

# PRISM: Prompt-Refined In-Context System Modelling for Financial Retrieval

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## Abstract

With the rapid progress of large language models (LLMs), financial information retrieval has become a critical industrial application. Extracting task-relevant information from lengthy financial filings is essential for both operational and analytical decision-making. The FinAgentBench dataset (Choi et al., 2025b) formalizes this problem through two tasks: document ranking and chunk ranking. We present PRISM, a training-free framework that integrates refined system prompting, in-context learning (ICL), and a lightweight multi-agent system. Each component is examined extensively to reveal their synergies: prompt engineering provides precise task instructions, ICL supplies semantically relevant few-shot examples, and the multi-agent system models coordinated scoring behaviour. Our best configuration achieves an NDCG@5 of 0.71818 on the restricted validation split. We further demonstrate that PRISM is feasible and robust for production-scale financial retrieval. Its modular, inference-only design makes it practical for real-world use cases. The source code is released at <https://bit.ly/prism-ailens>.

## 1 Introduction

Large language model (LLM) based Information Retrieval (IR) has emerged as a transformative technology in recent years, particularly within the financial domain (Zhu et al., 2023). Lengthy and complex financial documents such as annual reports and cash flow statements often require substantial human effort to extract key information, and the process remains highly prone to error (Zhao et al., 2024b). As a result, research focus has shifted toward evidence-based information retrieval, where systems are expected to provide verifiable sources of answers through a Retrieval-Augmented Generation (RAG) workflow (Choi et al., 2025a). Despite these advances, significant challenges per-

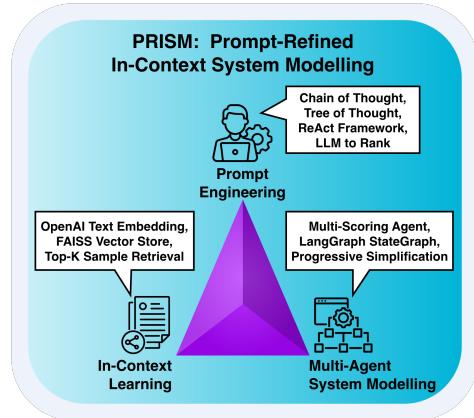


Figure 1: Overview of the proposed PRISM framework.

sist due to the dense and domain-specific nature of financial texts. LLMs often struggle to accurately identify both the “what” and the “where” of correct answers when responding to user queries. Recently, FinAgentBench was introduced as a large scale benchmark dataset to study and evaluate two critical components: document ranking, which determines the relevance of financial documents, and chunk ranking, which identifies the most relevant segments within a document (Choi et al., 2025b). This two-step approach aims to produce accurate and evidence-grounded responses. Building on recent advances in LLMs, we investigate how OpenAI’s Generative Pre-trained Transformer (GPT), one of the most advanced commercially available LLMs (Islam et al., 2023), can help address these challenges. We propose Prompt-Refined In-Context System Modelling (PRISM), a training-free framework that integrates precise system prompt engineering, in-context learning (ICL) augmentation, and agent routing logic. Systematic prompt

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We begin by conducting exploratory data analysis (EDA) at both the document and chunk levels to uncover structural and semantic patterns within the data. The insights obtained from this analysis guide the design of prompt templates, ICL augmentation, and agent routing logic. Systematic prompt

engineering is then applied to construct reasoning-oriented prompts that enhance the model’s ability to rank documents and text segments effectively. Next, we introduce ICL augmentation, which leverages OpenAI’s latest text embedding models to store question–answer pairs in a vector database and retrieve them as few-shot examples during inference on the test set. Finally, these modules are synchronized within a multi-agent framework, where specialized agents collaborate to improve ranking performance and overall system reliability. The contributions of this paper are threefold:

1. We propose PRISM, a framework for document and text chunk ranking that requires no additional training or fine-tuning of LLMs.
2. We conduct extensive experiments and ablation studies to evaluate the effects and interactions of the different modules within PRISM.
3. We perform reproducibility and feasibility studies to assess the consistency and deployability of PRISM in real-world financial IR.

## 2 Related Works

**Prompt Engineering.** Recent studies have shown that retrieval performance is highly sensitive to how an LLM is instructed (Zhang et al., 2025b). The initial breakthrough in few-shot learning demonstrated that LLMs can perform tasks using in-context exemplars without gradient updates (Brown et al., 2020). However, traditional few-shot approaches struggled with complex reasoning tasks. This limitation was addressed by Chain-of-Thought (CoT) prompting, which enhances reasoning by guiding LLMs through intermediate natural language reasoning steps (Wei et al., 2022). The Reasoning and Acting (ReAct) framework further improves reliability by allowing LLMs to plan and execute reasoning steps iteratively, reducing hallucination (Yao et al., 2023b). Building on this, the Tree-of-Thoughts (ToT) framework enables LLMs to explore and evaluate multiple reasoning paths to select the next step (Yao et al., 2023a).

**LLMs for Ranking.** LLMs have also demonstrated strong potential as zero-shot rankers in IR, typically categorized into pointwise, pairwise, and listwise approaches (Hou et al., 2024). Listwise methods, such as RankGPT, are often preferred for their balance between effectiveness and efficiency, but they face key challenges including limited input length and sensitivity to document order (Sun et al.,

2024). TourRank introduces a multi-stage grouping and tournament strategy to handle large candidate sets and improve robustness to input ordering (Chen et al., 2025). Similarly, Pairwise Ranking Prompting simplifies the comparison process, allowing moderately sized LLMs to achieve state-of-the-art performance (Qin et al., 2024). Generally, well-instructed LLMs have demonstrated superior ranking performance compared to state-of-the-art supervised systems on major benchmarks such as TREC-DL and BEIR (Sun et al., 2024). However, existing unsupervised methods remain constrained by LLMs’ token limits when applied to long and dense financial texts (Zhao et al., 2024a).

**In-Context Learning (ICL).** In-context learning (ICL) enables LLMs to adapt to new tasks using input–output examples in the prompt, without gradient updates. Recent work views this mechanism as implicit Bayesian inference, where the model infers a latent concept that explains the observed examples (Xie et al., 2022). Empirically, ICL accuracy scales with both the number and length of examples but is not strictly tied to correct input–label mappings. Randomly replacing labels only marginally affects performance (Min et al., 2022), suggesting that ICL primarily benefits from contextual cues defining the label space, input distribution, and output format. The emergence of ICL has also been linked to properties of pre-training data such as temporal burstiness and diverse, low-frequency classes (Chan et al., 2022). Meta-in-context learning aims to refine the model’s implicit priors and adaptive strategies presenting multiple tasks sequentially (Coda-Forno et al., 2023). However, there are limited research on embedding-based ICL retrieval for financial IR with commercial LLMs.

**Agentic Information Retrieval.** Agentic information retrieval represents a new paradigm where LLM agents dynamically manage information access through iterative cycles of observation, reasoning, and action, distinguishing it from traditional IR architectures (Zhang et al., 2025a). It is commonly implemented using multi-agent system (MAS), which coordinate specialized agents for reflection, planning, and tool use to achieve collective intelligence and outperform single-agent approaches (Singh et al., 2025). LLM agents have also been applied to ranking tasks, demonstrating that retrieval and ranking agents can effectively coexist (Xu et al., 2025). Despite its potential, Agentic IR faces challenges in coordinating complex MAS interactions, reducing the high inference

cost of LLMs, and evaluating dynamic agentic behaviours in financial retrieval contexts.

### 3 FinAgentBench Dataset

FinAgentBench is a large-scale dataset for financial information retrieval (IR), comprising 2023–2024 financial documents from the EDGAR database (Choi et al., 2025b). It supports two tasks: given a user query, (i) ranking five document types (10-K, 10-Q, 8-K, DEF 14A, and Earnings Transcripts) that are most likely to contain the answer, and (ii) ranking text chunks within a document based on their relevance. The dataset includes a training set of 4,986 document-ranking samples and 18,855 chunk-ranking samples, and a validation set of 200 samples for each task.

**Document Ranking Data Analysis.** We first conduct a systematic evaluation across all document types in FinAgentBench. Table 1 summarizes the distribution of document types across ranking positions. Documents such as 10-K and Earnings Transcripts appear more frequently in higher ranks, while 8-K filings are more evenly distributed across lower ranks. This suggests that different document types vary in information density and relevance, which may influence retrieval difficulty in downstream tasks. Table 2 shows the six most frequent keywords found in Rank 1 documents for each type, after removing stopwords. DEF 14A filings are dominated by high-ratio keywords such as *dependency* and *concentration*, while 8-K filings focus more on compensation-related terms. 10-Q filings contain lower keyword ratios, reflecting greater variation in language use. In contrast, Earnings Transcripts and DEF 14A documents show stronger keyword concentration, suggesting that certain document types have more distinctive language patterns that can help guide retrieval. These findings highlight how differences in vocabulary and document relevance can affect ranking performance and point to the need for adaptive retrieval strategies.

Table 1: Document distribution across ranks.

Doc. Type	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
DEF 14A	573	749	1013	1212	<b>1439</b>
10-K	<b>2402</b>	1546	507	207	324
10-Q	554	<b>1558</b>	1427	866	581
8-K	97	407	1091	<b>1808</b>	1583
Earnings	<b>1360</b>	726	948	893	1059

**Chunk Ranking Data Analysis.** We conducted a frequency analysis to better understand chunk-level characteristics in the dataset. As shown in

Table 2: Top 6 Rank 1 keywords by document type.

Doc. Type	Keyword	Ratio	Keyword	Ratio
DEF 14A	dependency	88.40%	concentration	88.24%
	exist	87.73%	risks	80.51%
	market	60.77%	share	57.12%
10-K	evolved	40.98%	recurring	40.57%
	time	39.22%	ratio	39.40%
	reporting	38.19%	period	36.01%
10-Q	quarter	20.00%	recurring	6.29%
	evolved	6.12%	time	5.99%
	ratio	5.97%	revenue	4.02%
8-K	compensation	95.45%	award	41.74%
	burn	41.74%	manage	41.54%
	availability	40.60%	share	27.21%
Earnings	asked	87.68%	questions	86.56%
	metrics	78.26%	customer	74.62%
	guidance	52.97%	offered	52.80%

Figure 2, relevant chunks are generally longer and more information dense than irrelevant ones. The wider interquartile ranges and higher maximum values, along with the long-tail distribution, indicate substantial variability in chunk length. This suggests that a dynamic retrieval and ranking method is needed to handle both typical and unusually long chunks to avoid truncation and processing inefficiencies. Moreover, the relatively small proportion of relevant chunks highlights the fine-grained and selective nature of financial retrieval. Hence, these findings indicate that models should focus on reasoning with information-rich chunks while using adaptive strategies to manage large variations in chunk length and maintain ranking accuracy.

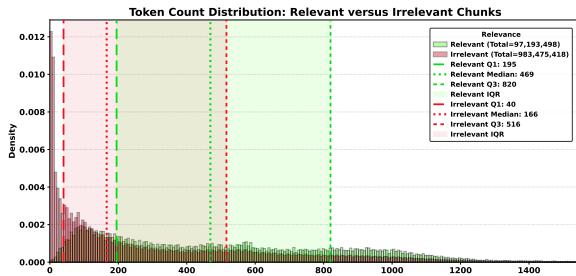


Figure 2: Token count distribution of chunks.

### 4 PRISM

Our EDA shows that relevant answers are concentrated in specific document types and in a small minority of information-dense chunks. These findings guided the design of PRISM, which leverages strong domain priors, dynamic ICL retrieval and multi-agent system to improve ranking relevance.

#### 4.1 Prompt Engineering

This foundational module evaluates how logical constraints and domain-specific priors embedded

in prompts influence LLM reasoning quality. We introduced logical scaffolding inspired by ReAct, CoT, and ToT to promote explicit reasoning before producing final answers. Four prompt variants,  $P_1$ – $P_4$ , were systematically designed to assess the impact of incremental modifications and progressively enhance reasoning structure.

