International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

IntelliFinance: A Rule-Based and AI-Driven Smart Financial Decision Support System for Personalized Financial Planning

Riya Atkari[1], Subodh Bobhate[2], Swanandi Bokshe[3], Aniket Moudekar[4], Prof. Sanjay S. Kalamdhad[5]

[5]Assistant Professor
Department of Computer Science and Business Systems,
St. Vincent Pallotti College of Engineering & Technology, Nagpur

Abstract

Effective personal financial management remains difficult for individuals who lack access to professional, personalized financial advice suited to their income, expenses, and goals. Most existing solutions address only a fragment of this problem: budgeting and expense-tracking applications record transactions but leave analysis and decision-making to the user; robo-advisory platforms focus narrowly on investment allocation; and conversational finance chatbots often generate numerical guidance directly from a language model, which can be inconsistent or unverifiable. This paper presents IntelliFinance, a web-based Smart Financial Decision Support System (SFDSS) that unifies these fragmented capabilities into a single, explainable platform. The system separates deterministic financial computation from natural-language explanation: a rule-based calculation engine computes budget allocations, emergency-fund targets, SIP/investment contributions, EMI and debt-repayment strategies, and an overall Financial Health Score, while a large-language-model-based AI Advisor interprets these results for the user in plain language and answers user-specific financial queries. The platform further introduces a Family Financial Mode for household-level planning and visibility. Drawing on evidence from a randomized controlled trial of low-income personal finance apps, a review of AI-based robo-advisory systems, and a machine-learning-based expense analytics platform, this paper positions IntelliFinance within the existing literature, identifies the specific gaps it addresses, and describes its proposed architecture, data flow, research hypotheses, and technology stack. The system is intended to function as an accessible, transparent, and trustworthy decision-support and financial-education tool, particularly for students, young professionals, and first-time earners.

Keywords—Financial Decision Support System, Personal Finance, Artificial Intelligence, Robo-Advisory, Financial Health Score, Rule-Based Engine, Explainable AI, Family Financial Planning.

1. Introduction

Personal financial management is central to achieving financial stability and long-term life goals, yet a large share of individuals struggle to manage income, expenses, savings, debt, and investments effectively. Traditional budgeting approaches rely on fixed, generic rules — such as uniform percentage splits between needs, wants, and savings — that do not adapt to a user's actual income level, dependents, existing

liabilities, or personal goals. This mismatch frequently produces advice that is either unrealistic for the user's circumstances or unnecessarily conservative, discouraging continued engagement with financial planning tools altogether.

Digital finance applications have made meaningful progress toward closing this gap. Budgeting and expense-tracking tools help users record and categorize spending; robo-advisory platforms automate investment allocation based on stated risk preferences; and conversational finance assistants use natural language to make financial guidance more approachable. Independent empirical and design-oriented research on each of these categories — reviewed in Section II — shows that they each solve part of the problem but rarely all of it together, and that trust, personalization, and engagement remain persistent challenges.

This paper introduces IntelliFinance, a Smart Financial Decision Support System (SFDSS) that is designed specifically to integrate the strengths of these three categories of tools — deterministic budgeting logic, robo-advisory-style computation, and conversational AI guidance — while avoiding their individual weaknesses. Central to the design is a strict separation between numerical computation, which is handled by a deterministic rule-based engine, and natural-language explanation, which is handled by a large language model (LLM). This separation is intended to keep every numerical recommendation verifiable while still allowing the system to communicate results in a personalized, conversational manner. The remainder of this paper reviews related work, defines the problem and research objectives, and describes the proposed system architecture, data flow, methodology, and expected contribution.

2. Literature Review

Existing work relevant to IntelliFinance can be grouped into three broad strands: empirical evidence on the behavioral efficacy of personal finance apps, conceptual and case-study work on AI-driven robo-advisory services, and applied machine-learning systems for automated expense analytics. Each strand is reviewed below, followed by a synthesis of the gap that motivates the proposed system.

