

FinMMR: Make Financial Numerical Reasoning More Multimodal, Comprehensive, and Challenging

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 [bupt-reasoning-lab.github.io/FinMMR](https://github.com/bupt-reasoning-lab/FinMMR)



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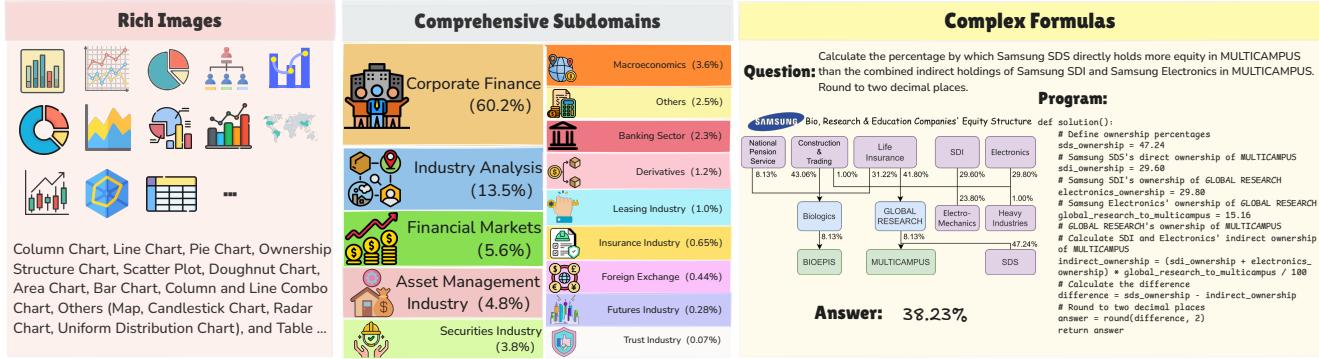


Figure 1. Overview of FinMMR. FinMMR presents three challenges: (1) **Visual Perception**: 8.7K financial images of 14 categories; (2) **Knowledge Reasoning**: 4.3K financial questions of 14 subdomains; (3) **Numerical Computation**: multi-step precise calculations.

Abstract

We present **FinMMR**, a novel bilingual multimodal benchmark tailored to evaluate the reasoning capabilities of multimodal large language models (MLLMs) in financial numerical reasoning tasks. Compared to existing benchmarks, our work introduces three significant advancements. (1) **Multimodality**: We meticulously transform existing financial reasoning benchmarks, and construct novel questions from the latest Chinese financial research reports. FinMMR comprises 4.3K questions and 8.7K images spanning 14 categories, including tables, bar charts, and ownership structure charts. (2) **Comprehensiveness**: FinMMR encompasses 14 financial subdomains, including corporate finance, banking, and industry analysis, significantly exceeding existing benchmarks in financial domain knowledge breadth. (3) **Challenge**: Models are required to perform multi-step precise numerical reasoning by integrating financial knowledge with the understanding of complex financial

images and text. The best-performing MLLM achieves only 53.0% accuracy on Hard problems. We believe that FinMMR will drive advancements in enhancing the reasoning capabilities of MLLMs in real-world scenarios.

1. Introduction

Recently, large reasoning models (LRMs) [21, 47, 48, 54, 56, 62], show powerful reasoning capabilities over multi-step reasoning tasks, with train-time scaling and test-time scaling [31, 45]. These reasoning models are proficient in code [11, 29], math [35, 41], and science [59]. Multimodal large language models (MLLMs) [5, 19, 46] also exhibit greater performance on multimodal reasoning [39, 65].

Despite significant advancements, there remains a notable gap in understanding the practical applicability of MLLMs in numerical reasoning within real-world scenarios, particularly in high-stakes fields such as finance and healthcare. As shown in Fig. 1, financial analysts in their daily work are required to read visually enriched finan-

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Rich Images Challenge Visual Perception

问题：计算2016年至2024年Q2期间，上海银行和上市城商行的个人住房贷款年均复合增长率之差，结果以百分比表示，保留两位小数。(Calculate the difference in the compound annual growth rate (CAGR) of personal housing loans between Bank of Shanghai and listed city commercial banks from 2016 to Q2 2024. Present the result as a percentage, rounded to two decimal places.)

Answer: 2.17

Compound Average Growth Rate (CAGR)

问题：请计算惠济新生对日照公司的间接持股比例，结果以百分比表示，保留两位小数。(Please calculate the indirect shareholding ratio of Huiji Xinheng in Rizhao Company. Present the result as a percentage, rounded to two decimal places.)

Answer: 13.65

Indirect Shareholding Ratio

问题：请计算2022年第四季度和2023年第一季度的总资本开支，并将其与2021年第四季度的资本开支进行比较，计算下降百分比，结果保留两位小数。(Calculate the total capital expenditure for Q4 2022 and Q1 2023 combined, and compare it to the capital expenditure for Q4 2021. Calculate the percentage decrease, rounded to two decimal places.)

Answer: -110.36

Comprehensive Subdomains Challenge Knowledge Reasoning

Q: Table 19.3 shows a book balance sheet for the Wishing Well Motel chain. The company's long-term debt is secured by its real estate assets, but it also uses short-term bank loans as a permanent source of financing. It pays 10% interest on the bank debt and 9% interest on the secured debt. Wishing Well has 10 million shares of stock outstanding, trading at \$90 per share. The expected return on Wishing Well's common stock is 18%. Calculate Wishing Well's WACC. Assume that the book and market values of Wishing Well's debt are the same. The marginal tax rate is 21%. Answer as a percentage to single decimal place.

Answer:

| | | | |
|--------------------------------|-------|---------------------|-------|
| Cash and marketable securities | 100 | Bank loan | 280 |
| Accounts receivable | 200 | Accounts payable | 120 |
| Inventory | 50 | Current liabilities | 400 |
| Current assets | 350 | | |
| Real estate | 2,100 | Long-term debt | 1,800 |
| Other assets | 150 | Equity | 400 |
| Total | 2,600 | Total | 2,600 |

TABLE 19.3 Book balance sheet for Wishing Well Inc. (figures in \$ millions)

Complex Formulas Challenge Numerical Computation

Q: What is the total weighted average Cash and Payment-In-Kind (PIK) interest rate payable under the subordinated and senior notes portfolio in the year 2022?

Answer:

$$\text{[average]} = \frac{\sum (\text{investment}_i \times \text{cash}_i)}{\sum \text{investment}_i} + \frac{\sum (\text{investment}_i \times \text{PIK}_i)}{\sum \text{investment}_i}$$

Answer: 12.0

Total Weighted Average Cash and Payment-In-Kind (PIK) Interest Rate

Q: John oversees a fund, with the returns for the first three years displayed below: What will be the holding period return (expressed as a percentage)? Answer to three decimal places.

Answer:

| Year | Investment | Return |
|------|------------|--------|
| 1 | \$ 500 | 12% |
| 2 | \$ 600 | 5% |
| 3 | \$ 1000 | 1% |

Formula:

$$[\text{HPR}] = \left(\frac{\sum (\text{investment}_i \times (1 + \text{return}_i))}{\sum \text{investment}_i} - 1 \right) \times 100$$

Answer: 4.762

Holding Period Return (HPR)

Q: What is the average quarterly share price in 2021 assuming each quarter had a completely uniform price distribution in high and low bid prices, measured in dollars?

Answer:

| Quarter Ended | High Bid | Low Bid |
|----------------------|----------|----------|
| October 31, 2021 (1) | \$ 4.51 | \$ 3.99 |
| July 31, 2021 | \$ 8.47 | \$ 2.30 |
| April 30, 2021 | \$ 13.00 | \$ 3.80 |
| January 31, 2021 | \$ 14.50 | \$ 0.015 |
| October 31, 2020 (2) | \$ 0.199 | \$ 0.01 |

Formula:

$$[\text{Average}] = \frac{1}{4} \sum_{i=1}^4 \frac{\text{High}_i + \text{Low}_i}{2}$$

Answer: 6.32

Average Quarterly Price

Figure 2. Sampled FinMMR examples with two language (*i.e.*, English and Chinese), rich images and different knowledge. The questions and images need expert-level visual perception, knowledge reasoning and numerical computation.

cial documents, extract key financial indicators from tables, images, and texts, and perform multi-step precise numerical calculations to support professional decision-making. Similarly, to achieve expert artificial general intelligence (AGI) [8, 25, 42, 43, 65], MLLMs are expected to comprehend complex domain-specific images akin to human experts, and apply domain knowledge to perform accurate numerical reasoning. This raises the question: **Can current MLLMs seamlessly integrate vision and text to perform**

domain-specific complex reasoning, matching the proficiency of LRMIs in pure text-based tasks?

Specifically, we choose the financial domain to evaluate the complex reasoning capabilities of MLLMs, where precision and transparent reasoning are paramount [32]. Existing numerical reasoning benchmarks for finance are limited in their text-based reasoning, coverage of specific financial knowledge, and complexity of reasoning [14, 15, 32, 67, 69]. FAMMA [63] is mainly modelled after textbooks

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and CFA exam questions, MathVista [39] does not involve the application of financial knowledge, MMMU [65] and MMMU-Pro [66] are restricted to multiple-choice questions, diverging from authentic financial problem-solving. The lack of high-quality, knowledge-intensive multimodal financial numerical reasoning benchmarks makes it challenging to objectively evaluate the actual reasoning capabilities of MLLMs and analyze their shortcomings.

