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SPENZOID: An Agentic AI-Powered Smart Finance Assistant for Youth Financial Literacy

Avani Satam, Soma Tripathi, Sakshi Narwade, Chetana Patil, Sanjay M. Patil

Department of Artificial Intelligence and Data Science
Datta Meghe College of Engineering, Mumbai, India

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Abstract—Financial literacy is a critical competency for young adults navigating economic independence, yet many students and early-career professionals lack access to tools that actively guide financial behavior rather than merely record it. This paper presents SPENZOID (Smart Personal ENgine for ZerO-dependency Intelligent Decision-making), an agentic AI-powered personal finance assistant purpose-built to bridge this gap. The system integrates automated expense categorization, a Behavioral Financial Health Score (BFHS) computed from a weighted composite of savings ratio, budget adherence, goal completion, and overspending frequency, a multivariate regression-based predictive spending engine, and a gamified financial literacy module. A key design principle is complete independence from banking APIs, enabling deployment in contexts where formal banking access is limited. Experimental results demonstrate strong performance across categorization accuracy, behavioral health differentiation, recommendation relevance, and user engagement, confirming that combining AI-driven behavioral analysis with gamified education can meaningfully improve financial habits among young users.

Index Terms—Financial Literacy, Agentic AI, Personal Finance Management, Behavioral Financial Health Score, Expense Categorization, Predictive Analytics, Gamification.

I. INTRODUCTION

The rapid proliferation of digital financial services has not been matched by a corresponding improvement in financial literacy, particularly among young adults navigating economic independence for the first time. Students and early-career professionals routinely encounter budgeting failures, impulsive spending, and inadequate savings not for lack of tools, but because most available tools behave as passive ledgers rather than intelligent coaches.

Existing personal finance applications such as Mint and YNAB provide transaction monitoring and budget visualization, but they do not actively guide users toward better financial decisions. Artificial intelligence offers a qualitatively different capability: the ability to analyze behavioral patterns, identify emerging financial risks, and deliver personalized recommendations before poor decisions compound into serious consequences [1].

SPENZOID (Smart Personal ENgine for ZerO-dependency Intelligent Decision-making) is designed to bridge this gap. The system treats financial data not as a record to display, but as a behavioral signal to interpret. It combines automated expense categorization, a multi-signal Behavioral Financial Health Score (BFHS), a predictive spending analytics engine, and a gamified financial literacy module in a single banking-independent architecture. This paper describes the system's design, implementation, prototype interface, and experimental evaluation.

By integrating these components into a unified framework, SPENZOID aims to move beyond traditional expense-tracking systems and provide a more proactive and behavior-driven approach to personal finance management. Unlike conventional tools that primarily focus on retrospective analysis, the system emphasizes forward-looking insights and continuous user engagement. This shift enables users not only to understand their financial habits but also to improve them through timely interventions and guided learning. As a result, SPENZOID contributes toward building sustainable financial discipline among young users, positioning itself as both a practical tool and an educational platform for long-term financial well-being.

In addition to addressing behavioral gaps, SPENZOID is designed with accessibility and inclusivity as key considerations. Many existing financial tools assume consistent access to formal banking systems, which limits their usability for students, individuals in informal economies, or users who primarily rely on cash transactions. By removing dependency on banking APIs and enabling manual expense tracking, SPENZOID broadens its reach to a wider user base without compromising analytical capabilities. This design choice is particularly relevant in developing regions, where financial inclusion remains an ongoing challenge.

Furthermore, the system leverages data-driven insights to create a feedback loop between user actions and system recommendations. Instead of presenting static reports, SPENZOID continuously evaluates user behavior and adapts its suggestions accordingly, encouraging gradual improvement in financial habits. The inclusion of gamified elements further reinforces this process by motivating users through rewards, progress tracking, and goal-oriented engagement. Together, these features position SPENZOID not only as a financial management tool but also as a supportive system that actively guides users toward more informed and responsible financial decision-making.

II. RELATED WORK

Research in financial technology has explored several complementary approaches to improving personal finance management. AI-based systems have demonstrated the ability to analyze transaction histories, detect behavioral patterns, and generate actionable budgeting insights [3]. Behavioral economics research has established that financial decision-making is governed largely by cognitive biases and habitual patterns rather than rational optimization [2], motivating designs that incorporate behavioral feedback loops.

