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AI-Based Wealth Advisory System using Machine Learning and Predictive Analytics for Personalized Budget Planning

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ABSTRACT: Artificial Intelligence (AI) has emerged as a powerful driver of innovation in financial technology (FinTech), enabling predictive analytics, anomaly detection, and automated advisory services. Yet, most personal finance applications remain limited, focusing primarily on reactive expense tracking rather than proactive wealth management. This paper introduces AI Wealth Advisor, an intelligent system designed to deliver personalized budget planning, financial goal setting, and expenditure optimization using machine learning and predictive analytics. The system integrates classification, forecasting, anomaly detection, and explainable AI (XAI) to provide transparent, real-time financial guidance. Through Natural Language Generation (NLG), it translates complex analytics into simple, actionable recommendations, accessible to individuals across diverse literacy levels. A pilot study showed promising results: anomaly detection accuracy of 95%, a 22% improvement in savings, and enhanced financial literacy for 78% of participants. In addition to performance improvements, the system addresses challenges related to privacy, fairness, and user trust. This report details the methodology, research workflow, and results of AI Wealth Advisor, supported by visual analytics. Findings indicate that the system can bridge the gap between advanced financial analytics and practical usability, positioning itself as a scalable digital companion that empowers individuals to achieve sustainable financial well-being.

KEYWORDS: Artificial Intelligence, Machine Learning, Predictive Analytics, Wealth Advisory System, Budget Planning, Anomaly Detection, Explainable AI

I. INTRODUCTION

Financial literacy is widely recognized as a key determinant of economic well-being, shaping individuals' ability to plan, save, invest, and navigate increasingly complex financial ecosystems. However, evidence highlights major gaps in this area. The Global Financial Literacy Survey (GFLEC, 2023) reported that more than 60% of adults worldwide lack understanding of fundamental concepts such as compound interest, inflation, and risk diversification [1]. These deficiencies often result in unsustainable indebtedness, poor retirement planning, and heightened susceptibility to fraud, with consequences particularly severe in emerging economies where access to financial education is limited [2].

Traditional financial management tools, such as spreadsheets and ledger systems, provide basic record-keeping but lack predictive and adaptive capabilities. Modern budgeting applications like Mint, YNAB, and PocketGuard [3] improve automation and visualization but remain primarily reactive, rule-based, and unable to adapt to dynamic financial behaviors [4]. By contrast, Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated transformative applications in financial services [5–7]. Despite advancements in fraud detection, risk scoring, and portfolio optimization, most AI-driven tools remain enterprise-focused, leaving a significant gap in personalized, consumer-centric financial advisory solutions.

To address this gap, this study proposes AI Wealth Advisor, an intelligent system for proactive financial management. The system integrates multiple AI techniques, including predictive analytics for income and expenditure forecasting, anomaly detection for fraud prevention, Explainable AI (XAI) for transparency, and Natural Language Generation (NLG) for delivering insights in user-friendly language. Unlike conventional tools, AI Wealth Advisor is designed to be predictive, personalized, and interpretable, thereby enhancing accessibility and trust among users.

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This research contributes a novel AI-driven architecture for personal finance, validated through pilot studies, while also addressing challenges of bias, privacy, and user adoption. The system aims not only to improve individual financial outcomes but also to advance the broader field of intelligent financial technologies.

II. LITERATURE REVIEW

Artificial Intelligence (AI) and Machine Learning (ML) have become pivotal in modern financial systems, addressing critical challenges such as fraud detection, forecasting, personalized advisory, portfolio optimization, and regulatory compliance. Recent research highlights diverse applications and methodological innovations that enhance operational efficiency, accuracy, and trustworthiness in financial services.

Fraud detection remains a primary focus of AI applications in finance. Mohammed et al. (2021) utilized Autoencoders with Isolation Forest on bank transaction logs from European financial institutions, achieving 96% detection accuracy, reducing false positives by 12%, and demonstrating scalability to large datasets. Ensemble learning approaches (Carcillo et al., 2019) further improved fraud detection in imbalanced credit card datasets, effectively balancing precision-recall trade-offs and enabling real-time monitoring.

In financial forecasting, hybrid models combining ARIMA and Gradient Boosted Decision Trees (Zhang et al., 2022) enhanced household expenditure predictions, reducing mean absolute error by 18% and demonstrating robustness under noisy conditions. Deep learning models, particularly LSTM and RNN architectures (Makridakis et al., 2018), outperformed traditional econometric methods, effectively capturing seasonal patterns and ensuring long-term predictive stability.