Therefore, we propose **FinMMR**, a bilingual multimodal numerical reasoning benchmark designed to evaluate the reasoning capabilities of MLLMs in the finance domain. The benchmark comprises 4.3K problems, covering 14 financial subdomains (*e.g.*, corporate finance and industry analysis), with 8.7K images derived from 14 categories (*e.g.*, tables and ownership structure charts). Each problem includes rich images, an unambiguous question, a Python-formatted solution, and a precise answer.

For multimodality, without representing financial tables as structured text, FinMMR represent all tables, charts, and diagrams as images. **For comprehensiveness**, FinMMR covers 14 financial subdomains and two languages (*i.e.*, English and Chinese), demanding domain knowledge such as option pricing and portfolio management. **For challenge**, FinMMR focus on multi-step numerical reasoning, requiring models to provide exact numerical answers under strict evaluation criteria (emphasizing units, percentages, and decimal places). Furthermore, we **mix each Chinese questions with two distractor images** that are contextually adjacent to the ground images, approaching real-world multimodal reasoning scenarios.

We evaluate 15 state-of-the-art (SOTA) MLLMs [18–21, 46–48, 56], utilizing Chain-of-Thought (CoT) [60] and Program-of-Thought (PoT) [13]. The experimental results on FinMMR reveals three key findings:

- **MLLMs Face Significant Challenges in Domain-Specific Multimodal Numerical Reasoning:** All evaluated models underperform on FinMMR. On the *Hard test* set, the best-performing model, Claude 3.7 Sonnet with 64K extended thinking, achieves only 53.00% accuracy, while OpenAI o1 achieves merely 48.40%. Through error analysis, we identify that visual perception, knowledge reasoning, and numerical computation collectively pose challenges to MLLMs. Current MLLMs still struggle with complex multimodal reasoning tasks in specialized domains, compared to text-based reasoning.
- **Better Synergy Between Visual Perception and Complex Reasoning Is Needed:** Distracting images lead to a greater than 10% drop in accuracy for Qwen2.5-VL-72B compared to ground images alone, indicating that irrelevant visual information severely impacts multimodal reasoning. By decoupling visual filtering and reasoning, Qwen2.5-VL-72B improved from 64.73% to 71.56%. Combining MLLMs with LRMAs, by efficiently

parsing visual information into structured text and leveraging the LRMs’ text-based reasoning capabilities, can also yield better performance. The combination of GPT-4o and DeepSeek-R1 achieves 86.72% accuracy on 1,160 tabular QA instances, outperforming Claude 3.7 Sonnet (83.53%).

- **Refined Structured Domain Knowledge Enhances MLLMs’ Complex Reasoning:** Leading MLLMs lack sufficient experience in applying rich domain knowledge when solving complex reasoning tasks. By annotating structured financial functions and leveraging the model’s ability to generate retrieval questions and make judgments, knowledge augmentation can significantly improve MLLMs’ performance. MLLMs achieve absolute improvements ranging from 2.76 to 4.31 percentage points, allowing weaker models to approach SOTA performance, while SOTA models exhibit further gains.

These findings highlight the bottlenecks of MLLMs in complex multimodal reasoning tasks in expert domains closer to real-world scenarios. They emphasize the need for continuous improvements in three key areas: more intricate visual perception, more specialized knowledge reasoning, and more accurate numerical computation. Alternatively, leveraging tools or model combinations can help achieve a balance between performance and cost, enabling MLLMs to perform expert-level reasoning tasks like human experts.

2. Related Work

2.1. LRMs and MLLMs

By integrating train-time scaling and test-time scaling [31, 45], LRMs have demonstrated remarkable reasoning capabilities [62]. However, most LRMs are limited to handling text-based problems. The growing demand for solving real-world tasks has spurred the development of MLLMs [5, 19, 55] and benchmarks designed to evaluate the perception and reasoning abilities of MLLMs [10, 23, 27, 30, 33, 36, 38, 64–66]. For instance, MME-CoT [30] evaluates models’ space-time understanding, while EMMA [27] focuses STEM subjects. Following this trend, domain-specific benchmarks which require deep domain expertise have emerged, such as MathVista [39] for mathematics and GMAI-MMBench [12] for medicine. Yet, financial reasoning remains an unexplored area in the current landscape of MLLM benchmarks.

2.2. Financial Benchmarks

The financial domain presents a distinct and more formidable set of challenges for model evaluation, which arise from its inherent complexity, information density, and dependence on expertise. The majority of existing text-only financial numerical reasoning benchmarks [14, 15, 32, 67–69] are constrained by limitations such as sub-optimal an-

| Property | Value |
|------------------------------------|------------------------|
| # Total Questions | 4,300 |
| # Easy/Medium/Hard | 1,300/1,500/1,500 |
| # Validation/Test | 900/3,400 |
| # Chinese/English | 2,150/2,150 |
| # Operators (Easy/Medium/Hard) | 1.75/2.97/ 5.34 |
| # Lines of Code (Easy/Medium/Hard) | 4.14/5.06/ 7.34 |
| # Parentheses (Easy/Medium/Hard) | 0.88/3.11/ 4.25 |
| # Difficulty (Easy/Medium/Hard) | 1.93/2.96/ 3.79 |

Table 1. Key statistics of FinMMR (Avg values of three subsets).

notation quality, narrow domain knowledge coverage, and overly simplistic reasoning tasks. Although FinanceReasoning [53] offers complex tasks with rich knowledge and high-quality annotations, its text-only modality limits multimodal reasoning evaluation.

Recent multimodal financial benchmarks have sought to bridge this gap but still possess limitations. FAMMA [63] being sourced from textbooks and examinations does not mirror the real-world tasks. FinMME [40] uses a multiple-choice format, which may overestimate model reasoning due to guesswork. MME-Finance [24] is constrained by coarse annotations and an isolated assessment of domain knowledge, limiting holistic evaluation of real-world financial reasoning.

3. FinMMR Benchmark

3.1. Overview of FinMMR

We introduce FinMMR, a bilingual (English and Chinese) multimodal benchmark for evaluating the reasoning capabilities of MLLMs in financial numerical reasoning tasks. FinMMR consists of 4,300 questions covering 14 financial subdomains (*e.g.*, corporate finance, industry analysis, financial markets, asset management). The key statistics are summarized in Tab. 1, and the composition of sub-domains and images is illustrated in Fig. 1. As illustrated in Fig. 2, FinMMR introduces three key challenges:

- **Rich Images Challenge Visual Perception:** FinMMR comprises 8.7K images from 14 categories (*e.g.*, bar charts, line charts, ownership structure charts). MLLMs must identify relevant images among distractors and extract critical information from the correct images.
- **Comprehensive Subdomains Challenge Knowledge Reasoning:** MLLMs need to flexibly apply diverse domain-specific financial knowledge from 14 sub-domains to solve multi-step reasoning tasks.
- **Complex Formulas Challenge Numerical Computation:** All questions require precise numerical answers, eliminating the potential bias from lucky guesses that

could occur in multiple-choice formats.

3.2. Data Curation Process

We first curated a subset of questions from public text-based financial reasoning benchmarks and systematically transformed them into multimodal problems using a unified standard. Subsequently, we constructed a novel multimodal Chinese Research Report Question Answering (CR-RQA) benchmark from scratch, merging two data sources into FinMMR. Each question is accompanied by an executable Python solution, yields a numerical answer and demonstrates a clear reasoning chain.

Update to Public Benchmarks We re-annotate 124 and 163 financial questions from MMMU [65] and MMMU-Pro [66], respectively. Following rigorous verification, these questions were directly incorporated into our dataset. Furthermore, we extracted 77, 288, and 795 questions from FinanceMath [67], CodeTAT-QA [32], and CodeFinQA [32], respectively. From DocMath-Eval [68], we further obtained 703 questions from its four subsets. For each question, we rendered any tabular data as images while removing the corresponding table information from the text, ensuring that MLLMs cannot rely solely on textual content.

Building a Novel Dataset from Scratch We collect 90 research reports, all of which are obtained through authorized access and cover diverse topics such as industry research, macroeconomic analysis, and strategy research. We use 360LayoutAnalysis [1] to extract informative images and discard those lacking explicit numerical data, reducing ambiguity. For each retained image, we prompt Qwen-VL-Max [6] to formulate questions requiring multiple reasoning steps or complex calculations. Each question is accompanied by an executable Python solution and a definitive numerical answer.

Furthermore, we introduce distractor images sourced from the same reports adjacent to ground images to challenge MLLMs in extracting relevant numerical information from structured, densely packed visuals.

Data Quality Assurance This process ensured that every question was clearly written, featured a detailed reasoning solution, and included an accurate final answer. The annotators included 16 graduate students in finance and two experts holding CFA certifications. With the aid of LLMs, this meticulous verification process spanned three months, culminating in a dataset that meets high standards of clarity and correctness.

