International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 1 (2026)

ISSN 2319-5991 www.ijerst.com
Vol. 22, No. 1(2), 2026

Peer Reviewed, Referred & Indexed Journal

Research Paper

FinIntel: An AI-Driven Predictive Ecosystem for Expense Forecasting and Investment Optimization

Avula Vennela[1], Akkati Harshith Reddy[2], Bandi Akhila[2], Boodidhi Shiva Shankar[2], Adapa Sruthi[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (Data Science)

[1,2]Vaagdevi College of Engineering (UGC-Autonomous), Bollikunta, Warangal, 506005, Telangana

Abstract

Effective financial planning and expense management are critical for ensuring long-term fiscal sustainability. Traditional manual record-keeping and reactive budgeting often fail to provide the predictive insights necessary for proactive asset allocation. This study presents FinIntel, an integrated financial intelligence framework that leverages deep learning and machine learning to automate expense forecasting and behavioral analysis. The system utilizes Long Short-Term Memory (LSTM) networks, specifically optimized for time-series data, to predict future expenditure patterns based on historical transaction records. Model performance is rigorously validated using Coefficient of Determination (R2) and Mean Squared Error (MSE) metrics. Complementing the predictive engine, K-Means clustering is applied to categorize spending behaviors, while VADER sentiment analysis evaluates user feedback to refine recommendation accuracy. Developed on a Django-based web architecture with a MySQL backend, the framework provides a secure, OTP-authenticated environment for real-time financial monitoring. Experimental results indicate that the hybrid LSTM-clustering approach significantly enhances forecasting precision compared to conventional linear models. By synthesizing predictive modeling with personalized investment heuristics, FinIntel offers a scalable solution for data-driven personal and institutional financial management.

Keywords: Financial planning, K-means clustering, Database management, Django framework, Long Short-Term Memory (LSTM).

Received: 06-02-2026 Accepted: 13-03-2026 Published: 20-03-2026

1. Introduction

Managing personal finances is often considered one of the most challenging aspects of daily life. It requires meticulous attention to detail, a thorough understanding of one's financial situation, and a well-organized approach to budgeting and spending. However, effective management of personal finances is crucial not only for maintaining financial stability but also for achieving long-term financial goals such as saving for retirement, buying a home, or funding a child's education. As the complexities of personal finance increase, the need for efficient tools to manage and track finances becomes ever more important. In this context, personal finance manager tools have become a valuable resource for individuals who wish to streamline their financial tracking and decision-making processes.

In today's fast-paced world, the majority of people find themselves struggling to balance their income and expenses, often leading to unplanned debt or savings shortfalls. A significant number of individuals either do not track their spending or do so ineffectively, resulting in poor financial planning. According to a report by the National Endowment for

Financial Education (NEFE), over half of the adult population in the United States lacks a personal financial plan and is ill-prepared for unforeseen financial challenges. This reflects a broader trend in financial illiteracy, where individuals are unable to make sound financial decisions due to a lack of understanding or tracking of their finances.

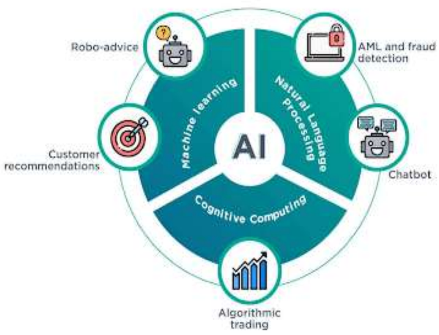

Fig. 1. Applications of Artificial Intelligence in Finance.

