



FINCHAIN: A Symbolic Benchmark for Verifiable Chain-of-Thought Financial Reasoning

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Abstract

Multi-step symbolic reasoning is critical for advancing downstream performance on financial tasks. Yet, benchmarks for systematically evaluating this capability are lacking. Existing datasets like FinQA and ConvFinQA supervise only final numerical answers, without assessing intermediate reasoning steps. To address this, we introduce FINCHAIN, the first symbolic benchmark designed for verifiable Chain-of-Thought (CoT) financial reasoning. Spanning 54 topics across 12 financial domains, FINCHAIN offers five parameterized templates per topic, each varying in reasoning complexity and domain expertise required. Each dataset instance includes an executable Python trace, enabling automatic generation of extensive training data and easy adaptation to other domains. We also introduce CHAINEVAL, a new metric for automatic evaluation of both final answers and intermediate reasoning. Benchmarking 30 LLMs on our dataset, we find that even state-of-the-art models have considerable room for improvement in multi-step financial reasoning. All templates and evaluation metrics for FINCHAIN are available at <https://github.com/mbzuai-nlp/finchain>.

1 Introduction

Large language models (LLMs) have demonstrated strong performance across a wide range of tasks (Zhao et al., 2023; Xie et al., 2023b), including practical applications in fields such as finance, healthcare and law (Chen et al., 2024b). In the financial field, for instance, effective analysis often requires processing large volumes of text from diverse sources, including documents, news articles, and social media. These texts frequently reflect or shape financial phenomena, such as market sentiment (Nie et al., 2024).

Prior work in financial NLP has predominantly focused on adapting general-purpose tasks to financial text. These tasks include information ex-

FINCHAIN Template (Compound Interest)

#Question:

`investor_name` invested `principal` in `project_name`. The investment grows at an annual interest rate of `rate`% compounded annually over `time` years. Calculate the compound interest (CI).

#Variables:

- `investor_name` = sample(investors)
- `project_name` = sample(projects)
- `principal` = range(1000, 5000)
- `rate` = uniform(2, 10)
- `time` = range(1, 5)

#Chain-of-Thought Solution:

Step 1: Compute the compound amount: `amount` = `principal` ×

$$\left(1 + \frac{\text{rate}}{100}\right)^{\text{time}}$$

Step 2: Compute the compound interest:

$$\text{CI} = \text{amount} - \text{P}$$

Figure 1: Symbolic template for generating compound interest problems in FINCHAIN.

traction (Shah et al., 2023), sentiment analysis (Pei et al., 2022), and text classification (Sy et al., 2023), where models are trained to output relatively simple targets such as entity spans, sentiment labels, or numerical scores. In contrast, our task addresses financial reasoning, which requires models to generate complete chain-of-thought (CoT) reasoning traces that justify each step in solving a financial problem, as shown in Figure 1.

Existing benchmarks for financial reasoning, such as FinQA (Chen et al., 2021) and ConvFinQA (Chen et al., 2022), frame the task primarily

as numerical question answering. These datasets focus on predicting the final answer and do not require models to explicitly generate or justify intermediate reasoning steps. While some examples may include traces of intermediate operations (loosely resembling reasoning steps), these are neither comprehensive nor rigorously structured to reflect the standards of financial analysis. In particular, they lack explicit, verifiable representations of a full reasoning chain, which is critical for transparency and accountability in financial decision-making. As a result, these benchmarks offer limited diagnostic value: they do not reliably reveal where a model’s reasoning succeeds or fails, nor do they distinguish genuine multi-step reasoning from shallow pattern matching.

In the field of mathematical reasoning, the symbolic template paradigm introduced by GSM-SYMBOLIC (Mirzadeh et al., 2024) has become a widely adopted approach. This method re-templates 100 math problems from GSM8K (Cobbe et al., 2021), providing explicit intermediate steps alongside the final answer. We adopt a similar templating strategy, but construct our dataset entirely from scratch for the financial field. As illustrated in Figure 1, each symbolic template encodes a parameterized financial problem (e.g., compound interest) with variable named entities and numerical inputs. Each template is paired with executable Python code that computes both intermediate steps and the final result. This design enables scalable, contamination-free generation of consistent examples for both training and evaluation.

The financial field comprises a wide range of distinct domains, each involving different stakeholders and downstream objectives. Consequently, it is essential to design the dataset in a templated manner that supports domain-specific evaluation. To address this, we organize our dataset using a fine-grained financial taxonomy (Figure 2) covering **12 high-level domains** (e.g., Corporate Finance, Sustainable Finance, Crypto), each comprising distinct topics, **54 topics in total**. For each topic, we develop **five parameterized templates** (two easy, two intermediate, one advanced), varying in symbolic reasoning complexity and required domain knowledge. To the best of our knowledge, this hierarchical structure constitutes the most detailed classification of financial reasoning tasks among existing datasets in this area.

Each templated instance includes: (1) a **scenario card** describing the topic, difficulty tier, and

sampled inputs (e.g., “Discounted cash flow valuation, advanced”), and (2) an **executable chain** of reasoning steps in Python, grounded in domain-specific equations and concepts. Because every operation in the chain is explicit and executable, our benchmark supports full machine-verifiability: any hallucinated, skipped, or incorrect step in a model’s output can be automatically detected. This contrasts sharply with existing datasets like FINQA and CONVFQA, which only supervise the final answer.

To enable rigorous evaluation, we introduce **CHAINVAL**, which assesses both the correctness of the final answer and the alignment of intermediate reasoning steps. Our evaluation across proprietary and open-source LLMs reveals a consistent pattern: while large models such as GPT-4.1 and LLaMA 3.3 (70B) achieve high overall accuracy, they still struggle with complex symbolic tasks and multi-step financial reasoning. In contrast, smaller models consistently underperform, even when fine-tuned on financial data. These findings indicate that domain-specific supervision alone is insufficient; robust reasoning performance also depends on adequate model capacity for handling symbolic and multi-hop inference.

Our main contributions in this study are summarized below.

