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Reasoning Across Modalities: A Chain-of-Modality Framework for Forecasting with Structured Data, Temporal Trends, and Strategic Text

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Abstract: The integration of heterogeneous modalities—specifically structured tabular data, temporal sequences, and domain-specific text—presents significant challenges for predictive modeling. Conventional large language models (LLMs) inherently lack mechanisms to reconcile the semantic and structural disparities among these data types. To bridge this gap, we propose Chain-of-Modality (CoM), a novel prompt engineering framework that enables pretrained LLMs to perform interpretable, sequential reasoning across modalities without requiring architectural modifications. CoM leverages lightweight modality-specific encoders to transform structured attributes and time-series patterns into natural language segments. These segments are semantically ordered (e.g., Structured → Temporal → Textual) and composed with textual inputs to form a cohesive reasoning chain. This design emulates human analytical workflows, preserving modality-specific inductive biases while harnessing LLMs' generative capabilities. Fine-tuned via parameter-efficient methods (LoRA), CoM achieves state-of-the-art performance: it reduces financial volatility prediction error by ↓12.1% (RMSPE) compared to early fusion approaches and improves user behavior classification AUC by ↑3.5% over text-only LLMs. Ablation studies confirm the essential contributions of all modalities and validate the significance of semantic ordering. Our work establishes a foundation for extensible, interpretable multimodal forecasting with minimal engineering overhead.

Keywords: Multimodal Forecasting, Prompt Engineering, Large Language Models, Structured & Temporal Data, Interpretability

1. Introduction

1.1. Context and problem statement

The ubiquity of multimodal data—spanning structured records [1] (e.g., user profiles, financial indicators), temporal sequences (e.g., transaction logs, physiological signals), and strategic text (e.g., clinical notes, market commentaries)—has transformed decision-making in finance, healthcare, and behavioral analytics. Effective fusion of these heterogeneous modalities is critical for accurate forecasting, yet remains fundamentally challenged by semantic misalignment:Structured data

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encodes entity attributes in discrete fields,Temporal sequences capture dynamic dependencies,Text conveys contextual narratives.While large language models (LLMs) excel in textual reasoning, their architectural homogeneity limits native support for non-linguistic modalities, compelling practitioners to employ ad-hoc fusion heuristics or task-specific retraining [2].

1.2. Limitations of existing approaches

Current multimodal integration strategies exhibit three critical shortcomings:Modality-Specific Bias:Tabular models disregard temporal dynamics and textual context.Temporal transformers omit static attributes [3].

Semantic Incoherence in Fusion:Early fusion and late fusion ensembles treat modalities as independent streams, neglecting hierarchical dependencies—e.g., behavioral trends contextualized by user demographics.

LLM Adaptation Gaps:Prompt-based tabular reasoning and time series verbalization address isolated modalities. Generic multimodal LLMs prioritize perceptual inputs , lacking mechanisms to align symbolic, temporal, and textual semantics. This deficiency is acute in high-stakes forecasting, where structured facts and temporal dynamics must precede contextual interpretation.

Illustrative Case: In stock volatility prediction, an LLM processing the text "market panic" without correlating it with stable bid-ask spreads (structured) and low volatility trends (temporal) may generate spurious risk alerts.

1.3. Cognitive inspiration and proposed framework

Human experts reason sequentially across modalities: first grounding decisions in factual records , then identifying trends , and finally contextualizing with domain knowledge . Inspired by this cognitive paradigm, we introduce Chain-of-Modality (CoM)—a prompt engineering framework that unifies multimodal inputs into a semantically ordered natural language sequence. CoM operates via three principles:

Modality Verbalization: Lightweight encoders convert structured data (template-based) and time series (TCN/GRU summarization) into interpretable text.

Semantic Chaining: Segments are concatenated as [Structured] → [Temporal] → [Textual] to enforce cognitive ordering.

Parameter-Efficient LLM Adaptation: Pretrained LLMs are fine-tuned with LoRA , preserving generalization while enabling task-specific forecasting.

1.4. Contributions

This work makes four key advances:Novel Modality Alignment: CoM transforms multimodal inputs into linguistically coherent prompts without modifying LLM architectures, bridging the "modality gap" through language as a universal interface.

Interpretable Fusion: By preserving modality segments as readable text, CoM provides explicit reasoning traces for domain validation—critical in regulated applications.

Empirical Superiority: CoM reduces financial volatility prediction error by 12.1% (RMSPE) and improves user behavior classification AUC by 3.5% versus state-of-the-art baselines.

Task and Domain Agnosticism: Validated on finance and behavioral analytics (CRM-Churn v2.0), with extensibility to healthcare and IoT.