2. Literature Survey

Ridzuan, et al. [1] identified key trends and suggested future research directions. The major findings included an overview of AI applications, benefits, challenges, and ethical issues in the banking and finance industries. Recommendations are provided to address these challenges and ethical issues, along with examples of existing regulations and strategies for implementing AI governance frameworks within organizations. The paper highlights innovation, regulation, and ethical issues in relation to AI within the banking and finance sectors. Analyzes the previous literature and suggests strategies for AI governance framework implementation and future research directions. Innovation in the applications of AI integrates with fintech, such as preventing financial crimes, credit risk assessment, customer service, and investment management. These applications improve decision making and enhance the customer experience, particularly in banks. Existing AI regulations and guidelines include those from Hong Kong SAR, the United States, China, the United Kingdom, the European Union, and Singapore. Challenges include data privacy and security, bias and fairness, accountability and transparency, and the skill gap. Therefore, implementing an AI governance framework requires rules and guidelines to address these issues. This paper makes recommendations for policymakers and suggests practical implications in reference to the ASEAN guidelines for AI development at the national and regional levels. Future research directions, a combination of extended UTAUT, change theory, and institutional theory, as well as the critical success factor, can fill the theoretical gap through mixed-method research. In terms of the population gap can be addressed by research undertaken in a nation where fintech services are projected to be less accepted, such as a developing or Islamic country.

Bayakhmetova, et al. [2] explored the intersection of AI and financial behavior using bibliometric analysis to identify trends, gaps, and emerging directions in this rapidly evolving field. A total of 1019 documents are available in Scopus for the period 1987–2024. The articles are analyzed using the Bibliometrix R package and the Bibliophagy graphical user interface. Key findings show a robust annual growth rate of 13.34%, highlighted the growing relevance of the topic. The analysis revealed central themes such as machine learning, decision-making, and financial inclusion, along with critical gaps in ethical considerations, regional disparities, and practical applications of AI for marginalized populations. Leading contributors and influential sources, including journals such as IEE Access and Expert Systems with Applications, were mapped to understand the intellectual structure of the field. The study highlights the urgent need to address and mitigate algorithmic biases to ensure fairness, transparency, and ethical outcomes in AI-driven systems. It also highlights the importance of improving financial literacy and adapting AI tools for fair financial inclusion.

Mhlanga, et al. [3] proposed the study used conceptual and documentary analysis of peer-reviewed journals, reports and other authoritative documents on AI and digital financial inclusion to assess the impact of AI on digital financial inclusion. The present study discovered that AI has a strong influence on digital financial inclusion in areas related to risk detection, measurement and management, addressing the problem of information asymmetry, availing customer support and helpdesk through chatbots and fraud detection and cybersecurity. Therefore, it is recommended that financial institutions and non-financial institutions and governments across the world adopt and scale up the use of AI tools and applications as they present benefits in the quest to ensure that the vulnerable groups of people who are not financially active do participate in the formal financial market with minimum challenges and maximum benefits.

Liu, et al. [4] investigated ChatGPT's applications in financial reasoning and analysis and evaluates ChatGPT-4o's effectiveness and limitations in conducting both basic and complex financial analysis tasks. By designing a series of multi-step, advanced reasoning tasks and establishing task-specific evaluation metrics, we assessed ChatGPT-4o's performance compared to human analysts. Results indicate that while ChatGPT-4o demonstrates proficiency in basic and some complex financial tasks, it struggles with deep analytical and critical thinking tasks, especially in specialized finance areas. The study underscores the need for meticulous task formulation and robust evaluation in AI financial applications. While ChatGPT enhances efficiency, integrating it with human expertise is crucial for effective decision-making.

Moura, et al. [5] proposed the study systematically reviewed academic research on artificial intelligence (AI) in financial fraud prevention. Employed a bibliometric approach, they analyzed 137 peer-reviewed articles published between 2015 and 2025, sourced from Scopus, Web of Science, and ScienceDirect. Using Bibliometrix, we mapped the field's intellectual structure, collaboration patterns, and thematic clusters. Research interest has surged since 2019, led mainly by China and India, though the literature is mostly technical, with limited social science engagement. Three main themes emerged: AI-based fraud detection models, blockchain and fintech integration, and big data analytics. Despite growing output, international collaboration and focus on ethical, regulatory, and organizational issues remain limited. These insights provide a foundation for advancing both research and practical AI-driven fraud mitigation.

