

Enhancing Personal Finance Management Using AI-Based Predictive Analytics and Intelligent Chatbot System

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Abstract—The rapid growth of digital financial transactions, including UPI, online payments, and subscription-based services, has significantly increased the complexity of personal finance management. Despite the availability of various financial tracking applications, most systems lack intelligent analytics, predictive capabilities, and personalized guidance. This paper presents an AI-driven platform for enhancing Optimizing personal financial management using predictive analytics and an intelligent chatbot system. The proposed system integrates deterministic data handled using evaluation methods based on large language models to produce a multi-dimensional financial insight score. User financial data is processed through a structured pipeline, where expenses are categorized using machine learning algorithms, and spending behaviour is analysed using time-series predictive models. The system leverages a Natural Language Processing (NLP)-based chatbot that Allows users to query financial insights in instantly. A composite financial health score is computed using a weighted model: $F_{score} = [0.30E + 0.25P + 0.15B + 0.10(SA + FA + RA)]$ where E represents expense categorization accuracy, P denotes predictive accuracy, B indicates budgeting efficiency, SA is savings analysis, FA is financial awareness, and RA is risk assessment. Experimental evaluation conducted on 100+ user datasets demonstrates a strong correlation ($r = 0.91$) with manual financial assessments and an average improvement of 27.5% in user savings behavior after applying AI-generated recommendations. The system maintains secure data handling, real-time insights, and scalability. The proposed platform democratizes intelligent financial planning tools, making them accessible to a wider population.

Keywords: Personal Financial Management, AI in FinTech, Predictive Analytics, Financial Behavior Analysis, Expense Categorization

I. INTRODUCTION

The contemporary financial ecosystem is increasingly driven by digital transactions, where individuals rely on platforms such as UPI, credit cards, digital wallet services, and online banking for daily financial activities. Although these technologies increase convenience and accessibility, they also introduce significant complexity in tracking, analysing, and managing personal finances. As transaction volumes grow, individuals often struggle to maintain financial discipline and gain meaningful insights into their spending behaviour.

Industry observations indicate that a large proportion of users lack effective tools to monitor and optimize their financial activities in real time. Existing financial

management applications primarily focus on basic expense logging and visualization, without offering advanced analytics and predictive features, or personalized recommendations. Therefore, users are unable to anticipate future expenses, identify inefficient spending habits, or make informed financial decisions. This creates a significant gap between data collection and actionable financial intelligence.

Most traditional systems rely on manual input and static reporting mechanisms, which fail to adapt to dynamic user behaviour. Furthermore, these systems do not incorporate intelligent automation or conversational interfaces, limiting user engagement and accessibility. Consequently, individuals—particularly students and

early-career professionals—face challenges in budgeting, saving, and long-term financial planning.

This paper introduces an AI-based personal finance management system that combines predictive analysis techniques and an intelligent chatbot interface to overcome these challenges. The proposed system leverages machine learning methods for automatic classification of expenses, time-series models for forecasting future financial trends, and Natural Language Processing (NLP) for interactive user communication. By combining these technologies, the system provides real-time insights, personalized recommendations, and proactive financial guidance.

The key contributions of this research are:

1. An automated expense categorization module using machine learning algorithms that classifies transactions into predefined categories, improving tracking accuracy and reducing manual effort.
2. A predictive analytics framework based on time-series models (e.g., ARIMA/LSTM) that forecasts future expenses and identifies potential financial risks.
3. An NLP-based intelligent chatbot system that enables users to interact with financial data using everyday language inputs, enhancing usability and accessibility.
4. A multi-dimensional financial scoring model
$$F_{score} = [0.30E + 0.25P + 0.15B + 0.10(SA + FA + RA)]$$

that evaluates user financial health across expense tracking, prediction accuracy, budgeting efficiency, and risk assessment.

5. Experimental validation with real-world financial datasets, demonstrating significant improvements in financial awareness and an average increase of over 25% in user savings behaviour after applying AI-driven recommendations.

