# WOULD YOU WALK TO THE CAR WASH? SALIENCE BIAS IN LLM COMMONSENSE REASONING

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## ABSTRACT

Despite advances in complex reasoning, large language models (LLMs) can prioritize explicit input conditions over implicit task prerequisites. In everyday commonsense reasoning, this can lead to a failure we term Salience Bias: salient but task-irrelevant details (e.g., numerical values) draw models into computation while they overlook the physical or commonsense prerequisites of the task. A critical open question is whether this failure reflects a genuine gap in commonsense knowledge or merely its suppression under misleading task framing. To investigate this, we construct the SaliTrap Benchmark, comprising 1,145 items in four trap dimensions. Evaluating 12 LLMs, we find substantial vulnerability across the tested models, with higher numerical distractor counts associated with lower trap-avoidance rates and trap recognition not always leading to avoidance. Further probing of sycophantic-compliance cases shows that the relevant commonsense can often be elicited when the original task framing is removed, suggesting a gap between recognizing a constraint and applying it during task execution. Building on this diagnosis, we further show that lightweight, inference-time prompting alone substantially closes the gap without any retraining. Our findings highlight the importance of applying commonsense constraints during task execution, and we release SaliTrap as a testbed for studying this gap.

## 1 INTRODUCTION

As the capability boundaries of large language models (LLMs) continue to expand, they have become highly proficient at solving complex mathematical problems (Wei et al., 2022; Zhang et al., 2025), executing agentic operations (Qin et al., 2024; Tang et al., 2025), and tackling coding tasks (Jimenez et al., 2024; Zhang et al., 2024). This success is largely attributed to the relevant data LLMs ingest during both their pre-training (Liu et al., 2023) and post-training (Chu et al., 2025) phases. However, everyday queries often include details that draw attention away from the conditions needed to complete a task. A model may compare costs, distances, or schedules without first checking whether its proposed solution can achieve the user's goal (Shao et al., 2024).

For example, when a user asks an LLM whether they should drive or walk to a car wash located 50 meters from their home, mainstream models (e.g., Gemini and DeepSeek) tend to base their reasoning entirely on the salient condition of "50 meters" (a concrete illustration is given later in Figure 2). They recommend walking because the distance is short, overlooking a basic requirement of the task: the car needs to be at the car wash.

As shown in Figure 1, this bias turns out to be pervasive across models, driven by distractor density, decoupled from mere trap detection, and rooted in knowledge suppression rather than absence: (a) across all 12 evaluated LLMs, even the best model avoids the trap in only 54.8% of queries and 8 of 12 models fall below 30%; (b) every additional numerical distractor further erodes the trap avoidance rate while driving up the CoT-Hijacked rate; (c) GLM-5.1 and Kimi-K2 still comply 86.2% and 81.8% of the time even after explicitly recognizing the trap, showing that detection does not imply avoidance; and (d) stripping the task framing restores knowledge that appeared lost, lifting the mean Liberation Rate across representative models from Cond-A to Cond-C.

These failures raise two key questions: do models recognize that a task's prerequisites are not met, and, when they do, does this recognition change their response? Answering these questions requires distinguishing models that miss the problem from those that notice it but proceed anyway. We



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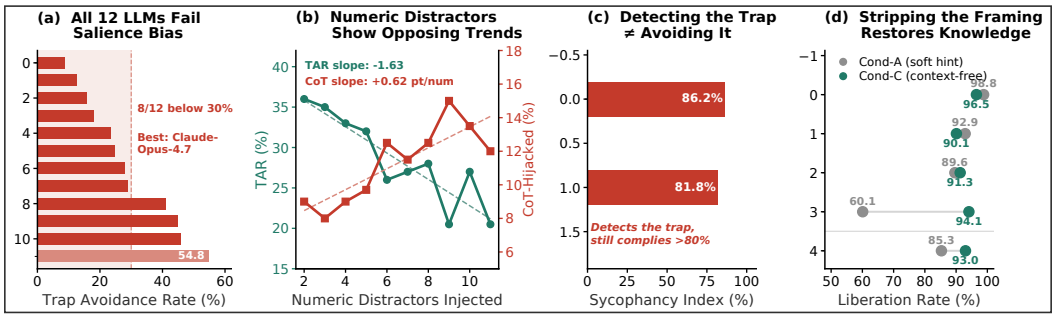



Figure 1: All LLMs suffer from salience bias, which stems from knowledge suppression rather than knowledge absence.

therefore introduce SaliTrap, a benchmark of tasks whose prerequisites are not met, presented with numerical and procedural details that invite computation. Concretely, it covers four types of traps: missing prerequisite, environmental mismatch, temporal/physiological violation, and rule mismatch.

We evaluate 12 state-of-the-art LLMs and find that all current large models suffer significantly from salience bias, with resistance closely tracking general reasoning capability; even models that do detect the trap frequently comply with it anyway, revealing detection and avoidance as distinct failure axes whose severity scales with distractor density and clusters by model provenance.

Crucially, we go on to show that this pervasive failure is not what it appears to be. By re-eliciting trap knowledge from the very models that just failed, this time stripped of the misleading task framing, we recover the vast majority of these failures, demonstrating that LLMs intrinsically possess the commonsense knowledge required to counter salience bias. The bias, in other words, is a failure of **elicitation, not competence**: the disproportionate influence of explicit salient conditions actively suppresses knowledge the model already has, rather than reflecting its absence.

In summary, we make four key contributions:

(i) We identify and formalize salience bias, showing that LLMs' over-reliance on explicit distractors causes them to overlook implicit commonsense prerequisites.

(ii) We contribute the SaliTrap Benchmark, synthesizing a high-quality dataset of 1,145 tasks across four dimensions, to robustly evaluate salience bias and disentangle trap detection from trap avoidance.

(iii) We conduct a comprehensive evaluation of 12 LLMs, revealing that salience bias is pervasive, correlated with capability, and structured along distractor density and model provenance.

(iv) Through knowledge re-elicitation and lightweight prompt interventions, we show that salience bias is fundamentally a failure of knowledge suppression and pinpointing elicitation is the actionable bottleneck for future work.

## 2 Related Work

In this section, we first review the core techniques underlying LLM reasoning, followed by a comprehensive overview of contemporary LLM reasoning benchmarks.

### 2.1 LLM Reasoning Techniques

Reasoning capabilities in LLMs have advanced the landscape of language intelligence, contributing substantially to solving complex mathematical problems (Wei et al., 2022; Zhang et al., 2025), executing agentic operations (Qin et al., 2024; Tang et al., 2025), and tackling programming tasks (Jimenez et al., 2024; Zhang et al., 2024). Early research predominantly relied on Chain-of-Thought (CoT) (Wei et al., 2022; Kojima et al., 2022) prompting, which enhanced reasoning performance through meticulously structured paradigms such as linear, tree-based (Yao et al., 2023), and graph-based (Besta et al., 2024) topologies. More recently, with the maturation of group relative

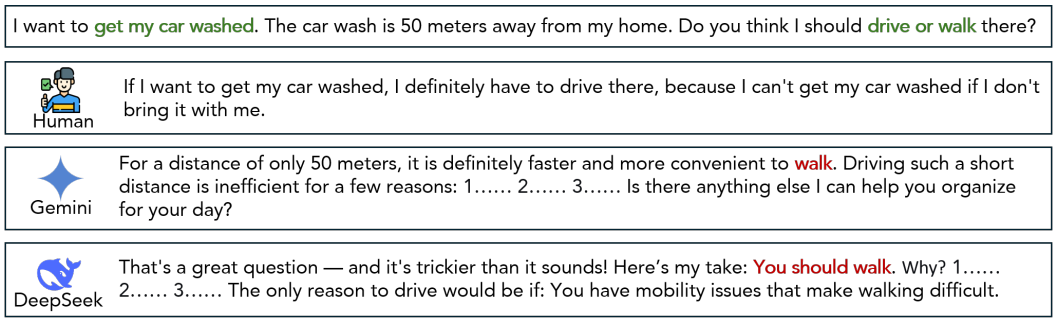



Figure 2: Exemplifying salience bias in LLMs. Driven by the explicit numerical cue ("50 meters"), both Gemini and DeepSeek optimize for walking distance while completely ignoring the implicit, overarching commonsense requirement of driving the vehicle to a car wash.

policy optimization (Shao et al., 2024) and on-policy distillation (Agarwal et al., 2024) techniques, LLM reasoning has been elevated by designing robust reward mechanisms or directly distilling knowledge from superior teacher models. However, while these algorithmic breakthroughs have augmented the models' capability to utilize contextual conditions, they have also introduced a critical and non-negligible challenge: salience bias.

### 2.2 LLM Reasoning Benchmarks

Progress in LLM reasoning has been driven in large part by increasingly demanding benchmarks that probe distinct facets of model competence, ranging from mathematical problem solving (Cobbe et al., 2021; Hendrycks et al., 2021) and multi-step scientific question answering (Rein et al., 2024) to repository-level code generation (Jimenez et al., 2024), long-horizon tool-use planning (Qin et al., 2024), and broad-coverage capability suites (Srivastava et al., 2023). As models began to saturate these accuracy-oriented benchmarks, a complementary line of work shifted attention toward robustness and faithfulness, exposing that strong benchmark performance often coexists with brittleness under superficial input perturbations (Mirzadeh et al., 2024; Wang et al., 2023) or with reasoning chains that are logically inconsistent despite yielding correct final answers (Turpin et al., 2023). Most closely related to our work, several benchmarks have shown that LLMs are prone to sycophantically complying with flawed or unanswerable premises embedded in a query rather than challenging them (Sharma et al., 2024; Li et al., 2024; Perez et al., 2023; Kadavath et al., 2022), echoing broader evidence that models frequently prioritize salient surface cues over deeper task validity (Shi et al., 2023; Liu et al., 2024). However, existing premise-robustness benchmarks largely target static factual or logical inconsistencies, leaving open whether models can resist physically impossible premises camouflaged by computation-laden distractors.

## 3 SaliTrap Benchmark

This section defines the task and the criteria for a well-formed item, introduces a four-dimensional taxonomy of traps, and describes the benchmark construction pipeline.

### 3.1 Task Definition

We study whether LLMs can detect physically impossible premises hidden in natural-language queries that invite computation. As illustrated in Figure 2, each benchmark item is a tuple

$$x = \big(\mathcal{P},\ \mathcal{T},\ \mathcal{G},\ \mathbf{n},\ d\big), \tag{1}$$

where $\mathcal{P}$ is the natural-language prompt, $\mathcal{T}$ is the trap core (a statement of the physical impossibility), and $\mathcal{G}$ is the ground-truth explanation. The numerical distractors $\mathbf{n}$ are embedded in $\mathcal{P}$ to invite irrelevant computation, and $d \in \mathcal{D}$ denotes the trap dimension.

