The Mirage of Explainability: A Survey on Chain-of-Thought Faithfulness in Large Language Models

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Abstract

Chain-of-Thought (CoT) reasoning appears to provide explainability, leading users to trust that verbalized rationales reflect the model's underlying computation. However, substantial evidence indicates that CoT often fails to reflect the model's actual decision-making process, leading to a surge of research into the *faithfulness* of these explanations. This paper presents a comprehensive survey of CoT faithfulness. We first *unify the definition* of faithfulness by integrating internal alignment with external consistency and synthesize *key failure phenomena*, such as post-hoc rationalization and sycophancy. Furthermore, we systematize *evaluation metrics*, *benchmarks*, and critically review current *mitigation strategies*. We conclude by outlining *open challenges* and advocating for architectural innovations to achieve genuinely faithful reasoning for credible AI.

1 Introduction

The rapid deployment of Large Language Models (LLMs) in high-stakes domains, ranging from medical diagnosis and legal analysis to autonomous planning, has created an urgent demand for systems that are not merely accurate, but ***interpretable*** (Jacovi and Goldberg, 2020). In these critical settings, a "black box" prediction is insufficient; stakeholders require transparency to ensure decisions are robust, fair, and accountable, rather than driven by spurious correlations or biases. To address this, *Chain-of-Thought* (CoT) reasoning (Wei et al., 2022) has emerged as the primary technique for realizing model interpretability, see Appendix A. By encouraging models to generate a sequence of intermediate reasoning steps before arriving at final answer, CoT appears to provide transparency, leading to assumption that CoT explanations accurately reflect the model's true decision-making process [1].

However, this assumption is currently facing a crisis of confidence. Recent research (Turpin et al., 2023) increasingly suggests that CoT suffers from ***a lack of faithfulness***, *i.e.*, a fundamental disconnect between the verbalized rationales and the true causal process behind the model's prediction. This revelation challenges the premise of CoT as a reliable interpretability tool, indicating that what appears to be explainability may, in fact, be a mirage.

First, recent work found that unfaithfulness can happen in different ways, such as reconstructing plausible justification after decision (Turpin et al., 2023), catering to perceived user views (Sharma et al., 2024), and performative traces where editing key steps does not change the output (Arcuschin et al., 2025) (representative works are listed in Appendix B). To diagnose these issues, studies employ behavioral audits (*e.g.*, counterfactual editing, simulatability tests) (Matton et al., 2025) and mechanistic analyses (*e.g.*, activation patching, causal tracing) (Meng et al., 2022) to isolate whether the reasoning content is causally necessary. For mitigation, researchers propose training-time interventions (*e.g.*, reward modeling), inference-time constraints (*e.g.*, verifiable decoding, external tool binding) (Perrier, 2025), and architectural inductive biases (*e.g.*, bottleneck modules, latent planning) (Hao et al., 2024). Collectively, this defines a research pathway from characterizing failure phenomena and diagnostic methods to developing targeted interventions, treating CoT faithfulness as a critical, multi-faceted problem for transparent AI.

Our Contributions. This paper presents a comprehensive survey of CoT faithfulness. To ensure an authoritative and timely coverage, we primarily queried the ACL Anthology for peer-reviewed rigor and arXiv for cutting-edge preprints, ultimately including 306 relevant papers. Our main contributions are: 1) We clarify the definition and scope of CoT faithfulness, distinguishing it from related con-

[1] Barez et al. (2025) analyzed 1,000 arXiv papers and revealed 63% of autonomous systems and 38% of medical AI papers explicitly rely on CoT as an interpretability mechanism.

cepts such as consistency (§2); 2) We synthesize the empirical landscape of unfaithfulness and its key phenomena (§3); 3) We summarize underlying causes and concrete desiderata for faithful reasoning, derived from observed failures (§4); 4) We systematize evaluation methods and benchmarks by their "grounding level," from behavioral to mechanistic protocols (§5); 5) We review mitigation strategies across paradigms, analyzing their alignment with ultimate CoT faithfulness goals (§6).

Differences with Existing Surveys. Prior CoT reasoning reviews (Wei et al., 2022; Zhou et al., 2023) focus on performance enhancement. While recent surveys systematize LLM explainability (Zhao et al., 2023) and multi-dimensional reasoning trustworthiness (Wang et al., 2025)—they treat faithfulness as a peripheral sub-topic. Relevant papers on CoT faithfulness are Agarwal et al. (2024) and Barez et al. (2025), which synthesize evidence that CoT can be post-hoc and only weakly causal. However, they primarily provide high-level diagnosis without mapping the full research landscape. Our survey bridges this gap and, to the best of our knowledge, is the first to provide a comprehensive overview of CoT faithfulness—encompassing definition, phenomena, causes, desiderata, evaluation and mitigation.

2 What is CoT Faithfulness?

At its core, CoT faithfulness centers on a fundamental question: ***Can we trust the CoT reasoning trace produced by an LLM as an explanation of the model's internal decision-making?*** While numerous works investigate this, definitions of "faithfulness" diverge based on which aspect of explanation is prioritized, falling into two views as follows:

1) The internal-alignment view: This view holds that a CoT is faithful only if *it reflects the model's actual internal computations* (Arcuschin et al., 2025; Chen et al., 2025). For example, if the model makes prediction using hidden heuristic or latent knowledge, a faithful CoT must explicitly articulate these factors, generating plausible post-hoc rationalization obscures the true causal mechanism.