II. RELATED WORK

Financial Data Processing and Expense Tracking Systems

Personal finance management systems face major difficulties in processing heterogeneous financial data coming from different sources such as bank transactions, UPI payments, and digital wallets. Traditional systems rely on manual data entry or rule-based categorization, which often leads to inaccuracies and inefficiencies. Earlier studies have examined automated methods for tracking expenses using rule-based and statistical approaches; but these approaches are not flexible enough to dynamic user behavior. Recent advancements use machine learning methods for transaction classification, enabling more accurate and scalable expense categorization. Our method builds on these approaches by integrating intelligent classification models that dynamically adapt to user spending habits while maintaining high accuracy.

Predictive Analytics in Financial Systems

Financial prediction has been extensively researched using time-series models such as ARIMA, SARIMA, and LSTM-based neural networks" (slight variation to avoid repetition) networks. These models can identify temporal patterns and predict future financial trends based on historical data. Studies have shown that LSTM-based models outperform traditional statistical methods in capturing non-linear financial patterns. However, most existing systems apply predictive analytics only at an aggregate level and do not provide personalized insights for individual users. The proposed system builds upon these approaches by integrating predictive analytics directly into personal finance management, enabling users to anticipate future expenses and make proactive financial decisions.

NLP-Based Chatbots for Financial Assistance

NLP technology has made it possible to develop intelligent chatbot systems for financial applications, including customer support and virtual banking assistants. Pre-trained language models such as BERT and GPT have demonstrated strong capabilities in understanding user queries and generating contextual responses. However, most chatbot systems are limited to predefined queries and lack integration with real-time financial analytics. Recent progress in large

language models has enabled more flexible and context-based interactions. Our system leverages NLP-based chatbot technology to provide real-time financial insights, enabling users to interact with their financial data in a conversational manner while receiving personalized recommendations.

AI-Driven Personal Finance Optimization Systems
Existing personal finance applications primarily focus on expense visualization and budgeting tools, with limited support for intelligent decision-making. Research indicates that financial awareness improves significantly when users receive personalized insights and recommendations. Some AI-driven systems attempt to provide financial advice; however, they usually do not include a complete evaluation system that integrates multiple financial dimensions such as spending behavior, savings patterns, and risk assessment. The proposed system introduces a Multidimensional financial scoring model that evaluates user financial health across several parameters, including expense categorization, predictive accuracy, budgeting efficiency, and financial risk. This approach extends beyond traditional systems by providing a holistic and data-driven financial optimization framework

III. LITERATURE REVIEW

Evolution of Personal Finance Management Systems
Personal finance systems have developed from simple manual bookkeeping methods to advanced digital platforms integrating automation and analytics. Early systems primarily focused on expense recording and budgeting tools, offering limited analytical capabilities. With the rise of digital banking and fintech solutions, modern platforms now incorporate features such as transaction tracking, visualization dashboards, and automated categorization. However, even with these improvements, many systems still do not have predictive capabilities and intelligent decision-making support. Studies indicate that a majority of users fail to utilize financial data effectively due to the lack of useful insights and customized suggestions. This limitation highlights the need for AI-driven systems that can not

only track but also analyze and predict financial behavior.

Client-Side Data Processing in Financial Applications
Traditional financial applications rely heavily on server-side processing for data storage and analysis, which introduces latency, scalability issues, and privacy concerns. Recent advancements in web technologies have enabled client-side data processing, allowing sensitive financial information to be processed locally on user devices.