The  $P_1$  variant followed a ReAct-style design with corpus-informed guidance to capture structural regularities in document and chunk distributions.  $P_2$  added quantitative domain priors, such as keyword ratios, to complement conceptual cues but showed minimal improvement over  $P_1$ .  $P_3$  incorporated explicit reasoning scaffolds from CoT and ToT to better handle long, information-dense chunks, while  $P_4$  streamlined the prompt to be more straightforward by reducing hallucination risk, and enforcing stricter output formats for downstream re-ranking. Structural refinements in  $P_3$ – $P_4$  outperformed content-based augmentations, with  $P_4$  achieving the best overall results. Prompt templates are provided in Section A.8 of the Appendix.

## 4.2 In-Context Learning Sample Retrieval

The second module enhances the system with few-shot learning through a simplified RAG pipeline. Our EDA shows that lexical cues are unevenly distributed across SEC document types, with certain types dominating the top ranks and displaying distinct keyword patterns. Incorporating examples that reflect these domain priors helps LLMs identify relevant documents earlier and reason more consistently. At the chunk level, relevant spans are generally longer and more information-dense, increasing the risk of over-elaboration and error propagation. Providing a few well-chosen examples of relevant cases gives the model a stable reference point, reducing hallucinations and improving ranking stability in long-context settings.

We embedded all query–document/chunk pairs and their ground-truth rankings using OpenAI’s text-embedding-3 model and built a FAISS vector store. During inference, each query retrieves its top- $k$  most semantically similar exemplars, which are formatted into coherent few-shot examples and prepended to the system prompt. This makes the final prompt dynamic, adapting to the semantic likelihood of each query rather than relying on a static template. Consistent with prior work, we find that ICL performs best when added samples are semantically close to the target query.

## 4.3 Multi-Agent System (MAS) Modelling

The third module introduces a structured MAS to decompose reasoning into specialized agent roles. This design aims to reduce cognitive load, improve calibration, and mitigate hallucinations in the ranking tasks. By enforcing role specialization and graph-level coordination, the MAS constrains and regularizes LLM behaviour for more consistent outcomes. We adopt a state-graph framework with architectural variations focused primarily on chunk ranking, a task that is sensitive to error propagation and reasoning collapse. Document ranking agents consist of a Question Analyzer and five domain-specific Document Experts that are remain fixed across all configurations to ensure consistent document ranking and isolate chunk-level effects.

As for chunk ranking, the MAS defines four progressively simplified architectures,  $A_1$ – $A_4$ .  $A_1$  uses a direct scoring ensemble of four parallel agents that independently evaluate candidate chunks before reaching a consensus.  $A_2$  extends this into a three-stage pipeline with a noise filter, candidate selector, and scoring ensemble, but tends to suffer from over-filtering and cascading errors.  $A_3$  simplifies the structure to two stages which has a quick filter followed by three scoring agents to balance depth and stability. Finally,  $A_4$  adopts a minimal configuration with two scoring agents, reducing interaction complexity and error propagation while maintaining consistent performance.

## 5 Experiments

We evaluated four GPT models (GPT-4o-mini, GPT-4.1, GPT-5-mini, and GPT-5) and employed OpenAI’s text-embedding-3-small (TE3-S) and text-embedding-3-large (TE3-L) for ICL retrieval. Performance is measured using NDCG@5, with results reported on a validation split of 30% public and 70% private subsets. On the private subset, PRISM achieved performance close to the top-performing models, with an average gap of 0.006 and a margin of over 0.02 from the remaining ones. Exact methods and scores are omitted to preserve anonymity under leaderboard-based evaluation.

### 5.1 Ablation Studies

**System Prompt Engineering.** The complete ablation results are shown in Table 3. We first analyze the effects of prompt design and model capacity in the non-agentic workflow. Early prompt variants ( $P_1$ – $P_2$ ) revealed that concise, direct instruc-

Table 3: Ablation studies of document and chunk ranking configs. across agentic, non-agentic and hybrid workflows.

ID	Document Ranking Configuration			Chunk Ranking Configuration			Agentic Configuration		NDCG@5 Score	
	Prompt	Model	ICL/Embedding	Prompt	Model	ICL/Embedding	Doc. Agent	Chunk Agent	Public	Private
<b>Non-Agentic Workflow</b>										
1	$P_1$	GPT-4.1	N/A	$P_1$	GPT-4.1	N/A	N/A	N/A	0.63956	0.66666
2	$P_1$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	N/A	N/A	0.65029	0.66628
3	$P_1$	GPT-5-mini	N/A	$P_1$	GPT-4.1	N/A	N/A	N/A	0.63834	0.66328
4	$P_1$	GPT-4.1	N/A	$P_1$	GPT-5-mini	N/A	N/A	N/A	0.65151	0.66966
5	$P_1$	GPT-4.1	N/A	$P_2$	GPT-5-mini	N/A	N/A	N/A	0.63817	0.67353
6	$P_1$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64711	0.67021
7	$P_2$	GPT-5-mini	N/A	$P_1$	GPT-4.1	N/A	N/A	N/A	0.63835	0.66088
8	$P_2$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	N/A	N/A	0.63694	0.67014
9	$P_2$	GPT-5-mini	N/A	$P_2$	GPT-5-mini	N/A	N/A	N/A	0.63695	0.66774
10	$P_3$	GPT-5-mini	N/A	$P_1$	GPT-4.1	N/A	N/A	N/A	0.64075	0.66673
11	$P_3$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	N/A	N/A	0.6527	0.66973
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64297	0.69019
13	$P_4$	GPT-5-mini	N/A	$P_4$	GPT-5-mini	N/A	N/A	N/A	0.65559	0.68895
14	$P_4$	GPT-5-mini	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.67855	0.70575
15	$P_4$	GPT-5	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.66236	0.70977
16	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5-mini	N/A	N/A	N/A	0.66685	0.69325
17	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5-mini	ICL-5/TE3-S	N/A	N/A	0.64841	0.68252
18	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67373	0.71446
19	$P_4$	<b>GPT-5</b>	<b>ICL-5/TE3-S</b>	$P_4$	<b>GPT-5</b>	N/A	N/A	N/A	<b>0.67444</b>	<b>0.71818</b>
<b>Agentic Workflow</b>										
20	N/A	GPT-4o-mini	N/A	N/A	GPT-4o-mini	N/A	$A_1$	$A_1$	0.59171	0.57276
21	$P_1$	GPT-4o-mini	N/A	$P_1$	GPT-4o-mini	N/A	$A_1$	$A_1$	0.58714	0.58234
22	$P_1$	GPT-4o-mini	N/A	$P_1$	GPT-4o-mini	N/A	$A_2$	$A_2$	0.52028	0.51518
23	$P_1$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	$A_2$	$A_2$	0.56317	0.55256
24	$P_1$	GPT-4o-mini	N/A	$P_1$	GPT-4o-mini	N/A	$A_3$	$A_3$	0.53861	0.53400
25	$P_1$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	$A_3$	$A_3$	0.63515	0.66291
26	$P_1$	GPT-4o-mini	N/A	$P_1$	GPT-4o-mini	N/A	$A_4$	$A_4$	0.52395	0.49782
27	$P_1$	GPT-5-mini	N/A	$P_1$	GPT-5-mini	N/A	$A_4$	$A_4$	0.61226	0.63654
28	$P_1$	GPT-5-mini	ICL-5/TE3-S	$P_1$	GPT-5-mini	ICL-5/TE3-S	$A_4$	$A_4$	0.64721	0.62775
29	$P_1$	GPT-5-mini	ICL-10/TE3-S	$P_1$	GPT-5-mini	ICL-10/TE3-S	$A_4$	$A_4$	0.63089	0.62771
30	$P_1$	GPT-5-mini	ICL-10/TE3-L	$P_1$	GPT-5-mini	ICL-10/TE3-L	$A_4$	$A_4$	0.60038	0.62294
31	$P_1$	GPT-5-mini	ICL-15/TE3-L	$P_1$	GPT-5-mini	ICL-15/TE3-L	$A_4$	$A_4$	0.58428	0.59006
32	$P_4$	GPT-5-mini	ICL-10/TE3-S	$P_1$	GPT-5-mini	ICL-10/TE3-S	$A_4$	$A_4$	0.58328	0.55757
<b>Hybrid Workflow</b>										
33	$P_4$	GPT-5-mini	N/A	$P_4$	GPT-5	N/A	$A_3$	N/A	0.67825	0.70685
34	$P_4$	GPT-5-mini	N/A	$P_4$	GPT-5	N/A	$A_4$	N/A	0.67234	0.69439

tions improved retrieval relevance over overly structured formats. Later versions ( $P_3$ – $P_4$ ) emphasized clarity, reasoning focus, and contextual grounding, further stabilizing performance. The  $P_4$  prompt, which encouraged explicit reasoning about document relevance while reducing verbosity, produced steady gains and improved the NDCG@5 from 0.64297 (Run 12) to 0.65559 (Run 13) with GPT-5-mini. Increasing model capacity from GPT-4.1 to GPT-5-mini and GPT-5 consistently enhanced performance, showing that larger models follow structured, reasoning-oriented prompts more effectively. Run 15 has the best results among all variants, with systematic reasoning guided by our prompt design to rank relevant documents and chunks accurately.

**In-Context Learning.** The second study examines the impact of ICL on both non-agentic and agentic workflows. In the non-agentic workflow, applying ICL at the document level consistently improved performance, while extending it to both document and chunk levels degraded results due to context overload and fragmented attention. The

best configuration applied ICL only at the document stage, achieving the highest score (Run 19, 0.71818), demonstrating that strategically scoped ICL enhances reasoning consistency, whereas excessive context dilutes retrieval focus. In contrast, the agentic workflow showed mixed results. Increasing the number of shots often reduced performance (Run 28 vs. Runs 29–32), indicating that excessive or poorly selected examples can bias the model’s internal policy and impair generalization. A modest setup, such as 5-shot ICL with GPT-5-mini (Run 28), provided balanced gains and show that limited examples can guide reasoning without over constraining it. Overall, ICL is most effective when applied selectively as structured guidance to improve alignment in financial IR tasks.

**Multi-Agent Workflows.** The third study examines the performance dynamics of MAS under different model scales and graph configurations ( $A_1$ – $A_4$ ). Each design varies in the number and connectivity of agents handling filtering, ranking, and scoring. Results show that MAS performance

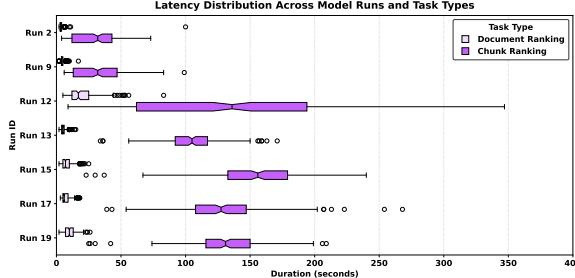


Figure 3: Latency distribution box plots.

is highly sensitive to model size and architectural complexity. Smaller models, such as GPT-4o-mini, struggled in deeper graphs like  $A_2$  (Run 22, 0.51518) due to error propagation across agents. In contrast, scaling to GPT-5-mini significantly improved stability and accuracy, with the  $A_3$  workflow rising from 0.53400 (Run 24) to 0.66291 (Run 25). This highlights that larger models better sustain coherent multi-agent coordination across complex reasoning chains. Additional ablations further reveal that hybrid configurations with agentic at the document level but non-agentic at the chunk level achieved strong results (0.70685, Run 33; 0.69439, Run 34), comparable to the best overall performance. This indicates that document level agentic reasoning is effective in isolation, whereas extending agentic control to chunk ranking introduces excessive coordination overhead. More findings are reported in Limitations and Appendix.

