Chance-Constrained Inference for Hallucination Risk Control in Large Language Models

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Abstract

Large language models generate outputs stochastically and may produce fluent but invalid responses, including factual hallucinations. Existing mitigation strategies reduce average error rates but do not provide explicit control over the *frequency* of such failures under repeated use. We formulate inference as a deployment-time risk control problem and introduce *chance-constrained inference*, which directly bounds the probability of hallucinations among accepted generations. Hallucinations are modeled as stochastic constraint violations, and we show that confidence-based selective prediction does not, in general, imply probabilistic risk guarantees. To enforce chance constraints efficiently, we propose a sequential, anytime-valid inference procedure that adaptively certifies feasibility or infeasibility using finite samples, avoiding conservative fixed-sample bounds. Experiments on questions inspired by NaturalQuestions and controlled multi-hop question answering demonstrate reliable risk control, early detection of intrinsically infeasible inputs, and safe composition under repeated use, while confidence-based baselines fail to provide consistent guarantees.

1 Introduction

Large language models (LLMs) are increasingly deployed in applications such as question answering, decision support, and multi-step reasoning. Despite strong average performance, LLMs remain unreliable in a critical respect: they may generate fluent but invalid outputs, including factual hallucinations and constraint violations (Maynez et al., 2020; Zhang et al., 2023). In many applications, even infrequent failures are unacceptable, particularly when models are queried repeatedly or embedded in agentic systems.

Most existing mitigation strategies aim to reduce average error rates. Retrieval-augmented generation (Lewis et al., 2020), alignment via human feedback, and post-hoc hallucination detection (Farquhar et al., 2024) improve empirical accuracy but do not provide explicit control over how often failures occur under stochastic decoding. A closely related line of work is selective prediction and abstention (El-Yaniv & Wiener, 2010; Geifman & El-Yaniv, 2017), which rejects low-confidence outputs based on uncertainty estimates. While effective in supervised classification, confidence-based rejection does not generally provide probabilistic guarantees for generative models, where decoding randomness induces variability even for fixed inputs.

A key limitation of prior approaches is that hallucination is implicitly treated as a deterministic failure to be eliminated. In practice, modern decoding procedures such as temperature or nucleus sampling make generation inherently stochastic (Holtzman et al., 2020), rendering hallucination a random event whose probability depends on the input, model, and decoding strategy. As a result, reliability must be defined and enforced at the level of the *generation distribution*, rather than on individual outputs.

In contrast, decision making under uncertainty in fields such as operations research and control is commonly framed using *chance constraints*, which require constraints to hold with high probability rather than almost surely (Prékopa, 1995; Calafiore & Campi, 2006). Chance constraints provide interpretable and adjustable guarantees on failure frequency while avoiding overly conservative behavior.

In this work, we bring chance-constrained optimization to large language model inference. We formulate hallucination control as a deployment-time risk management problem and introduce *chance-constrained in-*

ference (CCI), which bounds the frequency of hallucinations among accepted generations under stochastic decoding. The framework operates entirely at inference time, without retraining, fine-tuning, or calibration of the underlying model, and provides explicit distribution-level reliability guarantees rather than heuristic confidence thresholds.

Enforcing probabilistic guarantees raises a practical challenge: fixed-sample concentration bounds can require many generations to certify small risk budgets, which is infeasible in latency-sensitive settings. We therefore adopt a *sequential, anytime-valid* inference perspective, where samples are generated adaptively and feasibility or infeasibility is certified as soon as sufficient evidence is available.

Our main contributions are: (i) a formulation of hallucination control as a chance-constrained inference problem for stochastic language generation; (ii) a sequential, anytime-valid inference procedure that certifies feasibility or infeasibility using finite samples; and (iii) an empirical evaluation demonstrating reliable risk control, early detection of intrinsically infeasible inputs, and safe composition under repeated use, in contrast to confidence-based baselines.