Dataset Splitting and Release To classify the problems by difficulty, we employ a heuristic algorithm that takes into account the number of operators (o), code lines (l) and parentheses pairs (p) in the Python solution. Specifically, the difficulty of reasoning rc of a problem is defined as:

$$rc = \ln(\max(o, 1)) + \ln(\max(l + p, 1)) \quad (1)$$

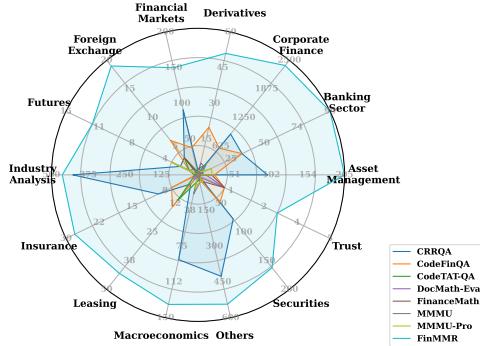


Figure 3. The comparison between finance-related benchmarks. These benchmarks vary in size, domain coverage, modalities, and question type, with some focusing on text-only data while others include images. Each axis has scale labels with varying ranges to measure the number of questions from each benchmark across different subdomains. In the Modalities, T means text input, I means Images input, P.I. means pure images input. In the Question Type, MC means multi-choice answer, NUM means numerical answer.

FinMMR is classified as *Easy* (1,300 examples), *Medium* (1,500 examples) and *Hard* (1,500 examples) based on this formula, with each level randomly split into *test* and *validation* sets. All questions are publicly available, while only the 300 validation answers per level are released, while test answers remain private to prevent data leakage [22, 50, 52]. We maintain an online evaluation platform that enables researchers to assess their models.

3.3. Comparisons with Existing Benchmarks

As illustrated in Fig. 3, previous work has studied multi-discipline multimodal reasoning [65, 66], general mathematical reasoning [39] or text-based financial QA [32, 67, 68]. FinMMR focus on multimodal financial numerical reasoning, curating 4,300 questions requiring a deep understanding of domain-specific images (*e.g.*, earnings reports, candlestick charts). To mimic real-world scenario, we deliberately incorporate 3,938 distractors into 2,150 questions to rigorously evaluate MLLMs’ visual perception capability. Compared to existing financial benchmarks, they suffer from narrow domain coverage [14, 69]. FinMMR encompasses 14 financial subdomains and 14 image categories, comprehensively evaluating MLLMs’ domain-specific reasoning capabilities.

4. Evaluation System

To facilitate the evaluation of complex reasoning on FinMMR, we established a dedicated evaluation system. All MLLMs evaluated were accessed through official APIs.

4.1. Multimodal Large Language Models

We systematically evaluate the multimodal reasoning capabilities of 15 recent MLLMs under the zero-shot setting. The evaluated MLLMs are: OpenAI o1 [46], GPT-4o [44], Claude 3.7 Sonnet (including thinking mode) [5],

Gemini 2.0 Flash Thinking [19], Gemini 2.0 Pro [20], Gemini 2.0 Flash [18], InternVL2.5-78B [16], Grok 2 Vision [61], Pixtral Large [2], Qwen2.5-VL-72B [7], QVQ-72B-Preview [55], Qwen-Omni-Turbo [57], Llama 4 Maverick [4], Gemma 3 27B [17], and Mistral Small 3.1 [3].

4.2. Prompting Methods

Our evaluation adopts CoT [60], PoT [13] and IO (without any external prompts) prompting methods. Due to budget constraints, we report OpenAI o1 performance on the *Hard* subset only. Detailed prompts can be found in the Appendix.

4.3. Answer Extraction and Evaluation

Following Zhao et al. [67], we extract answers based on the prompting methods. For CoT and IO outputs, we employ GPT-4o-mini to extract numerical answers. For PoT, we run the generated program for numerical results. Finally, we conduct a strict accuracy evaluation, comparing numerical results with ground truth and deeming the results accurate within a stringent error tolerance of 0.2%.

5. Experiments

We answer the following research questions (RQs): **RQ1**: Are MLLMs multimodal reasoners with extended thinking and PoT prompts? **RQ2**: What are the primary challenges facing MLLMs? **RQ3**: How can the visual perception difficulties of MLLMs be mitigated? **RQ4**: How can the knowledge reasoning capabilities of MLLMs be enhanced? **RQ5**: How can the numerical computation abilities of MLLMs be compensated for?

5.1. Main Results (RQ1)

The performance of the MLLMs evaluated using different prompting methods on FinMMR is shown in Tab. 2.

| Model | Size | Extended thinking | Hard | | | Medium | | Easy | | Avg. | | Token (M) | |
|---------------------------|------|-------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|--------------|
| | | | IO | CoT | PoT | CoT | PoT | CoT | PoT | CoT | PoT | CoT | PoT |
| Proprietary MLLMs | | | | | | | | | | | | | |
| Claude 3.7 Sonnet | | ✓ (64K) | 53.00 | 51.00 | 51.40 | 62.50 | 62.17 | 78.50 | 78.50 | 64.00 | 64.02 | 8.51 | 11.25 |
| Claude 3.7 Sonnet | | ✗ | 49.80 | 50.80 | 48.50 | 62.25 | 58.83 | 77.00 | 76.92 | 63.35 | 61.42 | 0.99 | 0.89 |
| OpenAI o1 | | ✓ | 48.00 | 48.40 | 44.70 | — | — | — | — | — | — | 2.52 | 2.12 |
| GPT-4o | | ✗ | — | 45.40 | 47.80 | 63.33 | 59.92 | 78.00 | 76.00 | 62.24 | 61.24 | 0.85 | 0.41 |
| Gemini 2.0 Pro | | ✗ | — | 46.50 | 47.30 | 60.58 | 57.92 | 75.50 | 75.67 | 60.86 | 60.30 | 0.85 | 0.45 |
| Gemini 2.0 Flash Thinking | | ✓ | — | 46.00 | 46.00 | 60.75 | 56.58 | 77.17 | 74.17 | 61.31 | 58.92 | 1.30 | 0.48 |
| Gemini 2.0 Flash | | ✗ | — | 44.40 | 45.90 | 57.83 | 53.42 | 74.92 | 73.75 | 59.05 | 57.69 | 0.79 | 0.43 |
| Grok 2 Vision | | ✗ | — | 27.80 | 25.50 | 41.50 | 35.83 | 73.08 | 72.83 | 47.46 | 44.72 | 1.13 | 0.60 |
| Qwen-Omni-Turbo | | ✗ | — | 17.50 | 27.30 | 35.83 | 48.00 | 57.50 | 61.67 | 36.94 | 45.66 | 0.90 | 0.42 |
| Open-source MLLMs | | | | | | | | | | | | | |
| Llama 4 Maverick | 17B | ✗ | — | 48.70 | 47.80 | 63.25 | 59.17 | 77.83 | 77.83 | 63.26 | 61.60 | 0.88 | 0.47 |
| Qwen2.5-VL-72B | 72B | ✗ | — | 43.30 | 46.20 | 63.42 | 64.17 | 77.42 | 75.83 | 61.38 | 62.07 | 1.05 | 0.44 |
| InternVL2.5-78B | 78B | ✗ | — | 37.40 | 44.00 | 60.50 | 61.17 | 70.92 | 70.58 | 56.27 | 58.58 | — | — |
| QVQ-72B-Preview | 72B | ✓ | 43.30 | 40.30 | 6.20 | 55.67 | 9.67 | 75.42 | 12.42 | 57.13 | 9.43 | 5.43 | 5.70 |
| Pixtral Large | 124B | ✗ | — | 19.70 | 25.00 | 39.83 | 39.75 | 70.00 | 70.17 | 43.18 | 44.97 | 1.15 | 0.75 |
| Gemma 3 27B | 27B | ✗ | — | 23.40 | 22.30 | 45.17 | 36.42 | 69.08 | 61.58 | 45.88 | 40.10 | 0.97 | 0.47 |
| Mistral Small 3.1 | 24B | ✗ | — | 19.70 | 15.20 | 38.42 | 29.75 | 67.67 | 49.42 | 41.93 | 31.46 | 1.15 | 0.60 |

Table 2. Results of different models using IO, CoT and PoT prompting methods on the *test* set of FinMMR. We use the best Accuracy on the *Hard* subset as the ranking indicator of model performance. The results underscore the superior performance of reasoning-enhanced MLLM (*i.e.*, Claude 3.7 Sonnet with 64K extended thinking) with PoT in complex multimodal numerical reasoning task.

Challenges of MLLMs in Domain-Specific Complex Numerical Reasoning As the difficulty increases, the average accuracy shows a continuous and significant decline. In CoT setting, the average accuracy rates on the *Easy*, *Medium*, and *Hard* subsets are 73.33%, 54.05%, and 38.14%, respectively. The currently best-performing model (*i.e.*, Claude 3.7 Sonnet with 64K extended thinking) consistently demonstrates superior performance across all difficulty subsets using CoT prompting method. **However, its accuracy on the *Hard* subset remains below the 60% passing threshold in both prompting methods.** On the overall *test* set, Claude 3.7 Sonnet achieves only 64.02% accuracy. These results highlight the challenging nature and rigorous standards of FinMMR, effectively assessing the limits of MLLMs’ reasoning capabilities and the disparities among models compared to previous benchmarks.

Does extended thinking help? Reasoning-enhanced models show consistent improvements, compared with non-reasoning-enhanced MLLMs. Claude 3.7 Sonnet with 64K extended thinking achieves 2.20 percentage points higher accuracy than the model without extended thinking (53.00% vs. 50.80%) on the *Hard* subset. This enhancement comes at the cost of using nearly 12 times more tokens for intricate thinking (4.06M vs. 0.34M). This trend also persists in the Gemini 2.0 Flash series.

