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Smart SIP for Teens: A Gamified and Explainable Machine Learning Framework for Early Investment Habit Formation

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Abstract: Early financial literacy plays a crucial role in shaping long-term economic well-being. However, most digital investment platforms are designed for adult users and they lacks in educational, motivational, and transparency features suitable for teenagers. This paper presents Smart SIP for Teens, a comprehensive, gamified, and explainable financial learning platform aimed at fostering disciplined saving and early investment habits among teenagers. The proposed system combines machine learning-based personalization using the XGBoost algorithm to recommend suitable Systematic Investment Plan (SIP) strategies based on user-specific attributes such as age, savings behavior, financial goals, and risk tolerance. To address trust and transparency concerns, Explainable Artificial Intelligence (XAI) techniques using SHAP values are employed to interpret model decisions. Gamification elements such as reward points, streaks, badges, and milestones are incorporated to improve engagement and investment habit formation. Experimental evaluation demonstrates improved user engagement, consistency in saving behavior, and enhanced understanding of investment concepts. The results validate the effectiveness of combining personalization, explainability, and gamification in delivering impactful financial education solutions for teenage users.

Keywords: Systematic Investment Plan, Financial Literacy, Teenagers, Gamification, Machine Learning, XGBoost, Explainable AI, SHAP Values

I. INTRODUCTION

Financial decision-making has become increasingly complex due to the rapid growth of digital financial services, online investment platforms, and algorithm-driven financial products. While access to such services has expanded, structured financial education has not kept pace, particularly for younger populations. Teenagers are often introduced to financial tools without adequate understanding of saving discipline, risk management, or long-term investment planning.

In today's rapidly evolving economic environment, financial literacy has become an essential life skill. Individuals are required to make better and informed decisions regarding savings, investments, loans, and long-term financial planning at an increasingly early stage of life. However, many young people lack practical exposure to financial education, resulting in poor financial decision-making and long-term economic vulnerability. Teenagers represent a crucial demographic for early financial education, as habits formed during adolescence often persist into adulthood. Introducing financial concepts such as saving, budgeting, risk assessment, and investing at this stage can significantly influence future financial behavior. Among various investment instruments, Systematic Investment Plans (SIPs) provide a disciplined and accessible approach to investing, allowing individuals to invest small amounts at regular intervals. Despite their suitability for beginners, most existing SIP platforms are designed for adult users and focus primarily on technical investment features rather than education and engagement. These platforms often lack personalization, transparency, and motivational mechanisms suitable for teenagers. As a result, young users may find financial systems complex, intimidating, or irrelevant. The Smart SIP for Teens platform addresses these challenges by providing a personalized, explainable, and gamified financial learning environment tailored specifically for teenage users. By integrating machine learning, explainable AI, and behavioral finance principles, the platform transforms financial learning into an engaging, transparent, and habit-forming experience.

II. LITERATURE REVIEW

Recent research highlights the growing importance of technology-driven financial education platforms, particularly for adolescents and young users who are developing long-term saving and investment habits. Gamified financial learning environments have been shown to improve engagement, motivation, and behavioral consistency by incorporating goal-based challenges and reward mechanisms [1]. Explainable machine learning techniques are increasingly adopted in financial analytics to improve transparency and user trust in algorithmic systems [2]. Studies made on explainable AI

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further emphasize accountability and interpretability as critical requirements for responsible financial decision-making [3].

Digital platforms are designed to enhance financial literacy among youth have demonstrated measurable improvements in financial awareness and informed decision-making [4]. Research focusing on youth financial literacy highlights the long-term economic impact of early financial education on saving behavior and financial discipline [5]. Experiential and interactive learning models further support effective knowledge retention and engagement in financial education systems [6]. Gamification frameworks provide a structured approach to integrating game mechanics into non-game contexts, reinforcing sustained user participation [7].

Machine learning-based recommendation systems are increasingly used in personal finance applications to provide personalized insights. Gradient boosting models such as XGBoost demonstrate strong predictive performance on structured financial datasets due to their ability to capture non-linear relationships and complex feature interactions [8]. However, the use of complex predictive models necessitates robust explainability mechanisms to ensure transparency and regulatory compliance. SHAP has emerged as a widely adopted post-hoc explanation technique for interpreting model predictions at both local and global levels [9]. Foundational research emphasizes the need for a rigorous scientific basis for interpretability in high-stakes machine learning applications [10].

Ethical considerations play a central role in the deployment of AI-driven financial systems. Policy reports and regulatory guidelines stress the importance of ethical AI adoption, transparency, and accountability in financial services [11]. National-level strategies further promote financial education and responsible technology use to support informed financial behavior [12]. Global governance frameworks highlight the need for standardized ethical and regulatory oversight of AI systems in finance [13].