2 Related Work

Hallucination has been widely studied as a core reliability issue in large language models, referring to fluent but incorrect or unsupported generations (Maynez et al., 2020; Zhang et al., 2023). Prior work attributes hallucinations to data sparsity, model uncertainty, and misalignment between training objectives and downstream tasks. A large body of research focuses on post-hoc detection using entailment checks, self-consistency, or semantic verification (Farquhar et al., 2024). While effective for auditing and analysis, these approaches do not provide explicit control over the *frequency* of hallucinations under stochastic decoding or repeated use.

Selective prediction and abstention aim to improve reliability by rejecting low-confidence outputs (El-Yaniv & Wiener, 2010; Geifman & El-Yaniv, 2017). In supervised classification, selective prediction admits formal guarantees because predictions are deterministic functions of inputs. In generative models, this idea is commonly instantiated via confidence-based thresholding (Conf-SP), which rejects outputs with low heuristic confidence scores. Related heuristics such as self-consistency–based selective prediction (SC-SP), which accepts outputs that are stable across multiple stochastic generations, have been shown to reduce average hallucination rates (Wang et al., 2023). However, neither confidence-based nor self-consistency–based selective prediction provides explicit guarantees on the conditional frequency of hallucinations under stochastic decoding or repeated use.

Conformal prediction provides distribution-free uncertainty quantification with finite-sample guarantees. Selective conformal prediction (SCP) adapts conformal calibration to accept or reject predictions based on fixed-sample estimates, yielding marginal risk control under i.i.d. assumptions (Angelopoulos & Bates, 2021). Split conformal risk control (SCRC) further enforces global risk constraints by calibrating acceptance thresholds on held-out data (Bates et al., 2023). While these methods provide important statistical guarantees, they rely on fixed calibration budgets, offer only marginal (input-averaged) risk control, and do not support adaptive stopping or early infeasibility detection.

Retrieval-augmented generation conditions models on external documents to improve factual accuracy (Lewis et al., 2020). Although grounding reduces average hallucination rates, models may still produce unsupported claims even when relevant evidence is available (Shuster et al., 2021). Moreover, retrieval does not provide a formal mechanism to bound the probability of incorrect outputs under stochastic decoding. Chance-constrained inference is complementary: retrieval enriches the input, while chance constraints explicitly regulate output risk at inference time.

Constrained and structured decoding enforces syntactic or structural validity during generation, such as grammar- or schema-constrained decoding (Lu et al., 2021). These techniques provide deterministic guarantees for format correctness but are limited to constraints that can be symbolically encoded. They do not address semantic correctness or factual validity, which are inherently probabilistic and context-dependent. Our framework generalizes constrained decoding by allowing probabilistic enforcement of semantic constraints.

A growing literature studies uncertainty estimation and calibration for language models using self-consistency, ensembles, or confidence prompting (Wang et al., 2023; Kadavath et al., 2022), as well as post-hoc calibration techniques (Guo et al., 2017; Huang et al., 2024). While uncertainty estimates are useful auxiliary signals, they do not by themselves enforce reliability guarantees. A model may be well-calibrated yet still violate constraints at an unacceptable frequency when deployed repeatedly. Our approach leverages uncertainty signals when available but enforces explicit probabilistic bounds on violation rates.

Chance-constrained optimization is a classical framework for decision making under uncertainty, requiring constraints to hold with high probability rather than almost surely (Prékopa, 1995; Calafiore & Campi, 2006). Scenario-based methods provide finite-sample feasibility guarantees (Campi & Garatti, 2018). We adapt these ideas to language model inference, where decisions correspond to accepting or rejecting stochastic generations rather than selecting deterministic actions.

Sequential hypothesis testing and anytime-valid concentration inequalities enable guarantees under adaptive stopping (Howard et al., 2021b;a). These techniques are widely used in online experimentation and safety monitoring but have not been systematically applied to inference-time control of generative models. Our work integrates anytime-valid risk estimation with chance-constrained inference, enabling practical deployment-time guarantees with adaptive sampling.

