CHAIN-OF-CODE COLLAPSE: Reasoning Failures in LLMs via Adversarial Prompting in Code Generation

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Abstract

Large Language Models (LLMs) have achieved remarkable success in tasks requiring complex reasoning, such as code generation, mathematical problem solving, and algorithmic synthesis - especially when aided by reasoning tokens and Chain-of-Thought prompting. Yet, a core question remains: do these models truly reason, or do they merely exploit shallow statistical patterns? In this paper, we introduce CHAIN-OF-CODE COLLAPSE, where we systematically investigate the robustness of reasoning LLMs by introducing a suite of semantically faithful yet adversarially structured prompt perturbations. Our evaluation — spanning 700 perturbed code generations derived from LeetCode-style problems — applies transformations such as storytelling reframing, irrelevant constraint injection, example reordering, and numeric perturbation. We observe that while certain modifications severely degrade performance (with accuracy drops up to -42.1%), others surprisingly improve model accuracy by up to 35.3%, suggesting sensitivity not only to semantics but also to surface-level prompt dynamics. These findings expose the fragility and unpredictability of current reasoning systems, underscoring the need for more principles approaches to reasoning alignments and prompting robustness. We release our perturbation datasets and evaluation framework¹ to promote further research in trustworthy and resilient LLM reasoning.

1 Introduction (Problem Statement)

Large Language Models (LLMs) have rapidly advanced in recent years, demonstrating impressive capabilities across a range of tasks—from natural language understanding and translation to code generation and complex reasoning (Brown et al., 2020; Chowdhery et al., 2022; OpenAI, 2023; Bai et al., 2023; Chen et al., 2021). With architectural improvements and techniques like instruction tuning, chain-of-thought (CoT) prompting (Wei et al., 2022), and reinforcement learning from human feedback, modern LLMs have achieved state-of-the-art performance on benchmarks once thought to require human-level intelligence.

Yet, despite their impressive breadth, LLMs remain vulnerable to adversarial inputs. Small changes in phrasing—often semantically irrelevant—can dramatically alter model behavior, especially in sensitive applications such as code generation. This vulnerability is not merely cosmetic: subtle prompt perturbations can cause models to ignore logic, omit constraints, or even produce insecure code. As prior work on DeceptPrompt (Wu et al., 2023) and prompt injection attacks has shown, these models often rely on superficial patterns in prompts, rendering them brittle in the face of real-world input variability.

Recent efforts have emphasized the emergent reasoning capabilities of LLMs. Through techniques like CoT prompting, models can now tackle tasks involving multi-step computation, logical inference, and algorithmic synthesis. These developments have sparked hope that LLMs may be evolving from stochastic parrots into true reasoners. However, the key question remains: do LLMs genuinely reason—or do they simulate reasoning only when cues align with familiar templates? This distinction is crucial, especially when evaluating robustness under linguistic or contextual variation.

To rigorously study this question, Mirzadeh et al. (2024) proposed GSM-Symbolic ((Mirzadeh et al., 2024)), a benchmark that perturbs math word problems using symbolic and semantic transformations while keeping their logical

¹https://github.com/jrohsc/ Chain-of-Code-Collapse

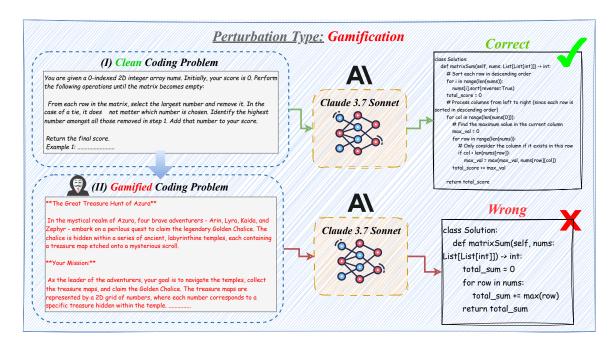


Figure 1: Overview of CHAIN-OF-CODE COLLAPSE

structure intact. Their results revealed significant accuracy drops under benign modifications—suggesting that reasoning performance is highly sensitive to surface form, even when task semantics remain unchanged.

In this work, we extend this line of inquiry to the domain of code generation. We introduce CHAIN-OF-CODE COLLAPSE (CoCC), a systematic framework for evaluating reasoning robustness in LLMs using semantically aligned yet adversarial prompt perturbations. Our perturbations span a diverse set of transformations—including storytelling, gamification, domain shifts, distracting constraints, and negation—that vary in narrative structure, lexical framing, and semantic drift. Crucially, each transformation preserves the core logic of the original task, allowing us to isolate how surface-level changes impact reasoning fidelity.

As shown in Figure 1, our methodology reveals striking differences in LLM behavior under these controlled perturbations. Some models collapse under low-preservation rewrites, while others paradoxically improve with narrative scaffolding. Unlike prior benchmarks focused on clean accuracy, our framework probes the cognitive stability of LLMs—highlighting the need for robustness evaluations that account for linguistic diversity, adversarial intent, and human-aligned prompting.

In the paper, we successfully implemented six

distinct perturbation methods-numeric perturbation, semantic clause injection, storytelling, gamification, domain shift, and negation. Among existing benchmarks on code generation tasks (Chen et al., 2021; Austin et al., 2021), we applied them to a curated set of 100 LeetCode-style problems from the LiveCodeBench dataset (Jain et al., 2024), resulting in 700 perturbed instances. We evaluated nine state-of-the-art LLMs using Pass@1 (Jain et al., 2024) (adapted from Live-CodeBench), code correctness via compilationbased execution, and manual inspection. Our results showed that performance on clean prompts ranged from 95.0% (Gemini-2.5-Flash) (Deep-Mind, 2024) to 17.0% (DeepSeek-Coder-1.3B) (Guo et al., 2025), while some perturbations like storytelling improved accuracy for specific models (e.g., +23.5% for LLaMA-3.1-Instruct (Meta, 2024)). In contrast, low-preservation attacks such as negation degraded performance by over 50% in several cases. We conducted a detailed ablation study and introduced semantic perturbation robustness as a new evaluation axis to characterize model sensitivity to benign linguistic changes.

The relevance of this work is twofold. First, as LLMs become integrated into development workflows and coding assistants, ensuring their reliability under diverse and imperfect inputs becomes paramount. Second, for the broader NLP community, our findings offer a new lens through which to assess model generalization—not just in terms of accuracy, but in terms of behavioral consistency under semantic perturbation. We believe this framework can serve as a foundation for future research on trustworthy and interpretable LLM reasoning.

2 Related work

The challenge of evaluating and ensuring true reasoning capabilities in Large Language Models (LLMs), particularly for complex tasks such as code generation, has been approached from several angles. While LLMs have demonstrated strong performance across multiple NLP tasks, significant challenges remain in ensuring their robustness, reliability, and the actual depth of their reasoning quality. Our work, builds upon and extends prior research in three key areas that inform our study on reasoning failures under adversarial prompt perturbations: the nature of reasoning in LLMs, specific advancements and evaluations in LLM-based code generation, and existing research on attacks against LLM reasoning.

2.1 Reasoning Large Language Models

Reasoning in LLMs encompasses analytical tasks like math problem-solving, code generation, and While traditional models logical inference. often rely on pattern recognition, reasoningenhanced models increasingly use techniques such as reasoning tokens and Chain-of-Thought (CoT) prompting (Wei et al., 2022). Reasoning tokens are designed as explicit markers within the training process to guide LLMs toward more structured reasoning, an approach that has shown improvements in handling complex reasoning challenges, especially in arithmetic and code-related tasks. CoT prompting (Wei et al., 2022) and its derivatives, like Zero-shot-CoT (Wang et al., 2023) and Program of Thoughts (Chen et al., 2022) (which aims to separate computation from reasoning), have demonstrably enhanced multistep reasoning. However, while CoT can improve performance on standard benchmarks, our work with CoCC investigates a critical subsequent question: whether such induced reasoning chains remain stable and effective when the problem's surface structure is perturbed, even if the core logic is preserved. This inquiry is crucial for understanding the true depth and transferability of the elicited reasoning.

surveys and comprehensive Recent reviews (Mondorf and Plank, 2024; Prasad et al., 2023; Golovneva et al., 2022) have further explored the reasoning behavior of LLMs beyond simple accuracy metrics, highlighting a prevalent concern: LLMs often rely on surface-level correlations rather than genuine logical inference. For instance, models might associate certain keywords or phrasing patterns with specific solution templates. CoCC directly tests this dependency by altering these patterns through methods like Storytelling, Gamification, and Domain Shift, all while maintaining the underlying semantic integrity of the task. This reliance on potentially superficial cues, even with advanced prompting techniques, underscores the need for evaluations like ours. In this work, we therefore aim to evaluate reasoning through more nuanced behavioral analyses rather than just final answer correctness, focusing on behavioral consistency under controlled linguistic and structural variations.