Pamuk et al. [6] proposed the process must include the required validation and coordination with regulatory authorities. An appropriate dashboard can help to shape and structure the process of model development, e.g., for credit assessment in the finance industry. In addition, the analysis of datasets must be included as an important part of the dashboard to understand the reasons for changes in model performance. Furthermore, a dashboard can undertake documentation tasks to make the process of model development traceable, explainable, and transparent, as required by regulatory authorities in the finance industry. This can offer a comprehensive solution for financial companies to optimize their models, improve regulatory compliance, and ultimately foster sustainable growth in an increasingly competitive market.

De Zarza et al. [7] proposed an optimization framework for individual budget allocation, aimed at maximizing savings by efficiently distributing monthly income among various expense categories. They then extend the model to households, wherein the complexity of handling multiple incomes and shared expenses is addressed. The cooperative model prioritizes not only maximized savings but also the preferences and needs of each member, fostering a harmonious financial environment, whether they are short-term needs or long-term aspirations. A notable innovation in our approach is the integration of recommendations from a large language model (LLM). Given its vast training data and potent inferential capabilities, the LLM provides initial feasible solutions to their optimization problems, acting as a guiding beacon for individuals and households unfamiliar with the nuances of financial planning. Their preliminary results indicate that the LLM-recommended solutions result in budget plans that are both economically sound, meaning that they are consistent with established financial management principles and promote fiscal resilience and stability, and aligned with the financial goals and preferences of the concerned parties.

Shaban et al. [8] proposed the impact of AI-driven financial transparency on corporate governance and regulatory reform, focusing on Jordan. Utilizing a stratified random sampling approach, data were collected from 564 corporate professionals across key economic sectors. Statistical analyses, including structural equation modeling (SEM) and multiple regression analysis, reveal that AI adoption significantly enhances corporate governance effectiveness ($R^2 = 0.582$), improves risk management ($R^2 = 0.502$), and increases stakeholder engagement ($R^2 = 0.681$). AI also facilitates regulatory compliance by automating monitoring processes and reducing human errors in financial disclosures. However, challenges such as bias in AI algorithms, data privacy concerns, and the need for regulatory adaptation persist.

Artene, et al. [9] investigated the synergies between artificial intelligence (AI), digital transformation (DT), and financial reporting systems within the business context. The central theme explores how organizations enhance their decision-making processes by integrating AI technologies into digital transformation initiatives, particularly in financial reporting. The focal point is comprehending how the synergy of these integrated systems can unlock substantial business value, instigate strategic innovation, and elevate overall financial analytics through the adoption of intelligent, data-driven decision-making methodologies. By harnessing advanced analytics, automation, and adaptive decision support capabilities, organizations navigate the complexities of a rapidly evolving business environment, in which neural networks emerge as a valuable tool for calibrating outcomes in the financial accounting environment, demonstrating effectiveness in processing complex financial data, identifying patterns, and making predictions, ushering in a new era of transformative possibilities.

Liu et al. [10] proposed a financial management platform based on the integration of blockchain and supply chain that has been designed and implemented. Blockchain is used to integrate supply chain finance to synchronize the bank account payment system and realize the automatic flow of funds. processed supervision and automatically settled account periods based on smart contracts. The four functional modules of the system are designed using unified modeling language (UML), and the model view controller (MVC) architecture is selected as the main architecture of the system. The results of the system test show that the proposed platform can effectively improve the system security and can use the information in the blockchain to provide multi-level financing services for enterprises in supply chain finance.

3. Proposed Methodology

This research presents a robust, data-driven framework designed for personalized expense forecasting and investment recommendation as demonstrated in Fig. 2. Built upon the Django web framework, the system provides users with advanced financial intelligence by moving beyond simple transaction tracking to predictive aframework;ral analysis. The core of the system lies in its two primary Machine Learning (ML) components: the Long Short-Term Memory (LSTM) network for high-accuracy time-series forecasting and K-Means Clustering for discovering hidden spending patterns. This architecture empowers users to gain a deep, statistical understanding of their financial position and future needs. The application operates as a three-tier system, integrating a centralized MySQL database for secure user management, a comprehensive Python back-end for data processing, and a dynamic web interface. User data security is prioritized through a multi-step authentication process that includes Base64 password encoding and Two-Factor Authentication (2FA) via OTP sent over SMTP. After logging in, users can upload their financial data (budget.csv), which is then prepared and scaled for the ML models.