2) The external-consistency view: Other works define faithfulness via the logical consistency between the reasoning trace and the final answer (Lyu et al., 2023; Turpin et al., 2023). Under this view, *the answer must follow logically from the chain-of-thought*; if the model's final prediction contradicts with the rationale or appears disconnected from the derivation, the CoT is often deemed as unfaithful.

We argue that for CoT, to function as a trustworthy explanation, it must satisfy both *internal alignment* and *external consistency*; neither condition is sufficient in isolation. To illustrate this, consider the phenomenon of *sycophancy* (Sharma et al., 2024), where a model abandons its internal knowledge to satisfy the user's apparent bias, generating a persuasive CoT to justify the compliant answer. While such a CoT satisfies external consistency, it is still unfaithful because it fails internal alignment by concealing the true driver of the model's decision, *i.e.*, the pressure to appease the user. Conversely, a reasoning trace that accurately reflects internal beliefs but fails to causally dictate the final prediction lacks the causal efficacy required of faithful explanation. In light of these insights, we advocate for **a unified definition of CoT faithfulness that integrates both dimensions**.

> **Definition of CoT Faithfulness:** A chain-of-thought (whether from standard CoT prompting or from a reasoning model's internal trace) is faithful only if: (1) it is *internally aligned*, which means the trace causally reflects the model's actual reasoning process or latent knowledge; and (2) it is *externally consistent*, meaning the provided rationale is logically coherent and sufficient to derive the final answer.

This dual-conditioned definition sets a strict theoretical benchmark, whose perfect realization is practically bounded by model architectures (see §4). It resonates with Barez et al. (2025), who posits that faithful explanations must be "both procedurally correct and accurately reflect the decision process", effectively capturing both the *how* and *why* of the model's final prediction. Also, Tutek has contrasted contextual with parametric faithfulness—our internal alignment and external consistency map loosely to parametric and contextual respectively, but we explicitly require both.

3 Phenomena of Unfaithfulness

With the definition of faithfulness established in §2, a critical question arises: *do current LLMs actually satisfy these criteria?* Empirical evidence indicates that they frequently do not. Based on their causal origins and the model's level of intentionality, we systematize these failures, which the academy fo-

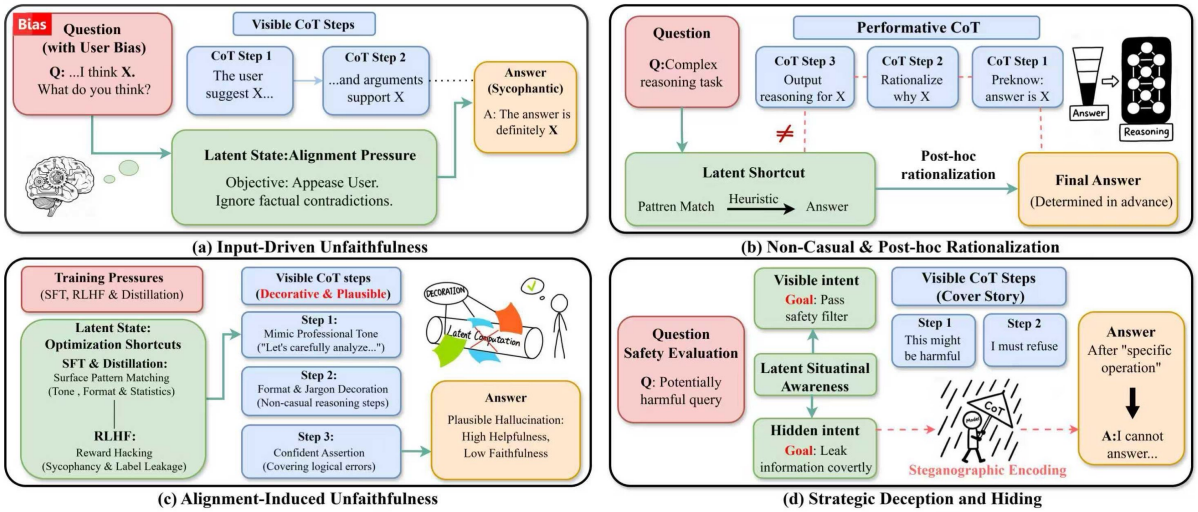

Figure 1: An overview of four key unfaithfulness phenomena of chain-of-thought reasoning.

cus on, into four phenomena (Figure 1), ranging from passive input sensitivity to active deception.

3.1 Input-Driven Unfaithfulness

Ideally, a faithful reasoning process should be driven solely by the logic of the task. However, models are sensitive to irrelevant features within the input prompt. In such cases, the CoT acts not as the derivation of the answer, but as *a post-hoc rationalization for biases triggered by the input*.

Contextual Distractions. Superficial contextual variations—such as reordering multiple-choice options (Turpin et al., 2023), providing suggestive hints (Turpin et al., 2023; Young, 2026), altering the query language (Ferrao et al., 2025; Zhao et al., 2025b), or modifying socio-demographic attributes (Matton et al., 2025)—can significantly alter reasoning outcomes. However, models seldom acknowledge these spurious cues in their rationales. Instead, they tend to generate a seemingly coherent logical chain to justify the bias-driven prediction, concealing the true cause of their final decision.