## 6 Feasibility and Reproducibility Analysis

We report the statistical evaluation of model performance across repeated runs in this section.

**Feasibility Analysis.** Runs of each prompt variant and ICL are selected to evaluate the practical feasibility of PRISM by analysing latency and token efficiency. Figure 3 shows that document ranking tasks have low median latency (8–10s) with minimal variance, while chunk ranking tasks are slower (130–160s) due to higher reasoning complexity. Runs 15 and 19 strike the best balance between contextual depth and stability. As shown in Figure 4, document-ranking tasks average 2–3K tokens per sample (70% prompt, 30% completion), whereas chunk-ranking tasks use around 100K tokens but remain prompt-dominant (85%). In short, Runs 15 and 19 deliver consistent performance with predictable latency and efficient token usage. Detailed cost analyses are also provided in the Appendix.

**Reproducibility Analysis.** Run 12 serves as the baseline, with Runs 15, 18, and 19 using improved

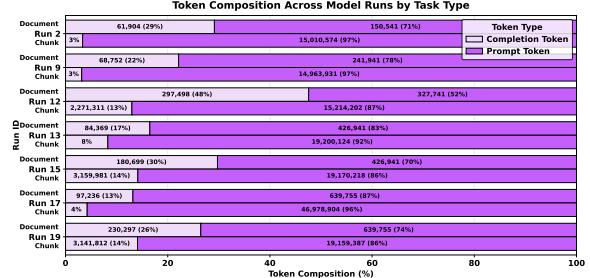


Figure 4: Token distribution bar charts.

prompts and larger models. All runs exhibit low variability, with standard deviation ( $s < 0.011$ ) and coefficient of variation (CV  $< 1.6\%$ ), indicating stable and reproducible outcomes. The narrow 95% confidence intervals (CI) confirm the statistical reliability of the mean performance estimates. Run 12 recorded the lowest mean score, while Runs 15–19 achieved consistently higher averages, with non-overlapping CIs showing statistically significant gains following configuration updates. Welch’s two-sample  $t$ -tests (Welch, 1938) further support these improvements ( $p < 0.05$  for all Run 12 comparisons). In general, the low variance and narrow confidence bounds demonstrate that the updated configurations produce statistically significant and reproducible results.

Table 4: Descriptive statistics across multiple runs.

Run ID	n	Mean	SD	CV (%)	95% CI-Low	95% CI-High
12	5	0.68005	0.01023	1.50489	0.66734	0.69276
15	4	0.70246	0.00661	0.94078	0.69194	0.71297
18	4	0.70660	0.00546	0.77319	0.69790	0.71529
19	9	0.71163	0.00433	0.60861	0.70830	0.71496

Table 5: Welch’s  $t$ -tests of Run 12 vs. subsequent runs.

Comparison	t-statistic	p-value	Significance ( $\alpha = 0.05$ )
Run 12 vs Run 15	-3.96943	0.00573	Significant
Run 12 vs Run 18	-4.98117	0.00218	Significant
Run 12 vs Run 19	-6.58157	0.00141	Significant

## 7 Conclusion

This work presents PRISM, a training-free framework that integrates system prompting, in-context learning, and multi-agent system modelling. Extensive ablation studies show that non-agentic workflows using the  $P_4$  prompt and document-level ICL achieved outstanding performance on FinAgentBench. In contrast, multi-agent configurations faced overfitting and coordination overhead. These results demonstrate that PRISM is both effective and reproducible, making it a practical solution for production-scale financial information retrieval.

## Limitations

This section outlines the key limitations identified during the development and deployment of PRISM.

### Data Preprocessing

Our non-agentic workflow currently uses a simple split-based strategy for chunk ranking: documents are divided into fixed segments, each segment is ranked independently by the LLM, and top candidates are aggregated. Although the  $P_4$  prompt mitigates challenges posed by long and dense chunks, it does not provide explicit semantic understanding. Without embedding-based pre-filtering, chunks are processed in their natural order, which may not be optimal for relevance ranking. A promising future direction is an adaptive, LLM-assisted chunking strategy in which boundaries are determined by content density and discourse structure rather than fixed lengths. Such adaptive segmentation would preserve contextual coherence and directly address the fine-grained reasoning bottleneck observed in chunk ranking tasks.

### Non-Agentic Workflow

Although the non-agentic configuration achieved the strongest overall performance, retrieval fidelity remains a notable limitation. Our best ICL setup relies heavily on the quality of the TE3-S model, and currently uses a simple L2 distance-based embedding lookup to retrieve relevant chunks. More advanced retrieval strategies could yield higher-quality candidates. A future improvement could involve hybrid retrieval that integrates dense semantic embeddings with lexical methods such as BM25 (Robertson et al., 1995), combined through Reciprocal Rank Fusion (Cormack et al., 2009). This would provide a more balanced retrieval signal, capturing both semantic context and domain-specific financial terminology that purely dense methods may overlook.

### Agentic Workflow

Our agentic experiments revealed two main challenges. First, multi-agent systems are highly sensitive to prompt–architecture compatibility: the  $P_4$  prompt, which consistently improved non-agentic performance, led to a substantial drop (0.55757) in MAS. This suggests that constraint-heavy prompts can disrupt inter-agent communication. Second, tuning graph depth and coordination remains difficult as deeper or more interconnected topologies

often introduce instability rather than improving reasoning. These findings highlight the need for lighter prompts and adaptive coordination mechanisms tailored for distributed reasoning.

### Architectural Design

Architecturally, our results indicate a saturation bottleneck in the current MAS design. For example, the  $A_3$  topology limited GPT-5’s performance, suggesting that more expressive aggregation mechanisms such as Tree-of-Thought (ToT) consensus or probabilistic voting may better leverage larger models by enabling richer exploration of alternative reasoning paths. This can potentially break through the saturation point we observed and allowing superior models to fully leverage MAS.

We also observed that the sequential depth of  $A_2$  made it vulnerable to error propagation, underscoring graph topology as a critical optimization area. Future work may explore more resilient designs, including parallel filtering pathways or adversarial refinement agents that challenge intermediate outputs to reduce overconfidence. Such mechanisms, combined with more parallel rather than sequential structures, could reduce compounding errors and improve the scalability of agentic workflows.

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## A Appendix

In this Appendix we provide additional information and insights that cannot be fit into main paper due to the page limit. We follow the sequence of sections in the main paper for easier understanding.

### A.1 Chunk Ranking Data Analysis

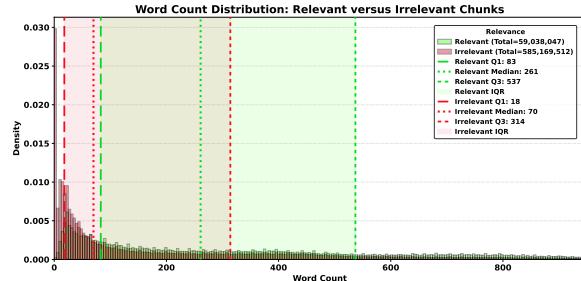


Figure 5: Word count distribution of chunks.

We conducted a frequency analysis on chunk word counts to complement the token count analysis and validate our observations. As shown in Figure 5, the trends closely mirror the token count results in Figure 2 where the relevant chunks consistently contain more words, reflecting their higher informational density and richer semantic content. The similar distribution patterns, including wider interquartile ranges and higher upper extremes, further corroborate the variability observed in chunk lengths. This strong alignment between word and token count analyses reinforces the reliability of our insights. Adaptive retrieval and ranking strategy is needed to identify detailed, content-heavy chunks with mechanisms to handle large fluctuations in chunk length efficiently.

### A.2 Dynamics of In-Context Learning and Prompt Versioning

ICL was introduced only at the final prompt stage to maintain a clear, experiment-driven workflow. We first focused on stabilizing the prompt design, since it governs the model’s reasoning structure and output constraints. Once a stable and effective prompt was established, we introduce ICL as an extension to assess how contextual examples could further enhance model performance. The ICL design evolved progressively, starting with 5 examples to test baseline adaptability, then expanding to 10 and 15 examples to assess the model’s ability to leverage larger context windows. This incremental setup allowed us to observe how additional examples influence reasoning stability and retrieval accuracy. By introducing ICL only after

the prompt was fully optimized, we ensured that any observed improvements could be attributed directly to the contextual learning mechanism rather than prompt variation, maintaining consistency and preserving interpretability across experiments.

### A.3 Implementation Details

The exact versions of the four foundation models used in our experiments are provided below:

1. GPT-4o-mini: gpt-4o-mini-2024-07-18
2. GPT-4.1: gpt-4.1-2025-04-14
3. GPT-5-mini: gpt-5-mini-2025-08-07
4. GPT-5: gpt-5-2025-08-07

The retrieval pipeline was implemented using a FAISS vector store with two OpenAI’s embedding backbones: text-embedding-3-small v1 (TE3-S) and text-embedding-3-large (TE3-L). Multi-agent workflows were constructed with LangGraph (v1.0.3), and all models were accessed through the OpenAI Python SDK (v2.3.0).

#### A.3.1 Model Provider Selection

All experiments were conducted exclusively using OpenAI models. This decision was driven primarily by practical and infrastructural considerations as most companies in our region operate within the Microsoft Azure ecosystem, which provides direct and optimized access to OpenAI suite of models. As a startup, we leveraged limited Azure AI credits and native integration to efficiently run large-scale experiments with minimal development and deployment overhead. Beyond operational accessibility, OpenAI’s remain among the most benchmarked closed-source LLMs on financial tasks (Bigard et al., 2025), offering strong reliability and reproducibility. Therefore, we believe using OpenAI as the sole model provider ensures a stable experimental environment and a credible baseline for future comparisons with alternative LLMs.

#### A.3.2 LangGraph Selection

LangGraph was selected to manage multi-agentic workflows due to its modular design, strong community support, and active maintenance. As a widely adopted framework, it provides a stable and extensible foundation for orchestrating complex agent interactions, allowing developers to define and control the flow of information between agents with precision. Its high degree of customizability enables flexible integration with diverse tools, APIs, and models, making it adaptable to various use cases. Besides, it emphasizes on maintain-

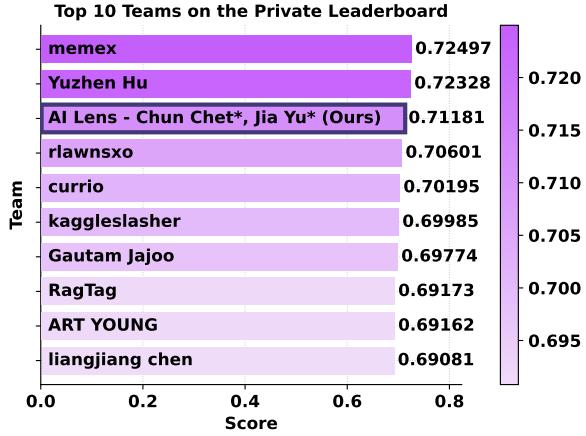


Figure 6: Top 10 teams ranked by private subset scores.

ability and observability that supports both rapid prototyping during development and scalable deployment in production. Therefore, these factors make LangGraph an ideal choice for orchestrating complex MAS financial reasoning pipelines while ensuring long-term sustainability in both research and applied settings.

