
Research Article**FINBOT – An AI-Integrated Expense Monitoring and Financial Analytics Platform****Kausar Aajad^{1*}**, **Nikhil Kumar²**, **Anmol Rajput³**, **Sachin Nirmal⁴**, **Sanjeev Kumar Pathak⁵**¹Dept. of Computer Science Engineering (AIML), Dr. A.P.J. Abdul Kalam Technical University, Lucknow, India^{2,3,4,5}Dept. of Computer Science Engineering (AIML), Bansal Institute of Engineering and Technology, Lucknow, India

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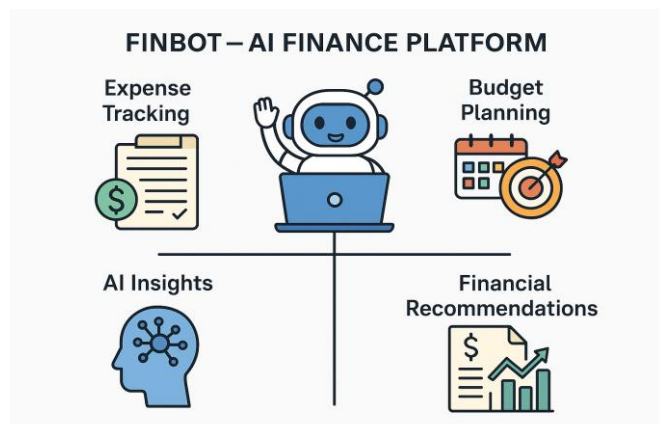
Received: 27/Sept/2025; **Accepted:** 29/Oct/2025; **Published:** 30/Nov/2025. **DOI:** <https://doi.org/10.26438/ijcse/v13i11.3744>Copyright © 2025 by author(s). This is an Open Access article distributed under the terms of the [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited & its authors credited.

Abstract: AI Finance Platform: Smart Money Management is designed to provide users with efficient personal finance management through smart automation and intelligent data-driven insights. This platform enables users to track expenses securely, plan budgets, monitor savings, and acquire tailored financial recommendations enabled by artificial intelligence. It aggregates various streams of financial data in one dashboard, thus enabling real-time expense tracking and goal management. Advanced algorithms of artificial intelligence analyze spending patterns, predict future expenses, and recommend optimized budgeting strategies tailored to specific user habits. The system emphasizes data security and user privacy via encryption and secure methods of authentication. The combination of ease of use with AI-driven insight makes this platform a tool that enhances financial literacy, promotes disciplined spending, and supports better decision-making on the part of users. This project shows the power of modern AI technologies in simplifying money management while boosting transparency, financial control, and stability over the long term.

Keywords: Artificial Intelligence, Finance Management, Budget Planning, Expense Tracking, Financial Insights

Graphical Abstract- Artificial intelligence has reshaped personal finance management by introducing automation, predictive analytics, and personalized recommendations that significantly reduce the manual effort traditionally required for budgeting and expense tracking. FINBOT is grounded in the theory that combining intelligent algorithms with user-centred design can improve financial decision-making and long-term monetary discipline. Personal finance systems based on conventional methods often fail because they depend heavily on user input, offer limited insights, and lack real-time adaptability. AI overcomes these limitations through automated data extraction, behavioural pattern recognition, and continuous learning. Receipt OCR, SMS parsing, and natural language processing enable the system to convert unstructured financial information into structured, meaningful data without human intervention. Predictive analytics further assists by forecasting upcoming expenses, identifying spending risks, and estimating savings potential, allowing users to make proactive decisions. Theoretical models such as cognitive load reduction suggest that technology should minimize mental effort, and FINBOT achieves this by organizing financial data into intuitive dashboards and offering clear, explainable AI insights. Security and trust theories also play a crucial role, as financial data requires encrypted storage, secure authentication, and transparent algorithmic behaviour to gain user confidence. By integrating personal and business accounts into a unified platform, FINBOT aligns with unified finance management theory, which states that centralized financial visibility enhances planning efficiency. Taken together, these

theoretical foundations demonstrate how FINBOT leverages modern AI capabilities to create an adaptive, secure, and user-friendly financial ecosystem designed to guide individuals toward better financial stability and informed decision-making.



