retire Early) target sum required for early retirement. It further categorizes user pathssuch as Lean, Fat, Barista, or Coastand identifies critical gaps in insurance coverage and emergency fund adequacy. By utilizing a transparent, logic-driven recommendation engine, the tool provides evidence-based prompts that curb personal credit risk and guide users toward sustainable wealth growth.*

Keywords: AI in Finance, Credit Risk, Financial Independence (FIRE), Investment Planning.

I. INTRODUCTION

Managing personal capital in the current economic landscape presents significant challenges due to volatile market conditions and shifting global financial trends. Many individuals face uncertainty regarding their long-term preparedness, often lacking the specific tools or technical knowledge required to achieve ambitious milestones like Financial Independence, Retire Early (FIRE). While traditional budgeting is common, it often lacks the structured analysis and predictive modeling necessary for informed decision-making in a complex environment.

The AI-Based Personal Finance and Investment Planning System was developed as a practical web-enabled solution to bridge this expertise gap. By inputting core monthly variables such as income, outgo, and existing safety nets, users receive a personalized roadmap designed to bolster their financial foundation. This system moves beyond simple spreadsheets by utilizing a unified dashboard to highlight critical areas, such as insurance adequacy and emergency fund strength.

IDENTIFY,RESEARCHANDCOLLECT IDEA

The development of the system began by addressing the "Interpretation Gap," where simply knowing monthly savings figures does not reveal if an individual is on track for financial independence. Research was conducted to bridge this divide by reviewing existing tools and academic literature. The process involved several key research areas:

Analysis of Current Models: Traditional credit scoring systems were found to focus primarily on historical payment behavior rather than forward-looking solvency or long-term financial strength.

Technological Feasibility: Research highlighted the importance of machine learning models, such as Random Forest and XGBoost, for identifying patterns in complex datasets and predicting financial risks with high accuracy.

Ethical Frameworks: Studies emphasized the need for transparency in financial AI to avoid "black box" models, leading to the integration of interpretable techniques and responsible design principles.

Financial Standards: Data on established planning principles was collected, such as the 4% withdrawal rule and the benchmark of maintaining emergency funds equal to three to six times monthly expenses.

Based on these gathered insights, the idea was developed to build a multi-tier architecture that utilizes automated data pipelines and logic-driven engines to provide personalized, accessible wealth management guidance.

II. STUDIES AND FINDINGS

The experimental study was conducted to evaluate the performance and analytical accuracy of the AI-based financial system. The findings demonstrate that a logic-driven approach can effectively interpret diverse financial profiles and provide actionable insights for long-term stability.

A. System Performance and Scalability

To assess real-world readiness, the system was tested with various datasets:

Standard Processing: A dataset of 500 user records was processed in 0.8 seconds using 45 MB of memory.

Complex Portfolios: 100 records representing multi-asset portfolios were processed in 0.3 seconds.

Edge Case Resilience: 50 rows of problematic data (e.g., negative income or missing age fields) were handled in 0.2 seconds.

Stability: Results confirmed that processing time scales proportionally with data size, indicating predictable behavior under load.

B. Financial Analysis and Risk Results

When applied to a standard user profile (5,000 rupees monthly expenses), the system generated the following insights:

FIRE Target: The total financial independence goal was calculated at 1,500,000 rupees.

Progress Tracking: With 150,000 rupees in savings, the user had achieved 10% of their retirement journey.

Savings Health: The average savings rate for the profile was 25%, reflecting a strong starting point.

Risk Categorization: Out of 500 users, 83% (415 users) were classified as **Normal Risk**, 9% (45 users) as **Critical Risk** due to insurance gaps, and 8% (40 users) as **High Risk** needing immediate debt or emergency fund intervention.

C. Recommendation Impact

The recommendation engine produced measurable steps for risk reduction:

Expense Optimization: Flagged high discretionary spending (often accounting for 42% of expenses), suggesting cuts that could boost monthly investment capacity by 8%.

Asset Allocation: For users holding 100% cash, the system recommended a shift to 60% equity, 30% debt, and 10% gold to improve long-term outcomes.

Safety Net Gap: A significant life insurance gap of 5,000,000 rupees was identified as a primary vulnerability in standard profiles, requiring urgent correction.

Overall Score Improvement: Implementation of all suggested improvements could result in a 15% increase in a user's total Financial Health Score.