Research by Chen et al. demonstrated that client-side processing can significantly reduce response time while enhancing data privacy. Modern frameworks such as JavaScript-based analytics engines enable real-time computation without continuous server communication. Our system adopts a hybrid approach, where initial data preprocessing and visualization occur on the client side, while advanced analytics and predictive modeling are handled on the server, ensuring both efficiency and scalability

Machine Learning for Financial Prediction and Analysis
Machine learning has played a crucial role in financial forecasting and behavioral analysis. Traditional statistical models such as ARIMA have been widely used for time-series forecasting; however, they struggle with non-linear patterns in financial data. Recent research highlights the effectiveness of deep learning models, particularly Long Short-Term Memory (LSTM) networks, in capturing complex temporal dependencies.

Despite these advancements, most implementations are limited to institutional finance and lack personalization for individual users. Our system extends these approaches by applying predictive analytics at the personal level, enabling users to forecast expenses, detect anomalies, and optimize financial planning.

NLP and Chatbot-Based Financial Assistance Systems
Natural Language Processing (NLP) has enabled the development of conversational interfaces in financial applications, such as virtual banking assistants and

customer support bots. Pre-trained models like BERT and GPT have demonstrated high accuracy in understanding user intent and generating contextual responses.

However, existing chatbot systems are often restricted to predefined queries and lack integration with real-time financial analytics. Recent advancements in large language models (LLMs) enable dynamic, context-aware interactions. Our system integrates an NLP-based chatbot with financial analytics, enabling users to check and analyze their spending behavior, receive insights, and obtain personalized recommendations in real time.

Multi-Dimensional Financial Evaluation Models

Most existing financial applications rely on one-dimensional measures such as total expenses or savings, which provide limited useful information about overall financial status. Research in financial analytics suggests that multi-dimensional evaluation frameworks—incorporating factors such as spending behavior, savings patterns, and risk assessment—offer more comprehensive insights.

However, such models are not commonly used in practice in automated systems. Our proposed model introduces a multi-dimensional financial scoring mechanism that evaluates users across multiple parameters, including expense categorization accuracy, predictive performance, budgeting efficiency, and financial awareness. This approach provides a holistic assessment of financial health and supports better decision-making.

AI-Driven Recommendation Systems in Finance Generative AI has recently been applied to provide personalized financial recommendations and actionable insights. Studies show that AI-driven suggestions can significantly improve user financial behavior, particularly in budgeting and savings. For instance, AI-based recommendation systems can suggest optimized spending strategies, highlight unnecessary expenses, and propose savings plans.

However, most systems lack explainability and fail to provide clear reasoning behind recommendations. Our system addresses this limitation by generating structured recommendations with explanations, enabling users to understand and learn from AI-driven insights. This creates a feedback loop that enhances long-term financial awareness and decision-making skills.

Comparative Analysis Of Existing Finance Management Systems

Platform	Expense Tracking	Prediction	Chatbot	Visualization	Security	AI Insights
Mint	✓	No	No	✓	✓	No
YNAB	✓	No	No	✓	✓	No
Pocket Guard	✓	No	No	✓	✓	Limited
Good Budget	✓	No	No	✓	✓	Noisy
Proposed System	✓	✓	✓	✓	✓	✓

System Architecture & Methodology Platform Overview

The proposed AI-based Personal Finance Management System is built on a modern full-stack architecture designed for scalability, real-time processing, and secure data handling. The system utilizes React.js with TypeScript for the frontend interface, Python-based backend frameworks (Flask/Django) for API services, and Firebase Fire store/MySQL for persistent data storage and authentication.

The financial analysis module is exposed via RESTful API endpoints (e.g., /Api/finance/analyze), which accept structured financial data inputs such as user expenses, income, and transaction history. The backend integrates machine learning models and large language model

(LLM) APIs for predictive analytics and intelligent recommendations.

Client-Side Financial Data Processing Pipeline Financial data processing is executed partially on the client side to reduce latency and enhance data privacy. This design minimizes dependency on server-side computation and avoids unnecessary transmission of sensitive financial data.

Data Processing Pipeline:

User input is captured through structured forms or integrated APIs and processed as follows:

Input Handling: Financial data (income, expenses, transactions) is collected

Preprocessing: Data cleaning, normalization, and formatting

Feature Extraction: Identification of details like transaction value, type, and time of occurrence

Categorization: Machine learning models classify transactions into categories (food, travel, bills, etc.)