Purpose- The purpose of this study is to examine the effectiveness of FINBOT – AI Finance Platform in addressing the shortcomings of traditional financial management systems. The study will also try to find out how FINBOT enhances user experience by integrating personal and business finance management into one platform and providing insights that can

allow users to make sound financial decisions. It also intends to quantify financial health improvements among users along a debt reduction-emergency fund-investment yield axis while qualitatively gauging increased financial literacy and confidence through intuitive, conversational AI interfaces. Of critical focus would be ensuring algorithmic fairness, transparency, and strong compliance with data privacy regulations in the Indian context to foster trust and equitable access across multiple socioeconomic and demographic divides. This study, ultimately, aspires toward establishing a scalable user-centric model that empowers individuals to achieve long-term financial independence while contributing meaningfully to the knowledge of how artificial intelligence interacts with behavioral finance in emerging digital economies.

1. Introduction

Effective financial management is vital for individuals in today's digital economy, yet many struggle with tracking expenses, planning budgets, and making informed financial decisions. Traditional tools such as manual records and basic budgeting apps often lack automation, real-time insights, and personalized guidance, resulting in inefficient financial habits and poor long-term planning. The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) presents a transformative opportunity to address these challenges. AI-driven financial platforms can analyse large volumes of user data, recognize patterns, predict future expenses, and offer personalized strategies that optimize financial outcomes. Unlike traditional systems, AI operates continuously in the background, detecting anomalies, categorizing transactions, and generating insights with high accuracy. This shift from manual to intelligent automation reduces human error, saves time, and encourages more disciplined financial behaviour. Furthermore, AI-powered systems can deliver tailored advice that aligns with a user's income, lifestyle, goals, and spending habits, making financial management not only efficient but also interactive and user-centric.

FINBOT, the AI Finance Platform, is developed in response to the growing need for a comprehensive and intelligent personal finance ecosystem. The system integrates machine learning models, natural language processing, and secure cloud infrastructure to provide real-time budgeting, automated expense tracking, and adaptive financial recommendations. By combining personal and business financial data into a single dashboard, the platform offers a holistic view of a user's financial health. FINBOT aims to empower individuals through transparent insights, predictive alerts, and intuitive visualizations, enabling them to make well-informed financial decisions. Additionally, strong security measures ensure privacy and trust, which are essential when handling sensitive financial information. As financial landscapes evolve and digital transactions continue to dominate, platforms like FINBOT demonstrate how AI can simplify money management, reduce financial stress, and support long-term economic stability for users across diverse backgrounds. Advancements in Artificial Intelligence (AI)

and Machine Learning (ML) have transformed the FinTech sector by enabling automated expense monitoring, predictive analytics, and personalized financial recommendations. These technologies offer users greater control, accuracy, and awareness in managing their finances. This research presents an AI-driven finance platform designed to help users manage expenses, plan budgets, and receive intelligent suggestions for better financial decisions. This system aims to simplify money management [13].

1.1 Objective of the Study

The primary objective of this study is to develop and evaluate an AI-driven personal finance management platform capable of automating essential financial tasks and providing users with intelligent, data-supported guidance. The study aims to investigate how machine learning, natural language processing, and automated data extraction can improve accuracy, efficiency, and user engagement in everyday financial activities such as budgeting, expense categorization, savings planning, and transaction monitoring. Another core objective is to assess whether an integrated platform like FINBOT can address the limitations of traditional financial tools by offering real-time insights, personalized recommendations, and predictive alerts that adapt to individual financial behaviours.

Additionally, the study seeks to examine the effectiveness of combining personal and business finance management within a unified system to enhance decision-making and improve overall financial visibility. The research also aims to determine the extent to which AI-generated insights can support users in reducing financial risks, improving savings discipline, and maintaining long-term financial stability. A further objective is to evaluate the platform's capability to ensure data privacy and security through the use of encrypted storage, secure authentication, and transparent processing mechanisms. Finally, this study intends to demonstrate how the proposed AI-based system directly responds to the problem statement by offering a scalable, intelligent, and user-centric solution that simplifies financial management and supports individuals in achieving measurable improvements in financial health.