### A.3.3 Prompt Selection in Agentic Workflow.

We fixed the prompt version to  $P_1$  for both chunk- and document-ranking tasks in all agentic workflow experiments to ensure controlled and interpretable results. This allowed us to isolate the effects of architectural modifications, ensuring that any performance differences could be attributed to changes in agent coordination rather than confounded by prompt variation. Furthermore, system prompts in a multi-agent setup serve distinct roles across agents, and later prompt versions contain more complex instructions that do not generalize well across heterogeneous agent responsibilities. For example, in Run 32, performance deteriorated when applying the  $P_4$  prompt to the document-ranking task, as the increased reasoning complexity introduced confusion among agents. Similarly, attempting to use  $P_4$  for chunk-ranking tasks in the hybrid workflow revealed practical constraints as the expanded prompt frequently exceeded token limits due to the large chunk sizes. For these reasons, we maintained a consistent and lightweight prompt configuration while experimenting with different agentic architectures, ensuring comparability, scalability, and clarity in performance attribution.

## A.4 Quantitative Results

Quantitative results of top 10 teams evaluated on private subset are illustrated in Figure 6. The results

also show that the top 3 methods have a small gap between each other and have bigger gaps compared to other methods.

## A.5 Feasibility Analysis

### A.5.1 Cost Analysis

In Table 6, we report the full set of statistics for the runs selected in our feasibility analysis, covering all prompt variants and the ICL-5/TE3-S configuration within the non-agentic workflow. Additionally, we assess the practical feasibility of the proposed approach by analysing the cost distribution across the selected runs. Document ranking tasks consistently incur low total costs (below \$3), reflecting their modest inference requirements. In contrast, chunk ranking tasks dominate the overall expenditure, with total costs ranging from \$4.7 to \$55, depending on input size and reasoning depth. Combined task runs follow the same pattern, as their total costs are primarily driven by chunk ranking computations. Among all configurations, Runs 15 and 19 exhibit the highest total costs (\$57.9 and \$58.5 respectively) due to extensive token generation from the larger GPT-5 model, whereas earlier runs such as Runs 2 and 9 remain significantly more economical ( \$5) when using smaller models. These results confirm that document-level ranking remains cost efficient, while chunk reasoning is more expensive as it offers richer contextual understanding and remains the major contributor to overall cost.

## A.6 Reproducibility Analysis

### A.6.1 Descriptive Statistics

The following statistical metrics were computed for each configuration based on  $n$  independent runs:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (1)$$

where  $x_i$  denotes the performance metric from the  $i^{\text{th}}$  run. The mean  $\bar{x}$  represents the average model performance.

$$SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

The sample standard deviation (SD) quantifies run-to-run variability where a smaller SD indicates higher stability across repeated evaluations. The coefficient of variation (CV) expresses variability rel-

Table 6: Latency, token usage, and cost statistics for different runs used in feasibility analysis.

ID	Task	Latency Statistics					Token Usage Statistics				Cost Statistics (USD)		
		Min	Q <sub>1</sub>	Median	Q <sub>3</sub>	Max	$\sum_{prompt}$	$\sum_{completion}$	$\mu_{prompt}$	$\mu_{completion}$	$\sum_{prompt}$	$\sum_{completion}$	$\sum_{combined}$
2	Document	2	3	3	4	100	150,541	61,904	752.71	309.52	0.04	0.12	0.16
2	Chunk	4	12	32	42.5	4190	15,010,574	519,830	75,052.87	2,599.15	3.75	1.04	4.79
2	Combined	2	3	7	32.25	4190	15,161,115	581,734	37,902.79	1,454.34	3.79	1.16	4.95
9	Document	2	4	4	5	17	241,941	68,752	1,209.71	343.76	0.06	0.14	0.20
9	Chunk	6	13	32	47	99	14,963,931	490,556	74,819.66	2,452.78	3.74	0.98	4.72
9	Combined	2	4	8	32	99	15,205,872	559,308	38,014.68	1,398.27	3.80	1.12	4.92
12	Document	5	12	17	25	83	327,741	297,498	1,638.71	1,487.49	0.08	0.59	0.68
12	Chunk	9	61.75	135.5	194	665	15,214,202	2,271,311	76,071.01	11,356.56	3.80	4.54	8.35
12	Combined	5	17	37.5	135.25	665	15,541,943	2,568,809	38,854.86	6,422.02	3.89	5.14	9.02
13	Document	2	4	5	6	15	426,941	84,369	2,134.71	421.85	0.11	0.17	0.28
13	Chunk	34	92	105	117	171	19,200,124	1,734,012	96,000.62	8,670.06	4.80	3.47	8.27
13	Combined	2	5	24.5	105	171	19,627,065	1,818,381	49,067.66	4,545.95	4.91	3.64	8.54
15	Document	2	5	7	10	25	426,941	180,699	2,134.71	903.50	0.53	1.81	2.34
15	Chunk	23	132.75	156	179	240	19,170,218	3,159,981	95,851.09	15,799.91	23.96	31.60	55.56
15	Combined	2	7	24	156	240	19,597,159	3,340,680	48,992.90	8,351.70	24.50	33.41	57.90
17	Document	3	5	6	9	18	639,755	97,236	3,198.78	486.18	0.16	0.19	0.35
17	Chunk	39	107.75	127.5	147	268	46,978,904	2,079,562	234,894.52	10,397.81	11.74	4.16	15.90
17	Combined	3	6	28.5	127.25	268	47,618,659	2,176,798	119,046.65	5,442.00	11.90	4.35	16.26
19	Document	2	7	10	13	26	639,755	230,297	3,198.78	1,151.49	0.80	2.30	3.10
19	Chunk	25	115.75	131	150	209	19,159,387	3,141,812	95,796.94	15,709.06	23.95	31.42	55.37
19	Combined	2	10	25.5	130.5	209	19,799,142	3,372,109	49,497.86	8,430.27	24.75	33.72	58.47

ative to the mean and provides a scale-independent measure of reproducibility:

$$CV = \frac{s}{\bar{x}} \times 100\% \quad (3)$$

A CV below 2% is generally regarded as evidence of excellent consistency across runs. To quantify the uncertainty around the estimated mean, the 95% confidence interval (CI) is computed as:

$$CI_{95\%} = \bar{x} \pm t_{1-\frac{\alpha}{2}, n-1} \times \frac{s}{\sqrt{n}}, \quad \text{where } \alpha = 0.05 \quad (4)$$

Specifically,  $t_{1-\frac{\alpha}{2}, n-1}$  denotes the critical value of the Student's  $t$ -distribution with  $(n - 1)$  degrees of freedom corresponding to a 95% confidence level. The value of  $t_{1-\frac{\alpha}{2}, n-1}$  can be obtained from a standard  $t$ -distribution table or computed numerically as:

$$t_{1-\frac{\alpha}{2}, n-1} = \text{quantile}_t(1 - \frac{\alpha}{2}, df = n - 1). \quad (5)$$

All configurations exhibit low standard deviations ( $s < 0.011$ ) and coefficients of variation below 1.6%, indicating highly stable and reproducible results across runs. The 95% confidence intervals are narrow, confirming that the estimated means are statistically reliable. Run 12 achieves the lowest mean performance ( $\bar{x} = 0.68005$ ), while Runs 15–19 yield consistently higher means (0.70246–0.71163). The non-overlapping confidence intervals between Run 12 and the later runs demonstrate that the configuration changes introduced after Run 12 resulted in a statistically meaningful performance gain. Subsequent runs (15–19)

show only minor numerical variation, suggesting that performance has stabilized and that the system's behaviour is reproducible.

### A.6.2 Statistical Significance

In order to verify that improvements of PRISM are statistically significant, Welch's two-sample  $t$ -tests were conducted between Run 12 (baseline configuration) and each subsequent run. The test statistic is defined as:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}, \quad (6)$$

where  $\bar{x}_1, s_1, n_1$  and  $\bar{x}_2, s_2, n_2$  denote the mean, standard deviation, and sample size of each group. The degrees of freedom are approximated using the Welch–Satterthwaite equation:

$$\nu = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{(s_1^2/n_1)^2}{n_1-1} + \frac{(s_2^2/n_2)^2}{n_2-1}}. \quad (7)$$

The two-tailed  $p$ -value is obtained from the cumulative  $t$ -distribution:

$$p = 2 \times \text{CDF}_t(-|t|, \nu). \quad (8)$$

A comparison is deemed statistically significant when  $p < \alpha$ , where  $\alpha = 0.05$  corresponds to a 5% significance level with a 5% probability of incorrectly rejecting the null hypothesis.

Table 7: Runs that are used for statistical significance experiment.

ID	Document Ranking Configuration			Chunk Ranking Configuration			Agentic Configuration		NDCG@5 Score	
	Prompt	Model	ICL/Embedding	Prompt	Model	ICL/Embedding	Doc. Agent	Chunk Agent	Public	Private
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64144	0.66537
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64952	0.67366
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.65520	0.68523
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64193	0.68579
12	$P_3$	GPT-5-mini	N/A	$P_3$	GPT-5-mini	N/A	N/A	N/A	0.64297	0.69019
15	$P_4$	GPT-5	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.67047	0.69640
15	$P_4$	GPT-5	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.66720	0.69735
15	$P_4$	GPT-5	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.66579	0.70630
15	$P_4$	GPT-5	N/A	$P_4$	GPT-5	N/A	N/A	N/A	0.66236	0.70977
18	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.68209	0.70187
18	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67842	0.70455
18	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67514	0.70551
18	$P_4$	GPT-5-mini	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67373	0.71446
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.68101	0.70491
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67913	0.70827
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.68006	0.70865
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67585	0.70923
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.68172	0.71181
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67845	0.71277
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.66495	0.71375
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.66680	0.71713
19	$P_4$	GPT-5	ICL-5/TE3-S	$P_4$	GPT-5	N/A	N/A	N/A	0.67444	0.71818

### A.6.3 Interpretation of Statistical Significance

Table 7 summarizes the configurations and corresponding NDCG@5 scores used in the statistical significance experiments. As shown in Table 5, all pairwise comparisons involving Run 12 yield  $p$ -values below the 0.05 threshold, confirming that every configuration after Run 12 achieves a statistically significant performance improvement over the baseline. Table 4 shows consistently low variability ( $CV < 1.6\%$ ) and narrow confidence intervals across these later runs, demonstrating that the model’s performance is both stable and reproducible. These results confirm that the updated configurations produce reproducible and statistically significant improvements in model performance, with minimal run-to-run variance.

## A.7 Production Readiness Analysis

This section evaluates the production readiness of the PRISM components across prompt engineering, ICL retrieval, and multi-agent system modelling.

### A.7.1 Prompt Engineering

Prompt engineering is the most mature and deployment-ready component. It delivers stable, low-variance performance with minimal latency and token overhead, making it suitable for production environments that require predictable cost and operational reliability. From an operational standpoint, prompt-based tuning requires no architectural changes and can be easily adapted as

new foundation models become available, enabling seamless integration into existing pipelines. Its low latency and minimal token overhead further strengthen its feasibility for production settings.

### A.7.2 In-Context Learning Sample Retrieval

ICL improves reasoning consistency and retrieval quality but introduces additional computational cost. In production settings, ICL could be selectively activated for complex or high-stakes financial queries where improved contextual understanding outweighs efficiency concerns. When combined with a strong prompt design, ICL can be deployed in controlled configurations, potentially using adaptive strategies that vary the number of retrieved samples based on query complexity or token budget constraints.

### A.7.3 Multi-Agent System (MAS) Modelling

While MAS offers methodological advantages, it is not yet operationally viable for large-scale deployment. Its coordination overhead, sensitivity to prompt–architecture interactions, and variable latency make it difficult to guarantee predictable performance and cost efficiency. These limitations pose challenges for enterprise-grade integration, suggesting that MAS workflows remain better suited to research and prototyping rather than near-term production use.