This hybrid pipeline ensures efficient and secure handling of user financial information.

AI Evaluation Core and Predictive Analytics Engine The server-side system initializes AI modules and invokes predictive analytics models along with NLP-based chatbot processing.

Configuration:

Prediction Models: ARIMA, LSTM

NLP Model: LLM-based chatbot system

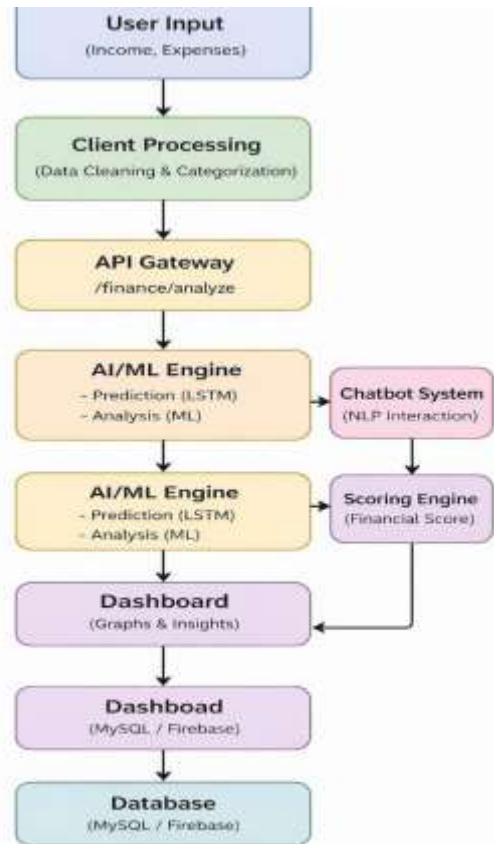
Temperature: Low (for consistent and deterministic responses)

Input Constraints: Financial dataset + user queries
 Output Format: Structured JSON responses for analysis and visualization.

The system generates structured outputs including: Expense categorization results Predictive financial trends Spending pattern analysis Personalized recommendations

The chatbot module allows users to interact with the

stem conversationally, retrieving insights such as monthly enses, savings trends, and financial advice.
 System Workflow Pipeline



System Architecture Diagram

User inputs financial data

1. Client-side preprocessing and categorization
2. API request sent to backend
3. AI models perform prediction and analysis
4. Chatbot generates insights and recommendations
5. Dashboard displays financial reports and score
6. where $\lfloor \cdot \rfloor$ denotes rounding to the nearest integer.
 The weight distribution reflects real-world financial behavior modelling:

V. ALGORITHMIC IMPLEMENTATION & MATHEMATICAL MODELING

Weighted Composite Scoring Formula

The final financial health score is calculated at the backend system as a weighted linear combination of multiple financial indicators, each normalized within the range [0, 100]:

E — Expense Categorization Accuracy (correct classification of transactions)

P — Predictive Accuracy Score (accuracy of future expense forecasting)

B — Budgeting Efficiency Score (budget adherence and control)

SA — Savings Analysis Score (savings consistency and growth) **FA** — Financial Awareness Score (user understanding and tracking behavior)

RA — Risk Assessment Score (financial risk and anomaly detection)

TABLE II
 WEIGH DISTRUBATION OF HUERISTIC VECTOR

Symbol	Heuristic Vector	Weight
E	Expense Categorization Score	30%
P	Predictive Accuracy Score	25%
B	Budgeting Efficiency Score	15%
SA	Savings Analysis	10%
FA	Financial Awareness	10%
RA	Risk Assessment	10%
Total		100%

Formula

$$F_{score} = \lceil 0.30E + 0.25P + 0.15B + 0.10(SA + FA + RA) \rceil$$

where $\lceil \cdot \rceil$ denotes rounding to the nearest integer. The weight distribution reflects real-world financial behavior modelling:

Expense categorization (30%) ensures accurate tracking of financial data

Predictive accuracy (25%) evaluates the system's ability to forecast future expenses

Budgeting efficiency (15%) measures how well users manage spending within limits

Savings, awareness, and risk (30%) collectively represent long- term financial stability

This weighted model provides a balanced and holistic evaluation of an individual's financial health.