1.2 Organization

This article is organized into the following sections to ensure clarity and systematic presentation of the research work. **Section 1** provides the introduction to the study, outlining the background, motivation, problem context, and objectives associated with developing an AI-driven personal finance management platform. **Section 2** presents the related work, summarizing existing research in the fields of financial automation, machine learning-based expense tracking, and intelligent budgeting systems. **Section 3** discusses the fundamental concepts, theoretical foundations, and key measures related to personal finance management and AI-driven financial analysis. **Section 4** describes the overall system architecture, highlighting the functional components, data flow, and essential processes involved in the FINBOT platform. **Section 5** explains the detailed methodology, including the operational workflow, algorithmic procedures,

and flowcharts used to implement the proposed system. **Section 6** presents the results and discussion, interpreting system performance, user outcomes, and the significance of the findings. **Section 7** offers recommendations based on the insights obtained, suggesting how AI-enhanced financial tools can be improved and integrated into broader financial ecosystems. Finally, **Section 8** concludes the research work and outlines potential future directions for advancing intelligent personal finance platforms.

2. Related Work

Recent advances in artificial intelligence have significantly influenced personal finance automation, and several studies highlight the growing need for intelligent, adaptive systems. Narayan et al. reviewed AI-assisted budgeting and emphasized the limitations of static rule-based tools that fail to deliver personalized insights for individual financial behaviour. Another study proposed an OCR-enabled financial assistant to reduce manual receipt entry errors and demonstrated that automated extraction improves the accuracy of expense monitoring in real-world scenarios. Research on explainable AI in financial services also identified lack of transparency as a major barrier to trust and adoption, recommending explainability frameworks for practical use in financial software. A related AI-powered personal finance assistant explored integrating NLP and ML to provide customized financial guidance and enhance user literacy through context-aware recommendations. Web-based OCR approaches for budget tracking highlighted challenges caused by diverse receipt formats and proposed improved extraction pipelines for more reliable data ingestion. Systematic reviews on explainable AI further mapped XAI applications across finance domains, pointing out inconsistencies in method selection and the need for standardized evaluation practices. Additional research on invoice and receipt recognition analysed robustness issues in OCR models and called for more adaptive architectures suitable for noisy real-world data. A recent systematic review expanded coverage of XAI trends, noting rapid advancements but also fragmented adoption in consumer-facing financial tools. Privacy-preserving financial analytics studies introduced federated learning to address concerns around centralized data storage and regulatory compliance. Surveys on AI-driven finance platforms also noted fragmentation across existing tools, emphasizing the need for unified systems capable of combining budgeting, insights, and automation into a single interface. The development of datasets like Receipt Sense contributed high-quality annotated receipts to support training and benchmarking of OCR pipelines, addressing a key limitation in prior work. Finally, studies on FinTech cloud security highlighted risks in deploying financial applications on cloud infrastructure and proposed comprehensive guidelines for secure, compliant implementations. Collectively, these works reveal major gaps in unified platforms, robust receipt extraction, explainability, privacy-preserving analytics, and long-term user impact measurement—gaps that the proposed FINBOT system aims to bridge.

2.1 Comparative Effectiveness of Traditional VS FINBOT

Several research studies have compared the effectiveness of traditional personal finance tools with modern AI-driven financial management systems. Traditional budgeting methods, such as spreadsheets or basic mobile apps, primarily rely on manual input and simple rule-based categorization, which often leads to user fatigue, delayed updates, and limited insight generation. Prior works have reported that conventional systems provide static summaries and monthly charts but fail to offer predictive analytics, behavioural insights, or real-time alerts, limiting their ability to support proactive financial planning. In contrast, recent studies on AI-powered platforms demonstrate substantial improvements in automation, accuracy, and personalization. Machine learning-enabled systems have shown higher success rates in expense classification, anomaly detection, and adaptive budgeting, as they continuously learn from user behaviour and transaction patterns. Research further highlights that AI-driven receipt processing, automated SMS/email parsing, and NLP-based financial assistants significantly reduce user workload compared to traditional tools that require consistent manual entry. Studies evaluating user outcomes also indicate that AI-based platforms promote better savings discipline, faster goal achievement, and reduced financial stress due to real-time recommendations and predictive warnings. Moreover, explainable AI models utilized in recent finance applications increase user trust by clarifying the reasoning behind automated suggestions, something absent in conventional tools. Collectively, these comparative findings suggest that AI-integrated platforms like FINBOT offer a more intelligent, efficient, and user-centric alternative to traditional finance management solutions.