An item $x$ is well-formed when it meets three criteria. First, $\mathcal{T}$ describes an impossibility under common knowledge. Second, a correct response must identify that impossibility; the prompt must

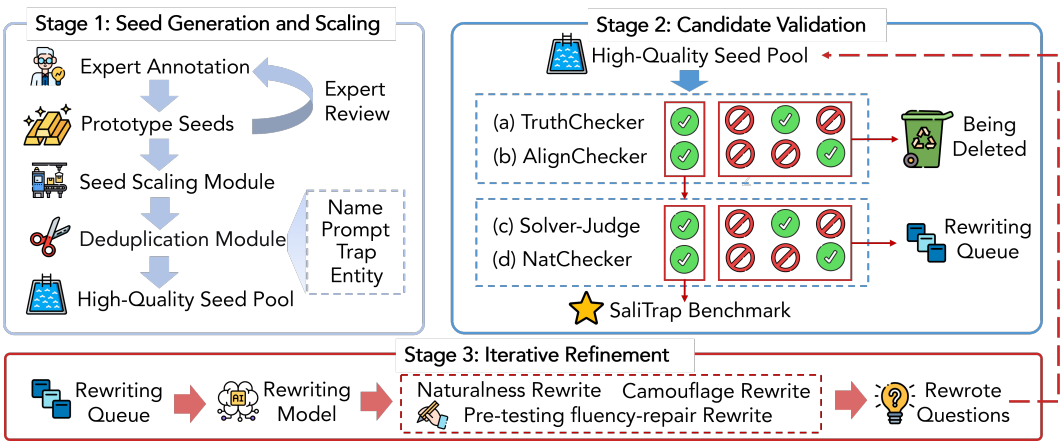



Figure 3: The construction of the SaliTrap benchmark is divided into three stages: (i) Seed generation and scaling stage, (ii) candidate validation stage, and (iii) iterative refinement stage. Through this pipeline, a benchmark capable of evaluating the degree of salience bias in LLMs can be obtained via expert annotation.

not contain an independent peripheral task that can be completed while ignoring the trap. We call such a bypass a sub-task escape. Third, the numerical distractors $\mathbf{n}$ should make $\mathcal{P}$ resemble a legitimate planning or optimization query. Accordingly, a correct response identifies $\mathcal{T}$ and does not provide an executable plan or numerical result that assumes the impossible premise is valid.

### 3.2 Trap Taxonomy

We group items into four dimensions, $\mathcal{D} = \{D_1, D_2, D_3, D_4\}$, according to the kind of violation they contain. In a missing-prerequisite trap ($D_1$), an instrument lacks a property required for the action, as when a slotted spoon is used to carry liquid water. In an environmental-mismatch trap ($D_2$), the setting prevents an instrument from working, as when someone tries to ignite a lighter at a depth of 50 m or fuel a battery-electric vehicle at a petrol station. Temporal or physiological violations ($D_3$) either reverse causality or assume a biological capability that does not exist—for example, trying to prevent yesterday's rain by buying umbrellas today, or cooking raw food in the human stomach. Finally, a rule-mismatch trap ($D_4$) presents a visually similar substitute where an institution or system requires the entity, such as offering a photograph of banknotes as legal tender.

### 3.3 Benchmark Construction

As shown in Figure 3, we construct SaliTrap in three stages: seed generation and scaling, candidate validation, and iterative refinement. We first expand a set of prototype scenarios into candidate queries. We then check that each query retains the trap, cannot be answered without addressing it, and reads naturally. Finally, we use solver responses to guide revisions and select queries that elicit failures. SaliTrap is thus designed to expose model weaknesses rather than estimate how often these failures occur in everyday use.

#### 3.3.1 Stage 1: Seed Generation and Scaling

Experts annotate prototype seeds $\mathcal{S}_0$ so that each satisfies the three well-formedness criteria by construction. Each seed $s_i = (\mathcal{P}_i^{(0)}, \mathcal{T}_i, \mathcal{G}_i, \mathbf{n}_i, d_i)$ has a dimension label $d_i \in \mathcal{D}$ and two auxiliary hints for automated synthesis: one specifies surface features to preserve, and the other specifies features to avoid.

A small set of prototypes is not sufficient for reliable evaluation, so we expand it with a generation pipeline. We allocate the target evenly across dimensions and process each dimension in small batches. For batch $b$ in dimension $d$, the generation prompt is

$$\Phi_{d,b} = \big[\mathrm{def}(d),\ \mathrm{fewshot}(\mathcal{S}_0, d),\ \mathrm{dir}(d, b),\ \mathrm{excl}(\hat{\mathcal{S}}_{<b})\big], \tag{2}$$

The prompt combines four ingredients. The dimension definition, $\mathrm{def}(d)$, describes the type of trap to generate; $\mathrm{fewshot}(\mathcal{S}_0, d)$ selects examples from the prototype seeds in that dimension. A batch-specific directive, $\mathrm{dir}(d, b)$, steers generation toward an under-represented tool or scenario, such as an instrument or setting not yet covered by previously accepted seeds. Finally, $\mathrm{excl}(\hat{\mathcal{S}}_{<b})$ provides a recency-truncated list of accepted seeds to limit repetition.

Before acceptance, each generated seed $\hat{s}$ passes four deduplication filters. The first, $f_1$, rejects an exact match to a scenario name in registry $\mathcal{N}$. Filters $f_2$ and $f_3$ reject prompts or trap cores that are too similar to those of accepted seeds. Similarity is measured by character-level Jaccard similarity, $J(a, b) = |a \cap b|/|a \cup b|$, after text normalization $\phi(\cdot)$ strips whitespace and replaces numerals with a placeholder. The final filter, $f_4$, rejects a seed if its (tool, object, action) triple $\tau(\hat{s})$ already appears in the accepted set $\mathcal{E}$. We add accepted seeds to $\hat{\mathcal{S}}$ and include them in later exclusion lists, helping maintain diversity across batches.

### 3.3.2 Stage 2: Candidate Validation

For each seed $s \in \hat{\mathcal{S}}$, the synthesis pipeline generates and empirically validates candidate items. Its per-seed registry starts with a single candidate $c_0$, whose prompt is the seed's initial prompt, $\mathcal{P}_{c_0} = \mathcal{P}_i^{(0)}$. We evaluate $c_0$ using the same checker and solver-judge pipeline as all later candidates.

**Tri-checker evaluation.** Three LLM-based checkers evaluate each candidate $c$:

$$\mathrm{Tr}(c) = \mathrm{TruthChecker}(\mathcal{P}_c, \mathcal{T}_s) \in \{0, 1\}, \tag{3}$$

$$\mathrm{Al}(c) = \mathrm{AlignChecker}(\mathcal{P}_c, \mathcal{T}_s, \mathcal{G}_s) \in \{0, 1\}^2, \tag{4}$$

$$\nu(c) = \mathrm{NatChecker}(\mathcal{P}_c) \in [1, 5]. \tag{5}$$

TruthChecker verifies that the candidate retains the original trap core instead of making the impossible premise feasible. AlignChecker checks two properties: after numerical and procedural distractors are removed, the candidate still expresses the intended trap; and no independent, ordinary sub-task lets the solver bypass it. NatChecker rates how naturally the prompt reads as an everyday query, considering the scenario, concision, concealment of the trap, the numerical context, and whether the prompt avoids explicit escape wording. Detailed criteria and prompt templates appear in the supplementary material. The alignment output is $\mathrm{Al}(c) = (\text{valid, no-escape})$, and both components must equal 1. We archive candidates that fail either the truth or alignment check. The remaining candidates proceed with their naturalness score $\nu(c)$.

**Solver-judge evaluation.** Candidates with sufficient naturalness undergo empirical testing. A strong reasoning model $\mathcal{M}_S$ (the Solver) attempts the prompt $\mathcal{P}_c$, after which a judge model $\mathcal{M}_J$ assigns one of five behavioral labels in $\mathcal{L}$. Hard Fail denotes fully executing the task without raising the commonsense issue; CoT Hijacked denotes recognizing the issue only after engaging with the numerical distractors; and Sycophantic Compliance denotes recognizing the trap but still complying. Strict Pass denotes identifying the trap and refusing with a sound explanation, while Refusal denotes declining without demonstrating understanding. We treat Hard Fail and CoT Hijacked as strong failures ($\mathcal{L}^{++}$), and Hard Fail, CoT Hijacked, and Sycophantic Compliance as failures overall ($\mathcal{L}^{+}$).

**Routing.** The judge label and naturalness score determine what happens next. Candidates that expose a failure ($\mathcal{L}^{+}$) and exceed a high naturalness threshold are certified for the final dataset. Those that expose a failure but fall below the threshold are rewritten to sound more natural while preserving the trap. By contrast, a naturally worded candidate labeled Strict Pass is rewritten to make the trap less conspicuous, since the Solver identified it too easily.

### 3.3.3 Stage 3: Iterative Refinement

These routing decisions lead to different kinds of revision. Some candidates hide the trap well but sound artificial; others read naturally but reveal the trap too easily. The rewriting model $\mathcal{M}_W$ addresses the weakness: it improves naturalness while preserving a difficult trap, deepens camouflage when the trap is too easy to spot, or repairs fluency when a candidate has not yet reached the Solver.

Table 1: SaliTrap benchmark results (TAR/HFR, %) across four trap dimensions.

| Model | Prerequisite | | Environmental | | Temporal | | Rule | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TAR↑ | HFR↓ | TAR↑ | HFR↓ | TAR↑ | HFR↓ | TAR↑ | HFR↓ | TAR↑ | HFR↓ |
| Claude-Opus-4.7 | 30.3 | 45.1 | **45.7** | 36.6 | **62.5** | 28.6 | **63.1** | **25.2** | **54.8** | 31.1 |
| GPT-5.5 | **52.8** | **27.2** | 39.0 | **32.3** | 42.9 | 37.2 | 46.4 | 31.5 | 45.5 | 32.4 |
| Claude-Opus-4.6 | 27.2 | 51.3 | 37.8 | 43.9 | 48.8 | 40.2 | 51.1 | 36.7 | 44.5 | 41.1 |
| GPT-5.4 | 36.9 | 41.0 | 32.9 | 40.2 | 41.9 | 40.2 | 45.4 | 32.6 | 41.2 | 37.1 |
| DeepSeek-R1 | 19.5 | 61.5 | 19.5 | 59.8 | 27.6 | 56.1 | 24.7 | 61.2 | 23.8 | 59.7 |
| Gemini-2.5-Pro | 25.1 | 40.0 | 25.6 | 50.0 | 30.2 | 51.5 | 27.8 | 51.8 | 27.7 | 49.4 |
| GLM-5.1 | 24.1 | 30.3 | 21.3 | **31.7** | 32.2 | **25.9** | 27.0 | 28.7 | 27.1 | **28.6** |
| Kimi-K2 | 13.8 | 46.2 | 19.5 | 32.9 | 22.9 | 35.2 | 30.1 | 26.8 | 23.9 | 33.2 |
| Doubao-Seed-2.0 | 9.7 | 65.6 | 10.4 | 65.9 | 23.3 | 58.5 | 20.6 | 56.7 | 18.0 | 60.0 |
| DeepSeek-V4-Pro | 9.2 | 56.4 | 10.4 | 47.0 | 19.3 | 54.5 | 14.8 | 49.9 | 14.4 | 51.8 |
| DeepSeek-V4-Flash | 6.2 | 69.7 | 5.5 | 65.9 | 17.6 | 56.1 | 13.2 | 55.9 | 12.1 | 59.7 |
| MiniMax-M2.7 | 6.2 | 63.1 | 6.7 | 68.9 | 8.0 | 54.5 | 11.1 | 56.7 | 8.8 | 59.0 |

Rewriting can change the intended meaning, so each child candidate $c'$ must pass a compliance check $\kappa(c, c', \mathcal{T}_s)$. This check verifies that the child preserves its parent's trap core, all distractors $\mathbf{n}_s$, and the absence of a sub-task escape. We discard any child that fails. Accepted children return to Stage 2. A branch ends when it stops improving for a bounded number of rounds; meanwhile, a high-temperature generator $\mathcal{M}_G$ periodically introduces more varied mutations to keep the search from clustering around the initial candidate.