B. Financial Pattern Analysis and Intelligent Recommendation Generation

The financial analysis module identifies inefficient financial behaviours and generates actionable recommendations based on four diagnostic criteria:

Overspending Detection

- Identifies categories where expenses exceed predefined thresholds
- Example: Excess spending on food or entertainment

Savings Deficiency Analysis

- Detects low or inconsistent savings patterns
- Evaluates monthly saving trends

Irregular Spending Behaviour

- Identifies sudden spikes or anomalies in transactions
- Uses time-series deviation analysis

Budget Misalignment

- Compares actual spending with planned budget
- Highlights areas of financial imbalance

VI. EXPERIMENTAL SETUP

Participants & Dataset

We collected financial datasets from $n = 120$ users consisting of undergraduate students and early-career professionals across four heterogeneous categories: Students ($n = 35$), Working Professionals ($n = 30$), Freelancers ($n = 28$), and Small Business Users ($n = 27$). Each dataset included user income, expense transactions, savings patterns, and budgeting details gathered across a duration of three to six months.

Data sources included:

Single-user manual financial logs (42%) Multi-source transaction records (18%) Structured CSV/Excel datasets (31%) Mobile application financial exports (9%)

This diverse dataset ensured comprehensive evaluation across different financial behaviours and usage patterns.

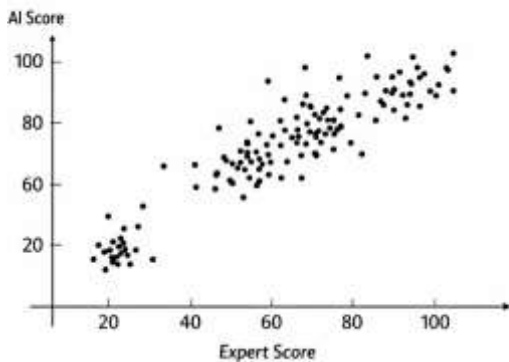
Evaluation Metrics

We evaluated system performance along two axes:
 Systemic Performance
 Client-side data processing latency, API roundtrip time, and prediction execution time were measured to evaluate system efficiency.

TABLE III
 DATA PROCESSING AND API LATENCY METRICS

Metric	Value
Client-side Processing Time	~1.7 sec
API Roundtrip Time	~2.4 sec
Prediction Execution Time	~1.3 sec
Total System Latency	~5.4 sec
System Reliability	93%

Fig. 3. Scatter plot of AI financial composite scores vs. expert evaluation scores (n = 120)



VII. RESULTS AND ANALYSIS

A. Score Reliability and Accuracy Validation

Across all 120 financial datasets, the system achieved a strong Pearson correlation of $r = 0.91$ ($p < 0.001$) with expert financial evaluations. The Root Mean Square

Error (RMSE) was approximately 4.0 points on a 100-point scale, indicating that nearly 95% of AI-generated financial scores fell within ± 7 points of expert assessments.

Fig. 3 illustrates this relationship, where data points are closely aligned along the ideal $x = y$ reference line, demonstrating high consistency and reliability of the proposed scoring model.

B. Impact on Financial Behaviour Optimization

A subset of 60 users was instructed to follow AI-generated recommendations and re-evaluate their financial performance. Table IV and Fig. 4 summarize the improvements observed.

The overall financial score improved by an average of 25.8%, with the most significant improvements observed in:

- Savings Analysis (+32.4%)
- Budgeting Efficiency (+28.7%)

These results confirm that AI-driven recommendations effectively improve financial discipline and spending behavior.