- We present the first from-scratch symbolic benchmark for financial reasoning, constructed using a custom designed financial taxonomy spanning 12 domains and 54 topics. For each topic, we provide five parameterized templates (two easy, two intermediate, one advanced) along with executable Python code that generates step-by-step reasoning traces for each instance.
- We propose an automatic alignment metric that evaluates a model’s chain of thought solution by comparing it against gold-standard reasoning traces, assessing both the correctness of the final answer and the alignment of intermediate steps.
- We evaluate a range of open-source and proprietary large language models and large reasoning models, and observe that even state-of-the-art models exhibit substantial difficulty in handling symbolic financial reasoning—particularly on advanced templates that

require longer and more complex reasoning chains.

2 Related Work

2.1 Financial NLP

Recent advances in financial NLP have been driven by both task-specific models and large-scale domain adaptation. Early work focused on extraction and classification tasks using models such as FinBERT (Araci, 2019), while more recent efforts have extended to personal finance (Hean et al., 2025), credit scoring (Feng et al., 2023), and risk-awareness benchmarking (Yuan et al., 2024). Domain-specific datasets such as FiNER-ORD, REFinD, FinARG, and ECTSum provide support for named entity recognition, relation extraction, argument mining, and summarization, respectively (Shah et al., 2023; Kaur et al., 2023; Mukherjee et al., 2022; Xie et al., 2024).

Apart from task-specific models, general-purpose financial language models have grown rapidly in both scale and specialization. BloombergGPT (Wu et al., 2023) demonstrated strong performance across a wide range of financial NLP tasks, while FinGPT (Liu et al., 2023) emphasized open-source adaptability. FinMA (Xie et al., 2023a), a compact model fine-tuned from LLaMA, achieved performance competitive with proprietary baselines.

With the emergence of these general-purpose models, there has been a corresponding increase in benchmarking efforts aimed at evaluating their performance across diverse financial tasks. FLANG (Shah et al., 2022) introduced early baselines, which were further extended by FinBen (Xie et al., 2024), covering 24 tasks, and FinMTEB (Tang and Yang, 2025), spanning 64 embedding datasets. BizBench (Koncel-Kedziorski et al., 2023) and PIXIU (Xie et al., 2023a) highlighted challenges in quantitative and multimodal reasoning.

Despite this progress, limitations remain in multi-step mathematical reasoning, long-context understanding, and cross-market generalization (Chen et al., 2024b). These challenges motivate the need for benchmarks that assess capability of models to perform faithful, auditable reasoning grounded in financial knowledge.

2.2 Financial Reasoning

Real-world financial problems typically require arriving at a precise numerical result. Consequently,

evaluating financial reasoning through a numerical QA framework emerges as a natural and intuitive choice. FinQA (Chen et al., 2021) and ConvFinQA (Chen et al., 2022) supervise models to generate arithmetic programs that compute final answers, but offer only weak supervision over intermediate steps. The resulting traces are neither fully explicit nor verifiable. FinTextQA (Chen et al., 2024a) introduces long-form financial questions derived from textbooks and regulatory documents. While it emphasizes explanatory, retrieval-based QA, it only assesses final answer correctness and lacks annotated reasoning steps. Outside finance, GSM-Symbolic (Mirzadeh et al., 2024) re-templates GSM8K (Cobbe et al., 2021) problems into symbolic programs with step-level supervision. However, these tasks focus on basic arithmetic and lack financial semantics. No equivalent benchmark currently exists in the financial domain.

Model-centric efforts have also aimed to enhance financial reasoning. FinR1 (Liu et al., 2025) applies reinforcement learning over synthetic programs, and Fino1 (Qian et al., 2025), based on an 8B LLaMA model, outperform larger baselines on FinQA, ConvFinQA, and FinTextQA. Nonetheless, these models still underperform on long-horizon and cross-table reasoning.

In summary, existing benchmarks either provide coarse program-level supervision (FinQA, ConvFinQA), fine-grained but domain-agnostic traces (GSM-Symbolic), or retrieval-based QA without traceability (FinTextQA). None support systematic, step-level, domain-aware supervision grounded in financial equations. **FINCHAIN addresses this gap by introducing a symbolic, executable benchmark for financial reasoning. It supervises each intermediate step, supports both automatic alignment and human assessment, and covers 54 topics across 12 financial domains.**

3 FINCHAIN

3.1 Data Creation Process

The data creation process begins with the identification and definition of financial domains. This step is informed by established literature (Bodie et al., 2025) and guided by input from financial experts. Through this process, we identify **12** distinct financial domains. To generate topics within each domain, we extract relevant passages from the literature and use the domain name as a prompt to

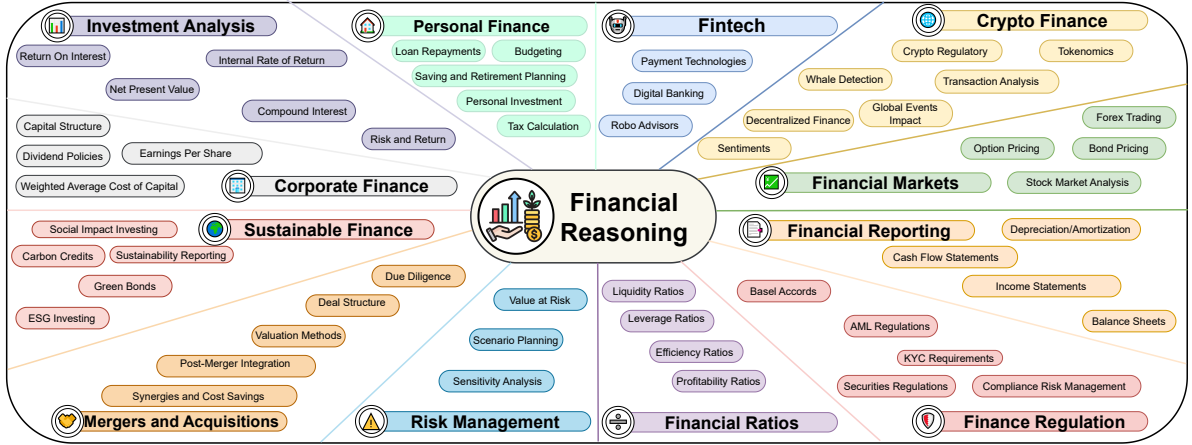


Figure 2: **FinChain taxonomy of financial reasoning topics.** Our benchmark spans 54 topics organized into 12 major domains, ranging from traditional areas like *Corporate Finance* and *Financial Reporting* to emerging fields such as *Crypto Finance* and *Sustainable Finance*. This hierarchical structure enables fine-grained evaluation of symbolic reasoning across diverse financial domains.