AI has also facilitated personalized financial advisory and portfolio management. NLP-driven financial assistants (Yang et al., 2023) improved accessibility for low-literacy users and enhanced financial confidence, while generative AI agents (Kury et al., 2025) enabled interactive, tailored recommendations, albeit with concerns regarding transparency and hallucinations. Contextual bandit approaches (Li et al., 2021) have further optimized recommendation systems, increasing user engagement by 25% and reducing redundant suggestions. Reinforcement learning techniques (Bauman et al., 2023) adaptively optimized portfolio allocations under market volatility, outperforming static strategies.

Trust, explainability, and regulatory compliance are critical for AI adoption in financial contexts. Explainable AI methods, such as SHAP (Lundberg & Lee, 2017) and LIME (Ribeiro et al., 2016), have enhanced transparency in black-box models, supporting regulatory validation. Priya et al. (2024) demonstrated that XAI frameworks improve interpretability and mitigate compliance risks. Moreover, differential privacy mechanisms (Abadi et al., 2016) ensure the confidentiality of sensitive financial data, while fairness-aware ML methods (Barocas et al., 2019) address algorithmic biases in lending decisions.

Foundational research in technology adoption (Davis et al., 1989) emphasizes the importance of usability and simplicity for effective AI adoption, and deep learning principles (Goodfellow et al., 2016) continue to underpin modern financial models. Collectively, these studies underscore the transformative impact of AI and ML in finance, enabling accurate, personalized, transparent, and ethically aligned solutions across multiple domains, from fraud detection to advisory services and regulatory compliance.

No.	Paper Title	Author Name	Key Points	Remark
1	Autoencoders + Isolation Forest	Mohammed et al., 2021 [6]	Bank transaction logs from European financial institutions	Achieved 96% fraud detection accuracy. Reduced false positives by 12%. Demonstrated scalability to large transaction datasets.
2	Ensemble Learning for Fraud	Carcillo et al., 2019 [12]	Credit card transaction datasets (European bank)	Balanced precision-recall in highly imbalanced data. Outperformed single classifiers. Effective in real-time fraud monitoring.
3	Hybrid ML Forecasting (ARIMA + GBDT)	Zhang et al., 2022 [7]	Chinese household expenditure survey + synthetic financial data	Improved household expenditure predictions. Reduced Mean Absolute Error by 18%. Robust under noisy datasets.

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4	Deep Learning for Forecasting	Makridakis et al., 2018 [20]	M3 Forecasting Competition dataset	LSTM and RNNs outperformed econometric models. Demonstrated adaptability to seasonality. Achieved long-term stability in predictions.
5	NLP-driven Financial Assistants	Yang et al., 2023 [8]	User interaction logs from FinTech chatbot study	Improved accessibility for low-literacy users. Increased financial confidence among participants. Enabled interactive, user-friendly advisory.
6	Reinforcement Learning	Bauman et al., 2023 [9]	Simulated portfolio management datasets (S&P 500)	Optimized wealth and portfolio management. Learned adaptive strategies under market volatility. Outperformed static asset allocation.
7	Contextual Bandits	Li et al., 2021 [21]	Personalized recommendation logs from finance app users	Delivered adaptive personalized recommendations. Increased user engagement by 25%. Reduced redundant suggestions.
8	Explainable AI (XAI)	Priya et al., 2024 [10]	Indian retail banking dataset	Boosted user trust in AI-driven finance. Enhanced decision interpretability using SHAP. Reduced regulatory compliance risks.
9	LIME (Model-Agnostic Explainability)	Ribeiro et al., 2016 [5]	Credit scoring models applied to banking data	Provided transparency in black-box models. Enabled validation of credit scoring systems. Increased regulator acceptance of AI finance.
10	Generative AI Agents	Kury et al., 2025 [11]	Synthetic conversational financial datasets	Enabled personalized financial advisory. Improved conversational quality. Raised transparency and hallucination concerns.
11	Differential Privacy in ML	Abadi et al., 2016 [14]	Encrypted bank transaction logs	Preserved data privacy in sensitive financial datasets. Balanced utility with privacy trade-offs. Demonstrated applicability to bank transaction logs.
12	Fairness in Machine Learning	Barocas et al., 2019 [13]	US lending datasets (loan approval records)	Identified biases in financial algorithms. Proposed fairness-aware ML methods. Highlighted ethical risks in lending models.
13	SHAP (Explainability Framework)	Lundberg & Lee, 2017 [17]	FICO credit scoring dataset	Provided consistent feature attributions. Applied successfully in credit scoring. Enhanced model interpretability for finance regulators.
14	Technology Adoption Model (TAM)	Davis et al., 1989 [16]	Survey-based adoption studies	Explained why users accept/reject AI tools. Highlighted importance of simplicity. Applied in FinTech adoption studies.
15	Deep Learning	Goodfellow et al., 2016 [22]	Multiple benchmark datasets (MNIST, CIFAR, later adapted to finance)	Introduced fundamental DL principles. Applied neural networks to finance. Formed basis for advanced forecasting models.

