AI Driven Financial Advisor

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***Abstract*— The AI-Driven Financial Advisor is an intelligent web-based platform developed to help users make informed financial and investment decisions through data-driven analysis. The system employs a hybrid AI approach, combining recommendation models and large language models (LLMs) to provide personalized investment suggestions, including Fixed Deposits, Mutual Funds, Gold/REITs, and Stock Market options. It evaluates multiple user factors such as age, income, savings, financial goals, dependents, and risk preferences to tailor recommendations. Additionally, the platform features an LLM-powered conversational interface that delivers explainable insights, helping users understand the rationale behind each suggestion. The system also includes financial planning tools and a dynamic news module to keep users informed about market trends. By integrating predictive analytics, explainable AI, and a user-friendly interface, the platform offers an accessible and intelligent financial advisory solution for modern investors.**

***Index Terms*— AI-Driven Financial Advisor, Hybrid Recommendation System, Large Language Model, Personalized Finance Assistant, Predictive Analytics, Explainable AI, Investment Guidance**

I. INTRODUCTION

The financial advisory field is undergoing a major shift as artificial intelligence (AI) becomes increasingly integrated into its processes. Traditional advisory services depend largely on human expertise and subjective judgments to provide investment recommendations. While effective in some cases, these conventional approaches are often slow, inconsistent, and lack the degree of personalization required in today's fast-moving and diverse financial environment. This gap has led to a rising demand for AI-powered solutions capable of delivering customized, real-time financial guidance aligned with individual goals, preferences, and profiles. To address this need, an AI-Driven Financial Advisor uses machine learning (ML) and hybrid based learning methods to deliver highly personalized financial recommendations. Unlike conventional systems that primarily try to predict market movements, this platform centers on adapting to each user's unique requirements. By factoring in variables such as age, income, and risk tolerance, it continually fine-tunes its suggestions to align with each person's financial objectives. Beyond personalized investment recommendations, the platform incorporates an interactive chatbot built on a financial ML model. This chatbot answers user queries and shares insights, ensuring constant, real-time assistance even without human input. In addition, a goal-tracking component enables users to monitor their financial progress and stay on course toward achieving their targets. To enrich the user experience further, the platform offers a dedicated news section featuring up-to-date financial information. By providing current market and economic updates, users are better equipped to make informed decisions and reduce the likelihood of uninformed investments. The evolution of financial advisory has been significantly influenced by artificial intelligence, enabling more personalized and data-driven guidance for users. This AI-driven system adopts a hybrid approach, combining recommendation models and large language models (LLMs) to deliver tailored investment strategies based on factors such as income, savings, financial goals, and risk preferences. Interactive chatbot interfaces enhance accessibility, helping users understand recommendations and engage with the platform effectively. Additionally, the system integrates financial planning tools and real-time market updates, while prioritizing ethical AI practices, data privacy, and transparency to ensure responsible and reliable financial guidance.

II. RELATED WORK

A. Machine Learning Approaches

Machine learning has become a key component of modern financial advisory systems. Supervised learning algorithms use user attributes such as age, income, savings, and financial goals to provide personalized investment suggestions. Techniques like decision trees, support vector machines, and logistic regression help classify investor risk profiles and recommend suitable portfolios. Unsupervised methods, particularly clustering, group users into distinct profiles, enabling more targeted asset allocation and financial product recommendations. Compared to traditional rule-based approaches, these AI systems can adapt to changing market conditions and evolving customer preferences, enhancing the quality and relevance of advice.

B. Hybrid AI and Recommendation System

Recent research has explored hybrid approaches that combine predictive models, recommendation engines, and large language models (LLMs) to improve financial advisory tools. These systems analyze multiple factors to generate customized investment guidance and provide explainable insights through interactive interfaces. Integrating recommendation models with LLM-based chatbots allows users to ask questions, understand reasoning behind suggestions, and access financial advice in natural language. This approach improves accessibility, supports continuous engagement, and reduces reliance on human advisors while ensuring personalized, data-driven recommendations

C. Conversational AI in Financial Advisory

Conversational AI has become an important feature in AI-driven finance platforms. Intelligent chatbots using deep learning-based natural language processing (NLP) interpret user queries, deliver tailored guidance, and clarify financial concepts. Some systems also provide multimodal interfaces with dashboards or voice assistants, enhancing usability and inclusivity. These technologies enable 24/7 support and improve financial literacy, particularly for novice investors.