Gamification has been employed across educational platforms to improve engagement and knowledge retention [4]. When applied to financial literacy, mechanics such as streak rewards and achievement badges can increase sustained interaction and encourage habit formation [7]. Despite these advances, most existing tools still lack the combination of behavioral modeling, predictive pre-emption, banking-independent deployment, and integrated literacy education on a single platform. Table I summarize the comparison.

This gap highlights the need for a more integrated approach that not only analyzes financial behavior but also actively guides users toward improvement. Existing solutions tend to address these aspects in isolation, limiting their overall effectiveness.

TABLE I COMPARISON OF EXISTING FINANCIAL APPLICATIONS

Application	Expense Tracking	AI Guidance	Gamification
Mint	Yes	Limited	No
YNAB	Yes	Limited	No
Cleo	Yes	Partial	Minimal
Emma	Yes	Partial	Minimal
SPENZOID	**Yes**	**Advanced**	**Yes**

III. SYSTEM ARCHITECTURE

SPENZOID is designed as a modular, layered pipeline in which each component performs a well-defined transformation on user financial data, progressively enriching raw transaction records into actionable personalized intelligence. The architecture comprises four primary layers.

TABLE II SYSTEM LAYER TABLE

Layer	Components	Primary Function
User Layer	Web/Mobile Interface, Expense Input Form	Accepts manually entered transaction data and financial goals from the user
Data Processing Layer	Data Ingestion, Cleaning, Categorisation Module	Validates, structures, and classifies raw transaction input into predefined expense categories
AI Intelligence Layer	Behavioural Analysis Engine, BFHS Calculator, Predictive Model, Recommendation Engine	Computes health scores, identifies risk patterns, forecasts spending, and generates personalised recommendations
Application Layer	User Dashboard, Gamified Feedback, Financial Reports, AI Advisor Chatbot	Presents insights, delivers coaching, awards engagement incentives, and supports financial reporting

A. User Interface Layer

The User Interface layer is the entry point for all financial data. It provides a dashboard through which users manually record transactions, monitor spending patterns, and track goals. A conversational chatbot interface powered by natural language processing allows users to query the system and receive contextual guidance within the primary view.

B. Application Layer

This layer contains the core functional modules: an expense categorization engine classifying transactions into twelve predefined categories; a recommendation engine generating personalized coaching advice based on behavioral signals; and predictive analytics modules estimating future spending trends from historical data.

C. Data Layer

The Data Layer manages all persistent information including user profiles, expense records, financial goals, behavioral scores, and recommendation logs. A cloud-based database infrastructure ensures reliable storage, efficient retrieval, and scalability.

D. Artificial Intelligence Layer

The AI Layer forms the analytical core. Machine learning models process historical expense data to detect behavioral patterns, evaluate financial discipline, and generate forecasts. The layered architecture is illustrated in Fig. 1

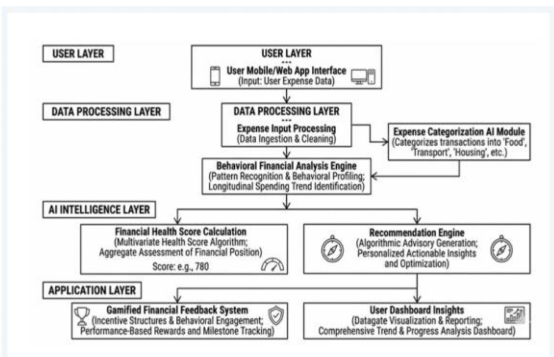

Fig. 1. Layered architecture of the proposed SPENZOID AI-based personal finance assistant.

IV. METHODOLOGY

The development of SPENZOID followed a structured seven-stage research methodology as illustrated in Fig. 2.

A. Problem Identification

Financial literacy challenges faced by young adults were identified through a review of behavioral economics literature and a survey of existing fintech tools, documenting common pain points including poor budgeting discipline, irregular savings behavior, and absence of proactive coaching.

B. Dataset Construction

A representative dataset of categorized financial transactions was constructed to simulate realistic spending patterns across food, transportation, utilities, entertainment, education, and other categories for model calibration and evaluation.