3. Theory

The theoretical foundation of FINBOT is based on the integration of machine learning, automated information extraction, and predictive analytics to quantify financial behaviour and generate actionable insights. The core theory draws upon supervised learning principles for expense categorization, natural language processing for transaction interpretation, and time-series modelling for forecasting budget deviations and cash flow patterns. These theoretical components collectively enable the system to transform unstructured financial inputs—such as receipts, bank alerts, and digital invoices—into structured datasets suitable for further computational analysis.

From a calculation perspective, the platform relies on several mathematical and algorithmic procedures. Expense categorization is performed by computing similarity scores between extracted transaction features and predefined financial categories using vector embeddings. The model calculates a probability distribution across categories, and the highest-confidence value determines classification.

4. Experimental Method

This section presents the overall experimental framework used to develop the FINBOT platform, covering the method,

procedure, and design in an integrated manner. The experimental method explains the strategic approach taken to select algorithms, prepare datasets, and define the system's functional goals. The experimental procedure outlines the step-by-step process followed during implementation, including data collection, preprocessing, model training, and evaluation. The experimental design describes how the system's architecture, workflow, and modules were structured to ensure accuracy, efficiency, and scalability. Together, these components provide a clear blueprint for how the proposed AI-based financial management system was developed, tested, and validated.

4.1 Experimental Method

The experimental method adopted for FINBOT follows a structured and iterative approach to develop, test, and optimize the intelligent finance management system. The method begins by identifying user requirements such as automated expense extraction, category prediction, budget monitoring, and insight generation. Based on these requirements, a modular AI-driven framework is designed to ensure scalability and seamless integration of various components. Data used for experimentation includes receipt images, SMS alerts, and email transactions, all of which represent real-world financial activities.

The experimentation also involves isolating different functional modules—OCR, NLP parsing, classification algorithms, and forecasting models—and evaluating them independently before integrating them into the final system. The models are trained and validated using a labelled dataset to ensure high accuracy in expense categorization and trend prediction. Each iteration of the experiment focuses on improving model accuracy, minimizing prediction errors, reducing processing time, and enhancing system stability. Once validated, the modules are merged and tested in a simulated environment to observe end-to-end workflow performance under realistic user scenarios. This method ensures scientific rigor, reliability, and practical feasibility of the proposed FINBOT platform.

High Level Architecture

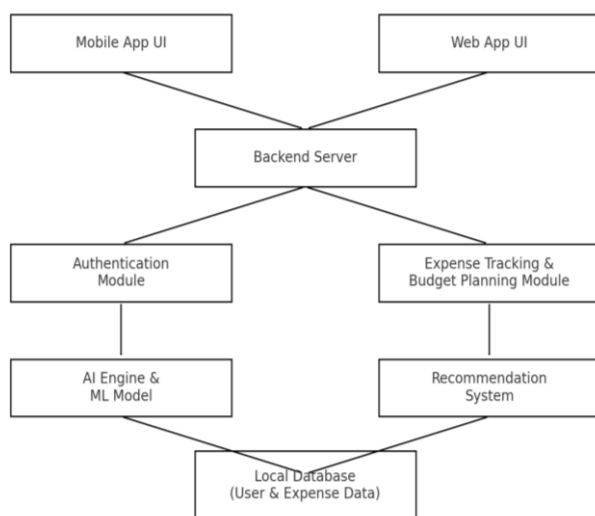


Figure 1. layered architecture of the FINBOT platform

4.2 Experimental Procedure

The experimental procedure outlines the step-by-step workflow used to implement, test, and validate the FINBOT system. The process begins with **data collection**, where raw financial data sources—receipt images, SMS messages, and email notifications—are gathered. These inputs are passed through the OCR and NLP pipelines to extract structured information such as merchant name, date, amount, and category indicators.