D. Current Challenges and Research Gaps

Despite progress, AI-based advisory systems face several challenges. Data quality remains a critical issue fragmented, incomplete, or inconsistent information can reduce prediction accuracy. Integrating multiple data sources, including APIs, manual inputs, and third-party feeds, requires robust preprocessing pipelines. Ethical and regulatory considerations are also essential: platforms must ensure fairness, transparency, and compliance with privacy and financial laws.

Existing research highlights gaps in explainability, bias mitigation, and adaptability. Many systems struggle to provide clear reasoning behind recommendations, and auditing tools to detect demographic or socioeconomic biases are limited. Compliance with evolving regulations such as GDPR or local financial rules remains a challenge, and user trust and acceptance of AI advisors are not fully understood.

Future AI-powered advisory tools must balance automation with ethical governance, offering personalized, adaptive, and inclusive guidance. Continuous learning from user interactions, enhanced explainability, multilingual support, and human oversight are critical to building trust and ensuring responsible deployment in financial services.

III. LITERATURE REVIEW

The application of artificial intelligence (AI) within financial advisory services has rapidly evolved in recent years. With continuous advancements in AI technologies, financial planning is becoming increasingly tailored, efficient, and accessible to a broader audience. Innovations led by machine learning, natural language processing (NLP), and generative AI are reshaping how people manage personal finances, investments, and financial decision-making. This literature review presents an overview of prominent research that investigates the integration of AI in financial advisory systems, offering valuable insights into the transformation of AI-powered financial services.

Several recent studies highlight the growing role of AI in financial advisory systems. EZfinance: Your Personal Financial Advisor (2025) demonstrates how reinforcement learning can personalize investment strategies based on user profiles, financial goals, and risk preferences, evolving through continuous feedback to maintain accuracy and relevance. Implementing Artificial Intelligence Empowered Financial Advisory Services: A Literature Review and Critical Research Agenda (2024) assesses existing AI

methodologies, emphasizing trust, interpretability, transparency, and ethical considerations such as user privacy and algorithmic fairness. Enhancing Financial Advisory Services with GenAI (2024) examines generative AI's impact on user engagement, showing that trust, ease of use, and explainability are crucial for adoption. Transforming Personal Finance Coaching through Artificial Intelligence (2024) proposes AI-driven financial coaching that adapts advice over time to promote healthier financial behaviors and bridge literacy gaps. AI Unleashed: Transforming Personal Finance with Artificial Intelligence (2024) highlights AI's role in budgeting, saving, and proactive investment management, reducing errors and impulsive decisions. Finally, Examining the Effects of AI Financial Advisor (2024) finds that AI advisors enhance user confidence, especially among those with limited financial knowledge, by providing consistent, impartial guidance.

AI and Machine Learning Applications in Modern Financial Planning: A Comprehensive Analysis (2023) provides an in-depth technical look into AI techniques such as neural networks, decision trees, and support vector machines. The study stresses the usefulness of these methods in predictive modeling, customer segmentation, and risk assessment. It also advocates for continuous model updates to reflect evolving market trends and user behaviors.

The paper AI-Driven Personal Finance Apps: Assessing the Impact on Financial Decision-Making and Marketing Strategies (2023) focuses on how users engage with AI-powered finance applications. It highlights the effectiveness of gamification, push notifications, and customizable dashboards in promoting user retention and better financial decisions. These features are particularly effective in raising financial awareness among young, digital-native users.

Machine Learning for Financial Planning: A Comparative Analysis of Traditional Approaches and New Technologies (2023) contrasts modern machine learning techniques with conventional advisory practices. The findings reveal that AI models significantly outperform manual systems in data processing efficiency, recommendation accuracy, and scalability. This reinforces the value of AI for large-scale, diverse user populations.

