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FINTRACK: Financial Decision Support using Agentic AI

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Abstract - Financial decision-making requires individuals to analyse income, expenses, savings, loans and goals together, yet most personal finance applications only record transactions and display dashboards, leaving interpretation to the user. This paper presents FINTRACK, an Agentic AI-based financial decision support system that interprets natural-language financial queries, decomposes them into sub-tasks, invokes deterministic financial tools and generates personalized, explainable recommendations. The architecture combines a Large Language Model (LLM) planning agent with a tool-calling layer for budget analysis, savings projection, EMI computation, goal-based planning and scenario comparison, followed by a recommendation agent and an explanation layer that exposes the factors and calculations behind each answer. The methodology covers data collection, preprocessing, financial analysis, agent development, recommendation generation, explainability and evaluation, and is implemented with Python, FastAPI, LangChain/LangGraph and a web interface. Evaluation is planned on recommendation accuracy, response quality, usability, consistency and reliability. The system is designed as a decision-support tool and not as a substitute for regulated financial advice, and it supports UN Sustainable Development Goal 8 by improving financial literacy and savings behaviour.

Key Words: Agentic AI, Financial Decision Support, Large Language Models, Personal Finance, Explainable AI, Budget Planning.

1. INTRODUCTION

Financial decision-making is an important part of personal and organizational financial management. Individuals must weigh income, expenses, savings, investments, loans and long-term goals, often without the financial knowledge or analytical tools needed to do this effectively. Conventional personal finance applications mainly provide expense tracking, dashboards, calculators and static recommendations, and they leave the interpretation of the results to the user.

Recent progress in Large Language Models (LLMs) and Agentic Artificial Intelligence (Agentic AI) offers a different approach. An AI agent can plan a task, select and call suitable tools, analyse the information returned and produce an actionable output [2], [4]. Applied to personal finance, this makes it possible to build a system that reasons over a user's complete financial situation instead of showing isolated statistics.

This paper presents **FINTRACK**, an Agentic AI-based Financial Decision Support System. The main contributions of the work are: (i) an agentic architecture in which a planning agent decomposes a financial query and coordinates specialized agents and tools; (ii) a tool-calling layer that delegates numerical computation (budgets, savings projections, EMI, goal planning) to deterministic financial functions rather than to free-form LLM arithmetic; (iii) an explanation layer that presents the factors and calculations behind every recommendation; and (iv) an evaluation plan covering accuracy, response quality, usability, consistency and reliability.

1.1 Problem Statement

Many individuals lack the financial knowledge and analytical tools required to make effective financial decisions. Existing applications often provide basic expense tracking and visualization but do not reason about a user's complete financial situation. There is therefore a need for an AI-powered system that can analyse financial data, understand user-specific goals and constraints, evaluate different options and provide personalized, explainable recommendations through an autonomous agent-based approach.

1.2 Scope

The system initially targets personal financial decision support: personal budgeting, expense optimization, savings planning, emergency fund planning, goal-based planning, loan/EMI comparison, investment scenario analysis, financial education and cash-flow forecasting. FINTRACK is a decision-support tool and not a replacement for a professional financial advisor; it must clearly distinguish decision support from regulated financial advice, particularly for investment-related recommendations. Extension to small businesses and other planning scenarios is left for future versions.

2. LITERATURE REVIEW

Research on LLMs in finance has grown quickly. Lee et al. [1] survey the use of LLMs in finance (FinLLMs), providing an overview of models, tasks and open challenges. Kim et al. [3] study how LLMs can support the analysis of corporate financial statements, showing that language models can contribute to financial analysis beyond text summarization.

A second group of studies focuses on agents. FinCon [2] proposes a synthesized LLM multi-agent system with conceptual verbal reinforcement for financial decision making. Saha et al. [4] discuss LLM agents for investment management, covering tool usage, planning and collaboration, together with benchmarks and research frontiers. Gen-Plan [5] addresses generalized planning in a finance agent, helping an agent divide complex tasks into smaller steps. Structured

agentic workflows with reflective feedback have also been applied to financial time-series modelling [6]. Finally, Gupta and Kumar [7] examine the role of AI in financial planning and financial literacy.

Table -1 summarizes these works and their relation to the present study. Most of them concentrate on investment management, trading, corporate financial analysis or time-series modelling; only a few address the everyday personal-finance questions (how much to save, whether a purchase is affordable, how to reduce expenses) that FINTRACK targets.

