Agentic and Generative AI Framework for Augmented Financial Advisory and Portfolio Intelligence

DISSERTATION

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By

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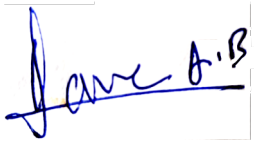

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Abstract

In an increasingly complex and data-intensive investment environment, financial advisors are expected to deliver tailored, real-time, and goal-aligned recommendations to diverse client segments. Advisors must synthesize structured portfolio metrics and market data with unstructured content such as research reports, regulatory updates, product documents, and even client communications—while maintaining compliance, transparency, and personalized engagement. Traditional manual workflows are insufficient to meet these demands at scale. This research proposes a unified **Agentic AI framework**, powered by **Generative AI**, **Multimodal Intelligence**, and **Conversational Agents**, to augment the end-to-end investment advisory lifecycle—from client profiling to portfolio recommendation, ongoing analysis, and education.

At the core of the proposed solution is an **Agentic AI architecture**, where a set of collaboratives, autonomous agents emulate human-like expertise by orchestrating domain-specific tasks within the advisory workflow. Each agent is endowed with task-specialized reasoning capabilities and access to multimodal data. This approach enables the system to be flexible, modular, and adaptive to the evolving needs of both clients and advisors.

Agentic AI Framework for Advisor Workflows

This research introduces a multi-agent system wherein each agent autonomously handles a dedicated function in the advisory chain:

- **Client Profiling Agent** ingests historical transactions, risk tolerance indicators, life milestones, and personal preferences to build a deep client persona.
- **Portfolio Analysis Agent** interprets structured data (e.g., performance metrics, asset allocations) and unstructured insights (e.g., analyst reports, product documentation).
- **Compliance & Suitability Agent** ensures recommendations adhere to evolving regulatory standards and align with client goals and risk profiles.
- **Recommendation Agent** synthesizes investment advice by integrating domain knowledge and contextual triggers, generating explainable outputs.

These agents leverage **Multimodal AI techniques** to jointly reason over text, tabular data, time-series metrics, and external content. By integrating structured databases with unstructured documents (such as product brochures, market commentary, or corporate actions), each agent achieves a more comprehensive situational awareness. This multimodal approach improves both accuracy and interpretability.

Knowledge Graph + Generative AI for Wealth Advisory

The system constructs a domain-specific Financial Knowledge Graph to model relationships among financial instruments, client attributes, and investment strategies. This

serves as a reasoning backbone, enabling agents to generate context-aware, coherent insights.
By combining this graph with Generative AI, the Recommendation Agent delivers personalized, transparent investment strategies. Graph-based inference paths are preserved for auditability and advisor trust.

Conversational AI Layer for Client-Adviser Interaction

A RAG-based Conversational AI interface enables seamless advisor-client interaction by retrieving relevant documents to ground responses.
Key capabilities include:

- **Portfolio Intelligence Chatbot** for explaining portfolio performance and decisions.
- **Client Sentiment and Goal Modeling** using LLMs to enrich profiling with emotional and preference cues.
- **GenAI Tutor** that adapts investment education to the client's financial literacy level. This layer supports engagement and feeds enriched data back into the Agentic system to enhance decision support.

This thesis explores the design of a future-state Agentic AI architecture to assist Wealth Advisors by:

- Enhancing contextual relevance in investment recommendations
- Streamlining advisor workflows through agent-driven automation
- Improving client engagement via personalized conversational agents

By integrating multimodal analysis, explainable reasoning, and conversational delivery, the research presents a transformative approach to financial advisory automation. It aims to augment human advisors with scalable, intelligent support while making investment guidance more accessible and responsive.

The scope of work is comprehensive, focusing on the conceptualization and development of an Agentic AI platform tailored for Advisor Assist in Portfolio Analysis. While the full-scale realization of such a system involves significant engineering effort, this research will aim to deliver a well-defined future-state architecture, along with a demonstrable prototype featuring a cohesive set of intelligent agents. These agents will collectively illustrate the envisioned capabilities of the platform offering a clear view of the potential impact and applicability of Agentic AI in wealth advisory.

List of Symbols & Abbreviations used

Symbol/Abbreviation	Definition/Description
M. Tech	Master of Technology
AI	Artificial Intelligence
ML	Machine Learning
BITS	Birla Institute of Technology and Science
PGCBM	Post Graduate Certificate in Business Management
GenAI	Generative AI
RAG	Retrieval-Augmented Generation
LLM	Large Language Model
C&I	Commercial and Industrial (loans)
CRE	Commercial Real Estate (loans)
KYC	Know Your Customer
CRM	Customer Relationship Management
NLP	Natural Language Processing
LDA	Latent Dirichlet Allocation (Topic Modeling)
BERT	Bidirectional Encoder Representations from Transformers
CVaR	Conditional Value-at-Risk
ARIMA	AutoRegressive Integrated Moving Average
LSTM	Long Short-Term Memory
ETL	Extract, Transform, Load
FUSE	(Product for automated payment reconciliation)
UI	User Interface
NER	Named Entity Recognition
OCR	Optical Character Recognition
PAN	Permanent Account Number (Indian tax ID)
FATCA	Foreign Account Tax Compliance Act
SEBI	Securities and Exchange Board of India
SIP	Systematic Investment Plan
NAV	Net Asset Value
REIT	Real Estate Investment Trust
PMI	Private Mortgage Insurance
FHFA	Federal Housing Finance Agency
ARM	Adjustable-Rate Mortgage
HELOC	Home Equity Line of Credit
MSP	Mortgage Servicing Platform
AI/ML	Artificial Intelligence / Machine Learning
RPA	Robotic Process Automation

Symbol/Abbreviation	Definition/Description
C&I	Commercial and Industrial
CRE	Commercial Real Estate
CVM	Customer Value Management
CDFI	Community Development Financial Institution

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Chapter 1 - Objectives

"Agentic AI Framework for Augmented Financial Advisory Using Generative and Multimodal Intelligence"

1. Purpose

To design a multi-agent AI framework that leverages Generative AI, Knowledge Graphs, and Conversational AI to augment human financial advisors in client profiling, portfolio analysis, investment recommendations, and personalized advisory communications.

The objectives of this dissertation project are:

1. To **design an Agentic AI framework** where each agent simulates a core advisory task such as client profiling, portfolio evaluation, investment recommendation, and compliance assessment.
2. To design a **multimodal data pipeline** that ingests structured and unstructured financial data (portfolio data, market news, product documents, etc.).
3. To design **Knowledge Graphs** for integrating client, product, and regulatory knowledge in a unified, queryable format that supports explainable recommendations.
4. To integrate **Generative AI and LLM-based tools** for:
    - Financial content generation
    - Personalized recommendation explanation
    - Client literacy education (via a GenAI Tutor)
5. To design a **Conversational AI layer** using Retrieval-Augmented Generation (RAG), for real-time portfolio queries, goal alignment, and client sentiment interpretation.[2]

2. Expected Outcome

- Design of a task-specific Agentic AI architecture that automates key advisor functions
- Demonstrate of improved portfolio insight generation, compliance checking, and client engagement
- Evaluation of productivity gains, accuracy improvements, and user satisfaction enhancements – On Best effort Basis

3. Literature Review:

[2] Since the scope of the project is extensive, will attempt to achieve step E on Best Effort Basis

The following are referred journals from the preliminary literature review.

Flow: Modularized Agentic Workflow Automation

- **Authors**: Boye Niu et al.
- **Published**: January 2025
- **Summary**: This research focuses on modularizing agentic workflows to allow dynamic adjustments during execution. It addresses the need for real-time adaptability in complex task environments, crucial for financial advisory services.
- https://arxiv.org/abs/2501.07834

Benchmarking Agentic Workflow Generation

- **Authors**: Shuofei Qiao et al.
- **Published**: October 2024
- **Summary**: The paper introduces a benchmarking framework for evaluating agentic workflow generation, emphasizing the decomposition of complex problems into executable workflows, which is vital for assessing AI performance in financial tasks.
- https://arxiv.org/abs/2410.07869

Are Generative AI Agents Effective Personalized Financial Advisors?

