INTELLIGENT FINANCIAL ASSISTANTS USING AI AND CHATBOTS FOR PERSONALIZED BANKING SERVICES

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Abstract. *The rapid growth of Artificial Intelligence (AI) is reshaping the interaction between financial institutions and their customers. This study introduces an intelligent financial assistant that enhances digital banking through conversational AI and personalized recommendations. The system integrates a chatbot capable of executing payments, navigating mobile interfaces, and suggesting products based on user behavior. Explainable AI (XAI) techniques such as SHAP and LIME ensure transparency and trust, while voice and biometric authentication improve security. To remain GDPR-compliant, the solution employs federated learning for distributed model training without transferring sensitive data. The combined use of personalization, explainability, and privacy protection establishes a secure and human-centered foundation for the next generation of digital finance.*

Key words: Artificial Intelligence, Chatbots, FinTech, Explainable AI, Federated Learning, Personalized Banking.

Introduction

The implementation of artificial intelligence (AI) makes it possible for financial institutions to handle and analyze data coming from a broad assortment of sources in a more efficient manner. These groundbreaking discoveries assist banks in overcoming the typical challenges they experience when providing essential services such as payment processing. These challenges are typical [1].

The application of machine learning and other forms of AI is becoming an increasingly essential trend. It provides assistance to FinTech business in automating regular operations and enhancing results in ways that are incomprehensible to the human brain. Financial technology business may be able to improve their ability to identify threats, prevent fraud, automate repetitive processes, and improve service quality through the early implementation of artificial intelligence [1].

Traditional banking channels while still relevant, often fall short in providing the immediacy and 24/7 accessibility required by today's consumers, especially younger demographics accustomed to insists digital interactions [2].

Modern mobile banking applications offer a wide portfolio of services, yet many users have trouble navigating complex interfaces, locating financial information, or executing transactions efficiently. At the same time, banks seek to increase personalization, sell products and automate routine customer interactions.

Conversational AI systems provide a promising solution, enabling customers to interact with digital banking through natural language (NL), voice commands, and personalized recommendations. Unlike traditional chatbots, modern AI assistants can understand context, detect user intent, autonomously perform banking operations, and explain their reasoning in a transparent manner.

The system is designed to operate inside the secure perimeter of a banking environment, ensuring that all financial operations and sensitive data remain strictly protected. This work proposes an integrated architecture for an Intelligent Financial Assistant, combining:

- NLP-based chatbot.
- Voice interaction.
- Navigation assistant.
- Payment execution.
- Personalized recommendation engine.
- XAI transparency module.
- GDPR-compliant Federated learning.
- Smart invoice recognition.
- Fraud-alert interaction system.

Motivation

As banks aim to improve customer service and reduce operational costs, Conversational Artificial Intelligence (AI) is emerging as a transformative solution. From a broader perspective, Conversational AI leverages advancements in natural language processing (NLP), machine learning and speech recognition to simulate human-like interactions with customers. Within banking, this technology manifests through virtual assistants, voice bots, and chatbots capable of handling a wide array of service requests – from account inquiries and loan applications to fraud detection and financial advice [3]. Prior research in financial AI focuses on automated customer support, payment categorization and execution, risk analysis, and conversation interfaces. Existing solutions remain limited in several critical aspects, including user-friendly navigation, seamless integration with real banking workflows such as payments, account inquiries, and limit management, as well as deep personalization based on spending patterns, financial goals, and user product usage. Current approaches often lack sufficient explainability regarding why a specific product or decision is recommended and do not fully address the requirements for GDPR-compliant model training in regulated financial environments.

This work builds upon state-of-the-art approaches in FinTech AI and extends them with explainability, security models, and federated training, aligning with regulatory requirements and real-world deployment constraints.