Table -1: Related work and gap with respect to this study

Ref.	Focus	Gap relative to FINTRACK
[1]	Survey of LLMs in finance	Survey; no personal decision-support system
[2]	LLM multi-agent decision making	Investment-oriented; not everyday budgeting
[3]	LLM financial statement analysis	Corporate statements, not personal finances
[4]	LLM agents for investment management	Investment focus over personal budgeting
[5]	Generalized planning in a finance agent	Task planning, not a complete personal finance solution
[6]	Agentic workflows for time-series modelling	Time-series focus; no budgeting or goals
[7]	AI in financial planning and literacy	Conceptual treatment of planning and literacy

2.1 Research Gap and Novelty

The novelty of FINTRACK lies in integrating Agentic AI with personal financial decision support. Unlike conventional applications that mainly track expenses or display statistics, the proposed system can understand financial queries in natural language, break complex problems into multiple tasks, select appropriate analytical tools automatically, combine information from different financial modules, compare multiple scenarios, provide personalized and explainable recommendations, and adapt recommendations as the user's data and goals change. The focus is therefore AI-assisted financial decision-making rather than simple financial tracking.

3. AIM AND OBJECTIVES

Aim: To develop an Agentic AI-based Financial Decision Support System that analyses a user's financial data and goals to provide personalized, explainable and actionable financial recommendations. The objectives are:

(1) to collect and organize user financial information such as income, expenses, savings, loans and goals; (2) to analyse spending patterns and identify unnecessary or excessive expenses; (3) to create personalized budgets and savings plans; (4) to use Agentic AI for multi-step financial analysis and decision support; (5) to compare financial alternatives against user-defined goals and constraints; (6) to provide explainable recommendations together with the reasoning behind them; and (7) to let users interact with the system in natural language.

4. PROPOSED METHODOLOGY

The user supplies financial information and a goal, for example "How much should I save every month?", "Can I afford to buy a new laptop?", "How can I reduce my monthly expenses?", "How long will it take me to reach my savings goal?" or "Which option is better for my current budget?". The agent interprets the request, determines the steps needed, retrieves the relevant data, performs calculations, evaluates alternatives and generates a personalized response. The work follows seven stages.

Step 1 – Data collection. User-provided financial information (income, expenses, savings, liabilities, goals and risk preferences) is collected and, where appropriate, supplemented with sample or publicly available financial datasets.

Step 2 – Data preprocessing. Financial transactions and user information are cleaned, categorized, normalized and structured.

Step 3 – Financial analysis. Financial indicators are computed and spending, saving and cash-flow patterns are identified.

Step 4 – Agent development. An agentic workflow is developed that understands user requests, plans tasks, calls tools and combines the results.

Step 5 – Recommendation generation. Personalized recommendations are generated from the analysis and the user's objectives.

Step 6 – Explainability. The factors and calculations used to reach each recommendation are presented to the user.

Step 7 – Testing and evaluation. The system is evaluated for recommendation accuracy, response quality, usability, consistency and reliability.

5. SYSTEM ARCHITECTURE

5.1 Basic Workflow

The basic workflow of FINTRACK is shown in Fig. 1. User input and financial data reach the AI agent, which performs planning and reasoning, calls financial tools and models, carries out decision analysis and returns a personalized recommendation with its explanation.



Fig -1: Basic workflow of the proposed system

5.2 Agentic AI Architecture

The agentic core contains specialized components (Fig. 2, Table -2), which allows the system to perform multi-step tasks instead of answering a single prompt.



Fig -2: Agentic AI architecture of FINTRACK

Table -2: Agentic AI architecture components

Component	Role
User Interaction Agent	Understands the user's natural-language request.
Planning Agent	Breaks a complex financial query into smaller tasks.
Financial Analysis Agent	Analyses income, expenses, savings, liabilities and goals.
Tool-Calling Layer	Uses calculators, databases, financial datasets and analytical models when required.
Decision / Recommendation Agent	Evaluates possible alternatives and generates a suitable recommendation.
Explanation Layer	Explains the recommendation in simple language.

5.3 Software Modules

The application is organized into eight modules (Table -3). The Agentic AI Module acts as the central intelligence: it interprets the request, plans actions, selects tools, performs multi-step reasoning and produces the final recommendation.

Table -3: Major software modules

Module	Function
User Profile and Financial Data	Stores income, expenses, savings, liabilities, goals and risk preferences.
Expense and Budget Analysis	Categorizes transactions, finds spending patterns, compares actual spending with the planned budget.
Financial Goal	Lets users define goals such as emergency fund, education, travel, vehicle or long-term savings.
Agentic AI	Interprets requests, plans actions, selects tools, reasons over multiple steps.
Financial Analysis	Budget analysis, savings projections, expense ratios, EMI, goal-based savings, investment scenario comparison, cash-flow analysis.
Recommendation	Generates personalized recommendations from profile, objectives, constraints and analysed data.
Explainability	Explains recommendations, including the important factors considered.
Conversational Interface	Natural-language interaction instead of complex dashboards.

6. IMPLEMENTATION DETAILS

6.1 Technology Stack and Platform

FINTRACK is implemented in Python with a FastAPI backend, an LLM API (a Gemini or OpenAI-compatible model) accessed through an agent framework such as LangChain/LangGraph, a relational or document database, and a React/Next.js or Streamlit frontend (Table -4). Development is carried out on a laptop with an Intel i5/AMD Ryzen 5 or equivalent processor, 8 GB RAM minimum (16 GB recommended), a 256 GB SSD or larger and an internet connection; a dedicated GPU is optional when cloud-based LLM APIs are used.