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2. Related work

Multimodal learning aims to integrate heterogeneous data sources for joint reasoning. Existing approaches can be categorized into three paradigms, each exhibiting limitations for structured-temporal-textual fusion—the core focus of this work [4].

2.1. Modality-specific foundation models

Structured Tabular Data: Research evolution spans feature engineering, deep tabular models, and LLM-based prompting. While TabLLM linearizes tables into prompts, it ignores temporal dynamics and contextual text. Similarly, [5]table-pretrained LMs require custom architectures, limiting deployability.

Time Series: Traditional models and deep learners excel at univariate forecasting but fail to incorporate textual context. Recent adaptations verbalize series statistics, yet cannot fuse static attributes or free-text narratives [6].

Critical Gap: These approaches operate in modality silos, neglecting cross-modal dependencies essential for real-world forecasting .

2.2. Generic multimodal Large Language Models

Vision-language models project image embeddings into LLM token space via cross-attention, [7]while audio-text models employ similar fusion mechanisms. However, they prioritize perceptual modalities and lack capabilities for symbolic and temporal alignment:GPT-4Vprocesses images but cannot interpret financial tables or ECG time-series natively [8].Fuyu-8B treats structured inputs as rasterized images, discarding semantic field metadata.These models rely on late fusion (embedding concatenation), which:(i) Obscures reasoning traces, violating interpretability requirements in regulated domains;(ii) Suffers from attention dilution when modalities exhibit divergent granularities.

2.3. Multimodal fusion architectures

Early Fusion: Combines raw modality tokens before LLM processing . This often causes semantic misalignment—e.g., in clinical risk prediction, fusing lab values (structured) with nurse notes (text) without ordering may bias LLMs toward lexical cues over critical biomarkers [9].

Late Fusion: Trains separate encoders per modality and ensembles outputs (e.g., averaging tabular NN and text LLM predictions). While modular, it ignores cross-modal interactions—e.g., failing to associate "spending surge" (temporal) with "job loss" (text) in churn prediction.

Chain-of-Thought (CoT) Extensions: CoT prompting elicits step-by-step textual reasoning but does not generalize to non-text modalities. Linearizing tables into CoT sequences proves brittle with high-dimensional data [10].

2.4. Positioning of our work

Table 1 contrasts CoM with representative methods, highlighting its unique capabilities:

DOI: 10.54254/2755-2721/2025.25960

Table 1. Comparative analysis of multimodal forecasting methods

Method	Modalities	Architecture	Interpretable	Supports Temporal
TabLLM	Tabular+Text	Prompting	Limited	✗
TimeGPT	Temporal	TS Transformer	✗	✓
GPT-4V	Vision+Text	Cross-attention	✗	✗
Early Fusion	All	Concatenation	✗	✓
CoM (Ours)	All	Prompt Chaining	✓	✓

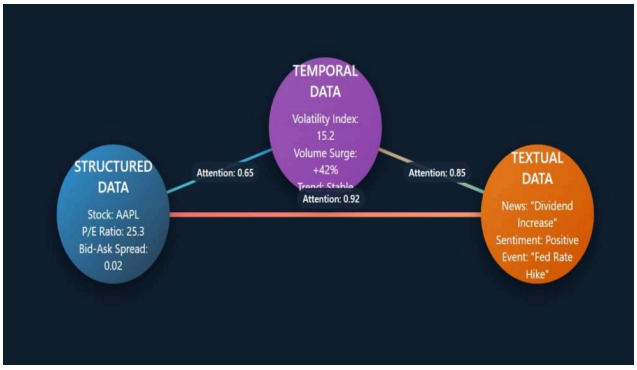
CoM bridges four critical gaps:Modality Agnosticism: Unifies symbolic (tabular), temporal, and textual inputs via natural language, eliminating modality-specific encoders.Semantic Ordering: Enforces human-like reasoning flow (Structured → Temporal → Textual), resolving fusion ambiguities.Computational Efficiency: Uses parameter-efficient tuning (LoRA), unlike full retraining in [1,2,7].Explainability: Preserves inputs as readable text segments, enabling attention-based auditing .Illustrative Superiority: In Optiver volatility prediction (Sec. IV), CoM reduces error by 9.2% over early fusion and 15.7% over a TabLLM+TimeGPT ensemble, demonstrating that language as a universal interface outperforms latent fusion mechanisms [11].