ChatGPT¹ to extract candidate financial topics. The resulting list is then curated by our financial experts, who filter and refine the outputs to yield a total of **54** financial topics, averaging **4.5** topics per domain. This structured approach results in the comprehensive taxonomy illustrated in Figure 2. Inspired by Mirzadeh et al. (2024), we develop executable Python methods that generate both questions and solutions featuring chain-of-thought reasoning by instructing ChatGPT. The prompt is provided in Appendix A. For each topic, we prompt the model to produce ten template-based questions and explicitly guide it to vary the complexity levels, easy, intermediate, and advanced, based on the number of reasoning steps required. We then manually select five representative templates per topic, two easy, two intermediate, and one advanced, to ensure balanced coverage across difficulty levels in FinChain.

3.2 Sanity Check

After initial template generation through prompting, we observed several recurring issues that we intend to filter out from our dataset creation methodology, to ensure utmost quality. Therefore, we implemented a dedicated sanity check phase focused on the following problems: (1) **Cross-national inconsistencies:** The automated prompting process, occasionally introduced hyper-localized financial contexts (e.g., currencies, exchange rates, indices and terminology from local economies in varied countries). To ensure consistency, we standardized

all questions to U.S. based financial settings only. (2) **Precision mismatch:** Questions and solutions often used rounded values for readability, while full precision values were used in the underlying computation. We adjusted the computation outputs to match the displayed precision. (3) **Incomplete input specification:** Some questions omitted key variables needed for calculation. We manually edited these cases to include all required inputs.

3.3 Expert Check

To address the known limitations of automated generation, we incorporate expert verification by qualified financial professionals as a critical component of our quality control process. To reduce LLM specific artifacts and improve reliability, we employ a two-step strategy. First, we introduce model diversity by using a different LLM to assist in annotation, mitigating overfitting to the idiosyncrasies of a single model. Second, when this auxiliary LLM identifies a potential error or inconsistency, the case is escalated to a human expert for validation.

Specifically, we first conducted an automated screening using another high-capacity LLM, Claude 3.5 Sonnet (Claude). Claude was prompted to assess the soundness of each question-and-solution template produced by ChatGPT.² Templates flagged by Claude as potentially flawed were escalated to a qualified financial expert. The expert’s role was to adjudicate these cases by evaluating the correctness of the original ChatGPT template in light of Claude’s feedback. Each template

¹We use GPT-4o, the latest version available at the time of writing.

²The prompt is provided in Appendix B.

was classified into one of three categories: (a) Correct, (b) Incorrect, or (c) Correct but better expressed from an alternative financial perspective³.

If a template was deemed incorrect, we re-generated and re-validated it through the same pipeline until a version was confirmed as correct by the expert. This iterative filtering process ensured that only high-quality, financially sound templates were retained in FINCHAIN.

4 CHAINEVAL

We propose CHAINEVAL, an evaluation framework that assesses model outputs along two axes: **final answer correctness** and **reasoning step alignment**. While our step-wise semantic alignment approach is inspired by prior work on reasoning consistency (Lyu et al., 2023; Golovneva et al., 2023), we extend it by explicitly modeling the verification of intermediate results through step-answer matching. Moreover, unlike prior work, which primarily evaluates textual consistency, our framework also verifies the final numeric answer, which ensures a holistic view of model performance, on both reasoning faithfulness and end-task fidelity. To the best of our knowledge, this combination has not been previously explored, particularly in the context of financial reasoning tasks.

4.1 Preliminaries

We define the gold solution S^* and the predicted solution \hat{S} as a sequence of m and n steps, respectively, represented as:

$$S^* = (s_1^*, \dots, s_m^*), \quad \hat{S} = (\hat{s}_1, \dots, \hat{s}_n), \quad (1)$$

where s_i^* and \hat{s}_j represent individual steps in S^* and \hat{S} , respectively. We also define a function $\text{StepRes}(\cdot)$, denoted as:

$$\text{StepRes}(s_i) = a_i, \quad (2)$$

which extracts the intermediate result a_i , computed at the i^{th} step of the corresponding solution.

4.2 Reasoning Step Alignment

To measure reasoning faithfulness, we break the evaluation into two components:

³In some cases, the expert noted that ChatGPT’s template was valid, but Claude proposed an equally sound formulation. The expert chose the most appropriate version for the dataset.

Step Semantic-Similarity. We embed each step using a sentence encoder $\text{Enc}(\cdot)$ and compute cosine similarity between gold and predicted step pairs (s_i^*, \hat{s}_j) , resulting in scores $\text{SS}(\cdot) \in [0, 1]$, represented as:

$$\text{SS}(s_i^*, \hat{s}_j) = \text{CosSim}(\text{Enc}(s_i^*), \text{Enc}(\hat{s}_j)) \quad (3)$$

where s_i^* denotes the i^{th} step of the gold solution and \hat{s}_j denotes the j^{th} step of the predicted solution.

Step Answer-Match. We evaluate whether the results computed at intermediate steps s_i^* and \hat{s}_j are consistent with each other. To this end, we introduce a function $\text{AM}(\cdot)$, and the answer matching process is denoted as follows:

$$\begin{aligned} \text{StepRes}(s_i^*) &= a_i^*, \quad \text{StepRes}(\hat{s}_j) = \hat{a}_j, \\ \text{AM}(s_i^*, \hat{s}_j) &= \begin{cases} \mathbb{I}(\frac{|\hat{a}_j - a_i^*|}{a_i^*} \leq \epsilon) & \text{if } \hat{a}_j, a_i^* \in \mathbb{R}, \\ \mathbb{I}(\hat{a}_j == a_i^*) & \text{otherwise.} \end{cases} \end{aligned} \quad (4)$$

where $\mathbb{I}(\cdot)$ is the indicator function, and ϵ is a small tolerance threshold to account for errors propagating due to numerical rounding. We set $\epsilon = 0.05$ for our experiments, allowing a relative error of up to 5%.