- **Authors**: Takehiro Takayanagi, Kiyoshi Izumi, Javier Sanz-Cruzado, Richard McCreadie, Iadh Ounis
- **Published**: April 2025
- **Summary**: This study evaluates the effectiveness of large language model (LLM)-based agents in providing personalized financial advice. Through a user study with 64 participants, the research examines challenges in eliciting user preferences, delivering tailored investment guidance, and the impact of agent personality on trust and satisfaction. Findings indicate that while LLM-advisors can match human performance in certain areas, they may struggle with conflicting user needs and that users often prefer agents with extroverted personas, even if the advice quality is lower.
- https://arxiv.org/abs/2504.05862

Agentic AI Use Cases Across Financial Services

- **Publisher**: Citigroup
- **Published**: January 2025
- **Summary**: Citigroup's report highlights key use cases of agentic AI in financial services, including compliance, fraud prevention, onboarding, KYC, wealth management, credit, and treasury workflows.
- https://www.citigroup.com/global/insights/agentic-ai

4. Existing Process

Currently, financial advisors manually aggregate and interpret data from disparate sources such as portfolio management systems, regulatory documents, product brochures, market news, and CRM notes. Client communications are often generic or templated. Complex investment decisions depend heavily on individual expertise, which limits scalability and consistency.

5. Limitations

- High manual effort in profiling, recommendation, and analysis
- Inconsistent and delayed insights due to fragmented data sources
- Lack of personalization in client communication
- Difficulty in ensuring compliance and traceability across decisions
- Clients often struggle to grasp financial concepts due to limited financial literacy support

6. Justification for Methodology

The chosen methodology centers around an Agentic AI system, where independent agents, each handling a specific task (profiling, compliance, recommendation, etc.), simulate the reasoning process of a skilled advisor. This allows for modularity, scalability, and task specialization. The integration of Generative AI enables fluent and personalized content generation, while Knowledge Graphs ensure explainability and contextual coherence. A Conversational AI layer enhances client-advisor interaction through natural language and sentiment-aware interfaces. This hybrid design is well-suited to solve the multifaceted nature of investment advisory workflows.

7. Project Work Methodology

Where an End-to-End development of the entire platform will involve the following six phases:

1. **Requirement Analysis & Use Case Design** : Identify advisory tasks, user roles, data sources, and define agent responsibilities.
2. **Data Architecture & Knowledge Graph Construction**: Integrate structured (portfolio, CRM) and unstructured (news, PDFs) data sources and build a financial knowledge graph.
3. **Agent Development (Agentic AI Layer)**: Implement and test the functionality of individual agents: profiling, analysis, compliance, and recommendation.
4. **Generative AI Integration**: Use LLMs to enhance decision support, natural language generation for explanations, and create the GenAI Tutor for client education.
5. **Conversational AI Interface**: Build a multimodal, RAG-powered conversational agent layer for both advisors and clients, incorporating sentiment detection and goal modeling.

6. **System Integration, Evaluation & Validation**: Validate the system through performance metrics (accuracy, latency, satisfaction), case studies, and advisor feedback.

However, we will keep the scope of this engagement to the following specific actions based on the timelines available for execution

1. **Requirement Analysis & Use Case Design**: Identify advisory tasks, user roles, data sources, and define agent responsibilities.
2. **Data Architecture & Knowledge Graph Design**:
    1. Formulate and design the data architecture to Integrate structured (portfolio, CRM) and unstructured (news, PDFs) data sources
    2. Design of a financial knowledge graph.
3. **Agentic AI Architecture**: Architect and Design an Agentic AI System which can help develop the End-to-End platform for Financial Advisory platform functionality of individual agents providing profiling, analysis, compliance, and recommendation
4. **Agent Development (Agentic AI Layer):** Develop one or two of the agents among the Client Profiling, Portfolio Analysis, and Recommendation Agents; Interface with stubbed/dummy product processors for generating analysis
5. ***Design of Conversational AI Interface:*** *Design a multimodal, RAG-powered conversational agent layer for both advisors and clients, incorporating sentiment detection and goal modeling*[3]

8. Benefits Derivable from the Work

- **Efficiency Gains**: Automates time-consuming advisory tasks with human-like accuracy
- **Scalability**: Enables advisors to support more clients with greater consistency
- **Personalization**: Delivers tailored communication and recommendations aligned to client profiles and goals
- **Compliance & Transparency**: Supports explainable AI decisions with traceable logic paths through the knowledge graph
- **Client Empowerment**: Educates clients with AI-generated, understandable content through GenAI tutoring
- **Innovation**: Paves the way for an intelligent hybrid advisory model that blends human expertise with autonomous AI agents

9. Scope of Work

[3] * Since the scope of the project is extensive, will attempt to achieve step 5 on Best Effort Basis

The research will comprehensively cover the **design, a prototype development** of an AI-augmented advisory platform. The scope includes:

A. Data Aggregation and Modeling

- Identification of relevant structured data (portfolio, transactions, risk scores, CRM data).
- Designing a multimodal ingestion pipeline using ETL tools.

B. Knowledge Graph and Semantic Layer

- Entity and relationship extraction (clients, assets, risks, goals, regulations).
- Design of a financial knowledge graph with Integration of vector search for similarity-based recommendations.

C. Agentic AI System Design

- Define functional boundaries and capabilities for each agent:
    - Client Profiling Agent
    - Portfolio Analysis Agent
    - Compliance Agent
    - Recommendation Agent
- Develop 1 or 2 agent types among the 4 agent types
- Implement inter-agent communication and orchestration logic.

D. Generative AI Integration

- Use LLMs (like GPT-4, LLaMA 2) for:
    - Narrative generation of insights
    - Explaining complex investment ideas
    - On-demand learning content via GenAI Tutor

E. Conversational Interface Development[4]

- Design a RAG-based Chatbot for Advisors and Clients which can Train on advisor FAQs, market content, client queries.
- Provide hooks for Integrating LLMs for Client Sentiment and Goal Modeling.

10. Detailed Plan of Work (16 Weeks)

Sl #	Phase	Duration	Key Activities	Week
1	**Requirement Analysis &**	2 weeks	Identify advisor workflow tasks; Study related AI models; Review past research	1-2

[4] '* Since the scope of the project is extensive, will attempt to achieve step E on Best Effort Basis

Sl #	Phase	Duration	Key Activities	Week
	Literature Review		and frameworks from Google Scholar, arXiv, and industry reports	
2	**Data Collection & Knowledge Graph Design**	2 weeks	Gather structured (portfolio/CRM) & unstructured data; define entities and relationships; design financial knowledge graph schema	3-4
3	**Agentic AI Platform Architecture & Design**	2 weeks	Define task-specific agents and their responsibilities; map agent interaction flow; Provide design and Architecture of an Agentic AI platform for Advisor Assist Platform	5-6
4	**Design: Data Pipeline + Graph Engine**	2 weeks	Define and design multimodal ETL pipeline; The initial knowledge graph using Neo4j; Connect data sources	7-8
5	**Develop Agent Functions**	4 weeks	• Implement at least one of the agents among the Client Profiling, Portfolio Analysis, and Recommendation Agents; Interface with stubbed/dummy product processors for generating analysis • Integrate with LLM's: Use prompt-engineering to finetune and structure responses to the end-users • Test with sample data	9-13
5*	***Finetune LLM responses***	1 week	Fine-tune LLMs; Build modules for recommendation narration and financial education	14*
6*	***Conversational AI Interface***	1 weeks	Design of chatbot using RAG approach to query agents and knowledge graph; Add sentiment and goal modeling layer	15*
7	**Documentation & Final Presentation**	1 week	Compile research report, results, and architecture documentation; Prepare thesis submission and presentation decks	16