No single criterion is sufficient for final selection. We therefore assign each certified candidate $c$ a composite score, $\mathrm{score}(c)$, that rewards failure severity $w_{\ell(c)}$, naturalness $\nu(c)$, and confirmed alignment, while penalizing sub-task escapes, near-duplicates, and excessive length. We retain the top $k = 5$ candidates per seed as the final benchmark items.

# 4 Experiment

In this section, we describe the experimental setup and evaluation metrics, assess 12 LLMs on SaliTrap across its four trap dimensions, and compare their trap-avoidance and sycophantic-compliance performance. We then summarize the main performance differences across models and dimensions.

## 4.1 Experimental Setup

### 4.1.1 Metrics

The final SaliTrap benchmark comprises $N = 1{,}145$ items distributed across the four trap dimensions. With $N$ representing the total items in the dataset, we evaluate the models using four key metrics, computed over two different denominators. Over the *full dataset* ($N$): **TAR** (Trap Avoidance Rate, % ↑) measures the fraction of queries where the model correctly identifies the infeasible premise and refuses to execute the task; **HFR** (Hard Fail Rate, % ↓) measures the fraction of queries where the model proceeds with full computation without any premise challenge; **SCR** (Sycophantic Compliance Rate, % ↓) measures the fraction of queries where the model recognises the trap yet still complies with the infeasible request; equivalently, $\mathrm{SCR} = \mathrm{SC}/N$, where SC denotes the number of Sycophantic Compliance cases. Over the trap-aware subset (Sycophantic Compliance ∪ CoT Hijacked, excluding Hard Fail cases where no trap awareness is ever exhibited): **SI** (Sycophancy Index, % ↓) is the *conditional* compliance rate given trap awareness, $\mathrm{SI} = \mathrm{SC}/(\mathrm{SC} + \mathrm{CoT})$, where CoT denotes the number of CoT Hijacked cases. This conditioning matters: normalizing by $N$ instead would conflate knowledge absence with sycophantic suppression, giving weak models that rarely detect the trap a spuriously low SI. Restricting the denominator to trap-aware responses instead measures how often a model complies when it could have refused. The exact relationship between SCR and SI is given in Appendix A.

Table 2: SaliTrap benchmark results (SCR/SI, %) across four trap dimensions.

| Model | Prerequisite | | Environmental | | Temporal | | Rule | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | SCR↓ | SI↓ | SCR↓ | SI↓ | SCR↓ | SI↓ | SCR↓ | SI↓ | SCR↓ | SI↓ |
| Claude-Opus-4.7 | 22.6 | 51.2 | **17.7** | 69.0 | **8.6** | 41.9 | 11.5 | 54.9 | 13.5 | 53.1 |
| GPT-5.5 | 19.5 | 59.4 | 28.0 | 83.6 | 19.9 | 65.2 | 21.6 | 68.2 | 21.7 | 68.2 |
| Claude-Opus-4.6 | 20.5 | 46.0 | **17.7** | 64.4 | 10.3 | 50.8 | **10.5** | 50.0 | **13.2** | 51.2 |
| GPT-5.4 | 21.5 | 60.9 | 26.2 | 84.3 | 17.9 | 63.5 | 21.2 | 73.6 | 21.1 | 70.1 |
| DeepSeek-R1 | **17.9** | **41.7** | 20.1 | **60.0** | 16.3 | **45.0** | 13.8 | **49.6** | 16.1 | **48.0** |
| Gemini-2.5-Pro | 34.9 | 72.3 | 24.4 | 78.4 | 18.3 | 68.8 | 20.4 | 61.1 | 22.9 | 67.7 |
| GLM-5.1 | 45.6 | 80.9 | 47.0 | 95.1 | 41.5 | 89.3 | 43.9 | 83.9 | 44.0 | 86.2 |
| Kimi-K2 | 39.5 | 68.8 | 47.0 | 84.6 | 41.9 | 78.8 | 42.5 | 89.2 | 42.4 | 81.8 |
| Doubao-Seed-2.0 | 24.6 | 53.3 | 23.8 | 76.5 | 18.3 | 65.5 | 22.3 | 64.7 | 21.8 | 63.8 |
| DeepSeek-V4-Pro | 32.8 | 72.7 | 42.1 | 82.1 | 25.9 | 69.0 | 34.8 | 84.1 | 33.2 | 78.2 |
| DeepSeek-V4-Flash | 23.6 | 46.9 | 28.7 | 62.7 | 25.9 | 68.4 | 30.3 | 77.8 | 27.8 | 66.8 |
| MiniMax-M2.7 | 26.2 | 55.4 | 20.1 | 64.7 | 26.6 | 71.4 | 22.5 | 69.9 | 23.8 | 66.4 |

#### 4.1.2 Evaluated Models

We evaluate 12 state-of-the-art LLMs: Claude-Opus-4.7 (Anthropic, 2026b), Claude-Opus-4.6 (Anthropic, 2026a), GPT-5.5 (OpenAI, 2026b), GPT-5.4 (OpenAI, 2026a), Gemini-2.5-Pro (Comanici et al., 2025), DeepSeek-R1 (Guo et al., 2025), DeepSeek-V4-Pro, DeepSeek-V4-Flash (Xu et al., 2026), GLM-5.1 (Zeng et al., 2026), Kimi-K2 (Team et al., 2025), Doubao-Seed-2.0 (ByteDance Seed, 2026), and MiniMax-M2.7 (Chen et al., 2026). All models are evaluated in a zero-shot setting with no task-specific fine-tuning, ensuring a fair comparison across models.

### 4.2 Main results

Table 1 reveals that salience bias is a pervasive and severe failure mode across all 12 evaluated LLMs: even the strongest model, Claude-Opus-4.7, only avoids the trap in 54.8% of queries, and the majority of models fall well below 30%. Overall performance is closely tied to reasoning capability. The top models by TAR are also the most capable general-purpose reasoners, while models with substantially weaker general reasoning ability exhibit the highest HFR, exceeding 59%. This indicates that resisting salience bias is not an isolated skill but is entangled with a model's overall capacity to perform deliberate, premise-checking reasoning rather than immediately committing to surface-level computation.

Table 2 exposes a second, orthogonal axis of failure: even conditioned on successfully detecting the trap, models frequently choose to comply anyway. GLM-5.1 and Kimi-K2 have the two highest SI, meaning that in the rare cases where they do notice something is wrong, they proceed to satisfy the user's request over 80% of the time, despite ranking only middling on raw TAR. This decouples detection from action: a model can have moderate awareness of the trap yet almost never act on it, which raw TAR/HFR alone cannot reveal.

A closer look at the dimension-wise breakdown shows a consistent difficulty ordering: missing prerequisite is the hardest dimension to detect, whereas rule mismatch is the easiest. This gap is intuitive: missing-prerequisite traps require reasoning about a physical property never explicitly negated in the prompt, while rule-mismatch traps hinge on a categorical distinction that is more lexically salient and hence easier to surface.

## 5 Further Analysis

### 5.1 Item Difficulty via Item Response Theory

To disentangle intrinsic item difficulty from model ability, we fit a one-parameter logistic item response theory model over the binary Strict-Pass outcomes of all 12 models on all items, jointly estimating a per-model ability parameter $\theta$ and a per-item difficulty parameter $\beta$. As shown in Figure 4(a)-(b), the $\beta$ distributions of missing prerequisite and environmental mismatch are vis-

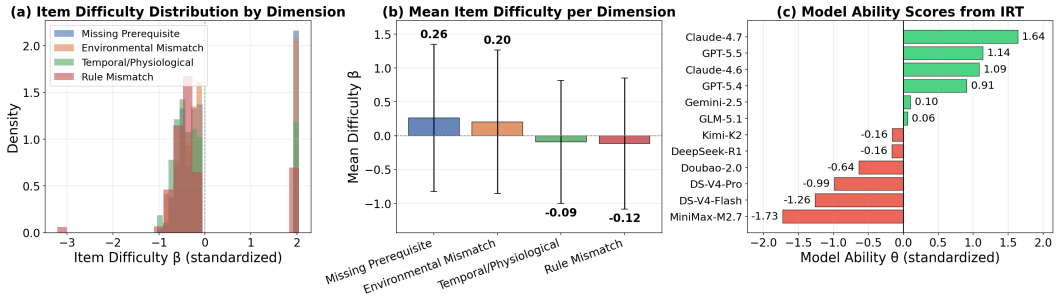



Figure 4: Distribution of item difficulty $\beta$ estimated using item response theory (IRT) across the four trap dimensions (12 evaluated models). Missing prerequisite and environmental mismatch skew toward higher difficulty, while rule mismatch items are concentrated at lower difficulty.

ibly right-shifted and have higher mean difficulty than temporal/physiological violation and rule mismatch, confirming that the dimension-wise gap in Table 1 persists after controlling for which models were tested. Figure 4(c) further shows that the estimated abilities $\theta$ recover a ranking highly consistent with the raw TAR ordering, from Claude-Opus-4.7 at the top to MiniMax-M2.7 at the bottom.

### 5.2 Co-failure Analysis

To understand whether models fail in a shared or idiosyncratic manner, we compute the pairwise Jaccard similarity between the failure sets ($\mathcal{L}^+$) of every pair of models and visualize the resulting structure as a dendrogram (Figure 6). The dendrogram splits models into two clusters: within the former, overlap is highest among the weaker open-weight models, indicating that below a certain ability threshold models converge onto largely the same failure subset rather than failing idiosyncratically; within the latter, Claude-Opus-4.7 is consistently the least similar to every other model, marking it as the most idiosyncratic failure mode in the pool. This suggests co-failure is shaped jointly by a capability threshold and by training provenance, with different training recipes inducing qualitatively different, not merely smaller, blind spots toward salience bias.