System Overview

The intelligent assistant consists of several core components:

1. NLP Chatbot: Handles natural language input, intent detection, context tracking, voice commands, and user queries.
2. Payment execution module: Allows the assistant to initiate transfers, schedule payments, adjust card limits, automate routine payments (e.g., bills). All operations require strong customer authentication.
3. Smart invoice recognition: Uses OCR + ML to extract invoice amounts, IBANs, beneficiary accounts, payment description.
4. Fraud Interaction System: Alerts users of suspicious transactions and allows contextual explanation and confirmation.
5. Recommendation Engine: Suggests products based on user behavior, historical transactions, and spending patterns.
6. Explainable AI (XAI): Uses SHAP and LIME to explain why a recommendation or decision is generated.
7. Federated Learning for GDPR: Allows AI models to be trained on distributed banking servers without transferring raw user data.

System Architecture

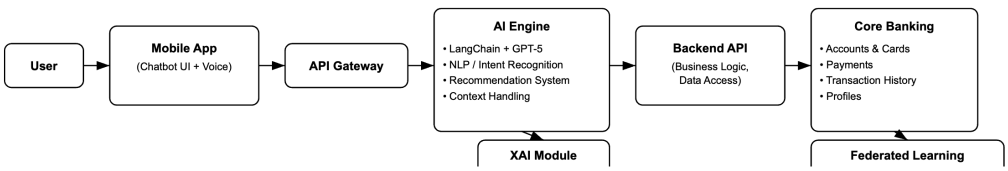

Figure 1. Architecture Diagram

AI Engine and Components

1. Natural Language Processing: Natural Language Processing (NLP) and Natural Language Understanding (NLU) are foundational components of conversational AI systems, enabling machines to interpret and process human language. NLP focuses on the syntactic analysis of language – tokenizing, tagging, and parsing input text – while NLU delves into the semantic layers to extract meaning, context, and user intent [4]. In banking, these technologies allow chatbots and virtual assistants to handle inquiries such as "What's my current balance?" or "Transfer $500 to my saving account." with high accuracy [3].

2. Voice interaction: Speech recognition and text-to-speech (TTS) systems from the voice interface layer of Conversational AI, enabling spoken communication between users and banking platforms. [5]. This component converts spoken commands into text through speech-to-text processing, extract users' intent from voice input using NL understanding pipeline and supports voice-based confirmation flows for sensitive operations such as payments. Optionally, voice biometric verification may be integrated as an additional security layer, providing stronger authentication while preserving usability and compliance with privacy requirements.

3. Recommendation Engine: The ultimate goal of behavioral analytics integrations is to map user behaviors to financial product affinity – understanding not just what users are doing, but which products they are most likely to benefit from or convert on. The mapping relies on both historical correlations and predictive associations between behavior and product interactions [6]. To achieve high personalization accuracy, the system employs a hybrid filtering approach that combines content-based analysis of a user's own transaction history with collaborative filtering techniques that compares behavioral patterns across similar customer profiles. The outputs of these models are then integrated through a score-fusion mechanism to generate a final, optimized recommendation.

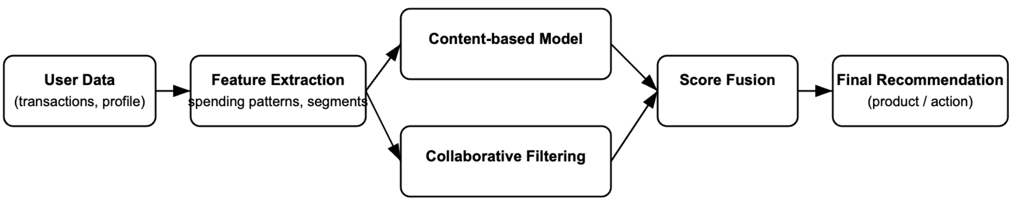

Figure 2. Recommendation Workflow

4. Explainable AI Module: Explainable Artificial Intelligence (XAI) is a key component of the proposed intelligent financial assistant, ensuring transparency, trust and regulatory compliance in automated decision-making. XAI refers to