Table -4: Software tools and technologies

Category	Tools
Programming language	Python
AI / ML	Scikit-learn; PyTorch/TensorFlow as required
Generative AI	LLM API such as Gemini / OpenAI-compatible model
Agent framework	LangChain / LangGraph or equivalent
Backend	FastAPI
Frontend	React/Next.js or Streamlit
Database	PostgreSQL/MySQL or MongoDB
Data processing	Pandas, NumPy
Visualization	Matplotlib / Plotly
Development	VS Code, Git, GitHub
Deployment	Docker and cloud platform as required

6.2 Financial Computation Tools

The tool-calling layer exposes deterministic functions so that numerical results do not depend on LLM arithmetic. Representative computations are given below. The savings rate and expense ratio describe the user's current position:

$$\text{Savings rate} = (\text{Income} - \text{Expenses}) / \text{Income} \quad (1)$$

$$\text{Expense ratio}_c = \text{Expense}_c / \text{Income} \quad (2)$$

where c denotes an expense category. For loan comparison, the equated monthly instalment (EMI) for principal P, monthly interest rate r and n monthly payments is

$$\text{EMI} = P \cdot r \cdot (1 + r)^n / [(1 + r)^n - 1] \quad (3)$$

and the monthly saving S needed to reach a target amount T in n months, assuming a monthly rate of return r, is

$$S = T \cdot r / [(1 + r)^n - 1] \quad (4)$$

For r = 0 the saving reduces to S = T / n. An emergency-fund target can be expressed as a number of months of essential expenses multiplied by the monthly essential expense.

6.3 Agent Workflow

For each query the agent executes the following sequence: (1) parse the query and identify the user's intent; (2) load the user profile and relevant data; (3) let the planning agent decompose the query into sub-tasks; (4) call the required financial tools for each sub-task; (5) combine the results and evaluate alternatives against the user's goals and constraints; (6) generate the recommendation; and (7) produce an explanation listing the inputs, formulas and assumptions used.

6.4 Illustrative Computation

To illustrate the tool outputs, consider a loan of INR 500,000 at 10% annual interest for 5 years. Eq. (3) with r = 0.10/12 and n = 60 gives an EMI of about INR 10,624, a total repayment of about INR 637,411 and total interest of about INR 137,411. Similarly, to save INR 80,000 for a laptop in 12

months at an assumed 6% annual return, Eq. (4) gives a monthly saving of about INR 6,485. These are worked examples of the formulas and not experimental results.

7. EVALUATION PLAN AND EXPECTED RESULTS

The system will be evaluated on the five parameters in Table -5. Measured values will be recorded after testing with sample and user-provided financial data.

Table -5: Evaluation parameters and planned measurement

Parameter	Planned measurement	Observed
Recommendation accuracy	Agreement of tool outputs with manually verified calculations	To be recorded
Response quality	Relevance and clarity of responses to test queries	To be recorded
Usability	User feedback on the conversational interface	To be recorded
Consistency	Stability of recommendations for repeated identical inputs	To be recorded
Reliability	Handling of incomplete or unusual inputs and API failures	To be recorded

The proposed system is expected to provide personalized financial insights; help users understand their spending patterns; generate practical budgeting and saving recommendations; support goal-based planning; compare financial scenarios and alternatives; reduce the effort required for manual financial analysis; and provide explainable recommendations through a conversational interface.

8. ETHICS, SAFETY, LIMITATIONS AND SDG ALIGNMENT

Ethics and safety. Personal financial information must remain private and confidential and be protected by secure storage and authentication. Data should be collected and processed only with the user's permission. The system should explain how its recommendations are produced, and AI-generated suggestions should be checked to reduce incorrect or misleading information.

Limitations. The system depends on accurate user-provided data; AI features may require an internet connection and external AI APIs, which can introduce cost, request limits and performance dependence; AI-generated recommendations may not always be accurate; and the current scope is mainly expense tracking, budgeting, savings and goal planning.

SDG alignment. FINTRACK mainly supports UN Sustainable Development Goal 8 (Decent Work and Economic Growth) by helping individuals understand their financial situation, manage expenses, plan budgets and improve savings habits. Its digital records also reduce paper-based financial documentation.

9. CONCLUSIONS AND FUTURE SCOPE

This paper presented FINTRACK, an intelligent system that combines financial analytics, generative AI and autonomous agent-based workflows to help users make informed financial decisions. Instead of merely displaying financial data, the system understands user goals, analyses relevant information, performs multi-step reasoning, compares alternatives and provides personalized, explainable recommendations, while keeping numerical computation in deterministic tools.

Future work includes integration with bank APIs and digital wallets, real-time transaction analysis, advanced predictive financial models, multi-agent financial planning, voice-based interaction, real-time market information where legally and technically appropriate, personalized risk profiling, automated financial reports, reinforcement learning for planning strategies, tax- and retirement-planning modules, a mobile application, and extension to small businesses.

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