A. Personal Finance Apps and Financial Capability (French, McKillop & Stewart, 2021)

French, McKillop, and Stewart (2021) report results from a randomized controlled trial (RCT) evaluating four smartphone finance apps — a loan-cost comparison app, a household-expenditure comparison app, an overdraft-avoidance app, and a debt-reduction app — distributed to 500 members of a Northern Ireland credit union serving predominantly lower-income households. Using an OLS-adjusted RCT design, the study found that the treatment group showed statistically significant improvements in self-confidence in financial decision-making, financial literacy, ability to delay self-gratification, and sense of being able to effect change over their financial situation. Financially capable behaviors also improved in specific respects: the treatment group was markedly better able to absorb an unexpected bill without resorting to credit, and somewhat more likely to check their account balance regularly.

Importantly, however, these gains in ability, mindset, and behavior did not translate into a measurable improvement in the household's overall financial well-being (e.g., reduced indebtedness or higher month-end savings) within the one-year trial period. The authors attribute part of this to insufficient user engagement: app usage declined steadily after an initial peak, a large share of infrequent users cited “forgetting about the app” or a lack of perceived relevance, and reinforcement mechanisms such as push notifications had only a marginal effect. In contrast, a prize-based gamified competition produced a strong,

if temporary, spike in engagement. Based on these findings, the authors recommend four design principles for personal finance apps: (i) target a specific, well-defined financial decision-making problem rather than many facets at once; (ii) keep the app design simple; (iii) incorporate gamification and personalization (e.g., two-way, relevant notifications) to sustain engagement; and (iv) pair the digital experience with some face-to-face or human-backed touchpoint to build legitimacy and trust.

This study is directly relevant to IntelliFinance in two ways. First, it demonstrates that low-income and financially-squeezed users can meaningfully benefit from structured, app-based financial guidance, supporting the broader case for accessible decision-support tools. Second, it identifies engagement and relevance as the binding constraint on real-world impact — a finding that motivates IntelliFinance's Financial Health Score (a simple, trackable, relevance-generating measure) and its planned use of personalized, computation-grounded conversational guidance rather than generic notifications.

B. Artificial Intelligence in Robo-Advisory Services (Liu, 2024)

Liu (2024) examines the development of AI-driven personal financial advisory services, framing them within the broader concept of AI-enabled "service robots" that can analyze user data, interact conversationally, and operate autonomously without direct human intervention. Using JD.com's JIMI assistant as a case study, the paper illustrates how an AI advisor can support users across the financial journey — from early-stage investment guidance (interpreting user intent and financial literacy from conversational history), to product recommendation, comprehensive portfolio evaluation using risk-profile and market data, and business-process assistance and identity verification for security purposes.

The paper also documents the scale and trajectory of robo-advisory adoption, citing industry estimates of assets under robo-management growing from near zero in 2012 toward an estimated multi-trillion-dollar market within a decade, alongside a patent landscape analysis showing rapid, internationally distributed innovation in financial-risk-monitoring technology. At the same time, the author explicitly identifies the central limitation of purely AI-driven advisory systems: because recommendations originate from the model's internal algorithm, they may be affected by model defects, overfitting to historical data, or degraded performance in novel market conditions — risks compounded by the sensitivity of financial data to privacy and security threats.

For IntelliFinance, this literature provides both motivation and a design constraint. It confirms strong real-world demand for AI-mediated financial advice and validates the conversational-advisor paradigm used by JIMI-style systems. However, it also substantiates the core design rationale of IntelliFinance: rather than letting an AI model generate numerical financial decisions directly (with the attendant risks of algorithmic error or unverifiable output that Liu highlights), IntelliFinance restricts the AI Advisor to explanation and natural-language interaction, while all monetary calculations are produced by a separately verifiable, deterministic rule engine.

C. AI-Powered Expense Analytics and Financial Advisory Systems (Khandait et al., 2026)

Khandait, Bohrapi, Dongre, Padlamwar, and Patil (2026) present an "AI-Powered Smart Expense Analytics & Financial Advisor" that automatically records and categorizes user transactions using machine learning (Naïve Bayes classification), analyzes monthly and category-wise spending trends, performs predictive analysis of future expenses using regression and time-series techniques, detects anomalous transactions, and generates budget and saving recommendations, all surfaced through an interactive

Streamlit dashboard. Their reported system pipeline — data collection, storage in a SQL database, preprocessing, categorization, trend analysis, prediction, anomaly detection, recommendation, and visualization — closely parallels a subset of the architecture proposed for IntelliFinance, and their working prototype (with a functioning transaction-analysis and spending-prediction dashboard) demonstrates the technical feasibility of ML-driven expense categorization and forecasting within a lightweight Python-based stack.

