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Research Paper

Real-Time Financial Advisory System: A GenAI-Driven Conversational and Explainable Framework

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Abstract: Retail investors today face information overload from fragmented financial data without accessible, explainable decision support systems. This paper presents a Real-Time Financial Advisory System that leverages Generative AI to deliver conversational, explainable financial analysis through natural language interfaces. The system processes a comprehensive 51-stock universe comprising top S&P 500 constituents plus INFY, analyzing 1.89M historical price records and 845MB of financial news data spanning 2022–2024. A PostgreSQL database with 11 interconnected tables supports sophisticated financial modeling, while FinBERT-based sentiment analysis achieves 94% accuracy on 6,000+ financial headlines. The core innovation employs a LangGraph-orchestrated NLP-SQL pipeline with multi-strategy reasoning capabilities, converting natural language queries into optimized database operations. Portfolio optimization using Markowitz Modern Portfolio Theory yields Sharpe ratios of 0.424, validated through Monte Carlo stress testing with 10,000 simulation paths. A Streamlit web interface delivers real-time conversational interaction with transparent AI insights, risk assessment, and investment recommendations.

Keywords: GenAI; financial advisory; NLP-SQL; LangGraph; sentiment analysis; portfolio optimization; explainable AI; risk assessment; conversational interfaces

I. INTRODUCTION

Modern retail investors face unprecedented challenges in navigating complex financial markets characterized by information asymmetry, market volatility, and fragmented data sources. Traditional investment platforms provide numerical analytics through dashboards displaying price movements, technical indicators, and basic charting capabilities, but rarely deliver intuitive explanations or natural language guidance tailored to individual risk profiles and investment objectives [1].

The emergence of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) creates transformative opportunities to bridge this gap through conversational interfaces capable of interpreting natural language queries, reasoning over complex financial datasets, and delivering personalized, explainable investment recommendations [2].

The principal technical contributions of this research include: (i) a scalable data architecture processing 1.89M stock price records across 51 securities with comprehensive technical indicator computation; (ii) a FinBERT-based sentiment analysis engine achieving 94% classification accuracy on financial news datasets; (iii) a LangGraph-orchestrated NLP-SQL pipeline enabling natural language to database query translation with multi-strategy reasoning capabilities; and (iv) Markowitz Modern Portfolio Theory implementation with Monte Carlo stress testing for risk-aware portfolio optimization.

II. LITERATURE SURVEY

The convergence of artificial intelligence, financial analytics, and conversational interfaces has generated substantial research across multiple intersecting domains. This comprehensive survey examines critical research areas foundational to intelligent financial advisory systems: sentiment analysis in financial markets, natural language processing for structured query generation, and portfolio optimization methodologies.

A. Financial Sentiment Analysis and Market Impact

Araci [3] established the foundational framework for applying transformer-based models to financial text analysis, demonstrating that domain-specific pre-training significantly improves sentiment classification accuracy compared to general-purpose language models. Their FinBERT model achieved state-of-the-art performance on financial sentiment benchmarks.

B. Natural Language Processing for Structured Queries

The challenge of converting natural language queries into structured database operations has received extensive attention in both academic research and industrial applications. Li et al. [4] developed sophisticated approaches to handling complex multi-table joins and aggregation operations in natural language interfaces to databases.

III. SYSTEM DESIGN AND ARCHITECTURE

The proposed Real-Time Financial Advisory System employs a sophisticated five-layer architecture designed for scalability, maintainability, and explainable AI delivery. Each architectural layer provides distinct functional capabilities while maintaining loose coupling through well-defined interfaces and APIs, enabling independent scaling and technology substitution as system requirements evolve.