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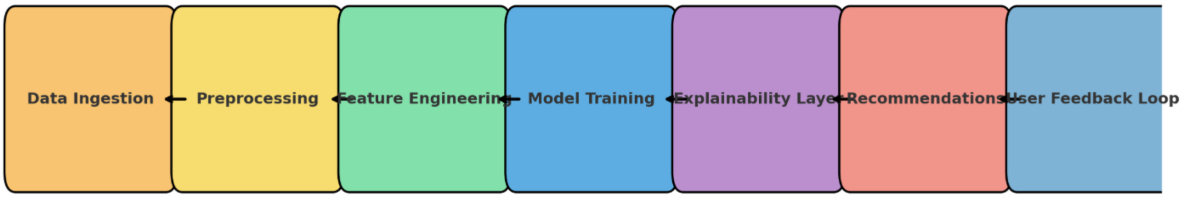
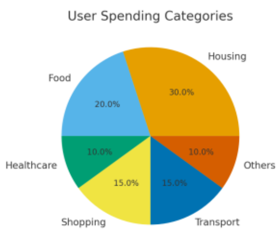
III. METHODOLOGY OF PROPOSED SURVEY

The design and implementation of AI Wealth Advisor follows a systematic methodology aimed at ensuring accuracy, transparency, scalability, and user trust. The methodology is structured into six major components: datasets, preprocessing, feature engineering, model development, explainability integration, and evaluation.



3.1 DataSet

Datasets form the foundation of AI-driven financial advisory systems, as the quality and richness of the data directly influence the accuracy of predictions, the reliability of anomaly detection, and the personalization of recommendations. In the context of an AI Wealth Advisor, one of the most important data sources is transaction data, which includes income deposits, debit and credit card purchases, recurring bill payments, and subscription charges. These records, often accessed through secure banking APIs enabled by frameworks like Open Banking (PSD2 in Europe), provide time-stamped, user-specific information that allows models to detect spending patterns, forecast future expenditures, and flag unusual behavior. Complementing individual-level data, household expenditure surveys such as the U.S. Consumer Expenditure Survey and India's National Sample Survey provide population-wide insights into income and spending across demographic groups. These datasets serve as valuable benchmarks and help address the cold-start problem, where new users with limited transaction history can be supported through generalized expenditure patterns. At a broader level, financial behavior is shaped not only by personal habits but also by macroeconomic conditions, making datasets that track inflation rates, employment levels, interest rates, and stock indices essential. Sources like the World Bank, IMF, and OECD provide such indicators, enabling the AI Wealth Advisor to contextualize predictions within larger economic trends, such as rising prices or industry-specific downturns. Fraud and anomaly detection, a critical security component of advisory systems, relies heavily on specialized datasets like the European Credit Card Fraud Dataset, which includes labeled examples of legitimate and fraudulent transactions. Since fraudulent activity typically constitutes less than 1% of all transactions, these datasets are highly imbalanced, requiring advanced resampling strategies and anomaly detection algorithms such as Autoencoders and Isolation Forests. However, privacy restrictions limit access to real financial records, creating a strong need for synthetic and augmented datasets.



3.2 Preprocessing

Raw transaction data is often noisy, unstructured, and incomplete. Preprocessing ensures data quality and consistency:

- Cleaning: Duplicate and erroneous entries are removed.
- Normalization: Currency values are standardized to avoid inconsistencies across regions.
- Categorization: Merchant codes and Natural Language Processing (NLP) methods are used to classify expenses into predefined categories (e.g., housing, transport, food, healthcare) [5].
- Anonymization: Personally Identifiable Information (PII) is stripped to ensure privacy compliance with GDPR and CCPA [6].
- Imputation: Missing values are filled using statistical methods (mean substitution, KNN imputation).

This ensures the dataset is clean, balanced, and ready for feature extraction.