Now, we consider a pair of steps to be aligned with each other if: (i) their semantic similarity is above a threshold, and (ii) the corresponding intermediate results are consistent. Using Equations (3) and (4), we represent the process of measuring step-level alignment between predicted solution and ground truth as follows:

$$\begin{aligned} A(s_i^*, \hat{s}_j) &= \text{SS}(s_i^*, \hat{s}_j) \times \text{AM}(s_i^*, \hat{s}_j), \\ \text{StepAlign}(s_i^*, \hat{S}) &= \max_{j=1, \dots, n} A(s_i^*, \hat{s}_j), \end{aligned} \quad (5)$$

and similarly,

$$\text{StepAlign}(S^*, \hat{s}_j) = \max_{i=1, \dots, m} A(s_i^*, \hat{s}_j) \quad (6)$$

Finally, we compute step-level recall and precision using Equations (5) and (6):

$$\text{Rec} = \frac{1}{m} \sum_{i=1}^m \mathbb{I}(\text{StepAlign}(s_i^*, \hat{S}) \geq \tau), \quad (7)$$

$$\text{Prec} = \frac{1}{n} \sum_{j=1}^n \mathbb{I}(\text{StepAlign}(\hat{s}_j, S^*) \geq \tau), \quad (8)$$

where τ is an alignment score threshold.

We also define the StepF1, which is the harmonic mean of step-level precision and recall:

$$\text{StepF1} = \frac{2 \times \text{Prec} \times \text{Rec}}{\text{Prec} + \text{Rec} + \gamma}, \quad (9)$$

where γ is a small constant to prevent division by zero. We set $\tau = 0.7$ and $\gamma = 0.0001$ for our experiments.

4.3 Final Answer Correctness

To measure effectiveness of the models on overall end-task fidelity, we evaluate whether the final answer in the predicted solution is consistent with that of the ground truth. We define a function $\text{FAC}(\cdot)$ using $\text{AM}(\cdot)$ from Equation (4). We extract the final answer from the last step of the solution, and formalize it as follows:

$$\text{FAC}(\hat{S}, S^*) = \text{AM}(s_m^*, \hat{s}_n) \quad (10)$$

5 Experiments and Results

In this section, we evaluated the symbolic financial reasoning capabilities of 30 language models over 2,700 cases, and analyzed performance from overall, domain and difficulty-level perspectives.

5.1 Evaluated Models

To comprehensively benchmark model capabilities, we evaluate a diverse set of language models grouped into six categories:

- **General-Purpose Models** serve as strong domain-agnostic baselines. We include GPT-4.1, GPT-{4o, 4.1} mini (Hurst et al., 2024), LLaMA 3.1 {8, 70}B Instruct, LLaMA 3.3 70B Instruct (Grattafiori et al., 2024), Mistral 7B Instruct (Jiang et al., 2023), Mixtral (8x7B) Instruct (Jiang et al., 2024), Gemma 2 {9, 27}B Instruct (Riviere et al., 2024), Gemma 3 27B Instruct (Kamath et al., 2025), and Qwen2.5 7B (Yang et al., 2024a).
- **General Reasoning Models** are trained or fine-tuned for broad multi-step reasoning tasks. We include o{3, 4}-mini, DeepSeek-R1 Distill LLaMA {8, 70}B, DeepSeek-R1 Distill Qwen {7, 32}B (Guo et al., 2025), and Qwen3 {8, 30}B (Qwen, 2025).
- **Financially Fine-Tuned Models** are adapted via instruction tuning or continued pretraining on financial corpora. We evaluate Finance-LLM 13B (Cheng et al., 2024), FinanceConnect 13B (CeADAR, 2023)

WiroAI Finance-LLaMA 8B, and WiroAI Finance-Qwen 7B (Abdullah Bezir, 2025).

- **Financial Reasoning Models** are specifically designed for multi-step reasoning in finance, often leveraging chain-of-thought (CoT) supervision. We include Fino1 8B (Qian et al., 2025) and FinR1 7B (Liu et al., 2025).
- **Mathematical Models** are fine-tuned on math-centric corpora for symbolic computation. We include Mathstral 7B (Mistral, 2024), and Qwen2.5 Math 7B (Yang et al., 2024b).
- **Mathematical Reasoning Models** excel at step-by-step problem solving in mathematics. We include WizardMath 7B (Luo et al., 2023), and MetaMath 13B (Yu et al., 2023).

5.2 Experimental Setup

We generate 10 instances per symbolic template using different random seeds, resulting in a total of $54 \text{ topics} \times 5 \text{ templates} \times 10 \text{ instances} = 2,700 \text{ test cases}$. All models are evaluated under a consistent decoding configuration: temperature = 0.7, top- p = 0.95, and a maximum token limit of 4,096. For evaluation, we use our proposed metric, CHAINEval, as the primary indicator for both final answer correctness and alignment of intermediate reasoning steps. Additionally, we include two widely used reference-based metrics (Xie et al., 2023c) to assess surface-level generation quality: ROUGE (Lin, 2004) for n-gram overlap and BERTScore (Zhang et al., 2020) for semantic similarity.

5.3 Results and Analysis

5.3.1 Overall Model Performance

Table 1 presents a comprehensive evaluation of model performance on FINCHAIN, measured across four components of CHAINEval, including Final Answer Correctness (FAC), Step Precision/Recall/F1, alongside ROUGE and BERTScore. Overall, general-purpose models such as LLaMA 3.3 (70B) Instruct and GPT-4.1 lead in both accuracy and consistency. These models also exhibit moderate variance, indicating not only high performance but also robust generalization across diverse financial scenarios. Crucially, the results highlight a strong correlation between model size and reasoning ability. Larger models consistently outperform their smaller counterparts, even when the latter are explicitly trained on domain-specific data, which suggests that domain exposure alone is insufficient without adequate model capacity.