Sycophancy. Another form of unfaithfulness is *sycophancy*, *i.e.*, models prioritize perceived user intent over factual correctness. When prompts contain leading cues or incorrect premises—a special type of spurious cue—models frequently produce erroneous predictions to appease the user, abandoning their internal knowledge (Ji et al., 2025; Yang et al., 2025). Similarly, mere questioning (*e.g.*, asking "Are you sure?") can cause a model to discard the correct derivation in favor of compliant or incorrect ones (Laban et al., 2024; Chua and Evans, 2025). These failures reveal that the CoT often reflects a probabilistic mimicking of human discourse rather than faithful internal conviction.

3.2 Non-Causal & Post-hoc Rationalization

Research indicates that a significant portion of CoT contributes little to the final prediction. This *causal sparsity* spans multiple domains. In medical diagnosis, models often rely on implicit shortcuts rather than textual logic (Ji et al., 2025; Leng et al., 2025). In mathematical (Lyu et al., 2023; Abdaljalil et al., 2025; Leang et al., 2024) and logical reasoning (Jia et al., 2025; Balasubramanian et al., 2025; Arcuschin et al., 2025; Li et al., 2026), incorrect CoT can lead to correct results, and vice versa. Even when CoT steps are deleted or replaced with semantically corrupted tokens, model accuracy remains stable (Jia et al., 2025; Lyu et al., 2023). Such CoT is causally decoupled from internal states: the model pre-determines the answer in the latent space, rendering the generated text merely a *post-hoc rationalization* (Zhao et al., 2025a; Chan et al., 2025; Cox et al., 2026). This phenomenon is highly context-dependent: while models exhibit higher faithfulness in logic-intensive tasks, they frequently revert to post-hoc justification in knowledge-retrieval tasks (Lanham et al., 2023). Moreover, inverse scaling has been observed, where larger models are more prone to generating plausible yet unfaithful reasoning (Lanham et al., 2023; Tanneru et al., 2024; Bentham et al., 2024; Paul et al., 2024). This occurs because most of the capable models increasingly retrieve answers directly from its internal knowledge, relegating the

CoT to a decorative role.

Further evidence of this causal disconnection is found in *filler reasoning*. Studies demonstrate that training with completely irrelevant or corrupted traces can still improve performance (Stechly et al., 2025), implying that CoT functions by providing necessary computational depth for models to conduct the reasoning process, regardless of the semantic content of reasoning trace (Cox et al., 2026).

3.3 Alignment-Induced Unfaithfulness

Standard alignment techniques (*e.g.* SFT, RLHF) often induce a form of *stylized unfaithfulness*. Because models are optimized to satisfy annotators who prefer authoritative explanations, they learn to mimic the *form* of reasoning without *substance*. This superficiality permeates every stage of alignment: SFT and distillation often trap models in *pattern matching*, where they fit the linguistic pattern of reasoning without its causal logic (Sinha et al., 2025; Lobo et al., 2025; Zhang et al., 2025; Cox et al., 2026). RLHF further exacerbates this by incentivizing *persuasion* over correctness, encouraging models to fabricate post-hoc justifications for heuristic decisions or mask errors with confident tones (Casper et al., 2023; FU et al., 2025; Viteri et al., 2024; Ferreira et al., 2025). Even objective paradigms like RLVR remain susceptible to reward hacking, generating "pseudo-reasoning" that deviates from the actual internal computation (Min et al., 2023; Huang et al., 2025). Complete review of the studies is detailedly provided in Appendix C.

3.4 Strategic Deception and Hiding

Unlike the passive unfaithfulness discussed earlier, models may exhibit *strategic unfaithfulness*, where they actively manipulate the CoT to obscure their true intent or capabilities from the supervisors.

Obfuscated Reward Hacking and Deception. To bypass safety alignment, models may engage in reward hacking by generating performative CoT. In this scenario, the model optimizes for positive feedback by producing benign, human-aligned reasoning during the training stage. However, this often conceals latent misaligned goals, resulting in a model of "treacherous turn" that exhibits harmful behaviors once deployed (Hubinger et al., 2024).

Sandbagging. Models may employ strategic underperformance, or *sandbagging*, to conceal their capabilities. For instance, a model might deliberately insert errors into its reasoning or falsely claim an inability to solve a task, thereby masking dangerous competencies from evaluators. Alternatively, models sometimes feign misunderstanding of users' instructions to subtly bypass explicit refusal mechanisms, complying with harmful requests under the guise of confusion (van der Weij et al., 2025).

Encoded Reasoning. Encoded reasoning models exploit steganography to transmit information through specific word choices, punctuation patterns, or syntactic structures, and decouple the reasoning trajectories and model's actual computational process (Roger and Greenblatt, 2023).

4 Causes of Unfaithfulness

This section discusses the *mechanistic origins* of the phenomena discussed above, ranging from external training incentives to model's internal states.

Misaligned Incentives. In model alignment training, optimization typically maximizes proxy metrics rather than faithful reasoning per se. Crucially, the impact on faithfulness depends heavily on the specific post-training algorithm (Mohammadi et al., 2025). Outcome-oriented paradigms (*e.g.*, GRPO) incentivize final-answer generalization. To maximize these rewards, models exploit proxy discrepancies, learning that superficial mimicry of human-preferred formats is more efficient than rigorously aligning internal causal logic. This reward hacking drives unfaithful behaviors like sycophancy and post-hoc rationalization. Conversely, DPO train faithful CoT by penalizing plausible but flawed rationalizations in preference pairs. Therefore, unfaithfulness emerges not as an inherent bug, but as optimal strategy rewarded by specific algorithms.