2.2 LLM for Code Generation

LLMs have shown remarkable capabilities in code generation, assisting developers by translating natural language descriptions into executable code. A comprehensive survey by Jiang et al. (Jiang et al., 2024) categorizes recent advancements in Code LLMs, covering aspects such as dataset curation, benchmark evaluations, and ethical implications. Evaluating the performance of LLMs in code generation remains a critical research area. Traditional methods primarily rely on executionbased metrics such as pass@k, which evaluates how often the generated code successfully runs and passes test cases. More recent LLMbased evaluation frameworks, such as CODE-JUDGE (Tong and Zhang, 2024), leverage language models themselves to assess the semantic correctness of generated code.

While these methods are valuable, metrics like pass@k primarily assess functional correctness on standard problem formulations, and LLM-based evaluators like CODEJUDGE, though assessing semantic correctness, may not fully capture how models respond when the presentation of the problem itself is adversarially yet semantically perturbed. Our study aligns with the goal of robust evaluation but extends it by focusing on the stability of the reasoning process leading to code generation when faced with such input variations. CoCC specifically assesses the impact of these adversarial modifications on the reasoning tasks inherent in code generation, probing whether the logical process itself is resilient.

2.3 Reasoning LLM Attacks

The robustness of LLMs has been scrutinized through various adversarial attack methodologies. Previous research has explored how seemingly small perturbations, such as typographical errors (Gan et al., 2024) or certain types of adversarial prompts (Wu et al., 2023), can significantly degrade model performance. The GSM-Symbolic benchmark (Mirzadeh et al., 2024), for instance, demonstrated that slight modifications to mathematical problem structures, such as altering numerical values or adding irrelevant clauses, can lead to drastic drops in accuracy, suggesting a fundamental brittleness in LLM reasoning when faced with inputs that deviate from learned patterns.

Adversarial attacks on code generation models have also been investigated. The DeceptPrompt framework (Wu et al., 2023) reveals that benignlooking natural language modifications can induce LLMs to generate insecure or incorrect code, exposing vulnerabilities in real-world applications. While DeceptPrompt reveals vulnerabilities leading to insecure code, CoCC explores a complementary set of semantically-focused perturbations (e.g., Storytelling, Gamification, Domain Shift, Distracting Constraints). These are designed not primarily to induce insecurity, but to test the stability and fidelity of the underlying reasoning chain required for correct code generation when familiar problem cues are altered. Our study examines how these adversarial modifications-ranging from narrative restructuring to the injection of logically inert information-impact reasoning models. A key distinction in our methodology is the emphasis on perturbations that, while adversarial in their structure or framing, are designed to be semantically faithful to the original problem's core logic. This allows us to isolate reasoning failures that are not due to misunderstanding a completely different task, but rather to an inability to reason robustly when the problem presentation changes.

In summary, prior work has established the potential of LLMs in complex reasoning and code generation, yet has also consistently highlighted their brittleness and potential over-reliance on learned superficial patterns. Existing evaluation methods and attack strategies provide valuable insights into model capabilities and vulnerabilities. However, a gap remains in systematically understanding how LLMs' reasoning chains for code generation withstand diverse, semanticallygrounded perturbations that alter problem presentation without changing the core logic. CoCC addresses this by introducing a novel framework and a suite of perturbation techniques specifically designed to probe these nuanced aspects of reasoning robustness in the domain of code generation.

3 Methodology

To systematically evaluate how semantically controlled modifications affect the code generation abilities of LLMs, we design a framework that perturbs existing coding problems through a set of natural language transformations. Our method centers on applying meaning-preserving or minimally diverging rewrites to problems, without altering their underlying logic or difficulty.

3.1 Problem Perturbation Framework

Unlike prior works (Mu et al., 2025; Zhu et al., 2025) that focus solely on adversarial attacks or CoT reasoning, our framework introduces semantically aligned rewrites of coding problems that preserve the structure of the original coding problem while varying its linguistic, narrative, or logical framing. Inspired by recent studies on symbolic noise (Mirzadeh et al., 2024), narrativebased jailbreaks (Shen et al., 2024; Song et al., 2025), and deceptive prompt manipulations (Wu et al., 2023), we propose four transformation strategies (or "attacks") that vary in their degree of logical preservation — ranging from fully equivalent reformulations (e.g., storytelling) to objective inversions (e.g., negation). Each strategy is instantiated via a consistent prompting template passed to LLaMA 3.1 8B-Instruct that guides the rewriting of the original problem, while explicitly preserving key components: Input, Output, Explanation, Examples, and Constraints. We designed different types of tests to check the language model's reasoning abilities in several key areas. Storytelling and Gamification test the model's ability to extract formal logic from informal, human-centric narratives, a common scenario in real-world user prompts. Domain Shift evaluates the core generalization capability by testing if the model's algorithmic knowledge is tied to specific terminological contexts. Distracting Constraints and Example Perturbation directly challenge the model's attentional mechanisms and its reliance on superficial pattern-matching versus robust logical deduction. Finally, the Negation transformations serve as a stress test for true logical manipulation, assessing whether models can invert a learned reasoning process rather than merely retrieving a familiar one. Together, these transformations cover a spectrum from plausible linguistic variation to direct logical challenge.

3.2 Perturbation Methods

In this subsection, we thoroughly describe each of the problem perturbation methods.

Attack Type	Score
Storytelling	8.89
Gamification	8.01
Domain Shift	7.07
Example Perturbation	6.71
Distracting Constraints	3.82

Table 1: Preservation Scores for Different Attack Types

Storytelling. Motivated by narrative jailbreaks in safety research (Shen et al., 2024; Song et al., 2025; Chan et al., 2025), this method reframes the problem as a story or adventure. The prompt preserves all critical components but introduces a narrative wrapper that may change surface-level structure. We use this transformation to study whether storytelling facilitates or hinders LLM reasoning in algorithmic contexts. The Storytelling prompt template explicitly instructs the models to "make the introduction engaging and fun", but not to alter the technical sections such as examples, constraints, or explanation by explicitly mentioning "keep the original intent and structure" in the prompt. This transformation tests whether LLMs benefit from more natural, humanreadable phrasings while still preserving problem semantics (see Figure 2).

Gamification. This transformation wraps the task in a challenge-based format (e.g., player or robots solving the task) while keeping the logic intact. Similar to storytelling, it introduces an-thropomorphic or thematic context, drawing inspiration from instruction-tuning setups that present tasks in game-like scenarios (Wu et al., 2023). We evaluate whether such gamified inputs boosts en-

gagement or distracts models from formal reasoning (see Figure 4).

Distracting Constraints. Inspired by the symbolic injection strategies in GSM-Symbolic (Mirzadeh et al., 2024), this method appends irrelevant but plausible-sounding constraints (e.g., "*input is a palindrome*") to the problem. While logically inert, these constraints test the model's ability to filter out irrelevant linguistic noise. Unlike classic adversarial examples, these do not change task correctness but increase input ambiguity (see Figure 6).

Domain Shift. This strategy replaces tokens and terminology from one context to another (e.g., "*array of integers*: becomes "*daily revenue*") or replacing terms with domain-specific equivalents (e.g., convert numbers to elevator floors, jobs, floors, days) (see Figure 7).

3.3 Logical Preservation Scoring

To quantify the degree of semantic deviation induced by each transformation, we developed a **Logical Preservation Score**. We employed the Claude-3.7-Sonnet model as an automated evaluator to ensure consistent and scalable scoring across all 700 perturbed instances. This approach mitigates potential human rater fatigue and subjectivity. The scoring is guided by a detailed rubricbased prompt (see Appendix F, Figure 10) that instructs the model to rate preservation on a scale of **1-10**, where 10 indicates perfect logical alignment and 1 indicates a complete semantic shift. These scores are used in later analysis to understand how semantic drift correlates with performance degradation.