In The Rise of AI and Robo-Advisors: Redefining Financial Strategies in the Digital Age (2022), the rapid expansion of robo-advisors is discussed. The paper outlines their benefits, including lower costs, 24/7 service availability, and algorithm-driven portfolio management. These platforms democratize access to financial advice by eliminating traditional entry barriers, making them attractive to both beginners and experienced investors.

Artificial Intelligence in Personal Finance Management: Opportunities and Challenges (2021) addresses broader concerns surrounding the use of AI in finance. The authors emphasize potential risks such as algorithmic bias, data security, and overreliance on AI systems. They argue for the inclusion of regulatory measures and system explainability to ensure ethical and responsible implementation.

Finally, FinAID: A Financial Advisor Application Using AI (2020) represents one of the earliest efforts to deploy AI for financial advisory purposes using decision tree algorithms. Despite its simplicity, the application provided basic personalized recommendations and laid the foundation for further innovations. Its focus on real-time interaction and intuitive user design remains influential in current AI financial tools

These studies provide a comprehensive view of AI in financial advisory, highlighting key factors such as personalization, user trust, ethical design, transparency, and adaptability. Building on these insights, the proposed Web-Based AI Financial Advisor delivers intelligent, secure, and tailored recommendations using a hybrid AI approach. The system learns from user behavior over time, adapts to changing financial goals and market conditions, and incorporates an NLP-driven conversational interface for improved accessibility. By supporting diverse risk preferences and promoting transparency, the platform addresses gaps in prior models and meets modern expectations for digital financial advisory services.

IV. EXISTING SYSTEM

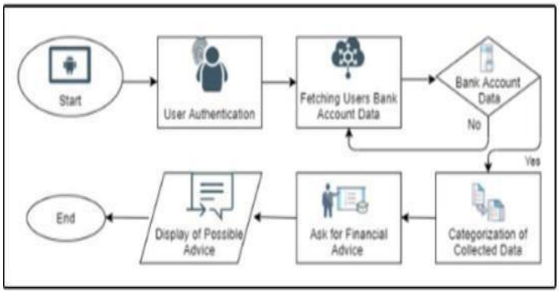

Fig. 1. Architecture of the Existing AI-Based Financial Advisor (FinAID)

The current landscape of AI-based personal finance tools, illustrated by FinAID: A Financial Advisor Application Using AI, represents an early effort to integrate artificial intelligence with money management. FinAID connects securely to users' bank accounts via the Plaid API, allowing access to transactions, income, and balances. This integration automates routine tracking and provides budgeting tips based on real-time financial data, offering convenience and immediate insights. However, its advisory engine remains largely rule-based and does not employ adaptive learning or advanced predictive techniques.

While FinAID leverages live financial data, recommendations are generated from predefined logic and static interpretations, limiting personalized insights or forward-looking investment strategies. Users can obtain basic spending analyses and budgeting guidance, but evolving financial goals or behavior-driven advice is not addressed. Additionally, FinAID lacks features such as integration with financial news, long-term goal planning, or AI-powered chatbots, which could enhance engagement and provide interactive, on-demand support. Its inability to adjust dynamically to changing user preferences or market trends highlights the need for more advanced AI advisory solutions.

The proposed web-based AI Financial Advisor addresses these limitations through a hybrid AI approach that combines recommendation models and large language models (LLMs). This system adapts over time to user behavior, delivering tailored investment recommendations and adjusting strategies in line with evolving goals and market conditions. Features such as financial news integration, interactive chatbot assistance, and goal-setting tools encourage continuous engagement and informed decision-making. Unlike FinAID, the platform not only monitors financial activities but also provides predictive, goal-oriented advice, transforming digital financial advisory into a proactive, intelligent, and user-centered service.