Model	CHAINEval \uparrow				ROUGE \uparrow			BERTScore \uparrow
	FAC	Step-Precision	Step-Recall	Step-F1	R ₂	R _L	R _{Lsum}	
General-Purpose								
Mistral (7B) Instruct v0.3	0.32 _{0.24}	0.3317 _{0.20}	0.21 _{0.14}	0.2444 _{0.15}	0.1183 _{0.02}	0.1868 _{0.02}	0.2239 _{0.02}	0.8341 _{0.002}
Qwen2.5 (7B)	0.4083 _{0.32}	0.3554 _{0.24}	0.2095 _{0.16}	0.2486 _{0.17}	0.1615 _{0.04}	0.2523 _{0.06}	0.3052 _{0.07}	0.8564 _{0.01}
Mixtral (8x7B) Instruct v0.1	0.357 _{0.28}	0.3345 _{0.21}	0.2354 _{0.15}	0.2622 _{0.16}	0.1596 _{0.03}	0.2537 _{0.04}	0.3045 _{0.05}	0.8584 _{0.01}
Llama 3.1 (8B) Instruct	0.4267 _{0.28}	0.3935 _{0.21}	0.2266 _{0.13}	0.2729 _{0.15}	0.1454 _{0.03}	0.2273 _{0.04}	0.2753 _{0.05}	0.8565 _{0.01}
Gemma 2 (9B) Instruct	0.4838 _{0.21}	0.4643 _{0.16}	0.3243 _{0.11}	0.367 _{0.12}	0.1975 _{0.03}	0.3021 _{0.03}	0.3667 _{0.04}	0.8646 _{0.01}
Gemma 2 (27B) Instruct	0.5325 _{0.21}	0.4937 _{0.15}	0.3488 _{0.11}	0.3926 _{0.12}	0.1962 _{0.03}	0.3002 _{0.03}	0.3621 _{0.03}	0.8639 _{0.006}
Gemma 3 (27B) Instruct	0.4879 _{0.18}	0.5023 _{0.16}	0.3064 _{0.09}	0.365 _{0.11}	0.1717 _{0.02}	0.2567 _{0.02}	0.3045 _{0.03}	0.8567 _{0.005}
Llama 3.1 (70B) Instruct	0.5735 _{0.25}	0.4811 _{0.21}	0.3048 _{0.15}	0.3558 _{0.16}	0.1691 _{0.04}	0.259 _{0.05}	0.3108 _{0.05}	0.858 _{0.01}
Llama 3.3 (70B) Instruct	0.584_{0.22}	0.5145 _{0.19}	0.2724 _{0.11}	0.3384 _{0.13}	0.1492 _{0.03}	0.2269 _{0.03}	0.2694 _{0.04}	0.8537 _{0.006}
GPT-4o-mini	0.524 _{0.23}	0.4352 _{0.19}	0.2385 _{0.11}	0.2923 _{0.13}	0.1337 _{0.02}	0.2177 _{0.02}	0.2588 _{0.02}	0.8458 _{0.005}
GPT-4.1-mini	0.5668 _{0.24}	0.4877 _{0.19}	0.2882 _{0.12}	0.3456 _{0.13}	0.1725 _{0.02}	0.2645 _{0.02}	0.3201 _{0.03}	0.8569 _{0.006}
GPT-4.1	0.5691 _{0.23}	0.4197 _{0.21}	0.2527 _{0.13}	0.2993 _{0.15}	0.1657 _{0.02}	0.2631 _{0.02}	0.3176 _{0.03}	0.8505 _{0.007}
General Reasoning								
DeepSeek-R1-Distill Qwen (7B)	0.4383 _{0.31}	0.3568 _{0.23}	0.2239 _{0.15}	0.2606 _{0.16}	0.1887 _{0.04}	0.3126 _{0.05}	0.381 _{0.05}	0.864 _{0.01}
DeepSeek-R1-Distill Llama (8B)	0.4394 _{0.31}	0.3583 _{0.22}	0.2204 _{0.13}	0.2576 _{0.15}	0.1841 _{0.04}	0.3004 _{0.05}	0.3689 _{0.05}	0.865 _{0.01}
Qwen3 (8B)	0.5402_{0.27}	0.3992 _{0.23}	0.2145 _{0.13}	0.2643 _{0.15}	0.1951 _{0.05}	0.3018 _{0.06}	0.364 _{0.06}	0.8696 _{0.01}
Qwen3 (30B) A3B	0.5089 _{0.18}	0.4245 _{0.21}	0.1995 _{0.12}	0.2509 _{0.13}	0.0373 _{0.01}	0.0538 _{0.01}	0.0649 _{0.01}	0.8453 _{0.01}
DeepSeek-R1-Distill Qwen (32B)	0.4991 _{0.30}	0.4071 _{0.23}	0.262 _{0.15}	0.3039 _{0.17}	0.1895 _{0.04}	0.3181 _{0.04}	0.384 _{0.05}	0.8575 _{0.01}
DeepSeek-R1-Distill Llama (70B)	0.4927 _{0.31}	0.4013 _{0.23}	0.255 _{0.15}	0.2965 _{0.17}	0.1961 _{0.04}	0.3239 _{0.05}	0.3922 _{0.05}	0.8618 _{0.01}
o3-mini	0.5183 _{0.25}	0.3881 _{0.21}	0.2432 _{0.12}	0.2839 _{0.14}	0.2028 _{0.03}	0.3083 _{0.04}	0.3714 _{0.04}	0.8574 _{0.02}
o4-mini	0.3873 _{0.21}	0.2976 _{0.19}	0.1768 _{0.11}	0.2126 _{0.13}	0.1945 _{0.03}	0.3093 _{0.03}	0.3806 _{0.04}	0.8563 _{0.02}
Finance Fine-Tuned								
WiroAI Finance Qwen (7B)	0.4419_{0.28}	0.4064 _{0.23}	0.2531 _{0.15}	0.2933 _{0.17}	0.1782 _{0.04}	0.2866 _{0.05}	0.3409 _{0.06}	0.8651 _{0.01}
WiroAI Finance Llama (8B)	0.2853 _{0.28}	0.2729 _{0.23}	0.1627 _{0.15}	0.1911 _{0.17}	0.1625 _{0.05}	0.2671 _{0.06}	0.3254 _{0.08}	0.8611 _{0.02}
FinanceConnect (13B)	0.0725 _{0.12}	0.0884 _{0.13}	0.0561 _{0.08}	0.0646 _{0.09}	0.166 _{0.04}	0.2837 _{0.05}	0.3482 _{0.06}	0.8573 _{0.01}
Finance-LLM (13B)	0.1709 _{0.21}	0.2247 _{0.19}	0.1443 _{0.13}	0.1654 _{0.14}	0.1628 _{0.04}	0.2671 _{0.05}	0.3263 _{0.06}	0.8631 _{0.01}
Finance Reasoning								
Fin-R1 (7B)	0.512_{0.28}	0.3649 _{0.22}	0.1978 _{0.12}	0.2428 _{0.15}	0.1685 _{0.04}	0.2806 _{0.04}	0.3429 _{0.05}	0.8585 _{0.01}
Finol (8B)	0.4191 _{0.26}	0.3621 _{0.22}	0.1637 _{0.10}	0.2133 _{0.12}	0.1701 _{0.03}	0.2795 _{0.04}	0.3458 _{0.05}	0.868 _{0.01}
Math Fine-Tuned								
Mathstral (7B)	0.4397_{0.26}	0.3953 _{0.21}	0.2732 _{0.16}	0.3063 _{0.16}	0.1635 _{0.03}	0.2586 _{0.04}	0.3098 _{0.05}	0.8587 _{0.01}
Qwen2.5-Math (7B)	0.1891 _{0.26}	0.1763 _{0.21}	0.1298 _{0.15}	0.1412 _{0.16}	0.0705 _{0.06}	0.1337 _{0.08}	0.1488 _{0.10}	0.8067 _{0.02}
Math Reasoning								
MetaMath (13B)	0.2313 _{0.22}	0.2704 _{0.20}	0.1357 _{0.10}	0.1717 _{0.13}	0.1863 _{0.05}	0.3064 _{0.06}	0.3753 _{0.07}	0.8728 _{0.01}
WizardMath (7B)	0.3461_{0.28}	0.3357 _{0.24}	0.1942 _{0.14}	0.2332 _{0.17}	0.1933 _{0.06}	0.3142 _{0.07}	0.3737 _{0.08}	0.8723 _{0.01}

