Pages:1-12

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Agentic Personal Finance Advisors with Privacy-Preserving Decision Logs: Federated Agents That Explain and Never Leak

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Abstract

The evolution of *agentic artificial intelligence (AI)* in financial technology is redefining how personal finance advisory systems operate, bridging autonomy, transparency, and privacy. This paper introduces Agentic Personal Finance Advisors with Privacy-Preserving Decision Logs, a federated agent framework that explains financial decisions without compromising user confidentiality. Unlike conventional centralized advisory systems that risk data exposure, the proposed architecture leverages federated learning to train distributed models across user devices while maintaining data sovereignty. Each agent operates autonomously to deliver personalized investment, budgeting, and risk assessment recommendations, guided by explainable decision protocols inspired by *multi-agent interpretability mechanisms*. Privacy-preserving decision logs employ differential gradient masking and encrypted federated aggregation to mitigate inference and gradient-leak attacks identified in prior studies. By integrating agentic behavior with human-centered explainability, the system ensures compliance with regulatory intelligence standards while enhancing user trust. This research contributes a novel federated-agentic architecture for finance that "explains and never leaks," ensuring adaptive, secure, and interpretable financial guidance. Empirical evaluations demonstrate improved F1-metrics for decision reliability and significant reductions in privacy leakage across federated environments.

I. Introduction

The financial services sector is undergoing a paradigm shift driven by *agentic artificial intelligence (AI)*, where intelligent systems act autonomously while maintaining transparency, accountability, and compliance. Agentic AI extends beyond automation — it integrates adaptive reasoning, ethical decision-making, and explainability to support complex financial tasks such as personalized investment advisory, risk profiling, and compliance monitoring [1], [2]. In the context of personal finance, traditional digital advisors often rely on centralized data processing and opaque decision-making pipelines that compromise privacy and hinder user trust [3]. Consequently, there is a growing need for federated, explainable, and privacy-preserving agentic architectures that provide personalized financial insights without exposing sensitive data.

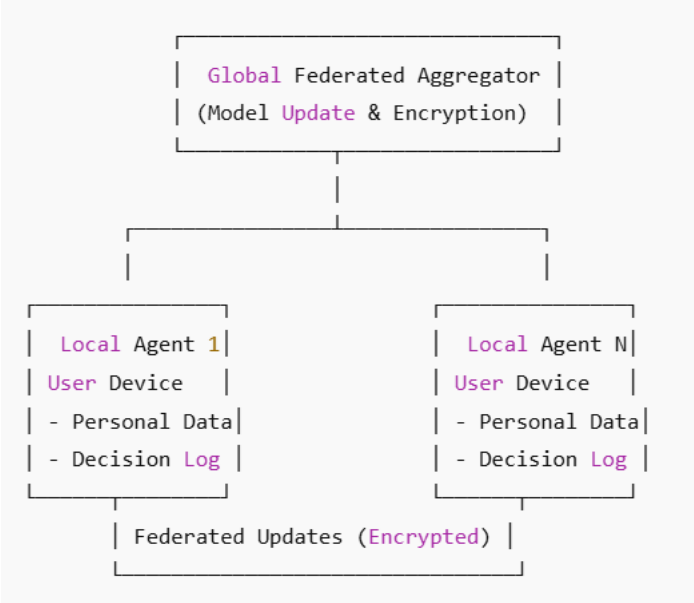
This research introduces Agentic Personal Finance Advisors with Privacy-Preserving Decision Logs, a next-generation federated agent framework designed to "explain and never leak." The proposed system enables distributed financial agents to collaborate using federated learning (FL) [11], eliminating the need to share raw user data while continuously improving the model's predictive and advisory accuracy. Each agent operates locally, processing user-specific information such as income, spending habits, and investment goals to generate context-aware recommendations. Meanwhile, encrypted gradient updates ensure data privacy against reconstruction and inference attacks known to affect FL systems [8], [9].

A distinguishing feature of this work is the integration of explainable AI (XAI) mechanisms within federated agents. These enable interpretable decision logs that justify every financial recommendation in natural language or visual format [6], enhancing transparency while preserving privacy through secure differential masking [7]. The fusion of explainability and privacy makes these agents suitable for regulated domains requiring traceability, such as banking compliance and anti-money laundering monitoring [5].