V. PROPOSED SYSTEM

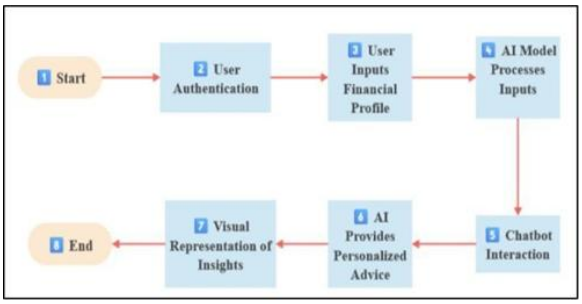

Fig. 2. Architecture of the Proposed Web-Based AI Financial Advisor

The process begins with the user initiating the system, followed by a secure authentication step to verify their identity. Once authenticated, the user is prompted to enter their financial profile, which may include details such as income, expenses, assets, and goals. This information is then analyzed by an AI model designed to interpret financial data. After processing the inputs, the system engages the user through a chatbot interface, allowing for interactive communication and clarification if needed. Based on the analysis, the AI generates personalized financial advice tailored to the user's specific situation. These insights are then presented visually, making the information easier to understand and act upon. The process concludes after the user receives and reviews the insights.

1.Home

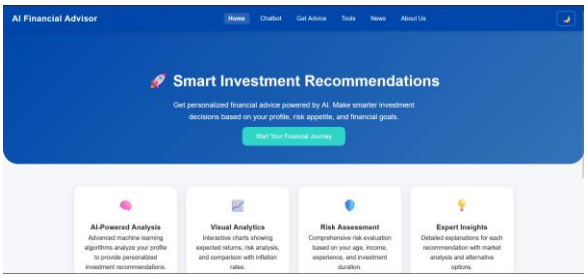

Fig. 3.Home Interface

The system launches with a clean and intuitive dashboard that presents all key features, including an AI-powered chatbot, personalized investment recommendations, financial planning tools, and real-time market news. Serving as the central hub, the dashboard ensures seamless navigation for both first-time and returning users, providing quick access to all core functionalities.

2.Chatbot

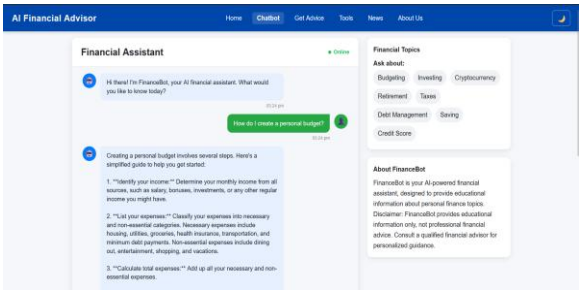

Fig. 4. Chatbot Interface

Users can interact with the AI-powered chatbot to ask questions about financial terms, investment options, or planning concepts. The chatbot provides instant, natural language responses, offering clear guidance and explanations, making complex financial ideas accessible even to beginners.

3.GetAdvice

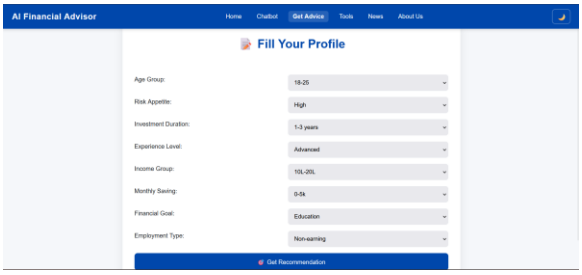

Fig. 5. Advice Interface

The system includes an intelligent Recommendation & Advice Engine that analyzes a user's financial profile, taking into account factors like earnings, savings habits, personal goals, and willingness to take risks. Using an XGBoost-based learning model, it transforms this information into tailored recommendations. identified as the most effective, to generate personalized investment suggestions. Recommendations are categorized by risk level, ranging from low-risk options such as fixed deposits, PPF, and government bonds, to moderate-risk instruments like mutual funds and REITs, and high-risk options including equities and other aggressive investments. The module also presents projected returns graphically, allowing users to visualize potential outcomes and make informed decisions.

The advisor not only delivers recommendations but also provides brief explanations for each suggestion. Key factors such as age, income, savings, and risk appetite are highlighted to help users understand why specific options are suitable for their profile. This transparency builds trust and supports financial education by giving users insight into the reasoning behind AI-generated advice.

After generating recommendations, the platform produces interactive and easy-to-understand graphs showing projected returns, risk–reward comparisons, and progress toward financial goals. These visualizations transform complex financial data into simple insights, enabling users to experiment with different inputs and immediately see how their choices affect outcomes.