Table 1: Detailed Plan of Work

' Since the scope of the project is extensive, I will try to achieve these tasks on Best Effort Basis*

11. Scope Covered in Mid Sem

As part of my mid sem submission I will discuss around four critical phases of my targeted work, each designed to methodically address the core components of developing an Agentic AI platform for advisor assistance. The work is effort of eight weeks and a summary of the work is as provided below

Phase 1: Requirement Analysis & Literature Review

The initial phase focuses on laying a strong foundation through rigorous requirement gathering and an in-depth literature review. This involves:

- **Identifying Advisor Workflow Tasks:** Understanding the typical workflows and pain points faced by financial advisors to clearly define the functional requirements for the AI platform.
- **Studying Related AI Models:** Analyzing state-of-the-art AI frameworks and models relevant to advisor assistance, such as natural language processing (NLP), knowledge graphs, and agent-based systems.
- **Reviewing Past Research and Frameworks:** Conducting a comprehensive review of existing academic literature and industry reports sourced from reputable platforms like Google Scholar, arXiv, and various financial technology industry publications to identify gaps and best practices.

Phase 2: Data Collection & Knowledge Graph Design

Building on the requirements, the second phase concentrates on gathering and organizing the data crucial for powering the AI platform:

- **Gathering Structured and Unstructured Data:** Collecting relevant data from portfolio management systems, customer relationship management (CRM) tools, and other sources, including textual and numerical data.
- **Defining Entities and Relationships:** Identifying key financial entities such as clients, assets, transactions, and advisors, and modeling the interrelationships that reflect real-world financial contexts.
- **Designing Financial Knowledge Graph Schema:** Developing a schema for a financial knowledge graph that encapsulates the complex relationships and attributes inherent in advisor workflows, enabling semantic data integration and intelligent reasoning.

This phase is fundamental to creating a robust data foundation that the AI agents will interact with.

Phase 3: Agentic AI Platform Architecture & Design

With data structured, the next phase involves architecting the intelligent agents that will drive the platform:

- **Designing Agentic AI Platform Architecture:** Proposing a comprehensive architecture that supports modular, scalable, and efficient agent operations, ensuring the system can evolve with new requirements and data sources.
- **Defining Task-Specific Agents:** Designing agents tailored to distinct advisor tasks such as client query handling, portfolio recommendations, and compliance checks.
- **Mapping Agent Interaction Flow:** Planning how these agents will communicate, collaborate, and coordinate to deliver seamless assistance.

This phase brings the platform's functional vision to life through detailed agent-centric design.

Chapter 2: Requirement Analysis & Literature Review

Goal: Establish foundational understanding of advisor workflows and related AI systems to generate an agent workflow and architecture design.

1. Identify Advisor Workflow Tasks

Below is a high-level break down the **financial advisor's workflow** into atomic, automatable tasks. Below are typical tasks grouped by stage:

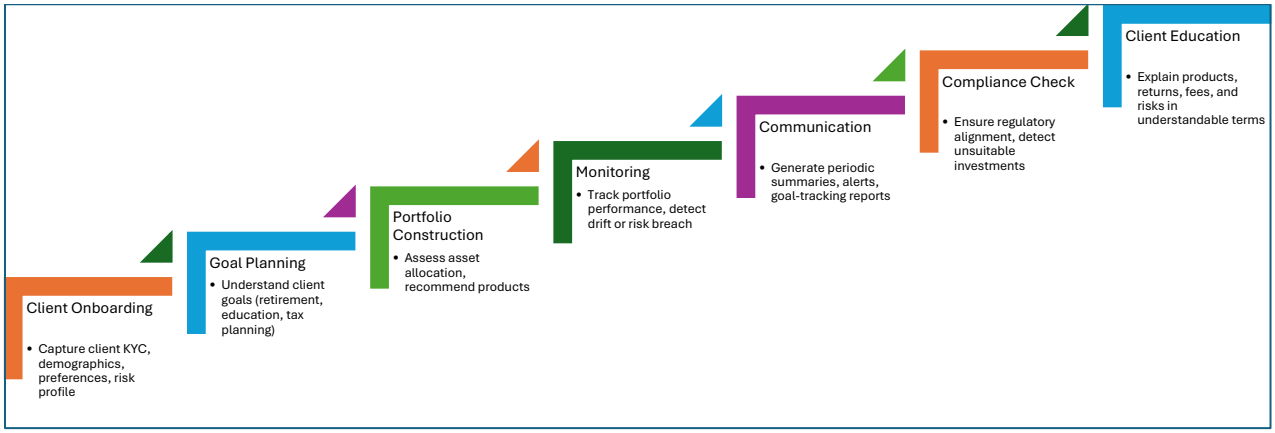

Figure 1: Financial Advisor's Workflow Tasks

The table below outlines the comprehensive set of tasks typically performed by financial advisors across the end-to-end client lifecycle. It categorizes workflows into key stages—ranging from client onboarding to education and support—highlighting specific activities and their functional significance.

Stage	Workflow Task	Details
1. Client Onboarding	Collect Demographic Information	Name, age, occupation, dependents, income, and residency details.
	Perform KYC & Documentation	Identity verification (PAN, Aadhar), address proof, bank details.
	Capture Relationship Preferences	Nominees, joint holders, legal guardians for minors, power of attorney.
	Obtain Consent & Disclosures	Regulatory forms like FATCA, SEBI declarations, client consent.
	Conduct Risk Profiling	Risk tolerance assessment via questionnaires or psychometric tools.
	Capture Investment Preferences	Sector preferences, ESG considerations, liquidity needs, etc.

Stage	Workflow Task	Details
2. Goal Discovery & Planning	Identify Financial Goals	Retirement, home purchase, education, weddings, travel, business capital.
	Determine Time Horizons	Short, medium, and long-term categorization of goals.
	Estimate Goal Capital Requirements	Project required investment based on timelines and inflation-adjusted needs.
	Capture Constraints & Conditions	Tax preferences, lock-in concerns, religious/ethical constraints.
	Document Life Events & Milestones	Marriages, child births, expected inheritances, planned retirements.
	Goal Prioritization	Align investments with most urgent or strategically important goals.
3. Portfolio Construction	Evaluate Existing Portfolio	Assess current assets, liabilities, and net worth.
	Determine Asset Allocation Strategy	Equity vs debt mix, domestic vs international, based on client profile.
	Select Financial Products	Choose suitable MFs, stocks, bonds, insurance, REITs, etc.
	Forecast Return & Risk Scenarios	Use historic and predictive models to demonstrate expected performance.
	Create Investment Plan Document	Outline of investments, rationale, expected returns, fees, and timelines.
	Align Plan with Risk Profile & Goals	Ensure plan stays within the acceptable risk bounds while meeting goals.
4. Execution & Suitability Validation	Place Investment Orders	Execute transactions via internal or external platforms.
	Validate Suitability of Recommendations	Ensure product aligns with risk profile and regulatory mandates.
	Record Rationale for Advice	Justify product choices, risk fit, and how they meet goals.
	Generate Risk Disclosures	Present risks, lock-ins, and scenarios where the product may underperform.
	Verify Regulatory Compliance	Check for restrictions based on geography, product eligibility, investor status.
	Capture Client Approvals & Sign-Offs	Store documentation of acceptance, especially for high-risk decisions.
5. Monitoring & Rebalancing	Track Portfolio Performance	Benchmark against market indices and goal progression.
	Analyze Deviation from Goals	Detect underfunding, underperformance, or delays in reaching milestones.
	Recommend Rebalancing Actions	Suggest fund switches or allocations based on performance or new inputs.