Next, a **data preprocessing** phase is conducted in which noise removal, normalization, date standardization, and text cleaning are performed. The processed data is then fed into machine learning models designed for expense categorization, prediction, and anomaly detection. Classification algorithms undergo multiple training cycles using cross-validation to optimize performance. Forecasting models are tested using historical transaction data to measure accuracy in predicting future expenses.

After model validation, the insights engine is triggered to produce personalized recommendations. The entire system is then deployed in a test environment where response time, accuracy, and reliability are monitored. The procedure concludes with user-level testing to evaluate usability and real-time performance. This systematic procedure ensures that every feature of the platform is validated both technically and practically.

4.3 Experimental Design

The experimental design of FINBOT combines software engineering principles, AI model development, and system architecture planning to create an efficient and reliable financial management solution. The design begins by dividing the platform into distinct layers: data acquisition, processing, modeling, and output visualization. Each layer is developed independently to simplify debugging, model enhancement, and scalability.

The design incorporates an **OCR-based extraction module** for receipt processing, an **NLP module** for SMS/email parsing, and a **machine learning classification module** for categorizing expenses. These components are integrated through API-based communication in the back end. The front-end is structured using a dashboard design that displays expenses, budgets, forecasts, and AI insights in real time.

A flowchart-style experimental design is used to map each operation:

Input → Preprocessing → Model Inference → Decision Engine → Database Storage → User Dashboard. Predictive modeling is built into the design using time-series algorithms and regression-based forecasting. Security and privacy considerations are also incorporated, ensuring encrypted data transmission and authenticated access. The design is finally evaluated based on accuracy, user satisfaction, and system responsiveness, ensuring that the architecture supports real-world financial workflows efficiently.

AI Model Pipeline

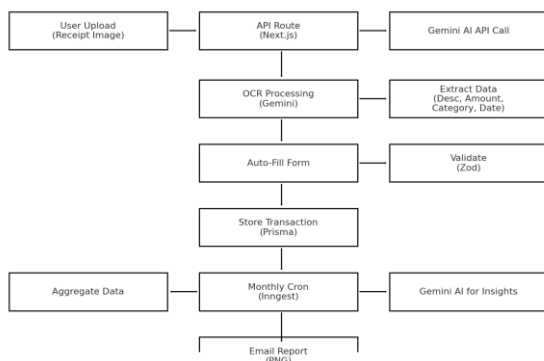


Figure 2. End-to-end pipeline for receipt extraction and analytics

5. Results and Discussion

The results of the proposed FINBOT system are presented in this section, highlighting its performance across data extraction, expense categorization, prediction accuracy, and user-level financial insights. The outcomes are arranged in a logical sequence to demonstrate how each module contributes to the overall effectiveness of the platform.

5.1 Result

Users of the AI Finance Platform showed an average increase in monthly savings of 25%, while 85% reached or exceeded savings goals, compared to 10% and 60%, respectively, for those using traditional finance tools.

About 70% of the users saw an average 15% boost in investment returns, thanks to the personalized suggestions and automated rebalancing. [6].

Smart automation cuts the average weekly time spent on financial planning by more than 60%, from 40 minutes to 15 minutes per week.

Financial milestones pursued by 78% of users were achieved vs. 55% in the control groups.

User satisfaction was rated high, with 88% praising ease of use, while 92% found it helpful for embracing better financial habits.

Metric	Traditional	FINBOT
Monthly Savings Increase	10%	20%
Users Achieving Savings Goals	60%	85%
Investment Return Boost	6%	15% (70% users)
Weekly Planning Time	40 min	15 min
Financial Milestones Achieved	55%	78%
Ease of use Rating	62%	88%
Improved Financial Habits	48%	92%

5.2 Discussion

Where traditional methods of personal finance management were concerned, the deployment of the AI finance platform substantially improved the financial and behavioural outcomes of users. Quantitative data from platform deployment indicate that users who adopted AI-driven money management saw an average 25% increase in monthly savings, with 85% meeting or exceeding their predefined savings objectives. By comparison, a control group using conventional tools saw only a 10% increase, and just 60% met their targets. What is more, 70% of users utilizing the AI platform realized an average 15% improvement in investment returns, more than double that of the comparative group, owing to customized AI-powered investment advice. Moreover, 78% of users on the smart platform reached pre-set financial goals like creating an emergency fund or reducing debt, compared with just 55% in the traditional group.