We observe that QVQ-72B-Preview lose basic code generation capabilities due to the reinforcement learning of text-based long thought, which is likely attributed to biases in training strategies and training data. On the *Hard* subset, this model achieves a code execution success rate of only 10.90%, resulting in an accuracy of merely 6.20% in

PoT setting, significantly lower than the 40.30% accuracy achieved with CoT. This finding highlights the importance of maintaining foundational capabilities, such as programming, while enhancing the reasoning abilities of MLLMs, to avoid rendering them ineffective in other basic tasks.

Does PoT help? Experimental results strongly validate the superiority of PoT over CoT in numerical reasoning tasks, especially on the *Hard* subset. PoT (not including QVQ-72B-Preview) achieves a mean accuracy of 37.64% versus 36.20% for CoT, representing an improvement of 1.44 percentage points. Furthermore, PoT encourages MLLMs to leverage structured code generation to reduce token consumption during reasoning. Under similar or lower token usage, PoT achieves similar or greater accuracy. For instance, GPT-4o achieves a 2.40 percentage points improvement in accuracy over CoT while consuming significantly fewer tokens in PoT setting. Similarly, Qwen2.5-VL-72B demonstrates the most pronounced efficiency gains: PoT improves accuracy to 64.17% from 63.42% while reducing token consumption by 58.88% (153K vs. 373K) on the *Medium* subset. **When addressing complex numerical reasoning problems, PoT avoids precise numerical calculations by utilizing external tools (*i.e.*, Python interpreter) and reduces the need for repetitive text-based reasoning, which is beneficial for most MLLMs.**

However, we also observe that for certain reasoning-enhanced models (*i.e.*, Claude 3.7 Sonnet with 64K extended thinking and OpenAI o1), due to the enforced requirement for long thought, they still engage in extensive text-based reasoning before generating code even in PoT setting, resulting in exceptionally high token consumption

| Subset | Test | | | Degradation | Validation | | |
|---|-------------------|-----------------------|--|-------------|-------------------|-----------------------|-------------|
| | Ground Images (%) | Distractor Images (%) | | | Ground Images (%) | Distractor Images (%) | Degradation |
| Hard | 57.18 | 47.23 | | ↓ 9.95 | 56.74 | 45.58 | ↓ 11.16 |
| Medium | 73.01 | 61.36 | | ↓ 11.65 | 77.78 | 64.73 | ↓ 12.35 |
| Easy | 61.59 | 53.64 | | ↓ 7.95 | 60.61 | 51.52 | ↓ 9.09 |
| The improvement achieved by the filtering-reasoning pipeline on the <i>Medium validation</i> set: $64.73 \rightarrow 71.56 \uparrow 6.83$ | | | | | | | |

Table 3. Degradation of Qwen2.5-VL-72B on all subsets due to distractor images and improvement achieved by the filtering-reasoning pipeline on the *Medium validation* set in PoT setting.

on the *Hard* subset (4.48M and 2.12M), which is more than 10 times that of other MLLMs. To further investigate this, we added an IO baseline without any external prompts for reasoning-enhanced models on the *Hard* subset. The IO group achieved the highest accuracy, which we attribute to the comprehensive built-in system prompts embedded in the tested proprietary models. **This highlights the need for future research to balance reasoning performance with the control of inefficient and redundant token generation, aiming to achieve a good trade-off between performance and cost, as well as to investigate whether PoT prompting can yield significant performance gains on open-source reasoning-enhanced models.**

5.2. Error Analysis (RQ2)

To better analyze the capabilities and limitations of MLLMs on FinMMR, we conduct a detailed error analysis for the Claude 3.7 Sonnet with 64K extended thinking in PoT setting. Error analysis is based on 100 sampled failure cases, which we categorize into three main error types, some of which involve compound errors. More details of error cases are provided in the Appendix.

- **Visual Perception Error** (30/100): The model incorrectly perceives, identifies, or interprets visual information from images, or mistakenly recognizes incorrect data, subsequently causing errors in calculations, broken reasoning chains, or incorrect conclusions.
- **Knowledge Reasoning Error** (38/100): Due to insufficient domain-specific knowledge, the model exhibits logical confusion or conceptual misunderstandings during reasoning, leading to incorrect answers.
- **Numerical Computation Error** (32/100): In problems involving mathematical operations and numerical reasoning, the model produces significant deviations from the correct answers due to errors in the calculation steps, precision control, or numerical hallucination.

5.3. Visual Filtering for Reasoning (RQ3)

As shown in Tab. 3, when processing multi-image inputs containing distractor images, Qwen2.5-VL-72B demonstrates significantly lower accuracy across all difficulty levels compared to ground images scenarios. This finding

aligns with conclusions from previous work [37, 51], indicating that irrelevant visual information substantially interferes with MLLMs' reasoning capabilities. In particular, the *Medium validation* set exhibits the most pronounced performance drop (77.78% ground images vs. 64.73% distractor images), attributed to two key characteristics: (1) moderate complexity making visual perception quality the performance bottleneck; (2) semantic relevance between distractors and questions increasing visual filtering difficulty. To address distractor image interference, we propose a two-stage multimodal reasoning pipeline:

- **Visual Filtering:** We first instruct MLLM to analyze the set of images \mathcal{I} and the question q , assessing the relevance of the image (relevant/irrelevant). Irrelevant images are excluded from subsequent reasoning.
- **Enhanced Reasoning:** Then, the filtered subset \mathcal{I}' and the question q are input into the MLLM for the final reasoning. The system automatically reverts to the original inputs \mathcal{I} if all images are mistakenly filtered.

Does the pipeline help? As illustrated in Tab. 3, we evaluate Qwen2.5-VL-72B on the 207 English questions with distractor images of the *Medium validation* set. Our method achieves an overall accuracy of 71.56%, representing a 6.83 percentage points improvement over direct reasoning. This result is only 6.22 percentage points away from the ideal accuracy of the ground images scenarios (77.78%). Detailed analysis reveals 73.43% (152/207) ground image recognition accuracy during filtering. When correctly identified, the accuracy of these problems increases to 81.58% (124/152). **This finding underscores the necessity to enhance the ability of MLLMs to filter out irrelevant image information, thereby strengthening their robustness in reasoning within more complex real-world scenarios.**

5.4. Knowledge Augmentation (RQ4)

To enhance the understanding and application capabilities of financial knowledge of MLLMs, we explore a method of refined knowledge augmentation to improve the performance of MLLM in domain-specific reasoning tasks.

- **Function Library Construction:** We annotate a comprehensive financial function library containing 3,133 Python functions from financial encyclopedia. Each func-

| Setting | PoT | RAG with PoT |
|---------------------------|-------|---------------|
| Gemini 2.0 Flash Thinking | 78.71 | 83.02 (+4.31) |
| GPT-4o | 80.60 | 83.62 (+3.02) |
| Claude 3.7 Sonnet | 81.21 | 85.43 (+4.22) |
| Claude 3.7 Sonnet (64K) | 83.53 | 86.29 (+2.76) |

Table 4. Improvements of different MLLMs with knowledge augmentation on the 1,160 instances of FinMMR in PoT setting.

tion includes precise functional descriptions, parameter explanations, and step-by-step implementation code.

- **MLLM-Instructed Knowledge Retrieval:** In financial problems with hybrid contexts, using short questions or full contexts for retrieval often fails to retrieve directly relevant knowledge [9, 49]. We observed that powerful MLLMs (*e.g.*, GPT-4o) can effectively summarize rich semantic information from contexts. Therefore, we first prompt the MLLM to generate precise retrieval queries based on the context [34, 58]. Then we use Contriever [28] to retrieve relevant financial Python functions, based on the semantic similarity between the refined queries and functional descriptions.
- **MLLM as Retrieval Judge:** Recent studies have shown that models are capable of judging the relevance of candidates retrieved for the question [26]. In this setting, we first retrieved the Top-30 financial functions and then prompted the MLLM to select the Top-3 functions most useful to answer the question, if any.

Does knowledge augmentation help? As shown in Tab. 4, all evaluated MLLMs enhanced with financial function knowledge achieved significant improvements, ranging from 2.76 to 4.31 percentage points. Leveraging the improved retrieval efficiency enabled by *MLLM-Instructed Knowledge Retrieval* and *MLLM as Retrieval Judge*, the knowledge augmentation approach achieves greater performance, boosting the accuracy of Claude 3.7 Sonnet with 64K thinking to 86.29%. Notably, Gemini 2.0 Flash Thinking, which has relatively weaker reasoning capabilities, also improved from 78.71% to 83.02%, approaching the performance of Claude 3.7 Sonnet (83.53%) without knowledge augmentation. **The results further illustrate that refined domain-specific reasoning knowledge can significantly enhance the performance of MLLMs in complex reasoning tasks within expert domains.**

5.5. Visual Parser with Reasoner (RQ5)

In complex multimodal numerical reasoning tasks, single models often struggle to simultaneously achieve visual perception, knowledge reasoning, and numerical computation. To investigate the potential of model collaboration, we instruct the MLLM to act as the **Visual Parser**, responsible for carefully converting images into structured textual data.