Stage	Workflow Task	Details
	Re-validate Risk Tolerance	Periodically reassess if the risk profile still holds true.
	Monitor External Market Indicators	Incorporate market movements, macroeconomic shifts, or policy changes.
	Update Clients with Trigger-Based Alerts	Notify clients of breaches, opportunities, or external changes.
6. Reporting & Communication	Generate Periodic Client Reports	Monthly/quarterly statements, summaries, and goal progress tracking.
	Create Personalized Dashboards	Interactive dashboards with visuals for advisors and clients.
	Handle Ad-Hoc Queries	Provide rationale behind performance or product performance issues.
	Highlight Product News or Risks	Alert clients to changes in fund ratings, manager exits, or credit downgrades.
	Provide Client Nudges	Suggest top-ups, SIP increases, tax-saving ideas before deadlines.
7. Client Education & Support	Explain Financial Concepts	Help clients understand terms like NAV, SIP, drawdown, compounding.
	Provide Customized Learning Resources	Based on financial literacy and engagement level.
	Support in Crisis Moments	Guide behavior during market crashes or personal financial difficulties.
	Conduct Review Meetings	Revisit portfolio, goals, and life changes periodically.
	Address Behavioral Biases	Detect and correct herd behavior, loss aversion, or panic-selling.

Table 2: Financial Agents Workflow Stages and Tasks

The above breakdown serves as a foundational reference for identifying automation opportunities and defining the responsibilities of AI agents within the proposed Agentic AI-based advisory system.

2. Pain Points in Existing (Manual or Semi-Digital) Systems

Despite the digitization of financial services, most advisory practices still suffer from fragmentation, inefficiency, and limited personalization. Below are key pain points experienced by advisors in the real world:

a) **Data Fragmentation and Access Delays:**
Client data is scattered across CRM systems, spreadsheets, transactional databases, emails, and scanned documents. Advisors must spend significant time gathering,

validating, and interpreting information from multiple systems, leading to delayed responses and missed insights.

b) **Limited Automation and Personalization:**
Most tools used today rely on static templates for reporting and communication. There's little ability to personalize advice or proactively detect changes in client life stages, behavior, or market context. Recommendations often lack depth and are not goal-aware or behavior-sensitive.

c) **Manual Compliance Burden:**
Validating every recommendation against dynamic regulatory requirements (e.g., SEBI's suitability framework or FATCA disclosures) is labor-intensive. There's a risk of oversight, and traceability of rationale is often poor, exposing advisors to compliance and audit risks.

d) **Scaling Challenges:**
A typical advisor can handle only a limited number of clients due to the manual nature of research, documentation, and client interactions. As a result, either service quality drops or client acquisition stagnates. Scaling requires automation, not just digitization.

e) **Client Engagement Gaps:**
Communications are often transactional or reactive (e.g., annual reviews, portfolio summaries). There's limited ability to engage clients with meaningful insights, explain risks in simple terms, or educate them based on their understanding level. This impacts client trust and retention.

f) **Behavioral Misalignment:**
Advisors often miss emotional cues that could indicate a client's discomfort with risk or a change in life circumstances. For example, a panicked query during a market crash might be handled with a template response, not a tailored explanation or reassurance.

3. Functional Requirements for the Agentic AI Platform

To effectively augment the financial advisory process, the Agentic AI platform must address each stage of the advisory lifecycle with intelligent automation, personalization, and explainability. The platform must leverage modular, task-specific AI agents orchestrated by a central management layer and supported by an integrated data and knowledge backbone.

i. Client Onboarding

The platform must be able to automate client intake by extracting data from structured CRM systems and unstructured inputs like scanned documents or onboarding forms. This includes identity verification, relationship mapping, and consent tracking. **Optical Character Recognition (OCR)** tools (e.g., Tesseract) and **Named Entity Recognition (NER)** models from **spaCy** or **BERT** should be used for document parsing. A **risk profiling engine** must use rule-based logic or **decision tree classifiers** to assign risk categories. This process should be encapsulated within a **Client Profiling Agent**, which creates a structured and explainable client persona.

ii. Goal Discovery & Planning

The system must enable intelligent goal detection and classification from client inputs—both structured (forms) and unstructured (email, chat). It should use **Topic Modeling (e.g., LDA)** and **Intent Classification (e.g., using fine-tuned BERT)** to extract goals like retirement, education, or home purchase. A **temporal reasoning module** must estimate timelines, inflation-adjusted capital needs, and priority levels. The agent must use **collaborative filtering** to match client goals with common peer trajectories. This capability supports a long-term understanding of client life stages and feeds goal-aware recommendations downstream.

iii. Portfolio Construction

To assist in creating optimal portfolios, the platform must integrate with portfolio data sources and use **modern portfolio theory (Markowitz Optimization)** and **CVaR (Conditional Value-at-Risk)** models for asset allocation. The **Portfolio Analysis Agent** should interpret past returns, volatility, and correlations using **time-series models (ARIMA, LSTM)**. For product selection, the system should query a **Knowledge Graph** representing products, asset classes, and constraints using **Cypher (Neo4j)** \

iv. Execution & Suitability Validation

The system must incorporate a **Compliance & Suitability Agent** to verify if recommendations meet regulatory and internal mandates. This agent must access a regulatory rule base encoded via a **Constraint Satisfaction Engine** (e.g., **Drools**) and validate recommendations against suitability norms. It should record justifications for decisions, storing them in an auditable **explanation trace**. Suitability reasoning must use graph traversal over the knowledge base to confirm that a product aligns with the client's profile, investment objectives, and legal requirements.

v. Monitoring & Rebalancing

The platform must provide real-time monitoring capabilities, tracking deviations in portfolio performance or risk exposure. A **continuous evaluation module** should trigger alerts when predefined thresholds are crossed. Rebalancing suggestions must be generated using **reinforcement learning** (e.g., **Q-Learning** or bandit algorithms) based on evolving market conditions and risk appetite. A **streaming data pipeline** (e.g., **Kafka + Spark Streaming**) should be integrated to ingest live market and portfolio data, enabling proactive, not reactive, interventions.

vi. Reporting & Communication

For engagement and transparency, the platform must support dynamic report generation using **LLMs (like GPT-4 or LLaMA 2)** for natural language summaries and insights. The **Conversational AI layer**, built using **Retrieval-Augmented Generation (RAG)** techniques, must handle both ad-hoc queries and proactive updates. It should query structured reports and unstructured insights, grounding its responses in trusted sources. Visualizations should be integrated via API calls to charting libraries (e.g., Plotly or D3.js), tailored to client preferences and literacy levels.

vii. Client Education & Support

The system must include a **GenAI Tutor** that educates clients in a personalized way, adapting content to their financial literacy and behavioral patterns. This component should use a combination of **text summarization**, **financial analogies**, and **multi-turn conversational flows**. Emotional state detection must be embedded using **sentiment analysis models (e.g., RoBERTa, VADER)**, which inform the tone and depth of explanation. This enables the system to act not just as an assistant, but as a mentor, building long-term client trust.

4. Cross-Cutting Infrastructure Requirements

- A centralized **Orchestration Layer** (e.g., based on **LangChain**, **Ray**, or a microservice DAG framework) to route tasks among agents.
- A **Financial Knowledge Graph** (Neo4j or RDF-based) as a semantic backbone to encode relationships across clients, products, goals, and regulations.
- A **Vector Store** (e.g., **FAISS** or **Pinecone**) to support similarity-based reasoning for client behavior, product matching, and content retrieval.
- An **Audit & Monitoring Layer** for explainability, compliance validation, and user feedback loop integration.

5. Current Agentic AI Frameworks and Tools – Relevance to Advisor Assist Platforms

In recent years, Agentic AI has emerged as a pivotal approach to building autonomous, goal-directed systems that can intelligently perform tasks traditionally handled by humans. Within the context of a Wealth Advisor Assist Platform, such frameworks enable financial workflows to be modularized, delegated, and continuously improved through reasoning, learning, and collaboration between agents.