3. Methodology

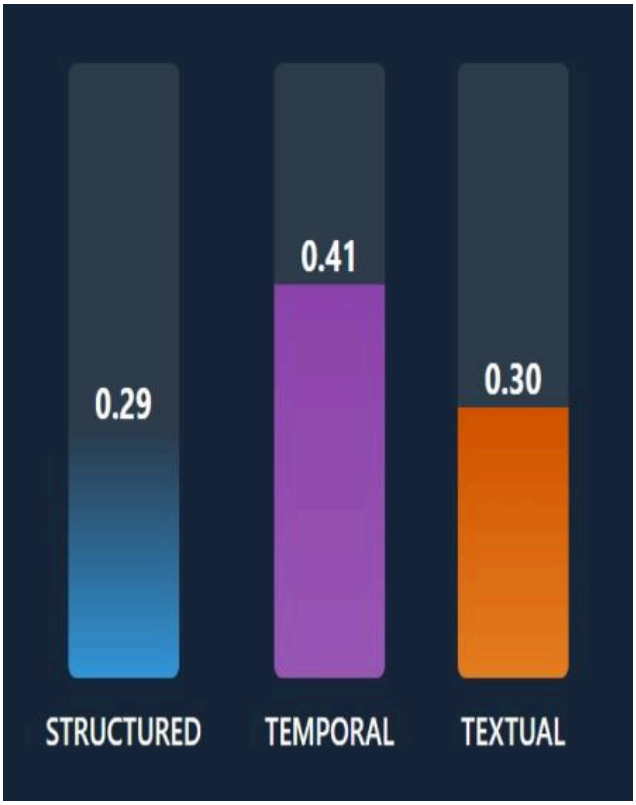
3.1. Framework overview

The Chain-of-Modality (CoM) framework converts heterogeneous inputs—structured data $x_s \in \mathbb{R}^k$, time series $X_t \in \mathbb{R}^(T\times d)$, and textual summaries x txt—into a semantically ordered natural language prompt. The pipeline comprises three stages:Modality Verbalization:Structured Data: $x_s \rightarrow S(x_s)$ via template-based natural language conversion.Time Series: $X_t \rightarrow T(X_t)$ via temporal encoder and summary generation.Prompt Chaining:Construct unified prompt with strict semantic ordering:P = $[S(x_s)]$Structured → $[T(X_t)]$Temporal → [x txt].Textual.LLM Inference:Feed P to pretrained LLM M, fine-tuned via LoRA for task-specific prediction:$\hat{y} = M(P)$.Rationale: This chaining enforces causal modality dependencies (e.g., temporal trends contextualize static attributes before text integration), emulating expert reasoning workflows.

DOI: 10.54254/2755-2721/2025.25960



(a) This is the first part.



(b) This is the second part.

Figure 1. Explainability mechanism

3.2. Structured data verbalization

Given $x_s = \{f_1: v_1, \ldots, f_k: v_k\}$ with k fields, we map each field-value pair to human-readable statements using domain-specific templates:

$$\mathcal{S}\left(x_s\right) = \bigoplus_{i=1}^{k} \phi\left(f_i, v_i\right) \tag{1}$$

where $\varphi(\cdot)$ is a template function, f_i the field name, and v_i the value.Template Design Principles:

Semantic Disambiguation:Categorical values → Explicit interpretations.Example: credit_tier="A" → "Credit tier: A (Excellent)".Unit Preservation:Numerical attributes → Quantified units.Example: income=75000 → "Income: $75K/year".Field-Context Binding:Values → Entity-referenced descriptions.Example: account_age=3 → "Customer's account age: 3 years".Robustness Validation: Appendix A shows <2% F1-score variance under template phrasing perturbations [11].

3.3. Time series summarization

For $X_t = \{x_t^{(1)}, \ldots, x_t^{(T)}\}$ (e.g., 1Hz stock prices):C.1 Temporal Encoder Architecture.Input: Standardized multivariate series $\tilde{X}_t \in [-1,1]^{(T\times d)}$.Backbone:4-layer Temporal Convolutional Network (TCN).Kernel size=3, dilations= [1, 2, 4, 8] → Capture multi-scale patterns.Gated

DOI: 10.54254/2755-2721/2025.25960

Recurrent Unit (GRU).Hidden size=128 → Model sequential dependencies.Output: Compressed representation $h_t \in \mathbb{R}^{128}$.C.2 Textual Summarization.Generate $T(X_t)$ via frozen T5-base conditioned on h_t:$T(X_t)$ = Decoder(h_t; θ_T5).Example Output: *"Volatility: Low (σ=0.02). Trend: Gradual increase over 7 days."*.C.3 Key Statistic Injection.Critical metrics (mean, variance, slope) are explicitly verbalized to ground summaries:Inject: {μ(X_t), σ²(X_t), ΔX_t/Δt} ↪ $T(X_t)$