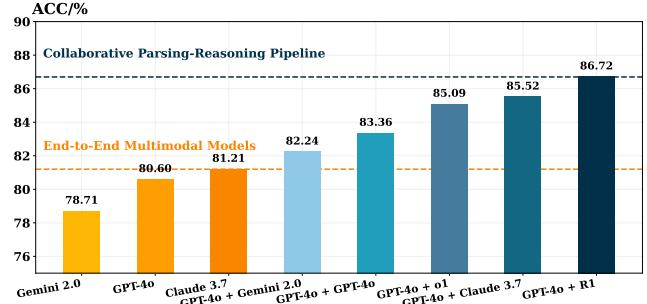


Figure 4. Results of model combinations and individual models.

Then, an LRM acts as the **Reasoner**, performing multi-step numerical reasoning based on the textual context.

Specifically, we filter 1,160 tabular QA instances from FinMMR and utilize **GPT-4o** as the Visual Parser, instructing it to separate table headers or cells with vertical bars (|) and rows with newlines. For the Reasoner component, in addition to **GPT-4o**, we evaluate several LRMs (*i.e.*, **Claude 3.7 Sonnet**, **Gemini 2.0 Flash Thinking**, **DeepSeek-R1**, and **OpenAI o1**).

Does model collaboration help? As shown in Fig. 4, the structured data from GPT-4o’s visual parsing significantly enhances downstream reasoning. The individual model (*i.e.*, GPT-4o with PoT) achieves an accuracy of 80.60%, while the combination of models improves the accuracy to 86.72% (*i.e.*, DeepSeek-R1 serving as the Reasoner with PoT). Performance variance emerges across reasoning-enhanced models using identical visual inputs. Claude 3.7 Sonnet reaches 85.52%, outperforming Gemini 2.0 Flash Thinking (82.24%), confirming the decisive impact of text-based reasoning capabilities. **This evidences that model collaboration effectively compensates for individual model limitations through complementary strengths.**

6. Conclusion

We introduce FinMMR, a multimodal, comprehensive, and challenging benchmark for evaluating the financial numerical reasoning capabilities of MLLMs. FinMMR challenges MLLMs’ intricate visual perception, specialized knowledge reasoning, and accurate numerical computation through its rich images, comprehensive subdomains, and complex formulas embedded in each multimodal financial question. The evaluation results reveal that 15 proprietary and open-source MLLMs still struggle with complex multimodal reasoning tasks in specialized domains. FinMMR highlights the bottlenecks of MLLMs and the need for continuous improvements, including reasoning-enhanced training, tool use, refined structured knowledge augmentation and model combinations, allowing models to perform expert-level reasoning tasks closer to the real-world scenarios.

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A. Error Analysis

We exhibit representative examples for the three primary error categories: **Visual Perception Error** (Fig. 6), **Knowledge Reasoning Error** with two cases (Fig. 7, Fig. 8), and **Numerical Computation Error** (Fig. 9). These errors were observed in the outputs of Claude 3.7 Sonnet with 64K extended thinking in PoT setting.

These error cases highlight critical limitations in current multimodal large language models (MLLMs). **Visual Perception** errors primarily stem from the misinterpretation of complex visual data (such as charts) or failures to accurately extract numerical information from tables. **Knowledge Reasoning** errors result from either incorrect factual knowledge stored in the model or flawed logical reasoning processes. **Numerical Computation** errors occur due to inaccuracies in the model’s internal computation mechanisms during reasoning. Consequently, FinMMR underscores the need for improvements in three core capabilities: intricate visual perception, specialized knowledge reasoning, and accurate numerical computation.

B. Augmentation Methods

B.1. Visual Filtering for Reasoning

Fig. 10 illustrates a representative example demonstrating our proposed two-stage filtering-reasoning pipeline applied to a multimodal numerical reasoning task. Specifically, the task requires calculating fifth-year sales revenue for the respiratory category, comparing it with third-year data, and computing the growth rate. Among the three input images, Images 1 and 2 contain task-relevant tables, while Image 3 is an irrelevant distractor. Without visual filtering, although the model correctly avoided extracting numerical information from the irrelevant image, it misinterpreted values from relevant tables, resulting in a significant deviation from the reference answer. When implementing our pipeline, the MLLM first assesses image relevance, correctly identifying Images 1 and 2 as [USEFUL] and Image 3 as [USELESS], thus eliminating distractors from downstream reasoning.

B.2. Knowledge Augmentation

Fig. 11 presents a representative financial multimodal reasoning task, demonstrating the efficacy of our domain knowledge augmentation method. Specifically, the task requires calculating the impact on net income from switching inventory accounting methods from LIFO to FIFO, based on a provided financial table. In the baseline without augmentation (“Original Output”), the model incorrectly treated the entire 2014 LIFO reserve as income, violating U.S. GAAP which stipulates that **only changes in LIFO reserve** impact current-year net income. This caused significant income overstatement. Conversely, with our augmentation approach (“Augmented Output”), the model correctly computed the effect using the **year-over-year change in LIFO reserve** with proper tax effect adjustment, achieving accurate income quantification. This case highlights the critical importance of domain knowledge augmentation for MLLMs. Complementing this, Fig. 12 illustrates a representative financial function retrieved from our library.

B.3. Visual Parser with Reasoner

Fig. 13 demonstrates our two-stage parsing-reasoning pipeline comprising a **Visual Parser** and a **Reasoner**. The task requires calculating anticipated portfolio returns under two economic scenarios using probability-weighted returns from a tabular image. We first instruct GPT-4o (as Visual Parser) to convert tabular data into structured markdown format. This structured output then enables a large reasoning model (LRM) to perform numerical reasoning. Compared to directly reasoning on raw visual inputs, GPT-4o’s parsed data significantly enhances the downstream LRM’s accuracy, underscoring the efficacy of model collaboration in multimodal reasoning.

C. Prompt Templates

C.1. Chain-of-Thought (CoT)

The CoT prompt directs MLLMs to decompose complex reasoning tasks into sequential intermediate steps. This approach enhances performance on mathematical, logical, and analytical problems by requiring explicit articulation of each reasoning stage before final answer generation. See Fig. 14 for the complete template.

C.2. Program-of-Thought (PoT)

The PoT prompt guides MLLMs to formulate solutions as executable code. By translating problems into programs with variables, functions, and logical operations, this approach enables precise computation and transparent reasoning, particularly effective for quantitative tasks. The complete template is provided in Fig. 15.

C.3. Retrieval-Augmented Generation (RAG)

The RAG prompt integrates retrieval of external knowledge with generative reasoning. This hybrid approach enables MLLMs to supplement parametric knowledge with dynamically retrieved information, enhancing answer accuracy for knowledge-intensive tasks. See Fig. 16 for implementation details.

C.4. Function Relevance Judgment

This prompt evaluates the utility of retrieved financial functions for answering specific questions. It assesses both relevance and reliability, permitting only qualified knowledge to inform downstream reasoning. The complete template is available in Fig. 17.

C.5. Visual Relevance Judgment

This prompt assesses image relevance for financial problem-solving. It classifies each input image as [USEFUL] or [USELESS], with uncertainty favoring retention to prevent critical information loss. See Fig. 18 for details.

D. Experimental Details

D.1. Model Specifications

Tab. 5 details the 15 MLLMs evaluated on FinMMR, covering models from 8 leading organizations. Each entry includes the official model identifier to ensure full experimental reproducibility.

D.2. Validation Set Results

Tab. 2 presents the accuracy metrics of 12 MLLMs on the **validation** set of FinMMR across three difficulty tiers. Models are evaluated using both Chain-of-Thought (CoT) and Program-of-Thought (PoT) prompting methods under standardized conditions.

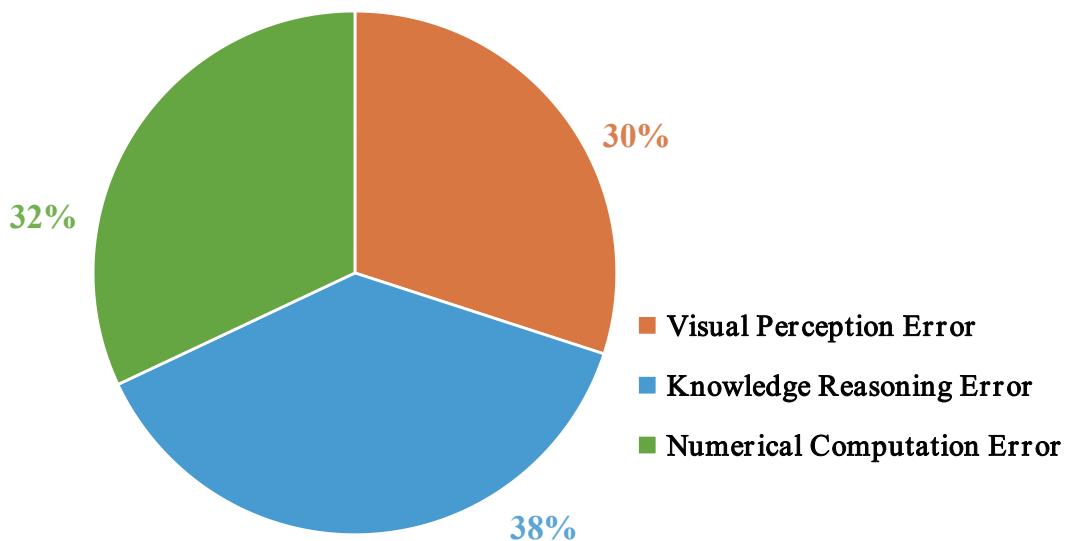


Figure 5. Error Distribution: Claude 3.7 Sonnet on FinMMR

Question: What is the increase in the percentage of the total contract assets proportion to the total accounts receivable from December 31, 2019 to June 30, 2020 in percentage? Rounded to 2 decimal places.