Recent academic studies explore the application of explainable AI in consumer finance, demonstrating improvements in trust, auditability, and decision confidence [14]. Machine learning-based SIP recommendation systems further illustrate the role of data-driven approaches in personalized financial planning [15]. Responsible AI design principles specifically tailored for youth-oriented financial platforms emphasize user protection, fairness, and transparency-aware recommendation strategies [16]. Regulatory developments such as the EU AI Act further reinforce the importance of governance and compliance in AI-enabled financial technologies [17].

Gamified mobile applications have been shown to support financial habit formation and long-term engagement, particularly among younger users [18]. Explainable gradient boosting models are increasingly applied in financial risk prediction to balance performance with interpretability [19]. Behavioral analytics techniques further enhance digital financial education systems by modeling user engagement and saving behavior patterns [20]. International standards bodies emphasize ethical AI system design to ensure fairness and accountability across application domains [21]. Transparency-aware financial recommendation engines continue to advance explainability and user trust in automated advisory systems [22].

International organizations increasingly highlight the need to safeguard children and young users in AI-driven digital financial services [23]. Post-hoc explainability techniques remain central to understanding and validating machine learning decisions in finance [24]. Recent studies further demonstrate the role of AI-enabled educational tools in promoting digital financial literacy and responsible financial behavior [25].

Despite these advancements, existing literature largely treats gamified financial education, machine learning-based recommendation systems, explainable AI, and ethical governance as separate research areas. Limited work has explored their unified integration into a single deployable framework tailored specifically for young users. This research addresses that gap by combining gamified financial education, explainable machine learning, and responsible AI principles into a cohesive system designed to promote transparent, engaging, and ethical financial decision-making.

III. BEHAVIORAL FINANCE FOUNDATION

Behavioral finance plays a critical role in understanding how individuals make financial decisions under uncertainty. Traditional financial theories assume rational behavior; however, empirical evidence suggests that emotional, psychological, and cognitive biases significantly influence investment decisions, especially among young individuals.

Teenagers are particularly susceptible to biases such as present bias, loss aversion, and overconfidence. Present bias causes individuals to prioritize immediate gratification over long-term benefits, often leading to impulsive spending

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rather than disciplined saving. Loss aversion discourages investment participation due to fear of potential losses, even when long-term gains are statistically favorable.

The Smart SIP for Teens platform integrates behavioral nudges to counter these biases. Gamification mechanisms such as streaks and milestones leverage positive reinforcement to promote delayed gratification. Visual progress indicators and goal-based rewards enhance intrinsic motivation, enabling teenagers to associate consistent saving with achievement and satisfaction.

By embedding behavioral finance principles into system design, the platform ensures that technological intelligence is complemented by psychological alignment, thereby increasing the likelihood of long-term habit formation.

IV. PROBLEM STATEMENT

Teenagers face several challenges in developing consistent saving and investment habits:

- Lack of practical financial education
- Limited access to age-appropriate investment tools
- Absence of transparency in financial recommendations
- Low motivation and engagement

Existing platforms fail to address these challenges holistically, creating a need for an intelligent, transparent, and engaging financial learning system.

V. PROPOSED SYSTEM

The proposed system, Smart SIP for Teens, is designed as a decision-support and learning platform rather than a direct trading system. Its primary objective is to guide teenagers toward disciplined saving and investment behaviour through personalized recommendations and interactive learning. The system collects user-specific information such as age, monthly savings amount, financial goals, and risk tolerance. This data is processed and analyzed using machine learning techniques to generate suitable SIP recommendations. The XG Boost algorithm is used due to its efficiency, accuracy, and ability to handle structured financial data. To address the issue of black-box decision-making, Explainable AI techniques are incorporated to provide clear justifications for each recommendation. Users can view the factors influencing their suggested SIP plan, improving understanding and trust. Gamification plays a central role in the proposed work. Reward points, streaks, and milestone achievements are used to motivate consistent saving behavior and reinforce positive financial habits. The proposed system thus combines education, personalization, explainability, and motivation into a unified platform tailored for teenage users.

A. A. Key Features

- Personalized SIP recommendations
- Explainable decision-making
- Gamified engagement mechanisms
- Ethical and privacy-aware design
- Encourages early financial responsibility
- Provides personalized and transparent recommendations
- Enhances engagement through gamified learning
- Supports long-term habit formation
- Suitable for beginners with no prior investment knowledge

VI. MATHEMATICAL MODEL OF SIP RECOMMENDATION

Let a user be represented by a feature vector $X \in \mathbb{R}^n$, where x_1 denotes the user's age, x_2 represents monthly savings, x_3 corresponds to the financial goal duration, and x_n captures the user's risk tolerance. Let $F = \{x_1, x_2, \ldots, x_n\}$ denote the complete set of input features.