the development of AI models and frameworks that make decision-making process interpretable to humans. The goal of XAI is not only to improve model transparency but also to enhance user understanding, confidence, and accountability [7]. The system integrates two complementary explainability techniques, SHAP and LIME, to provide transparent and human-understandable insights in AI-driven decisions. SHAP is used to explain the contribution of individual features to a model's output, enabling the system to justify recommendations by highlighting the most influential behavioral factors, such as frequent spending suggesting the suitability of a debit card with lower foreign exchange fees. In parallel, LIME is applied to simulate model behavior around a single prediction, producing localized, human-readable explanations that clarify why a specific recommendation or action is generated in each user context.

Security, Privacy and Federated Learning

Federated learning is a framework that enables multiple parties to collaboratively train AI models, while each party retains control of its own data, no sharing with others. As such, it resolves some of the legal and technical challenges with basic multiparty computation. Federated learning relies on edge computing, a distributed computing model in which processing of raw data take place on local devices, close to or where it was generated. Only results from local analysis using edge computing are sent to external data centers to collaboratively train a global AI model [8]. This enables AI personalization while fully complying with GDPR, EBA guidelines, and internal bank policies.

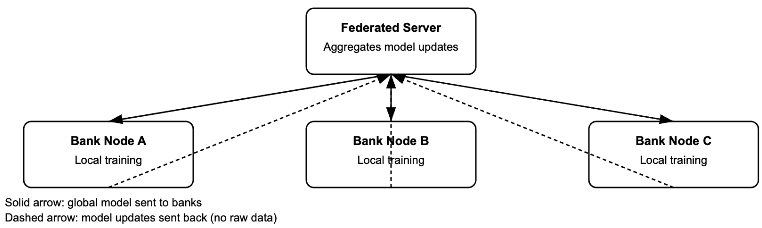

Figure 3. Federated Learning Setup

Conclusion

This paper presents a comprehensive solution for an AI-powered intelligent financial assistant capable of enhancing mobile banking through natural language interaction, personalized recommendations, explainable decision-making, and privacy-preserving learning. The proposed architecture demonstrates feasibility for deployment in real banking systems while maintaining security and regulatory compliance. This approach positions conversational AI as a key element of next-generation digital banking.

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References

[1] G. Arnone, *AI and Chatbots in Fintech*, Springer, 2023

[2] S. Guruvayur, Cognitive Banking Architecture-Human Centric AI framework for automated Customer Engagement in Banking

[3] C. Ikeh, Conversational AI in Banking Services: Enhancing Customer Engagement through Adaptive Dialogue Systems and Natural Language Understanding, *International Journal of Advance Research Publication and Reviews*, 2025, Vol. 2, Number 4, pp. 355–376, `https://doi.org/10.5281/zenodo.15386047`

[4] C. Abiagom, T. Ijomah, Enhancing customer experience through AI-driven language processing in service interactions, *Open Access Research Journal of Engineering and Technology*, 2024 Jan.

[5] O. Emi-Johnson, K. Nkrumah, A. Folasole, T. Kolade Amusa, Optimizing Machine Learning for Imbalanced Classification: Application in U.S. Healthcare, Finance, and Security, *International Journal of Engineering Technology Research & Management (IJETRM)*, 2023, 07 (11), `https://doi.org/10.5281/zenodo.15188490`

[6] Adegbola Ogedengbe, Oyetunji Oladimeji, Joshua Oluwagbenga Ajayi, A Hybrid Recommendation Engine for Fintech Platforms: Leveraging Behavioral Analytics for User Engagement and Conversion , 2022 Jan, `https://doi.org/10.54660/IJMER.2022.3.1.23-35`

[7] Jordan Nelson, The Role of Explainable AI (XAI) in Enhancing Transparency and Trust in FinTech Applications, October 2023

[8] M. Kobayashi, Federated Learning, 2025 Aug, pp. 45-66, `https://doi.org/10.1007/978-981-96-9223-1_4`

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