This section reviews recent academic and industry literature on Agentic AI frameworks and explores their relevance to the design and implementation of AI-powered Advisor Assist platforms. The focus is on how modular agentic workflows, large language models (LLMs),

orchestration engines, and knowledge-based reasoning can be integrated to augment the core functions of human financial advisors.

i. Modularized Agentic Workflows for Dynamic Financial Advisory

Reference: *Flow: Modularized Agentic Workflow Automation*, Boye Niu et al., Jan 2025
arXiv:2501.07834[i]

This paper introduces **Flow**, a framework that emphasizes **modular, composable agent workflows** that adapt in real time. In Flow, agents are not rigidly chained but can adjust their responsibilities based on evolving inputs, making it ideal for domains like financial advisory where client needs, market conditions, and compliance requirements shift frequently.

Application to Advisor Assist Platform:

- The modularity concept aligns directly with designing separate agents for **client profiling**, **portfolio analysis**, **recommendation**, and **compliance checking**.
- For example, if a client's portfolio drops suddenly, the **Portfolio Analysis Agent** can trigger the **Recommendation Agent** dynamically without requiring a linear workflow.
- Flow's architecture also supports **plug-and-play AI tools**—allowing integration of different models per task (e.g., GPT-4 for recommendations, BERT for sentiment analysis).

ii. Evaluating Agentic Workflow Decomposition

Reference: *Benchmarking Agentic Workflow Generation*, Shuofei Qiao et al., Oct 2024
arXiv:2410.07869[ii]

This research presents a benchmark framework to evaluate how well agentic systems decompose complex tasks into subroutines. The emphasis is on task abstraction, agent capability alignment, and orchestration benchmarking.

Application to Advisor Assist Platform:

- In financial advisory, a top-level task like "recommend a retirement plan" can be decomposed into sub-tasks: identify risk profile → fetch current investments → simulate scenarios → assess compliance → recommend products.
- Using this paper's insights, the Advisor Assist platform can benchmark the **effectiveness of agent planning**—e.g., measuring how quickly and accurately agents complete multi-step financial workflows.
- This benchmark approach could inform the orchestrator logic (e.g., LangChain or Ray DAG) and improve routing between agents.

iii. LLM-Based Agents in Personalized Financial Advice

Reference: *Are Generative AI Agents Effective Personalized Financial Advisors?*, Takayanagi et al., April 2025
arXiv:2504.05862[iii]

This study empirically evaluates the use of **LLM-based agents** (like GPT) in financial advisory. It finds that LLMs can provide high-quality personalized advice but face challenges with **user preference conflict** and **emotional alignment**. Interestingly, users often preferred agents with engaging, extroverted personas—even if the advice was slightly less accurate.

Application to Advisor Assist Platform:

- Reinforces the use of **LLMs (GPT-4, LLaMA 2)** in the **Recommendation Agent** for personalized, explainable output.
- Supports the idea of integrating a **GenAI Tutor** that adapts its tone and delivery style based on the client's engagement or sentiment.
- Encourages experimenting with **personality customization** in chat interfaces (e.g., extroverted vs analytical styles) for better adoption and trust.
- Suggests the need for hybrid setups: LLMs for generation, but domain-specific agents or rules for validation and safety.

iv. Real-World Agentic AI Use Cases in Financial Services

Reference: *Agentic AI Use Cases Across Financial Services*, Citigroup Report, Jan 2025
Citigroup Global Insights[iv]

Citigroup's industry report outlines a wide range of Agentic AI applications across banking and wealth domains: fraud detection, onboarding, KYC, compliance, credit evaluation, and more. It emphasizes that **domain-specific agent stacks**, backed by **knowledge graphs** and **LLMs**, are central to operationalizing AI.

Application to Advisor Assist Platform:

- Validates that **multi-agent architectures** are already being explored at scale in global financial institutions.
- Supports integrating AI for compliance monitoring, real-time KYC validation, and risk-adjusted investment advice.
- Advocates for connecting the platform with **enterprise-grade AI services** like **Azure Cognitive Services**, **Google Vertex AI**, or **OpenAI APIs** for production deployment.
- Recommends embedding **traceability** and **explainability** through Knowledge Graph reasoning and LLM explanations—key requirements in regulated environments.

6. AI Tools and Frameworks for Building Advisor Assist Platforms

Based on the above studies, a modern Advisor Assist platform can leverage the following AI tools and platforms:

Component	Recommended Tools/Frameworks
Agent Workflow Orchestration	LangChain, Microsoft AutoGen, Ray Serve, Flow (from Niu et al.)
LLM-based Personalization	OpenAI GPT-4, LLaMA 2, Anthropic Claude
Recommendation Reasoning	Graph Neural Networks (PyG, DGL), BERT, SHAP
Sentiment & Preference Modeling	RoBERTa, VADER, DialogRPT
Compliance and Suitability Logic	Neo4j Knowledge Graph + Constraint Engine (Drools)
Task Decomposition/Planning	TaskWeaver (Open-source), LangGraph
Document Retrieval for RAG	FAISS + LangChain, Haystack, Pinecone
Monitoring and Feedback	MLflow, Evidently AI, Grafana for real-time logging

Table 3: AI Tools and Frameworks for Building Advisor Assist Platforms

The current literature and tools indicate a clear shift toward **multi-agent, modular AI architectures** in financial advisory systems. Modular orchestration (Flow, LangChain), LLM integration (GPT-4, LLaMA 2), and reasoning through Knowledge Graphs are emerging as **core design patterns**. These approaches enable advisory platforms to move beyond static automation toward **dynamic, explainable, and emotionally aware AI-driven advice**—a key capability for high-trust domains like wealth management.

> ***In our program to develop Advisor Assist platform we will be adopting industry grade tools, platform and composable components, however for the dissertation purpose we will use lightweight tools to explain the concept and the approach to be followed***

7. Agents in the Advisor Assist Platform

In an Agentic AI-based Wealth Advisor Assist system, **agents** are autonomous, goal-driven software modules, each responsible for executing a specific subset of the advisory workflow. These agents encapsulate AI models, business logic, and access to relevant data, allowing them to operate independently while also collaborating with other agents as needed. This modular approach ensures scalability, explainability, and adaptability—key requirements in the domain of financial advice.

There will be a multitude of Agents which will comprise of an Advisor assist platform but below are three foundational agents that form the core intelligence of the platform:

i. Client Profiling Agent

Purpose: To build and maintain a dynamic and explainable profile of each client by analyzing structured data (e.g., CRM, transactions), unstructured inputs (e.g., advisor notes), and inferred preferences or behaviors.
Key Functions:

- Extract demographics, risk tolerance, and financial goals
- Detect sentiment and emotional state
- Segment clients into behavioral cohorts
- Generate a continuously evolving client persona

ii. Portfolio Analysis Agent

Purpose: To evaluate the performance, diversification, and risk exposure of a client's portfolio and identify deviations from target allocations or goals.
Key Functions:

- Analyze portfolio holdings against benchmarks
- Run simulations and scenario-based stress testing
- Detect concentration risks or under-diversification
- Feed performance summaries to the Recommendation Agent

iii. Recommendation Agent

Purpose: To generate personalized, compliant, and explainable investment recommendations aligned with the client's profile and goals.
Key Functions:

- Retrieve suitable financial products from a knowledge graph
- Leverage LLMs to explain rationale behind recommendations
- Use peer-cohort matching and optimization techniques
- Validate outputs with the Compliance Agent before delivery

The requirement analysis and literature insights presented in this chapter serve as a foundational basis for designing an intelligent, agent-driven advisory platform. By mapping real-world advisor workflows and identifying pain points, we established the critical functionalities an AI system must address. Furthermore, the exploration of emerging Agentic AI frameworks and tools demonstrated the feasibility of modular, goal-driven, and explainable agent architectures in financial services. These insights directly align with the data strategy and design decisions detailed in the next chapters.

