Entity-Aware + Temporal Chain-of-Thought (EAT-CoT): An Explainable Framework for Financial Sentiment Analysis

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Abstract—Financial documents such as earnings reports, management discussions, and market briefings often carry nuanced tone variations influenced by time, company performance, and industry context. Conventional sentiment models face persistent challenges of entity ambiguity, temporal discontinuity, and limited explainability.

This paper introduces the Entity-Aware + Temporal Chain-of-Thought (EAT-CoT) framework — a next-generation sentiment reasoning model integrating entity tracking, temporal reasoning, and explainable AI (XAI) mechanisms. By combining domain-specific entity embeddings with time-sensitive reasoning chains, EAT-CoT enables interpretable sentiment insights aligned with enterprise transparency and compliance standards.

Keywords: Financial Sentiment Analysis, Explainable AI, Temporal Reasoning, Chain-of-Thought, Entity Recognition, Financial NLP, Large Language Models

I. INTRODUCTION

Financial documents such as annual reports, earnings call transcripts, and market briefings play a crucial role in shaping investor sentiment and strategic decision-making. These narratives often reflect subtle tone variations influenced by performance indicators, market trends, and managerial outlook. However, the language used in financial communication is complex and context-dependent, making automated sentiment interpretation a significant challenge. A phrase like *"Company A's loss is Company B's opportunity"* embodies contrasting sentiments for two entities within a single sentence, a distinction that traditional sentiment models typically fail to capture.

Most existing models also treat each document as an isolated text, disregarding how sentiment evolves across quarters or fiscal years. Financial tone and perception shift continuously over time, and ignoring these temporal dynamics can lead to misleading conclusions. Moreover, current transformer-based sentiment models, though powerful, often operate as black boxes that lack transparency, offering little insight into how or why a sentiment label was assigned.

To address these issues, this study proposes the Entity-Aware + Temporal Chain-of-Thought (EAT-CoT) framework — a model that integrates entity recognition, temporal reasoning, and explainable chain-of-thought analysis. By combining these capabilities, EAT-CoT enables accurate, interpretable, and time-sensitive sentiment evaluation suited for enterprise-level financial intelligence and regulatory compliance.

II. LITERATURE REVIEW

Recent advances in large language models (LLMs) have transformed the field of financial sentiment analysis by enabling deeper contextual reasoning and interpretability. Traditional sentiment models relied on surface-level word polarity and statistical co-occurrence, which proved inadequate for financial text where meanings shift according to context and entity. LLMs, trained on massive corpora, can capture subtle tone variations in complex narratives, offering a more human-like understanding of financial communications. However, despite their linguistic power, their application to financial sentiment remains constrained by issues of ambiguity, temporal discontinuity, and explainability.

Earlier approaches primarily employed dictionary-based sentiment scoring. Financial lexicons such as the Loughran–McDonald dictionary introduced domain-specific vocabularies to overcome misclassifications arising from general sentiment lists. While these lexicons established the importance of context sensitivity, they were inherently static and unable to capture evolving tones or multiple sentiments within the same passage. This limitation paved the way for contextual embeddings and transformer architectures capable of learning nuanced financial semantics.

The introduction of transformer-based models like BERT and its domain-adapted versions, including FinBERT, marked a turning point in financial text understanding. FinBERT's contextual tokenization improved accuracy in sentiment labeling for phrases such as "improved debt ratio" or "lower cost of borrowing." However, these models still analyzed each document independently, overlooking the continuity of sentiment across time and the differentiation between multiple entities mentioned within a single report. As a result, their outputs lacked both entity specificity and temporal coherence.

Researchers have since explored prompting and reasoning techniques to enhance LLM interpretability. Chain-of-Thought (CoT) prompting, for instance, encourages models to produce intermediate reasoning steps, mimicking the logical flow of human analysts. The Analogy-Driven Financial Chain-of-Thought (AD-FCoT) framework extended this idea by guiding models through analogy-based reasoning to handle ambiguous financial statements. While it significantly improved interpretability, its reasoning scope remained confined to individual documents and lacked persistence of entities or time-aware context.