III. METHODOLOGY AND SYSTEM LOGIC

The system architecture is designed as a web-enabled solution utilizing a logic-driven recommendation engine to automate financial planning.

The methodology focuses on processing user-provided data including income, expenditures, and risk appetite through a multi-tier pipeline to generate actionable insights.

A. Risk Profiling and Assessment

The system begins with a quantitative risk profiling questionnaire that evaluates ten distinct financial and psychological variables. Each response is scored to categorize the user into one of three risk levels: Low, Medium, or High. These levels serve as the foundational parameters for subsequnt asset allocation and investment strategy prompts.

B. Retirement and FIRE Target Logic:

The core of the financial independence calculation relies on the 25x multiplier rule. The engine calculates a primary FIRE (Financial Independence, Retire Early) target by multiplying annual expenses by 25. It further identifies specialized paths, including:

- **Lean FIRE:** Targeted at 20 times annual expenses.
- **Fat FIRE:** Targeted at 30 times annual expenses.
- **Barista FIRE:** Calculated as 70% of current annual expenses multiplied by the 25x factor.
- **Coast FIRE:** Determined by calculating the present value of the primary FIRE target over the user's remaining years to retirement.

C. Safety Net and Insurance Gap Analysis:

The methodology incorporates rigorous safety net benchmarks to identify vulnerabilities. Emergency fund adequacy is measured against a requirement of three to six times monthly expenses. Life insurance needs are calculated as 15 times the annual salary, while a health insurance baseline is set at 500,000 rupees to mitigate critical risk.

D. Investment Allocation and SIP Strategies:

Asset allocation is dynamically adjusted according to the identified risk level. A standard profile is typically allocated 60% equity, 30% debt, and 10% gold to optimize long-term outcomes. The system also calculates the necessary Monthly Systematic Investment Plan (SIP) required to bridge the gap between current savings and the target retirement corpus.

E. Composite Financial Health Score:

The final output is a Financial Health Score on a scale of 0 to 100, which serves as a metric for overall solvency. This score is a composite weighted calculation based on five key performance indicators:

- Savings Rate (25 points): Based on the percentage of surplus income.
- Emergency Fund Status (20 points): Based on liquidity reserves relative to monthly expenses.
- Insurance Coverage (20 points): Based on the reduction of identified coverage gaps.
- SIP Adequacy (25 points): Based on current investment levels versus the required SIP.
- Expense Ratio (10 points): Based on the optimization of discretionary spending.

VI. IMPROVEMENTASPERREVIEWER COMMENTS

In alignment with the feedback gathered during the peer review, several refinements were implemented to elevate the professional quality and technical precision of the study. The following enhancements were made to the system and the resulting report:

Methodological Detail: The application layer documentation was expanded to provide a more thorough explanation of the Flask framework components and the specific logic used for financial calculations.

Enhanced Data Presentation: The results section was updated with more rigorous comparisons between untreated financial data and the treated results generated by the AI system.

Visual Refinement: Tables and dashboard cards were redesigned to communicate complex metrics, such as the FIRE target and emergency fund status, with greater clarity and effectiveness.

Error Correction and Validation: Minor calculation and formatting discrepancies identified by reviewers were addressed to ensure the reliability of the Financial Health Score.

Precision in Conclusions: The study’s final conclusions were modified to more accurately reflect the data findings, particularly emphasizing the significance of specific investment mix proportions and insurance gap detection.

Technical Standards: Language and presentation styles were polished to meet academic standards, ensuring better readability for a professional audience.

V. CONCLUSION

The stability of a personal financial plan is significantly enhanced through automated insights that eliminate manual calculation errors. By identifying critical insurance gaps and strengthening emergency fund reserves, the system provides a measurable increase in long-term solvency.

Key takeaways from the study include:

Engine Effectiveness: The logic-driven recommendation engine proved most effective when calculating precise targets for financial independence and suggesting diversified investment options.

Fiscal Performance: This automated combination provides users with maximum security and a documented improvement in overall personal fiscal performance.

Methodological Efficiency: The implementation of this AI-based system offers an economical, efficient, and user-friendly method for stabilizing personal finances.

Resilience: The tool is highly suitable for individuals navigating current economic uncertainty who aim to build lasting financial resilience.

Through the reduction of non-essential spending and the optimization of the user's budget, this system bridges the expertise gap in modern wealth management.

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