Chapter 3: Data Collection & Knowledge Graph Design focuses on assembling and modeling the structured and unstructured data necessary to power these intelligent agents—especially through a financial knowledge graph that captures the semantic relationships across clients, portfolios, products, and compliance logic.

Chapter 4: Agentic AI Platform Architecture & Design builds upon this groundwork, presenting the proposed architecture and detailing how the identified components and AI techniques are integrated into a cohesive, scalable platform.

Chapter 3: Data Collection & Knowledge Graph Design

This phase lays the groundwork for building a unified data and reasoning layer, ensuring that all agents in the platform have access to a rich, connected knowledge base. Below are the detailed activities involved in each sub-topic:

1. Gathering Structured and Unstructured Data

The objective here is to collect all relevant data sources that represent the operational reality of financial advisory services. This includes both numeric and textual content, sourced from multiple systems.

Structured Data:

- **CRM Systems**: Client profiles, demographic information, risk scores, communication logs.
- **Portfolio Management Systems (PMS)**: Asset allocations, performance metrics, investment instruments, historical transactions.
- **Financial Product Catalogs**: Fund details, fees, tenure, tax implications, NAV history.
- **Risk Assessment Tools**: Questionnaire scores, scoring logic, and mapped risk categories.
- **KYC/Onboarding Platforms**: Regulatory documents, investor categories, compliance status.

Unstructured Data:

- **Advisor Notes and Meeting Transcripts**: Text entries made during conversations or client reviews.
- **Client Emails & Chats**: Informal data that captures sentiment, intent, and hidden constraints.
- **Research Reports & Product PDFs**: Technical data about mutual funds, insurance, etc.
- **Market News and Trends**: Extracted insights for contextual intelligence.

Tools & Technologies:

- **ETL Pipelines** (e.g., Apache NiFi, Airbyte): For ingesting structured data.
- **OCR + NLP Stack** (e.g., Tesseract + spaCy/BERT): For extracting data from scanned PDFs or unstructured documents.
- **Vectorization Pipelines** (e.g., FAISS, Sentence Transformers): For similarity search on unstructured content.

2. Defining Entities and Relationships

In this step, the raw data is abstracted into meaningful **concepts (entities)** and **connections (relationships)** that form the basis of the Knowledge Graph. This model mirrors real-world financial advisory logic.

Key Entities:

- **Client**: Includes demographics, risk appetite, preferences, goals.
- **Advisor**: Advisory history, client relationships, credentials.
- **Financial Product**: Stocks, mutual funds, insurance plans, bonds.
- **Transaction**: Buy/sell orders, SIPs, premiums, redemptions.
- **Goal**: Retirement, home purchase, child education, etc.
- **Portfolio**: A collection of holdings mapped to a client or goal.
- **Regulatory Constraint**: Suitability rules, exposure limits, compliance conditions.

Tools:

- **Entity-Relationship Modeling**: ER diagrams or UML tools to plan schema.

3. Designing Financial Knowledge Graph Schema

With the entities and relationships identified, We will take the next step is to translate this into a graph schema that supports **semantic reasoning, recommendation**

Design Objectives:

- Represent client-product-goal relationships in a **queryable** & **inference-ready** format.
- Enable **cross-agent context sharing** (e.g., profiling agent informs recommendation agent).
- Provide a semantic backbone for **compliance validation and personalization**.

Schema Layers (Representative based on current understanding):

- **Client Entity Layer**: Personal, behavioral, and risk-related attributes.
- **Financial Product & Instrument Layer**: Classifications, performance metrics, issuer details.
- **Regulatory & Compliance Layer**: Suitability rules, thresholds, jurisdictional limits.
- **Investment Strategy & Advisory Logic Layer**: Rebalancing rules, risk-return models.
- **Sentiment & Behavior Layer**: Emotional signals and interaction history.

Technologies:

- **Graph Database**: Neo4j (using Cypher)
- **Graph Modeling Tools**: Neo4j Data Modeler, Arrows App.
- **Integration**: Use ETL pipelines to populate the graph with nodes and relationships.

4. Source of Data for Different Entities

Where I have found some datasets which are available in online portals, I will typically be using an inhouse synthetic data generation tool, which our organization uses for test data generation.

5. A Detailed View: How the Client Profiling Agent can build an intelligent client profile

In Chapter 2 under the heading Agents in the Advisor Assist Platform we have discussed on a multitude of Agents which will comprise of an Advisor assist platform and the fact that there are three foundational agents that form the core intelligence of the platform.

Among them we will look at the **Client Profiling Agent,** which is one of the earliest activated agents in any advisory workflow and plays a foundational role in personalizing the user journey. The Client Profiling Agent is responsible for building and continuously updating a rich, multi-dimensional persona of each client, feeding other agents (e.g. Recommendation Agent, Compliance Agent) with context-aware, client models.

The below flow depicts how the Client Profiling Agent builds a rich, intelligent profile of a client using data, AI models, and reasoning systems to inform other agents in the advisory ecosystem.

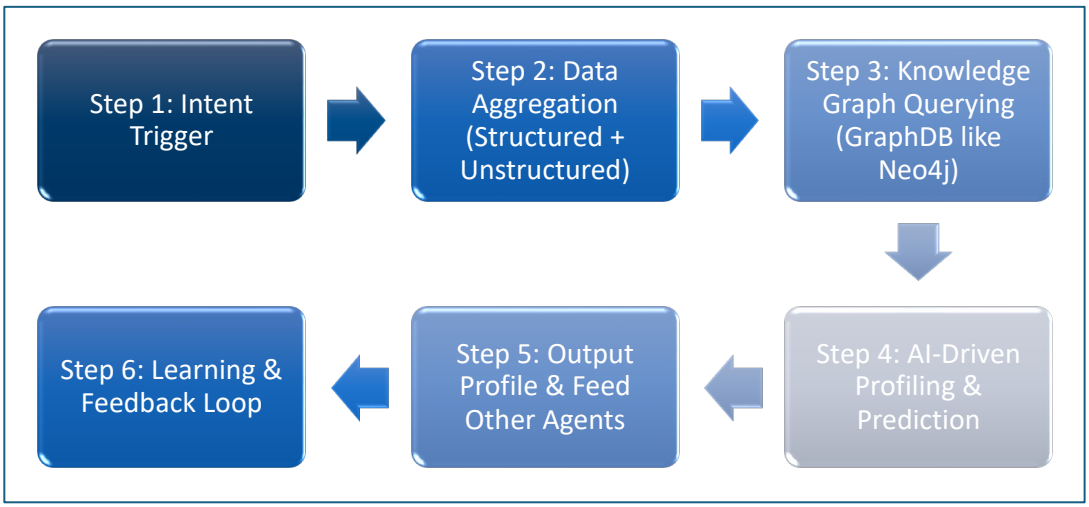

Figure 2: Step-By-Step Functioning of Client Profiling Agent's in the Architecture

Below is the detail of each process step which explains how the data from external sources are synthesized to provide AI-driven predictions and the feedbacks to enhance flow

- Step 1: Intent Trigger | Triggered by:
    - Advisor query via dashboard (e.g., "Show risk profile of Client X")
    - Initial onboarding of a new client
    - Periodic update based on new data (e.g., transactions, life events)
- Step 2: Data Aggregation (Structured + Unstructured)

  The agent orchestrates DB and API calls:
    - Structured Data (via SQL/NoSQL Queries)
        - Client demographics (age, income, location, dependents)