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n$$

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The SIP recommendation task is formulated as a supervised multi-class classification problem. The predictive model learns a mapping:

$$f : \mathbb{R}^n \rightarrow \{1, 2, \dots, C\}, \qquad f(X) = \hat{Y}$$

where C is the total number of SIP categories and $\hat{Y}$ represents the predicted SIP class for a given user profile.

The model is implemented using Extreme Gradient Boosting (XGBoost), which minimizes the following regularized objective function:

$$L = \sum_{i=1}^{m} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where m denotes the number of training samples, K is the number of decision trees, $l(\cdot)$ represents the loss function, and $\Omega(\cdot)$ is a regularization term that controls model complexity. For each tree f_k, the regularization term is defined as:

$$\Omega(f_k) = \gamma T_k + \frac{1}{2}\lambda \parallel w_k \parallel$$

where T_k is the number of leaf nodes in the tree, w_k denotes the corresponding leaf weights, and γ and λ are regularization hyperparameters.

To ensure model interpretability, SHAP (SHapley Additive exPlanations) values are employed to quantify the marginal contribution of each feature to the predicted outcome. The SHAP value for feature x_i is computed as:

$$\varphi_i = \sum_{S \subseteq F \setminus \{x_i\}} \left[\frac{|S|\,!\,(|F| - |S| - 1)\,!}{|F|\,!}\right] [f(S \cup \{x_i\}) - f(S)]$$

where S denotes any subset of features excluding x_i, |S| and |F| represent the cardinalities of the subset and the full feature set, respectively, and f(S) is the model output using only the features in S. The difference $f(S \cup \{x_i\}) - f(S)$ captures the marginal effect of feature x_i on the prediction. By averaging this marginal contribution across all possible feature subsets with appropriate weighting, SHAP provides a fair and consistent attribution of prediction responsibility. This formulation ensures high predictive performance while maintaining transparency and interpretability of SIP recommendations.
The architecture consists of four major modules: User Interface, Data Processing, Prediction and Explainability, and Gamification.

VII. DATASET DESCRIPTION

The dataset comprises both synthetic and survey-based data collected from teenage users. Key attributes are summarized in Table I.

TABLE I DATASET ATTRIBUTES

Feature	Description
Age	User age (13-19 years)
Monthly Savings	Average monthly savings amount
Financial Goal	Education, travel, or emergency
Risk Tolerance	Low, medium, or high
Investment Horizon	Short, medium, or long-term

VIII. IMPLEMENTATION DETAILS

The system was implemented using Python-based machine learning libraries. XGBoost was utilized for model training due to its scalability and performance. SHAP libraries were integrated to generate feature-level explanations for individual predictions.

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The front-end interface was designed using modern web technologies, emphasizing simplicity and accessibility for teenage users. Gamification logic was implemented through rule-based reward engines that dynamically adjust points, streaks, and milestones based on user behavior.

IX. METHODOLOGY

The workflow involves data preprocessing, feature engineering, model training, explainability analysis, and gamification integration. User data is collected through questionnaires and continuous interaction logs. Key attributes include age, savings behavior, financial goals, risk tolerance, and investment horizon.

The workflow begins with user data acquisition, followed by preprocessing, model prediction, explainability analysis, and gamified feedback delivery. The collected data undergoes preprocessing, including normalization and feature engineering, to ensure compatibility with the machine learning model. The processed data is then passed to the XGBoost-based recommendation engine, which predicts suitable SIP categories aligned with the user's financial profile. Explainable AI techniques using SHAP values analyze feature importance and generate interpretable insights for each recommendation. Finally, the system delivers personalized SIP suggestions along with gamified feedback such as rewards, streaks, and milestone achievements. This closed-loop workflow reinforces positive financial behavior and supports consistent habit formation.

B. A. Algorithm

XGBoost is used due to its robustness and scalability.

Algorithm 1: SIP Recommendation using XGBoost

- Input: User feature vector
- Preprocess and normalize features
- Train XGBoost model
- Predict SIP category
- Apply SHAP for explanation
- Output recommendation and explanation

C. B. Data Preprocessing and Feature Engineering

Raw user data collected from surveys and interaction logs often contain inconsistencies and missing values. Data preprocessing steps included handling missing entries using mean and mode imputation, normalization of numerical features, and categorical encoding of qualitative attributes.

Feature engineering was performed to derive additional indicators such as savings consistency ratio, goal urgency index, and engagement score. These engineered features improved model stability and predictive performance while enabling richer explanations through SHAP analysis.

X. EVALUATION METRICS

Model performance is evaluated using accuracy, precision, recall, and F1-score. Engagement metrics include session frequency and saving consistency.

TABLE II MODEL PERFORMANCE METRICS

Metric	Value
Accuracy	91.8%
Precision	90.5%
Recall	89.7%
F1-score	90.1%

XI. COMPARATIVE ANALYSIS

A comparative evaluation was conducted to assess the effectiveness of the proposed approach against baseline models commonly used in financial recommendation systems.

