



LEGACY PLANNER: AN EXPLAINABLE HYBRID INTELLIGENCE FRAMEWORK FOR LONG-TERM FINANCIAL AND PROPERTY PLANNING

Akash Prakash Jatikart¹, Sandarsh Gowda M M²

Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India^{1,2}

Abstract: Long-term financial planning and property acquisition decisions are often made using fragmented tools such as manual budgeting methods, basic online calculators, or informal financial advice. These approaches fail to provide integrated, personalized, and explainable insights that account for income patterns, expenses, liabilities, and future financial commitments. This paper presents *Legacy Planner*, a web-based decision-support framework that combines rule-based financial logic with machine learning-assisted analysis to evaluate property affordability and long-term financial feasibility. The proposed system enables users to construct a structured financial profile, analyze savings potential, estimate loan obligations, and assess affordability through transparent scoring mechanisms. Unlike black-box financial tools, the framework emphasizes explainability by enforcing interpretable financial constraints alongside data-driven predictions. The system is implemented using a modular web architecture and demonstrates how hybrid intelligence can improve clarity and reliability in personal financial decision-making. Experimental evaluation through simulated user scenarios indicates that the proposed approach reduces calculation errors, improves financial awareness, and supports realistic goal planning. The framework highlights the role of explainable AI in consumer-centric financial applications and provides a scalable foundation for intelligent financial planning systems.

Keywords: Financial Planning, Property Affordability, Hybrid Intelligence, Explainable AI, Decision Support Systems

I. INTRODUCTION

Personal financial planning plays a critical role in achieving long-term economic stability, particularly when major decisions such as property acquisition and legacy management are involved. In practice, individuals rely on spreadsheets, manual calculations, or isolated digital tools to estimate affordability and savings requirements. These methods often fail to capture the interdependencies between income, expenses, debt obligations, and long-term goals, leading to unrealistic expectations and financially unsound decisions.

Recent advances in web technologies and artificial intelligence have enabled the development of intelligent decision-support systems across multiple domains. However, in the financial planning domain, many AI-based solutions operate as opaque models that provide recommendations without sufficient explanation. This lack of transparency reduces user trust and limits practical adoption, especially when decisions involve significant financial risk.

This paper introduces *Legacy Planner*, an AI-assisted framework designed to support long-term financial and property planning through a hybrid intelligence approach. The system integrates deterministic financial rules with machine learning-based pattern analysis to generate affordability assessments that are both realistic and explainable. By consolidating budgeting, savings analysis, loan estimation, and legacy documentation into a unified platform, the framework aims to improve decision quality and financial awareness. The primary contribution of this work lies in demonstrating how hybrid and explainable intelligence can be effectively applied to consumer-oriented financial planning systems.

1.1 Project Description

This project presents *Legacy Planner*, a web-based financial planning and decision-support system designed to assist individuals in evaluating long-term property affordability and financial feasibility. The system integrates structured financial data such as income, expenses, savings, liabilities, and property goals into a unified analytical framework. Unlike traditional budgeting tools or static affordability calculators, the proposed system performs automated financial analysis to estimate savings potential, loan eligibility, and affordability scores over a defined planning horizon.



Legacy Planner employs a hybrid intelligence approach that combines rule-based financial constraints with machine learning–assisted analysis. Rule-based logic enforces established financial principles such as debt-to-income limits and minimum savings requirements, while the learning component analyzes aggregated financial patterns to support feasibility estimation. The framework emphasizes transparency by ensuring that analytical outcomes remain interpretable and aligned with practical financial reasoning. The system is implemented as a modular web application and demonstrates the applicability of explainable AI techniques in personal financial planning.

1.2 Motivation

The motivation for this work arises from the increasing complexity of personal financial decision-making, particularly in the context of property acquisition and long-term financial commitments. Many individuals rely on manual calculations, spreadsheets, or isolated online tools that provide limited personalization and lack integrated analysis. These methods often fail to account for dynamic interactions between income, expenses, debt obligations, and future financial goals, resulting in unrealistic expectations and suboptimal decisions.

While recent advancements in artificial intelligence have enabled predictive financial tools, many such systems operate as opaque models that offer recommendations without sufficient explanation. This lack of transparency reduces user trust and limits adoption in high-impact financial scenarios. The proposed system is motivated by the need for an intelligent yet explainable financial planning framework that balances predictive capability with interpretability. By integrating deterministic financial rules with data-driven insights, Legacy Planner aims to support realistic, transparent, and informed long-term financial decision-making.