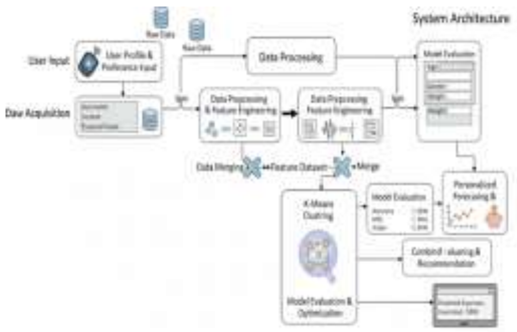

Fig. 2: Proposed system architecture.

The system also features a sentiment analysis module using VADER, allowing the service provider to continuously gauge and respond to user satisfaction regarding the financial tools. The predictive and advisory workflow is comprehensive. The LSTM model is trained on historical daily expense data (using year, month, and day features) to generate precise forecasts of future expenditure. These forecasts are not just for display; they are directly utilized in the recommendation engine to calculate the actionable surplus (hypothetical income minus predicted expenses), providing a concrete amount for savings or investment. Hypothetical income means clustering visually segments spending by category and amount, offering an immediate behavioral diagnostic of the user's spending habits, thus achieving the goal of making financial data both predictive and highly personalized.

User Registration and Login: Users create an account by providing essential details such as name, email, contact information, and address. The login process is secured through an OTP verification system sent to the user's email, ensuring only authorized access. This step establishes a secure and personalized environment for financial data management.

Loading and Processing Expense Data: After login, users upload their expense dataset containing transaction details like date, category, and amount. The system preprocesses this data by converting date formats, normalizing values, and preparing it for analysis. This ensures that the data is accurate, consistent, and ready for predictive modeling.

Expense Prediction: The system uses historical expense data to predict future spending trends. By analyzing patterns in past transactions, the platform estimates upcoming expenses for selected dates. This allows users to anticipate their financial needs and plan budgets proactively.

Spending Pattern Analysis: FinIntel groups expenses based on categories and amounts using clustering techniques. This analysis identifies patterns in user spending behavior, highlighting major expense areas and recurring costs. Users gain insight into how and where their money is being spent.

Investment and Savings Recommendation: Using the predicted expenses and user income, the system calculates personalized recommendations for investment or savings. This ensures that users can allocate funds efficiently, minimize overspending, and make informed financial decisions to achieve their future goals.

Feedback Collection and Sentiment Analysis: Users can provide feedback about system performance or recommendations. The system performs sentiment analysis to classify feedback as positive, neutral, or negative. These insights are used to refine predictions and improve the overall quality of financial guidance.

3.1 K-Means Clustering

K-means is an unsupervised clustering algorithm used here to segment user expenses. Its goal is to partition data points (expenses) into distinct, non-overlapping subsets (clusters) such that each data point belongs to the cluster with the nearest mean (centroid). The process is iterative: it starts with K random centroids, assigns every data point to the closest centroid, and then recalculates the centroid's position as the mean of all points assigned to it. This process minimizes the Within-Cluster Sum of Squares (WCSS), ensuring expenses grouped together are highly similar in terms of category and amount. The algorithm stops when the centroids no longer move significantly or a maximum number of iterations is reached.

Initialization: Select K random data points from the dataset to serve as the initial cluster centroids.

Assignment Step: Calculate the Euclidean distance between every data point and all K centroids. Assign each data point to the cluster whose centroid is closest.

Update Step: Recalculate the position of each of the K centroids by taking the mean (average) of all data points currently assigned to that cluster.

Convergence Check: Check if the centroids have changed position. If the movement is below a tolerance level or the maximum iterations are met, stop. Otherwise, return to Step 2.

Output: Assign the final cluster labels to each expense, allowing for visualization and analysis of distinct spending groups.