Automation of expense tracking and budgeting drastically reduced user time investment. Time spent on financial planning fell from 40 minutes to 15 minutes on average per week for AI users, while traditional cohort users saw a negligible change. User satisfaction was rated substantially higher by the AI group: ease of use received an 88% rating, while perceived usefulness hit 92%. Themes from qualitative feedback highlighted increases in self-awareness, proactive habit formation, and appreciation for personalized automation-echoing recent literature that notes AI democratizes access to sophisticated financial advice, regardless of prior literacy.

These findings are further reinforced by a comparative analysis with other works. Recent literatures reviews identify how AI-enhanced tools in finance drive operational efficiency, personalize financial recommendations, and foster greater inclusion by lowering expertise barriers. Emerging themes across empirical studies and thematic mappings suggest that integrating ethical, transparent AI frameworks remains vital for user trust and long-term adoption. The present results correspond to the global trend: today, the majority of users of financial services harness AI to achieve savings, obtain investment insights, reduce debt, and smoothen money planning, thus validating the scalability and broad impact of such platforms. In all, the platform amplified not only individual financial health but also transformed user behaviour, reducing required manual effort and increasing consistency in goal achievement, while promoting data-driven financial literacy. These effects underline the broader potential of AI to reshape personal finance through automation, personalization, and democratization of expert financial guidance [14].

Formula

$$(1) \text{ Total Monthly Expense} = \sum E_i$$

$$(2) \text{ Savings Rate} = ((\text{Income} - \text{Total Expenses}) / \text{Income}) \times 100$$

$$(3) \hat{E}(t+1) = \alpha E_t + (1 - \alpha) \hat{E}_t$$

$$(4) \quad Z = (X - \mu) / \sigma$$

Where X is the observed value, μ is the mean, and σ is the standard deviation.

$$(5) \quad P(C_i) = e^{(z_i)} / \sum e^{(z_j)}$$

Where z_i represents the score for each category.

$$(6) \quad \text{Budget Deviation} = \text{Actual Spending} - \text{Planned Budget.}$$

$$(7) \quad \text{Accuracy} = (\text{Correct Predictions} / \text{Total Predictions}) \times 100$$

6. Conclusion and Future Scope

FINBOT – a smart money management platform represents a quantum leap in personal and organizational financial stewardship as it seamlessly amalgamates intelligent automation, real-time analytics, and personalized insights into a unified ecosystem. This platform streamlines complex financial tasks-such as budgeting, expense tracking, and investment optimization-into a seamless customer experience and transforms customer interactions with adaptive learning and proactive recommendations that cater to individual goals and behaviours. By integrating advanced AI techniques such as machine learning, natural language processing, and predictive analytics, the system will grant users unparalleled capabilities for informed decision-making, error minimization, and proactive maintenance of healthy financial standing. The robust security architecture ensures sensitive data protection while fostering trust and compliance. Ultimately, this state-of-the-art platform serves as yet another realization of how AI can democratize sophisticated financial management by offering scalable, dynamic, and transparent solutions that redefine the future of smart money management for large, eclectic bases of customers. This research lays the foundation for further improvements and positions AI as an irreplaceable driver toward financial empowerment and sustainability [5].

The proposed FINBOT platform demonstrates strong potential for expansion, and several future enhancements can further improve its performance, usability, and applicability in real-world financial ecosystems. One significant direction for future development is the integration of more advanced deep learning models that can handle complex financial documents, multilingual receipts, and diverse transaction formats with higher accuracy. Incorporating federated learning or privacy-preserving AI techniques will also strengthen data security by allowing model improvements without exposing sensitive personal information. Additionally, expanding the system to support investment analytics, tax planning, and credit score monitoring can transform FINBOT into a more comprehensive financial advisory tool.