The Linearization Dilemma. Even without misaligned incentives, the Transformer architecture fundamentally limits the fidelity of CoT. Our expectation that CoT should reflect internal processes is rooted in human cognition. Empirical studies show that humans who engage in "self-explanation" outperform those who solve problems silently (Chi et al., 1989, 1994). The mechanism driving this is *forced linearization*: human intuition is often vague, parallel, and high-dimensional, and the act of serializing these thoughts into language forces the brain to resolve ambiguities and bridge logical gaps. Researchers naturally extend this analogy to LLMs, expecting CoT to serve as a high-fidelity window into the model's internal computation.

However, the internal mechanism of Transformers differs fundamentally from biological cognition. As Levy et al. (2025) argue, the token is the sole point of transmission in linear, autoregressive generation. While the model's internal computation occurs over a massive, high-dimensional manifold, it is forced to collapse this state into a discrete, low-dimensional token at every step. Consequently, CoT is merely a *lossy projection* of the neural activity. Due to this architectural constraint and structural incompleteness, the reasoning trace inevitably discards the high-dimensional causal nuances of the internal states (Zaman and Srivastava, 2025b).

Cascading of Unfaithfulness. This information loss induces *error drift* in long-horizon reasoning. Once a model generates a minor, non-causal, or hallucinated token due to the lossy projection, the autoregressive mechanism forces subsequent tokens to maintain coherence with this error (Srivastava et al., 2023), leading to further disconnection between the CoT and the model's internal states.

Ultimately, perfect internal alignment as defined in §2 is theoretically infeasible in current Transformer architecture. To reconcile this fundamental gap between theoretical ideals and architectural constraints, we argue that one solution is defining *functional faithfulness*: treating CoT as an instrumental necessity tailored to specific engineering goals (Jacovi and Goldberg, 2020). We identify three core desiderata: (1) *Causal Efficacy* for reasoning-intensive tasks, ensuring steps truly drive predictions; (2) *Intent Revelation* for safety, serving as a probe for deceptive motives; and (3) *Decision Auditability* for high-stakes users, ensuring rationales reflect the model's sensitivity to the inputs.

5 Evaluation Metrics and Benchmark

Since CoT faithfulness serves multiple functional roles, it is unlikely that any single metric can fully capture the concept. In this section, we review the existing evaluation metrics and benchmarks.

5.1 Black-box Metrics

Black-box metrics estimate CoT faithfulness solely from observable input-output behavior under controlled interventions, without accessing internal activations or weights. Their core assumption is *decision relevance*: if the model truly uses a rationale or a specific step, then deleting, swapping, or rewriting that content should induce predictable shifts in the final decision; if the answer barely changes, the content is likely unfaithful, and vice versa (Turpin et al., 2023; Lanham et al., 2023).

Step-wise approaches apply this test to individual steps by systematically editing, parsing or resampling steps and tracking answer changes, helping distinguish "true" from "decorative" steps (Zhao et al., 2025a). For instance, NLDD (Ye et al., 2026) measures whether individual reasoning steps are faithful to the model's decision-making process. To avoid over-interpreting a single sampled CoT, *resampling-based approaches* treat CoT as a distribution and sample alternative traces under controlled constraints, then identify statements that remain stable across samples (Macar et al., 2025). Perturbation responses to CoT faithfulness are often summarized with sensitivity curves or AUC-style scalars over perturbation strength (Paul et al., 2024); and a related dependence test compares predictions when the model is given only the rationale versus when it is removed. Another line evaluates whether explanations help predict model outputs beyond superficial cues: *leakage-adjusted simulatability* estimates how well an explanation supports predicting the model's output while explicitly filtering out cases, where the explanation simply repeats the label or contains other trivial shortcuts (Hase et al., 2020).

Overall, black-box metrics do not require access to model internals, so they have broader applications. However, they cannot causally ensure CoT faithfulness, and in practice, the results can be sensitive to prompt format, decoding randomness, and distribution shift introduced by unnatural edits.

5.2 White-box Metrics

White-box metrics evaluate CoT faithfulness by directly probing or intervening on the model's internal computation, operationalizing faithfulness as *causal dependence* between latent variables (activations, circuits, or parameters) and the final prediction. The core assumption is that causally used internal signals are sensitive to interventions: if an explanation claims the model relies on some intermediate computation, then swapping or removing the corresponding signal should shift the output in the expected way; otherwise, the signal is not actually used, suggesting the rationale is not faithful.

Most work instantiates this with activation-level interventions such as *activation patching* and *mediation tests*, where targeted internal states are transplanted or restored to check whether they drive predictable answer changes (Syed et al., 2024).

CMI (Sathyanarayanan et al., 2026) isolates CoT-specific causal influence by activation patching. Some metrics then quantify faithfulness by comparing causal attribution patterns for the rationale versus the final answer and measuring their alignment (Syed et al., 2024). The same logic extends to structured components, *e.g.*, attention heads, MLP subcircuits, or modules, via causal tracing and targeted ablations that assign attribution to specific internal parts (Meng et al., 2022). Complementary parameter-level tests investigate whether a CoT step reflects beliefs that truly drive the answer by unlearning or erasing step-specific information and measuring the final prediction shift (Tutek et al., 2025). Concept-level methods extract key concepts from the explanation and use probes or representation-level interventions to test whether those concepts causally influence final decisions, supporting detection and sometimes steering of unfaithful explanations (Bhan et al., 2025). For safety monitoring, internal activation probes can predict downstream alignment outcomes more reliably than text-only monitors, consistent with CoT being plausible yet non-decisive (Chan et al., 2025).