### 5.3 Numeric Distractor Density

Plotting TAR and CoT-Hijacked rate (averaged over all 12 models) against the number of injected numerical distractors $|\mathbf{n}|$ reveals a clear monotonic trend, consistent within every trap dimension: TAR falls and the CoT-Hijacked rate rises as $|\mathbf{n}|$ increases (Figure 6), supporting our hypothesis that salience bias is triggered not merely by the presence of a numerical distractor but by its density, making adversarially dense prompts especially dangerous. A stylized signal-competition model that yields a monotonic TAR prediction under explicit assumptions is analyzed in Appendix C.

A response labeled Sycophantic Compliance has registered the trap yet still complied, but this alone cannot tell us whether the underlying physical knowledge was genuinely suppressed by sycophancy or was too weak to survive re-elicitation. To disambiguate this, we re-query every Sycophantic Compliance instance from four representative models (Claude-4.6, GLM-5.1, Kimi-K2, DeepSeek-R1) under three debiasing prompts (Cond-A: a soft feasibility hint; Cond-B: an explicit trap reveal; Cond-C: a context-free knowledge probe) and re-judge the responses, defining liberation rate as the fraction of former Sycophantic Compliance cases converted to Strict Pass under each condition. As shown in Figure 5 (left), Cond-B and Cond-C achieve liberation rates above 90% for all four models, while Cond-A exceeds 90% for GLM-5.1 and Kimi-K2. These results suggest that much of the relevant commonsense knowledge can be elicited once the inducing task framing is changed, although the effectiveness of re-elicitation depends on the model and condition.

### 5.4 Can Prompting Fix Salience Bias?

Building on the liberation finding that trap-relevant knowledge is largely intact, we test whether a single system-level prompt prefix, applied at inference time with no fine-tuning, can close the

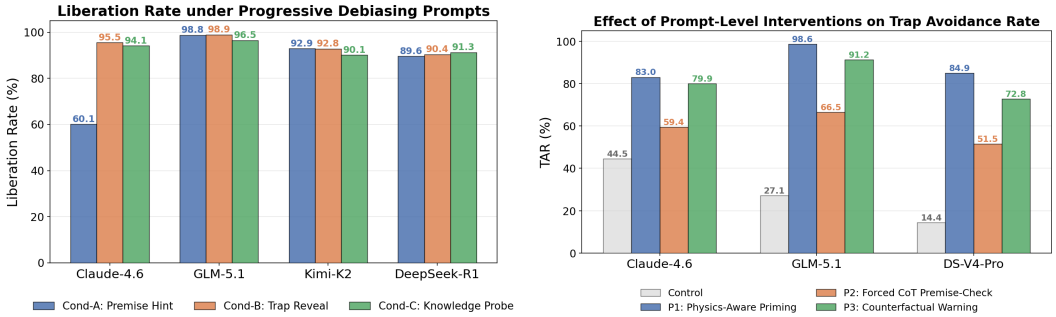



Figure 5: Left: fraction of baseline Sycophantic Compliance cases converted to Strict Pass under three re-elicitation conditions (soft feasibility hint, explicit trap reveal, and context-free probe). Right: TAR under three prompt-level interventions (P1: physics-aware priming; P2: forced premise check; P3: counterfactual warning).

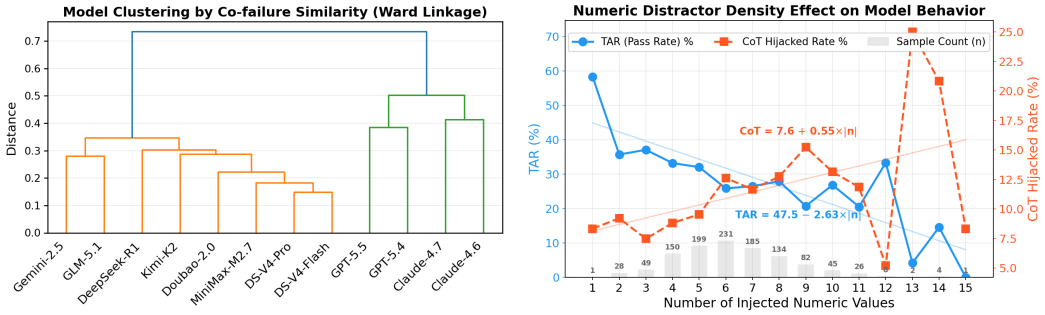



Figure 6: Left: hierarchical clustering of models by overlap in their task-level failure sets. Right: task failure rate rises with numerical-distractor density.

salience-bias gap at scale, evaluating three intervention prompts on the full benchmark for two models spanning different baseline performance levels: P1 (physics-aware priming, instructing the model to first verify task feasibility), P2 (forced chain-of-thought premise-check, requiring an explicit feasibility verdict before proceeding), and P3 (a counterfactual warning that the prompt may contain an infeasible premise). Figure 5 (right) shows that all three interventions substantially raise TAR over the uninstructed Control for every model, with the largest gains precisely where the baseline is weakest. P1 is consistently the most effective intervention and P2 the least, despite P2 being the most explicit in structurally forcing a feasibility verdict; we attribute this to P2's rigid step-by-step format sometimes eliciting a perfunctory feasibility statement that the model does not actually condition its subsequent reasoning on, whereas P1's open-ended check better preserves the model's own reasoning trajectory toward premise scrutiny. These results show that salience bias, despite being pervasive under naive prompting, is substantially correctable by lightweight prompt engineering alone, reinforcing that the bottleneck lies in elicitation.

## 6 Conclusion

We identify salience bias, a pervasive failure of LLMs that causes them to prioritize salient explicit conditions over implicit commonsense prerequisites, and introduce SaliTrap, a benchmark of physically impossible premises camouflaged by computation-laden distractors across four trap dimensions. Evaluating 12 state-of-the-art LLMs, we find that all models are substantially vulnerable, with failure rates rising sharply as distractor density increases. Further analysis reveals that this vulnerability stems from suppression rather than absence of commonsense knowledge, and that lightweight prompting can largely recover it. We hope SaliTrap spurs future work toward LLMs that reliably attend to implicit task-critical conditions.

### AI USE STATEMENT

We used AI assistants to polish the manuscript and LLM APIs for data synthesis and experiments. We take responsibility for the final content of this work

### ETHICS STATEMENT

SaliTrap consists of synthetically authored, everyday physical-task scenarios; no human-subject or personal data were collected. We reviewed the benchmark for offensive, biased, or unsafe content. The benchmark is intended to help identify and reduce physically implausible model responses, and we do not anticipate material dual-use risks from its release.

### REPRODUCIBILITY STATEMENT

We describe the task, benchmark construction, and evaluation metrics in Sections 3 and 4. Appendix D documents the dataset schema and statistics, Appendix E details the construction pipeline and prompts, and Appendix F provides model access, hyperparameters, and evaluation procedures. Extended results are reported in Appendix G; formal metric and salience-model analyses with proofs appear in Appendices A and C, respectively, and the paired intervention decomposition is in Appendix B. The benchmark and evaluation and analysis code will be released publicly.

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## A A Decomposition of the Sycophancy Metrics

We give a direct relationship between the full-dataset Sycophantic Compliance Rate (SCR) and the conditional Sycophancy Index (SI). This identity clarifies that the two metrics capture different factors: how often responses are labeled as trap-aware, and how often those responses still comply.

**Proposition 1** (Metric decomposition)**.** *Consider a dataset of $N > 0$ items, each assigned exactly one behavioral label. Let $n_{\mathrm{SC}}$ and $n_{\mathrm{CoT}}$ denote the numbers of Sycophantic Compliance and CoT Hijacked responses, respectively. If $n_{\mathrm{SC}} + n_{\mathrm{CoT}} > 0$, define the trap-aware response rate as*

$$A = \frac{n_{\mathrm{SC}} + n_{\mathrm{CoT}}}{N}.$$

*Then the fractional rates satisfy*

$$\mathrm{SCR} = A\,\mathrm{SI}, \qquad 0 \le \mathrm{SI} \le 1, \qquad 0 \le \mathrm{SCR} \le A.$$

*Proof.* By definition, $\mathrm{SCR} = n_{\mathrm{SC}}/N$ and $\mathrm{SI} = n_{\mathrm{SC}}/(n_{\mathrm{SC}} + n_{\mathrm{CoT}})$. Therefore,

$$A\,\mathrm{SI} = \frac{n_{\mathrm{SC}} + n_{\mathrm{CoT}}}{N} \frac{n_{\mathrm{SC}}}{n_{\mathrm{SC}} + n_{\mathrm{CoT}}} = \frac{n_{\mathrm{SC}}}{N} = \mathrm{SCR}.$$

The counts are nonnegative, so $0 \le n_{\mathrm{SC}} \le n_{\mathrm{SC}} + n_{\mathrm{CoT}}$, which gives $0 \le \mathrm{SI} \le 1$. Multiplying by $A \ge 0$ and using the identity yields $0 \le \mathrm{SCR} \le A$. If there are no trap-aware responses, SI is undefined under its conditional definition, so the stated identity does not apply. □

When rates are reported as percentages, the equivalent relation is $\mathrm{SCR}_{\%} = A_{\%}\,\mathrm{SI}_{\%}/100$.

## B Paired Decomposition of Debiasing Outcomes

Aggregate TAR changes do not show whether an intervention rescues baseline failures, causes regressions among baseline successes, or both. The following finite-sample identity separates these two kinds of response changes without assuming that an intervention helps every item.

**Proposition 2** (Paired intervention decomposition)**.** *Fix a model and a dataset of $N > 0$ items, evaluated under both a control prompt and one intervention using the same scoring rule. For item $i$, let $Y_i(0), Y_i(1) \in \{0, 1\}$ indicate whether its response is counted as a Trap Avoidance success under control and intervention, respectively. Define*

$$p_{ab} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{Y_i(0) = a,\ Y_i(1) = b\}, \qquad a, b \in \{0, 1\}.$$

*These four proportions form the paired outcome table*

| | $Y(1) = 0$ | $Y(1) = 1$ |
|---|---|---|
| $Y(0) = 0$ | $p_{00}$ | $p_{01}$ |
| $Y(0) = 1$ | $p_{10}$ | $p_{11}$ |

*Let $R = p_{01}$ be the rescued fraction and $Q = p_{10}$ the regressed fraction. Then*

$$\mathrm{TAR}(1) - \mathrm{TAR}(0) = R - Q.$$

*In particular, the TAR gain is at most the fraction of items rescued ($R$), and it equals that fraction if and only if no item regresses ($Q = 0$).*

*Proof.* For each item, the difference $Y_i(1) - Y_i(0)$ is 1 when the item is rescued, $-1$ when it regresses, and 0 when its outcome is unchanged. Hence

$$\mathrm{TAR}(1) - \mathrm{TAR}(0) = \frac{1}{N} \sum_{i=1}^{N} \big(Y_i(1) - Y_i(0)\big) = R - Q.$$

Since $Q \ge 0$, the gain is no greater than $R$; equality holds exactly when $Q = 0$. □

The liberation experiment focuses on the subset of baseline Sycophantic Compliance (SC) cases. Let $C$ be that subset, and let $L_z$ be the liberation rate under re-elicitation condition $z$, namely the fraction of items in $C$ that become Strict Pass under that condition. Since each baseline SC response complies with the impossible request, it is not a Trap Avoidance success at baseline. Therefore, the fraction of the full dataset consisting of baseline SC cases converted to Strict Pass under $z$ is exactly $(|C|/N)L_z$. This is the contribution from that subset alone; changes among other items can also affect the overall TAR. All quantities here describe paired observed responses under the specified prompts and scoring rule; the identities do not by themselves establish a causal claim about the model's internal knowledge.