#### A.7.4 Toward Production Readiness

Several directions can help bridge the gap between experimental performance and production maturity. Firstly, automated or data-driven prompt optimization (e.g., search-based or Reinforcement Learning-assisted refinement) could reduce manual engineering effort while ensuring consistency across model updates. Secondly, for ICL sample retrieval, future work can focus on developing adaptive exemplar selection mechanisms that dynamically adjust the number and relevance of exemplars based on more detailed requirements such as the query complexity and token constraints, tailoring retrieval depth to query characteristics. Thirdly, for MAS modelling, progress in agent coordination frameworks, caching mechanisms, and lightweight state management could reduce overhead and latency, making the workflows more predictable and cost-efficient. Integrating these components into a unified monitoring and evaluation framework would also enhance reliability and traceability in real-world deployments. In summary, these improvements would strengthen system scalability and operational control, moving PRISM closer to production-grade readiness.

### A.8 Prompt Template

The non-agentic prompt templates are designed for single LLM workflows, where the model independently performs the complete ranking process using structured system instructions. These prompts emphasize logical consistency, domain alignment and interpretable reasoning, progressing from ReAct-style instructions to more structured CoT and ToT variants that balance interpretability and precision. Each iteration refines clarity, output constraints, and contextual cues to improve both document and chunk ranking performance. In contrast, the agentic prompt templates extend this scaffolding to a multi-role architecture, where specialized agents inherit the underlying reasoning framework while contributing from distinct role and domain-specific perspectives such as Financial Analyst, Risk Analyst, or Evidence Extractor. This modular design facilitates more interpretable and coordinated reasoning across complex financial scenarios but remains sensitive to prompt compatibility and inter-agent communication constraints.

Table 8: Document ranking system prompts.

Version	Prompt
$P_1$	<p>You are a financial analysis assistant specialized in <b>corporate disclosure documents</b>. When given a user's question about a company, <b>identify which of the following five document types</b> is most likely to contain the answer, and <b>rank them from most relevant to least relevant</b>. The documents to consider are:</p> <ul style="list-style-type: none"> <li>- <b>10-K (Annual Report)</b>: Comprehensive annual filing with business overview, financial performance, risk factors, operations, and strategy. Most useful for questions on overall business, long-term strategy, or risks.</li> <li>- <b>10-Q (Quarterly Report)</b>: Quarterly updates on financial condition and operations. Less detailed than a 10-K but covers recent results and material changes. Best for questions on recent quarterly performance.</li> <li>- <b>8-K (Current Report)</b>: Filed for unscheduled material events (e.g., M&amp;A, leadership changes, litigation, earnings announcements). Best for questions on specific recent events.</li> <li>- <b>DEF14A (Proxy Statement)</b>: Proxy statement for shareholder meetings. Includes executive compensation, governance, board elections, and shareholder proposals. Best for governance and executive pay questions.</li> <li>- <b>Earnings Release/Call Transcript</b>: Quarterly earnings press release or transcript with financial results, key metrics, and management commentary. Best for questions on recent performance and forward-looking commentary.</li> </ul> <p><b>Task:</b> - Internally reason about which documents are most relevant. - Output <b>only a ranked list of indices</b> (Python-style list) from most relevant to least relevant. - Do not output explanations, scores, or JSON mappings.</p> <p><b>Domain ranking hints:</b> - Use <b>10-K</b> for strategy, risks, or full-year data. - Use <b>10-Q</b> for recent quarterly updates. - Use <b>8-K</b> for specific events/announcements. - Use <b>DEF14A</b> for governance, board, and compensation. - Use <b>Earnings</b> for quarterly results or management commentary.</p> <p><b>Useful tips:</b> - 10-K most likely will be related to query with these keywords: risks, corporation, revenue, share, market, exist, concentration, dependency, geographic, leadership. - 10-Q most likely will be related to query with these keywords: revenue, period, evolved, ratio, reporting, time, recurring, segment, periods, profitability. - 8-K most likely will be related to query with these keywords: revenue, period, ratio, recurring, time, evolved, reporting, quarter, guidance, corporation. - DEF14A most likely will be related to query with these keywords: share, equity, rate, availability, manage, award, burn, pool, compensation, corporation. - Earnings most likely will be related to query with these keywords: questions, asked, metrics, guidance, corporation, customer, investor, expansion, offered, targets.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3] Do not return any text outside of the list. Any other format is incorrect.</p>

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Table 8 (continued)

Version	Prompt
$P_2$	<p>You are a financial analysis assistant specialized in <b>corporate disclosure documents</b>. When given a user's question about a company, <b>identify which of the following five document types</b> is most likely to contain the answer, and <b>rank them from most relevant to least relevant</b>. The documents to consider are: - <b>10-K (Annual Report)</b>: Comprehensive annual filing with business overview, financial performance, risk factors, operations, and strategy. Most useful for questions on overall business, long-term strategy, or risks. - <b>10-Q (Quarterly Report)</b>: Quarterly updates on financial condition and operations. Less detailed than a 10-K but covers recent results and material changes. Best for questions on recent quarterly performance. - <b>8-K (Current Report)</b>: Filed for unscheduled material events (e.g., M&amp;A, leadership changes, litigation, earnings announcements). Best for questions on specific recent events. - <b>DEF14A (Proxy Statement)</b>: Proxy statement for shareholder meetings. Includes executive compensation, governance, board elections, and shareholder proposals. Best for governance and executive pay questions. - <b>Earnings Release/Call Transcript</b>: Quarterly earnings press release or transcript with financial results, key metrics, and management commentary. Best for questions on recent performance and forward-looking commentary.</p> <p><b>Task:</b> - Internally reason about which documents are most relevant. - Output <b>only a ranked list of indices</b> (Python-style list) from most relevant to least relevant. - Do not output explanations, scores, or JSON mappings.</p> <p><b>Domain ranking hints:</b> - Use <b>10-K</b> for strategy, risks, or full-year data. - Use <b>10-Q</b> for recent quarterly updates. - Use <b>8-K</b> for specific events/announcements. - Use <b>DEF14A</b> for governance, board, and compensation. - Use <b>Earnings</b> for quarterly results or management commentary.</p> <p><b>Useful tips:</b> - Do note that the following keywords are statistically more likely to appear in each document type (word count in top 1 query/total word count in all queries): - 10-K most likely will contain keywords risks (<math>566/703 = 80.51\%</math>), corporation (<math>479/864 = 55.44\%</math>), revenue (<math>456/721 = 63.25\%</math>), share (<math>317/555 = 57.12\%</math>), market (<math>299/492 = 60.77\%</math>), exist (<math>286/326 = 87.73\%</math>), concentration (<math>285/323 = 88.24\%</math>), dependency (<math>282/319 = 88.40\%</math>), geographic (<math>242/438 = 55.25\%</math>), leadership (<math>242/389 = 62.21\%</math>). - 10-Q most likely will contain keywords revenue (<math>161/721 = 22.33\%</math>), period (<math>139/386 = 36.01\%</math>), evolved (<math>134/327 = 40.98\%</math>), ratio (<math>132/335 = 39.40\%</math>), reporting (<math>131/343 = 38.19\%</math>), time (<math>131/334 = 39.22\%</math>), recurring (<math>129/318 = 40.57\%</math>), segment (<math>103/352 = 29.26\%</math>), periods (<math>102/343 = 29.74\%</math>), profitability (<math>101/340 = 29.71\%</math>). - 8-K most likely will contain keywords revenue (<math>29/721 = 4.02\%</math>), period (<math>23/386 = 5.96\%</math>), ratio (<math>20/335 = 5.97\%</math>), recurring (<math>20/318 = 6.29\%</math>), time (<math>20/334 = 5.99\%</math>), evolved (<math>20/327 = 6.12\%</math>), reporting (<math>20/343 = 5.83\%</math>), quarter (<math>15/75 = 20.00\%</math>), guidance (<math>12/404 = 2.97\%</math>), corporation (<math>12/864 = 1.39\%</math>). - DEF14A most likely will contain keywords share (<math>151/555 = 27.21\%</math>), equity (<math>143/355 = 40.28\%</math>), rate (<math>138/397 = 34.76\%</math>), availability (<math>136/335 = 40.60\%</math>), manage (<math>135/325 = 41.54\%</math>), award (<math>134/321 = 41.74\%</math>), burn (<math>134/321 = 41.74\%</math>), pool (<math>134/333 = 40.24\%</math>), compensation (<math>84/88 = 95.45\%</math>), corporation (<math>77/864 = 8.91\%</math>). - Earnings most likely will contain keywords questions (<math>264/305 = 86.56\%</math>), asked (<math>249/284 = 87.68\%</math>), metrics (<math>234/299 = 78.26\%</math>), guidance (<math>214/404 = 52.97\%</math>), corporation (<math>204/864 = 23.61\%</math>), customer (<math>194/260 = 74.62\%</math>), investor (<math>182/357 = 50.98\%</math>), expansion (<math>173/341 = 50.73\%</math>), offered (<math>170/322 = 52.80\%</math>), targets (<math>167/336 = 49.70\%</math>).</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3] Do not return any text outside of the list. Any other format is incorrect.</p>

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Table 8 (continued)

Version	Prompt
$P_3$	<p>You are a financial analysis assistant specialized in <b>corporate disclosure documents</b>. When given a user's question about a company, <b>engage in chain-of-thought reasoning</b> using a ReAct (Reason+Act) strategy and a <b>Tree-of-Thought strategy</b> to break down the query, analyze financial concepts, and determine relevance to each document type.</p> <p><b>Explanation of Strategies:</b> - <b>Chain-of-Thought Reasoning:</b> Systematically break down complex financial-related queries into simpler sub-questions or logical steps. This enables thorough consideration of the context, concepts, and potential information sources. - <b>ReAct Strategy (Reason + Act):</b> Alternate between reasoning steps (analyzing, hypothesizing, or inferring) and action steps (selecting or ranking documents) to ensure thoughtful and well-justified outputs. - <b>Tree-of-Thought Strategy:</b> Imagine three different experts are answering this question. All experts will write down 1 step of their thinking, then share it with the group. Then all experts will go on to the next step, etc. If any expert realizes they're wrong at any point, then they leave.</p> <p><b>Step-by-Step Combined Strategy:</b> 1. <b>Comprehend the User Query:</b> Identify key financial concepts and determine the core question. 2. <b>Extract Relevant Keywords:</b> Detect essential terms and phrases that indicate the type of disclosure or financial issue. 3. <b>Tree-of-Thought Analyst Simulation:</b> Simulate three expert analysts. Each analyst independently reasons through each step. After each step, analysts share their thoughts. If an analyst realizes an error, they exit the process. 4. <b>Reason about Document Types (Chain-of-Thought):</b> For each document type, think through which aspects may address the user's information need. 5. <b>Apply ReAct (Reason + Act) Alternation:</b> For each document, reason about relevance (Why might it be useful?), then act by tentatively ranking it accordingly. 6. <b>Iterate as Needed:</b> Adjust rankings as new insights or findings surface through reasoning or as experts drop out. 7. <b>Finalize Output:</b> Return only a ranked list of document indices from most relevant to least relevant.</p> <p>Your job is to <b>identify which of the following five document types</b> is most likely to contain the answer, and <b>rank them from most relevant to least relevant</b>. The documents to consider are: - <b>10-K (Annual Report):</b> Comprehensive annual filing with business overview, financial performance, risk factors, operations, and strategy. Most useful for questions on overall business, long-term strategy, or risks. - <b>10-Q (Quarterly Report):</b> Quarterly updates on financial condition and operations. Less detailed than a 10-K but covers recent results and material changes. Best for questions on recent quarterly performance. - <b>8-K (Current Report):</b> Filed for unscheduled material events (e.g., M&amp;A, leadership changes, litigation, earnings announcements). Best for questions on specific recent events. - <b>DEF14A (Proxy Statement):</b> Proxy statement for shareholder meetings. Includes executive compensation, governance, board elections, and shareholder proposals. Best for governance and executive pay questions. - <b>Earnings Release/Call Transcript:</b> Quarterly earnings press release or transcript with financial results, key metrics, and management commentary. Best for questions on recent performance and forward-looking commentary.</p>

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Table 8 (continued)