The authors' own literature review notes that despite these advances, most existing expense-tracking systems still lack personalization tailored to individual behavior, and few integrate tracking, analysis, prediction, and recommendation into a single unified platform. Their proposed system addresses the integration gap but is still scoped primarily around expense tracking and forecasting; it does not incorporate an explicit, composite financial-health metric, does not extend planning to goal-based investment (SIP) or debt/EMI structuring, and is designed for a single user rather than a household.

D. Synthesis and Research Gap

Read together, these three strands of literature point to a consistent gap. Budgeting and expense-tracking systems, including the ML-based analytics platform of Khandait et al. (2026), automate categorization and forecasting well but generally stop short of goal-based investment planning, debt strategy, or a single composite indicator of financial health, and are built for individual rather than household use. Robo-advisory and AI-advisor systems, as discussed by Liu (2024), can converse naturally and personalize recommendations but carry a documented risk of unverifiable or model-dependent numerical output. Field evidence from French et al. (2021) shows that even well-designed finance apps struggle to sustain engagement and to convert improved financial capability into improved financial outcomes unless the tool is simple, relevant, and reinforced through personalization or light gamification.

IntelliFinance is designed to sit at the intersection of these findings: it adopts a rule-based calculation core (addressing the verifiability concern raised by Liu, 2024), extends automated analytics into budgeting, emergency-fund planning, SIP recommendations, and EMI/debt strategy in one platform (addressing the integration gap noted by Khandait et al., 2026), introduces a Financial Health Score and Family Financial Mode as relevance- and engagement-generating features (responding directly to the engagement findings of French et al., 2021), and uses an LLM-based AI Advisor purely for explanation and natural-language interaction rather than for numerical decision-making.

3. Problem Definition and Research Objectives

A. Problem Statement

There is a need for a web-based system that dynamically computes a personalized monthly financial plan — covering budgeting, emergency-fund adequacy, SIP/investment contributions, and debt repayment — directly from a user's actual financial data; that expresses the user's overall financial well-being through a single, explainable Financial Health Score; and that communicates the resulting recommendations through a natural-language conversational interface, while also supporting shared, family-level financial planning.

B. Research Objectives

- To design a system that dynamically analyses a user's income and expenses instead of relying on fixed, generic budgeting rules.

- To build a rule-based financial calculation engine for budget allocation, emergency-fund planning, SIP/investment recommendations, and debt (EMI) analysis.
- To generate an overall Financial Health Score based on savings rate, emergency-fund adequacy, debt burden, and investment rate.
- To integrate a conversational AI advisor that explains recommendations and answers user-specific financial questions in natural language, grounded in the calculation engine's verified output.
- To extend planning beyond the individual through a Family Financial Mode that supports shared goals and household-level financial visibility.

4. Proposed System: Intellifinance

IntelliFinance follows a layered architecture in which user-supplied financial data flows through a deterministic calculation engine before reaching the AI advisory layer, ensuring that every numerical recommendation is produced by verifiable financial rules rather than by the language model itself. This separation of computation and explanation is the central design principle of the system: it keeps numerical output auditable while still allowing the advisory layer to communicate results in natural, personalized language and to support what-if scenario discussion.

A. System Architecture

User inputs — income, expenses, savings, goals, and risk profile — are collected through a React.js front end and sent to a FastAPI back end. The back end's financial engine computes essential versus discretionary expenses, emergency-fund targets, SIP projections, goal-based savings requirements, and debt-repayment plans. An LLM-based AI Advisor then consumes these calculated results to explain the recommendations, answer natural-language questions, and support scenario analysis. All data is persisted in a relational database. Table I summarizes the layer-wise technology mapping.