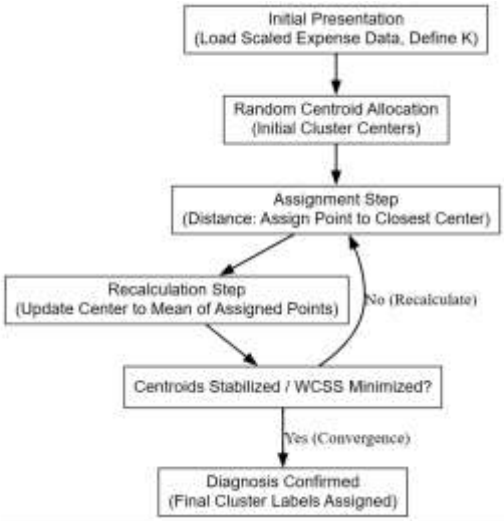

Fig. 3: K-Means clustering algorithmic flow with clinical decision logic.

Long Short-Term Memory Network (LSTM)

The LSTM is a specialized type of recurrent neural network designed to overcome the vanishing gradient problem, enabling it to learn long-term dependencies essential for time-series forecasting (like expense trends). Its core strength lies in the memory cell and three gates that regulate the flow of information: the Forget Gate decides which information to discard from the cell state; the Input Gate decides which new information to store in the cell state; and the Output Gate determines which part of the current cell state is outputted as the hidden state for the current timestamp. This gating mechanism allows the LSTM to remember patterns that occurred months ago (like annual fees or seasonal spending) and integrate them effectively into the current day's expense prediction.

Gating Mechanism: The LSTM's memory cell is controlled by three gates: the Forget Gate, which decides which old information to discard; the Input Gate, which determines what new information to store in the cell; and the Output Gate, which decides what part of the cell state will be output as the hidden state. This gating system enables the model to remember seasonal or recurring expenses and integrate them into current predictions.

Data Preparation: Raw input data, including date features (year, month, day) and total expenses, are first scaled to a normalized range. The input features are then reshaped into sequences in 3D format ([samples, timesteps, features]) to match the requirements of the LSTM network. This ensures the model can process sequential information correctly.

Forward Pass (Per Timestep): For each timestep in a sequence, data passes through the three gates in order. The Forget Gate filters out unnecessary past information, the Input Gate adds relevant new information to the cell state, and the Output Gate generates the hidden state for the current timestep. The cell state is updated accordingly, combining past and current information to capture temporal dependencies.

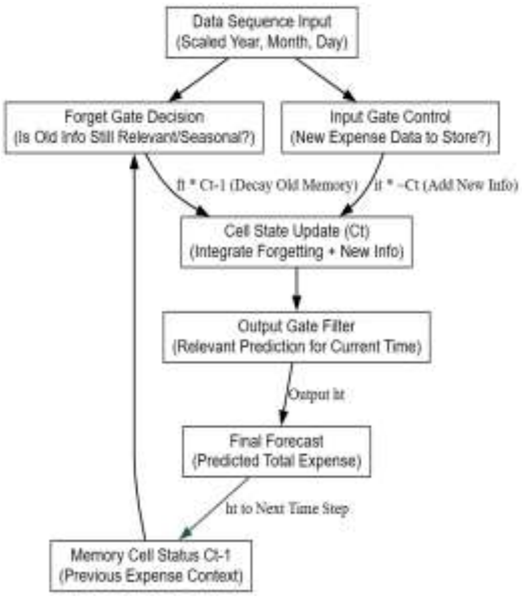

Fig. 4: LSTM gating mechanism flow using controlled decision logic.

Prediction: After processing the full sequence, the final hidden state is passed through a dense layer to produce a single-day expense forecast. This output represents the predicted total expense for the target date based on historical patterns.

Backpropagation and Optimization: The prediction error is calculated using the Mean Squared Error (MSE) loss function. The network weights are then updated using the Adam optimizer, minimizing the error and improving model accuracy over time.

Iteration and Training: The forward pass and backpropagation steps are repeated over multiple epochs. Through this iterative training process, the LSTM learns complex patterns in the user's financial data, allowing it to provide accurate and reliable expense predictions for future dates.

4. Results description

The system successfully predicts user expenses with high accuracy using the LSTM-based prediction model, allowing users to plan their budgets effectively. Clustering analysis provides insights into spending behavior by categorizing expenses into meaningful groups, highlighting areas where savings can be made. Sentiment analysis on user feedback helps gauge satisfaction and identify areas for improvement. The recommendation module suggests optimal investment amounts based on predicted expenses, while secure login and OTP verification ensure safe access to personal financial data.