Accounts Receivable

The components of accounts receivable are as follows:

| | As of | |
|---------------------------------|---------------|-------------------|
| | June 30, 2020 | December 31, 2019 |
| Trade receivables | \$ 4,592 | \$ 6,425 |
| Unbilled receivables | 1,763 | 1,857 |
| Other short-term receivables | 19 | 7 |
| Allowance for doubtful accounts | (716) | (1,816) |
| Total accounts receivable | \$ 5,658 | \$ 6,473 |

Context: The timing of revenue recognition, billings and cash collections results in billed accounts receivable, unbilled receivables (contract assets), and customer advances and deposits (contract liabilities) on the consolidated balance sheets. In our Air Pollution Control Technology segment, amounts are billed as work progresses in accordance with agreed-upon contractual terms. Generally, billing occurs subsequent to revenue recognition, resulting in contract assets. These assets are reported on the consolidated balance sheet on a contract-by-contract basis at the end of each reporting period. At June 30, 2020 and December 31, 2019, contract assets were approximately \$1,763 and \$1,857, respectively, and are included in accounts receivable on the consolidated balance sheets.

```
def solution():
    # Define variables name and value
    contract_assets_june_2020 = 1763
    total_accounts_receivable_june_2020 = 5058 (x) 5058 (x) — 5658 (✓)
    contract_assets_dec_2019 = 1857
    total_accounts_receivable_dec_2019 = 6473

    # Calculate the proportion of contract assets to total accounts
    # receivable
    proportion_june_2020 = contract_assets_june_2020 /
    total_accounts_receivable_june_2020
    proportion_dec_2019 = contract_assets_dec_2019 /
    total_accounts_receivable_dec_2019

    # Compute the percentage increase in proportion
    percentage_increase = ((proportion_june_2020 - proportion_dec_2019) /
    proportion_dec_2019) * 100

    # Return answer rounded to 2 decimal places
    return round(percentage_increase, 2)
```



Answer: 21.5

Ground Truth: 2.47



Figure 6. Visual Perception Error Case

Question: For each of the following \$1,000-parvalue bonds, assuming annual interest payment and a 40% tax rate, calculate the after-tax cost to maturity using the approximation formula. What is the after-tax cost to maturity for Bond C? Answer as a percentage to two decimal places.

| Bond | Life (years) | Underwriting fee | Discount (-) or premium (+) | Coupon interest rate |
|------|--------------|------------------|-----------------------------|----------------------|
| A | 20 | \$25 | -\$20 | 9% |
| B | 16 | 40 | +10 | 10 |
| C | 15 | 30 | -15 | 12 |
| D | 25 | 15 | Par | 9 |
| E | 22 | 20 | -60 | 11 |

```
def solution():
    # Define bond parameters
    par_value = 1000    # Par value of the bond
    discount = -15     # Discount for Bond C ($15)
    life = 15          # Bond life in years
    coupon_rate = 0.12  # Coupon interest rate (12%)
    tax_rate = 0.40    # Tax rate (40%)
    underwriting_fee = 30 # Underwriting fee ($30)
    annual_interest = par_value * coupon_rate
    after_tax_interest = annual_interest * (1 - tax_rate) (x)
    net_proceeds = par_value + discount - underwriting_fee
    numerator = after_tax_interest + ((par_value - net_proceeds) / life)
(x)
    denominator = (par_value + net_proceeds) / 2
    after_tax_cost = (numerator / denominator) * 100    # Convert to
percentage
    return round(after_tax_cost, 2)
```



Error Analysis: The error occurred because the tax rate was applied prematurely to the interest payment, while the amortized issuance cost was left untaxed, leading to an incorrect calculation. The correct approach is to first compute the pre-tax cost and then apply the tax rate to the entire cost to ensure consistency.

Ground Truth: 7.55



Figure 7. Knowledge Reasoning Error Case 1

Question: What percentage of the total leased locations are in Texas? Answer to three decimal places.

| State | Number of Locations(1) |
|--------------------------|------------------------|
| California | 57 |
| Florida | 26 |
| Georgia | 22 |
| Texas | 19 |
| Minnesota, New York | 9 |
| Illinois, Ohio, Maryland | 8 |
| Pennsylvania | 7 |
| Other | 63 |

```
def solution():
    # Define the number of locations in different states
    locations = {
        "California": 57,
        "Florida": 26,
        "Georgia": 22,
        "Texas": 19,
        "Minnesota, New Yorkx)
        "Illinois, Ohio, Marylandx)
        "Pennsylvania": 7,
        "Other": 63
    }
    # Calculate the total number of locations
    total_locations = sum(locations.values())
    # Compute the percentage of locations in Texas
    texas_percentage = (locations["Texas"] / total_locations) * 100
    # Return the result rounded to 3 decimal places
    return round(texas_percentage, 3)
```



Error Analysis: The error reflects a model reasoning issue, where multiple distinct states are incorrectly grouped as single entities—“Minnesota, New York” as one instead of two, and “Illinois, Ohio, Maryland” as one instead of three. This misclassification can lead to flawed inferences and inaccuracies in downstream analysis. In addition to the data shown in the image, the context also specifies that the company leases approximately 81 locations outside the United States. Taken together with the U.S.-based leased properties listed in the image, this brings the total number of leased locations to 292.

Ground Truth: 6.507



Figure 8. Knowledge Reasoning Error Case 2

Question: On February 17, 2017, what was the company's market capitalization as reported on the NYSE? Answer to three decimal places.

| 2016 | High | Low |
|----------------------------|----------|---------|
| Quarter ended March 31 | \$102.93 | \$83.07 |
| Quarter ended June 30 | 113.63 | 101.87 |
| Quarter ended September 30 | 118.26 | 107.57 |
| Quarter ended December 31 | 118.09 | 99.72 |
| 2015 | High | Low |
| Quarter ended March 31 | \$101.88 | \$93.21 |
| Quarter ended June 30 | 98.64 | 91.99 |
| Quarter ended September 30 | 101.54 | 86.83 |
| Quarter ended December 31 | 104.12 | 87.23 |

Context: Part II, Item 5. Market for Registrant's Common Equity, Related Stockholder Matters and Issuer Purchases of Equity Securities. The following table presents the reported quarterly high and low per share sale prices of our common stock on the NYSE for the years 2016 and 2015. On February 17, 2017, the closing price of our common stock was \$108.11 per share as reported on the NYSE. As of February 17, 2017, we had 427,195,037 outstanding shares of common stock and 153 registered holders.

```
def calculate_market_cap():
    closing_price_per_share = 108.11
    outstanding_shares = 427_195_037
    market_capitalization = closing_price_per_share *
outstanding_shares
    market_cap_billions = round(market_capitalization /
1_000_000_000, 3) (x)
    return market_cap_billions
print(calculate_market_cap())
```



Error Analysis: The model arbitrarily converted the market capitalization into billions, despite the absence of any such requirement in the problem statement. This reflects a misalignment between the model's assumptions and the explicit task constraints.

Ground Truth: 46184055450.078



Figure 9. Numerical Computation Error Case

Question: 请根据图中数据，计算呼吸在第五年的销售额，并将其与第三年进行比较，计算增长率；请保留两位小数。

(Calculate the sales revenue of the “Respiratory” category in the fifth year based on the data in the table. Then, compare it with the third year and calculate the growth rate. Please round the result to two decimal places.)

Image 1:

| | 2021 | 2022 | 2023 | 2024E | 2025E | 2026E |
|-------|---------|---------|---------|---------|---------|---------|
| 总收入 | 1118.57 | 1363.35 | 1387.74 | 1542.15 | 1818.67 | 2117.58 |
| YOY | -1.07% | 21.88% | 1.79% | 11.13% | 17.93% | 16.44% |
| 毛利率 | 42.36% | 43.19% | 45.89% | 43.76% | 43.94% | 44.42% |
| 归母净利润 | 106.09 | 166.57 | 192.49 | 220.85 | 269.86 | 323.18 |
| YOY | -30.71% | 57.00% | 15.56% | 14.74% | 22.19% | 19.76% |
| 1.麻醉 | 349.08 | 409.45 | 467.73 | 493.46 | 592.15 | 710.58 |
| YOY | 8.67% | 17.30% | 14.23% | 5.50% | 20.00% | 26.00% |
| 毛利率 | 53.27% | 54.81% | 56.41% | 56.00% | 56.00% | 56.00% |
| 占比 | 31.21% | 30.03% | 33.70% | 32.00% | 32.56% | 31.56% |
| 2.导尿 | 290.40 | 424.19 | 382.21 | 443.36 | 523.16 | 627.80 |
| YOY | 5.24% | 46.07% | -9.90% | 16.00% | 18.80% | 20.00% |
| 毛利率 | 27.16% | 28.05% | 29.27% | 30.00% | 30.00% | 30.00% |