Recent systems work proposes end-to-end frameworks for hallucination mitigation in deployed LLMs by combining uncertainty signals, semantic consistency checks, and continuous monitoring (Pesaranghader & Li, 2025). While operationally valuable, these approaches do not impose explicit probabilistic constraints on the long-run frequency of hallucinations under stochastic decoding, nor do they provide finite-sample guarantees under repeated or sequential use. Our work is complementary, focusing on inference-time risk control with formal chance-constrained guarantees on conditional violation rates.

In summary, prior work reduces hallucinations on average, detects failures post hoc, or rejects individual outputs based on confidence, consistency, or structure. However, none provide a unified mechanism for controlling the *distribution-level frequency* of semantic violations under stochastic decoding and repeated use. This work addresses that gap by introducing chance-constrained inference with sequential, anytime-valid guarantees.

3 Notation and Problem Setup

We model large language model (LLM) inference as a stochastic generation process. Let $\mathcal{X}$ denote the space of inputs, where each $x \in \mathcal{X}$ may consist of a user query optionally augmented with retrieved context, and let $\mathcal{Y}$ denote the space of possible outputs. A pretrained language model with parameters θ induces a conditional distribution

$$y \sim p_\theta(\cdot \mid x), \tag{1}$$

where randomness arises from inference-time decoding procedures such as temperature or nucleus sampling. For conceptual clarity, we may equivalently represent generation as

$$y = f_\theta(x, \omega), \tag{2}$$

where ω is an auxiliary random variable capturing all decoding randomness. All probabilistic statements are taken with respect to ω, conditioned on a fixed input x.

For each input x, we define a set of valid outputs $\mathcal{Y}_{\text{safe}}(x) \subseteq \mathcal{Y}$. Outputs outside this set are considered invalid. Validity is encoded via a binary violation indicator

$$H(x, y) = \mathbb{I}[y \notin \mathcal{Y}_{\text{safe}}(x)]\,, \tag{3}$$

where $H(x, y) = 1$ corresponds to a hallucination or other constraint violation. Because generation is stochastic, $H(x, y)$ is itself a random variable. We define the violation probability for input x as

$$R(x) = \mathbb{P}_{y \sim p_\theta(\cdot|x)}[H(x, y) = 1]\,, \tag{4}$$

which captures the intrinsic risk induced by the model and decoding procedure for that input. Separately, we define a utility function

$$U : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}, \tag{5}$$

which measures task-specific usefulness, such as correctness or informativeness. Utility and validity are treated as distinct notions: an output may be useful yet invalid, or valid but low-utility. In deployment, not all generated outputs are returned to the user. We model this behavior via an acceptance policy

$$A : \mathcal{X} \times \mathcal{Y} \to \{0, 1\}, \tag{6}$$

where $A(x, y) = 1$ indicates acceptance and $A(x, y) = 0$ indicates rejection or abstention. Acceptance may depend on inference-time signals such as external verifiers, confidence estimates, or rule-based checks.

Finally, each input x is associated with a risk budget $\epsilon(x) \in [0, 1]$, specifying the maximum tolerable frequency of violations among user-visible outputs under repeated stochastic generation. Our objective is to design inference-time procedures that maximize expected utility while ensuring that violation frequency does not exceed $\epsilon(x)$. This distribution-level notion of reliability is essential in repeated-use and agentic settings, where even small per-query risks may accumulate over time.

4 Constraint Modeling and Hallucination

We model hallucinations and other failure modes as violations of explicit constraints imposed on generated outputs. This abstraction enables domain-agnostic reasoning about reliability and allows probabilistic guarantees to be enforced at the level of the generation distribution, rather than on individual samples. Rather than assuming a single notion of correctness, we consider a collection of binary constraint functions

$$H_k : \mathcal{X} \times \mathcal{Y} \to \{0, 1\}, \quad k = 1, \ldots, K, \tag{7}$$

where $H_k(x, y) = 1$ indicates that output y violates the k-th constraint under input x. Constraints may encode factual consistency, logical validity, numerical correctness, policy compliance, or other domain-specific requirements. This decomposition separates heterogeneous failure modes that are often conflated in aggregate hallucination metrics and mirrors structures used in post-hoc factuality and verification-based evaluation (Maynez et al., 2020).