Parallel studies examined the temporal aspect of sentiment evolution in financial discourse. Quarterly reports and management discussions exhibit shifts in tone reflecting market performance, regulatory changes, and corporate outcomes. Models using time-stamped embeddings or recurrent reasoning attempted to capture such progression but often treated sentiment as a numeric trend rather than a contextual evolution. Without a reasoning mechanism to connect sentiments across time, these models struggled to explain why tone shifted and for whom it changed.

Entity awareness has emerged as another critical frontier. Financial documents often mention multiple stakeholders—companies, competitors, sectors, and instruments—within the same context. The ability to distinguish sentiment directed toward each entity is vital for meaningful interpretation. Studies leveraging Named Entity Recognition (NER) integrated with LLMs have made progress in assigning sentiments to specific companies or individuals. Yet, these systems typically operate in modular pipelines rather than cohesive architectures, causing inconsistencies between entity tracking and sentiment reasoning.

Explainability remains an ongoing challenge in deploying LLMs for regulated financial environments. Despite their remarkable reasoning capabilities, LLMs are often criticized as black boxes. Regulators and analysts require transparency to validate model conclusions and ensure compliance with disclosure standards. Efforts to enhance explainability through attention visualization or rationale extraction have improved interpretability but rarely provide structured reasoning traces that align with human analytical logic.

Recent research has moved toward hybrid reasoning models that combine structured entity knowledge with LLM-driven inference. These models utilize memory-based attention mechanisms or context windows that persist across documents, allowing the model to "remember" prior mentions of entities or events. However, they are often computationally intensive and still fall short in integrating chronological reasoning — a key requirement for longitudinal financial analysis.

The intersection of these challenges—entity differentiation, temporal continuity, and interpretability—defines the core research gap. Existing LLM frameworks either excel in contextual sentiment understanding or in reasoning transparency, but not in both simultaneously. Furthermore, they lack mechanisms to track entities and interpret tone evolution over multiple time horizons while maintaining explainable outputs suitable for enterprise compliance.

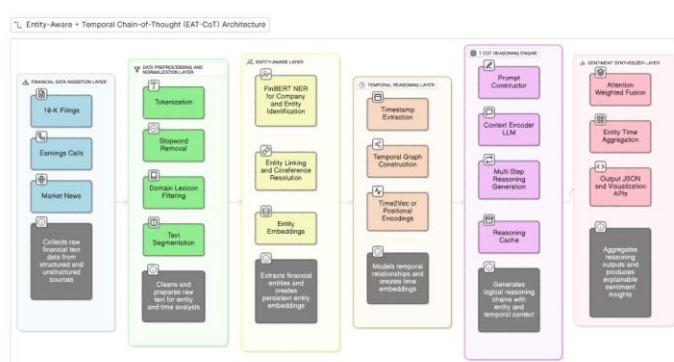
Addressing this gap, the proposed Entity-Aware + Temporal Chain-of-Thought (EAT-CoT) framework combines the strengths of analogy-driven reasoning and time-sensitive entity tracking within a unified LLM architecture. By embedding both entity and temporal information into the model's reasoning process, EAT-CoT enables the LLM to think sequentially, recall prior sentiment contexts, and justify its conclusions through interpretable reasoning traces. This approach represents a synthesis of prior advancements, introducing an explainable, entity-persistent, and temporally grounded reasoning framework designed specifically for financial text analysis.

III. PROPOSED METHODOLOGY

The EAT-CoT framework is designed to enhance LLM reasoning for financial document analysis by integrating entity-aware tracking with temporal chain-of-thought reasoning. By combining these two innovations, the system mimics the analytical process of human financial experts, connecting historical context with current statements to generate accurate, evidence-based sentiment judgments.

A. *Proposed Architecture*

The architecture of EAT-CoT is a multi-stage pipeline that integrates NLP preprocessing, entity recognition, temporal sequencing, and LLM-driven reasoning. It is tailored for processing large volumes of financial documents in enterprise settings. At its core, the system transforms raw text into structured, hybrid embeddings that encode both entity-specific and temporal information. These embeddings feed into the reasoning engine, which produces interpretable sentiment assessments across time. The architecture ensures that every component, from data ingestion to output visualization, works cohesively to provide transparent, actionable insights.