4 Experimental Setting

Model	Easy	Medium	Hard	Overall
Gemini-2.5-Flash	100.0	98.0	76.5	95.0
Claude-3.7-Sonnet	100.0	92.0	64.7	90.0
DeepSeek-14B	97.0	92.0	58.8	88.0
Gemini-2.0-Flash	97.0	86.0	47.1	83.0
DeepSeek-7B	90.9	70.0	35.3	71.0
Qwen2.5-Coder	81.8	52.0	35.3	59.0
DeepSeek-Coder-33B	84.8	48.0	11.8	54.0
Claude-3-Haiku	51.5	32.0	41.2	40.0
LLaMA-3.1-8B-Instruct	36.4	12.0	5.9	19.0
DeepSeek-Coder-1.3B	36.4	8.0	5.9	17.0
Avg. Accuracy	77.6	59.9	38.3	67.6

Table 2: Accuracy (%) of models across different difficulty levels under the no attack setting.

Storytelling Prompt Template

Instruction: Rewrite the problem in a storytelling format, while preserving its logic. **Guidelines:**

- Keep Input, Output, Explanation, Example, and Constraints sections unchanged.
- Frame the problem as an engaging story or programming narrative.

{original_content}
No additional explanation needed. Just output the modified problem.

Figure 2: Prompt template for Storytelling transformation.

4.1 Dataset and Evaluation Metrics

We conduct our experiments using the Live-CodeBench dataset (Jain et al., 2024), a recent benchmark designed to evaluate LLM performance on code generation under interactive and test-driven settings. For our study, we select a curated subset of 100 LeetCode problems from the **Code Generation** split of the LiveCodeBench, which provides rich problem descriptions and test cases suitable for both modifications and evaluation. To assess model performance, we adopt the standard **Pass@1** metric (Jain et al., 2024), which measures the proportion of problems for which the model's first generated solution passes all provided test cases.

4.2 Model Selection

We evaluate both **black-box API models** and **open-source models** spanning general-purpose reasoning and code-specialized capabilities. For consistency with prior work, we include models from the **LiveCodeBench leaderboard**² as well as strong code-focused baselines not originally part of the benchmark.

We test four proprietary black-box LLMs known for their reasoning abilities: Gemini-2.5-Flash-Preview, Gemini-2.0-Flash (Deep-Mind, 2024), Claude-3.7-Sonnet, and Claude-3-Haiku (Anthropic, 2024). To assess opensource reasoning, we include DeepSeek-R1-Distill-Qwen-7B and -14B (Guo et al., 2025), which are distilled DeepSeek-R1 models with robust reasoning capabilities and native support for *reasoning token generation*, facilitating finegrained trace analysis. For code-focused models, we evaluate: Qwen2.5-Coder and DeepSeek**Coder-33B**, both of which are optimized for code generation but not explicitly tuned for reasoning. Finally, we include the **LLaMA-3.1-8B-Instruct** (Meta, 2024), a general-purpose instruction-tuned model. Although not code-nor reasoning-specialized, LLaMA-3.1 performs competitively and supports inference-time CoT prompt engineering, making it a valuable reference point in our analysis.

5 Results and Analysis

In this section, we present both aggregate and manual case-level results from our evaluation of LLMs under perturbations. While overall accuracy and reasoning scores provide a high-level view of model robustness, a closer examination of specific instances reveals nuanced patterns. We identify cases where perturbations help models reason better and others where they introduce confusion, highlighting the diverse impacts of prompt formulation on code generation.

5.1 Clean Performance Overview

We begin by benchmarking all models on the original (unmodified) version of 100 LeetCodestyle problems (Table 2). As expected, models optimized for instruction-following and reasoning, such as Gemini-2.5-Flash (95.0% overall) and Claude-3.7-Sonnet (90.0%), outperform codespecific models like Qwen2.5-Coder (59.0%) and DeepSeek-Coder-33B (54.0%). ON average, performance declines sharply from Easy (77.6%) to Hard (38.3%) tasks, reflecting the inherent challenge of generalization across reasoning complexity.

²https://livecodebench.github.io/ leaderboard.html

Models	Distracting Constraints	Domain Shift	Example Perturbation	Gamification	Storytelling	Avg. Acc.
Gemini 2.5 Flash	95.48% (+0.5%)	89.81% (-5.2%)	93.09% (-1.9%)	96.93% (+1.9%)	97.37% (+2.4%)	94.94%
Gemini 2.0 Flash	88.78% (+5.8%)	72.47% (-10.5%)	95.02% (+12.0%)	89.76% (+6.8%)	90.38% (+7.4%)	87.28%
DeepSeek-14B	83.84% (-4.2%)	75.53% (-12.5%)	84.10% (-3.9%)	86.76% (-1.2%)	91.16% (+3.2%)	84.28%
Qwen2.5-Coder	65.03% (+6.0%)	68.33% (+9.3%)	83.51% (+24.5%)	70.11% (+11.1%)	79.69% (+20.7%)	73.33%
DeepSeek-7B	65.06% (-5.9%)	58.28% (-12.7%)	71.18% (+0.2%)	73.30% (+2.3%)	82.99% (+12.0%)	70.16%
DeepSeek-Coder-33B	58.44% (+4.4%)	55.26% (+1.3%)	70.00% (+16.0%)	67.44% (+13.4%)	70.45% (+16.5%)	64.32%
Claude-3.7-Sonnet	47.89% (-42.1%)	35.66% (-54.3%)	62.87% (-27.1%)	50.00% (-40.0%)	63.35% (-26.6%)	51.95%
Claude-3-Haiku	41.04% (+1.0%)	37.98% (-2.0%)	60.12% (+20.1%)	45.14% (+5.1%)	57.69% (+17.7%)	48.39%
LLaMA3-8B-Instruct	37.59% (+18.6%)	22.03% (+3.0%)	54.30% (+35.3%)	37.78% (+18.8%)	44.68% (+25.7%)	39.28%
Avg. Acc.	64.57%	57.70%	75.24%	68.80%	75.64%	–

Table 3: Attack accuracy (%) and delta Δ from clean performance. Rows are sorted by average accuracy.

5.2 Perturbation Resilience and Gains

Table 3 reveals that **semantic perturbations do not uniformly degrade performance**. On the contrary, several perturbation types — particularly Storytelling and Gamification — *consistently improve performance*, especially for models tuned for human-aligned reasoning.

Notably, Gemini-2.0-Flash, which ranks 4th in clean accuracy, **outperforms its original baseline** on four perturbation types, improving up to +12.0% on Example Perturbation. Similarly Qwen2.5-Coder and LLaMA-3.1, both nonreasoning-specialized, exhibit large performance gains (+24.5% and +35.3%, respectively) under storytelling-style or pattern-breaking rewrites. Based on these findings, we noticed that certain models benefit from more natural or decentered problem formulations. This suggests that rigid, minimalistic problem statements may actually underutlize LLM capabilities.

This is further supported by our manual inspection of Gemini-2.5-Flash outputs, where in 11 cases of Distracting Constraints attack, the perturbed versions with added constraints produced correct solutions while the original did not. These constraints, though labeled as "distracting", may have made implicit assumptions explicit, improv-This aligns with findings by Xu ing clarity. et al. (2024), who show that structured context in prompts can enhance generation accuracy. This finding challenges prior assumptions that naturallanguage verbosity of format deviation is always detrimental (Zhu et al., 2024). Instead, we observe that semantically richer prompts can elicit better program synthesis.

5.3 Semantic Robustness

Despite general trends, not all models are equally resilient to semantic shift. Claude-3.7-Sonnet exhibits massive accuracy degradation under lowpreservation transformations, losing up to -68.0% in medium difficulty tasks for Distracting Con-In contrast, Gemini-2.5-Flash and straints. DeepSeek-14B are remarkably stable, showing <5% deviation across all tasks. Through these experimental results, we demonstrate a novel axis of defined as the standard deviation in performance across logic-preserving rewrites. This axis captures a model's ability to maintain performance under benign yet diverse formulations of the same task. We argue that this robustness is as critical as clean accuracy, especially in real-world applications where user queries are linguistically varied and imperfectly phrased.

This phenomenon is visible in models like Claude-3.7-Sonnet, where code generated from perturbed prompts is often simpler and less complete compared to the original. It appears that the model relies on surface-level patterns in the original prompt to retrieve structured code, and perturbations disrupt this retrieval behavior. As Cai et al. (2024) observe, such perturbations likely increase tokenlevel entropy and variance, making the model less confident and more prone to errors.