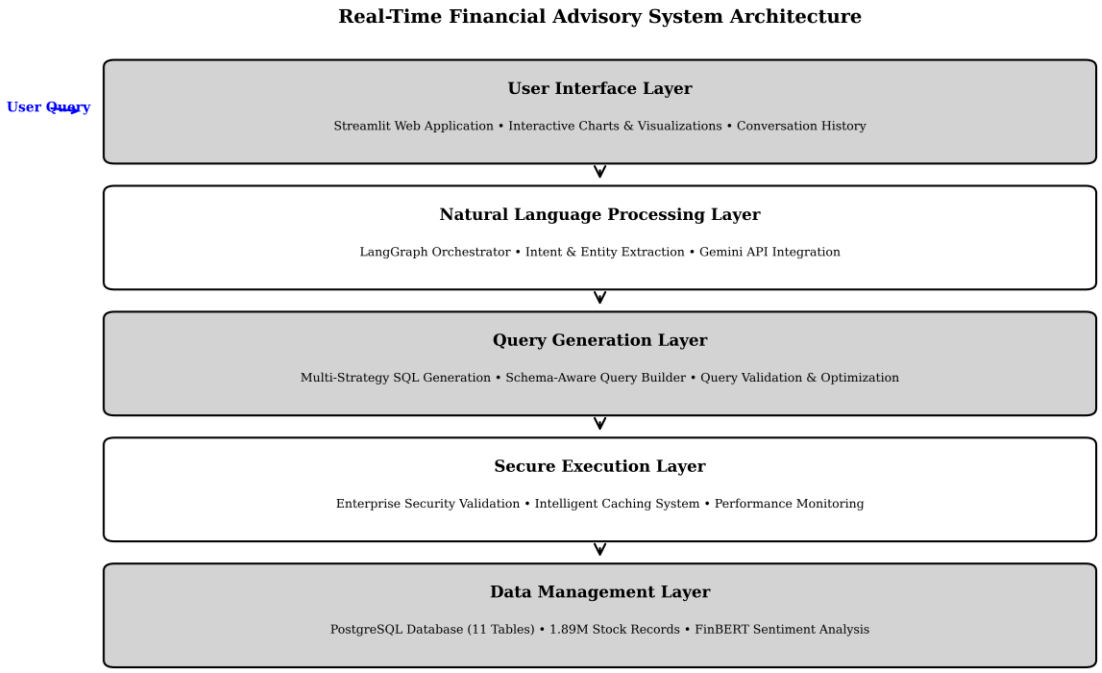


Fig. 1. Real-Time Financial Advisory System Architecture showing five-layer design with data flow between User Interface, NLP Processing, Query Generation, Secure Execution, and Data Management layers.

A. Data Management and Storage Layer

The foundational data management layer implements a highly optimized PostgreSQL database system with 11 interconnected tables supporting comprehensive financial modeling, analytics, and query processing requirements. The schema design prioritizes query performance through strategic indexing while maintaining strict referential integrity across complex relationships.