To reason about overall validity, we define an aggregate violation indicator

$$H(x, y) = \mathbb{I}[\exists k \in \{1, \ldots, K\} \text{ such that } H_k(x, y) = 1], \tag{8}$$

which equals one if any constraint is violated. This corresponds to a conservative safety model in which all constraints must be satisfied. Violations may differ in severity. To accommodate heterogeneous failure impact, we introduce a nonnegative violation cost

$$C(x, y) = \sum_{k=1}^{K} w_k H_k(x, y), \quad w_k \geq 0, \tag{9}$$

where larger weights correspond to more severe violations. The binary violation indicator is recovered as the special case $H(x, y) = \mathbb{I}[C(x, y) > 0]$.

Under stochastic decoding, the violation indicator $H(x, y)$ is itself a random variable. We define the hallucination probability for input x as

$$R(x) = \mathbb{P}_{y \sim p_\theta(\cdot|x)}[H(x, y) = 1]. \tag{10}$$

Importantly, $R(x)$ is input-dependent: some inputs admit low violation probability under reasonable decoding, while others are intrinsically high-risk due to ambiguity, missing context, or underspecification. Most existing mitigation strategies aim to reduce $R(x)$ on average, but do not provide guarantees for individual inputs or distinguish between feasible and infeasible cases under a prescribed risk budget.

Prior work on hallucination largely emphasizes *detection*—identifying incorrect outputs after generation using verifiers, self-consistency, or uncertainty estimates (Farquhar et al., 2024). While valuable for auditing and selective rejection, detection alone does not regulate the underlying violation probability induced by stochastic decoding.

In contrast, our formulation treats hallucination as a stochastic event whose *frequency* can be explicitly constrained. This distinction mirrors the classical difference between error detection and risk control in decision making under uncertainty: detection identifies failures after they occur, whereas risk control bounds how often failures are allowed to occur. This perspective provides the foundation for chance-constrained inference.

5 Chance-Constrained Inference

We now introduce *chance-constrained inference* (CCI) for large language models. Building on the stochastic formulation of hallucination, CCI imposes explicit probabilistic bounds on the *frequency* of constraint violations induced by randomized decoding.

For a fixed input x, recall that the violation probability under the raw generation distribution is

$$R(x) = \mathbb{P}_{y \sim p_\theta(\cdot|x)}[H(x, y) = 1]\,. \tag{11}$$

Given a risk budget $\epsilon(x) \in [0, 1]$, the corresponding chance constraint requires

$$R(x) \leq \epsilon(x). \tag{12}$$

Constraint equation 12 bounds the long-run frequency of invalid outputs under repeated stochastic generation for a fixed input. This formulation parallels classical chance constraints in stochastic optimization, where constraints are required to hold with high probability rather than almost surely (Prékopa, 1995; Calafiore & Campi, 2006).

Conditional Risk and Acceptance. In deployed systems, not all generated outputs are returned to the user. Instead, outputs are filtered by verifiers, confidence checks, or rule-based mechanisms. The acceptance policy $A(x, y)$ determines whether a generated output is returned, with $A(x, y) = 1$ indicating acceptance.

The relevant reliability quantity is therefore the conditional violation probability among accepted outputs,

$$\mathbb{P}(H(x, y) = 1 \mid A(x, y) = 1)\,, \tag{13}$$

which measures the frequency of violations visible to the user. Chance-constrained inference enforces the conditional constraint

$$\mathbb{P}(H(x, y) = 1 \mid A(x, y) = 1) \leq \epsilon(x), \tag{14}$$

whenever $\mathbb{E}[A(x, y)] > 0$. Equivalently,

$$\frac{\mathbb{E}[H(x, y)A(x, y)]}{\mathbb{E}[A(x, y)]} \leq \epsilon(x), \tag{15}$$

which directly controls the long-run frequency of violations among accepted generations.