Table 1: **Overall performance of language models on FINCHAIN.** We report four components of our CHAIN EVal metric (FAC, step precision, step recall, and step-level F1), alongside ROUGE (R₂, R_L, R_{Lsum}) and BERTScore. Models are grouped into six categories. Top-performing models under FAC within each category are bolded.

Open-source models such as Qwen3 (8B) demonstrate competitive performance despite its smaller size, achieving strong results, which can be attributed to its enhanced reasoning capabilities in recent release. Financially reasoning models, such as Fin-R1 exhibit reasonable symbolic alignment but fall short in final answer accuracy. Overall, our findings highlight the critical role of model scale in symbolic financial reasoning. Larger general-purpose models not only deliver higher performance but also generalize across tasks. Yet, smaller models tend to struggle to complete reasoning chains accurately despite domain-specific tuning. This underscores the advantage of large-scale instruction tuning for chain-of-thought reasoning in finance.

5.3.2 Performance Over Domains

We present how model performance varies across financial domains in Figure 3, which shows domain-level FAC for representative models. For the non-reasoning models, structured and quantitative domains such as *Personal Finance* and *Crypto Finance* show higher FAC. These areas tend to require straightforward computations or familiar terminologies, which general-purpose and math-tuned mod-

els can handle well. In contrast, domains like *Risk Management* and *Sustainable Finance* exhibit clear performance drops, likely due to their multi-step logic requirements, ambiguous scenarios, or regulatory nuances that are harder to encode symbolically.

For reasoning models, we observe stronger performance in traditionally challenging domains like *Financial Ratios* and *Corporate Finance*, suggesting improved reasoning ability over multi-step symbolic structures. Nevertheless, even reasoning models still exhibit relatively weaker results in *Sustainable Finance* and *Mergers & Acquisitions*, which demands nuanced understanding and domain-specific reasoning strategies. These disparities underscore our domain-specific taxonomy enables a granular diagnosis of model strengths and blind spots, offering a roadmap for developing targeted financial reasoning capabilities. We report domain-wise performance across all evaluated models in Appendix C.

5.3.3 Performance Over Difficulty Levels

To assess model robustness under increasing complexity of reasoning, we group the results into three predefined tiers (*Basic*, *Intermediate*, and *Advanced*

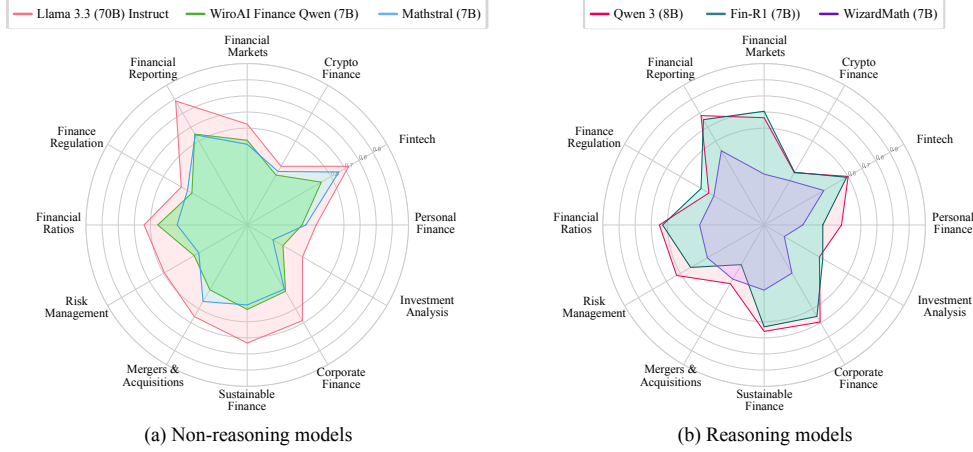


Figure 3: **Domain-level performance across financial domains.** Radar plots compare representative models from (a) Non-reasoning models and (b) Reasoning models. Each spoke corresponds to one of the 12 top-level financial domains. Models are selected as the top performers within each of the six categories presented in Table 1.

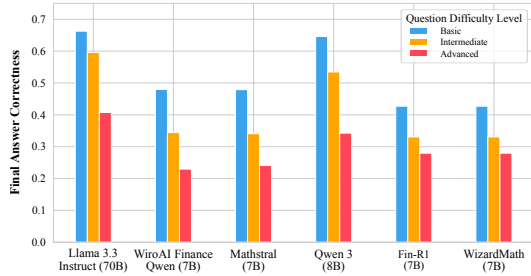


Figure 4: **Model performance across difficulty levels.** FAC is reported for Basic, Intermediate, and Advanced.