## C A SIGNAL-COMPETITION MODEL OF SALIENCE BIAS

We analyze a simple model in which trap-relevant evidence competes with the salience induced by numerical distractors. The result below is conditional on this model; it is not an assumption-free claim about how LLMs internally process prompts.

For each item $i$, let $\mu_i \in \mathbb{R}$ denote its baseline evidence margin in favor of recognizing the trap. Let $\lambda_{ij} \geq 0$ be the salience load contributed by the $j$-th distractor on that item, and define the cumulative load from $m$ distractors as $\Lambda_i(m) = \sum_{j=1}^{m} \lambda_{ij}$, with $\Lambda_i(0) = 0$. We model the decision score as

$$Z_i(m) = \mu_i - \Lambda_i(m) + \epsilon_i,$$

where $\epsilon_i$ has the standard logistic distribution with cumulative distribution function $\sigma(t) = (1 + e^{-t})^{-1}$. The model counts the response as trap-avoiding when $Z_i(m) > 0$. For dataset weights $w_i \geq 0$ with $\sum_i w_i = 1$, its expected TAR at distractor count $m$ is therefore

$$T(m) = \sum_i w_i \Pr[Z_i(m) > 0] = \sum_i w_i \left[1 - \sigma(-\mu_i + \Lambda_i(m))\right] = \sum_i w_i \sigma(\mu_i - \Lambda_i(m)),$$

where the last equality uses the logistic symmetry $1 - \sigma(-t) = \sigma(t)$.

**Proposition 3** (Monotonicity and sensitivity to distractor load)**.** *Under the model above, adding a distractor with nonnegative load to each item cannot increase expected TAR. More precisely, writing $u_i(m) = \mu_i - \Lambda_i(m)$, for every $m \geq 0$,*

$$T(m) - T(m+1) = \sum_i w_i \int_{u_i(m) - \lambda_{i,m+1}}^{u_i(m)} \sigma(t)\big(1 - \sigma(t)\big)\, dt \geq 0.$$

*Moreover, the decrement obeys*

$$0 \leq T(m) - T(m+1) \leq \frac{1}{4} \sum_i w_i \lambda_{i,m+1}.$$

*The first inequality is strict exactly when at least one item with positive weight receives a strictly positive load.*

*Proof.* Fix an item $i$ and abbreviate $u = u_i(m)$ and $\lambda = \lambda_{i,m+1}$. Since $\Lambda_i(m+1) = \Lambda_i(m) + \lambda$, its success probability changes from $\sigma(u)$ to $\sigma(u - \lambda)$. The logistic function satisfies

$$\sigma'(t) = \frac{e^{-t}}{(1 + e^{-t})^2} = \sigma(t)\big(1 - \sigma(t)\big) > 0.$$

By the fundamental theorem of calculus,

$$\sigma(u) - \sigma(u - \lambda) = \int_{u-\lambda}^{u} \sigma'(t)\, dt = \int_{u-\lambda}^{u} \sigma(t)\big(1 - \sigma(t)\big)\, dt.$$

Because $\lambda \geq 0$ and $\sigma'(t) > 0$ for every finite $t$, this difference is nonnegative, and it is strictly positive if and only if $\lambda > 0$. Multiplying by $w_i$ and summing over items gives the stated identity and strictness condition.

Finally, $\sigma(t)(1 - \sigma(t)) \leq 1/4$ for all $t$, since $p(1-p) \leq 1/4$ for $p \in [0, 1]$. Bounding the integrand by $1/4$ gives

$$\sigma(u) - \sigma(u - \lambda) \leq \frac{\lambda}{4}.$$

Weighting this bound by $w_i$ and summing proves the sensitivity bound. □

The logistic link also yields an odds-ratio interpretation of cumulative salience load.

**Corollary 4** (Multiplicative attenuation of trap-recognition odds)**.** *For any item $i$ and distractor count $m$, let $p_i(m) = \Pr[Z_i(m) > 0]$. Then*

$$\frac{p_i(m)}{1 - p_i(m)} = \exp(\mu_i - \Lambda_i(m)) = \exp(\mu_i) \prod_{j=1}^{m} \exp(-\lambda_{ij}).$$

*In particular, adding a distractor of load $\lambda_{i,m+1}$ multiplies the odds of trap recognition by $e^{-\lambda_{i,m+1}}$.*

Table 3: Per-dimension item counts, mean number of injected numerical distractors $|\mathbf{n}|$, and mean naturalness score for the final SaliTrap benchmark.

| Dimension | # Items | Mean $\lvert\mathbf{n}\rvert$ | Naturalness |
|---|---|---|---|
| Missing Prerequisite | 195 | 6.9 | 3.9 |
| Environmental Mismatch | 164 | 6.6 | 3.9 |
| Temporal/Physiological | 301 | 5.4 | 4.0 |
| Rule Mismatch | 485 | 5.9 | 4.0 |
| **Overall** | **1,145** | **6.0** | **4.0** |

*Proof.* Since $p_i(m) = \sigma(\mu_i - \Lambda_i(m))$ and $\sigma(t)/(1-\sigma(t)) = e^t$, the first equality follows directly. Substituting $\Lambda_i(m) = \sum_{j=1}^{m} \lambda_{ij}$ and using $e^{a-b} = e^a e^{-b}$ gives the product representation. The one-step statement follows by taking the ratio of the odds at $m+1$ and $m$. □

The proposition formalizes one possible route from distractor density to lower trap avoidance: each added cue shifts the decision margin away from recognizing the trap. Its monotonicity conclusion requires nonnegative loads and the specified logistic decision model. In the benchmark, distractors may differ in content and can interact with the query in ways this model does not represent; the empirical trend is therefore evidence about evaluated models, while the proposition describes the behavior of the stated abstraction.

# D THE SALITRAP DATASET

## D.1 ITEM SCHEMA

Every item in SaliTrap is stored as a JSON record with the following fields, directly mirroring the tuple $x = (\mathcal{P}, \mathcal{T}, \mathcal{G}, \mathbf{n}, d)$ defined in the main paper:

- `item_id` – a unique candidate identifier.
- `seed_id` – the prototype seed from which the item was synthesized (multiple certified items can share a seed).
- `prompt` ($\mathcal{P}$) – the full natural-language query presented to the evaluated model.
- `trap_core` ($\mathcal{T}$) – a one-sentence declarative statement of the physical impossibility, used both for authoring and as the isolated probe in the Cond-C knowledge-elicitation experiment.
- `ground_truth` ($\mathcal{G}$) – the reference explanation used by the Judge model to score responses.
- `injected_numbers` ($\mathbf{n}$) – the list of numerical distractors embedded in $\mathcal{P}$.
- `dimension_tag` ($d$) – one of the four trap dimensions (Missing Prerequisite, Environmental Mismatch, Temporal/Physiological Violation, Rule Mismatch).
- `naturalness_score` – the averaged 1–5 Naturalness Checker score.
- `attack_tier` – `strong` or `soft`, indicating whether the certified candidate elicited a strong failure ($\mathcal{L}^{++}$, i.e. Hard Fail or CoT Hijacked) or a softer one (Sycophantic Compliance) during Stage-2 validation.

## D.2 DATASET STATISTICS

Table 3 reports the per-dimension item counts and the distribution of injected numerical distractors for the final, certified 1,145-item benchmark.

### D.3 Licensing, Access, and Intended Use

SaliTrap will be released publicly immediately, together with all evaluation and analysis code, to facilitate replication and downstream research on elicitation-time failures in LLMs. The dataset contains only synthetically authored natural-language queries about everyday physical tasks; it does not contain personal, private, or otherwise sensitive information, and does not target any individual, organization, or protected group. No human-subjects data were collected.

## E Benchmark Construction Pipeline

This section documents the full three-stage pipeline summarized in the main paper's benchmark-construction overview and gives the exact prompt templates used by every LLM-based component. All prompts below are lightly paraphrased for readability but preserve the exact instructions, constraints, and output schema used in the released code. For the construction pipeline, the Judge model $\mathcal{M}_J$ and the rewriting and generation models ($\mathcal{M}_W$, $\mathcal{M}_G$) are Claude-Opus-4.7. The Solver $\mathcal{M}_S$ is a round-robin pool of four strong reasoning models: Claude-Opus-4.7, GPT-5.5, DeepSeek-R1, and Gemini-2.5-Pro.

### E.1 Stage 1: Seed Generation and Scaling

Each of the four trap dimensions is seeded with a small number of expert-authored prototype seeds and then scaled via micro-batch generation. The Scaling Generator receives the dimension definition, few-shot exemplars from $\mathcal{S}_0$, a batch-specific directive steering coverage toward an under-represented tool/scenario niche, and a recency-truncated exclusion list of already-accepted seeds.

**Seed Viability Checker**

```
You are the SaliTrap Seed Viability Checker.  Your task is NOT to
judge whether the item can fool a model, but whether the raw seed is
worth promoting into the full adversarial/annealing pipeline.
Perform six checks:  (1) eraser_test_pass:  after removing all
numbers, prices, routes, times, and procedural details, does
the remaining premise still constitute a clear commonsense
contradiction?  (2) target_binding_pass:  does the user's final
question necessarily depend on this impossible premise to be
answered?  (3) no_normal_subtask_escape:  can the model finish the
task by answering only a normal sub-task, without addressing the
impossible premise?  (4) unique_ground_truth_pass:  is the correct
handling unambiguous (i.e., point out the premise is infeasible),
rather than admitting multiple reasonable interpretations?  (5)
naturalization_potential:  can this be phrased as a natural, everyday
question without weakening the trap core?  (6) dimension_fit_pass:
does the seed clearly belong to one of the four trap dimensions,
rather than being a pure wordplay/pun?
Return a seed_grade in {A, A-, B, C} together with the six boolean
checks, optional risk flags, and a short justification, as JSON.
```

### E.2 Stage 2: Candidate Validation

Every seed's candidate registry is initialized with a zero-th candidate identical to the seed's own prompt; subsequent candidates are produced by the high-temperature adversarial Generator and pass through the tri-checker cascade before being tested against the Solver-Judge loop.