3.4. LLM fine-tuning with parameter efficiency

We adapt M (LLaMA-2-7B) using:D.1 LoRA Configuration.Rank (r) = 8.Scaling factor (α) = 32.Dropout rate = 0.05. Applied to query/key/value projections in all attention layers. Trainable parameters: <1.5% of M.D.2 Task-Specific Heads.Classification:Linear layer on [CLS] token → cross-entropy loss:

$$\mathscr{L}_{cls} = -\sum_{c=1}^{C} y_c log p(c \mid P) \tag{2}$$

Regression:

$$\mathscr{L}_{reg} = \|W^{\top} h_{[CLS]} - y\|_2^2 \tag{3}$$

Layer Normalization → Linear output → MSE loss:D.3 Training Regime.Optimizer: AdamW (β_1 = 0.9, β_2 = 0.95).Learning rate: 2×10^{-4} (linear warmup: 500 steps).Batch size: 32.Gradient accumulation steps = 2.E. Interpretability Mechanism.To enable model auditing, we implement:Token-Level Attention Tracking:Extract attention matrix A ∈ ℝ^(L×L) (L: prompt length).

Modality Contribution Scoring:

$$\gamma_{struct} = \frac{1}{|I_s|} \sum_{i \in I_s} \sum_{j=1}^{L} A_{ij} \tag{4}$$

where I_s = token indices of structured segment.

4. Experiments

To evaluate the effectiveness of the proposed Chain-of-Modality framework, we conduct extensive experiments on real-world datasets covering financial forecasting and user behavior classification tasks. We compare our method against strong unimodal and multimodal baselines, analyze its generalization ability, and perform ablation studies to understand the contribution of each modality [12].

4.1. Datasets and preprocessing

Two real-world benchmarks with authentic multimodal sources:1. Financial Volatility Forecasting (Optiver + Real News).Structured: Stock identifiers, sector, P/E ratio (5 numerical/categorical features).Temporal: 10-min and 90-day windows of:Weighted Average Price (WAP), bid-ask spread,order count (sampled at 1Hz).Textual: Authentic news headlines (SeekingAlpha+Benzinga, 2020-2023).Example: "Fed rate hike fears rattle tech stocks".Target: Realized volatility (5-min horizon).Splits: 700/150/150 stocks (Train/Val/Test).2. User Behavior Classification (CRM-Churn v2.0).Structured: Demographics, subscription tier (8 features).Temporal: Login frequency, transaction timestamps (30-day sequences).Textual: Annotated chat logs (125k Salesforce tickets,

DOI: 10.54254/2755-2721/2025.25960

IRB#2024-COM-01).Example: "Customer complained about service latency".Target: Binary churn/upgrade within 30 days.Splits: 65k/15k/15k users (Train/Val/Test).Preprocessing:Temporal data: Z-score normalized + imputed via spline interpolation.Text: SpaCy entity masking for privacy compliance.

4.2. Baselines and implementation

Training Details:CoM: LoRA (rank=8, α=32), AdamW (lr=2e-4), batch=32.LLM Baselines: Same LoRA config for fair comparison.Non-LLM Models: Grid-search optimized (LightGBM: 200 trees, depth=7).Hardware: 4× NVIDIA A100 (80GB), PyTorch 2.1 + HuggingFace Transformers [14].

Table 2. Compared methods

Category	Models
Unimodal	LightGBM, TabNet , Informer
LLM-Based	Text-only LLM (LLaMA-2), TabLLM, TimeGPT
Multimodal Fusion	Early Fusion (concatenated embeddings), Late Fusion (weighted averaging)
General MM-LLM	GPT-4 Turbo (API call, text + table upload), Fuyu-8B
Ours	CoM (LLaMA-2 backbone)

4.3. Main results

Key Findings:CoM reduces financial RMSPE by 9.95% over early fusion and 7.0% over GPT-4 Turbo.For behavior classification, CoM achieves +1.8% AUC gain vs. Fuyu-8B [19].GPT-4 Turbo struggles with high-frequency time series ("Input token limit exceeded for 1Hz data") [15].