4.Tools

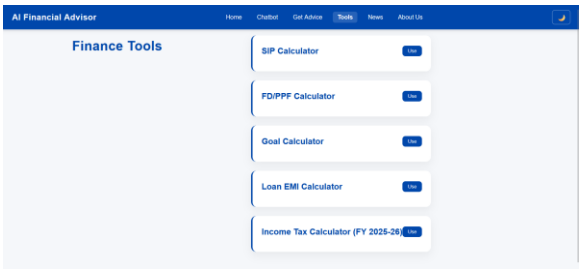

Fig. 6.Tools Interface

The Financial Tools section offers a comprehensive suite of calculators to support informed decision-making, including a SIP planner, FD/PPF calculator, loan EMI estimator, goal-based savings tracker, and income-tax calculator. These tools enable users to evaluate the long-term impact of their financial choices, plan effectively for future goals, and make data-driven decisions tailored to their individual circumstances.

5. News

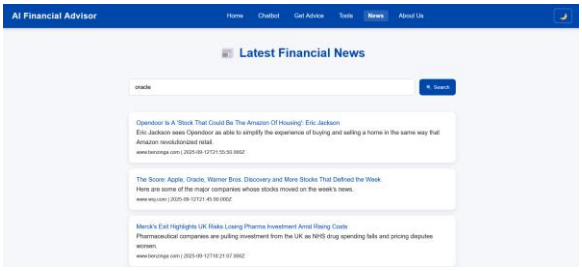

Fig. 7. News Interface

The News and Updates Feed integrates an API that delivers real-time financial news tailored to user-specified keywords. By providing live, context-relevant information, the system keeps users informed about market movements and economic developments that may impact their investment decisions, enabling timely and well-informed financial planning.

VI. ALGORITHMS AND DATASET USED

Table I. Evaluation Metrics

Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.8711	0.87	0.87	0.87
Gradient Boosting	0.8649	0.87	0.86	0.86
Decision Tree	0.8586	0.86	0.86	0.86
Random Forest	0.8545	0.87	0.85	0.86
SVM (RBF)	0.8337	0.84	0.83	0.84
K-Nearest Neighbors	0.8170	0.82	0.82	0.82
Logistic Regression	0.6653	0.66	0.67	0.66

To evaluate the suitability of various classification algorithms for the proposed system, a comparative analysis was conducted using four standard performance metrics: accuracy, precision, recall, and F1-score. The models tested included Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine (RBF), Gradient Boosting, and XGBoost. Among these, XGBoost demonstrated the most consistent and superior performance, achieving an accuracy of 87.11%. The precision score of 0.87 indicates a strong ability to minimize false positives, while the recall of 0.87 reflects its effectiveness in identifying true positive cases. The F1-score, also 0.87, confirms a balanced trade-off between precision and recall, which is especially important in datasets with class imbalance. These results highlight XGBoost's robustness and generalization capability, making it the ideal choice for deployment in the proposed architecture.

For generating personalized investment recommendations, content-based filtering is employed. This method analyzes the user profile including risk type, financial goals, and investment horizon and matches it with attributes of investment products such as mutual funds or SIPs. The system then suggests options that align closely with the user's preferences, ensuring relevant and customized advice. The system offers a conversational assistant that lets users ask financial questions in simple, everyday language. Built on the Mistral large language model and trained with finance-focused data, it provides clear, relevant answers to investment-related queries, making financial guidance easier to access and more engaging for users. To provide reliable guidance, rule-based logic is combined with machine learning. User goals, such as retirement or home buying, are mapped to suitable strategies based on risk tolerance and investment horizon. The hybrid recommendation engine integrates rule-based logic, supervised learning, and reinforcement-inspired methods to deliver adaptive, personalized financial advice. Risk assessment is performed using Decision Tree or Logistic Regression models, classifying users into Low, Medium, or High risk categories based on factors such as income, age, and goals. The chatbot, integrated via API, offers real-time investment tips, portfolio updates, and financial education. Interactive visualization tools, including Plotly, Seaborn, and Chart.js, present portfolio performance through clear, engaging charts, helping users make informed decisions.