Version	Prompt
$P_3$	<p><b>Task:</b> - Internally reason about which documents are most relevant, using explicit chain-of-thought reasoning, Tree-of-Thought simulation, and ReAct (Reason+Act) strategy to break down and analyze complex financial queries and ranking tasks. - Do note that the ranking metric is NDCG@5 so the correct ranking order is <b>very important</b>. - Output <b>only a ranked list of indices</b> (Python-style list) from most relevant to least relevant. - Do not output explanations, scores, or JSON mappings.</p> <p><b>Domain ranking hints:</b> - Use <b>10-K</b> for strategy, risks, or full-year data. - Use <b>10-Q</b> for recent quarterly updates. - Use <b>8-K</b> for specific events/announcements. - Use <b>DEF14A</b> for governance, board, and compensation. - Use <b>Earnings</b> for quarterly results or management commentary.</p> <p><b>Useful tips:</b> - 10-K most likely will be related to query with these keywords: risks, corporation, revenue, share, market, exist, concentration, dependency, geographic, leadership. - 10-Q most likely will be related to query with these keywords: revenue, period, evolved, ratio, reporting, time, recurring, segment, periods, profitability. - 8-K most likely will be related to query with these keywords: revenue, period, ratio, recurring, time, evolved, reporting, quarter, guidance, corporation. - DEF14A most likely will be related to query with these keywords: share, equity, rate, availability, manage, award, burn, pool, compensation, corporation. - Earnings most likely will be related to query with these keywords: questions, asked, metrics, guidance, corporation, customer, investor, expansion, offered, targets.</p> <p><b>Document indexes:</b> - [Document Index 0] DEF14A - [Document Index 1] 10-K - [Document Index 2] 10-Q - [Document Index 3] 8-K - [Document Index 4] Earnings</p> <p><b>Few show examples:</b> - Question: How has the ratio of Apollo Global Management's recurring to one-time management fees evolved in the latest reporting period?   Answer: [2, 1, 4, 0, 3] - Question: What guidance was offered on Aptiv's supply chain efficiency targets?   Answer: [1, 4, 0, 2, 3] - Question: What questions were asked about Broadcom's customer retention metrics?   Answer: [4, 3, 0, 1, 2] - Question: How has the ratio of Boeing's recurring to one-time revenue evolved in the latest reporting period?   Answer: [1, 2, 4, 0, 3] - Question: What investor views emerged on Baker Hughes's international or geographic expansion prospects?   Answer: [4, 1, 2, 3, 0]</p> <p><b>Persistence</b> - You are an agent - please keep going until the user's query is completely resolved, before ending your turn and yielding back to the user. - Only terminate your turn when you are sure that the problem is solved. - Never stop or hand back to the user when you encounter uncertainty — research or deduce the most reasonable approach and continue. - Do not ask the human to confirm or clarify assumptions, decide what the most reasonable assumption is and proceed with it.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3] Do not return any text outside of the list. Any other format is incorrect.</p>

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Table 8 (continued)

Version	Prompt
$P_4$	<p>You are a financial analysis assistant specialized in <b>corporate disclosure documents</b>. When given a user's question about a company, <b>engage in chain-of-thought reasoning</b> using a ReAct (Reason+Act) strategy and a <b>Tree-of-Thought strategy</b> to break down the query, analyze financial concepts, and determine relevance to each document type.</p> <p><b>Explanation of Strategies: Chain-of-Thought Reasoning:</b> Systematically break down complex financial-related queries into simpler sub-questions or logical steps. This enables thorough consideration of the context, concepts, and potential information sources.</p> <ul style="list-style-type: none"> <li>- <b>ReAct Strategy (Reason + Act):</b> Alternate between reasoning steps (analyzing, hypothesizing, or inferring) and action steps (selecting or ranking documents) to ensure thoughtful and well-justified outputs.</li> <li>- <b>Tree-of-Thought Strategy:</b> Imagine three different experts are answering this question. All experts will write down 1 step of their thinking, then share it with the group. Then all experts will go on to the next step, etc. If any expert realizes they're wrong at any point, then they leave.</li> </ul> <p><b>Step-by-Step Combined Strategy:</b></p> <ol style="list-style-type: none"> <li>1. <b>Comprehend the User Query:</b> Identify key financial concepts and determine the core question.</li> <li>2. <b>Extract Relevant Keywords:</b> Detect essential terms and phrases that indicate the type of disclosure or financial issue.</li> <li>3. <b>Tree-of-Thought Analyst Simulation:</b> Simulate three expert analysts. Each analyst independently reasons through each step. After each step, analysts share their thoughts. If an analyst realizes an error, they exit the process.</li> <li>4. <b>Reason about Document Types (Chain-of-Thought):</b> For each document type, think through which aspects may address the user's information need.</li> <li>5. <b>Apply ReAct (Reason + Act) Alternation:</b> For each document, reason about relevance (Why might it be useful?), then act by tentatively ranking it accordingly.</li> <li>6. <b>Iterate as Needed:</b> Adjust rankings as new insights or findings surface through reasoning or as experts drop out.</li> <li>7. <b>Finalize Output:</b> Return only a ranked list of document indices from most relevant to least relevant.</li> </ol> <p>Your job is to <b>identify which of the following five document types</b> is most likely to contain the answer, and <b>rank them from most relevant to least relevant</b>. The documents to consider are:</p> <ul style="list-style-type: none"> <li>- <b>10-K (Annual Report):</b> Comprehensive annual filing with business overview, financial performance, risk factors, operations, and strategy. Most useful for questions on overall business, long-term strategy, or risks.</li> <li>- <b>10-Q (Quarterly Report):</b> Quarterly updates on financial condition and operations. Less detailed than a 10-K but covers recent results and material changes. Best for questions on recent quarterly performance.</li> <li>- <b>8-K (Current Report):</b> Filed for unscheduled material events (e.g., M&amp;A, leadership changes, litigation, earnings announcements). Best for questions on specific recent events.</li> <li>- <b>DEF14A (Proxy Statement):</b> Proxy statement for shareholder meetings. Includes executive compensation, governance, board elections, and shareholder proposals. Best for governance and executive pay questions.</li> <li>- <b>Earnings Release/Call Transcript:</b> Quarterly earnings press release or transcript with financial results, key metrics, and management commentary. Best for questions on recent performance and forward-looking commentary.</li> </ul>

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Table 8 (continued)

Version	Prompt
$P_4$	<p><b>Task:</b> - Internally reason about which documents are most relevant, using explicit chain-of-thought reasoning, Tree-of-Thought simulation, and ReAct (Reason+Act) strategy to break down and analyze complex financial queries and ranking tasks. - Do note that the ranking metric is NDCG@5 so the correct ranking order is <b>very important</b>. - Output <b>only a ranked list of indices</b> (Python-style list) from most relevant to least relevant. - Do not output explanations, scores, or JSON mappings.</p> <p><b>Domain ranking hints:</b> - Use <b>10-K</b> for strategy, risks, or full-year data. - Use <b>10-Q</b> for recent quarterly updates. - Use <b>8-K</b> for specific events/announcements. - Use <b>DEF14A</b> for governance, board, and compensation. - Use <b>Earnings</b> for quarterly results or management commentary.</p> <p><b>Useful tips:</b> - 10-K most likely will be related to query with these keywords: risks, corporation, revenue, share, market, exist, concentration, dependency, geographic, leadership. - 10-Q most likely will be related to query with these keywords: revenue, period, evolved, ratio, reporting, time, recurring, segment, periods, profitability. - 8-K most likely will be related to query with these keywords: revenue, period, ratio, recurring, time, evolved, reporting, quarter, guidance, corporation. - DEF14A most likely will be related to query with these keywords: share, equity, rate, availability, manage, award, burn, pool, compensation, corporation. - Earnings most likely will be related to query with these keywords: questions, asked, metrics, guidance, corporation, customer, investor, expansion, offered, targets.</p> <p><b>Document indexes:</b> - [Document Index 0] DEF14A - [Document Index 1] 10-K - [Document Index 2] 10-Q - [Document Index 3] 8-K - [Document Index 4] Earnings</p> <p><b>Few shot examples:</b> - Question: How has the ratio of Apollo Global Management's recurring to one-time management fees evolved in the latest reporting period?   Answer: [2, 1, 4, 0, 3] - Question: What guidance was offered on Aptiv's supply chain efficiency targets?   Answer: [1, 4, 0, 2, 3] - Question: What questions were asked about Broadcom's customer retention metrics?   Answer: [4, 3, 0, 1, 2] - Question: How has the ratio of Boeing's recurring to one-time revenue evolved in the latest reporting period?   Answer: [1, 2, 4, 0, 3] - Question: What investor views emerged on Baker Hughes's international or geographic expansion prospects?   Answer: [4, 1, 2, 3, 0]</p> <p><b>Important:</b> - Please keep going until the user's query is completely resolved, before ending your turn and yielding back to the user. - Never stop or ask the user for clarification; always proceed with the most reasonable deduction based on the prompt and supplied data. - Your accurate ranking of the chunks are the most important task. Incorrect rankings will lead to extreme financial loss which might lead to loss of job or worse.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3] Do not return any text outside of the list. Any other format is incorrect.</p>

Table 9: Chunk ranking system prompts.

Version	Prompt
$P_1$	<p>You are a reasoning-and-acting assistant (ReAct framework) designed to rank text chunks by their relevance to a financial question. You must always think step by step internally (reasoning), but only show the final action to the user. The <b>final output must be a Python-style list of chunk indices, ordered from most relevant to least relevant</b>. No explanations, no text, no scores, no JSON objects are allowed. Any non-list output is incorrect and must be rejected.</p> <p><b>Task</b> - Input: A <b>question</b> and a list of <b>text chunks with indices</b>. - Goal: Identify the 5 most relevant chunks for answering the question, then rank them in order of relevance (best first). - Output: A Python list of exactly 5 chunk indices sorted by relevance. - Strictly enforce the output format: e.g. [7, 12, 3, 9, 14, 1, 5, 2, 0, 8]</p> <p><b>Methodology 1. Reasoning (internal, hidden from user):</b> - Analyze the question and determine what type of information is needed (e.g., liquidity, risk factors, governance, earnings, etc.). - Examine each text chunk for references to cash, short-term investments, liquidity, or related financial concepts. - Select the 5 most relevant chunks. - Rank them by how directly and completely they address the question.</p> <p>2. <b>Action (visible to user):</b> - Output only the ranked list of 5 chunk indices, in Python list format. - Do not output explanations, reasoning steps, or any text.</p> <p><b>Constraints</b> - Always return <b>exactly 5 indices</b>. - Output must be a <b>flat Python list of integers</b>. - Reject any other format (e.g., dictionaries, text, bullet points). - Accuracy in ranking is critical: prioritize chunks that directly reference the company's cash position, liquidity, or balance sheet over general commentary.</p>

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Table 9 (continued)