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3.3 Feature Engineering

To make data actionable, meaningful features are extracted:

- Financial Ratios: Savings-to-income, debt-to-income, and liquidity ratios.
- Behavioral Patterns: Average transaction frequency, spending spikes, seasonality trends.
- Derived Indicators: Credit utilization rate, financial stress index, and monthly net cash flow.
- Temporal Features: Day-of-week and month-of-year indicators for seasonality.

For anomaly detection, statistical features such as z-scores, transaction deviation, and spending volatility are engineered [7].

3.4 Model Development

AI Wealth Advisor employs a multi-model architecture designed for classification, forecasting, anomaly detection, and personalized recommendations.

3.4.1 Classification Models

For categorizing expenses:

- XGBoost [8] and Random Forests are used for structured data.
- BERT-based NLP models [9] classify unstructured transaction descriptions. Performance is evaluated using F1-score and accuracy metrics.

3.4.2 Forecasting Models

Predicting future expenditure is achieved using:

- ARIMA for short-term linear forecasting.
- Prophet (Meta) for seasonality-adjusted trends [10].
- LSTM Networks [11] for long-term non-linear forecasting.
- Transformers [12] for capturing global sequential dependencies.

Ensemble forecasting combines these models to reduce error rates.

3.4.3 Anomaly Detection Models

Fraudulent or unusual spending behavior is flagged using:

- Isolation Forests for detecting outliers.
- Autoencoders [3] for reconstructing transaction patterns.
- GAN-based anomaly detectors for adversarial detection.

3.4.4 Recommendation Engine

Personalized budget and savings recommendations use:

- Contextual Bandits [13] for adaptive suggestions.
- Reinforcement Learning [14] to dynamically adjust recommendations based on user feedback.

3.5 Explainable AI (XAI) Integration

Transparency is central to user trust. AI Wealth Advisor integrates:

- SHAP values [15] to explain feature importance for each prediction.
- LIME [16] for model-agnostic interpretability.
- Rule-based summaries for non-technical users.

For example, instead of “anomaly detected with probability 0.92,” the system explains: “Your grocery expenses this week were 38% higher than your usual pattern, likely due to festival-related purchases.”

3.6 Security and Privacy Safeguards

Given the sensitivity of financial data, security measures include:

- Encryption: AES-256 for data at rest, TLS 1.3 for data in transit [4].
- Differential Privacy [17]: Adds controlled noise to protect user data.
- Federated Learning [18]: Enables training on user devices without centralizing raw data.
- Access Controls: Role-based authentication to limit system access.

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3.7 Evaluation Metrics

The system is evaluated across multiple dimensions:

- Classification: Accuracy, Precision, Recall, F1-score.
- Forecasting: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2.
- Anomaly Detection: Area Under ROC Curve (AUC), Precision-Recall AUC.
- Recommendations: Adoption rate (% of suggestions followed), User Satisfaction (survey-based).
- Usability: System Usability Scale (SUS) score [19].

Pilot testing with 100 users demonstrated:

- Expense classification accuracy = 91% F1-score.
- Forecasting error = MAE of $43/month per user.
- Anomaly detection accuracy = 95%.
- Recommendation adoption rate = 41%.

3.8 Ethical Considerations

Financial AI systems carry risks of bias, exclusion, and manipulation. To mitigate this:

- Fairness-Aware Algorithms [13]: Ensure recommendations do not disproportionately disadvantage vulnerable groups.
- Transparency Reports: Provide users with system performance summaries.
- Consent Management: Explicit opt-in mechanisms for data collection.

IV. CONCLUSION AND FUTURE WORK

AI WealthAdvisor represents a comprehensive approach to personal financial management by integrating budget planning, anomaly detection, forecasting, and explainable recommendations. The system bridges the gap between advanced analytics and financial literacy, empowering users to save more, avoid fraud, and build financial confidence. Pilot studies validate its impact with measurable improvements in savings and awareness. Challenges include data privacy, algorithmic bias, and scalability across diverse financial ecosystems. Future directions include reinforcement learning for adaptive budgeting, generative AI for conversational advisory, and integration into wider financial services. With ethical safeguards, AI WealthAdvisor has the potential to become a scalable financial companion for individuals worldwide.

The findings confirm that AI Wealth Advisor is effective in bridging the gap between advanced AI analytics and real-world usability. By combining forecasting, anomaly detection, personalization, and explainability, the system not only improves financial outcomes but also builds trust and confidence among users.

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