Table II. Dataset Preview

	age_group	risk_appetite	investment_duration	experience_level	income_group	monthly_saving	financial_goal	employment_type	recommended_plan
2	36-45	Low	<1 year	Beginner	20L+	0-5k	Emergency Fund	Non-earning	FD/PPF/Bonds
3	60+	High	<1 year	Advanced	10L-20L	30k+	Wealth Creation	Unstable	Stock Market
4	26-35	High	5+ years	Advanced	10L-20L	30k+	Wealth Creation	Unstable	Stock Market
5	26-35	High	5+ years	Advanced	10L-20L	30k+	Wealth Creation	Unstable	Stock Market
6	26-35	Medium	<1 year	Advanced	<5L	15k-30k	Education	Non-earning	Gold/REITs
7	46-60	Medium	1-3 years	Intermediate	5L-10L	15k-30k	Emergency Fund	Stable	Gold/REITs
8	18-25	Medium	<1 year	Advanced	20L+	0-5k	Tax Saving	Non-earning	FD/PPF/Bonds
9	46-60	Medium	1-3 years	Advanced	20L+	30k+	Emergency Fund	Non-earning	FD/PPF/Bonds
10	18-25	High	3-5 years	Advanced	5L-10L	30k+	Wealth Creation	Unstable	Stock Market
11	18-25	Medium	3-5 years	Beginner	5L-10L	15k-30k	Retirement	Non-earning	FD/PPF/Bonds
12	36-45	Medium	1-3 years	Intermediate	<5L	15k-30k	Emergency Fund	Stable	Gold/REITs
13	36-45	Low	<1 year	Intermediate	10L-20L	15k-30k	Emergency Fund	Non-earning	FD/PPF/Bonds

The dataset used in this study comprises over 2,000 structured records, each representing a unique user investment profile. It includes five key input features: age group, risk appetite, investment duration, investment goal, and annual salary. These attributes were carefully selected to capture the primary factors influencing financial decision-making. The age group reflects the user's life stage (e.g., 18–25, 26–35) and influences investment horizon and risk capacity. Risk appetite (Low, Medium, High) represents tolerance for financial risk, while investment duration indicates the intended period, ranging from short-term (1 year) to long-term (10+ years). Investment goals include practical objectives such as Retirement, House, Travel, Education, Emergency Fund, and Wealth Creation. Annual salary is categorized into income brackets (<3L, 3L–6L, 6L–10L, 10L+) to represent financial capacity and potential for regular investment. Each record is linked to a corresponding investment recommendation, classified into plan types such as Fixed Deposit (FD), PPF/Bonds, Mutual Fund (SIP or Lumpsum), Stock Market/Direct Equity, or Gold/REITs.

The proposed system leverages this dataset to develop an AI-driven financial advisory platform that delivers personalized investment recommendations. Machine learning algorithms analyze user profiles, assess risk tolerance, and align strategies with individual financial goals. The platform integrates interactive visual analytics, enabling users to interpret complex financial data through charts showing returns, risks, and inflation-adjusted outcomes. Comprehensive risk assessment considers factors such as income, age, and investment duration, while expert insights provide explanations and alternative strategies based on market analysis. This work demonstrates how artificial intelligence can enhance personal finance decision-making, reduce dependence on manual advisory services, and empower individuals to make informed, tailored investment choices.

VII. CONCLUSION AND FUTURE SCOPE

This research presents an AI-Driven Financial Advisor that leverages machine learning and hybrid recommendation techniques to provide personalized, adaptive, and accessible financial guidance. By considering user-specific factors such as age, income, savings, financial goals, and risk appetite, the system delivers tailored investment recommendations, interactive visualizations, and real-time financial insights. The integration of a chatbot, financial planning tools, and live news feeds enhances usability, engagement, and informed decision-making.

The study demonstrates that AI can significantly transform personal financial planning by offering scalable, unbiased, and data-driven advice, reducing dependence on traditional advisory services while empowering users to make confident investment decisions.