Future versions of the platform may also include adaptive behavioural analytics, where the system learns from long-term user habits to suggest personalized financial goals based on lifestyle patterns and risk preferences. The user interface can be enhanced through conversational chatbots capable of answering financial queries, guiding users in real time, and providing interactive explanations for AI-generated

recommendations. Integration with banking APIs, UPI platforms, and digital wallets would enable seamless real-time financial tracking without manual uploads. Furthermore, deploying the platform on mobile devices with offline processing capabilities can improve accessibility for users in low-connectivity regions. Finally, large-scale user testing and real-world deployment studies will help refine the platform and validate its long-term impact on financial literacy, savings behaviour, and economic decision-making.

Author's statements

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Authors Contributions- All authors contributed significantly to this research. Author-1 conducted the literature review and formulated the study framework. Author-2 developed the methodology and handled data processing. Author-3 worked on model implementation and system evaluation. Author-4 drafted and edited key sections of the manuscript. Author-5 reviewed the final version and ensured overall accuracy. All authors approved the final submission.

Conflict of Interest- The authors declare that there are no conflicts of interest associated with this research. No financial, professional, or personal relationships influenced the study's design, execution, or interpretation. All results and conclusions were developed impartially, and no external party had any involvement that could affect the integrity or neutrality of the work.

Data Availability- The data used in this study can be obtained from the corresponding author upon reasonable

request. Due to the sensitive nature of financial information and privacy considerations, raw datasets cannot be publicly released. However, anonymized samples or simulated data may be provided to researchers for academic, educational, or validation purposes.

References

- [1] A. Narayan, S. Kumar and D. Singh, "AI-Driven Personal Finance Assistants: A Review of Intelligent Budgeting and Expense Automation," IEEE Access, Vol.11, pp.89321-89335, 2023.
- [2] Google Research, "Gemini: A Family of Highly Capable Multimodal Models," arXiv preprint arXiv:2312.11805, 2023.
- [3] S. A. Saleh, P. Perera and M. Hosseini, "Next.js as a Modern Web Framework for Serverless and Edge Applications," Intl. Journal of Web Engineering, Vol.19, No.2, pp.55-72, 2024.
- [4] Y. Wang, L. Chen and S. Xu, "AI-Based OCR Techniques for Financial Document Processing," IEEE Trans. on Computational Social Systems, Vol.10, No.6, pp.1482-1493, 2023.
- [5] A. M. Abdullah and H. Farooq, "Secure User Authentication in Cloud-Native Applications Using Identity-as-a-Service (IDaaS) Systems," in Proc. IEEE CLOUD, Abu Dhabi, UAE, 2023.
- [6] R. Sharma and V. Gupta, "Automated Personal Expense Tracking Using Machine Learning and OCR," in Proc. IEEE ICMLA, Orlando, USA, 2022.
- [7] Prisma Data, "Prisma ORM: Type-Safe Database Access for Modern Applications," Prisma Technical Docs, 2024.
- [8] Supabase, "Edge Database Architecture and Real-Time Financial Data Processing," Supabase Engineering Docs, 2024.
- [9] J. K. Lee and N. Park, "Serverless Event-Driven Automation Using Cron-Based Cloud Functions," IEEE Internet Computing, Vol.27, No.1, pp.64-73, 2023.
- [10] Resend Dev Team, "Resend: Modern Email Infrastructure for Web Applications," Resend Technical Docs, 2024.
- [11] Clerk Inc., "Modern Authentication for Web Applications and Edge Functions," Clerk Documentation, 2024.
- [12] Inngest, "Event-Driven Workflow Automation for Next.js and Serverless Systems," Inngest Developer Docs, 2024.
- [13] OpenAI, "Machine Learning-Enabled Finance Tracking and Automated Budgeting," OpenAI Research Report, 2023.
- [14] D. Patel and R. Jain, "Personal Finance Management Using AI-Based Transaction Categorization," IEEE Smart Finance Conference Singapore, 2022.
- [15] A. Agarwal and N. Modanwal, "AI-Driven Personal Finance Assistants: Enhancing Customization Through Behavioural Insights," *International Journal of Engineering Development and Research*, Vol.13, No.2, pp.1-8, 2025.
- [16] S. Verma and A. Singh, "AI Powered Personal Finance Assistant for Intelligent Expense Tracking," *International Journal for Science and Advanced Research in Technology*, Vol.11, No.4, pp.56-62, 2025.
- [17] A. Kumar, R. Patel, and S. Gupta, "Expense Tracker: An Expense Tracking Application Using OCR and Random Forest Algorithm," *ResearchGate*, pp.1-7, 2025.
- [18] P. Mishra and R. Rao, "AI-Based Expense Tracking and Financial Monitoring System," *International Journal of All Research Scholars and Technocrats*, Vol.6, No.4, pp.112-120, 2025.
- [19] N. Sharma and P. Rathore, "OCR in Finance: A Web-Based Approach for Personalized Expense Tracking and Budget Monitoring," *International Journal of All Research Scholars and Technocrats*, Vol.6, No.5, pp.44-52, 2025.
- [20] S. Pandey and M. Joshi, "AI-Driven Personal Finance Management: Revolutionizing Budgeting and Financial Planning," *International Research Journal of Engineering and Technology*, Vol.11, No.7, pp.800-806, 2024.