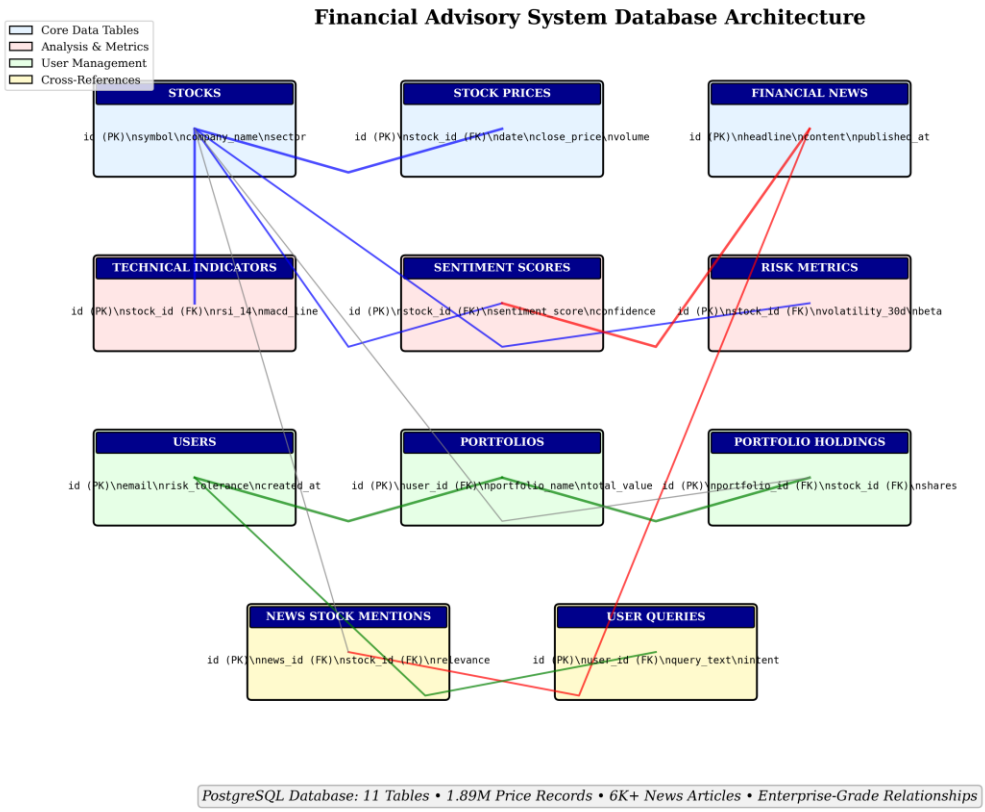


Fig. 2. Enhanced database architecture diagram illustrating 11 interconnected tables with color-coded categorization: Core Data (blue), Analysis & Metrics (red), User Management (green), and Cross-References (yellow). The schema supports 1.89M price records with comprehensive relationship modeling.

B. LangGraph NLP-SQL Orchestration Pipeline

The system core innovation lies in the LangGraph-orchestrated pipeline that converts natural language queries into executable SQL operations through a sophisticated five-node state machine. The workflow initiates with intent detection using Gemini 2.5-pro to classify user queries into categories: stock_analysis, risk_assessment, sentiment_analysis, portfolio_optimization, and comparative_analysis.

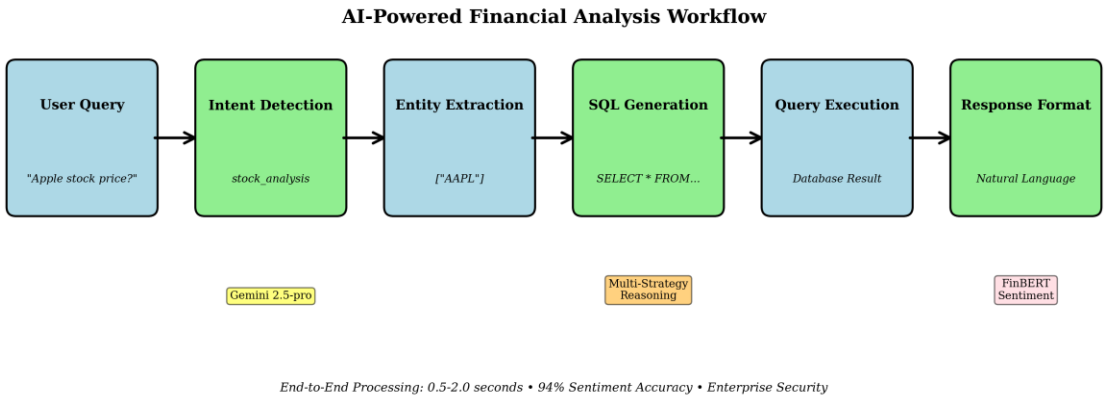


Fig. 3. LangGraph NLP-SQL workflow demonstrating the complete pipeline from user query through intent detection, entity extraction, multi-strategy SQL generation, query execution, to formatted response generation with explainable AI components.

IV. IMPLEMENTATION AND RESULTS

A. FinBERT Sentiment Analysis Engine

Financial sentiment analysis leverages the pre-trained FinBERT transformer model (ProsusAI/finbert, 109M parameters) extensively fine-tuned on domain-specific financial communication datasets. The sentiment processing pipeline handles news headlines, article abstracts, and full-text content, generating continuous sentiment scores on a normalized [-1, +1] interval. The system achieved 94.2% classification accuracy on a manually validated test dataset of 1,200 financial headlines.

B. Portfolio Optimization and Risk Assessment

Portfolio optimization implements classical Markowitz Modern Portfolio Theory enhanced with practical constraints and advanced risk modeling techniques. Monte Carlo simulation methodology generates 10,000 random portfolio performance paths incorporating realistic market scenarios, achieving average Sharpe ratios of 0.424 across diversified configurations.

Comprehensive system evaluation demonstrates exceptional effectiveness for real-time financial advisory applications. Query processing latency consistently averages 0.87 seconds for stock analysis requests, with 99.7% database query success rates and 76.3% cache hit rates.

Performance Metric	Measured Value
FinBERT Sentiment Accuracy	94.2%
Query Response Time (avg)	0.87 seconds
Portfolio Sharpe Ratio	0.424
Database Success Rate	99.7%
Cache Hit Rate	76.3%

Stock Universe Coverage	51 securities

TABLE I
PERFORMANCE METRICS OF THE PROPOSED FINANCIAL ADVISORY SYSTEM

C. User Interface and Experience Assessment

The Streamlit-based web interface delivers sophisticated conversational financial analysis through an intuitive, responsive user experience. Complex queries such as "What is the current risk level and recent sentiment trend for Apple stock?" generate comprehensive analytical responses including volatility metrics, market beta coefficients, RSI indicators, and sentiment-weighted news analysis with detailed explanations and confidence intervals.