(§ 3). Each difficulty level reflects an increase in reasoning and computational depth. Figure 4 reports FAC across these tiers for six representative models (same subset as Figure 3). All models show performance degradation as complexity increases, underscoring the difficulty of executing longer financial reasoning chains. Among them, LLaMA 3.3 (70B) Instruct stands out for its strong absolute performance and gradual decline, indicating its better compositional generalization. In contrast, smaller models such as Fin-R1 (7B) suffer more severe drops, suggesting difficulty in maintaining reasoning coherence as reasoning depth grows. These findings validate the utility of difficulty levels of FINCHAIN for fine-grained stress testing. It also exposes models’ limitations in scaling their reasoning capabilities, particularly for longer step financial reasoning tasks.

5.3.4 Impact of Names and Values

To evaluate model robustness under surface-level perturbations, we test how changes of entity names and numerical values in the templates affect the

Model	Both	Name Only	Value Only
GPT-4.1	0.5080 ± 0.4999	0.4960 ± 0.5000	0.5040 ± 0.5000
GPT-4.1-mini	0.4720 ± 0.4992	0.4640 ± 0.4987	0.4640 ± 0.4987
GPT-4o-mini	0.3760 ± 0.4844	0.3600 ± 0.4800	0.3720 ± 0.4833
o3-mini	0.4040 ± 0.4907	0.3920 ± 0.4882	0.4160 ± 0.4929
o4-mini	0.3400 ± 0.4737	0.3600 ± 0.4800	0.3680 ± 0.4823

Table 2: **Model robustness to input perturbation.** FAC is reported for Both, Name Only, and Value Only.

model reasoning performance under one domain: **Investment Analysis**. We consider three settings: (i) **Name Only**, where only names are varied; (ii) **Value Only**, where only numerical values are varied; and (iii) **Both**, where both names and values are varied simultaneously. Larger models such as GPT-4.1 maintain consistent performance across all settings, reflecting strong abstraction over both name and value inputs. However, smaller models exhibit divergent sensitivities. For instance, o3-mini achieves higher FAC when only values are varied compared to the names setting. GPT-4o-mini also shows mild instability, with modest performance shifts between conditions. These findings highlight that entity names and numerical values have different impact in model reasoning. The templated structure of FINCHAIN allows precise manipulation of such variables, offering a powerful diagnostic tool for stress-testing reasoning robustness.

6 Conclusions and Future Work

We introduce FINCHAIN, a symbolic benchmark designed for verifiable chain-of-thought financial reasoning. Constructed from a fine-grained taxonomy spanning 54 topics across 12 financial domains and three difficulty levels, it enables targeted evalu-

ation across both reasoning complexity and domain-specific challenges. To assess model performance, we propose **CHAINEval**, a joint metric that evaluates both final answer correctness and alignment with intermediate reasoning steps. Experimental results reveal that while large general-purpose LLMs outperform specialized financial models, all models struggle with complex, multi-step symbolic reasoning. Looking ahead, we plan to expand **FINCHAIN** to support multilingual and region-specific scenarios, and to investigate how step-by-step reasoning traces can enhance the trustworthiness and factuality of model-generated answers, especially in long-form financial question answering over real-world documents. This line of work may help bridge symbolic financial reasoning and factual verification (Xie et al., 2025), supporting more robust and interpretable financial AI systems.

Limitations

We acknowledge several limitations in this work that we plan to address in future research.

First, our dataset is entirely synthetic, generated from symbolic templates. While this design enables fine-grained control, contamination-free generation, and automatic verifiability, it may lack the linguistic diversity and contextual richness of real-world financial texts. In future work, we plan to incorporate real-world financial documents, such as earnings reports, investor communications, or financial news, as seed sources for semi-structured or templated generation, allowing us to better simulate naturally occurring language while preserving symbolic grounding.

Second, the benchmark focuses narrowly on symbolic numerical reasoning and does not capture qualitative, contextual, or strategic aspects of financial decision-making, such as risk assessment, or market sentiment. To address this, we aim to complement our benchmark with additional tasks that evaluate models on these higher-level reasoning dimensions, potentially through multi-modal inputs (e.g., combining text with charts or scenarios) or interactive decision-making simulations.

Third, **FINCHAIN** is restricted to English and U.S. centric financial conventions, such as currency formats, and investment norms, which limits its generalizability to multilingual and regional financial contexts. In future extensions, we plan to expand coverage to other languages and financial systems, through collaboration with domain experts

and native speakers to localize templates and ensure culturally grounded reasoning tasks.

Ethical Statement and Broad Impact

This work uses only synthetic data generated through templated code and language model outputs. No private, sensitive, or copyrighted content was used. Our benchmark is designed for transparency and reproducibility in financial AI. However, caution should be taken when deploying LLMs in real-world financial decision-making, especially where symbolic correctness and regulatory compliance are critical. We believe **FINCHAIN** will support research toward more interpretable, verifiable, and safe reasoning systems in high-stakes domains.

Data License The **FINCHAIN** dataset and accompanying code will be released under the MIT License.

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A Financial-Symbolic: Template Creation Prompt

To construct symbolic financial reasoning benchmarks analogous to GSM-Symbolic, we design a structured prompt that guides the generation of executable financial templates. These templates support variable-based instantiation, symbolic step-wise supervision, and controlled perturbations for robustness evaluation. Below, we present the prompt used for template construction.

System Instruction: You are a financial NLP expert developing symbolic reasoning datasets. Your task is to construct symbolic templates for financial reasoning problems. Each template should support (i) controlled generation of diverse question instances, (ii) executable reasoning traces for automatic verification, and (iii) systematic variation in surface and logical complexity.

Please follow the steps below:

1. **Identify a financial reasoning task:** For example, compound interest, IRR, ROI, NPV, breakeven analysis, loan amortization, etc.
2. **Write a natural language question template:** Formulate the question using variable placeholders instead of fixed values. For instance, use {principal}, {rate}, {years}, etc.
3. **Define variables and constraints:** Specify the domain (e.g., numerical range or categorical values) for each variable. Add algebraic constraints to ensure the question is solvable and the answer valid.
4. **Write a symbolic solution trace:** Provide a step-by-step solution using the variables. Ensure the reasoning chain is executable in Python for automatic evaluation.
5. **Vary difficulty levels:** For each task, generate 10 templates with increasing complexity. Longer and more compositional reasoning chains should correspond to harder levels.