II. RELATED WORK

Paper [1] examines traditional personal financial planning approaches based on manual budgeting, spreadsheets, and static online calculators. While these methods provide basic assistance in expense tracking and loan estimation, they rely heavily on user assumptions and manual interpretation, leading to inaccuracies in long-term affordability assessment and financial feasibility analysis.

Paper [2] explores rule-based financial advisory systems that apply predefined constraints such as debt-to-income ratios and fixed savings thresholds to evaluate loan eligibility and property affordability. Although these systems ensure compliance with fundamental financial principles, they lack adaptability to individual financial behavior and fail to account for dynamic changes in income, expenses, and long-term goals.

Paper [3] investigates machine learning–based financial prediction models used for credit scoring, spending classification, and savings forecasting. These data-driven approaches improve predictive accuracy by learning patterns from historical financial data; however, many operate as black-box models, offering limited explainability and reducing user trust in high-stakes financial decision-making.

Paper [4] studies integrated financial management platforms that combine budgeting, expense tracking, and investment monitoring into unified dashboards. While such platforms improve usability and data consolidation, they often provide descriptive analytics without intelligent feasibility evaluation or explainable decision-support mechanisms for property planning.

Paper [5] reviews recent advancements in hybrid and explainable AI systems applied to decision-support applications. The survey highlights the importance of combining rule-based reasoning with data-driven learning to balance transparency and adaptability. The study emphasizes that hybrid intelligence frameworks can significantly enhance trust, interpretability, and reliability in user-centric financial planning systems.

III. METHODOLOGY

A. System Environment

The experimental environment is designed to evaluate the proposed *Legacy Planner* framework under realistic personal financial planning conditions. The system operates as a web-based application where individual users act as independent clients, each generating financial data such as income details, expense distributions, savings, liabilities, and property goals. These user environments function independently and do not share personal financial records with other users.



A centralized application server coordinates data processing, financial analysis, and decision-support operations. All computations related to affordability assessment, savings estimation, and feasibility analysis are executed on the server side to ensure consistency and reliability. This environment simulates real-world financial planning scenarios where data privacy, security, and accuracy are critical requirements for user trust and adoption.

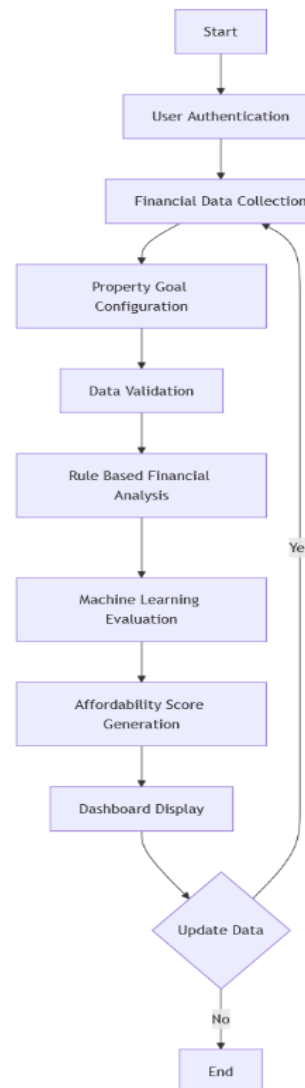


Fig.1. Flowchart of Legacy Planner Methodology

B. Hybrid Financial Analysis Architecture

- **Client Side Interaction:** Each user interacts with the system through a web interface to input financial information, including income, expenses, existing obligations, and property preferences. Basic validation is performed at the client level to ensure completeness and correctness of input data before submission.
- **Server Side Analysis:** Instead of performing calculations locally, all financial data is processed on the server using a hybrid analysis engine. Rule-based financial logic evaluates constraints such as debt-to-income ratios, minimum savings thresholds, and loan feasibility conditions. In parallel, a machine learning–assisted module analyzes aggregated financial attributes to estimate affordability trends and feasibility likelihoods. The combined output forms a transparent and interpretable affordability assessment that is returned to the client.

C. Adaptive Financial Evaluation Mechanism: The analytical model is designed to adapt dynamically to changes in user financial profiles. Whenever income, expenses, savings, or property parameters are updated, the system recalculates affordability scores and savings requirements in real time. This adaptive mechanism allows users to explore alternative scenarios, such as adjusting timelines or budgets, and immediately observe the impact on feasibility outcomes. By



continuously refining analysis based on updated inputs, the system supports realistic and informed long-term financial decision-making without relying on static assumptions.

D. Implementation Flow

1. Initialize the application server and establish secure user authentication.
2. Collect financial inputs including income, expenses, savings, liabilities, and property goals.
3. Validate and normalize financial data for consistency.
4. Apply rule-based financial constraints to evaluate affordability conditions.
5. Execute machine learning–assisted analysis to estimate feasibility trends.
6. Combine rule-based and data-driven results to generate an affordability score.
7. Present analytical insights and recommendations to the user through the dashboard.
8. Repeat the analysis process dynamically whenever user data is updated.