Future work includes expanding the system to integrate directly with banking platforms for automated tracking, incorporating emerging asset classes such as cryptocurrencies, and providing portfolio management through a unified dashboard. Additionally, voice-enabled interaction and multilingual support could further enhance accessibility, inclusivity, and user engagement. Continuous improvement through user feedback and adaptive learning models will help refine recommendations and maintain relevance in dynamic financial markets

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REFERENCES

[1] Y. N. Gadhave, V. Goraksh, A. B. Dabhade, and S. J. Gadhave, “EZfinance: Your Personal Financial Advisor,” *International Journal of Research Publication and Reviews*, vol. 6, no. 2, pp. 4294–4297, 2025. [Online]. Available: https://ijrpr.com/uploads/V6ISSUE2/IJRPR39070.pdf

[2] H. Zhu, O. Vigren, and I.-L. Söderberg, “Implementing Artificial Intelligence Empowered Financial Advisory Services: A Literature Review and Critical Research Agenda,” *Journal of Business Research*, vol. 174, 2024. [Online]. Available: https://doi.org/10.1016/j.jbusres.2023.114494

[3] Q. Yang and Y.-C. Lee, "Enhancing Financial Advisory Services with GenAI: Consumer Perceptions and Attitudes Through Service-Dominant Logic and Artificial Intelligence Device Use Acceptance Perspectives," *Journal of Risk and Financial Management*, vol. 17, no. 10, p. 470, 2024. [Online]. Available: https://doi.org/10.3390/jrfm17100470

[4] A. Mushtaq, R. Chirumamilla, P. Kadiyala, R. Guntupalli, V. Goel, A. Chauhan, and K. Verma, "Transforming Personal Finance Coaching through Artificial Intelligence," *International Journal of Engineering and Computer Science*, vol. 13, no. 11, pp. 26607–26618, 2024. [Online]. Available: https://doi.org/10.18535/ijecs/v13i11.4929

[5] M. Bahoo, M. Cucculelli, X. Goga, and J. Mondolo, "AI Unleashed: Transforming Personal Finance with Artificial Intelligence," *SSRN Electronic Journal*, June 2024. [Online]. Available: https://doi.org/10.2139/ssrn.4842208

[6] A. Ghosh, O. A. Acar, C. Wiertz, and A. Banerjee, "Examining the Effects of AI Financial Advisor Attributes on Their Adoption," *SSRN Electronic Journal*, Mar. 26, 2024. [Online]. Available: https://doi.org/10.2139/ssrn.4738877

[7] P. Uppaluri, "AI and Machine Learning Applications in Modern Financial Planning: A Comprehensive Analysis," *International Journal of Computer Engineering and Technology (IJCET)*, vol. 15, no. 6, pp. 1765–1774, 2024. [Online]. Available: https://doi.org/10.34218/IJCET_15_06_150

[8] R. Gupta and C. Bisaria, "AI-Driven Personal Finance Apps: Assessing the Impact on Financial Decision-Making and Marketing Strategies," *International Journal of Management (IJM)*, 2023.

[9] H. S. O. H. Al Dhaheri, "Machine Learning for Financial Planning: A Comparative Analysis of Traditional Approaches and New Technologies," *International Journal of Innovative Science and Research Technology*, vol. 8, no. 10, 2023. [Online]. Available: https://doi.org/10.5281/zenodo.10088726

[10] O. Onabowale, "The Rise of AI and Robo-Advisors: Redefining Financial Strategies in the Digital Age," *Journal of Financial Technology and Analytics*, 2022.

[11] S. K. Gorai and A. Maurya, "Artificial Intelligence in Personal Finance Management: Opportunities and Challenges," *IOSR Journal of Computer Engineering (IOSR-JCE)*, vol. 27, no. 1, pp. 07–17, 2021. [Online]. Available: https://doi.org/10.9790/06612701010717

[12] A. Shah, P. Raj, P. Kumar, S. P., and A. H. V., "FinAID: A Financial Advisor Application Using AI," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 9, no. 1, pp. 2282–2286, May 2020. [Online]. Available:https://doi.org/10.35940/ijrte.A2951.059120