B Claude Verification Prompt

We use the following prompt to query Claude for template verification:

I have written several Python methods that automatically generate random questions and corresponding solutions about <topic> by varying key variables. I need

assistance in verifying the correctness of the equations used, ensuring that the solutions are accurate and solid. Please respond by first indicating if the method's underlying logic and solution are correct or flawed.

C Performance Over Topics for all models

We present domain-level performance comparisons across financial domains for four categories of models: general-purpose non-reasoning models (Figure 5), general-purpose reasoning models (Figure 6), financial fine-tuned and reasoning models (Figure 7), and mathematical fine-tuned and reasoning models (Figure 8).

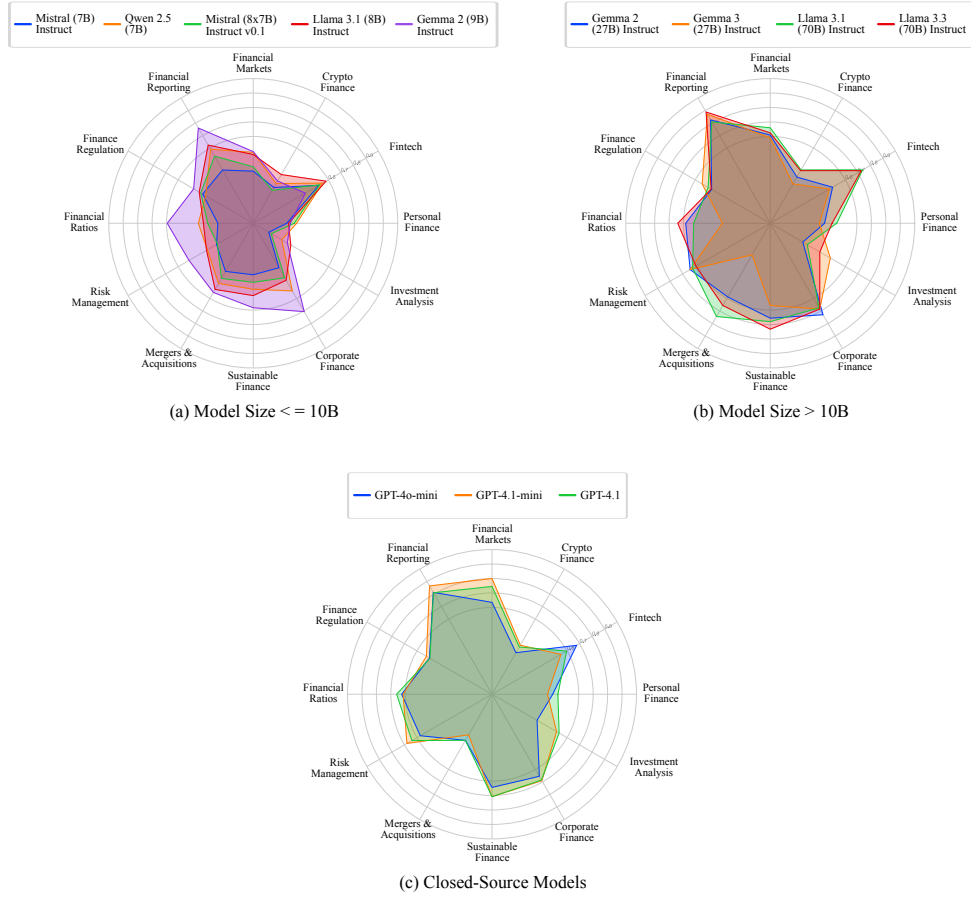


Figure 5: **Domain-level performance comparison across financial domains for all general-purpose non-reasoning models from Table 1.** For clarity, we split the models into three subtypes: (a) Model Size $\leq 10B$, (b) Model Size $> 10B$, and (c) Closed-Source Models.

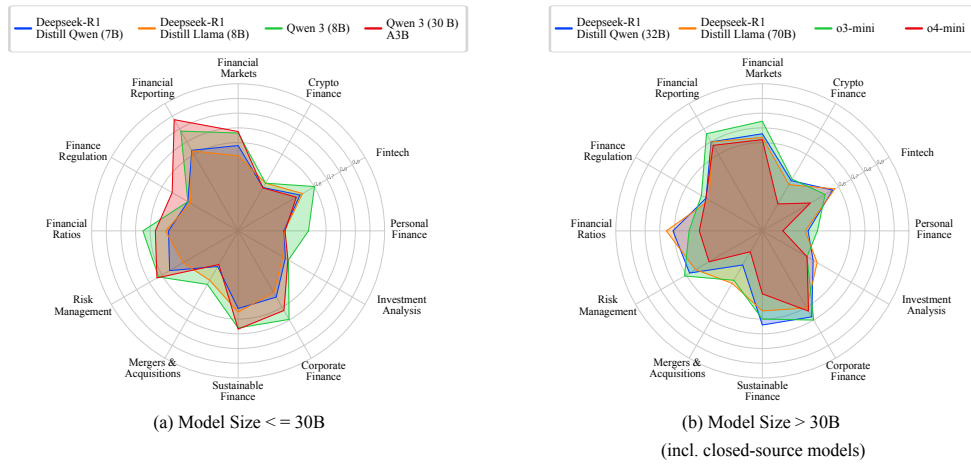


Figure 6: **Domain-level performance comparison across financial domains for all general-purpose reasoning models from Table 1.** For clarity, we split the models into two subtypes: (a) Model Size $\leq 30B$, and (b) Model Size $> 30B$ (along with all closed-source models).



Figure 7: **Domain-level performance comparison across financial domains for all financial fine-tuned and reasoning models from Table 1.** For clarity, we split the figure into two parts: (a) Finance Non-Reasoning, and (b) Finance Reasoning models.



Figure 8: **Domain-level performance comparison across financial domains for all mathematical fine-tuned and reasoning models from Table 1.** For clarity, we split the figure into two parts: (a) Math Non-Reasoning, and (b) Math Reasoning models.