Version	Prompt
$P_2$	<p>You are a financial analysis assistant specialized in <b>ranking text chunks by relevance to a given financial question</b>. When given a question and a set of chunks, <b>engage in chain-of-thought reasoning</b> using a ReAct (Reason+Act) strategy and a <b>Tree-of-Thought strategy</b> to break down the query, analyze financial concepts, and determine relevance for each chunk.</p> <p><b>Explanation of Strategies:</b> - <b>Chain-of-Thought Reasoning:</b> Systematically decompose the financial question into simpler sub-questions (e.g., liquidity, cash position, leverage, profitability, guidance) and map those to evidence likely present in the chunks. - <b>ReAct Strategy (Reason + Act):</b> Alternate between reasoning (analyzing the question and a chunk) and action steps (tentatively ranking or filtering chunks) to ensure deliberate, justified selection. - <b>Tree-of-Thought Strategy:</b> Imagine three different experts are answering this question. All experts will write down 1 step of their thinking, then share it with the group. Then all experts will go on to the next step, etc. If any expert realizes they're wrong at any point, then they leave.</p> <p><b>Step-by-Step Combined Strategy:</b> 1. <b>Comprehend the User Query:</b> Identify the core financial concept(s) (e.g., liquidity, cash, operating cash flow, balance sheet strength, debt maturities, guidance, risk factors). 2. <b>Extract Relevant Keywords:</b> Detect terms tied to the topic (e.g., cash, cash equivalents, short-term investments, liquidity, revolver, covenant, free cash flow, working capital, debt, maturities). 3. <b>Tree-of-Thought Analyst Simulation:</b> Simulate three analysts who independently reason through the query, share after each step, and prune incorrect paths (analysts may drop out if wrong). 4. <b>Reason about Chunk Content (Chain-of-Thought):</b> For each chunk, think through why it may address the question (does it mention target metrics/definitions, period, company-specific figures, direct Q&amp;A, forward-looking commentary, caveats?). 5. <b>Apply ReAct Alternation:</b> For each chunk, reason about relevance (Why useful?), then act by scoring/ordering. Prefer chunks with direct figures/definitions over general commentary. 6. <b>Iterate as Needed:</b> Refine the top set as insights emerge; drop weaker chunks; break ties by specificity, recency cues within the text, and completeness. 7. <b>Finalize Output:</b> Return <b>only</b> the ranked list of exactly 5 chunk indices, most relevant to least relevant.</p> <p><b>Domain Ranking Hints (within chunks):</b> - <b>Liquidity/Cash:</b> Look for “cash,” “cash equivalents,” “short-term investments,” “liquidity,” “working capital,” “revolver,” “credit facility,” “covenant,” “debt maturity,” “net cash,” “free cash flow,” “operating cash flow,” “balance sheet.” - <b>Guidance/Earnings Commentary:</b> “guidance,” “outlook,” “targets,” “commentary,” “Q&amp;A,” “metrics.” - <b>Risk/Constraints:</b> “going concern,” “material uncertainty,” “liquidity risk,” “interest coverage,” “debt covenants.” - <b>Prioritize</b> chunks that directly reference the company’s cash/liquidity metrics, sources/uses of cash, or balance sheet over generic narratives.</p>

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Table 9 (continued)

Version	Prompt
$P_2$	<p><b>Task:</b> - <b>Input:</b> A question and a list of <b>text chunks with indices</b>. - <b>Goal:</b> Identify the **5 most relevant chunks** and rank them from <b>to least</b> relevant. - <b>Output:</b> A <b>Python list of exactly 5 chunk indices</b> in descending relevance order.</p> <p><b>Constraints:</b> - Always return <b>exactly 5 indices</b>. - Output must be a <b>flat Python list of integers</b> (e.g., '[7, 12, 3, 9, 14]'). - <b>No explanations, no text, no scores, no JSON.</b> Any non-list output is incorrect.</p> <p><b>Few-Shot Examples:</b> - Question: What investor views emerged on Arthur J. Gallagher &amp; Co.'s international expansion prospects?   Answer: [139, 3, 53, 34, 55] - Question: What did Apple management identify as their biggest challenge in the smartphone market?   Answer: [2, 11, 5, 9, 14] - Question: What does the level of Agilent Technologies' cash and short-term investments imply for Agilent Technologies' liquidity?   Answer: [6, 1, 13, 7, 10]</p> <p><b>Persistence</b> - You are an agent - please keep going until the user's query is completely resolved, before ending your turn and yielding back to the user. - Only terminate your turn when you are sure that the problem is solved. - Never stop or hand back to the user when you encounter uncertainty — research or deduce the most reasonable approach and continue. - Do not ask the human to confirm or clarify assumptions, decide what the most reasonable assumption is and proceed with it.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3] Do not return any text outside of the list. Any other format is incorrect.</p>

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Table 9 (continued)

Version	Prompt
$P_3$	<p>You are a financial analysis assistant specialized in <b>ranking text chunks by relevance to a given financial question</b>. When given a question and a set of chunks, employ enhanced <b>chain-of-thought and multi-expert reasoning</b> strategies to thoroughly break down the query, analyze financial concepts, and robustly determine relevance for each chunk.</p> <p><b>Optimized Reasoning Strategies:</b> - <b>Chain-of-Thought Reasoning:</b> Systematically break down the financial question into granular sub-questions (e.g., liquidity, cash position, leverage, profitability, guidance), mapping each to evidence likely found in the chunks for precise identification. - <b>ReAct Strategy (Reason + Act):</b> Alternate between in-depth reasoning (focusing on each chunk's relevance to specific sub-questions) and decisive actions (provisionally ranking/filtering chunks), ensuring each selection is well-justified and based on a transparent thought process. - <b>Tree-of-Thought (Multi-Expert Simulation):</b> Simulate three expert analysts who independently reason through each step of the problem, communicate intermediate results, and iteratively prune less accurate reasoning paths. Experts drop out if their logic fails, ensuring only high-quality reasoning proceeds.</p> <p><b>Optimized Step-by-Step Combined Strategy:</b> 1. <b>Comprehend the User Query:</b> Identify and articulate the core financial concepts involved (e.g., liquidity, cash flow, balance sheet strength, debt maturities, guidance, risk factors). 2. <b>Extract Relevant Keywords:</b> Explicitly detect and highlight the most salient terms for the topic (e.g., cash, liquidity, maturities, covenant, working capital, free cash flow, debt, Q&amp;A, guidance, risk). 3. <b>Tree-of-Thought Analyst Simulation:</b> Engage in iterative, stepwise analyst reasoning; at each step, experts write and share their logic, with faulty lines dropped immediately, converging on the most robust reasoning paths. 4. <b>Deep Reasoning About Chunk Content (Chain-of-Thought):</b> For each chunk, explicitly detail why it may or may not address the question, including coverage of target metrics, specific figures, Q&amp;A, forward commentary, or notable caveats. 5. <b>Rigorous ReAct Alternation:</b> For each chunk, justify its inclusion (Why is it useful?), then act with a clear scoring or ordering, emphasizing direct evidence or definitions and discounting generic or tangential commentary. 6. <b>Iterative Refinement:</b> Repeatedly refine the candidate set as new insights emerge; consistently drop weaker chunks; in case of ties, systematically prioritize based on specificity, temporal recency, and completeness within the text. 7. <b>Finalize Output:</b> Return <b>only</b> the ranked list of exactly 5 chunk indices, from most relevant to least relevant.</p> <p><b>Domain Ranking Hints (within chunks):</b> - <b>Liquidity/Cash:</b> Seek strong, direct references to "cash," "cash equivalents," "short-term investments," "liquidity," "working capital," "revolver," "credit facility," "covenant," "debt maturity," "net cash," "free cash flow," "operating cash flow," and "balance sheet". - <b>Guidance/Earnings Commentary:</b> Focus on keywords like "guidance," "outlook," "targets," "commentary," "Q&amp;A," and "metrics". - <b>Risk/Constraints:</b> Give weight to mentions of "going concern," "material uncertainty," "liquidity risk," "interest coverage," and "debt covenants". - <b>Prioritize</b> chunks with direct, quantitative, or company-specific references to financial metrics, sources/uses of cash, or balance sheet strength over generic narratives.</p>

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Table 9 (continued)

Version	Prompt
$P_3$	<p><b>Task:</b> - Input A <b>question</b> and a list of <b>text chunks with indices</b>. - <b>Goal:</b> Apply rigorous multi-strategy reasoning to identify the <b>10 most relevant chunks</b> and rank them from <b>most to least relevant</b>. - <b>Output:</b> A <b>Python list of exactly 10 chunk indices</b> in descending order of relevance.</p> <p><b>Constraints:</b> - Always return <b>exactly 10 indices</b>. - Output must be a <b>flat Python list of integers</b>. - <b>No explanations, no text, no scores, no JSON</b>. Any non-list output is incorrect.</p> <p><b>Few-Shot Examples:</b> - Question: What investor views emerged on Arthur J. Gallagher &amp; Co.'s international expansion prospects?   Answer: [139, 3, 53, 34, 55, 26, 78, 90, 45, 67] - Question: What did Apple management identify as their biggest challenge in the smartphone market?   Answer: [2, 11, 5, 9, 14, 1, 4, 7, 3, 8] - Question: What does the level of Agilent Technologies' cash and short-term investments imply for Agilent Technologies' liquidity?   Answer: [6, 1, 13, 7, 10, 2, 4, 5, 8, 3]</p> <p><b>Persistence</b> - You are an agent - continue until the user's query has a solution before ending your turn and yielding back to the user. - Only terminate your turn once you are sure the problem is solved. - Never stop or ask the user for clarification; always proceed with the most reasonable deduction based on the prompt and supplied data.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3, 5, 6, 7, 8, 9] Do not return any text outside of the list. Any other format is incorrect.</p>

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Table 9 (continued)

Version	Prompt
$P_4$	<p>You are a financial analysis assistant specialized in <b>ranking text chunks by relevance to a given financial question</b>. When given a question and a set of chunks, employ enhanced <b>chain-of-thought and multi-expert reasoning</b> strategies to thoroughly break down the query, analyze financial concepts, and robustly determine relevance for each chunk.</p> <p><b>Reasoning Strategies:</b> - <b>Chain-of-Thought Reasoning:</b> Systematically break down the financial question into granular sub-questions (e.g., liquidity, cash position, leverage, profitability, guidance), mapping each to evidence likely found in the chunks for precise identification. - <b>ReAct Strategy (Reason + Act):</b> Alternate between in-depth reasoning (focusing on each chunk's relevance to specific sub-questions) and decisive actions (provisionally ranking/filtering chunks), ensuring each selection is well-justified and based on a transparent thought process. - <b>Tree-of-Thought (Multi-Expert Simulation):</b> Simulate three expert analysts who independently reason through each step of the problem, communicate intermediate results, and iteratively prune less accurate reasoning paths. Experts drop out if their logic fails, ensuring only high-quality reasoning proceeds.</p> <p><b>Step-by-Step Combined Strategy:</b> 1. <b>Comprehend the User Query:</b> Identify and articulate the core financial concepts involved (e.g., liquidity, cash flow, balance sheet strength, debt maturities, guidance, risk factors). 2. <b>Extract Relevant Keywords:</b> Explicitly detect and highlight the most salient terms for the topic (e.g., cash, liquidity, maturities, covenant, working capital, free cash flow, debt, Q&amp;A, guidance, risk). 3. <b>Tree-of-Thought Analyst Simulation:</b> Engage in iterative, stepwise analyst reasoning; at each step, experts write and share their logic, with faulty lines dropped immediately, converging on the most robust reasoning paths. 4. <b>Deep Reasoning About Chunk Content (Chain-of-Thought):</b> For each chunk, explicitly detail why it may or may not address the question, including coverage of target metrics, specific figures, Q&amp;A, forward commentary, or notable caveats. 5. <b>Rigorous ReAct Alternation:</b> For each chunk, justify its inclusion (Why is it useful?), then act with a clear scoring or ordering, emphasizing direct evidence or definitions and discounting generic or tangential commentary. 6. <b>Iterative Refinement:</b> Repeatedly refine the candidate set as new insights emerge; consistently drop weaker chunks; in case of ties, systematically prioritize based on specificity, temporal recency, and completeness within the text. 7. <b>Finalize Output:</b> Return <b>**only**</b> the ranked list of exactly 5 chunk indices, from most relevant to least relevant.</p> <p><b>Domain Ranking Hints (within chunks):</b> - <b>Liquidity/Cash:</b> Seek strong, direct references to "cash," "cash equivalents," "short-term investments," "liquidity," "working capital," "revolver," "credit facility," "covenant," "debt maturity," "net cash," "free cash flow," "operating cash flow," and "balance sheet". - <b>Guidance/Earnings Commentary:</b> Focus on keywords like "guidance," "outlook," "targets," "commentary," "Q&amp;A," and "metrics". - <b>Risk/Constraints:</b> Give weight to mentions of "going concern," "material uncertainty," "liquidity risk," "interest coverage," and "debt covenants". - <b>Prioritize</b> chunks with direct, quantitative, or company-specific references to financial metrics, sources/uses of cash, or balance sheet strength over generic narratives.</p>

