Agentic AI for Investment Research and Market Analysis

Course: AAI-520 — Natural Language Processing and Generative AI

University of San Diego — Applied Artificial Intelligence Program

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GitHub : https://github.com/usd-aai-sri/AAI520_AgenticAI_Finance

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Abstract

This project explores the application of Agentic Artificial Intelligence (AI) in financial market analysis. Agentic AI refers to systems capable of autonomous planning, reasoning, and self-improvement—moving beyond static machine learning pipelines. This research presents an autonomous Investment Research Agent that integrates multiple financial and macroeconomic data sources, including Yahoo Finance, SEC EDGAR filings, FRED economic indicators, and financial news datasets. The agent demonstrates three workflow patterns—Prompt Chaining, Routing, and Evaluator–Optimizer—to perform market research, evaluate results, and refine outputs iteratively. The analysis focuses on ten major Indian stocks between 2020 and 2025, combining price data, sentiment evaluation, and macroeconomic context. Results reveal a 40–50% long-term appreciation for key tickers such as RELIANCE.NS, with an overall balanced sentiment distribution across sectors. This study demonstrates how Agentic AI can transform financial research into a dynamic, self-improving analytical process, offering insights into future directions for reinforcement learning and LLM-driven market reasoning.

1. Introduction

Financial research and investment analysis increasingly rely on advanced artificial intelligence systems capable of processing vast, multi-modal datasets. Traditional analytical tools remain limited by their static design, requiring manual feature selection and interpretation. Agentic AI systems, however, extend these capabilities by enabling autonomous reasoning, self-reflection, and decision-making across interconnected workflows (Jurafsky & Martin, 2023). This project introduces a modular agentic framework for investment research that autonomously gathers, processes, and evaluates financial data to generate structured insights.

2. Literature and Conceptual Background

The emergence of Agentic AI represents a paradigm shift from traditional Natural Language Processing (NLP) models to goal-oriented, reasoning-driven systems. Unlike static models that perform single-task inference, agentic systems can plan, route information, evaluate outputs, and refine future actions based on feedback loops. Previous studies in financial modeling primarily relied on rule-based or statistical models, which lacked adaptability to changing market conditions. Agentic AI addresses this gap by introducing self-evaluation and memory persistence mechanisms that emulate human-like analytical reasoning.

3. Data and Methods

The system integrates structured and unstructured data sources, combining quantitative stock performance indicators with qualitative news sentiment and macroeconomic data. The primary data sources include Yahoo Finance for stock prices, SEC EDGAR for company filings, FRED for macroeconomic indicators, and mock Kaggle financial news data for textual sentiment. Data from ten major Indian equities (e.g., RELIANCE.NS, TCS.NS, INFY.NS) were collected, merged, and analyzed for the 2020–2025 period.

Preprocessing steps included type normalization, imputation of missing values, and generation of derived metrics such as Volatility20, SMA20, and Momentum20. The final dataset comprised 12,380 records with 19 features after merging across all sources.

4. Workflow Patterns

The agent was designed using three fundamental workflow archetypes central to Agentic AI architectures:

1. Prompt Chaining — a sequential process that ingests, preprocesses, classifies, extracts, and summarizes data, mirroring human research workflows.
2. Routing — directs data to specialized analyzers (earnings, macroeconomic, or general news) based on content characteristics.
3. Evaluator–Optimizer — enables self-assessment of output completeness and coherence, refining results through automated feedback and note retention.

5. Experimental Results and Findings

The agent executed full financial research cycles for all selected tickers. Hybrid sentiment analysis integrated quantitative signals (price delta, volatility, macro indicators) with qualitative cues (keyword and tone analysis). The sentiment distribution across all companies is summarized below.

Table 1. Sentiment Trends by Ticker

Ticker	Positive	Neutral	Negative
RELIANCE.NS	519	156	563
HDFCBANK.NS	538	166	534
INFY.NS	501	165	572
TCS.NS	494	167	577
ICICIBANK.NS	522	178	538

Results reveal a balanced sentiment landscape, with minor variations across sectors. The banking and IT sectors show nearly symmetric positive–negative ratios, reflecting cyclical investor confidence. Reliance Industries demonstrated the most stable sentiment trajectory with steady long-term gains.

6. Analysis and Discussion

Visual analyses across stock prices, profits, and macroeconomic factors provide a holistic view of agentic reasoning outcomes. From 2020 to 2025, RELIANCE.NS exhibited a consistent uptrend of approximately 40–50%, despite temporary corrections. Daily profit analysis indicated moderate volatility and mean-reverting behavior, with rolling mean profit oscillating near zero. The 5-year cumulative profit reached 32.3%, emphasizing the advantages of long-term holding strategies.

Table 2. Long-Term Holding Returns

Holding Period (Years)	Total Profit (%)
1	5.8
2	13.8
3	25.1
4	17.6
5	32.3

Macroeconomic context derived from GDP, CPI, and Unemployment Rate correlations confirmed that market optimism aligned with post-pandemic recovery phases. The Evaluator–Optimizer mechanism produced consistent self-assessment scores (3/3), verifying completeness in agent-generated outputs.

7. Evaluation and Self-Reflection

The self-reflective Evaluator–Optimizer loop assessed the presence of critical analytical elements such as volatility computation, news summary, and closing price references. Where gaps were detected, textual refinements were automatically appended. This feedback-driven iteration mimics metacognitive behavior—an essential aspect of agentic intelligence.

8. Conclusion and Future Work

This project successfully demonstrates the design and implementation of an Agentic AI system for investment research. By autonomously orchestrating data retrieval, sentiment analysis, and evaluation, the system illustrates how multi-agent architectures can emulate human financial reasoning. Future enhancements include reinforcement learning integration for adaptive decision-making, vectorized long-term memory for contextual reasoning, and LLM-based evaluators for qualitative feedback synthesis.