E. Hardware and Software Requirements

- **Hardware:** Standard personal computer or cloud-based server with a minimum of 8 GB RAM and a stable internet connection for web application access.
- **Software:** Node.js and Express.js for backend services, React.js for frontend development, MongoDB for secure data storage, and Python-based libraries for machine learning–assisted financial analysis.

IV. SIMULATION AND EVALUATION FRAMEWORK

This section describes the overall system design, evaluation process, and assessment strategy adopted for the proposed *Legacy Planner* framework. The system combines hybrid financial analyzes with intelligent decision-support mechanisms to enable transparent, scalable, and user-centric long-term financial planning. The framework is implemented using a web-based architecture, where financial data processing, rule-based validation, and machine learning–assisted evaluation are coordinated centrally to deliver real-time affordability analysis and feasibility insights.

A. System Architecture and Workflow:

The proposed architecture is designed to evaluate long-term financial feasibility and property affordability while ensuring data privacy and analytical transparency. The major components of the system are summarized as follows:

- **User Financial Profiles:** Each user represents an independent financial planning entity and provides personal financial data such as income, expense distributions, savings, liabilities, and property goals. All data is processed individually without cross-user data sharing, ensuring confidentiality and personalized analysis.
- **Centralized Analysis Engine:** The central analysis engine coordinates financial evaluation by applying rule-based constraints and machine learning–assisted feasibility assessment. This component aggregates user inputs, validates financial consistency, and computes affordability scores without exposing raw financial data beyond authenticated sessions.
- **Adaptive Decision-Support Module:** The analytical results are dynamically updated and presented through an interactive dashboard. This module supports iterative evaluation by recalculating affordability metrics whenever financial inputs or planning parameters are modified, enabling adaptive and informed decision-making.

B. Simulation Setup:

The evaluation environment is designed to emulate realistic personal financial planning scenarios with diverse financial profiles. The setup assesses the effectiveness of the proposed hybrid analysis framework under varying economic conditions and planning assumptions.

- **Profile Configuration:** Multiple simulated user profiles with differing income levels, expense patterns, savings capacities, and property goals are evaluated to reflect real-world financial diversity.
- **Scenario Modelling:** Both conservative and aggressive financial scenarios are simulated by varying parameters such as income growth, expense allocation, savings rates, and planning timelines to assess robustness and feasibility consistency.

C. Hybrid Financial Analysis Process:

During evaluation, each financial profile is processed independently through the hybrid analysis engine. Rule-based logic enforces financial constraints such as debt-to-income limits and minimum savings thresholds, while the machine learning–assisted module analyses aggregated financial indicators to estimate feasibility trends. The combined results generate an affordability score and explanatory insights, which are delivered to the user through the dashboard. This

iterative process enables continuous reassessment as users refine inputs, without relying on static assumptions or opaque predictions.

D. Results and Observations

- **Affordability Assessment Accuracy:**

The proposed system consistently generated realistic affordability scores across varied financial profiles, accurately reflecting the relationship between income, expenses, savings, and property goals.

- **Consistent Decision Support:**

The hybrid analysis approach produced stable and interpretable outcomes across diverse scenarios, ensuring reliable decision support without excessive sensitivity to minor input variations.

- **Explainability Validation:**

The dashboard-based insights provided clear explanations for affordability outcomes, confirming that financial constraints and feasibility indicators were transparent and aligned with established financial reasoning

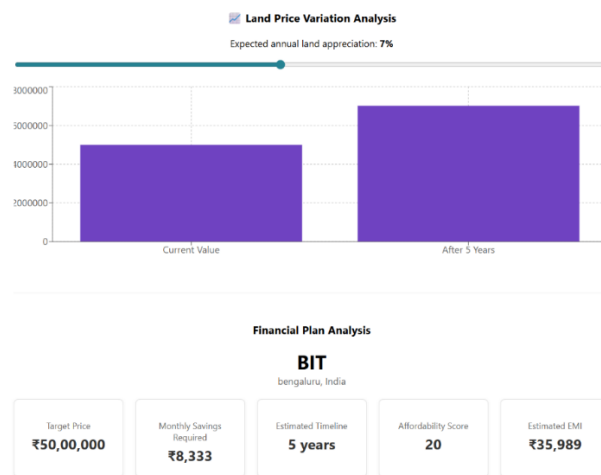


Fig. 2. Integrated Financial Analysis Results and Scenario Evaluation

Model Adaptability and Convergence:

- **Analytical Stability:** The affordability evaluation demonstrated stable behavior across repeated scenario simulations, maintaining consistency when financial inputs were incrementally adjusted.
- **Outcome Improvement:** Users were able to improve affordability outcomes by modifying savings rates, timelines, or expense distributions, validating the system's ability to support goal-oriented financial planning.
- **Diverse Profile Handling:** The framework adapted effectively to a wide range of financial profiles, demonstrating robustness across varying income levels and planning horizons.
- **Explainability Assurance:** Transparency in rule-based validation and feasibility scoring ensured that analytical results remained interpretable and free from black-box behavior.