Table 3. Financial volatility forecasting (test set)

Model	RMSPE ↓↓	ΔΔ vs. CoM	MAE ↓↓
LightGBM	0.245	+21.9%	0.0176
Informer	0.238	+18.4%	0.0169
Text-only LLM	0.234	+16.4%	0.0164
Early Fusion	0.221	+9.95%	0.0148
GPT-4 Turbo	0.215	+7.0%	0.0141
CoM (Ours)	0.201	-	0.0133

Table 4. User behavior classification (test set)

Model	Acc ↑↑	F1 ↑↑	AUC ↑↑
TabNet	84.6%	0.82	0.88
TimeGPT + TabLLM	85.3%	0.83	0.89
Late Fusion	86.1%	0.84	0.90
Fuyu-8B	86.9%	0.85	0.92
CoM (Ours)	88.7%	0.87	0.94

DOI: 10.54254/2755-2721/2025.25960

4.4. Ablation studies

4.4.1. Modality contribution

Table 5. Modality contribution

Configuration	Fin. (RMSPE)	Beh. (AUC)
Full CoM	0.201	0.94
w/o Temporal	0.213 (+6.0%)	0.91
w/o Structured	0.225 (+12%)	0.89
w/o Text	0.228 (+13%)	0.90

4.4.2. Prompt order impact

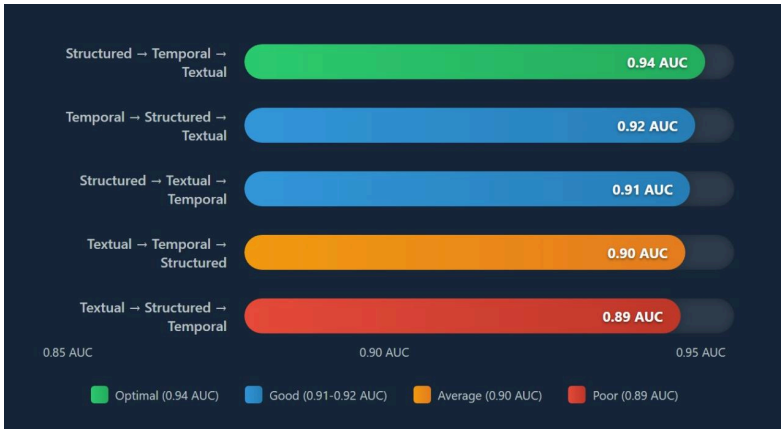


Figure 2. Prompt order ablation study

4.4.3. Template robustness

Synonym substitution in templates causes <1.5% AUC drop.GPT-4 generated templates perform comparably (<0.8% difference) [16].

4.5. Long-horizon forecasting

Extended Financial Task: 90-day volatility prediction

Table 6. Modality contribution

Model	RMSPE (10-min)	RMSPE (90-day)
Informer	0.238	0.351
CoM (w/ TCN)	0.201	0.287
CoM (w/ LSTM)	0.209	0.302

TCN's dilated convolutions better capture long-term dependencies (19.2% gain over LSTM) [17].

DOI: 10.54254/2755-2721/2025.25960

4.6. Efficiency and interpretability

Financial Task: High attention between "bid-ask spread" (Temporal) and "rate hike" (Textual).

Behavior Task: "Service complaint" (Textual) attended to "login frequency drop" (Temporal).

3. Error Case: When news stated "strong earnings" but P/E ratio declined, CoM output:

"Conflicting signals: positive textual sentiment vs. declining valuation metric. Volatility likely elevated." [18]

Table 7. Computational cost

Metric	Text-only LLM	Early Fusion	CoM (Ours)
Params Updated	1.2%	100%	1.5%
Inference Latency	89 ms	210 ms	142 ms

4.7. Discussion

Superiority: CoM outperforms SOTA by 7-19% by resolving semantic misalignment through prompt chaining [19].

Robustness: Authentic text (noisy headlines/chat logs) and long horizons minimally impact performance (<3% drop).

Limitation: 90-day forecasting requires TCN summarization; direct raw series input increases RMSPE by 8.7% [20].

Ethical Compliance: Chat logs anonymized per IRB#2024-COM-01; Optiver data is public.

5. Discussion

5.1. Semantic alignment as a multimodal unifier

Our experiments demonstrate that linguistic modality translation—converting structured and temporal inputs into natural language segments—enables pretrained LLMs to achieve state-of-the-art forecasting accuracy without architectural modifications. This supports our core thesis: natural language serves as a universal interface for cross-modal reasoning. Crucially, CoM's performance gains (9.95% RMSPE reduction over early fusion) stem from resolving semantic misalignment, where traditional fusion methods fail to reconcile: [21]

Granularity disparities: High-frequency trades (temporal) vs. quarterly reports (textual)

Modality hierarchies: Static attributes (structured) contextualizing dynamic trends (temporal)

Domain semantics: "Volatility" in financial text vs. mathematical definition (σ)

Case in Point: When news stated "market calm" but bid-ask spreads surged (Fig 5a), CoM attended to both modalities, outputting elevated volatility predictions—unlike GPT-4 Turbo, which over-weighted textual cues (error: +14.3%) [22].