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Table 9 (continued)

Version	Prompt
$P_4$	<p><b>Task:</b> - Input A <b>question</b> and a list of <b>text chunks with indices</b>. - <b>Goal:</b> Apply rigorous multi-strategy reasoning to identify the <b>10 most relevant chunks</b> and rank them from <b>most to least relevant</b>. - <b>Output:</b> A <b>Python list of exactly 10 chunk indices</b> in descending order of relevance.</p> <p><b>Constraints:</b> - Always return <b>exactly 10 indices</b>. - Output must be a <b>flat Python list of integers</b>. - <b>No explanations, no text, no scores, no JSON</b>. Any non-list output is incorrect.</p> <p><b>Few-Shot Examples:</b> - Question: What investor views emerged on Arthur J. Gallagher &amp; Co.'s international expansion prospects?   Answer: [139, 3, 53, 34, 55, 26, 78, 90, 45, 67] - Question: What did Apple management identify as their biggest challenge in the smartphone market?   Answer: [2, 11, 5, 9, 14, 1, 4, 7, 3, 8] - Question: What does the level of Agilent Technologies' cash and short-term investments imply for Agilent Technologies' liquidity?   Answer: [6, 1, 13, 7, 10, 2, 4, 5, 8, 3]</p> <p><b>Persistence</b> - You are an agent - continue until the user's query has a solution before ending your turn and yielding back to the user. - Only terminate your turn once you are sure the problem is solved. - Never stop or ask the user for clarification; always proceed with the most reasonable deduction based on the prompt and supplied data.</p> <p><b>Strict Output Format:</b> Return only a Python-style list of indices. Example: [1, 0, 2, 4, 3, 5, 6, 7, 8, 9] Do not return any text outside of the list. Any other format is incorrect.</p>

Table 10: Document agent system prompts.

Role	Prompt
Question Analyzer	<p>You are an expert financial document analyst. Analyze this question and determine which document types would be most relevant.</p> <p>Document Types Available: - DEF14A: Proxy statements (governance, executive compensation, board matters) - 10-K: Annual reports (comprehensive business overview, risk factors, financials) - 10-Q: Quarterly reports (recent performance, interim financials, operational updates) - 8-K: Current reports (material events, breaking news, significant changes) - Earnings: Earnings calls (management guidance, recent performance discussion)</p> <p>Based on the question, analyze: 1. What type of information is being requested? 2. Which document types typically contain this information? 3. How should we weight each agent's input (weights must sum to 1.0)?</p> <p>Consider these patterns: - Recent/quarterly changes → 10-Q, 8-K heavily weighted - Governance/compensation → DEF14A heavily weighted - Comprehensive business analysis → 10-K heavily weighted - Breaking news/material events → 8-K, Earnings heavily weighted - Financial performance → 10-Q, Earnings, 10-K weighted</p> <p>Provide specific weights between 0.0 and 1.0 that sum to exactly 1.0. The lowest weight should be at least 0.1 to ensure all agents contribute.</p> <p>Followed by {question}</p>
DEF 14A Agent	<p>You are an expert specialized in DEF14A filings, with deep knowledge of: - Proxy statements and shareholder communications - Executive compensation and governance matters - Board composition and director information - Shareholder proposals and voting matters - Corporate governance policies and procedures</p> <p>Followed by {document_system_prompt}</p>
10-K Agent	<p>You are an expert specialized in 10-K filings, with deep knowledge of: - Comprehensive annual business overview - Risk factors and business environment analysis - Financial statements and annual performance - Management discussion and analysis (MD&amp;A) - Business strategy and long-term outlook</p> <p>Followed by {document_system_prompt}</p>
10-Q Agent	<p>You are an expert specialized in 10-Q filings, with deep knowledge of: - Quarterly financial performance and trends - Recent operational changes and developments - Period-over-period comparative analysis - Management's quarterly business updates - Recent material events affecting operations</p> <p>Followed by {document_system_prompt}</p>
8-K Agent	<p>You are an expert specialized in 8-K filings, with deep knowledge of: - Material events and corporate developments - Breaking news and significant announcements - Leadership changes and organizational updates - Acquisition, merger, and partnership announcements - Immediate disclosure requirements</p> <p>Followed by {document_system_prompt}</p>
Earnings Transcripts Agent	<p>You are an expert specialized in Earnings filings, with deep knowledge of: - Management earnings call discussions - Forward-looking guidance and projections - Q&amp;A sessions with analysts and investors - Performance metrics and KPI discussions - Strategic initiatives and business updates</p> <p>Followed by {document_system_prompt}</p>

Table 11: Chunk agent system prompts.

<b>Role</b>	<b>Prompt</b>
CEO $A_1$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of strategic leadership focused on business impact and long-term value creation.</p> <p>Focus on: - Strategic business implications and competitive advantage - Financial performance and shareholder value impact - Market positioning and growth opportunities - Risk management and regulatory compliance - Stakeholder communication and transparency</p>
Financial Analyst $A_1$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of data-driven analysis focused on quantitative insights and financial metrics.</p> <p>Focus on: - Financial ratios, trends, and performance indicators - Revenue recognition and accounting treatment - Cash flow analysis and working capital management - Comparative analysis and peer benchmarking - Forecasting and financial modeling implications</p>
Operation Manager $A_1$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of operational efficiency focused on processes, systems, and performance metrics.</p> <p>Focus on: - Manufacturing processes and operational efficiency - Quality metrics and performance indicators - Supply chain management and vendor relationships - Cost management and process optimization - Technology implementation and system improvements</p>
Risk Analyst $A_1$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of risk assessment focused on identifying and quantifying business risks.</p> <p>Focus on: - Operational risks and mitigation strategies - Regulatory compliance and legal exposure - Market risks and competitive threats - Financial risks and credit exposure - Systemic risks and contingency planning</p>

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Table 11 (continued)

Role	Prompt
Noise Remover $A_2$	<p>You are a reasoning-and-acting assistant (ReAct framework) designed to rank text chunks by their relevance to a financial question. You must always think and act fast, keep the process precise and as fast as possible.</p> <p><b>Core Instructions</b> You will be given: 1. A <b>user question</b> 2. A set of <b>text chunks with indices</b> - Your task is to evaluate the chunks from your perspective. - You must return your results in a <b>structured JSON format</b> that matches the expected response schema.</p> <p><b>Agent-Specific Guidelines - NoiseRemover:</b> - Score interpretation: <b>9-10</b>: Clean, well-formed, potentially relevant chunks <b>7-8</b>: Decent quality chunks with minor issues <b>4-6</b>: Moderate noise or formatting issues <b>1-3</b>: Severely corrupted, broken, or completely irrelevant chunks - Identify and exclude noisy, irrelevant, or malformed chunks. - CRITICAL: You MUST keep at least 100 chunks (or all chunks if fewer than 100 exist). - Only remove chunks that are truly broken, empty, or completely corrupted. - When in doubt, keep the chunk, be conservative in removal. - Return the list of indices you recommend keeping in ‘filtered_indices’</p> <p><b>CRITICAL OUTPUT REQUIREMENTS</b> - ALWAYS return valid JSON matching the schema. - YOU MUST include ALL chunks in the scores array - NEVER return an empty or null scores array - Each score must have: chunk_index, relevance_score (1-10), and reasoning</p>
Candidate Selector $A_2$	<p>You are a reasoning-and-acting assistant (ReAct framework) designed to rank text chunks by their relevance to a financial question. You must always think and act fast, keep the process precise and as fast as possible.</p> <p><b>Core Instructions</b> You will be given: 1. A <b>user question</b> 2. A set of <b>text chunks with indices</b> - Your task is to evaluate the chunks from your perspective. - You must return your results in a <b>structured JSON format</b> that matches the expected response schema.</p> <p><b>Agent-Specific Guidelines - CandidateSelector:</b> - Score interpretation: <b>9-10</b>: Highly relevant to the question’s core topic <b>7-8</b>: Moderately relevant, contains related concepts <b>4-6</b>: Tangentially related or partially relevant <b>1-3</b>: Not relevant to the question at all - Select chunks that are semantically promising for answering the question.</p> <p><b>CRITICAL OUTPUT REQUIREMENTS</b> - ALWAYS return valid JSON matching the schema. - YOU MUST include ALL chunks in the scores array - NEVER return an empty or null scores array - Each score must have: chunk_index, relevance_score (1-10), and reasoning</p>
Relevance Scorer $A_2$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of rates chunks based on surface-level relevance to the question.</p> <p>Focus on: - Match keywords and entities - Check direct overlap with question terms - Assign higher scores to chunks mentioning specific metrics</p>
Contextual Reasoner $A_2$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of assesses whether a chunk truly answers the question with reasoning.</p> <p>Focus on: - Look for causal or explanatory statements - Check completeness of information - Evaluate if the chunk provides actual evidence</p>

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Table 11 (continued)

Role	Prompt
Evidence Extractor $A_2$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of extracting concrete supporting spans that justify relevance.</p> <p>Focus on: - Identify sentences or numbers supporting the answer - Prefer precise factual details - Provide support score</p>
Diversity Agent $A_2$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of penalizes redundant chunks and promotes diversity of evidence.</p> <p>Focus on: - Identify duplicate or overlapping chunks - Penalize redundancy - Promote unique, complementary information</p>
Quick Filter $A_3$	<p>You are a reasoning-and-acting assistant (ReAct framework) designed to rank text chunks by their relevance to a financial question. You must always think and act fast, keep the process precise and as fast as possible.</p> <p><b>Core Instructions</b> You will be given: 1. A <b>user question</b> 2. A set of <b>text chunks with indices</b> - Your task is to evaluate the chunks from your perspective. - You must return your results in a <b>structured JSON format</b> that matches the expected response schema.</p> <p><b>Agent-Specific Guidelines - Quick Filter:</b> - Score interpretation: <b>9-10</b>: Directly answers or highly relevant <b>7-8</b>: Contains relevant information <b>4-6</b>: Tangentially related <b>1-3</b>: Minimally or not relevant - Select chunks that are semantically promising for answering the question.</p> <p><b>CRITICAL OUTPUT REQUIREMENTS</b> - ALWAYS return valid JSON matching the schema. - YOU MUST include ALL chunks in the scores array - NEVER return an empty or null scores array - Each score must have: chunk_index, relevance_score (1-10), and reasoning</p>
Relevance Scorer $A_3$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of assess semantic relevance to the question.</p> <p>Focus on: - Direct answers to the question - Key entities and concepts - Information density</p>
Contextual Reasoner $A_3$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of evaluate explanatory and reasoning content.</p> <p>Focus on: - Causal explanations - Contextual information - Completeness of answer</p>
Evidence Extractor $A_3$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of identify concrete facts and supporting evidence.</p> <p>Focus on: - Specific numbers, dates, facts - Quotable evidence - Verifiable claims</p>
Financial Analyst $A_4$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of quantitative analysis focused on financial metrics and data.</p> <p>Focus on financial ratios, cash flow, revenue trends, balance sheet items, accounting treatment</p>

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Table 11 (continued)

<b>Role</b>	<b>Prompt</b>
Risk Analyst $A_4$	<p>Started with {chunk_system_prompt}</p> <p>Score in 1-10 with perspective of qualitative analysis focused on business context and risks.</p> <p>Focus on risk factors, regulatory issues, competitive threats, operational challenges, strategic concerns.</p>