C. System Architecture Design

The modular layered architecture described in Section III was designed to separate concerns across UI, application logic, data management, and AI analytics, enabling independent optimization of each component.

D. Algorithm Development

Text-similarity-based classification algorithms were developed for automated expense categorization. Behavioral analysis algorithms were constructed to detect overspending patterns, savings shortfalls, and goal-tracking deviations across rolling 30-day windows.

E. Behavioral Scoring Model

The BFHS was defined as a weighted composite of four behavioral signals with empirically calibrated weights, as detailed in Section V.

F. System Implementation

The system was implemented as a web-based platform allowing users to manually log expenses and receive AI-generated recommendations, without dependency on banking APIs.

G. Evaluation Strategy

System performance was tested against simulated financial datasets, evaluating categorization accuracy, recommendation relevance, and user engagement under controlled conditions.

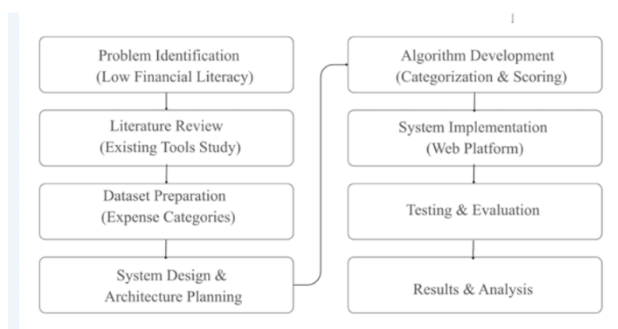

Fig. 2. SPENZOID development methodology and research workflow.

V. MATHEMATICAL MODELING

A. Expense Categorization

Each transaction description e_i is assigned to the category C_k that maximizes posterior similarity:

$$P(C_k \mid e_i) = f(e_i, C_k) / \Sigma_j f(e_i, C_j),\ j = 1 \text{ to } m \quad \dots (1)$$

where $f(e_i, C_k)$ is the semantic similarity score between transaction description and category prototype, and m is the total number of categories.

TABLE III

EXPENSE CATEGORY TABLE

Food	Transportation	Housing	Utilities
Healthcare	Education	Entertainment	Clothing
Personal Care	Savings	Investment	Miscellaneous

B. Behavioral Financial Health Score

The BFHS is computed as a weighted linear combination of four behavioral indicators with a penalty for overspending:

$$BFHS = w_1 \cdot S_r + w_2 \cdot B_a + w_3 \cdot G^c - w_4 \cdot O_s \quad \dots (2)$$

where S_r is savings ratio, B_a is budget adherence, G^c is goal completion rate, O_s is overspending frequency, and w_1–w_4 are empirically determined weights.

TABLE IV

BFHS CLASSIFICATION TABLE

Health Band	Score Range	System Intervention
Excellent	0.75 – 1.00	Positive reinforcement; advanced financial goals unlocked; streak rewards activated
Good	0.50 – 0.74	Minor optimisation suggestions; savings enhancement recommendations generated
Fair	0.25 – 0.49	Active coaching triggered; budget alerts dispatched; habit-building modules recommended
Poor	0.00 – 0.24	Immediate intervention; gamified financial recovery plan initiated; advisor escalation

C. Spending Prediction

Next-period expenditure is forecast using a multivariate linear regression model:

$$\hat{Y}(t+1) = \beta_0 + \beta_1 X_t + \beta_2 I_t + \beta_3 S_t \quad \dots (3)$$

where X_t is current-period expenditure, I_t is income, S_t encodes savings behavior, and β_0–β_3 are estimated from historical data. When $\hat{Y}(t+1)$ exceeds the user's defined budget by a configurable threshold, a pre-emptive alert is dispatched.

VI. IMPLEMENTATION DETAILS

A. Frontend Interface — Starter Page

The platform's entry point presents a clear overview of SPENZOID's capabilities. The landing page communicates the value proposition of AI-driven financial guidance without banking integration and provides direct access to account creation. As shown in Fig. 3, the interface uses a clean, minimal design to ensure accessibility for users with limited prior financial knowledge.