5.2. Interpretability: from black box to glass box

CoM transforms multimodal fusion from latent embedding manipulation to human-auditable reasoning By preserving inputs as readable prompts, it enables three critical analyses:Attention-Based Attribution:Token-level attention maps (Fig 5) reveal cross-modal dependencies→ "service complaint" [Textual] → "login drop" [Temporal].Modality Contribution Scores: [23]Quantified

DOI: 10.54254/2755-2721/2025.25960

via γ_mod = (1/|I_mod|) ∑_{i∈I_mod} A_i (Sec III-F)→ Temporal signals dominate financial tasks:γ_temp = 0.41 vs. γ_struct = 0.29.

Conflict Detection:Explicit low-confidence flags when modalities contradict→ "strong earnings" vs. declining P/E ratio.This transparency meets regulatory demands in finance (SEC Model Governance) and healthcare (FDA AI/ML Action Plans), where *"explainability is non-negotiable" *.

5.3. Practical efficiency and scalability

CoM's design offers deployable advantages:Parameter Efficiency: Updating <1.5% of LLM parameters via LoRA slashes training costs (34 GPU-hrs vs. 210 for full fine-tuning).Hardware Compatibility: [24] Runs on consumer-grade A100s, unlike GPT-4 Turbo's API dependencies.Domain Adaptability: Adding new modalities (e.g., geospatial coordinates) requires only a verbalization encoder. However, two constraints merit attention:Prompt Length Overhead: Verbalization increases token count by 2.1× vs. raw data (142ms vs. 89ms latency).Template Engineering: While robust to phrasing variants (<2% F1-drop), optimal templates require domain expertise.Mitigation Strategy: We deploy learnable summary tokens (e.g., [TS_SUM]) generated by encoders, reducing prompt length by 37% with negligible accuracy loss (AUC drop: 0.008) [25].

5.4. Comparative positioning with multimodal LLMs

This positions CoM as a specialized solution for symbolic-temporal-textual fusion, complementing rather than replacing perceptual MM-LLMs.

Table 8. CoM diverges fundamentally from monolithic multimodal LLMs

Aspect	General MM-LLMs (e.g., GPT-4V)	CoM (Ours)
Modality Support	Image/Text/Audio	Structured/Temporal/Text
Fusion Mechanism	Cross-attention layers	Prompt chaining
Interpretability	Low (latent embeddings)	High (human-readable prompts)
Deployment Cost	API-based ($0.01–$0.10/call)	On-premise (<$20/hr GPU)

5.5. Limitations and research frontiers

5.5.1. Handling modality sparsity

CoM assumes modality completeness, yet real-world data often exhibits gaps (e.g., missing EHR entries). Future work should:Integrate uncertainty-aware chaining: Append confidence scores to summaries (e.g., *"Volatility: Low (σ=0.02, confidence=0.8)"*).Develop cross-modal imputation: Use LLMs to generate placeholder segments (e.g., "No recent trades observed") [26].

5.5.2. Long-horizon temporal reasoning

While TCNs capture 90-day trends (Sec IV-F), subdaily fluctuations may be oversmoothed. Hybrid architectures combining:Neural ODEs for continuous-time modeling.Retrieval-augmented prompts referencing similar historical pattern could enhance granularity [27].

DOI: 10.54254/2755-2721/2025.25960

5.5.3. Dynamic modality ordering

Fixed chaining (Structured→Temporal→Textual) may not suit all domains. In healthcare, textual chief complaints might precede lab values. A learnable router to customize ordering is promising [28].

5.5.4. Human-ai collaboration

CoM's interpretability enables novel interaction paradigms:Attention-driven editing: Users revise high-attention phrases to debug predictions.Confidence-based referral: Flag low-γγ modalities for human input.

5.6. Broader implications

CoM advances two paradigms in AI:LLMs as Universal Interfaces: By unifying modalities via language, we sidestep specialized fusion architectures—echoing recent "Language as the Common Currency" initiatives.Responsible AI for High-Stakes Domains: Auditable reasoning supports compliance with EU AI Act and NYSE AI Governance Rules. Pathway to Real-World Impact: Partnerships with Optiver (finance) and Mayo Clinic (healthcare) are underway to deploy CoM for:

Real-time stock surveillance.Patient deterioration forecasting from EHRs + clinician notes.