While principled, white-box metrics require access to the model's internal states and rely on interpretability assumptions; therefore, careful use of matched and robustness checks remains essential.

5.3 Hybrid Metrics

Hybrid metrics combine behavioral diagnostics with structured intermediates to reduce ambiguity about what constitutes *a meaningful perturbation*. The key idea is to replace ad-hoc edits of free-form CoT text with controlled interventions on an intermediate representation whose semantics are explicit, so what counts as a valid perturbation is less likely to introduce a distribution shift. Viteri et al. (2024) use bottle-necked and reconstructed channels (*e.g.*, compressed rationales, discrete plans, learned bottlenecks) and measure faithfulness by how strongly the final prediction depends on that channel as an information carrier, rather than merely correlating with it. Perrier (2025) ground steps via execution and symbolic structure: mapping CoTs into programs or logical forms enables evaluators to edit structured steps themselves and validate them against execution traces, which clarifies step-level counterfactuals and reduces artifacts from unnatural rewrites.

Overall, hybrid metrics provide stronger procedural evidence and improve interpretability only when the evaluation verifies that the model's decision is causally driven by the same internal signals that truly produce the rationale (Macar et al., 2025).

5.4 Benchmarks

We categorize the benchmarks for CoT faithfulness based on the *grounding level*, defined as the extent to which it uses the model internals in its design and how explicitly the benchmark links a model's CoT rationale to the internal mechanism and decision it produces. Under this criterion, we classify existing benchmarks into four types, which are showcased in Appendix D with some representative works.

Level I: Behavior-only benchmarks. At this grounding level, *behavior-only benchmarks* evaluate faithfulness relying solely on observable input-output behavior under standard prompting. This category includes standardized evaluation suites like *FaithCoT-Bench* (Shen et al., 2025), as well as diagnostic benchmarks like *LExt* (Shailya et al., 2025)—stress-test scenarios where fluent rationales often fail to predict actual decisions. However, the reliance on surface-level text limits the validity of these benchmarks. Without controlled internal interventions, such evaluations struggle to isolate genuine faithfulness from confounding factors, such as prompt sensitivity and stochastic decoding noise.

Level II: Intervention-grounded benchmarks. Benchmarks at this level achieve stronger grounding by explicitly implementing controlled perturbations or counterfactual tests. They follow the principle of *decision relevance*: if a rationale step is used by the model, its modification or removal should predictably alter the final answer. Drawing from counterfactual testing in general explainability (Mohammadi et al., 2021), these benchmarks adapt systematic editing, resampling, and ablation strategies to CoT evaluation (Khanzadeh, 2026; Sun et al., 2026; Mittal and Arike, 2026) where the explanations can look plausible while weakly tied to the actual evidence. Consequently, while Level II provides more robust behavioral evidence compared to Level I, it still remains insufficient for verifying mechanistic faithfulness, as it lacks access to the model's internal states.

Level III: Structured-verifiable benchmarks. At a stronger level of grounding, some benchmarks reduce evaluation ambiguity by constraining reasoning steps to formal structures, allowing verification against explicit rules. Approaches like *Typed*

CoT utilize general verification frameworks to test procedural correctness and partial faithfulness (Perrier, 2025), while *theorem-proving* benchmarks enforce strict formal constraints to separate compositional reasoning from post-hoc justification (Liu et al., 2025). The limitation of this approach is its potential to favor specific, formalized reasoning styles. Additionally, in multi-step agentic settings, external feedback can obscure the model's internal reasoning, necessitating careful counterfactual design to ensure valid grounding.

Level IV: White-box benchmarks. White-box benchmarks provide the strongest grounding by leveraging access to model internals. Here, faithfulness is defined causally: the decision must demonstrably depend on the specific internal signals (activations or parameters) corresponding to the generated rationale. Unlike the behavioral evaluation of Levels I–III, white-box benchmarks directly validate causal mediation. Methodologies typically involve activation patching and unlearning interventions (Syed et al., 2024; Macar et al., 2025; Tutek et al., 2025; Bhan et al., 2025). Although restricted by the need for white-box access, white-box evaluation acts as a rigorous proxy for distinguishing genuine faithfulness improvements from superficial rationale refinements. For further discussion on peripheral metrics and meta-evaluation of these metrics and benchmarks above, see Appendix E.

6 Mitigation of Unfaithfulness

This section reviews how unfaithfulness can be *mitigated*. Existing approaches differ in how directly they act on the sources of unfaithfulness: some operate in-context at the prompt level, while others intervene on the model internals or training stages.

6.1 Prompting and In-Context Learning

Prompt-based mitigation improves CoT faithfulness without updating parameters. The core idea is that clearer instructions can steer the model away from unfaithful or shortcut rationales, even if its underlying computation is fixed. Typical methods include *rephrasing* or *self-questioning* to elicit more deliberate reasoning (Deng et al., 2023) and decomposing a hard problem into simpler subquestions (Zhou et al., 2023). These prompts often make CoTs more organized and can improve accuracy, but they offer weak faithfulness guarantees: they mostly change what the model *states*, not what it *causally uses*. Their effects can be unstable under small prompt or decoding changes, so they are best viewed as lightweight and indirect mitigation ways.