Table I
Research Methodology–Layer-Wise Technology Mapping

Layer	Purpose	Technology
Frontend	Dashboard, forms, charts, AI chat interface	React.js, Recharts / Chart.js
Backend	API layer and orchestration	Python, FastAPI
Calculation Engine	Deterministic budget, SIP, EMI and score computation	Rule-based Python modules
Analytics	Expense trend prediction, anomaly detection	Pandas, NumPy, scikit-learn
AI Advisor	Natural-language explanation and Q&A	LLM API integration
Database	Persistent storage of user and financial data	PostgreSQL

B. Data Flow Design

The system's information flow is modelled across three levels of decomposition. At Level 0 (context level), the User (Individual/Family) submits financial profile, income, expenses, goals, risk profile, and queries to the SFDSS; the system returns a personalized plan, recommendations, reports, AI advice, alerts, and a Financial Health Score, while exchanging computed context and natural-language queries with an external AI Advisor (LLM service) and storing/retrieving user data from a PostgreSQL database.

At Level 1, the context process is decomposed into five subprocesses: (1.0) User Management, which handles registration and login and stores user records; (2.0) the Financial Calculation Engine, which consumes profile and financial data and produces processed financial results, storing and retrieving financial records; (3.0) the Data Analytics Module, which derives analytics results and calculated outputs from processed financial data and historical analytics; (4.0) the AI Advisor Module, which exchanges context and user queries with the external LLM service to produce AI responses; and (5.0) the Report & Visualization Module, which generates recommendations, reports, the Financial Health Score, and alerts for the user, storing generated reports.

At Level 2, four of these processes are further decomposed. The Financial Calculation Engine splits into an Income & Expense Processor (2.1), a Goal & Risk Evaluator (2.2), and a Debt & EMI Analyzer (2.3), all writing calculated financial results to the Financial Data store. The Data Analytics Module splits into Expense Trend Prediction (3.1), Anomaly Detection (3.2), and Spending Insights
(3.3), drawing on historical expenses, spending patterns, and user financial data. The AI Advisor Module splits into an LLM Prompt Generator (4.1), which assembles calculated results, analytics insights, and the user's query into a prompt for the external LLM service, and a Response Processor (4.2), which turns the LLM's reply into AI advice, answers, and explanations for the user. Finally, the
Report & Visualization Module splits into a Report Generator (5.1) and a Dashboard & Visualization Builder (5.2), which together transform calculated results, analytics results, and the Financial Health Score into reports, charts, and dashboards stored for later retrieval.

C. Distinctive Feature Modules

- **Financial Health Score:** a single, composite, explainable indicator combining savings rate, emergency-fund adequacy, debt burden, and investment rate, intended to give users an at-a-glance, trackable measure of progress — directly addressing the relevance and engagement gap identified in the RCT evidence of French et al. (2021).
- **Conversational Financial Query System:** an LLM-based interface that explains why a recommendation was generated and answers free-form financial questions, without itself performing the underlying arithmetic.
- **Family Financial Mode:** a household-level extension allowing multiple members to plan and track shared financial goals and visibility together, an area the reviewed literature (particularly Khandait et al., 2026, and the single-user focus of most robo-advisors discussed by Liu, 2024) identifies as largely underserved.

5. Work Plan, Hypotheses, And Evaluation Methodology

To evaluate whether IntelliFinance's design choices achieve their intended effect, four study hypotheses are proposed, each paired with a corresponding null hypothesis to be tested during system evaluation (Table II). These hypotheses are informed directly by the literature reviewed in Section II: H1 and H2 respond to the relevance and self-confidence findings of French et al. (2021); H3 responds to the verifiability concerns raised by Liu (2024); and H4 addresses the household-planning gap noted across the reviewed systems.