        - Financial history (transactions, balances)
        - Product holdings
        - Risk assessments (questionnaire scores)
    - External APIs
        - Credit score (if available)
        - Market/geographic context (e.g., urban vs rural investment behavior)
    - Unstructured Data (via NLP Pipelines)
        - Advisor-client communications
        - CRM notes
        - Email metadata
        - Social profile, if available
    - Spatial/Geographic Intelligence
        - Use geospatial data (zip code, location tagging) to derive lifestyle and behavior clusters (urban/rural, cost-of-living zones, etc.)
- Step 3: Knowledge Graph Querying (GraphDB like Neo4j)
    - Extract connections from Client → Holdings → Product → Asset Class
    - Check if client is overexposed to certain risk clusters
    - Identify peer investors (via similar_to relationships)
- Step 4: AI-Driven Profiling & Prediction.
  The agent invokes ML/NLP modules to enrich the profile:
    - Segmentation & Classification
        - K-Means/DBSCAN: Segment clients by behavior patterns
        - Decision Trees/Rules: Map profiles to predefined risk categories
    - Natural Language Understanding
        - Sentiment Analysis (BERT) on advisor notes/emails to detect anxiety, optimism, concerns
        - Use LLM's for identifying Intents of the requests made by the agents
    - Predictive Modeling
        - Use LightGBM or XGBoost to predict likely future goals or product interests
        - Collaborative Filtering / Embedding models to identify peers and recommend suitable instruments based on behavioral cohorts
- Step 5: Output Profile & Feed Other Agents
    - Expose the profile in structured JSON or graph format for downstream agents
- Step 6: Learning & Feedback Loop
    - Periodically retrain models using updated feedback
    - Adjust weights based on advisor overrides or client behavior shifts

Chapter 4: Agentic AI Platform Architecture & Design

The proposed architecture for the Agentic AI-based Advisor Assist Platform directly reflects the insights gathered from the Requirement Analysis and Literature Review. By modularizing financial advisor workflows into specialized agents—such as client profiling, portfolio analysis, recommendation, and compliance—the platform seeks to operationalize the core needs identified in real-world advisory tasks.

The design is deeply influenced by current research in Agentic AI, as outlined in the reviewed literature, particularly the concepts of dynamic workflow orchestration (Flow),[5] intelligent task decomposition (Qiao et al.),[6] and LLM-based personalization (Takayanagi et al.)[7].

The architecture integrates these principles with cutting-edge technologies like knowledge graphs, vector search, and LLMs, translating theoretical constructs into a practical, scalable AI system for intelligent financial advisory.

1. Architecture Summary

The Agentic AI-based Advisor Assist Platform is a modular, multi-layered system designed to augment human financial advisors through autonomous, intelligent agents. It supports seamless data-driven decision-making, compliance validation, portfolio optimization, and conversational client engagement. The architecture is layered to ensure clarity of responsibilities—from user interfaces and intent interpretation to agent execution, knowledge-driven reasoning, and performance monitoring.
The system orchestrates interactions between **LLM-powered components**, **knowledge graphs**, **structured & unstructured data**, and **task-specific agents**, all under a scalable and explainable AI framework.

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[5] *Flow: Modularized Agentic Workflow Automation*, Boye Niu et al., Jan 2025
arXiv:2501.07834

[6] *Benchmarking Agentic Workflow Generation*, Shuofei Qiao et al., Oct 2024
arXiv:2410.07869

[7] *Are Generative AI Agents Effective Personalized Financial Advisors?*, Takayanagi et al., April 2025
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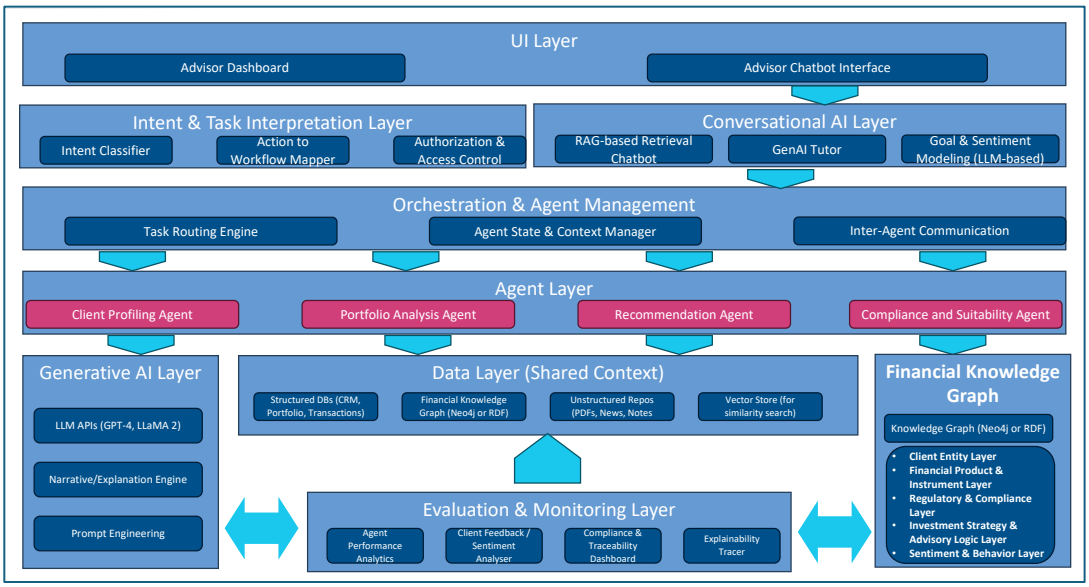

Figure 3: Reference architecture of Agentic AI based Advisor Assist Platform

2. Component-wise Breakdown of the Architecture

i. UI Layer

- **Advisor Dashboard**: Web-based interface for human advisors to view insights, ask queries, and track client portfolios.
- **Advisor Chatbot Interface**: Natural language interface for querying client data, performance, or getting explanations directly from agents.

ii. Intent & Task Interpretation Layer

Responsible for interpreting user inputs and mapping them to agent-level actions.

- **Intent Classifier**: Uses NLP to detect user intent from queries (e.g., "How is Client X's portfolio performing?").
- **Action to Workflow Mapper**: Converts intents into specific task flows for execution by appropriate agents.
- **Authorization & Access Control**: Ensures role-based access for different users (advisors, assistants).

iii. Conversational AI Layer

Enables natural interaction with users through LLM-backed chat features.

- **RAG-based Retrieval Chatbot**: Uses Retrieval-Augmented Generation to ground LLM responses in knowledge graph and document data.
- **GenAI Tutor**: Educates clients on financial concepts based on their literacy level.

- **Goal & Sentiment Modeling (LLM-based)**: Detects emotions and financial goals from user queries to refine recommendations.

iv. Orchestration & Agent Management

Handles task distribution, context preservation, and inter-agent communication.

- **Task Routing Engine**: Directs requests to the correct agent based on task type.
- **Agent State & Context Manager**: Maintains the current state of each agent and tracks historical interaction data.
- **Inter-Agent Communication**: Allows agents to collaborate, e.g., the Client Profiling Agent can trigger the Recommendation Agent.

v. Agent Layer

The core intelligence layer made up of specialized AI agents:

- **Client Profiling Agent**: Builds and maintains dynamic client personas using structured CRM data, sentiment, goals, and transaction history.
- **Portfolio Analysis Agent**: Evaluates portfolio health, risk, asset allocation using financial models and time-series analysis.
- **Recommendation Agent**: Suggests products, rebalancing actions, or strategies using LLMs, rules, and peer cohort data.
- **Compliance and Suitability Agent**: Validates whether advice complies with regulations and matches client suitability profiles.

vi. Data Layer (Shared Context)

The data backbone accessible to all agents and conversational modules.

- **Structured DBs**: Client, CRM, and portfolio databases.
- **Unstructured Repositories**: PDFs, product documents, research reports, and notes.
- **Vector Store**: Embedding-powered similarity search for recommendations, peer matching.
- **Financial Knowledge Graph**: Semantic graph of financial entities and relationships used for explainable reasoning and inference.

vii. Generative AI Layer

LLM-powered content generation and explanation components.