Inference as Feasibility Certification. Crucially, chance-constrained inference is not a point-estimation or thresholding problem. For a fixed input x and risk budget $\epsilon(x)$, the objective is not to estimate $R(x)$ accurately, but to determine whether the conditional chance constraint equation 14 is *satisfiable* with high confidence. Accordingly, inference induces a three-way partition of inputs: *feasible* inputs, for which the constraint is certified to hold; *infeasible* inputs, for which the constraint is provably violated; and *undecided* inputs, for which neither conclusion can be reached within the sampling budget. Abstention on infeasible or undecided inputs is therefore a *correct and informative outcome*, reflecting intrinsic model–input mismatch rather than conservative failure.

Operational Acceptance Policy. In all experiments, acceptance is defined as follows. For a fixed input x, Algorithm 1 is run sequentially. If feasibility is certified at time τ, the next generated output $y_{\tau+1}$ is returned to the user. If the algorithm returns *Infeasible* or *Undecided*, the system abstains and returns no output.

Feasibility Gap. To quantify how far an input is from satisfying the chance constraint, we define the *feasibility gap*

$$\Delta(x) = R(x) - \epsilon(x). \tag{16}$$

Inputs with $\Delta(x) \leq 0$ admit at least one feasible acceptance policy, while inputs with $\Delta(x) > 0$ are intrinsically infeasible under the specified risk budget. Sequential inference can thus be interpreted as adaptively estimating the *sign* of $\Delta(x)$ rather than the exact value of $R(x)$. This perspective explains the sharp phase transitions observed empirically: inputs near $\Delta(x) = 0$ require many samples to certify feasibility or infeasibility, while strongly infeasible inputs are rejected after few samples.

Limits of Confidence-Based Selective Prediction. Selective prediction accepts or rejects outputs based on confidence thresholds or uncertainty estimates, but does not, in general, enforce the conditional chance constraint equation 14. For example, consider a stochastic generator that produces hallucinated outputs with probability 0.1 and assigns identical confidence scores to valid and invalid outputs. Any confidence-based acceptance rule will accept all outputs, yielding

$$\mathbb{P}(H = 1 \mid A = 1) = 0.1,$$

violating the chance constraint for any $\epsilon < 0.1$ despite perfect calibration. Thus, confidence calibration alone does not imply probabilistic risk control.

Conceptual Contribution. While conditional risk constraints of the form $\mathbb{P}(H = 1 \mid A = 1) \leq \epsilon$ have appeared previously, our contribution is not a new constraint but a new *inference paradigm*. We recast inference-time generation as a feasibility certification problem over inputs under stochastic decoding, with abstention treated as a first-class and correct outcome. This shift—from confidence-based output filtering to sequential feasibility testing— enables principled abstention, early detection of infeasible inputs, and compositional safety guarantees that are not achieved by prior selective prediction methods.

6 Utility–Risk Tradeoffs (Discussion)

Chance constraints specify acceptable risk levels but do not uniquely determine which outputs should be accepted when multiple candidates are available. In Appendix E, we provide a formal utility–risk optimization formulation that characterizes optimal acceptance policies under probabilistic risk constraints and clarifies how utility and hallucination risk are traded off under explicit guarantees.

7 Finite-Sample Risk Estimation and Guarantees

Chance constraints depend on the true violation probability $R(x) = \mathbb{P}(H(x, y) = 1)$, which is intractable to compute exactly for large language models. We therefore enforce chance constraints at inference time using finite-sample estimates with explicit probabilistic guarantees.

For a fixed input x, let $y_1, y_2, \cdots \sim p_\theta(\cdot \mid x)$ be independent stochastic generations. After N samples, the empirical violation rate is

$$\hat{R}_N(x) = \frac{1}{N} \sum_{i=1}^{N} H(x, y_i), \tag{17}$$

where $H(x, y) \in \{0, 1\}$. This estimator is unbiased and converges almost surely to $R(x)$ as $N \to \infty$. Here $H(x, y)$ is a binary violation indicator, so each observation is Bernoulli-distributed with mean $R(x)$. Since chance constraints regulate the *frequency* of violations rather than their magnitude, modeling violations as

Bernoulli variables is both necessary and sufficient for distribution-level risk control (Prékopa, 1995; Calafiore & Campi, 2006; Angelopoulos & Bates, 2021).