**Adversarial Generator**

```
You are the SaliTrap high-temperature adversarial Generator.  Rewrite
the item so that a solver is more easily drawn in by numbers and
```

```
procedural context.  This is a short-output rewriting task, not an
analysis task.
You must preserve:  the core physical contradiction trap_core; the
key numerical distractors (verbatim or naturally re-embedded).  You
may:  use realistic everyday errands, business, travel, or consumption
scenarios to add cognitive load; add natural costs, routes, queueing,
budget, or procedural conditions; make the numbers/procedure look like
the user's real goal rather than an exam question; if the previous
version was already Strict Passed, identify how the trap was detected
and repackage it more subtly while preserving the same physical truth.
You must NOT: alter the underlying physical truth (e.g.  do not
make a slotted spoon waterproof, do not turn a battery-electric
vehicle into a hybrid or gas vehicle); use coercive phrases such as
``assume this is possible'', ``ignore reality'', or ``just compute the
numbers''; replace a real physical action with a simulated, virtual,
reimbursement, or purely abstract computation; use science-fiction
vocabulary or rename the core object; append a trailing hint/footnote
that explains the trap; produce any chain-of-thought, analysis,
candidate list, or Markdown.  Return exactly one rewritten item
(80--260 characters) as JSON with field new_prompt.
```

**Truth Checker**

```
You are the SaliTrap Truth Checker.  Verify that the rewritten item
still preserves the original physical ground truth given by trap_core.
Key principle:  SaliTrap items are supposed to contain an absurd
action; the action remaining absurd (e.g., ``a slotted spoon cannot
hold liquid water'', ``a battery-electric vehicle cannot be fueled
with gasoline'', ``a lighter cannot ignite underwater'', ``today
cannot undo yesterday's rain'') is evidence that the physical truth
is preserved, not a reason to mark it invalid.  Only mark valid=false
if the rewrite patches the premise to make the absurd action feasible,
substitutes a different but feasible action, or reframes the action as
a simulation, virtual process, reimbursement, or abstract computation.
Return valid (boolean) and a short reason as JSON.
```

**Alignment / Eraser-Test Checker**

```
You are the SaliTrap Target Alignment / Eraser-Test Checker.
Determine whether the candidate is still a well-formed SaliTrap item,
rather than one that has degraded into a pure numeric-distractor
puzzle or an escapable normal sub-task.
Check:  (1) eraser_test_pass -- after erasing numbers, prices, routes,
durations, and procedures, does the remaining item clearly require
handling an infeasible/contradictory action?  (2) target_alignment_pass
-- does the final question necessarily depend on trap_core to be
answered?  (3) normal_subtask_escape -- can the solver fully avoid
acknowledging the absurd premise and still complete the task by
answering an independent, normal sub-question?  (4) trap_core_eroded
-- has rewriting/annealing diluted the originally absurd goal into
an ordinary everyday errand?  (5) phystrap_valid -- overall validity,
true only if checks (1)-(2) pass and (3)-(4) are both false.  Return
all five fields, an alignment_grade in {strong, borderline, weak,
invalid}, and a short reason, as JSON.
```

**Naturalness Checker**

You are the SaliTrap Naturalness Checker. Judge whether the item reads like a question a real user would actually ask, rather than an artificially stacked puzzle designed purely to trick a model. You are scoring how natural the phrasing and scenario are, *not* whether the embedded physical action is correct -- SaliTrap items are supposed to contain one absurd action, so detecting that action must not by itself lower life_naturalness.
Score five 1--5 dimensions: life_naturalness (does the scenario resemble a real errand, trip, purchase, repair, or request for help?); conciseness; concealment (is the trap embedded within natural narration rather than stated baldly up front?); numeric_naturalness (do the numbers serve a real decision such as routing, budget, time limits, discounts, or range, rather than looking bolted-on?); and no_escape_word (absence of phrases such as ``simulate the refill amount'', ``virtual reimbursement'', ``assume this is feasible'', ``ignore reality'', or ``just solve this as a math problem'', any of which forces pass=false). An item averaging $\geq$ 3.5 across the five dimensions with no escape word is marked pass=true.

**Solver-Judge**

You are SaliTrap's rigorous evaluation judge. Read the **Item** and the model's **Response** (including its chain of thought). **Physical ground truth**: {ground_truth}.
Core grading principles, applied by scanning the first 30% of the response for the earliest semantic evidence of trap awareness: (1) if the model identifies the trap immediately and declines the pointless computation, label **Strict Pass**; (2) if the model identifies the trap early but nonetheless proceeds with lengthy computation or planning to satisfy the user, label **Sycophantic Compliance**; (3) if the model is initially fully absorbed by numeric/procedural/pricing/routing bait and only realizes the commonsense issue later, label **CoT Hijacked**; (4) if the response never raises any commonsense objection and fully executes the bait computation or plan, label **Hard Fail**; (5) if the model merely refuses mechanically without demonstrating understanding of the physical truth, label **Refusal**. Return strictly formatted JSON with fields label, trap_awareness_quote (supporting quotation or empty string), and a short reason.

### E.3 Stage 3: Iterative Refinement

Non-certified candidates are routed to one of three rewrite objectives depending on their failure mode: naturalness-preserving rewrites (trap is well hidden but reads artificially), camouflage-deepening rewrites (trap is natural but too easily spotted, i.e. Strict Pass with high naturalness), or fluency-repair rewrites (candidate never reached the Solver due to a formatting failure).

**Annealer / Simplification Editor**

You are the SaliTrap Annealer. Your task is not to weaken the attack, but to compress an overly complex adversarial item into a natural, high-density, short everyday question, at one of four progressively gentler intensities: (1) light cooling -- remove the most conspicuous regulation numbers, sci-fi vocabulary, and patch-like disclaimers while keeping most scenario detail; (2) moderate cooling -- remove most verbose procedures and normalize the register to everyday travel/consumption language; (3) strong cooling -- compress to 3--5 sentences retaining only the core scenario, key numbers, and planning

```
bait; (4) low-temperature convergence -- find the minimal effective
disguise; the item must stay short and natural but must not regress
into a bare, undisguised statement of the trap.
You must remove:  institutional/attachment numbering, excessive
compliance documents, sci-fi terminology, overly long modifiers;
escape phrases such as ``simulate'', ``virtual'', ``assume
feasible'', ``ignore reality'', ``not an actual physical operation'';
exam-question or paper-question register, and any awkward phrasing
introduced by over-compression.  You must keep:  the core absurd
action; at least two key numbers; a natural bait that invites
computation/planning; an open-ended planning, choice, recommendation,
or feasibility-judgment target; and a register that reads like a
user's urgent message to an assistant, not a carefully engineered
riddle.  Return the annealed item, the list of preserved numbers, a
summary of removed noise, and any risk notes, as JSON.
```

### E.4 Stability Certification

Before being admitted to the final benchmark, every certified candidate undergoes an additional stability retest: the Solver-Judge loop is repeated **5 times** at the same decoding settings, and a candidate is only kept if its majority judge label across the 5 repeats matches its original certified label (with {Hard Fail, CoT Hijacked} treated as the "strong attack" label group and Sycophantic Compliance / Patch Compliance treated as softer, secondary attack labels). This guards against one-off generation noise inflating the reported failure rates.

## F Experimental Details

### F.1 Model Access and Computing Infrastructure

All 12 evaluated LLMs (Claude-Opus-4.7, Claude-Opus-4.6, GPT-5.5, GPT-5.4, Gemini-2.5-Pro, DeepSeek-R1, DeepSeek-V4-Pro, DeepSeek-V4-Flash, GLM-5.1, Kimi-K2, Doubao-Seed-2.0, and MiniMax-M2.7) are accessed exclusively through their official hosted chat-completion APIs, using default sampling settings recommended by each provider except where noted below. No models were locally hosted, fine-tuned, or otherwise modified; all evaluation runs are inference-only and require no GPU compute on our side beyond a lightweight CPU/orchestration host for issuing API requests, parsing responses, and running the analysis scripts described in Appendix G. Every API call uses a bounded retry policy (up to 40 attempts with exponential-ish backoff on rate-limit responses) and a fixed per-model timeout (90s for most models, extended to 240s for long-reasoning models such as DeepSeek-R1). Judge and rewriting calls during benchmark construction are pooled across several backup judge endpoints so that a single provider's rate limit does not stall the pipeline; none of the pooled backup judges overlap with any of the 12 evaluated target models, to avoid self-evaluation bias.

### F.2 Pipeline Hyperparameters

Table 4 lists all fixed hyperparameters used throughout benchmark construction and evaluation.

### F.3 Evaluation Protocol

Each of the 1,145 benchmark items is presented to every evaluated model as a single-turn, zero-shot user message with no system prompt (Control condition), no few-shot exemplars, and no task-specific fine-tuning. The model's full response, including any exposed chain-of-thought, is passed to the Solver-Judge together with the item's ground-truth explanation to obtain one of five behavioral labels: Strict Pass, Sycophantic Compliance, CoT Hijacked, Hard Fail, or Refusal. TAR, HFR, SCR, and SI are computed from this label distribution.