5.4 Accuracy vs. Logic Preservation

In Figure 3, we plot average model accuracy against our logical preservation scores (Table 1. A positive, albeit nonlinear, correlation emerges: Storytelling (score: 8.89) and Gamification (8.01) lead to improved or stable performance. Distracting Constraints (3.82) and Negation Objective (1.83) consistently degrade it. However, we no-

Attack	Model	Easy Acc.	Medium Acc.	Hard Acc.
	Gemini-2.5-Flash	93.9% (-6.1%)	96.0% (-2.0%)	88.2% (+11.7%)
	Gemini-2.0-Flash	90.9% (-6.1%)	82.0% (-4.0%)	52.9% (+5.8%)
Storytelling	Claude-3.7-Sonnet	48.5% (-51.5%)	34.0% (-58.0%)	47.1% (-17.6%)
Storytening	Claude-3-Haiku	45.5% (-6.0%)	26.0% (-6.0%)	35.3% (-5.9%)
	DeepSeek-14B	93.9% (-3.1%)	82.0% (-10.0%)	52.9% (-5.9%)
	DeepSeek-7B	97.0% (+6.1%)	62.0% (-8.0%)	23.5% (-11.8%)
	Gemini-2.5-Flash	89.8% (-10.2%)	96.0% (+0.0%)	82.4% (+5.9%)
	Gemini-2.0-Flash	72.5% (-24.5%)	80.0% (-6.0%)	58.8% (+11.7%)
Domain Shift	Claude-3.7-Sonnet	35.7% (-64.3%)	24.0% (-68.0%)	11.8% (-52.9%)
Domain Shift	Claude-3-Haiku	30.3% (-21.2%)	18.0% (-14.0%)	5.9% (-35.3%)
	DeepSeek-14B	54.5% (-42.5%)	62.0% (-30.0%)	29.4% (-29.4%)
	DeepSeek-7B	45.5% (-45.4%)	38.0% (-32.0%)	17.6% (-17.7%)
	Gemini-2.0-Flash	97.0% (+0.0%)	92.0% (+6.0%)	64.7% (+17.6%)
	Gemini-2.5-Flash	93.9% (-6.1%)	84.0% (-14.0%)	70.6% (-5.9%)
Example Perturbation	Claude-3.7-Sonnet	51.5% (-48.5%)	34.0% (-58.0%)	23.5% (-41.2%)
Example renurbation	Claude-3-Haiku	45.5% (-6.0%)	28.0% (-4.0%)	35.3% (-5.9%)
	DeepSeek-14B	81.8% (-15.2%)	68.0% (-24.0%)	47.1% (-11.7%)
	DeepSeek-7B	72.7% (-18.2%)	42.0% (-28.0%)	35.3% (+0.0%)
	Gemini-2.5-Flash	84.8% (-15.2%)	96.0% (-2.0%)	82.4% (+5.9%)
	Gemini-2.0-Flash	81.8% (-15.2%)	80.0% (-6.0%)	58.8% (+11.7%)
Distracting Constraints	Claude-3.7-Sonnet	36.4% (-63.6%)	24.0% (-68.0%)	11.8% (-52.9%)
Distracting Constraints	Claude-3-Haiku	36.4% (-15.1%)	12.0% (-20.0%)	17.6% (-23.6%)
	DeepSeek-14B	78.8% (-18.2%)	70.0% (-22.0%)	41.2% (-17.6%)
	DeepSeek-7B	57.6% (-33.3%)	36.0% (-34.0%)	29.4% (-5.9%)
	Gemini-2.5-Flash	100.0% (+0.0%)	92.0% (-6.0%)	88.2% (+11.7%)
	Gemini-2.0-Flash	97.0% (+0.0%)	74.0% (-12.0%)	58.8% (+11.7%)
Gamification	Claude-3.7-Sonnet	48.5% (-51.5%)	30.0% (-62.0%)	23.5% (-41.2%)
Gammeation	Claude-3-Haiku	51.5% (+0.0%)	34.0% (+2.0%)	35.3% (-5.9%)
	DeepSeek-14B	84.8% (-12.2%)	64.0% (-28.0%)	52.9% (-5.9%)
	DeepSeek-7B	75.8% (-15.1%)	46.0% (-24.0%)	29.4% (-5.9%)

Table 4: Accuracy (%) for Reasoning-focused LLMs under various attacks, broken down by difficulty level.

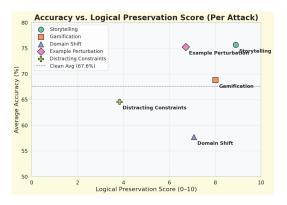


Figure 3: Accuracy vs. Logical Preservation Score for each attack type. Storytelling and Example Perturbation improve performance despite non-trivial rephrasings, while Distracting Constraints degrades accuracy significantly.

ticed that performance does not degrade proportionally with logical drift. Some logically preserved rewrites improve accuracy, while a single line of structurally trivial edits (like Distracting Constraints) dramatically hurt it. This suggests that cognitive alignment — not logical alignment alone — governs LLM success. LLMs are more sensitive to semantic distractors than to narrative abstraction.

5.5 Difficulty Analysis

As shown in Table 4, models often retain high accuracy on Easy problems across all attacks, but break under Hard tasks even for high-preservation rewrites. This confirms that reasoning complexity, not just input phrasing, lead to model breakdown. However, storytelling notably **boosts hardproblem performance** for Gemini-2.5 (+11.7%) and LLaMA3.1 (+23.5%), indicating that humanfriendly reformulations may facilitate deeper reasoning under challenge.

5.6 Errors through Prompt Clarity

To interpret why some perturbations help while others hinder, we draw on recent findings that connect model uncertainty to error rates. Cai et al. (2024) observe that errors in LLMs are more likely to occur at tokens with high entropy and variance regions where the model is unsure of the

Attack	Model	Easy Acc.	Medium Acc.	Hard Acc.
Storytelling	Qwen2.5-Coder DeepSeek-Coder-33B LLaMA3-8B-Instruct	84.8% (+3.0%) 81.8% (-3.0%) 45.5% (+9.1%)	54.0% (+2.0%) 34.0% (-14.0%) 4.0% (-8.0%)	35.3% (+0.0%) 23.5% (+11.7%) 29.4% (+23.5%)
Example Perturbation	Qwen2.5-Coder	84.8% (+3.0%)	66.0% (+14.0%)	41.2% (+5.9%)
	LLaMA3-8B-Instruct	45.5% (+9.1%)	28.0% (+16.0%)	11.8% (+5.9%)
	DeepSeek-Coder-33B	72.7% (-12.1%)	44.0% (-4.0%)	17.6% (+5.8%)
Distracting Constraints	Qwen2.5-Coder DeepSeek-Coder-33B LLaMA3-8B-Instruct	57.6% (-24.2%) 54.5% (-30.3%) 30.3% (-6.1%)	42.0% (-10.0%) 26.0% (-22.0%) 8.0% (-4.0%)	17.6% (-17.7%) 29.4% (+17.6%) 17.6% (+11.7%)
Gamification	Qwen2.5-Coder	75.8% (-6.0%)	52.0% (+0.0%)	23.5% (-11.8%)
	DeepSeek-Coder-33B	69.7% (-15.1%)	50.0% (+2.0%)	35.3% (+23.5%)
	LLaMA3-8B-Instruct	42.4% (+6.0%)	20.0% (+8.0%)	23.5% (+17.6%)
Domain Shift	Qwen2.5-Coder	64.3% (-17.5%)	41.2% (-10.8%)	20.0% (-15.3%)
	DeepSeek-Coder-33B	48.5% (-36.3%)	26.0% (-22.0%)	17.6% (+5.8%)
	LLaMA3-8B-Instruct	15.2% (-21.2%)	2.0% (-10.0%)	11.8% (+5.9%)

Table 5: Accuracy (%) for Code Generation Models under various attacks.

next step. When we perturb prompts, especially with vague or extraneous constraints, the resulting prompt may distribute the model's attention more diffusely, increasing uncertainty and leading to incorrect generations.

This highlights a dual nature of perturbations: when they disrupt expected patterns without adding structure, they degrade performance; but when they elaborate or scaffold problem context, they may improve reasoning as we see above for certain models in Table 5. Future models may benefit from tuning not only on correct answers, but on uncertainty aware reasoning paths.