Fig. 5: Register page for personal finance manager

Fig. 5 shows the New User Signup Page allows users to create accounts by entering a username, password, contact number, email, and address, followed by a submit button. A message guides the user through the registration process, emphasizing that signing up enables access to expense prediction and recommendations. The right side displays a cloud-themed AI illustration, reinforcing the modern and secure system concept.

Fig. 6: OTP Verification page

Fig. 6 shows the OTP Validation Page of the AI-Based Personal Finance Manager web application. At the top, the navigation bar provides links to Home, User Login, and New User Signup Here. The page displays a message indicating that a one-time password (OTP) has been sent to the user's registered email for verification. Below this, there is an input field where the user enters the OTP, followed by a Validate button to confirm their identity. A futuristic cloud graphic is also featured, emphasizing the application's modern, AI-driven, and secure cloud-based financial management theme.

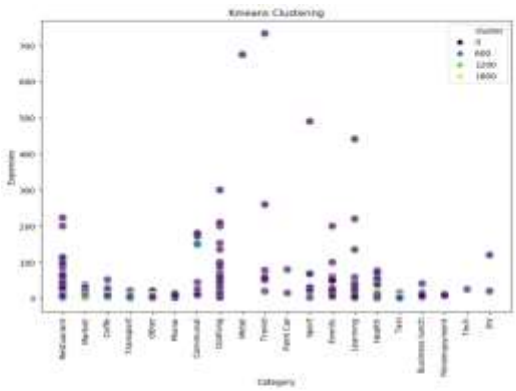

Fig. 7: K-means clustering for personal finance

Fig. 7 visualizes clustered expenses across various categories like market, transport, and tech. Each cluster represents similar spending patterns, helping users understand their financial behavior and identify areas for optimization. The distinct color coding highlights anomalies and recurring spending trends.

Fig. 8: LSTM Spending

Fig. 8 compares actual (red line) and predicted (green line) expenses, demonstrating the model's ability to capture spikes and trends over time. This enables users to anticipate future expenditures and plan budgets effectively. Fig. 10 combines financial analytics with cloud technology visuals, featuring a glowing cloud and network lines at the top, implying the use of secure digital or AI-driven services for personal finance management. The maroon backdrop creates a striking contrast for the text overlay, which presents hypothetical financial values and recommendations for investment amounts. The presence of negative income and expenses suggests this panel could be the result of a stress test or demonstration phase for the system's recommendation logic, highlighting its ability to calculate advice even when confronted by unusual or unrealistic inputs. Such data provides insight into how the underlying algorithms handle unexpected scenarios, possibly for debugging, robustness evaluation, or illustrative purposes. Overall, the image serves both as a technical demonstration of financial forecasting and an example of user guidance using advanced cloud computing infrastructure.

Fig. 9: Recommend budget.

Fig. 10: Feedback.

Fig. 10 displays a feedback confirmation interface, featuring a digital cloud and network backdrop at the top that evokes themes of security and cloud-based services. On the maroon background, centered text indicates that feedback has been accepted, and the system has performed a sentiment analysis, determining the user's feedback. The combination of these visual elements and the concise message demonstrate an automated sentiment detection feature in the platform, highlighting how user input is both received and analysed by the underlying AI to monitor and respond to user satisfaction

5. Conclusion

The FinIntel research successfully demonstrates the development of an AI-driven personal finance management system. By integrating LSTM-based expense prediction, K-means clustering for spending behavior analysis, and sentiment analysis for user feedback, the system provides users with accurate forecasts, insightful recommendations, and enhanced engagement. The platform ensures secure access through OTP verification and offers a user-friendly web interface built with Django. Overall, the research achieves its objective of empowering users to make informed financial decisions, optimize savings and investments, and gain a clear understanding of their spending patterns. The results show high predictive accuracy, robust clustering insights, and effective feedback interpretation, establishing SFinIntel as an intelligent and reliable tool for personal financial planning.

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