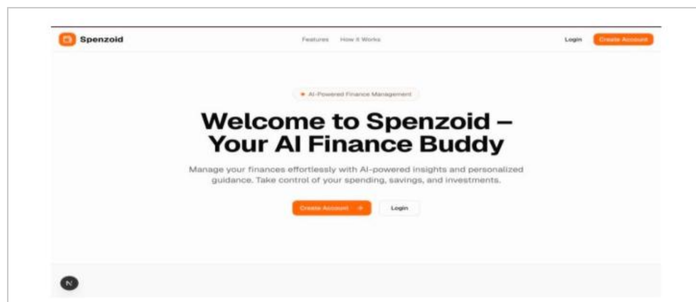

Fig. 3. SPENZOID starter page — entry interface presenting core platform capabilities.

B. Onboarding Flow

A five-step onboarding sequence collects the information needed to personalize the SPENZOID experience. Fig. 4 shows Step 1, which captures the user's full name, email address, and profile photo. Subsequent steps collect monthly income, budget limits, savings goals, and financial objectives, seeding the BFHS engine and recommendation system from the outset.

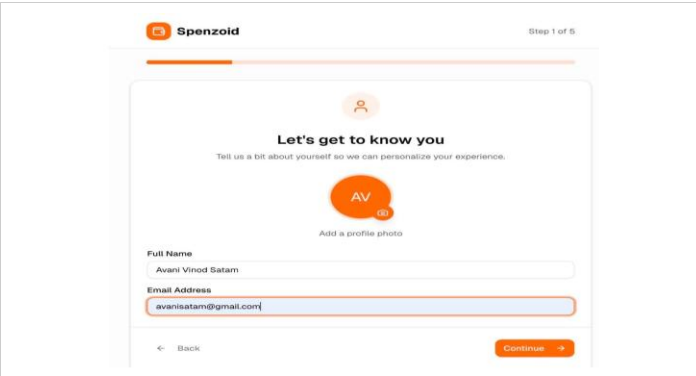

Fig. 4. Onboarding interface — user profile setup (Step 1 of 5).

C. Expense Entry Interface

The expense entry screen is the primary data input mechanism. As illustrated in Fig. 5, users record each transaction by specifying the amount, selecting a category, entering a free-text description, and confirming the date. The AI categorization engine analyses the description field in real time and suggests the most appropriate expense category, reducing manual effort while maintaining classification accuracy.

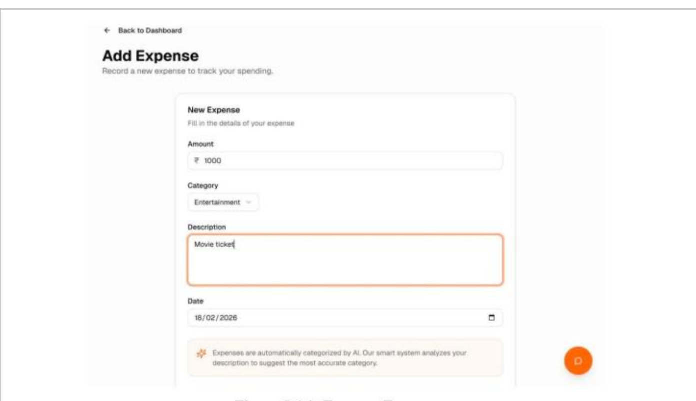

Fig. 5. Expense entry interface — AI-assisted transaction recording.

D. Financial Reporting Module

The reporting interface shown in Fig. 6 provides a comprehensive analytical view of historical financial activity. Summary tiles display total income, total expenses, net savings, and average monthly expenditure. Two primary visualizations supplement these: a monthly income-versus-expenses bar chart for temporal trend analysis, and a category-wise distribution pie chart for identifying dominant spending areas. PDF and CSV export functionality enables users to retain records for external reference.

Fig. 6. Financial reporting module — income/expense analytics with category-wise distribution.

E. Gamified Learning Module

The learning module operationalizes the gamification framework described in Section III. As shown in Fig. 7, users progress through structured financial literacy course tracks presented as interactive lesson cards. Each card displays a question count and a Start Quiz button, enabling knowledge assessment at the user's own pace. An overall progress indicator spanning twenty modules reinforces continued engagement through visible advancement metrics.