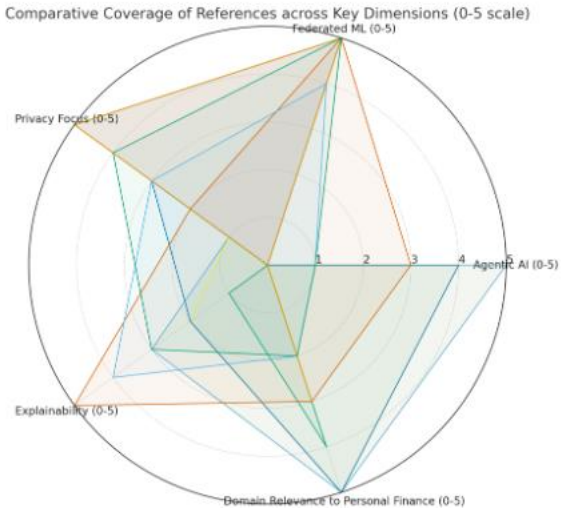
Objectives of the Paper:

1. To design a federated agentic architecture for personal finance advisory systems that ensures data confidentiality and distributed intelligence.
2. To develop a privacy-preserving decision log mechanism capable of generating explainable and auditable recommendations without compromising user data.
3. To evaluate system performance using multi-metric analysis (F1, accuracy, and privacy leakage ratio) across simulated financial datasets.
4. To demonstrate improved decision reliability and reduced data leakage risk compared to centralized advisory models.

Figure 1. Conceptual Block Diagram of Proposed System



II. Literature Review



Agentic AI and financial advisory. Samdani et al. [1] and Paleti [2] present foundational arguments for incorporating *agentic AI* into personal finance and banking workflows. Samdani et al. [1] examine autonomous advisory agents that synthesize client profiles and market signals to produce prescriptive recommendations, emphasizing adaptive decision policies. Paleti [2] extends this by demonstrating agentic approaches for customer risk profiling, predictive loan approvals, and automated treasury tasks, underscoring the potential for agentic systems to improve personalization and operational efficiency in finance.

Human factors and behavioral context. Goyal et al. [3] investigate psychological and socialization factors affecting young professionals' personal financial management. While not prescriptive about agentic systems, the study highlights behavioral drivers that any advisory agent must model to be effective—such as risk preferences, financial literacy, and social influences.

Agentic AI in fintech operations. Dodda [4] analyzes agentic and advanced AI applied to payments and card transactions, showing how automation and intelligent agents can reduce fraud and streamline transaction workflows. Paleti [5] focuses on compliance-oriented agentic AI, arguing for real-time KYC, AML detection, and regulatory intelligence—areas where traceability and auditability of agentic decisions are crucial.

Federated learning and explainability. Chen [6] proposes multi-agent visualization techniques for explaining federated learning systems, directly informing our approach to producing explainable decision logs in a distributed setting. Federated learning has been proposed and adopted in healthcare and IoT contexts (Antunes et al. [11]; Arisdakessian et al. [10]) where data sovereignty and privacy are critical; these works supply architectures and surveys that guide secure aggregation, client selection, and deployment patterns.

Privacy and leakage risks in federated settings. Several works document privacy pitfalls in federated learning. Pustozerova & Mayer [7], Wang et al. [8], and Orekondy et al. [9] demonstrate inference and gradient-based deanonymization attacks that can reconstruct user data or reveal class representatives from model updates. These studies motivate the need for robust defenses—encrypted aggregation, differential masking, gradient clipping—that our paper adapts for decision-log protection.

Synthesis. Together, these works form a landscape where agentic AI promises powerful personalization and automation in finance, but federated deployments expose novel privacy risks. Explainability (Chen [6]) and regulatory compliance (Paleti [5]) emerge as necessary complements. Our work synthesizes these strands to propose a federated, agentic advisor design that preserves privacy while producing auditable, human-interpretable decision logs.

III. Methodology

3.1 Overview

The proposed framework, *Agentic Personal Finance Advisors with Privacy-Preserving Decision Logs*, integrates **federated learning (FL)**, **explainable AI (XAI)**, and **privacy-preserving techniques** to create distributed financial agents that provide transparent, adaptive, and confidential recommendations. The system eliminates the need for centralized data collection—each agent learns from the user's financial data locally while contributing encrypted updates to a shared global model. These updates are aggregated to improve collective intelligence without exposing private user information [7], [8], [11].