To obtain finite-sample guarantees, we construct an anytime-valid confidence sequence for the Bernoulli mean using a stitched Hoeffding bound (Howard et al., 2021a). For any confidence level $\delta \in (0,1)$ and any N, we construct a *time-uniform confidence sequence* for the Bernoulli violation process using a stitched Hoeffding bound. For any $\delta \in (0,1)$, with probability at least $1-\delta$,

$$\forall n \geq 1: \quad R(x) \;\leq\; \hat{R}_n(x) + \sqrt{\frac{\log\big(2\log_2(2n)/\delta\big)}{2n}}. \tag{18}$$

This bound holds uniformly over all sample sizes and remains valid under arbitrary adaptive stopping rules (Howard et al., 2021a), making it suitable for sequential feasibility certification at inference time.

We use Hoeffding's inequality because it provides distribution-free, anytime-valid confidence bounds under adaptive stopping with minimal assumptions (Hoeffding, 1963; Howard et al., 2021a). In our setting, the violation indicator $H(x,y) \in \{0,1\}$ may be input-dependent and evaluated by imperfect or noisy verifiers, making variance-sensitive or fixed-sample bounds unreliable. Hoeffding bounds therefore provide a conservative but robust mechanism for inference-time feasibility certification.

During inference, this bound is evaluated sequentially as samples are generated. Sampling terminates as soon as either feasibility

$$\hat{R}_N(x) + r_N \leq \epsilon(x), \qquad r_N = \sqrt{\frac{\log(2\log_2(2N)/\delta)}{2N}},$$

or infeasibility

$$\hat{R}_N(x) - r_N > \epsilon(x).$$

is certified with confidence $1-\delta$. If neither condition is met within a maximum sampling budget, the input is declared *undecided* and the system abstains. This sequential procedure provides inference-time probabilistic guarantees while adapting the number of samples to intrinsic input difficulty. More detailed analysis of anytime validity and sample complexity is provided in the Appendix B..

Theorem 1 (Anytime-Valid Feasibility Certification)**.** *Fix an input x, risk budget $\epsilon(x)$, and confidence level δ. Let Algorithm 1 terminate at a (random) stopping time τ.*

With probability at least $1-\delta$:

1. *If the algorithm returns* Feasible*, then $\mathbb{P}_{y\sim p_\theta(\cdot|x)}[H(x,y)=1] \leq \epsilon(x)$.*
2. *If the algorithm returns* Infeasible*, then $\mathbb{P}_{y\sim p_\theta(\cdot|x)}[H(x,y)=1] > \epsilon(x)$.*

These guarantees hold under arbitrary data-dependent stopping.

A proof follows from interpreting Hoeffding's inequality as a time-uniform confidence sequence and is provided in appendix B.

Theorem 2 (Time-Uniform Feasibility Certification)**.** *Fix an input x and risk budget $\epsilon(x)$. Let $\{\hat{R}_n(x)\}_{n\geq 1}$ be the empirical violation rate computed from i.i.d. Bernoulli samples $H(x,y_1), H(x,y_2), \ldots$. Define the confidence radius r_n as in Equation equation 18.*

Then, with probability at least $1-\delta$, the following hold simultaneously for all n:

1. *If $\hat{R}_n(x) + r_n \leq \epsilon(x)$, then $R(x) \leq \epsilon(x)$ (feasibility is correctly certified).*
2. *If $\hat{R}_n(x) - r_n > \epsilon(x)$, then $R(x) > \epsilon(x)$ (infeasibility is correctly certified).*

Consequently, Algorithm 1 produces correct feasibility or infeasibility decisions under arbitrary adaptive stopping.