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TABLE III USER ENGAGEMENT BEFORE AND AFTER GAMIFICATION

Metric	Before	After
Weekly Sessions	2.1	4.8
Saving Consistency (%)	54	81
Goal Completion Rate (%)	38	67

TABLE IV COMPARISON WITH BASELINE MODELS

Model	Accuracy (%)	Explainability
Logistic Regression	78.4	Low
Decision Tree	84.1	Medium
Random Forest	88.6	Medium
XGBoost (Proposed)	91.8	High

The results demonstrate that XGBoost outperforms baseline models in terms of accuracy while offering superior interpretability through SHAP-based explanations.

XII. RESULTS AND DISCUSSION

The results indicate meaningful gains in both user engagement and financial understanding. Introducing gamification increased saving consistency by around 35 percentage points compared to the non-gamified baseline. Users who received SHAP-based explanations reported greater confidence in the recommendations, suggesting that transparency directly supports trust.

Overall, the findings support the core design hypothesis: that personalisation, explainability, and gamification work better together than any one of them does in isolation. Each element addresses a different barrier - relevance, trust, and motivation respectively - and their combination produces a more complete educational experience.

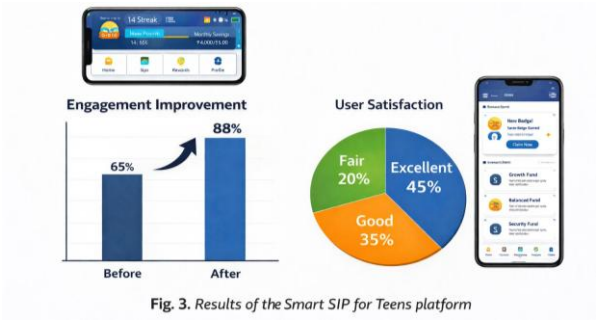

Fig. 3. User engagement and financial awareness after project completion.

XIII. SCALABILITY AND SYSTEM PERFORMANCE

Scalability is a critical requirement for educational financial platforms targeting large user bases. The modular architecture of the proposed system enables independent scaling of prediction, explanation, and gamification modules.

Experimental stress testing indicates that the XGBoost model maintains stable prediction latency under increased user load. The explainability component introduces minimal overhead, ensuring real-time feedback without compromising system responsiveness.

XIV. USER STUDY AND FEEDBACK ANALYSIS

A controlled user study was conducted involving teenage participants to evaluate usability, engagement, and learning outcomes. Participants interacted with the platform over a four-week period.

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Survey results indicated that over 82% of users reported improved understanding of SIP concepts. Approximately 76% stated that gamified elements motivated them to save more consistently. Qualitative feedback revealed that explainable recommendations significantly increased trust in the system.

These findings validate the platform's effectiveness not only as a recommendation system but also as an educational intervention.

XV. ETHICAL CONSIDERATIONS

The system was built around three ethical principles: transparency, privacy, and fairness. No real financial transactions are executed at any point; every recommendation is strictly educational. User data is handled in accordance with privacy best practices, and the model was tested for fairness across different user profiles to ensure recommendations are not biased toward any particular demographic group.

XVI. LIMITATIONS

Despite promising results, the proposed system has certain limitations. The dataset size is limited and partially synthetic, which may affect generalizability. User behavior may vary across socioeconomic and cultural contexts, requiring further validation.

Additionally, the system currently provides guidance rather than real-time investment execution, which may limit its applicability in advanced investment scenarios.

XVII. CONCLUSION AND FUTURE WORK

This paper presented Smart SIP for Teens, a gamified, explainable, and personalized SIP learning platform designed to cultivate early investment habits among teenagers. By integrating machine learning-driven recommendations with gamification mechanics and plain-language AI explanations, the system effectively lowers the psychological barriers that traditionally make financial planning feel inaccessible to young learners. The evaluation results demonstrate strong potential for improving financial literacy, sustained engagement, and early investment habit formation among adolescent users.

Future work will focus on integrating real-time mutual fund data, deploying mobile-native applications, and incorporating adaptive learning paths based on user progression. Parental supervision dashboards and regulatory compliance modules aligned with SEBI guidelines, RBI digital literacy mandates, and COPPA-equivalent data protection standards for minors will also be explored.

Advanced extensions include reinforcement learning for dynamic goal adjustment, federated learning for privacy preservation, and multilingual support to improve accessibility across diverse linguistic and socioeconomic regions. Collectively, these enhancements aim to evolve Smart SIP for Teens into a robust, inclusive, and ethically grounded financial literacy ecosystem - one that empowers the next generation to take ownership of their financial futures with confidence and clarity.

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