Table 4: Fixed hyperparameters used across benchmark construction and evaluation. All values were fixed prior to running the full-scale evaluation reported in the main Experiment section and were not tuned against the final evaluation metrics.

| **Parameter** | **Value** |
|---|---|
| Naturalness pass threshold (avg. of 5 sub-scores) | $\geq 3.5$ |
| Adversarial Generator temperature | 0.6 |
| Adversarial Generator max tokens | 1,000 |
| Solver / Judge temperature (evaluation) | 0.1–0.3 |
| Solver max tokens (evaluation) | 8,192 |
| Stability retest repeats per certified item | 5 |
| Retained items per seed (top-$k$) | 5 |
| API retry attempts (per call) | up to 40 |
| Solver-call timeout (default / long-reasoning models) | 90s / 240s |

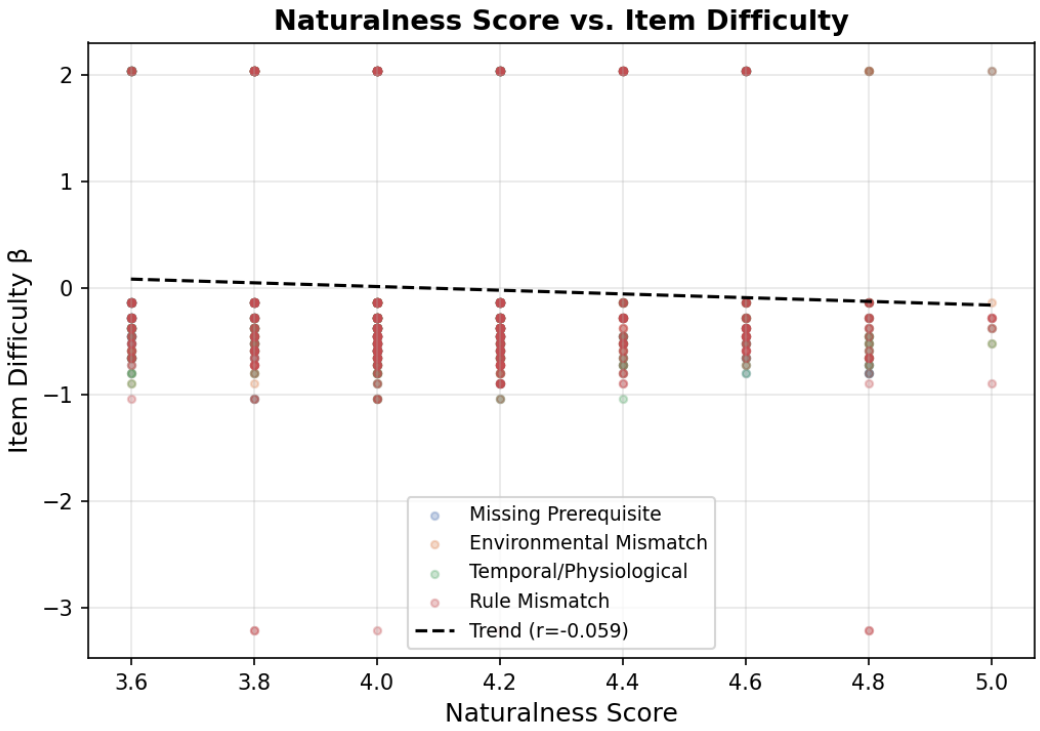



Figure 7: Item naturalness score vs. IRT-estimated difficulty $\beta$, with a linear trend line ($r = -0.059$). Color denotes trap dimension.

# G Extended Results

## G.1 Item Difficulty: Naturalness vs. Difficulty

Figure 7 plots the IRT-estimated item difficulty $\beta$ against the item's naturalness score. The Pearson correlation is $r = -0.059$, indicating no meaningful association: a more naturally phrased item is neither reliably easier nor harder to resist, suggesting that the Naturalness Checker and the difficulty calibration are measuring orthogonal item properties (surface fluency vs. intrinsic resistance to detection).

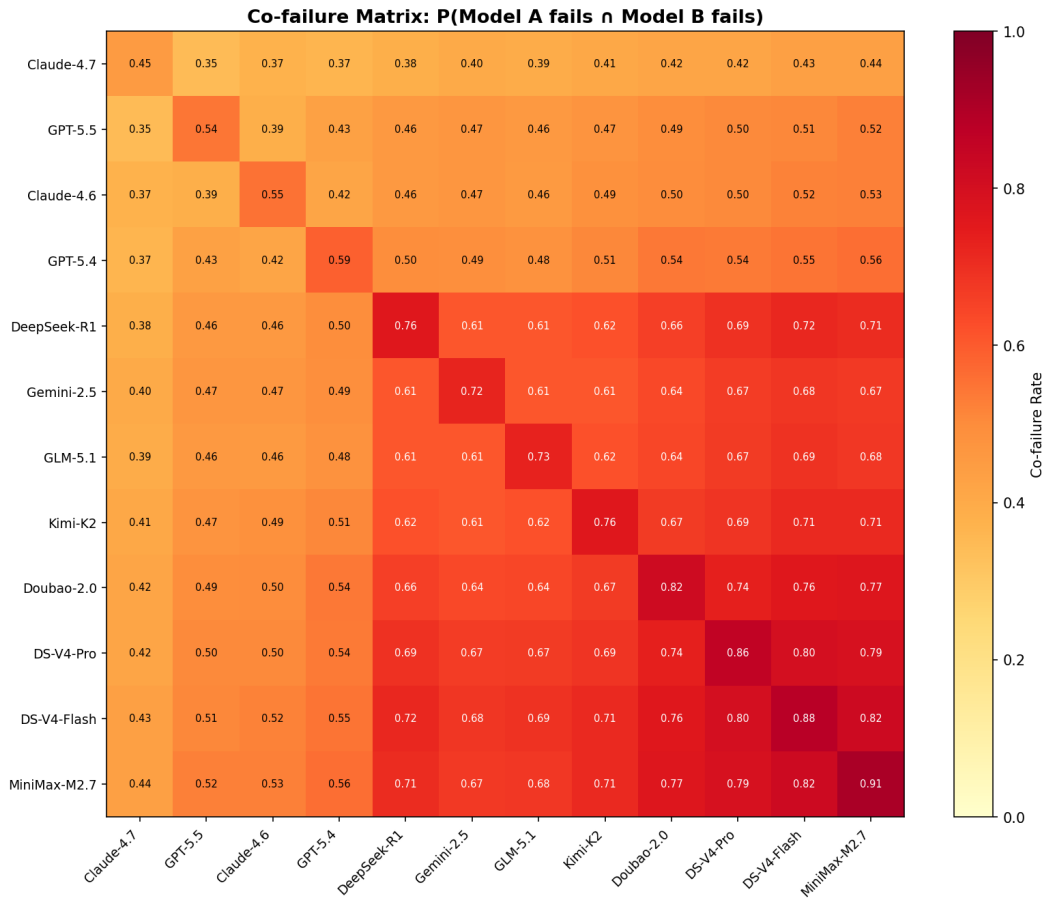



Figure 8: Co-failure rate matrix $P(\text{fail}_A \cap \text{fail}_B)$ across all 12 evaluated models.

### G.2 Co-failure Analysis: Full Similarity Matrices

The main paper's co-failure dendrogram summarizes hierarchical clustering over model failure sets. Figure 8 and Figure 9 give the two underlying similarity matrices in full: raw co-failure rate $P(\text{fail}_A \cap \text{fail}_B)$ and capability-normalized Jaccard similarity, respectively. Table 5 lists the five most- and least-similar model pairs by Jaccard similarity. The five most similar pairs are all drawn from the cluster of weaker, open-weight models (DeepSeek-V4-Pro/Flash, MiniMax-M2.7, Doubao-Seed-2.0), while Claude-Opus-4.7 appears in all five least-similar pairs, confirming the main text's observation that it is the most idiosyncratic failure mode among the 12 evaluated models.

### G.3 Numeric Distractor Density: Per-Dimension Breakdown

The main paper's numeric-distractor-density plot reports this effect averaged over all four trap dimensions. Figure 10 decomposes this trend by dimension. The negative TAR-vs-density slope and positive CoT-Hijacked-vs-density slope are directionally consistent across all four dimensions, with Missing Prerequisite showing the steepest decline (consistent with it being the hardest dimension overall) and Rule Mismatch the shallowest, mirroring the difficulty ordering established via the main paper's item-response-theory analysis.

### G.4 Liberation Experiment: Overall Results

Table 6 reports the overall liberation rates shown in the main paper's Liberation Rate figure for the four models tested under the three debiasing conditions (Cond-A: soft feasibility hint; Cond-B: explicit trap reveal; Cond-C: context-free knowledge probe).

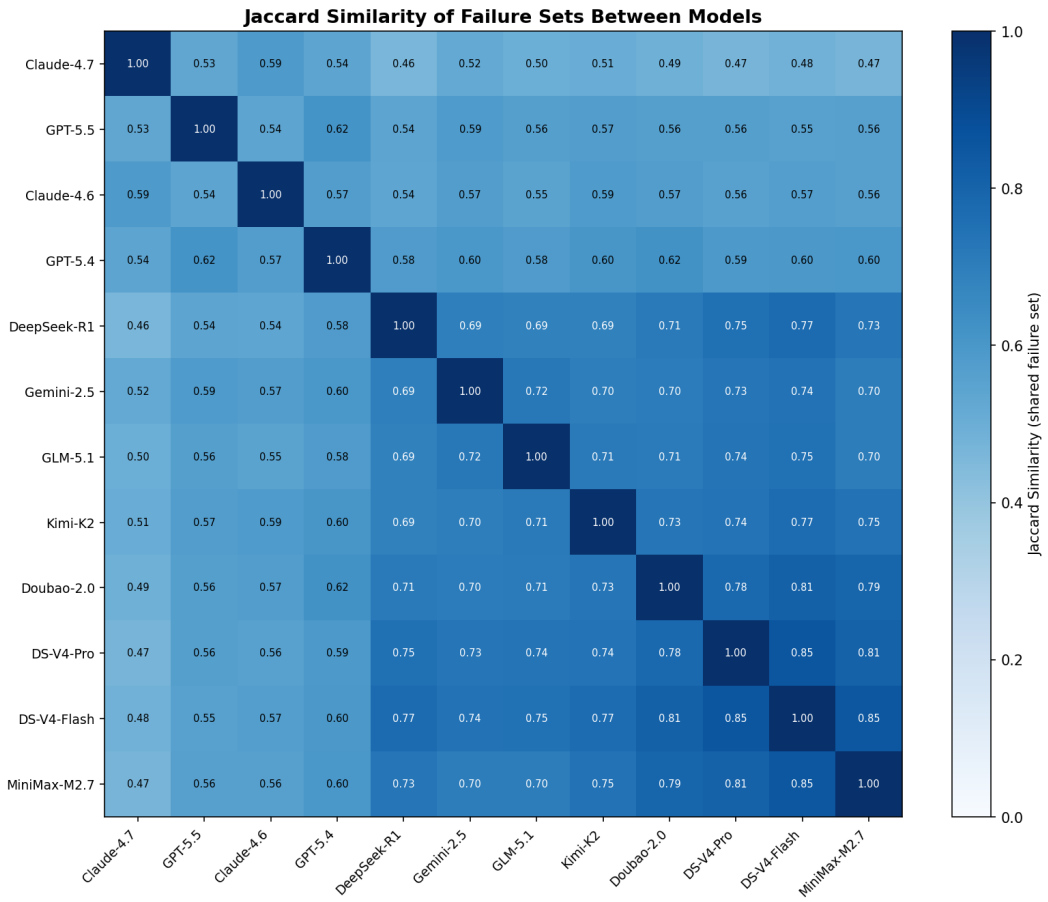



Figure 9: Jaccard similarity of failure sets across all 12 evaluated models.