5.7 Comment-Driven Reasoning Behaviors

A notable behavioral pattern emerged when analyzing Claude-3.7-Sonnet's performance under the Gamification prompt variant. While Claude-3.7 demonstrates strong performance under clean conditions (90.0% overall accuracy; Table 2), its accuracy drops dramatically by -40.0% under Gamification (Table 3). Manual inspection of model outputs (Table 6) revealed a consistent shift in behavior: Claude's code responses on unperturbed prompts routinely included inline comments clarifying control flow logic, edge case handling, or the purpose of specific variables. In contrast, responses under gamified prompt formulations lacked such explanatory commentary.

The absence of natural language comments appeared to correlate with degraded code quality. Logic that was correctly implemented in the clean setting often became brittle or misaligned under perturbation, indicating reduced internal reasoning coherence. This trend is consistent with findings by Dou et al. (Dou et al., 2024), who showed that a higher frequency of comments in LLMgenerated code is associated with enhanced reasoning capabilities and fewer bugs. Their results suggest that encouraging comment generation during code synthesis can improve reasoning—even without model fine-tuning.

Our results extend this insight by proposing that comment generation serves not only as a reflection of internal reasoning, but also as a mediating factor in model robustness. When Claude-3.7 omits comments under prompt perturbation, its performance deteriorates significantly—despite the underlying task semantics remaining unchanged. This supports the hypothesis that comment-driven reasoning may serve a stabilizing role in preserving performance across diverse linguistic formulations of the same task.

5.8 Deeper dive in domain shift

A detailed analysis of the evaluation logs reveals distinct behavioral patterns. To begin with, Llama-3.1's robustness appears to stem from its capability to abstract the underlying logical task from the superficial narrative. Its reasoning often involved re-stating the problem with the new domain terms and then applying the correct, generalized algorithm, effectively handling the semantic shift (see Appendix C.1). Furthermore, the performance gain for Qwen2.5-Coder suggests that shifting to domains more aligned with common programming tasks or utilizing more concrete terminology (e.g., "employee_salaries" instead of abstract

Original Prompt Output	Perturbed Prompt Output	Original Result	Perturbed Result
<pre>class Solution: def countSeniors(self, details: List[str]) - > int: # Counter for passengers older than 60 count = 0 for passenger in details: # The age is stored in the 11th and 12th characters age = int(passenger[11:13]) # Check if the age is strictly greater than 60 if age > 60: count += 1 return count</pre>	<pre>class Solution: def countSeniors(self, details: List[str]) - > int: count = 0 for record in details: age = int(record[12:14]) if age > 60: count += 1 return count</pre>	[True, True]	[False]

Table 6: Comment-driven reasoning behaviors under prompt perturbation: comparison of Claude-3.7-Sonnet's code responses and resulting accuracies under clean (original) versus gamified (perturbed) prompts.

"nums") might have enhanced its understanding or triggered more relevant learned patterns. It consistently adopted new terminologies while correctly implementing the core logic (see Appendix C.1). On the other hand, Claude's substantial accuracy drop highlights a significant fragility when faced with unfamiliar thematic contexts. In several instances, Claude's reasoning (output) would correctly re-state the objective in the new domain, yet its generated solution_code would be drastically incomplete, address a much simpler version of the problem, or fail to implement the core preserved logic. For example, in the minIncrementOperations task (originally about making an array "beautiful" based on a sliding window condition, shifted to stabilizing task_priorities based on a similar window), Claude correctly understood and re-stated the complex windowed objective in the new domain terms. However, its subsequent code implemented a much simpler, incorrect element-wise check, completely missing the required windowed logic (see Appendix C.2). This indicates that while it can process surfacelevel semantic changes, the mapping to the correct complex algorithmic solution becomes unreliable. DeepSeek-14B, while not failing as comprehensively as Claude, still showed difficulties. Its errors often involved a correct general algorithmic idea but flawed execution within the new domain, such as misinterpreting new terms or making errors in adapting conditions, indicating challenges in accurately translating familiar logic to novel semantic contexts (see Appendix C.1).

6 Ablation Study

To probe the boundary of semantic robustness, we conduct an ablation study focused on **Negation Objective (Hard)** and **Negation Objective (Soft)**

transformations. These rewrites are designed to test whether models can adapt to **inverted or subtly reversed objectives**, while preserving the format and structural elements of the original problem.

6.1 Methods

Negation Objective (Hard). This method fully inverts the core task (e.g., "maximize" \rightarrow "minimize" or "include" \rightarrow "exclude"). A part of the transformation prompt asks the LLM to: "rewrite it with the opposite objective ... ensure the examples and output are updated accordingly: (see Figure 8). While the input, output, explanation and constraints are preserved, the solution logic must change, requiring the model to recompute from a new problem intent. The preservation score was recorded as 1.83 based on Claude-3.7.

Negation Objective (Soft). This variant applied milder semantic reversals (e.g., asking for "non-decreasing" instead of "increasing") without flipping the task entirely. The instruction explicitly states: "*Do NOT fundamentally change the problem's task ... adjust the examples minimally*" (see Figure 9). This design tests whether models are robust to subtle linguistic tweaks that alter logic while retaining solvability. The preservation score was recorded as 2.56 based on Claude-3.7, a little higher than the hard negation.

6.2 Results

Table 7 summarizes the impact of negation-based perturbations. Hard negation proves highly disruptive, causing average accuracy drops of over 50% across all difficulty levels. For instance, Gemini-2.5-Flash drops from 95.0% to 42.6%, and Claude-3.7 falls from 90.0% to 15.0%. Even instruction-following models struggle to adapt, as reasoning reversal—not just language adaptation—is required. In contrast, soft negation shows more variability, with some models like LLaMA-3.1 improving from 19.0% to 29.4%. However, others like DeepSeek-14B and Claude-3.7 still suffer large drops, showing that even subtle logical shifts can disrupt reasoning.

6.3 Analysis

Negation Objective (Soft) Analysis. Under soft negation, Llama-3.1-8B-Instruct's improved accuracy was sometimes linked to genuine adaptation when test cases were correctly aligned with the modified textual objective (see Appendix A.1). However, a prevalent issue was test case misalignment: Llama, despite correct logical adaptation to modified text, often failed tests still expecting original problem answers (e.g., for sumOfSquares, Appendix A.2). Conversely, models like DeepSeek-14B sometimes "passed" by ignoring the modification, as their test cases also remained unchanged. Failure patterns for other models included partial adaptation, where only parts of the negated logic were implemented (e.g., Gemini-2.5-Flash on matrixSum, Appendix A.3), and archetype override, where models reverted to known problem solutions despite contradictory modified instructions (e.g., Gemini-2.5-Flash on maximumOr, Appendix A.4). DeepSeek-14B, in particular, consistently ignored modifications. While Llama-3.1 demonstrated better semantic fidelity to textual changes, its overall accuracy increase is a nuanced outcome influenced by both genuine adaptation and the complex interplay with test case consistency. True robustness assessment hinges on meticulously aligned problem prompts and test evaluations.

Negation Objective (Hard) Analysis. The Negation Objective (Hard) perturbation led to near-total task failure across models, with reported accuracies (0% - 17%) not reflecting genuine capability in handling inverted objectives due to pervasive **test case misalignment**. Observed "successes" typically arose when models solved the *original* problem against un-updated test cases (e.g., Qwen2.5-Coder on count_seniors, Appendix B.1; Gemini-2.5-Flash on min_extra_char, Appendix B.4). Conversely, models that correctly implemented simple negated logic often failed these misaligned tests (e.g., Claude, DeepSeek, Gemini on count_seniors, Appendix B.2). No model consistently demonstrated reasoning reversal. Instead, common behaviors included defaulting to original problem archetypes, code instability (DeepSeek-14B on complex negations, Appendix B.3), and failure to implement correctly inverted logic even when acknowledging the textual change (e.g., on matrixSum, Appendix B.5). Hard negation thus exposes profound limitations in current LLMs' ability to perform genuine goal and logic reversal, emphasizing the need for rigorously aligned evaluations.

In conclusion, negation-based rewrites expose a critical blind spot in LLM reasoning: the inability to reinterpret or invert logical objectives even when all structural information is preserved. In addition, the model collapse under negation objective suggests that task framing overrides instruction tuning, and that models struggle to recompute from inverse logic. Finally, soft negation reveals the fragility of lexical understanding: small semantic perturbations that humans consider minor can lead to cascading failures in reasoning paths.

7 Limitation

One limitation of our work is that we evaluated only a subset of the LiveCodeBench LeetCodestyle problems — specifically, 100 our of 235 problems. Additionally, our study did not cover other task types available in LiveCodeBench, such as code execution, test output prediction, and selfrepair. While LiveCodeBench includes a diverse set of problems sources from platforms like At-Coder and Codeforces in addition to LeetCode, our evaluation was restricted to the LeetCode subset. This decision was primarily driven by limited computational resources, as inference time increases substantially with model size, particularly for open-source models. To ensure fair comparison across different models, we maintained a consistent evaluation set.