Image 2:

| | | | | | | |
|--------|--------|--------|---------|--------|--------|---------|
| 占比 | 25.96% | 31.11% | 27.54% | 28.75% | 28.77% | 29.65% |
| 3.泌尿外科 | 169.56 | 196.04 | 203.44 | 189.20 | 223.26 | 263.44 |
| YOY | 27.84% | 15.62% | 3.77% | -7.00% | 18.00% | 18.00% |
| 毛利率 | 80.35% | 80.15% | 75.90% | 76.00% | 76.00% | 76.00% |
| 占比 | 15.16% | 14.38% | 14.66% | 12.27% | 12.28% | 12.44% |
| 4.护理 | 134.02 | 159.44 | 135.13 | 189.18 | 227.01 | 215.66 |
| YOY | 39.52% | 18.96% | -15.25% | 40.00% | 20.00% | -5.00% |
| 毛利率 | 19.17% | 23.20% | 28.24% | 25.00% | 25.00% | 25.00% |
| 占比 | 11.98% | 11.69% | 9.74% | 12.27% | 12.48% | 10.18% |
| 5.呼吸 | 61.87 | 64.33 | 87.73 | 100.01 | 120.01 | 150.01 |
| YOY | -9.87% | 3.98% | 36.36% | 14.00% | 20.00% | 25.00% |
| 毛利率 | 31.58% | 37.69% | 38.31% | 37.00% | 37.00% | 37.00% |
| 占比 | 5.53% | 4.72% | 6.32% | 6.48% | 6.60% | 6.08% |
| 6.血液透析 | 73.11 | 81.02 | 68.46 | 75.30 | 82.82 | 91.12 |
| YOY | 3.74% | 10.82% | -15.51% | 10.00% | 0.00% | -10.00% |
| 毛利率 | 26.41% | 24.46% | 29.51% | 28.00% | 28.80% | 28.00% |
| 占比 | 6.54% | 5.94% | 4.93% | 4.88% | 4.57% | 4.30% |

Image 3:

| 公司名称 | 代码 | 收盘价(元) | 归母净利润(亿元) | | | | PE |
|-------|-----------|--------|-----------|--------|--------|--------|-------|
| | | | 23A | 24E | 25E | 26E | |
| 康德莱 | 603987.SH | 7.46 | 2.31 | 2.24 | 2.48 | 2.81 | 14.23 |
| 三鑫医疗* | 300453.SZ | 7.74 | 2.07 | 2.45 | 2.86 | 3.36 | 16.66 |
| 博济医疗 | 605369.SH | 28.72 | 109.13 | 193.66 | 251.00 | 308.57 | 33.00 |
| 平均水平 | | | | | | | 15.11 |
| 强力医疗 | 603309.SH | 11.74 | 1.92 | 2.21 | 2.70 | 3.23 | 18.33 |
| | | | | | | | 12.87 |
| | | | | | | | 10.58 |

Original Output:

```
def solution():
    # Define variables name and value
    year_3_sales = 87.73
    year_5_sales = 150.01 (x)
    # Do math calculation to get the answer
    growth_rate = ((year_5_sales - year_3_sales) / year_3_sales)
    * 100
    # return answer
    return round(growth_rate, 2)
    # Call the function and print the result
    print(solution())
```



Augmented Output:

```
def solution():
    # Define variables name and value
    year_3_sales = 87.73
    year_5_sales = 120.01
    # Do math calculation to get the answer
    growth_rate = ((year_5_sales - year_3_sales) / year_3_sales)
    * 100
    answer = round(growth_rate, 2)
    # return answer
    return answer
```



Groud Truth: 36.79

Figure 10. Example of Filtering-Reasoning Pipeline

Question: Assuming the cash flow from financing activities according to U.S. GAAP is: Answer to a single decimal place.

Image:

| | |
|---|----------|
| Net income | \$55,000 |
| Depreciation | \$60,000 |
| Taxes paid | \$25,000 |
| Interest paid | \$5,000 |
| Dividends paid | \$10,000 |
| Cash received from sale of company building | \$40,000 |
| Issuance of preferred stock | \$45,000 |
| Repurchase of common stock | \$20,000 |
| Purchase of machinery | \$20,000 |
| Issuance of bonds | \$40,000 |
| Debt retired through issuance of common stock | \$45,000 |
| Paid off long-term bank borrowings | \$10,000 |
| Profit on sale of building | \$15,000 |

Original Output:

```
def solution():
    # Define variables name and value
    lifo_reserve_2014 = 82 # in thousands
    tax_rate = 0.30 # 30%

    # Do math calculation to get the answer
    income_increase_before_tax = lifo_reserve_2014 (x)
    tax_on_increase = income_increase_before_tax * tax_rate
    income_increase_after_tax = income_increase_before_tax -
tax_on_increase

    # Return answer to one decimal place
    return round(income_increase_after_tax, 1) X
```

Augmented Output:

```
def solution():
    # Define variables name and value
    lifo_reserve_current = 82 # LIFO reserve for 2014 (in
    thousands)
    lifo_reserve_previous = 64 # LIFO reserve for 2013 (in
    thousands)
    tax_rate = 0.30 # 30% corporate tax rate

    # Do math calculation to get the answer
    change_in_lifo_reserve = lifo_reserve_current -
lifo_reserve_previous
    pre_tax_income_increase = change_in_lifo_reserve
    additional_tax = pre_tax_income_increase * tax_rate
    net_income_increase = pre_tax_income_increase -
additional_tax
    answer = round(net_income_increase, 1)

    return answer ✓
```

Error Analysis: The second implementation incorrectly assumes that the entire 2014 LIFO reserve (\$82k) should be released and added to net income, resulting in an overstatement. In reality, only the change in LIFO reserve from 2013 to 2014 (\$18k) impacts 2014 income when switching to FIFO. The first implementation correctly uses this difference and accounts for taxes, leading to an accurate calculation.

Ground Truth: 45000.0

Figure 11. Example of Knowledge Augmentation

Financial Function

```
def calc_net_return(init_investment: float,
                    growth: float, fee_rate: float, inc_rate:
                    float, hurdle: float) -> float:
    """
    Calculate the net return for an investor in
    a hedge fund given various parameters.

    Args:
        initial_investment (float): The initial
        amount invested in the hedge fund...

    Returns:
        net_return (float): The net return for the
        investor after fees, in millions.
    """
    end_value = init_investment * (1 + growth)
    fee = end_value * fee_rate
    net_value = end_value - fee
    hurdle_value = init_investment * (1 + hurdle
                                      )
    inc_fee = max(0, (net_value - hurdle_value)
                  * inc_rate)
    net_return = end_value - (fee + inc_fee) -
    init_investment
    return round(net_return, 2)
```

Figure 12. Example of Retrieved Financial Function

Question: What is the anticipated portfolio return made by an investment company analyst named Maud, under two scenarios of portfolio returns in various economic conditions (expressed as a percentage) ? Answer to a single decimal place.

Image:

| Scenario | Probability of scenario (%) | Portfolio return | Probability of return (%) |
|-------------------------|-----------------------------|------------------|---------------------------|
| good economic situation | 70 | 20% | 50 |
| good economic situation | 70 | 10% | 50 |
| bad economic situation | 30 | 5% | 60 |
| bad economic situation | 30 | -10% | 40 |

Structured Data:

```
| Scenario | Probability of scenario (%) | Portfolio return | Probability of return (%) |
| good economic situation | 70 | 20% | 50 |
| good economic situation | 70 | 10% | 50 |
| bad economic situation | 30 | 5% | 60 |
| bad economic situation | 30 | -10% | 40 |
```

Figure 13. Example of Parsing-Reasoning Pipeline

| Model | Organization | Source |
|------------------------------|-----------------|-------------------------------------|
| Claude 3.7 Sonnet (Thinking) | Anthropic | claude-3-7-sonnet-20250219 |
| Claude 3.7 Sonnet | Anthropic | claude-3-7-sonnet-20250219 |
| GPT-4o | OpenAI | gpt-4o-2024-11-20 |
| OpenAI o1 | OpenAI | o1-2024-12-17 |
| Gemini 2.0 Flash Thinking | Google DeepMind | gemini-2.0-flash-thinking-exp-01-21 |
| Gemini 2.0 Pro | Google DeepMind | gemini-2.0-pro-exp-02-05 |
| Gemini 2.0 Flash | Google DeepMind | gemini-2.0-flash |
| Gemma 3 27B | Google DeepMind | gemma-3-27b-it |
| Qwen-Omni-Turbo | Alibaba Qwen | qwen-omni-turbo-2025-01-19 |
| Qwen2.5-VL-72B | Alibaba Qwen | qwen2.5-vl-72b-instruct |
| QvQ-72B-Preview | Alibaba Qwen | qvq-72b-preview |
| Pixtral Large | MistralAI | pixtral-large-latest |
| Mistral Small 3.1 | Mistral AI | mistral-small-3.1-24b-instruct |
| InternVL2.5-78B | OpenGVLab | OpenGVLab/InternVL2.5-78B |
| Grok 2 Vision | xAI | grok-2-vision-1212 |
| Llama 4 Maverick | AI@Meta | llama-4-maverick |

Table 5. Specifications of MLLMs Evaluated on FinMMR.