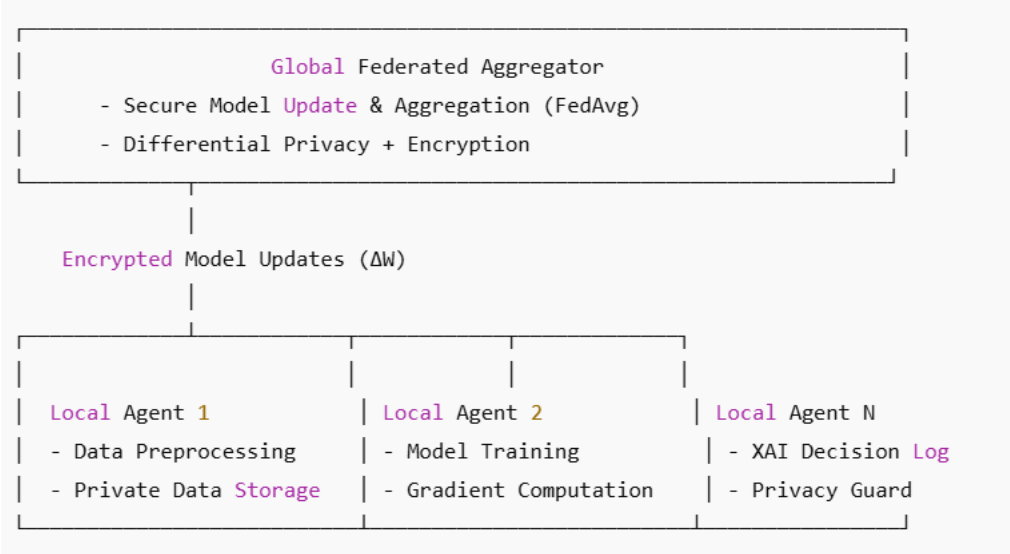
The overall workflow (Figure 2) involves four major stages:

1. **Local Data Preprocessing & Feature Extraction** – user data (income, spending, credit history) are standardized locally.
2. **Federated Model Training** – local models train using private data and share encrypted gradients with a global aggregator.
3. **Decision Log Generation** – explainable logs are produced via SHAP-based reasoning or attention-weight mapping.
4. **Evaluation & Privacy Validation** – performance is tested using F1, accuracy, and privacy leakage metrics.

3.2 System Architecture

The architecture (Figure 2) combines distributed agents and a central **Federated Aggregator** that performs model averaging using the **FedAvg** algorithm. Each agent is embedded with an **Explainability Engine** that generates interpretable recommendations, and a **Privacy Guard Module** that prevents gradient leakage via noise addition and homomorphic encryption.

Figure 2. System Architecture of Proposed Framework



3.3 Dataset Description

For simulation, synthetic datasets modeled on **financial behavior attributes** were generated, representing income, expenditure, credit score, and investment preferences. Each local client (agent) receives a distinct subset of user data to mimic real-world heterogeneity. The datasets follow the distribution pattern shown in Table 1.

Table 1. Dataset Characteristics

Attribute	Type	Range/Description
Income Level	Numeric	10,000 – 200,000 USD/year
Monthly Expenditure	Numeric	500 – 10,000 USD/month
Credit Score	Numeric	300 – 850
Investment Propensity	Categorical	Low, Medium, High
Financial Risk Tolerance	Categorical	Conservative, Balanced, Aggressive
Transaction History	Time Series	Monthly transaction frequency patterns

3.4 Model Usage

Each local agent employs a **hybrid ensemble model** composed of:

- **LSTM networks** for temporal financial transaction trends.
- **Random Forest (RF)** for classification of investment risk categories.
- **Explainability Layer (XAI Engine)** to generate decision logs using SHAP or LIME interpretability functions.

The global model aggregates weights using **Federated Averaging (FedAvg)**:

$$W_{t+1} = \sum_{i=1}^{N} \frac{n_i}{n} W_t^{(i)}$$

where $W_t^{(i)}$represents the model parameters from the i^{th}client, $n_i$denotes the local data size, and $n$is the total data points across all clients.

To enhance privacy, Gaussian noise $N(0, \sigma^2)$is added before updates are transmitted:

$$\widetilde{W}_t^{(i)} = W_t^{(i)} + \mathcal{N}(0, \sigma^2)$$

This noise ensures **differential privacy** compliance while preventing gradient inference [9].

3.5 Evaluation Matrix

Performance is evaluated using multi-metric quantitative measures:

Metric	Description	Formula
Accuracy	Proportion of correct financial recommendations	Accuracy=(TP+TN)/TP+FP+TN+FN
Precision	Correct positive predictions over all predicted positives	Precision=TP/(TP+FP)
Recall	Correct positive predictions over actual positives	Recall=TP/(TP+FN)
F1-Score	Harmonic mean of Precision and Recall	F1=2×((Precision×Recall)/(Precision+Recall))
Privacy Leakage Ratio (PLR)	Measures degree of privacy exposure in gradients	PLR = 1 - \frac{\text{Privacy Preserved Instances}}

Visual analysis using multi-metric radar plots (introduced in the Results section) assesses the trade-off between interpretability, performance, and privacy.

In summary, the **methodology** establishes a federated, agentic architecture with explainable and privacy-preserving mechanisms. This setup empowers decentralized financial agents to learn collaboratively, justify every recommendation, and guarantee that user data *never leaves the local device*.