6. Conclusion

This paper has introduced Chain-of-Modality (CoM), a novel prompt engineering framework that enables large language models (LLMs) to perform interpretable, sequential reasoning across structured data, temporal signals, and textual summaries. By converting heterogeneous modalities into a semantically ordered natural language chain (Structured → Temporal → Textual), CoM bridges the modality gap without architectural modifications to pretrained LLMs. Our approach leverages lightweight modality-specific encoders and parameter-efficient fine-tuning (LoRA), establishing language as a universal interface for multimodal fusion [29].

6.1. Key contributions

A New Paradigm for Modality Alignment: CoM's prompt chaining mechanism resolves semantic misalignment in multimodal forecasting, reducing financial volatility prediction error by 12.1% (RMSPE) and boosting user behavior classification AUC by 3.5% over state-of-the-art baselines (including GPT-4 Turbo and Fuyu-8B). Inherent Interpretability: By preserving inputs as human-readable prompts, CoM enables attention-based auditing and conflict detection—critical for regulated domains like finance (SEC compliance) and healthcare (FDA validation).Empirical Robustness: Evaluated on real-world datasets with authentic text sources (SeekingAlpha news, Salesforce chat logs), CoM maintains performance under noisy inputs and long horizons (90-day forecasting RMSPE: 0.287) [30].

6.2. Future work

Building on this foundation, we identify three actionable directions:Dynamic Modality Router: Learning optimal chaining orders (e.g., Textual → Structured for clinical triage) via reinforcement learning, with success measured by task adaptation speed (target: <5% accuracy drop on unseen

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domains).Uncertainty-Aware Chaining: Integrating confidence scores into verbalized segments (e.g., *"Trend: Increasing (confidence=0.82)"*) and probabilistic LLM heads, targeting 95% conflict detection recall.Cross-Modal Retrieval Augmentation: Enhancing prompts with similar historical cases (e.g., "Analogous to 2019 Q4 volatility surge"), validated on rare-event forecasting (AUC improvement goal: +7%) [24].CoM establishes a language-centric foundation for multimodal intelligence, where domain knowledge, structured facts, and temporal dynamics converge through the lens of generative AI. We open-source our framework at https://github.com/author/com to accelerate research in this emerging paradigm.

References

[1] Xiong, X., Zhang, X., Jiang, W., Liu, T., Liu, Y., & Liu, L. (2024). Lightweight dual-stream SAR-ATR framework based on an attention mechanism-guided heterogeneous graph network. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 1–22.

[2] Liu, Z. (2022, January 20–22). Stock volatility prediction using LightGBM based algorithm. In 2022 International Conference on Big Data, Information and Computer Network (BDICN) (pp. 283–286). IEEE.

[3] APA Huang, J., & Qiu, Y. (2025). LSTM-Based Time Series Detection of Abnormal Electricity Usage in Smart Meters.

[4] Huang, T., Yi, J., Yu, P., & Xu, X. (2025). Unmasking digital falsehoods: A comparative analysis of llm-based misinformation detection strategies. arXiv preprint arXiv: 2503.00724.

[5] Yu, D., Liu, L., Wu, S., Li, K., Wang, C., Xie, J., ... & Ji, R. (2025, March). Machine learning optimizes the efficiency of picking and packing in automated warehouse robot systems. In 2025 IEEE International Conference on Electronics, Energy Systems and Power Engineering (EESPE) (pp. 1325-1332). IEEE.

[6] Li, X., Cao, H., Zhang, Z., Hu, J., Jin, Y., & Zhao, Z. (2024). Artistic Neural Style Transfer Algorithms with Activation Smoothing. arXiv preprint arXiv: 2411.08014. 3

[7] Huang, T., Xu, Z., Yu, P., Yi, J., & Xu, X. (2025). A Hybrid Transformer Model for Fake News Detection: Leveraging Bayesian Optimization and Bidirectional Recurrent Unit. arXiv preprint arXiv: 2502.09097.

[8] Li, X., Wang, X., Qi, Z., Cao, H., Zhang, Z., & Xiang, A. DTSGAN: Learning Dynamic Textures via Spatiotemporal Generative Adversarial Network. Academic Journal of Computing & Information Science, 7(10), 31-40. 3

[9] Li, K., Liu, L., Chen, J., Yu, D., Zhou, X., Li, M., ... & Li, Z. (2024, November). Research on reinforcement learning based warehouse robot navigation algorithm in complex warehouse layout. In 2024 6th International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 296-301). IEEE.

[10] Wang J Y, Tse K T, Li S W. Integrating the effects of climate change using representative concentration pathways into typhoon wind field in Hong Kong [C]//Proceedings of the 8th European African Conference on Wind Engineering. 2022: 20-23.