| Model | Size | Extended thinking | Hard | | Medium | | Easy | | Avg. | | Token (M) | |
|---------------------------|------|-------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|-------------|
| | | | CoT | PoT | CoT | PoT | CoT | PoT | CoT | PoT | CoT | PoT |
| Claude 3.7 Sonnet | | ✓ (64K) | 50.67 | 50.33 | 66.00 | 63.00 | 75.67 | 75.33 | 64.11 | 62.89 | 2.44 | 3.02 |
| Claude 3.7 Sonnet | | ✗ | 50.33 | 49.00 | 63.67 | 60.00 | 75.33 | 74.00 | 63.11 | 61.00 | 0.27 | 0.24 |
| Qwen2.5-VL-72B | 72B | ✗ | 41.33 | 48.67 | 66.00 | 64.00 | 77.00 | 70.00 | 61.44 | 61.45 | 0.28 | 0.12 |
| GPT-4o | | ✗ | 46.00 | 47.67 | 66.00 | 63.67 | 73.33 | 73.67 | 61.78 | 61.67 | 0.23 | 0.11 |
| InternVL2.5-78B | 78B | ✗ | 38.00 | 47.67 | 57.00 | 60.67 | 69.00 | 69.33 | 54.67 | 59.22 | — | — |
| Gemini 2.0 Flash Thinking | | ✓ | 46.67 | 46.67 | 67.00 | 60.33 | 73.67 | 73.33 | 62.45 | 59.00 | 0.33 | 0.13 |
| Gemini 2.0 Flash | | ✗ | 46.67 | 46.00 | 63.33 | 55.67 | 70.00 | 71.33 | 60.00 | 57.67 | 0.31 | 0.12 |
| Gemini 2.0 Pro | | ✗ | 45.00 | 44.00 | 61.33 | 62.00 | 71.33 | 71.33 | 59.22 | 59.78 | 0.23 | 0.12 |
| OpenAI o1 | | ✓ | — | 45.00 | — | — | — | — | — | — | — | 0.61 |
| QvQ-72B-Preview | 72B | ✓ | 40.33 | 6.00 | 58.33 | 8.33 | 73.33 | 11.00 | 57.33 | 8.44 | 1.46 | 1.54 |
| Qwen-Omni-Turbo | | ✗ | 18.33 | 30.33 | 35.67 | 45.33 | 53.67 | 60.67 | 35.89 | 45.44 | 0.24 | 0.11 |
| Grok 2 Vision | | ✗ | 27.67 | 26.33 | 42.67 | 33.67 | 72.00 | 73.00 | 47.45 | 44.33 | 0.30 | 0.16 |
| Pixtral Large | 124B | ✗ | 25.00 | 27.00 | 38.67 | 38.00 | 65.33 | 67.33 | 43.00 | 44.11 | 0.28 | 0.20 |

Table 6. Results of different models using CoT and PoT prompting methods on the *validation* set of FinMMR. We use the best Accuracy on the *Hard* subset as the ranking indicator of model performance.

CoT Prompt Template

```
SYSTEM_INPUT = '''You are a financial expert, you are supposed to answer the given
→ question based on the provided image and context. You need to first think through
→ the problem step by step, identifying the exact variables and values, and
→ documenting each necessary step. Then you are required to conclude your response
→ with the final answer in your last sentence as 'Therefore, the answer is {final
→ answer}'. The final answer should be a numeric value.'''
USER_INPUT = '''The following question context is provided for your reference:
{question_context with image tags like <image1>}
Question:
{question_question}
Let's think step by step to answer the given question.'''

```

Figure 14. CoT Prompt Template

PoT Prompt Template

```
SYSTEM_INPUT = '''You are a financial expert, you are supposed to generate a Python
↪ program to answer the given question based on the provided image and context. The
↪ returned value of the program is supposed to be the answer. Here is an example of
↪ the Python program:
```python
def solution():
 # Define variables name and value
 revenue = 600000
 avg_account_receivable = 50000

 # Do math calculation to get the answer
 receivables_turnover = revenue / avg_account_receivable
 answer = 365 / receivables_turnover

 # return answer
 return answer
```
'''

USER_INPUT = '''The following question context is provided for your reference:
{question_context with tags like <image1>}
Question:
{question_question}
Please generate a Python program to answer the given question. The format of the
↪ program should be the following:
```python
def solution():
 # Define variables name and value

 # Do math calculation to get the answer

 # return answer
```

Continue your output:
```python
def solution():
 # Define variables name and value
```
'''
```

Figure 15. CoT Prompt Template

RAG Prompt Template

```
SYSTEM_INPUT = '''You are a financial expert, you are supposed to answer the given
→ question. You need to first think through the problem step by step, identifying
→ the exact variables and values, and documenting each necessary step. Then you are
→ required to conclude your response with the final answer in your last sentence as
→ 'Therefore, the answer is {final answer}'. The final answer should be a numeric
→ value.'''
USER_INPUT = '''The following question context is provided for your reference:
{question_context with image tags like <image1>}
Question:
{question_question}

To assist you in solving the problem, I will provide some financial functions for
→ reference.
Important Notes:
1. Do not directly call or use the provided reference functions in your
→ implementation.
2. The reference functions are only intended to help you understand the logic and
→ approach for solving the problem, when it is appropriate.
3. You must implement the solution from scratch, using your own code and logic.
4. Ensure that your implementation is independent and does not rely on the provided
→ functions.
5. If the reference functions are not applicable to the problem, ignore them entirely
→ and focus on solving the problem based on your own understanding.

The following are the financial functions for your reference:
{financial_function}'''
```

Figure 16. CoT Prompt Template

Function Relevance Judgment Prompt Template

```
SYSTEM_INPUT = '''You are a financial expert, you are supposed to judge whether the
→ given financial function is useful for answering the question.

For each function, follow these guidelines:
1. Determine if the function can directly address the user's problem, considering the
→ function's purpose, input parameters, and return values.
2. Consider the applicability range of the function, assumptions, limitations, and
→ restrictions when evaluating if it's relevant.
3. If the function can effectively contribute to solving the problem or is essential
→ for the calculation or analysis required, respond with [USEFUL].
4. If the function cannot effectively help in solving the problem, or is irrelevant
→ based on its scope and assumptions, respond with [USELESS].

Use financial domain knowledge to ensure that each judgment is precise and aligned
→ with common practices for problem-solving in the finance domain.'''
USER_INPUT = '''Given a financial question and financial functions, I want you to
→ analyze each of these function to assess if it can be useful in solving the
→ question.

For each financial function:
1. You need to decide if it is useful based on its fit with the problem's requirements
→ and constraints.
2. If the function is relevant to solving my problem, output [USEFUL].
3. If it is not helpful, output [USELESS].
Do not include any additional explanation, just the relevant outputs for each
→ function.

Question:
{financial_question}

Functions:
{financial_function}

Output the results in the following format:
[USEFUL, USELESS, USELESS, ...]'''
```

Figure 17. CoT Prompt Template

Visual Relevance Judgment Prompt Template

```
SYSTEM_INPUT = '''Given a complex financial numeric reasoning question and a set of
→ images, analyze each image and decide if it is useful for solving the question.
Guidelines:
1. Determine the content displayed and described in each image. Determine whether the
→ image contains data or information that is used (directly or indirectly) in the
→ multi-step calculations leading to the answer.
2. If the image's content does not contribute to the solution, output [USELESS].
3. In cases of uncertainty, lean towards labeling an image as [USEFUL] rather than
→ [USELESS]. The question is designed such that at least one image contains
→ necessary data. If you think none are clearly helpful, choose the one image most
→ likely to contain relevant data and label it [USEFUL].
4. You need to first think through the problem step by step, documenting each
→ necessary step. Then you are required to conclude your response with the final
→ answer in your last sentence as 'Therefore, the answer is {final answer}'. The
→ final answer should be the labels in the order of the images. For example:[USEFUL,
→ USELESS, USELESS, ...]
Example: For such a question that "Based on the data in the image, calculate the
→ growth rate of bauxite imports from 2021 to 2022, and round the result to two
→ decimal places."For this problem, you may infer that in order to solve it, the
→ import amounts for 2021 and 2022 must be obtained from the images. Once you
→ identify an image that contains the relevant data, label that image as [USEFUL].
You may encounter other styles of charts such as bar charts, line charts, etc. with
→ clear data. Regardless of the category of the image, please carefully consider and
→ analyze the data in the image according to the above rules.'''
USER_INPUT = '''Given a complex financial numeric reasoning question and a set of
→ images, analyze each image and decide if it is useful for solving the question.
Guidelines:
1. Determine whether the image contains data or information that is used (directly or
→ indirectly) in the multi-step calculations leading to the answer.
2. If the image's content does not contribute to the solution, output [USELESS].
3. In cases of uncertainty, lean towards labeling an image as [USEFUL] rather than
→ [USELESS]. The question is designed such that at least one image contains
→ necessary data. If you think none are clearly helpful, choose the one image most
→ likely to contain relevant data and label it [USEFUL].
4. You need to first think through the problem step by step, documenting each
→ necessary step. Then you are required to conclude your response with the final
→ answer in your last sentence as 'Therefore, the answer is {final answer}'. The
→ final answer should be the labels in the order of the images. For example:
→ [USEFUL, USELESS, USELESS, ...]
Example: For such a question that "Based on the data in the image, calculate the
→ growth rate of bauxite imports from 2021 to 2022, and round the result to two
→ decimal places." For this problem, you may infer that in order to solve it, the
→ import amounts for 2021 and 2022 must be obtained from the images. Once you
→ identify an image that contains the relevant data, label that image as [USEFUL].
→ You may encounter other styles of charts such as bar charts, line charts, etc.
→ with clear data. Regardless of the category of the image, please carefully
→ consider and analyze the data in the image according to the above rules. Let's
→ think step by step to answer the given question.
Question:
{financial_question}
'''
```

Figure 18. CoT Prompt Template