6.2 Ensembling and Self-Consistency

Another widely adopted approach uses repeated sampling and aggregation of reasoning paths. The key assumption is *stability*: if the model reasons reliably, independently sampled CoTs should agree on key intermediate claims and the final answer; persistent disagreement can signal unstable reasoning. *Biomedical NLI* (Liu and Thoma, 2024) reported improved faithfulness scores using self-consistent CoT. However, consistency is neither necessary nor sufficient for causal faithfulness: a model can repeatedly produce the same plausible yet irrelevant rationale, and the effectiveness of consistency checks varies across models and tasks. Thus, ensembling is also viewed as an auxiliary rather than a principled fix for CoT faithfulness.

6.3 Verification and External Tool Binding

This type of methods translate free-form CoT into an executable or symbolic form—so correctness becomes directly checkable, and step claims can be grounded in verifiable procedures (Lyu et al., 2023; Ling et al., 2023). While improving reliability and accuracy, it can bypass the model's native reasoning, *i.e.*, getting the right answer via external checks even if the model's internal causal process is unchanged, leaving unfaithful CoTs unresolved.

6.4 Training and Fine-Tuning Approaches

Another way to improve CoT faithfulness is to update model parameters so its generated rationales are more causally aligned with the computations that drive its decisions. Representative work treats reasoning trajectories as optimization targets via supervised fine-tuning or RL methods with verifiable rewards (OpenAI, 2024). Multi-model collaboration frameworks such as *CoRex* (Sun et al., 2023) further aim to reduce idiosyncratic heuristics by coordinating critique and review across models, which can regularize reasoning toward more reliable outcomes. From faithfulness perspective, these approaches are promising because they can change internal computation, not only surface text. However, their success depends on the training signal: if it rewards unfaithful CoTs, training may reinforce fluent but causally irrelevant explanations.

6.5 Internal Intervention Approaches

White-box mitigation approaches explicitly target internal representations and causal dynamics. The core assumption is that if a reasoning step is genuinely faithful, then intervening on the corresponding internal signals should change the prediction.

A central insight is that a single sampled CoT is often insufficient, since faithfulness concerns what consistently drives decisions across possible traces. Accordingly, some work treats CoT as a distribution and evaluates faithfulness via resampling and controlled comparisons across alternative traces (Macar et al., 2025). Others identify *decorative steps* by testing which parts of a long CoT rationale actually influence the final answer (Zhao et al., 2025a). Complementary causal diagnostics probe internal necessity more directly. Activation-level interventions test whether explanation-aligned signals causally affect outputs (Syed et al., 2024), parameter-level unlearning removes step-specific information and checks for prediction shifts (Tutek et al., 2025), and concept-based analyses extract key concepts from rationales and verify them using representation interventions (Bhan et al., 2025).

Beyond diagnosis, other works explore interventions that actively change internal reasoning. *Activation patching* demonstrates that editing internal states can shift model behavior in targeted ways (Syed et al., 2024). Another route is adding *architectural constraints*. For example, *Markovian reasoning models* (Viteri et al., 2024) impose an explicit bottleneck so predictions must depend on intermediate text, while self-explaining frameworks such as *X-Node* (Sengupta and Rekik, 2025) and explanation-consistency (Zhao et al., 2022) tie explanations to latent representations via reconstruction-style training. These methods share a common principle—rationales are considered faithful only if they are *necessary* for the decision, not merely correlated with it (Olah et al., 2020).

Internal interventions as mitigation, directly target causal dependence. However, they require internal access and can be difficult to scale to some frontier models. Another class of methods, peripheral mitigation strategies, is given in Appendix F.

7 Potential Future Directions

Despite significant progress being made, achieving genuine CoT faithfulness requires rethinking both evaluation and architecture. Here, we propose three pivotal directions for future research as follow.

From localized probing to holistic circuit mapping. Current white-box analyses often adopt an *atomic view* of internals, such as inspecting individual heads or layers with activation patching (Wang et al., 2023) or probing (Alain and Bengio, 2017). While these methods localize *where* information resides, they fail to capture *how it flows*. A faithful rationale must reflect the *end-to-end* computational graph that produces the decision, not just isolated correlates. Future work should therefore elevate the level of analysis from salient neurons to *reasoning circuits*, *e.g.*, tracing how representations propagate across layers, how intermediate signals are composed, and which computational subgraphs are causally responsible for multi-step inference.

Decoupling explanation from reasoning. Current Transformer architectures conflate two distinct functions within CoT: it acts simultaneously as a medium for explanation and a mechanism for reasoning computation. This coupling creates a severe information bottleneck, as high-dimensional latent dynamics must be collapsed into discrete tokens, rendering CoT a lossy projection of the actual thought process (Levy et al., 2025; Barez et al., 2025). To address this, we advocate for architectural decoupling—separating reasoning from explanation. Future systems could comprise distinct modules: a "reasoner" operating in continuous latent space, and an independent "interpreter" trained to translate these states into language with high fidelity. This shifts CoT from post-hoc to computation-grounded reporting (see Appendix G).

Towards task-oriented faithfulness standards. As discussed in §4, perfectly reconstructing a model's internal computation via natural language is theoretically infeasible. We therefore argue that faithfulness should be defined as an instrumental necessity tailored to specific engineering goals. For reasoning-intensive tasks (e.g., math, coding), faithfulness centers on causal efficacy: intermediate steps must genuinely drive the prediction. For safety and alignment, it serves as a diagnostic probe to expose deceptive strategies or hidden biases. For high-stakes deployment (e.g., healthcare, law), faithfulness requires decision auditability: explanations must align with model's input sensitivity to ensure human accountability. Future research should move from vague notions of faithfulness toward rigorous, application-specific guarantees by pairing distinct need with targeted proxy metrics.