Despite these constraints, we conducted a largescle robustness analysis by generating and evaluating 700 perturbed instances (100 clean problems \times 7 perturbation types), allowing us to systematically assess model behavior under diverse logical modifications.

Another limitation is the exclusion of GPTseries models (e.g., GPT-4), which are among the top-performing proprietary models for code generation according to the LiveCodeBench leaderboard. Due to access limitations, we were unable to include them in our evaluation, leaving their robustness under these perturbations as an open question for future work.

8 Conclusion

In this work, we presented CoCC, a systematic framework for evaluating reasoning robustness in LLMs under adversarial prompting in code generation tasks. By introducing semantically plausible but logically challenging perturbations such as storytelling, gamification, distracting constraints, and negation objectives, we revealed key vulnerabilities in current state-of-the-art models. Through comprehensive experiments across nine LLMs and 700 perturbed instances, we found that while some perturbations surprisingly improved model performance, others, especially those involving subtle semantic drift, led to significant reasoning failures.

Our analysis introduced a novel evaluation axis, semantic perturbation robustness, which quantifies a model's ability to generalize across logically equivalent but linguistically diverse inputs. These findings underscore that high clean accuracy does not imply robust reasoning and highlight the need for more cognitively aligned model training.

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A Detailed Examples for Negation Objective (Soft) Analysis

A.1 Example A.1: countBeautifulPairs — Llama's Successful Adaptation

Original Problem Objective (Summarized): Count pairs of numbers (nums[i], nums[j]) where i < j such that the first digit of nums[i] and the last digit of nums[j] are coprime (i.e., GCD is 1).

Modified Problem Objective (Soft Negation): Count pairs where the first digit of nums[i] and the last digit of nums[j] are **not coprime** (i.e., GCD greater than 1).

Input Instance: nums = [30, 72, 9, 96, 82]

Llama-3.1-8B-Instruct Performance: (result: True)

- **Reasoning Snippet:** "The problem asks us to count the number of non-beautiful pairs... A pair is non-beautiful if the first digit of nums[i] and the last digit of nums[j] are not coprime. This means their greatest common divisor (GCD) is greater than 1."
- Relevant solution_code Logic:

```
if gcd(first_digit_i, last_digit_j) > 1:
    count += 1
```

- Result Details: {'output': '3', 'expected': '3'}
- · Analysis: Llama correctly implemented the modified logic and matched the expected result.

Claude-3.7-Sonnet Performance: (result: False)

- Reasoning/Code Logic: Implemented logic to count GCD == 1 (original problem). Outputted 7.
- Result Details: { 'output': '7', 'expected': '0' }
- Analysis: Failed to adapt to negated task and failed its own test.

DeepSeek-14B Performance: (result: False)

• Same as Claude: Used original problem logic. Output: 7, Expected: 0.

Gemini-2.5-Flash-Preview Performance: (result: False)

- Reasoning: Adapted to negated logic correctly.
- Output: 3, but Expected: 0.
- Analysis: Misalignment between adapted logic and test case expectation.

Comparative Summary: Llama succeeded with aligned logic and expectation. Gemini partially succeeded. Claude and DeepSeek failed to adapt.

A.2 Example A.2: sumOfSquares — Llama Adapts, Test Case Expects Original

Original Problem Objective (Summarized): Sum the squares of elements nums [i] where the 1-based index i divides n (i.e., n % i == 0).

Modified Problem Objective (Soft Negation): Sum the squares of elements where the index i does not divide n (i.e., n & i != 0).

Input Instance: nums = [1, 2, 3, 4] (n = 4)

• Original correct result: $1^2 + 2^2 + 4^2 = 21$

• Modified correct result: $3^2 = 9$

Llama-3.1-8B-Instruct Performance: (result: False)

• Relevant solution_code Logic:

sum(num ** 2 for i, num in enumerate(nums, start=1) if n % i != 0)

• Output: 9, Expected: 21

• Analysis: Llama correctly followed the modified logic but failed due to the test case expecting the original problem's output.

```
DeepSeek-14B Performance: (result: True)
```

• Relevant solution_code Logic:

```
if n % i == 0:
ans += nums[i-1]**2
```

- Output: 21, Expected: 21
- Analysis: DeepSeek ignored the modified instruction and solved the original problem. It passed due to misaligned test case expectations.

Comparative Summary: Llama faithfully applied the negated logic but failed the test due to incorrect expectation. DeepSeek ignored the instruction change and passed, highlighting the need for aligned evaluation pipelines.

A.3 Example A.3: matrixSum — Partial Adaptation by Gemini

Original Problem Objective (Summarized): From each row, remove the largest element, take the maximum among them, and add it to the score.

Modified Problem Objective (Negation): From each row, remove the smallest element, take the minimum among them, and subtract it from the score.

Gemini-2.5-Flash-Preview Performance: (result: False)

• Relevant solution_code Logic:

```
for row in nums:
    row.sort()
for j in range(num_cols):
    removed_this_round = []
    for i in range(num_rows):
        removed_this_round.append(nums[i][num_cols - 1 - j])
    min_val = min(removed_this_round)
    score -= min_val
```

• Analysis: Gemini correctly applied subtraction and switched from max to min aggregation, but still removed the largest element from each row—failing to fully adapt the problem logic.

A.4 Example A.4: maximumOr — Archetype Override by Gemini

Original Problem Objective (Summarized): Given nums and k operations (each allowing one number to be multiplied by 2), maximize the bitwise OR of all elements.

Modified Problem Objective (Negation): Minimize the bitwise OR value after k operations.

Gemini-2.5-Flash-Preview Performance: (result: True)

- **Reasoning Behavior:** Despite the instruction to minimize, Gemini solved for the **maximum** OR. The output matched the original test case, which remained unchanged.
- Input: nums = [12, 9], k = 1
- Output: 30, Expected: 30
- Analysis: Gemini overrode the negated objective, likely due to overfitting to the known problem pattern, and passed because the test case was still aligned with the original formulation.

Comparative Summary: Example A.3 illustrates partial adaptation: Gemini recognized the transformation (e.g., subtraction, min) but failed in row-level logic. In Example A.4, the model defaulted to the original objective entirely, reflecting the dominance of memorized archetypes over prompt instructions.

B Detailed Examples for Negation Objective (Hard) Analysis

B.1 Example B.1: count_seniors — Test Misalignment & False Success

Original Problem Objective (Summarized): Count passengers strictly older than 60.

Modified Problem Objective (Hard Negation): Count passengers strictly 60 years old or less (i.e., $age \le 60$).

Input Instance: details = ["7868190130M7522", "5303914400F9211", "9273338290F4010"]

- Original correct output (age > 60): 2 (for ages 75, 92)
- Modified correct output (age \leq 60): 1 (for age 40)

```
Qwen2.5-Coder Performance: (result: [True, True])
```

• Relevant solution_code Logic:

```
if age > 60: # Original problem logic
    count += 1
```

- Result Details: {'output': '2', 'expected': '2'}
- Analysis: Qwen ignored the negated prompt ("60 or less"), implemented the original logic ("greater than 60"), and passed. This strongly indicates its test case expected the original problem's answer.

Claude-3.7-Sonnet / DeepSeek-14B / Gemini-2.5-Flash Performance: (result: [False])

• Analysis: See Appendix B.2. These models implemented the correct negated logic but failed.

Comparative Summary: Qwen "succeeded" by solving the original task against a misaligned test. Other models correctly adapted to the negated text but failed the same misaligned test.

B.2 Example B.2: count_seniors — Correct Negation Fails Misaligned Test

Objectives & Input Instance: Same as Appendix B.1.

- Original correct output: 2
- Modified correct output: 1

```
Claude-3.7-Sonnet Performance: (result: [False])
```

• Relevant solution_code Logic:

```
if age <= 60: # Correct negated logic
    count += 1</pre>
```

- Result Details: { 'output': '1', 'expected': '2', 'error_message': 'Wrong Answer' }
- Analysis: Claude correctly implemented the logic required by the modified prompt ("60 or less") but failed because the test case expected the output corresponding to the original prompt ("greater than 60").

DeepSeek-14B & Gemini-2.5-Flash Performance: (result: [False])

• Logic & Result Details: Identical outcome to Claude. Both implemented age <= 60, outputted 1, but the test expected 2.