Table II
Study Hypotheses And Corresponding Null Hypotheses

Hypothesis	Statement	Corresponding Null Hypothesis (H0)
H1	Personalised, dynamically-computed budgeting improves perceived relevance over fixed-percentage rules.	There is no significant difference in perceived relevance between rule-based, adaptive budget recommendations and fixed-percentage budgeting rules.
H2	A composite Financial Health Score improves users' understanding of their financial condition.	A composite Financial Health Score does not improve users' understanding of their financial condition relative to viewing individual metrics.
H3	Grounding the AI advisor in deterministically computed results increases user trust and engagement.	Grounding the AI advisor in deterministically computed results does not increase user trust or engagement compared to ungrounded AI-generated advice.
H4	A Family Financial Mode improves household coordination and financial transparency.	A Family Financial Mode does not improve coordination or transparency in household financial decisions.

Evaluation is planned to follow an approach broadly comparable to French et al. (2021): comparing user outcomes (self-reported relevance, confidence, and engagement) between users of the full IntelliFinance system and users of a simplified control version lacking the Financial Health Score, grounded AI explanations, or Family Financial Mode, with statistical adjustment for socio-economic and demographic covariates where a between-subjects design is used.

6. Implementation Requirements

Table III summarizes the hardware/software components required to implement the proposed system, consistent with the layered architecture described in Section IV-A.

Table III
Hardware and Software Requirements

Component	Requirement
Frontend	React.js with Chart.js / Recharts for data visualisation
Backend	Python (FastAPI), with Node.js for auxiliary services
Database	PostgreSQL for relational storage of user and financial data
Analytics	Pandas, NumPy, scikit-learn for trend prediction and anomaly detection
AI Advisor	LLM API integration for grounded, conversational, natural-language responses

7. Discussion

The proposed design directly responds to limitations documented in each of the three reviewed studies. First, French et al. (2021) found that even a well-executed RCT of finance apps produced only a "small number" of behavioral improvements and no measurable gain in overall household financial well-being within one year, with declining engagement identified as a central cause; the authors explicitly recommend targeting a specific problem, keeping the design simple, and using personalization and light gamification to sustain use. IntelliFinance's Financial Health Score functions as a simple, recurring, personally-relevant signal in the spirit of this recommendation, while the Family Financial Mode offers a natural, socially-reinforced reason to return to the app regularly.

Second, Liu (2024) documents rapid real-world growth in AI-driven robo-advisory assets under management, alongside an explicit caution that AI systems may make erroneous decisions due to model defects or overfitting, and that financial data carries heightened privacy and security risk. IntelliFinance's architectural decision to compute every numerical output through a deterministic, auditable rule engine — reserving the LLM strictly for explanation, and not for arithmetic or financial-decision generation — is a direct, structural response to this documented risk, rather than a marketing claim of "explainability" layered on top of an opaque model.

Third, Khandait et al. (2026) demonstrate that an integrated pipeline of categorization, trend analysis, prediction, anomaly detection, and recommendation is technically feasible with a lightweight Python/ML stack, and their own review notes that most comparable systems are not personalized and do not unify all these functions in one platform. IntelliFinance extends this integrated pipeline concept from expense analytics into the additional domains of emergency-fund planning, SIP-based investment guidance, and EMI/debt-repayment strategy, and adds the single composite Financial Health Score and household-level Family Financial Mode that are absent from that system's scope.

Taken together, the reviewed literature suggests that the value of a personal-finance decision-support tool depends less on any single technical capability and more on the combination of computational reliability, personalized relevance, and sustained engagement. IntelliFinance's contribution is not any one of the individual techniques used — rule-based computation, ML-based analytics, or an LLM-based advisor —

each of which has precedent in the reviewed work, but their combination within a single explainable architecture aimed explicitly at the specific gaps that this literature identifies.

8. Need of The Proposed Research Work

Financial literacy and access to affordable, personalized financial advice remain limited for a large proportion of the population, particularly students, young professionals, and first-time earners who cannot afford professional financial advisors. Poor financial planning at an early stage — inadequate emergency funds, high debt burden, or delayed investing — can have long-term consequences for an individual's financial security. This concern is reinforced by French et al.'s (2021) finding that even a targeted, well-resourced intervention for financially squeezed households produced only partial and short-lived behavioral gains, underscoring how difficult sustained financial-capability improvement is to achieve without careful, evidence-informed design.