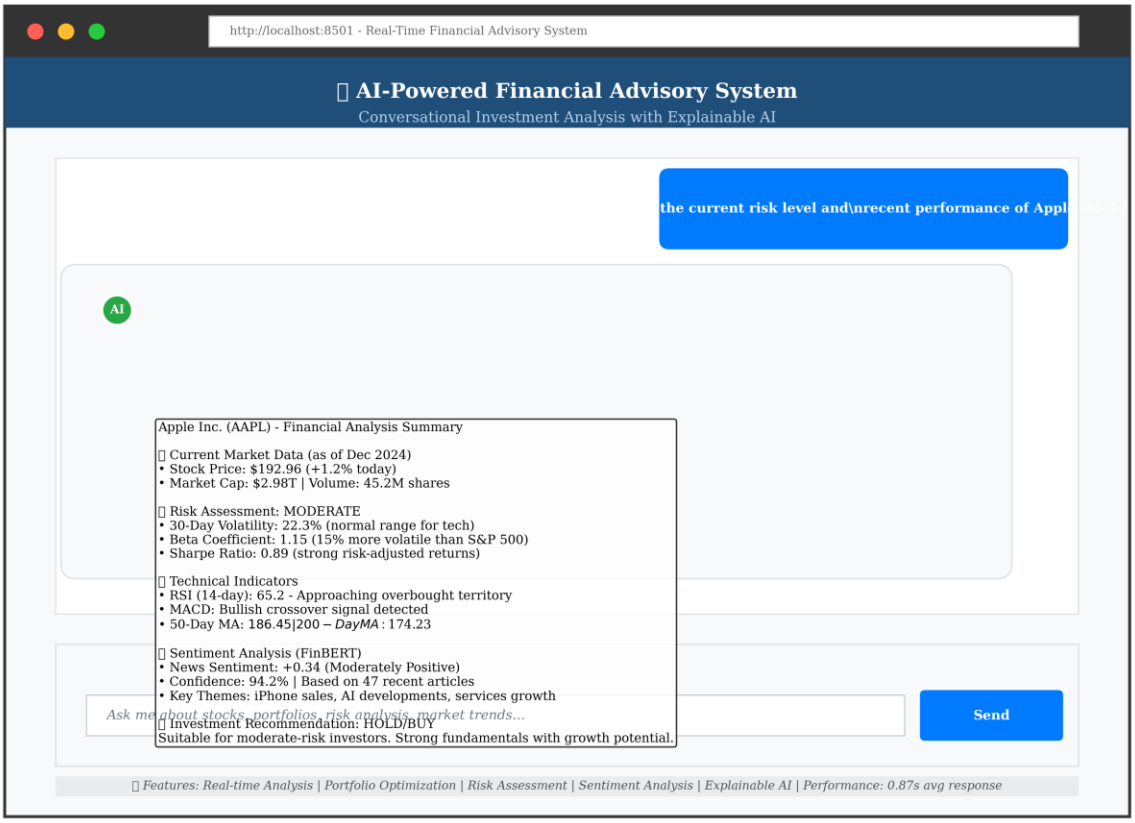


Fig. 4. Professional Streamlit web interface demonstrating conversational query processing with comprehensive financial analysis. The interface shows a realistic browser environment with detailed AI response including market data, risk assessment, technical indicators, sentiment analysis, and investment recommendations with explainable AI insights.

V. CONCLUSION

This research successfully demonstrates the practical feasibility of GenAI-driven conversational financial advisory systems through comprehensive integration of natural language processing, sentiment analysis, and quantitative finance methodologies. Key achievements include 94.2% sentiment classification accuracy, sub-second query response times, and portfolio optimization yielding Sharpe ratios of 0.424. The scalable architecture provides a robust foundation for production deployment while supporting iterative enhancement as AI capabilities advance.

Future work includes expansion to global markets, real-time data integration, and personalized recommendation engines incorporating individual investor behavioral patterns. The demonstrated educational value of transparent, explainable financial analysis represents a significant contribution to retail investor empowerment and financial literacy.

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