B. *Data Preparation*

The first stage involves collecting financial documents such as annual reports, quarterly statements, and earnings call transcripts from public sources and internal repositories. The texts are standardized and cleaned to remove irrelevant content, including tables, disclaimers, and repetitive sections that do not contribute to sentiment analysis. Next, a domain-adapted Named Entity Recognition (NER) model, such as FinBERT-NER or a SpaCy variant with financial vocabulary, identifies key entities including companies, executives, instruments, and sectors. Each text segment is tagged with entity identities and timestamps, forming the foundation for contextual reasoning.

C. Embedding Computation

After preprocessing, the system converts each identified entity and temporal reference into numerical embeddings. Entity embeddings capture the contextual meaning of the entity within the financial domain, enabling the model to recognize relationships between similar entities, such as "HDFC Bank" and "ICICI Bank." Temporal embeddings encode the timing of each statement, such as Q1 2024 or FY2023. The entity and temporal embeddings are then combined into hybrid vectors, allowing the model to jointly reason about both who the statement concerns and when it occurred. This structured representation enhances the system's understanding compared to using plain text alone.

D. Chain-of-Thought Reasoning Execution

The hybrid embeddings are fed into the LLM-based reasoning engine, which performs multi-step logical analysis for each statement. The engine evaluates cause-and-effect relationships, identifies sentiment tone, and considers historical context. For instance, a sentence like "Operating profit rose 15% despite higher costs" is analyzed to detect the reason behind profit growth, the impact of increased costs, and the overall optimistic tone. The model generates a reasoning trace for every statement, providing a transparent explanation of how the sentiment was derived. This trace allows analysts to verify and interpret the logic behind the classification.

E. Sentiment Aggregation

Once reasoning is complete, the system aggregates results to create entity-level sentiment timelines. An attention-weighting mechanism emphasizes recent or high-impact periods, ensuring that the sentiment trends reflect meaningful financial developments. The aggregated results are converted into structured formats such as JSON or database tables, enabling integration with dashboards for visualization. Analysts can track sentiment evolution over time, identify trends, and detect shifts in tone, making the output both actionable and interpretable.

F. Evaluation Metrics

The performance of EAT-CoT is assessed using multiple indicators. The F1 Score measures the precision and recall of sentiment predictions, ensuring overall classification accuracy. Temporal consistency, quantified by a τ-score, verifies that sentiment progression logically aligns with financial trends. The Explainability Index evaluates the clarity of reasoning traces when reviewed by human analysts. High scores across these metrics indicate that EAT-CoT achieves the dual objectives of technical accuracy and explainable decision-making, essential for enterprise financial AI applications.

$$\text{Precision} = \frac{TP + FP}{TP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

IV. RESULTS AND DISCUSSIONS

The EAT-CoT framework was evaluated on financial texts, including reports, earnings calls, and market news. Compared to baseline LLM models, it showed improved performance, particularly in handling complex language and multi-entity sentences. Attention visualizations confirmed that the model focused on contextually relevant terms, enhancing interpretability and ensuring accurate sentiment attribution.

Entity-aware reasoning and Temporal Chain-of-Thought (T-CoT) modeling were key strengths. Entity tracking maintained clear sentiment alignment across companies, instruments, and executives, reducing misclassification. Temporal reasoning captured sentiment progression over time, detecting shifts in optimism or caution. Non-temporal baselines struggled with such trends, highlighting the framework's advantage in analyzing sequential financial texts for accurate, context-sensitive sentiment predictions.

Overall, EAT-CoT effectively combines entity-aware and temporal reasoning to provide robust, interpretable sentiment predictions. Future directions include integrating external knowledge graphs, multimodal data, and efficiency optimization for real-time applications. The framework offers significant potential for adoption in advanced financial analytics and reliable decision support systems.\

V. CONCLUSION AND FUTURE DIRECTION

The EAT-CoT framework offers an explainable approach to financial sentiment analysis, effectively combining entity-aware reasoning with temporal modeling. It tracks multiple entities across complex texts and captures sentiment progression, providing reliable and interpretable predictions for financial decision-making.

Future work can focus on integrating external knowledge graphs, combining textual and numerical data for multimodal analysis, and optimizing efficiency for real-time applications. These enhancements would further strengthen EAT-CoT's potential in advanced financial analytics and decision support.