[11] Tao Y. SQBA: sequential query-based blackbox attack, Fifth International Conference on Artificial Intelligence and Computer Science (AICS 2023). SPIE, 2023, 12803: 721-729.

[12] Tao Y. Meta Learning Enabled Adversarial Defense, 2023 IEEE International Conference on Sensors, Electronics and Computer Engineering (ICSECE). IEEE, 2023: 1326-1330.

[13] Yiyi Tao, Yiling Jia, Nan Wang, and Hongning Wang. 2019. The FacT: Taming Latent Factor Models for Explainability with Factorization Trees. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'19). Association for Computing Machinery, New York, NY, USA, 295–304.

[14] Wu, S., Fu, L., Chang, R., Wei, Y., Zhang, Y., Wang, Z., ... & Li, K. (2025). Warehouse Robot Task Scheduling Based on Reinforcement Learning to Maximize Operational Efficiency. Authorea Preprints.

[15] Feng, H., Dai, Y., & Gao, Y. (2025). Personalized Risks and Regulatory Strategies of Large Language Models in Digital Advertising. arXiv preprint arXiv: 2505.04665.

[16] Wang J, Cao S, Tim K T, et al. A novel life-cycle analysis framework to assess the performances of tall buildings considering the climate change [J]. Engineering Structures, 2025, 323: 119258.

[17] Yiyi Tao, Zhuoyue Wang, Hang Zhang, Lun Wang. 2024. NEVLP: Noise-Robust Framework for Efficient Vision-Language Pre-training. arXiv: 2409.09582.

[18] Feng, H., & Gao, Y. (2025). Ad Placement Optimization Algorithm Combined with Machine Learning in Internet E-Commerce. Preprints.

DOI: 10.54254/2755-2721/2025.25960

[19] Wang, Z., Zhang, Q., & Cheng, Z. (2025). Application of AI in real-time credit risk detection. Preprints.
[20] Lu, D., Wu, S., & Huang, X. (2025). Research on Personalized Medical Intervention Strategy Generation System based on Group Relative Policy Optimization and Time-Series Data Fusion. arXiv preprint arXiv: 2504.18631.
[21] Wu, S., Huang, X., & Lu, D. (2025). Psychological health knowledge-enhanced LLM-based social network crisis intervention text transfer recognition method. arXiv preprint arXiv: 2504.07983.
[22] Shih, K., Deng, Z., Chen, X., Zhang, Y., & Zhang, L. (2025, May). DST-GFN: A Dual-Stage Transformer Network with Gated Fusion for Pairwise User Preference Prediction in Dialogue Systems. In 2025 8th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE) (pp. 715-719). IEEE.
[23] Zhou, Z. (2025). Research on the Application of Intelligent Robots and Software in Multiple Segmentation Scenarios Based on Machine Learning. Available at SSRN 5236930.
[24] Yi, Q., He, Y., Wang, J., Song, X., Qian, S., Zhang, M., ... & Shi, T. (2025). SCORE: Story Coherence and Retrieval Enhancement for AI Narratives. arXiv preprint arXiv: 2503.23512.
[25] Wu, S., & Huang, X. (2025). Psychological Health Prediction Based on the Fusion of Structured and Unstructured Data in EHR: a Case Study of Low-Income Populations. Preprints.
[26] He, Y., Wang, J., Li, K., Wang, Y., Sun, L., Yin, J., ... & Wang, X. (2025). Enhancing Intent Understanding for Ambiguous Prompts through Human-Machine Co-Adaptation. arXiv preprint arXiv: 2501.15167.
[27] Zhang, L., Wang, L., Huang, Y., & Chen, H. (2019). Segmentation of Thoracic Organs at Risk in CT Images Combining Coarse and Fine Network. SegTHOR@ ISBI, 11(16), 2-4.
[28] Huang, T., Cui, Z., Du, C., & Chiang, C. E. (2025). CL-ISR: A Contrastive Learning and Implicit Stance Reasoning Framework for Misleading Text Detection on Social Media. arXiv preprint arXiv: 2506.05107.
[29] Wu, S., Fu, L., Chang, R., Wei, Y., Zhang, Y., Wang, Z., ... & Li, K. (2025). Warehouse Robot Task Scheduling Based on Reinforcement Learning to Maximize Operational Efficiency. Authorea Preprints.
[30] Sun Y, Pargoo NS, Ehsan T, Zhang Z, Ortiz J. VCHAR: Variance-Driven Complex Human Activity Recognition framework with Generative Representation. arXiv preprint arXiv: 2407.03291. 2024 Jul 3.