IntelliFinance addresses this need by making structured, personalized, and explainable financial guidance accessible through a web application. By combining a verifiable, rule-based calculation engine with a conversational AI advisor, the system aims to build user trust in a domain where transparency is critical — a concern made explicit in the robo-advisory literature (Liu, 2024). The addition of a Financial Health Score gives users a simple, trackable measure of progress, while the Family Financial Mode extends the benefit of structured planning to entire households, an area largely underserved by existing single-user finance applications, including comparable ML-based expense-analytics systems (Khandait et al., 2026).

9. Limitations and Future Scope

- The current work covers system architecture, data-flow design, and the calculation-engine specification; empirical evaluation of the stated hypotheses (Table II) against real users remains future work, following the RCT/OLS-adjustment methodology used by French et al. (2021).
- As with any LLM-integrated system, the AI Advisor's explanations must be continually validated against the rule engine's output to prevent drift or hallucinated figures reaching the user; automated consistency checks between the two layers are planned.
- Data security and privacy safeguards for sensitive financial and household information, flagged as a key risk by Liu (2024), will require dedicated design attention (encryption at rest/in transit, access control for Family Financial Mode) before any production deployment.
- Future iterations may incorporate gamification elements and personalized, two-way engagement prompts, consistent with the reinforcement strategies found effective by French et al. (2021), to sustain long-term usage beyond an initial adoption period.

10. Conclusion

This paper presented IntelliFinance, a web-based Smart Financial Decision Support System that integrates a deterministic financial calculation engine, ML-based analytics, an explainable conversational AI advisor, a composite Financial Health Score, and a Family Financial Mode into a single platform. By reviewing empirical evidence on the behavioral efficacy and engagement challenges of personal finance apps (French, McKillop, & Stewart, 2021), the opportunities and risks of AI-driven robo-advisory services (Liu, 2024), and the technical feasibility of integrated ML-based expense-analytics platforms (Khandait et al.,

2026), this paper identified a consistent gap — the absence of a single, trustworthy, and engaging system that combines verifiable computation, personalized relevance, and household-level planning — and positioned IntelliFinance's architecture as a direct response to that gap. Future work will focus on implementing the described architecture, conducting a controlled evaluation of the proposed hypotheses, and refining the system's engagement and security design based on that evaluation.

References

1. D. French, D. G. McKillop, and E. Stewart, "Personal finance apps and low-income households," Strategic
2. Change, vol. 30, no. 4, pp. 367–375, 2021. [Online]. Available: https://doi.org/10.1002/jsc.2430 Z. Liu, "Artificial Intelligence as Personal Financial Advisor in the Future? – A Case Study Based onAlgorithmic Innovation Strategies," in Proc. 2nd Int. Conf. Management Research and Economic Development, 2024, pp. 272–278. [Online]. Available: https://doi.org/10.54254/2754-1169/87/202410308
3. S. P. Khandait, N. Bohrapi, P. Dongre, P. Padlamwar, and P. Patil, "Research paper on AI poweredfinancial adviser," Int. J. Engineering Development and Research, vol. 14, no. 2, pp. 505–512, 2026.
4. S. Bagwell, C. Hestbaek, E. Harries, and A. Kail, "Financial capability outcomes framework," London, UK,2014. [Online]. Available: www.fincap.org.uk/uk_strategy
5. OECD INFE, "Measuring financial literacy: Core questionnaire in measuring financial literacy,"Organisation for Economic Co-operation and Development, Paris, 2011.
6. OECD INFE, "Digitalisation and financial literacy," Organisation for Economic Co-operation andDevelopment, Paris, 2018.
7. Reserve Bank of India, "Financial Literacy and Consumer Protection reports." [Online]. Available: https://www.rbi.org.in
8. Securities and Exchange Board of India (SEBI), "Investor Education resources." [Online]. Available: https://www.sebi.gov.in
9. "FastAPI – Modern, Fast Web Framework for Building APIs with Python," Official Documentation.[Online]. Available: https://fastapi.tiangolo.com
10. PostgreSQL Global Development Group, "PostgreSQL Documentation." [Online]. Available: https://www.postgresql.org/docs/
11. F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," J. Machine Learning Research. [Online]. Available: https://scikit-learn.org