Comparative Summary: Multiple models faithfully adapted to the simple negation in the text but were incorrectly penalized by test cases expecting the original problem's behavior.

B.3 Example B.3: find_missing_and_repeated_values — DeepSeek Code Instability on Complex Negation

Original Problem Objective (Summarized): Find the number that appears twice and the number that is missing in a range derived from a grid's elements.

Modified Objective (Hard Negation - Illustrative): Could be inverted to find numbers that appear once and are present, or other complex logical reversals.

```
DeepSeek-14B Performance: (result: [-4])
```

• Relevant solution_code Snippet (Illustrative): Often involves complex comprehensions or logic attempting to handle the negated task.

```
# Code failed during execution
# Example error: 'NoneType' object is not iterable
```

- Result Details: {'error': 'TypeError("NoneType object is not iterable")', 'error_code': -4}
- Analysis: DeepSeek's attempt to reason over complex inverted logic led to runtime errors. This suggests that reversing objectives on difficult problems exceeds the model's capacity, leading to unstable code.

B.4 Example B.4: min_extra_char — Gemini's False Success via Original Logic

Original Problem Objective (Summarized): Find the **minimum** number of extra characters remaining after optimally breaking a string s using words from a dictionary.

Modified Problem Objective (Hard Negation): Find the maximum number of extra characters.

Input Instance: s = "leetscode", dictionary = ["leet", "code", "leetcode"]

- Original correct output (minimum extra): 1 (using "leetcode")
- Modified correct output (maximum extra): 9 (using no words)

Gemini-2.5-Flash Performance: (result: [True, True])

- Reasoning Snippet (output): Describes dynamic programming approach to find the *minimum* number of extra characters.
- Relevant solution_code Logic:

```
# dp[i] will store the minimum number of extra chars
# ... logic calculates minimum ...
return dp[n]
```

- Result Details: Passed test cases. Execution time indicates successful run.
- Analysis: Gemini ignored the negated objective ("maximum") and solved for the original ("minimum"). Success indicates that test cases were misaligned with the negated prompt.

Comparative Summary: Gemini succeeded by reverting to the known original problem archetype, likely due to a misaligned test case that still evaluated the original objective.

B.5 Example B.5: matrixSum — Model Confusion on Complex Negation

Original Problem Objective (Summarized): Iteratively remove the largest number from each row, find the maximum among these, and add it to the score.

Modified Problem Objective (Hard Negation): Iteratively remove the **smallest** number from each row, find the **lowest** among these, and **subtract** it from the score.

DeepSeek-14B Performance: (result: [False])

- **Reasoning Snippet:** "So the process is: 1. For each row, remove the smallest element. 2. Find the minimum among these. 3. Subtract this minimum... Wait, no..."
- Relevant solution_code Logic:

```
rows = [deque(row) for row in nums]
sum_min = 0
while any(rows):
    # Find and accumulate min_val
    sum_min += min_val
return -sum_min
```

- Result Details: Marked "Wrong Answer".
- Analysis: DeepSeek attempted a form of the negated logic but displayed confusion in both reasoning and implementation.

Claude, Gemini, Qwen Performance: (result: [False])

• Analysis: All models failed. Gemini showed prompt confusion; Qwen reverted to simplified logic; Claude struggled with objective inversion.

Comparative Summary: The multi-step, logically inverted nature of this task caused failure across all models. This reveals a common weakness in handling procedural negations that require non-trivial reasoning adjustments.

C Detailed Examples for Domain Shift Analysis

C.1 Example C.1: Problem - "Count Pairs Whose Sum is Less than Target" (Easy Difficulty)

Original Problem Objective (Summarized): Given a 0-indexed integer array 'nums' and an integer 'target', return the number of pairs '(i,j)' such that '0 = i j j nums.length' and 'nums[i] + nums[j]; target'.

Modified Problem Objective (Domain Shift Example): "You are given a list of employee salaries 'employee_salaries' and a target 'bonus_threshold'. Your task is to count the number of pairs of employees (i, j) such that employee 'i' comes before employee 'j' in the list, and the sum of their salaries 'employee_salaries[i] + employee_salaries[j]' is strictly less than the 'bonus_threshold'." (Wording adapted from Llama's log). The core logic of iterating through pairs and checking a sum against a threshold is preserved.

Input Instance (from original problem, used for all models here): 'nums = [-1,1,2,3,1]', 'target = 2'.

Correct Output for this Instance (Original and Shifted Logic): 3.

Llama-3.1-8B-Instruct Performance: (result: True)

- **Reasoning Snippet (output):** "The problem asks us to count the number of pairs of employees (i, j) such that i ; j and their combined salaries ('employee_salaries[i] + employee_salaries[j]') are strictly less than a given 'bonus_threshold'... We can iterate through all possible pairs of employees (i, j) with i ; j. For each pair, we calculate the sum of their salaries. If the sum is less than 'bonus_threshold', we increment a counter."
- Relevant solution

_code Snippet:

- Result Details (metadata_output): 'output': '3', 'inputs': '[[-1, 1, 2, 3, 1], 2]', 'expected': '3', ...'
- Analysis: Llama successfully understood the domain shift, correctly used the new terminology, and implemented the correct pair-counting logic, matching the expected output.

Qwen2.5-Coder Performance: (result: True)

- Reasoning Snippet (output): "The problem asks us to count the number of pairs of employees (i, j) such that 'employee_salaries[i] + employee_salaries[j]; bonus_threshold'."
- Relevant solution_code Snippet: Correct implementation using new domain variable names, similar to Llama.
- Result Details (metadata_output): 'output': '3', 'inputs': '[[-1, 1, 2, 3, 1], 2]', 'expected': '3', ...'
- Analysis: Qwen also successfully adapted, supporting the idea that shifts to concrete programming scenarios can be handled well.

DeepSeek-14B Performance: (result: False)

- Reasoning Snippet (output): Minimal reasoning, often directly outputting code.
- Relevant solution_code Snippet (example of failure for this problem):

```
# Might correctly implement the logic but use original names, or make subtle errors
class Solution:
    def countPairs(self, nums: List[int], target: int) -> int: #Note: uses 'nums','target
        n = len(nums)
        count = 0
        # ... (correct loop structure) ...
        # if nums[i] + nums[j] < target: count += 1
        return count # For this instance, output was 0</pre>
```

- Result Details (metadata_output): 'output': '0', 'inputs': '[[-1, 1, 2, 3, 1], 2]', 'expected': '3', ...'
- Analysis: DeepSeek-14B failed. The failure could be due to not fully adapting to new variable names if the test harness strictly expected them, or other subtle logical errors when attempting to apply the algorithm in the new context. Its output of 0 for an expected 3 is a clear miscalculation.

Comparative Summary for Example C.1: Llama and Qwen successfully generalized for this pair-counting task. DeepSeek's failure indicates difficulty in accurately reapplying the algorithm in the new semantic context. Claude's typical failures on other problems (as seen in C.2) show a more severe disruption.

C.2 Example C.2: Problem - minIncrementOperations - Claude-3.7-Sonnet's Failure via Oversimplification

Original Problem Objective (Summarized): Given 'nums' and 'k', find minimum increment operations such that for every subarray of length 3, at least one element is 'i = k'. (This is a dynamic programming problem).

Modified Problem Objective (Domain Shift Example for Claude): "You are managing project tasks. 'task_priorities' is an array of initial priority scores. 'min_threshold' is an integer. An operation involves increasing a task's priority by 1. A project schedule is 'stable' if, for every sequence of 3 consecutive tasks, at least one task has a priority score ξ = 'min_threshold'. Return the minimum number of priority increases to make the schedule stable."

Input Instance: 'nums = [2,3,0,0,2]' (becomes 'task_priorities'), 'k = 4' (becomes 'min_threshold').

Correct Output for this Instance (Original and Shifted Logic): 3.