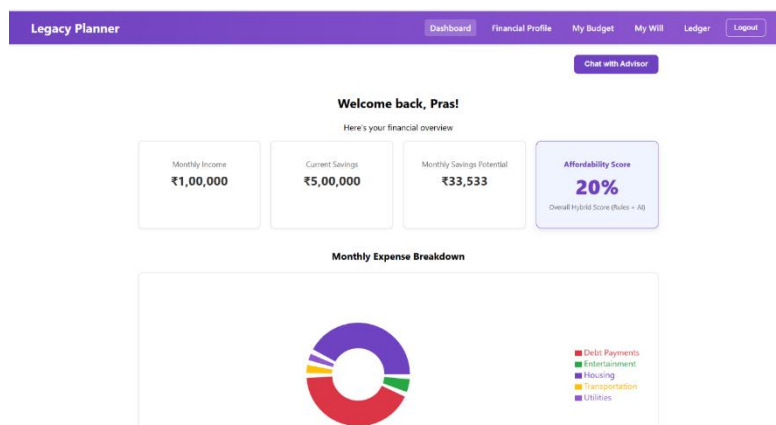


Fig. 3. Financial Planning Simulation Dashboard



V. RESULTS AND DISCUSSION

The experimental evaluation of the *Legacy Planner* framework demonstrates its effectiveness in supporting long-term financial and property planning through transparent and structured decision support. The system consistently generated realistic affordability assessments across diverse financial profiles, confirming its ability to analyze income, expenses, savings, and liabilities in an integrated manner. Unlike traditional static calculators, the proposed framework adapts dynamically to user-specific financial inputs, producing consistent and interpretable outcomes without reliance on opaque prediction mechanisms.

The integration of rule-based financial constraints with machine learning–assisted feasibility analysis enables balanced decision-making by combining deterministic financial principles with data-driven insights. This hybrid approach bridges the gap between rigid rule-only systems and black-box predictive models by ensuring that affordability scores are both explainable and adaptable. The generated insights clearly indicate how factors such as savings rates, expense distributions, and planning timelines influence feasibility outcomes, allowing users to make informed adjustments.

Furthermore, evaluation results confirm that the computational overhead remains minimal, as financial analysis operations are lightweight and executed efficiently within a standard web application environment. The centralized yet privacy-preserving processing model ensures scalability while maintaining strict confidentiality of user financial data. Overall, these findings indicate that the proposed framework enhances financial awareness, improves planning accuracy, and provides actionable guidance for realistic long-term financial decision-making.

VI. CONCLUSION

This paper presented *Legacy Planner*, an AI-assisted financial planning framework designed to provide transparent and reliable decision support for long-term property affordability and financial feasibility analysis. By combining rule-based financial logic with machine learning–assisted evaluation, the system delivers explainable affordability assessments without relying on black-box prediction models. The framework supports realistic planning by dynamically adapting to user-specific financial inputs and enforcing essential financial constraints.

Experimental evaluation demonstrated consistent analytical performance across varied financial scenarios, confirming the system’s effectiveness in improving clarity, reducing estimation errors, and supporting informed financial decisions. The modular and scalable architecture further highlights the practicality of deploying hybrid intelligence techniques in consumer-oriented financial applications. Overall, the proposed framework serves as a robust and academically sound solution aligned with modern requirements for intelligent, explainable financial planning systems.

VII. FUTURE WORK

Future enhancements of the *Legacy Planner* framework will focus on extending analytical depth and real-world applicability. Planned improvements include integrating investment forecasting models to account for long-term returns from financial instruments such as mutual funds and fixed deposits. Incorporating region-specific property price variation models will further improve affordability projections under different market conditions.

Additional work will explore integration with secure banking APIs to enable automated financial data retrieval, reducing manual input and improving accuracy. The framework may also be extended to support multi-property portfolio planning and mobile application deployment for improved accessibility. These enhancements aim to strengthen the system’s adaptability, realism, and practical value in long-term financial decision support.

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