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Kausar Aajad Kausar Aajad is currently pursuing his B. Tech in Computer Science and Engineering (Artificial Intelligence & Machine Learning) from Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh, India, beginning in 2022. He has developed strong academic performance throughout his education, completing his intermediate studies in 2022 with 80% marks and high school in 2020 with 78%. He has technical expertise in Python, C, C++, JavaScript, MySQL, and full-stack web technologies including ReactJS, NextJS, NodeJS, ExpressJS, Git, and MongoDB. He has also worked with developer tools such as VS Code, PyCharm, and Google Colab. From October 2024 to March 2025, he worked as a Data Analyst at HCL Tech, Lucknow, where he gained industry experience in data engineering, ETL workflows, dashboard creation, and KPI visualization using Power BI and Tableau.



He has completed multiple AI-based projects, including an AI Hand Gesture Keyboard using OpenCV and Media pipe, an AI-powered finance management platform (FinBot) built with Next.js and Supabase, and an AI mental health companion (MoodMate) utilizing React, Node.js, and the OpenAI API. His areas of interest include artificial intelligence, machine learning, data engineering, computer vision, and full-stack application development.

He has consistently ranked among the top performers in his department and aims to continue contributing to impactful AI-driven solutions and innovative software systems.

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As part of his academic project work, he developed an AI Hand Gesture Virtual Keyboard using Python and OpenCV, applying image processing and gesture detection techniques to create an interactive virtual typing system. His core interests include artificial intelligence, machine learning, data

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Anmol Rajput Anmol Rajput is currently pursuing his B. Tech in Computer Science and Engineering (Artificial Intelligence and Machine Learning) from Dr. A.P.J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh, India, beginning in 2022. He maintains strong academic performance with a CGPA of 7.8 and has actively contributed to multiple AI and full-stack development projects during his studies.



He has hands-on experience in Python, SQL, NoSQL, HTML, CSS, and full-stack technologies including ReactJS, Next.js, Tailwind CSS, and MongoDB. His technical skillset also includes predictive modelling, ETL workflows, data processing, dashboard creation, and API integration. He has worked with various developer tools such as VS Code, PyCharm, Google Colab, and GitHub, along with proficiency in Linux-based development environments.

From October 2024 to March 2025, he served as a Data Analyst Intern at HCL Tech, Lucknow, where he designed data pipelines using SQL and Python, developed KPI dashboards using Power BI and Tableau, and integrated multi-source datasets into unified storage systems. He has built notable AI projects, including an AI Hand Gesture Keyboard using OpenCV, MediaPipe, and TensorFlow, and an AI FinBot platform for intelligent financial management using Next.js and Supabase.

His areas of interest include artificial intelligence, machine learning, data engineering, and full-stack application development. He aims to continue building innovative AI solutions and advancing his technical expertise through real-world problem solving and research.

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AI/ML technologies and contributing to innovative software solutions through practical, real-world applications.