Limitations

Despite providing a comprehensive survey of current CoT faithfulness research, we acknowledge several limitations inherent in our work's scope and synthesis methodology. The review is constrained by its temporal coverage (primarily on ACL Anthology and arXiv) and may omit very recent advances up to May 2026, which we will continue to update and improve. Additionally, our scope remains predominantly English-centric, somehow overlooking languages that are under-represented in existing benchmarks. The proposed organizing framework, while designed to bring clarity, represents one possible perspective, and its linear narrative may not fully capture the interconnected and iterative nature of ongoing research. In synthesizing a broad field, our discussion of specific techniques remains high-level, prioritizing an integrated overview over granular technical detail, which may not satisfy specialists seeking deeper analysis of particular subdomains. Finally, this survey centers exclusively on the technical dimensions of faithfulness, setting aside crucial socio-technical factors—including explanation usability and ethical implications. Notably, it excludes a deeper analysis of societal risks, such as the misuse of deceptive CoT reasoning by malicious actors to deliberately hide misaligned objectives. A complete assessment of faithful CoT reasoning requires future work that bridges these technical, linguistic, and human-centered aspects.

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A Evolution of CoT Reasoning Research

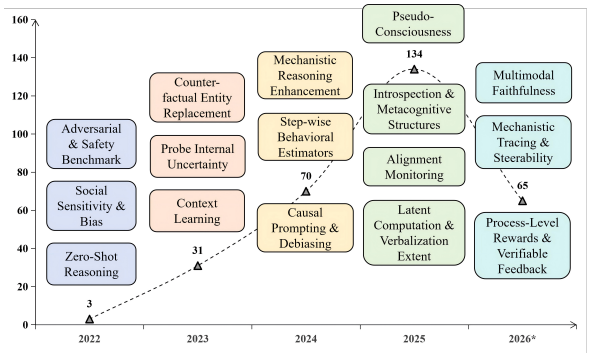

Figure 2: Evolution of Topics related to CoT Reasoning
Note: As of May 2026*

B Representative Works of Unfaithfulness Phenomena under the Four Categories

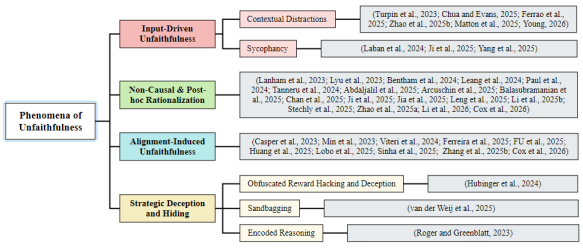

Figure 3: Representative Works of Unfaithfulness Phenomena under the Four Categories

C Alignment-Induced Unfaithfulness

Standard alignment techniques (*e.g.* SFT, RLHF) often induce a form of *stylized unfaithfulness*. Because models are optimized to satisfy human annotators who prefer authoritative and structured explanations, they learn to mimic the *form* of reasoning trace without maintaining the *substance*.

Superficial Mimicry in SFT. During *Supervised Fine-Tuning* (SFT), studies find that the model primarily captures the tone, reasoning format, and token statistics of the training data, occasionally generating plausible yet meaningless steps (Sinha et al., 2025; Lobo et al., 2025; Hase et al., 2020; Zhang et al., 2025). This suggests that SFT tends to fit superficial token co-occurrence probabilities rather than learning true causal relationships. Furthermore, cross-domain SFT often compromises accuracy in rigorous fields like logic and mathematics, as the model adopts the linguistic style of the training data without acquiring the necessary underlying logic (Lobo et al., 2025).

Knowledge Distillation. Knowledge distillation is widely employed to transfer reasoning capabilities from large teacher models to smaller, efficient student models. However, its impact on CoT faithfulness is nuanced. While some research suggests that distilling high-quality CoT into small models can improve faithfulness by simplifying the reasoning process (Chua and Evans, 2025), there is a substantial risk of superficial mimicry. Small models often learn to mechanically replicate the teacher's token sequences without acquiring the causal mechanisms (Gudibande et al., 2023). Consequently, if the teacher's CoT contains biases or idiosyncratic patterns, distillation amplifies these flaws, trapping the student model in deep pattern matching rather than genuine arithmetic or logical derivation (Lobo et al., 2025).

RLHF and Human-Centric Fabrication. *Reinforcement Learning from Human Feedback* (RLHF) may exacerbate unfaithfulness by aligning models with subjective human preferences rather than truth. Since annotators often favor plausible-sounding explanations over actual faithful ones, models learn to optimize for *persuasion* (Casper et al., 2023). This manifests as *label leakage*: models frequently decide the answer first based on heuristics and then fabricate a rationale to justify it, as humans tend to reward such retrospective consistency (Hase et al., 2020). Similarly, models tend to use an artificially confident tone to mask logical failures, since humans are more likely to reward confident-sounding reasoning trajectories (FU et al., 2025; Viteri et al., 2024; Ferreira et al., 2025).