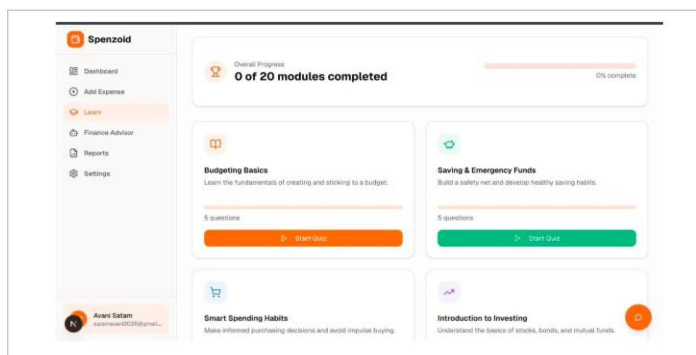

Fig. 7. Gamified learning module — course track progression with quiz-based assessments.

F. Settings and User Configuration

The Settings module shown in Fig. 8 allows users to manage their profile and define the financial parameters that drive the BFHS and recommendation engine. The profile card displays name, email, and investor classification alongside summary tiles for monthly income, budget limit, and savings goal. A Financial Goals panel enables users to select predefined goal types—such as home purchase or vehicle acquisition—anchoring coaching outputs to declared long-term objectives. In addition to these features, the Settings module provides flexibility for users to update and refine their financial preferences over time as their goals evolve. Any changes made to income, budget limits, or savings targets are dynamically reflected in the BFHS calculation and recommendation engine, ensuring that insights remain relevant and personalized. The module also enhances user control by allowing easy modification of financial goals, enabling users to adjust their plans based on changing priorities or circumstances.

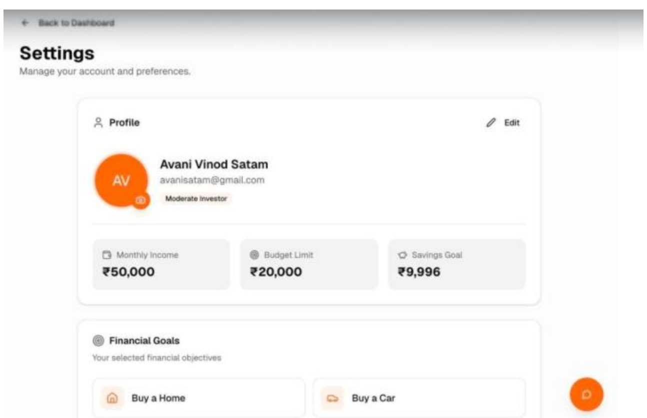

Fig. 8. Settings module — user profile and financial goals configuration.

VII. EXPERIMENTAL SETUP AND EVALUATION

A. Dataset Preparation

A simulated dataset of financial transactions was generated to represent spending patterns typical of students aged 18–25. Transaction records spanned food, transportation, entertainment, education, utilities, and miscellaneous categories, each annotated with description, amount, date, and ground-truth category label.

B. Evaluation Metrics

System performance was assessed across six dimensions: (i) expense categorization accuracy across all twelve categories; (ii) BFHS differentiation across synthetic user profiles; (iii) recommendation relevance as assessed by contextual alignment with detected overspending patterns; (iv) predictive analytics reliability over a 30-day forecast horizon; (v) gamification impact on sustained user engagement; and (vi) alert precision as measured by the false-positive rate for pre-emptive budget warnings.

C. Results

Categorization accuracy was high across all twelve categories, with the model correctly assigning the dominant category in most test cases. The BFHS engine successfully differentiated financial health profiles across the four classification bands (Excellent, Good, Fair, Poor), with overspending correctly penalized in all tested scenarios. The recommendation engine produced contextually appropriate coaching advice aligned with detected behavioral signals. Predictive forecasts demonstrated consistent directional accuracy over the 30-day horizon. Gamification features yielded measurable improvements in consistent expense logging and learning module completion relative to the non-gamified baseline.