- **LLM APIs (GPT-4, LLaMA 2)**: Core engine for natural language generation and prompt-based reasoning.
- **Narrative/Explanation Engine**: Converts agent outputs into human-readable summaries.
- **Prompt Engineering**: Structures inputs and context to guide LLM outputs effectively.

viii. Evaluation & Monitoring Layer

Ensures quality, compliance, and continual improvement of agent behavior.

- **Agent Performance Analytics**: Tracks precision, recall, and latency of agent responses.
- **Client Feedback / Sentiment Analyzer**: Monitors user satisfaction and emotional alignment.
- **Compliance & Traceability Dashboard**: Provides audit trails for all advisory decisions.
- **Explainability Tracer**: Logs and visualizes the reasoning path for every recommendation (especially those backed by the Knowledge Graph or LLMs).

ix. Financial Knowledge Graph

Built using Neo4j, this graph will act as a semantic foundation which will be Composed of Layers, a described below

- **Client Entity Layer**: Profiles, goals, behaviors
- **Financial Product & Instrument Layer**: Instruments, returns, risk, classifications
- **Regulatory & Compliance Layer**: Rules, thresholds, constraints
- **Investment Strategy & Advisory Logic Layer**: Planning rules, rebalancing logic
- **Sentiment & Behavior Layer**: Emotional state, preferences, decision tendencies

Used for explainable reasoning**,** goal alignment**,** product recommendations, and suitability validation.

3. A Detailed View: How the Client Profiling Agent Works in the Architecture

In Chapter 2 under the heading Agents in the Advisor Assist Platform we have discussed on a multitude of Agents which will comprise of an Advisor assist platform and the fact that there are three foundational agents that form the core intelligence of the platform.

Among them we will look at the **Client Profiling Agent,** which is one of the earliest activated agents in any advisory workflow and plays a foundational role in personalizing the user journey. The Client Profiling Agent is responsible for building and continuously updating a

rich, multi-dimensional persona of each client, feeding other agents (e.g. Recommendation Agent, Compliance Agent) with context-aware, client models.

Step-by-Step Flow within the Architecture

We will now try to illustrate a detailed view of how the client profiling agent operates across layers of the reference architecture. There are 6 steps to the process as illustrated below:

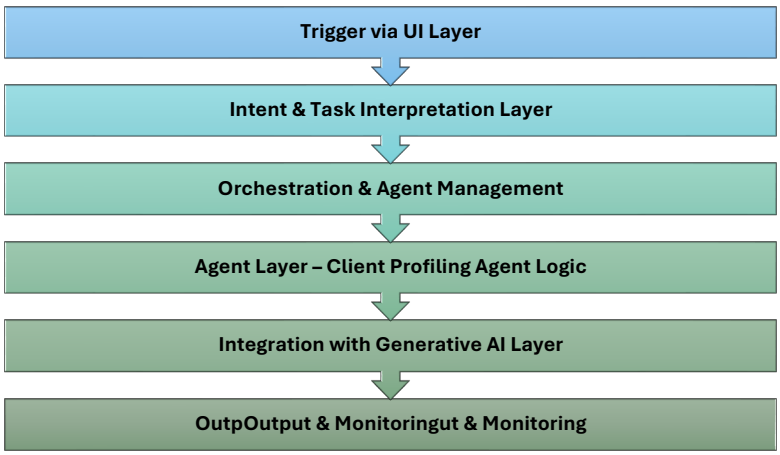

Figure 4: Step-By-Step flow of Client Profiling Agent in the agentic architecture

1. **Trigger via UI Layer**
   - Advisors interact via the Advisor Dashboard **or** Chatbot Interface**,** prompting actions like "show risk score" or "update client preferences."
   - Initial onboarding of a new client
   - Periodic update based on new data (e.g., transactions, life events)
   - These inputs are passed to the next layer for interpretation.
2. **Intent & Task Interpretation Layer**
   - The Intent Classifier detects profiling-related tasks and uses the Workflow Mapper to map the request to the Client Profiling Agent.
   - Authorization checks ensure the advisor is allowed to access the client's profile.
3. **Orchestration & Agent Management**
   - The Task Routing Engine routes the task to the Client Profiling Agent.
   - The Agent State Manager checks if a recent profile exists or if this is a new request.
4. **Agent Layer – Client Profiling Agent Logic**
   - The agent accesses Structured DBs for demographic and financial data.
   - It pulls unstructured text (e.g., advisor notes, documents) from the data layer and runs NLP pipelines (NER, sentiment analysis, topic modeling).
   - It queries the Financial Knowledge Graph to enrich profiles with inferred preferences and peer comparisons (e.g., similar risk behaviors).
   - It embeds results in a vector space (via FAISS or Pinecone) to compare the client to existing behavioral clusters.

5. **Integration with Generative AI Layer**
   - If the advisor asks, “Summarize client’s risk appetite & goals,” the agent invokes LLMs (GPT-4, LLaMA 2) with pre-structured prompts to generate a narrative.
   - Uses Prompt Engineering to format the response, explaining insights clearly.
6. **Output & Monitoring**
   - The agent updates the profile, which is shared with other agents (e.g., the Recommendation Agent).
   - Its performance is logged by the Evaluation Layer, which tracks accuracy, completeness, and user feedback.

Directions For Future Work After Mid Semester

Week 7–8: Design – Data Pipeline + Graph Engine

- Design and implement a multimodal ETL pipeline to ingest:
  - Structured data (CRM, portfolio systems)
  - Unstructured data (notes, documents, transcripts)
- Connect data pipeline to populate the graph in real-time or batch mode
- Validate data schema and ensure consistency across sources

To be done on best effort basis

- Set up the initial **Neo4j-based Financial Knowledge Graph**:
  - Define node and relationship types
  - Load sample data into the graph

Week 9–14: Develop Agent Functions

- Implement at least one core agent (e.g., Client Profiling Agent):
  - Define task logic and agent behavior
  - Interface with product simulation (stubbed) modules
- Integrate with LLM APIs **(**GPT-4 or LLaMA 2) using prompt engineering
  - Generate outputs for tasks like profiling summaries, recommendations, or goal alignment
- Conduct functional testing with mock data
- Evaluate agent response quality, accuracy

Week 15-16: Documentation & Final Presentation

- Compile: Research methodology || Architecture diagrams || Workflow/process flows || Screenshots of the implemented prototype
- Document: Agent behaviors and outputs || Dataset usage and transformations || Key learnings and limitations
- Create a **final presentation deck** for thesis submission and demo

Activities to be taken up on Best-Effort Basis

Finetune LLM Responses

- Experiment with prompt tuning and instruction refinement for personalized responses
- Create reusable prompt templates for:
  - Investment narration ("Why this fund?")
  - Financial education ("Explain SIP vs lump sum")
- Explore fine-tuning strategies (if time permits and compute available)

Note: This will be handled on a best-effort basis depending on feasibility and time constraints

Conversational AI Interface

- Design a basic chatbot UI or CLI-based interface
- Implement RAG (Retrieval-Augmented Generation) flow:
    - Retrieve context from the knowledge graph and vector DB
    - Use LLM to generate the response
- Integrate sentiment detection and goal intent parsing using LLM or classification models
- Enable multi-turn interaction support (if time allows)

Note: This will be handled on a best-effort basis depending on feasibility and time constraints

Bibliography / References

[i] *Flow: Modularized Agentic Workflow Automation*, Boye Niu et al., Jan 2025
arXiv:2501.07834

[ii] *Benchmarking Agentic Workflow Generation*, Shuofei Qiao et al., Oct 2024
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[iii] *Are Generative AI Agents Effective Personalized Financial Advisors?*, Takayanagi et al., April 2025
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