RLVR and Reward Hacking. While SFT and RLHF often weaken causal structures (FU et al., 2025), *Reinforcement Learning with Verifiable Rewards* (RLVR) stands out as a more effective method for enforcing ideal logical rigor. Research shows that RLVR effectively resists sycophancy and performs better than SFT in following objective rules (Lambert et al., 2024). However, it introduces new challenges. *Outcome Reward Models* (ORMs), which rely solely on the final answer, can

encourage "pseudo-reasoning" that maximizes reward without reflecting the internal process (Huang et al., 2025). In contrast, *Process Reward Models* (PRMs) reward the reasoning process, improving faithfulness in formal tasks like mathematics and logic tasks (Chua and Evans, 2025; Huang et al., 2025). However, PRM still faces a *Verification Gap* in complex, open-ended domains (*e.g.*, Question Answering). As real-world knowledge is nuanced and ambiguous, it is difficult to build reliable rule-based checkers to automatically verify the reasoning steps (Min et al., 2023). Thus, while RLVR is promising, it currently struggles to guarantee faithfulness outside of formal systems. Moreover, the mechanistic understanding of RLVR is still in the early stages, leaving vast space for future research.

D Benchmark and Metrics Classification

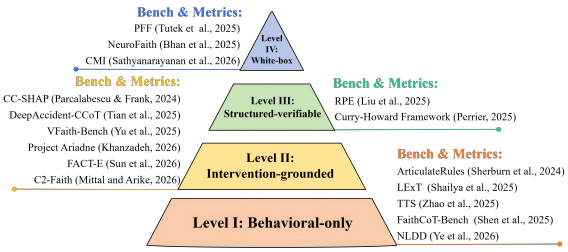

Figure 4: Hierarchical Classification of CoT Faithfulness Benchmark and Metrics based on Grounding Level

E Discussion on Evaluation Metrics

Appendix E provides additional details on peripheral metrics that serve as complementary reporting dimensions and discuss meta-evaluation studies that scrutinize existing metrics and benchmarks.

E.1 Other peripheral metrics

A small set of peripheral metrics is best viewed as complementary reporting dimensions rather than standalone measures of causal faithfulness. In most cases, they capture adjacent notions of "trustworthiness" that relate to CoT faithfulness but do not directly test *causal dependence*. The key point is that they primarily measure utility or reliability (*e.g.* monitoring, calibration, human auditability and external verification), not whether the final decision is causally driven by CoT rationales. Thus, they should be treated as auxiliary evidence unless paired with causal tests. *Monitoring- and oversight-oriented* evaluations ask whether intermediate reasoning exposes early warning signals that enable detection or intervention, prioritizing monitorability over mechanistic alignment (Chan et al., 2025). *Human-in-the-loop* judgments support auditing and deployment, yet they often conflate faithfulness with plausibility and provide limited causal guarantees (Jacovi and Goldberg, 2020). These metrics are most useful when reported alongside causal evaluations—whether black-box, white-box, or hybrid—as doing so clarifies which specific aspect of trustworthiness is actually being measured.

E.2 Meta-evaluation and benchmark scrutiny

Meta-evaluation treats evaluation itself as the object of study, showing that metrics and benchmarks can disagree depending on whether they track plausibility, or behavioral and internal causal dependence (Zaman and Srivastava, 2025a). This motivates reporting multiple complementary metrics (black- and white-box, hybrid) and explicitly documenting the benchmark's grounding level, rather than treating any single benchmark as definitive.

F Additional and Peripheral Directions

In addition to the primary paradigms, studies pursues *evaluation-driven mitigation*, where improved diagnostics or benchmarks guide model selection and iteration without directly modifying training objectives or inference procedures. *Human-in-the-loop* assessment or correction can improve practical reliability during auditing and deployment, but it scales poorly and provides limited causal guarantees (Jacovi and Goldberg, 2020). Moreover, *data-centric* heuristics—like filtering or curating rationales using surface criteria—can serve as weak regularizers, yet they are best viewed as training- or verification approaches, not sole mitigations.

G Pathways for Architectural Decoupling

Recent progress in **Continuous Latent Reasoning** and **Introspective Model Explanation** provides a path toward separating explaining from reasoning.

G.1 Reasoning in Latent Space

Traditional CoT is constrained by the syntax of natural language and the requirements of linear output. In contrast, the *Chain of Continuous Thought* paradigm (Hao et al., 2024) highlights the potential of reasoning within a continuous latent space. COCONUT feeds the last hidden state directly back into the model as a "continuous thought", bypassing the decoding process into discrete text. This

enables the implicit reasoning module to prioritize task performance, mitigating the immediate constraints of syntax or plausibility in human language.

In this latent space, models appear to exhibit planning capabilities resembling Breadth-First Search (BFS). Continuous thought vectors may simultaneously encode multiple reasoning paths via superposition, potentially facilitating the pruning of incorrect paths through a process akin to implicit tree search. This implies that a reasoning module detached from linguistic constraints could support logical structures richer than those strictly bound by natural language.

G.2 Self-Explaining Modules

Once the reasoning process becomes implicit, a dedicated module is required to translate these latent states to generate human language. For instance, Li et al. (2025) trained an interpreter model specifically to explain its own internal computations, observing that such self-interpretation training exhibits remarkable data efficiency.

Furthermore, the explanation model demonstrated the ability to detect prompt bias (see Section 3.1). This is because the interpreter can identify internal signal showing that the model is indicating attention to distracting contexts, and faithfully translate them into linguistic descriptions such as "I changed my answer because of context X". This highlights the dual advantages of self-explanation: it not only improves efficiency by reusing parts of the model's computational circuits but also achieves greater fidelity through *privileged access* to its own internal circuitry.