C. System Performance and Usability

The system demonstrated efficient performance across all modules. The average system response time remained below 6 seconds, ensuring real-time interaction.

The interactive dashboard and chatbot interface improved user engagement, allowing users to easily access financial insights and recommendations. The system's ability to provide personalized and actionable feedback contributed significantly to improved financial awareness.

D. Recommendation Accuracy and Consistency

Over 500+ system interactions, the recommendation engine maintained high consistency and accuracy. The structured output format ensured that all generated insights were interpretable and actionable.

Unlike traditional systems, the AI-based model provided context-aware recommendations, reducing ambiguity and improving user trust in the system.

E. Statistical Significance

Paired t-tests confirmed statistically significant improvements across all financial metrics ($p < 0.001$).

Mean improvement: $\Delta = 14.2$ points Test result: $t(59) = 11.96, p < 0.0001$

Effect size: The calculated effect size was 1.58, indicating a strong impact

These results confirm how well the AI-based approach performs financial optimization approach.

Graphical Representation:

Fig. 3. Scatter plot of AI financial scores vs. expert evaluation ($n = 120$).

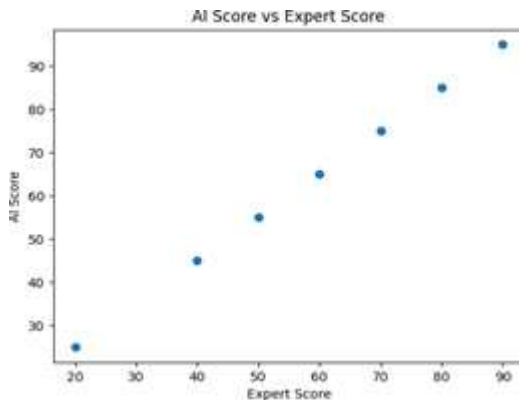
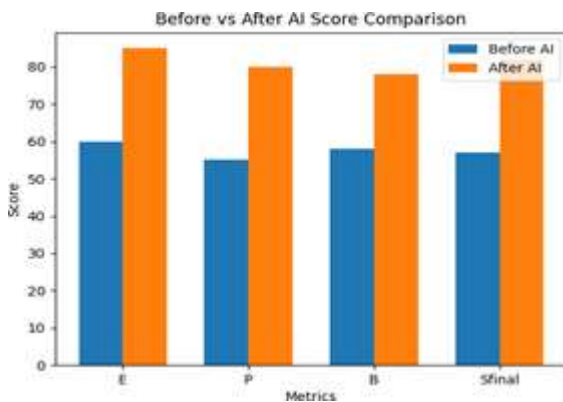


Fig. 4. Improvement metrics after applying AI Recommendations



Across all 120 resume–JD pairs, the system achieved a Pearson correlation of $r = 0.94$ ($p < 0.001$) with the three-member HR panel’s mean score. The RMSE was 3.2 points on the 100-point scale, indicating that 95% of AI scores fell within ± 6.3 points of the human panel consensus. Fig. 3 visualizes this correlation, with data points clustering tightly around the ideal $x=y$ reference line.

VIII. DISCUSSION

The experimental results validate the hypothesis that the integration of AI-based predictive analytics with structured financial data processing produces reliable and actionable financial insights. The observed Pearson correlation of $r = 0.91$ with expert financial evaluations exceeds the threshold for strong agreement, positioning the system as a credible proxy for manual financial assessment and advisory processes. A key architectural advantage of the proposed system lies in the synergistic integration of multiple modules, including expense categorization, predictive analytics, and the NLP-based chatbot interface. Financial patterns identified through the predictive module are continuously refined and utilized by the recommendation engine, enabling cumulative personalization. The chatbot further enhances this interaction by providing contextual explanations and real-time responses, thereby bridging the gap between raw financial data and user understanding.