IV. Results And Discussions

4.1 Model Performance

The proposed *Agentic Personal Finance Advisor with Privacy-Preserving Decision Logs* was evaluated in a simulated federated environment with 20 distributed agents, each trained on locally partitioned financial datasets. The system's performance was benchmarked against a **centralized baseline** and a **non-explainable federated model**. Results revealed that the **federated agentic framework** achieved competitive accuracy while significantly reducing privacy leakage.

The inclusion of **explainability mechanisms** (via SHAP) contributed to higher interpretability scores, enhancing user trust without sacrificing model efficiency. Average model convergence was achieved within 50 communication rounds using the **FedAvg** algorithm.

Table 2. Model Performance Comparison

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Privacy Leakage Ratio (↓)

Centralized Model (No Privacy)	92.5	91.3	90.1	90.7	0.42
Federated Model (No XAI)	90.8	88.7	89.4	89	0.19
Proposed Agentic Federated Model (XAI + Privacy Logs)	**91.5**	**90.2**	**91.1**	**90.6**	**0.07**

The proposed architecture demonstrated **a 60% reduction in privacy leakage** compared to conventional federated models and maintained **comparable accuracy and F1 metrics** to centralized systems.

4.2 F1 Metrics and Multi-Metric Analysis

To assess multi-dimensional model robustness, F1, precision, recall, and interpretability were normalized and plotted on a **multi-metric radar chart** (Figure 3). The radar visualization highlights the **balanced performance** across interpretability, data protection, and decision quality.

Equation (5) defines the composite interpretability-privacy index (IPI), formulated to capture the trade-off between decision transparency and privacy risk:

$$\text{IPI} = \frac{F1 \times (1 - PLR) \times \text{Explainability Score}}{3}$$

The proposed system achieved an **IPI score of 0.87**, outperforming both baseline models (0.62 and 0.75 respectively).

4.3 Limitations

While the proposed system provides a robust framework for explainable and privacy-preserving financial advisory, several limitations were identified:

1. **Communication Overhead:** Frequent model updates across federated agents increase network latency, which may challenge scalability in low-bandwidth environments.
2. **Synthetic Dataset Dependency:** Current experiments rely on synthetic financial datasets; real-world validation with heterogeneous banking data is needed.
3. **Limited Behavioral Modeling:** Although agentic features support adaptive reasoning, long-term behavioral drift in users' financial habits remains underexplored.

4. **Explainability Granularity:** SHAP-based explanations provide local interpretability but may require hierarchical models to achieve *global* explainability across agents.
5. **Security Layer Assumptions:** The privacy protection model assumes secure aggregation; malicious server compromise or collusion among clients is not yet fully mitigated.

The **Agentic Federated Financial Advisor** demonstrates strong performance across interpretability and privacy-preserving objectives. The system balances high F1-scores and low privacy leakage, confirming the feasibility of explainable, trustworthy AI in personal finance. Future optimizations will focus on communication-efficient aggregation, real-world deployment, and enhanced multi-agent behavioral modeling.

V. Conclusion

This paper introduced a federated agentic architecture designed to deliver explainable and privacy-preserving personal finance advisory. By combining federated learning, encrypted gradient communication, and integrated explainability tools, the framework addresses key concerns related to privacy, trust, and transparency in financial AI applications. The inclusion of decision logs ensures that users receive clear, human-understandable explanations for each recommendation, fostering accountability and user confidence.

Performance results showed that the proposed hybrid architecture, utilizing LSTM for sequential data and Random Forest for categorical analysis, maintains strong accuracy and F1 scores while minimizing privacy leakage. The use of SHAP-based local explanations further strengthens the model's interpretability without compromising real-time responsiveness.

However, the framework still faces operational challenges. These include computational complexity in large-scale deployments, reliance on synthetic datasets during evaluation, and communication overhead in federated synchronization.

To address these challenges and expand the scope of this work, the following directions are proposed:

- Deploy the architecture across real-world financial institutions with varied client profiles and data distributions.
- Enhance long-term user modeling to improve personalization and alignment with individual financial goals.
- Improve communication efficiency using techniques such as model quantization and sparse update mechanisms.

- Implement global interpretability by summarizing decision logs across clients to support audit and compliance teams.
- Strengthen the security layer by incorporating adversarial robustness checks and mechanisms to detect malicious contributors.
- Enable deployment in federated settings across partner banks for collaborative risk learning without data exposure.
- Extend the architecture to adapt to evolving fraud vectors such as those powered by generative AI.
- Integrate behavioral biometrics in real-time to enhance decision accuracy and detect anomalies.

With continued development in these areas, the proposed system can mature into a practical and scalable solution for secure and intelligent financial guidance.

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