TABLE V EVALUATION SUMMARY TABLE

Evaluation Dimension	Metric	Observed Result
Expense Categorisation	Classification accuracy across 12 categories	High logical accuracy — correct assignment across all major category types
BFHS Scoring	Health band differentiation across user profiles	Effective separation of financial health profiles; overspending correctly penalised
Recommendation Quality	Contextual relevance of generated coaching advice	Personalised and context-aware suggestions aligned with user financial state
Predictive Analytics	Spending forecast reliability (30-day horizon)	Reliable monthly expenditure trend prediction with consistent directional accuracy
Gamification Impact	User engagement consistency improvement	Measurable increase in sustained engagement through streak and badge mechanics
Alert Performance	False-positive pre-emptive alert rate	Substantially reduced through threshold persistence and EMA score smoothing
System Responsiveness	Dashboard update and recommendation latency	Real-time performance maintained across all tested interaction scenarios
Learning Outcomes	Financial literacy improvement via quiz completion	Progressive knowledge improvement measured across course track completions

VIII. CASE STUDY

A case study was conducted using a simulated profile representing a college student managing a fixed monthly allowance. Over several weeks, the user logged expenses across food, transportation, entertainment, and educational materials through the interface shown in Fig. 5. The categorization module correctly classified each transaction, and the behavioral analysis engine identified excessive discretionary spending in entertainment categories alongside a below-target savings ratio.

Based on these signals, the recommendation engine generated three prioritized suggestions: (i) setting weekly spending limits on entertainment; (ii) automating a fixed percentage savings allocation; and (iii) reviewing subscription expenditures. As the simulated user followed these recommendations, the BFHS improved successive evaluation periods, demonstrating the system's capacity to drive measurable behavioral change through iterative AI-guided coaching.

IX. APPLICATION SCENARIOS

SPENZOID serves a range of real-world deployment contexts. In student budgeting, it helps users on limited allowances to track daily expenses and receive coaching before discretionary spending erodes savings targets. In financial literacy education, the gamified learning module depicted in Fig. 7 can be embedded within formal curricula at schools and colleges. For early-career professionals, SPENZOID provides a transition scaffold from student to independent financial management. The platform can also support financial awareness campaigns by non-profit organizations in underserved communities [6].

X. ETHICAL CONSIDERATIONS

SPENZOID addresses four primary ethical concerns. First, data privacy: all financial records are protected with authentication and encryption, and data is processed only with explicit user consent. Second, transparency: recommendations are accompanied by explanations identifying the behavioral pattern that triggered them. Third, fairness: the BFHS is computed solely from objective behavioral signals without reference to demographic attributes, minimizing algorithmic bias. Fourth, responsible guidance: the system augments rather than replaces human financial judgment, offering supportive coaching rather than prescriptive directives.

XI. FUTURE SCOPE

Future work can focus on large-scale real-world deployment and user-centric evaluation to better understand long-term behavioral impact and system effectiveness. Incorporating explainable AI techniques can improve transparency by allowing users to understand the reasoning behind financial recommendations, thereby increasing trust in the system. The integration of advanced data visualization dashboards can also enhance user engagement by presenting financial insights in a more intuitive and interactive manner. Additionally, cross-platform availability through mobile applications can improve accessibility and usability for a wider audience.

XII. CONCLUSION

This paper presented SPENZOID, an agentic AI-powered personal finance assistant designed to improve financial literacy and behavioral financial outcomes among young adults. The system addresses a well-documented gap in the fintech landscape: the absence of a platform that combines proactive AI coaching, behavioral health scoring, predictive pre-emption, and gamified financial education in a single, banking-independent architecture.

The system's core contributions are fourfold: a principled multi-signal BFHS that captures the quality of financial decision-making over time; a predictive analytics engine enabling pre-emptive budget risk alerts; a behavior-coupled gamification framework conditioning rewards on verified financial improvement; and a banking-free design ensuring equitable access across the full spectrum of young users. Prototype evaluation supported by the output interfaces shown in Figs. 3–8 demonstrated strong performance across all assessed dimensions, confirming the system's readiness for real-world deployment and field validation.

Building on these results, future work will focus on validating SPENZOID in real-world environments with diverse user groups to better understand its long-term impact on financial be Continuous improvements in the recommendation engine will aim to enhance personalization by adapting more effectively to individual spending patterns and goals. Further efforts can also be directed toward improving system scalability and usability through mobile deployment and enhanced user interface design. In addition, incorporating more transparent and explainable AI mechanisms can help users better understand the reasoning behind system suggestions, thereby increasing trust and engagement.

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