- Claude-3.7-Sonnet Performance: (result: [False])
 - Reasoning Snippet (output): "The problem asks us to find the minimum number of 'priority increases' (operations) to make a schedule 'stable'. A schedule, represented by an array 'task_priorities', is stable if every sequence of 3 consecutive tasks has at least one task with a priority score greater than or equal to 'min_threshold'..."
 - Relevant solution_code Snippet:

```
class Solution:
    def minIncrementOperations(self, task_priorities: List[int], min_threshold: int)->int
    n = len(task_priorities)
    ans = 0
    # Incorrectly makes EACH element >= threshold, not the windowed condition
    for i in range(n):
        if task_priorities[i] < min_threshold:
            ans += min_threshold - task_priorities[i]
    return ans
```

- Result Details (metadata_output): 'output': '13', 'inputs': '[[2,3,0,0,2], 4]', 'expected': '3', 'error_code': -2, 'error_message': 'Wrong Answer''
- Analysis of Failure: Claude's reasoning correctly re-stated the objective in the new domain, including the crucial "every sequence of 3 consecutive tasks" condition. However, the generated code implemented a much simpler and incorrect logic: it calculated the operations needed to make *every single task* meet the 'min_threshold' individually, ignoring the more complex windowed requirement. This is a clear case where, despite understanding the shifted problem's textual goal, the model failed to map it to the correct complex algorithm and instead defaulted to an oversimplified solution.

D Negation Objective and Negation Objective (Soft) Results

E Prompt Templates for Modification

Gamification Prompt Template

Instruction: Rewrite the problem as a challenge involving agents or players.

Guidelines:

- Preserve all technical components (Input, Output, Explanation, Constraints).
- Add a game-like narrative layer (e.g., robot navigation, puzzle solving).

Prompted Task: Embed the problem into a goal-driven challenge structure.

{original_content}
No additional explanation needed.

Figure 4: Prompt template for Gamification transformation.

F Preservation Score Prompt Template

Attack	Model	Easy Acc.	Medium Acc.	Hard Acc.	Overall Acc.
	DeepSeek-7B	3.0% (-87.9%)	2.0% (-68.0%)	0.0% (-35.3%)	14.0% (-57.0%)
	DeepSeek-14B	3.0% (-94.0%)	0.0% (-92.0%)	0.0% (-58.8%)	5.7% (-82.3%)
	Qwen2.5-Coder	33.3% (-48.5%)	20.0% (-32.0%)	23.5% (-11.8%)	47.2% (-11.8%)
Negation Objective	LLaMA3-8B-Instruct	3.0% (-33.4%)	0.0% (-12.0%)	0.0% (-5.9%)	8.3% (-10.7%)
0 0	DeepSeek-Coder-33B	18.2% (-66.6%)	22.0% (-26.0%)	5.9% (-5.9%)	36.9% (-17.1%)
(Hard)	Claude-3-Haiku	12.1% (-39.4%)	4.0% (-28.0%)	5.9% (-35.3%)	21.2% (-18.8%)
	Claude-3.7-Sonnet	6.1% (-93.9%)	2.0% (-90.0%)	5.9% (-58.8%)	15.0% (-75.0%)
	Gemini-2.5-Flash	27.3% (-72.7%)	18.0% (-80.0%)	23.5% (-53.0%)	42.6% (-52.4%)
	Gemini-2.0-Flash	18.2% (-78.8%)	26.0% (-60.0%)	11.8% (-35.3%)	43.2% (-39.8%)
	DeepSeek-7B	3.0% (-87.9%)	0.0% (-70.0%)	0.0% (-35.3%)	5.7% (-65.3%)
	DeepSeek-14B	0.0% (-97.0%)	0.0% (-92.0%)	0.0% (-58.8%)	1.1% (-86.9%)
	Qwen2.5-Coder	36.4% (-45.4%)	22.0% (-30.0%)	5.9% (-29.4%)	46.9% (-12.1%)
Negation Objective	LLaMA3-8B-Instruct	21.2% (-15.2%)	6.0% (-6.0%)	5.9% (+0.0%)	29.4% (+10.4%)
Negation Objective	DeepSeek-Coder-33B	0.0% (-84.8%)	25.0% (-23.0%)	0.0% (-11.8%)	37.5% (-16.5%)
(Soft)	Claude-3-Haiku	15.2% (-36.3%)	0.0% (-32.0%)	11.8% (-29.4%)	22.5% (-17.5%)
	Claude-3.7-Sonnet	12.1% (-87.9%)	2.0% (-90.0%)	5.9% (-58.8%)	25.4% (-64.6%)
	Gemini-2.5-Flash	21.2% (-78.8%)	24.0% (-74.0%)	11.8% (-64.7%)	41.5% (-53.5%)
	Gemini-2.0-Flash	15.2% (-81.8%)	30.0% (-56.0%)	5.9% (-41.2%)	40.6% (-42.4%)

Table 7: Accuracy (%) for problem set perturbed with Negation Objective and Negation Objective (Soft).

Example Perturbation Prompt Template

Instruction: Modify only the examples to make them confusing for LLMs. **Guidelines:**

- Keep Input/Output logic correct.
- Shuffle values, insert noise (e.g., swapped labels, edge-case placements).

Prompted Task: Make the examples harder to pattern-match while maintaining validity.

{original_content}
No additional explanation needed.

Figure 5: Prompt template for Example Perturbation transformation.

Distracting Constraints Prompt Template

Instruction: Add irrelevant but realistic constraints to the problem.

Guidelines:

- Do not alter solvability.
- Insert edge cases, meaningless jargon, or constraints that distract models.

Prompted Task: Inject non-functional complexity into the problem description.

{original_content}

No additional explanation needed.

Figure 6: Prompt template for Distracting Constraints transformation.

Domain Shift Prompt Template

Instruction: Shift the problem into a different but equivalent domain. **Guidelines:**

- Retain logical structure and constraints.
- Replace nouns and context (e.g., integers \rightarrow salaries, arrays \rightarrow elevator floors).

Prompted Task: Change the framing without affecting logic.

{original_content}
No additional explanation needed.

Figure 7: Prompt template for Domain Shift transformation.

Hard Negation Objective Prompt Template

Instruction: Invert the objective of the coding task. **Examples:**

- $Max \rightarrow Min$
- Increasing \rightarrow Not Increasing
- Include \rightarrow Exclude

Prompted Task: Rewrite the problem with the opposite intent and updated examples.

{original_content}

No additional explanation needed.

Figure 8: Prompt template for Hard Negation Objective transformation.

Soft Negation Prompt Template

Instruction: Apply a light semantic reversal without changing the task's core logic.

Examples:

- · Non-decreasing instead of increasing
- Non-minimum instead of minimum

Guidelines:

- · Preserve input/output, examples, and difficulty.
- Adjust only the task description and minimal example logic.

Prompted Task: Rewrite with slight negation while keeping format identical.

{original_content}

No additional explanation needed.

Figure 9: Prompt template for Soft Negation transformation.

Logical Preservation Evaluation Prompt Template

System Prompt: You are a meticulous evaluator tasked with assessing the logical preservation of coding problems. You will be given two versions of a coding problem: the **Original Problem** and the **Modified (Perturbed) Problem**. Your goal is to evaluate whether the Modified Problem faithfully preserves:

- the fundamental task,
- the input/output specifications,
- the logical structure,
- and all critical details of the Original Problem.

You must judge strictly according to the rubric provided. Be critical but fair: minor rewordings are acceptable, but changes to task meaning, core logic, or critical information are not. You must output your evaluation in a structured format.

User Prompt: You will now receive two problems: an Original Problem and a Modified Problem.

{original_problem}
{modified_problem}

Please answer the following evaluation questions carefully:

- 1. Task Consistency: Does the Modified Problem ask the user to solve the same fundamental task as the Original?
- 2. Input/Output Preservation: Are the input format, output format, and constraints logically identical?
- 3. Logical Integrity: Is the problem's solution path and necessary reasoning preserved?
- 4. Critical Information: Is all important information (constraints, conditions, definitions) preserved without distortion?
- 5. Overall Preservation Score (0–10):
 - 10 = Perfect preservation, only cosmetic wording changes.
 - 8–9 = Very minor harmless changes; core task fully intact.
 - 6–7 = Some small logical shifts; still mostly solvable similarly.
 - 4–5 = Major logical shifts; significant omissions or confusing edits.
 - 1–3 = Core task altered; substantial confusion introduced.
 - 0 = Task completely changed or adversarially broken.
- 6. **Reasoning:** Write a brief but detailed explanation justifying the score. Point out any specific differences or issues if any exist.

Format your output exactly like this:

```
Task Consistency: [Yes/No]
Input/Output Preservation: [Yes/No]
Logical Integrity: [Yes/No]
Critical Information: [Yes/No]
Preservation Score: [0{10]
Reasoning:
- [Brief, clear explanation highlighting matching parts or critical deviations]
```

Figure 10: Prompt template for evaluating logical preservation between original and modified coding problems.