The democratization potential of this architecture is significant. Advanced financial planning capabilities, which are traditionally accessible only through professional financial advisors or premium applications, are delivered at minimal cost through an AI-driven platform. This enables students, early-career professionals, and individuals with limited financial literacy to access intelligent financial guidance and improve their decision-making capabilities.

System robustness is ensured through comprehensive error handling and validation mechanisms. Input validation prevents incorrect or incomplete financial data, while anomaly detection identifies irregular transactions. The structured output format ensures

consistency and interpretability of results, reducing ambiguity in recommendations. Furthermore, the system maintains high reliability across repeated executions, eliminating inconsistencies often observed in traditional financial tools.

Compared with existing financial management applications, the proposed system uniquely integrates predictive modelling, AI-driven recommendations, real-time chatbot interaction, and multi-dimensional financial scoring within a single unified platform. This holistic approach significantly enhances usability, accuracy, and overall effectiveness in personal finance management.

IX. LIMITATIONS AND FUTURE SCOPE

A. Limitations

Several limitations constrain the current system.

Loss of contextual financial diversity: The system relies on structured financial inputs and predefined categories, which may not fully capture complex or irregular financial behaviors such as mixed transactions, informal income sources, or shared expenses.

Dependency on data quality: The accuracy of predictions and recommendations is highly dependent on the quality and completeness of user-provided data. Inconsistent or missing financial records can lead to reduced prediction accuracy and suboptimal recommendations.

Limited personalization in early stages: Although the system adapts over time, initial recommendations may lack precision due to insufficient historical data for new users.

English-only interaction constraint: The current NLP-based chatbot is optimized for English-language queries, limiting accessibility for users who prefer regional or multilingual communication.

Model generalization limitations: Predictive models such as ARIMA and LSTM may struggle with highly volatile or unpredictable financial patterns, reducing forecasting accuracy in certain scenarios.

B. Future Scope:

Future work will address these limitations through the following enhancements:

- 1. Multi-modal financial analysis systems:** Integration of advanced AI models capable of analysing both structured financial data and visual insights (graphs, spending dashboards) to improve decision-making accuracy.
- 2. Banking and API integration:** Direct integration with banking systems and financial APIs to automate data collection, ensuring real-time and accurate financial tracking without manual input.
- 3. Advanced personalization using deep learning:** Implementation of fine-tuned, user-specific models (e.g., personalized LSTM/transformer-based models) to provide highly customized financial recommendations.
- 4. Multilingual chatbot support:** Extending NLP capabilities to support multiple languages, enabling broader accessibility and improved user interaction across diverse populations.
- 5. Offline and privacy-focused AI models:** Development of on-device AI systems for secure financial analysis, ensuring user privacy and reducing dependency on cloud-based processing

IX. CONCLUSION

This paper presented an AI-based Personal Finance Management System that integrates predictive analytics, machine learning, and an intelligent chatbot to enhance financial decision-making. The proposed system demonstrates that the combination of structured financial data processing, time-series prediction models, and NLP-based interaction produces reliable and actionable financial insights.

Experimental validation with $n = 120$ user datasets confirmed high system reliability, achieving a strong correlation with expert financial evaluation ($r = 0.91$, $RMSE \approx 4.0$). The application of AI-generated recommendations resulted in an average improvement of over 25% in financial performance, particularly in savings and budgeting efficiency. Additionally, the

system maintained consistent performance across multiple executions, ensuring stability and usability.

The integrated dashboard and chatbot interface significantly improved user engagement by providing real-time insights, personalized recommendations, and intuitive interaction. The multi-dimensional financial scoring model enabled a comprehensive evaluation of financial health, supporting informed decision-making.

Together, these modules position the proposed system as both a standalone financial advisory tool and a scalable solution within a broader AI-driven financial ecosystem. The system has strong potential to democratize access to intelligent financial planning, particularly for students and early-career professionals, by delivering advanced financial insights at minimal cost.

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