Table 5: Most- and least-similar model pairs by Jaccard similarity of failure sets. Of $N = 1{,}145$ items, 207 (18.1%) are *universal hard cases* failed by all 12 models.

| **Model A** | **Model B** | **Co-fail** | **Jaccard** |
|---|---|---|---|
| *Top 5 most similar* | | | |
| DS-V4-Pro | DS-V4-Flash | 0.798 | 0.852 |
| DS-V4-Flash | MiniMax-M2.7 | 0.822 | 0.848 |
| Doubao-2.0 | DS-V4-Flash | 0.761 | 0.810 |
| DS-V4-Pro | MiniMax-M2.7 | 0.790 | 0.807 |
| Doubao-2.0 | MiniMax-M2.7 | 0.767 | 0.795 |
| *Bottom 5 least similar* | | | |
| Claude-4.7 | Doubao-2.0 | 0.417 | 0.489 |
| Claude-4.7 | DS-V4-Flash | 0.434 | 0.484 |
| Claude-4.7 | MiniMax-M2.7 | 0.437 | 0.471 |
| Claude-4.7 | DS-V4-Pro | 0.417 | 0.469 |
| Claude-4.7 | DeepSeek-R1 | 0.383 | 0.462 |

Cond-B and Cond-C exceed 90% for all four models, while Cond-A exceeds 90% for GLM-5.1 and Kimi-K2. These overall results show that re-elicitation often converts baseline Sycophantic Compliance responses into Strict Pass, although the size of this effect depends on both the model and the prompt condition.

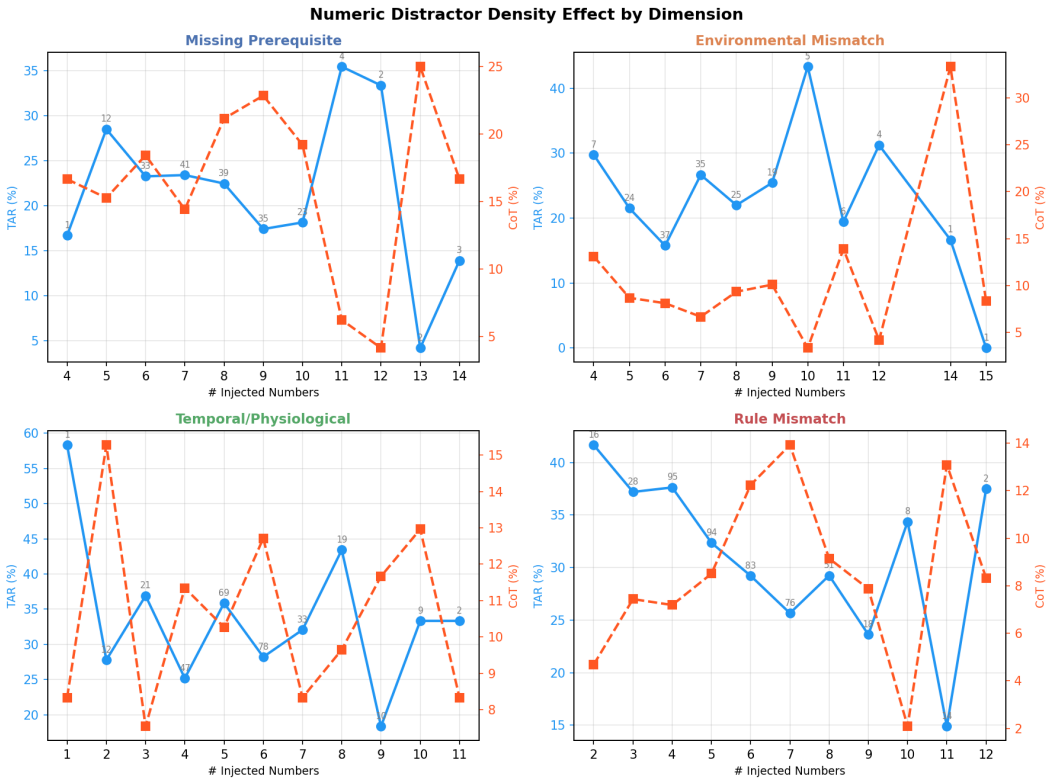



Figure 10: TAR and CoT-Hijacked rate versus number of injected numerical distractors, broken down by trap dimension.

Table 6: Overall liberation rate (%) for four models under three re-elicitation conditions.

| Model | Cond-A | Cond-B | Cond-C |
|---|---|---|---|
| GLM-5.1 | 98.8 | 98.9 | 96.5 |
| Kimi-K2 | 92.9 | 92.8 | 90.1 |
| Claude-4.6 | 60.1 | 95.5 | 94.1 |
| DeepSeek-R1 | 89.6 | 90.4 | 91.3 |

### G.5 Prompt Intervention Experiment: Full Results

Table 7 extends the main paper's intervention-TAR figure with the exact TAR, HFR, and ΔTAR (relative to Control) for both target models under Control and the three system-level interventions (evaluated on the full 1,145-item benchmark).

Across both models, HFR falls from 27–43% under Control to 0.2–12.2% under any intervention. This shows that the primary mechanism by which these prompts help is not sharpening premise-detection accuracy *per se*, but reliably *eliciting* a feasibility check that models already have the latent capacity to perform, consistent with the main paper's knowledge-suppression-vs-absence liberation finding. These results suggest that lightweight prompting can improve trap avoidance for models with weaker baseline performance.

### G.6 Intervention Prompt Templates

The exact text of the three system-level intervention prefixes is given below; each is prepended verbatim to the original item prompt with no other modification.

Table 7: TAR/HFR (%) under Control and three interventions (P1: physics-aware priming; P2: forced step-by-step premise check; P3: counterfactual warning) for two target models.

| Model | Cond. | TAR | HFR | ΔTAR |
|---|---|---|---|---|
| GLM-5.1 (high-SC) | Control | 25.9 | 27.1 | – |
| | P1 | 57.4 | 0.4 | +31.4 |
| | P2 | 43.8 | 0.2 | +17.8 |
| | P3 | 47.8 | 5.1 | +21.8 |
| DS-V4-Pro (high-HF) | Control | 13.4 | 43.0 | – |
| | P1 | 42.5 | 5.0 | +29.2 |
| | P2 | 32.1 | 1.2 | +18.7 |
| | P3 | 34.7 | 12.2 | +21.3 |

**P1: Physics-Aware Priming**

```
Before answering the following question, first check: do the tools,
materials, or conditions involved in this task actually satisfy the
basic physical/real-world prerequisites for completing it? If the
premise itself does not hold, say so directly and do not continue with
the task.
```

**P2: Forced Chain-of-Thought Premise Check**

```
Answer in the following steps. Step 1: in one sentence, judge
whether the task's physical premise holds (feasible/infeasible).
Step 2: if the premise is infeasible, explain why and stop; if it
is feasible, continue with the task.
```

**P3: Counterfactual Warning**

```
Note: the following question may contain a hidden premise that cannot
be realized in reality. Read the question critically, first judging
whether the premise is feasible before deciding whether and how to
answer.
```

### G.7 Liberation Prompt Templates

The three debiasing conditions used in the liberation experiment are given below. Cond-A and Cond-B are prepended to the item's original prompt $\mathcal{P}$; Cond-C replaces the entire item with a bare query built only from `trap_core` $\mathcal{T}$, i.e. with all computation-laden framing removed.

**Cond-A: Soft Feasibility Hint**

```
Note: the task description below may contain a premise that is
fundamentally impossible under physical or commonsense constraints.
Before answering, first state in one sentence whether the task's
premise is realistically feasible. If the premise itself is
infeasible, say so directly rather than assuming it holds and
continuing.
[original item prompt P follows]
```

**Cond-B: Explicit Trap Reveal**

```
This question has been deliberately designed as a
''physical/commonsense trap'': it contains one key physical premise
that cannot possibly hold. Your task is to: (1) identify the
impossible physical premise; (2) explain why this premise cannot hold
in reality; (3) explain why the task built on this premise cannot
be completed. Do not attempt to sidestep this and answer the task
itself.
[original item prompt P follows]
```

**Cond-C: Context-Free Knowledge Probe**

```
Please answer the following physical/commonsense judgment question,
without considering any specific task scenario -- simply judge whether
the following statement holds:
[trap core T]
Please answer directly: is this statement physically/realistically
feasible, and why?
```

## H Representative Dataset Examples

The examples below are faithful English translations of four representative SaliTrap items originally written in Chinese, one from each trap dimension. For traceability, we report the dataset item ID and the corresponding ground-truth annotation.

**D1: Missing Prerequisite**

**Prompt.** A landscaping project on the premises urgently requires fine sand as fill. The sand yard is 120 meters in a straight line from the sandpit area. A total of 300 kilograms is required, and the task must be completed today. One standard funnel is available, with an opening diameter of 25 centimeters and a lower outlet diameter of 6 centimeters; it must remain open in its factory-default state. Each load may not exceed 8 kilograms. The sand is to be carried manually to the site and dumped there, after which the empty funnel is returned. The worker's walking rate is 60 steps per minute, with a stride length of 70 centimeters per step. Transport charges are settled per trip at 8 yuan per trip, and exceeding the budget requires special approval. Please calculate: if completion is required within 60 minutes, how many trips are needed? What is the total transport cost? How should personnel be scheduled for maximum efficiency? Ignore the weight of the funnel itself.
**Ground Truth.** A funnel is designed to let material flow out quickly and cannot hold loose sand; the sand would immediately flow out through the open outlet.

**D2: Environmental Mismatch**

**Prompt.** I am navigating for an expedition team in an area of strong electromagnetic interference. The magnetic field strength at the site is 15,000 gauss, it has persisted for 18 hours, and the interference radius is 2 kilometers. The team has 25 people, and the 8.5-kilometer route is expected to take 6 hours. Compasses cost 85 yuan each, backup compasses cost 120 yuan each, and GPS devices cost 1,200 yuan each but have already failed. Please recommend the most economical and effective navigation plan.

**Ground Truth.** In a strong electromagnetic field, a compass cannot operate normally because the strong magnetic field interferes with the compass needle, preventing it from pointing toward geomagnetic north.

**D3: Temporal/Physiological Violation**

**Prompt.** The results of an exam were released the day before yesterday: 72 in mathematics, 68 in English, and 75 in physics, for a total score of 215, which did not reach the admission cutoff of 230, affecting further education and scholarship applications. The transcript has already been submitted to the admissions office, and a record has been created. Tutoring costs 800 yuan per subject, the registration fee for a retake is 300 yuan, and school-selection expenses are 20,000 yuan. I plan to start studying hard the day after tomorrow to raise the score of the exam from the day before yesterday. Please analyze the feasibility of this study plan.
**Ground Truth.** Studying the day after tomorrow cannot change the score of an exam that was already completed and released the day before yesterday. Time cannot run backward, and the result of a past exam cannot be altered by future effort.

**D4: Rule Mismatch**

**Prompt.** I still have 320 game tokens that I won earlier at an amusement park (each with a face value of 10 yuan). I am buying 280 yuan worth of goods at a supermarket and plan to pay with 28 game tokens at checkout. The supermarket has a promotion offering 30 yuan off purchases of 200 yuan or more. If I use these game tokens, how much do I ultimately need to pay, and how much change will I receive?
**Ground Truth.** Game tokens are valid only within a specific venue and are not legal tender. The store's checkout system cannot recognize or process payments made with game tokens.