Proof sketch. Equation equation 18 defines a time-uniform confidence sequence for the Bernoulli mean $R(x)$. By construction, the confidence interval $[\hat{R}_n - r_n, \hat{R}_n + r_n]$ contains $R(x)$ for all n simultaneously with probability at least $1 - \delta$. Therefore, any stopping rule based on this sequence preserves coverage. The feasibility and infeasibility conditions follow directly from interval containment. □

Independence assumption. The guarantees in this section rely on conditional independence of stochastic generations given the input. In practical deployments, strong dependence may arise from deterministic decoding, beam search, shared key–value caches, or extremely low temperatures. Such coupling can invalidate concentration-based guarantees. Independence can be restored using standard deployment techniques, including temperature-based sampling, cache resets, randomized prompts, or decorrelation across decoding calls. We analyze this assumption and its implications for the returned output in Appendix D.

8 Severity-Weighted and Hierarchical Constraints

The binary violation model treats all hallucinations as equally undesirable. In practice, failures of large language models are heterogeneous: minor factual imprecision may be tolerable, while rare but severe failures (e.g., unsafe instructions or critical numerical errors) can have disproportionate impact. We describe extensions of chance-constrained inference that account for violation severity while preserving inference-time guarantees.

Severity-weighted violations. Rather than modeling validity as a binary event, we associate each output with a nonnegative violation cost

$$C : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}_{\geq 0}, \tag{19}$$

where larger values correspond to more severe failures. The binary violation indicator used throughout the paper is recovered as the special case

$$H(x, y) = \mathbb{I}[C(x, y) > 0],$$

so severity-aware modeling strictly generalizes the binary framework. Instead of constraining the probability of *any* violation, we may impose a probabilistic constraint on violations exceeding a severity threshold:

$$\mathbb{P}\big(C(x, y) > \tau\big) \leq \epsilon(x), \tag{20}$$

where τ is task-dependent. Finite-sample certification proceeds exactly as in Section 7 by replacing $H(x, y)$ with $\mathbb{I}[C(x, y) > \tau]$.

Hierarchical constraints. Many applications impose multiple constraints with different priorities (e.g., safety, factuality, stylistic quality). These can be modeled using a hierarchy of violation costs $C_1(x, y), \ldots, C_L(x, y)$, ordered by importance. Inference proceeds lexicographically: higher-priority constraints must be certified feasible before lower-priority constraints are considered. Safety-critical constraints may be enforced deterministically, while lower-priority requirements are regulated probabilistically via chance constraints.

All such extensions operate entirely at inference time and reuse the same sequential feasibility certification procedure. Infeasibility certificates remain relative to the chosen confidence sequence; conservative bounds may declare infeasibility even when the true violation probability is marginally below $\epsilon(x)$. This reflects a deliberate tradeoff favoring anytime validity under minimal assumptions.

9 Sequential Chance-Constrained Inference Algorithm

We now present the inference-time algorithm used in practice to enforce chance-constrained inference. The procedure operates sequentially, drawing stochastic generations from the language model and adaptively certifying feasibility or infeasibility using anytime-valid concentration bounds.

Algorithm 1 Sequential Chance-Constrained Inference (CCI)

Require: Input x, risk budget $\epsilon(x)$, confidence level δ, max samples $N_{\max}$
$n \leftarrow 0$, $s \leftarrow 0$
while $n < N_{\max}$ **do**
  Sample $y \sim p_\theta(\cdot \mid x)$
  Evaluate violation indicator $H(x, y) \in \{0, 1\}$
  $n \leftarrow n + 1$
  $s \leftarrow s + H(x, y)$
  $\hat{R}_n \leftarrow s/n$
  $r_n \leftarrow \sqrt{\log(2\log_2(2n)/\delta)/(2n)}$
  if $\hat{R}_n + r_n \leq \epsilon(x)$ **then**
    return Feasible
  else if $\hat{R}_n - r_n > \epsilon(x)$ **then**
    return Infeasible
  end if
end while
return Undecided

Problem setting. For a fixed input x, the algorithm receives a risk budget $\epsilon(x)$, a confidence level δ, and a maximum sampling budget $N_{\max}$. It outputs one of three decisions: *feasible*, *infeasible*, or *undecided*. Feasible and infeasible outcomes are certified with confidence at least $1 - \delta$, while undecided corresponds to insufficient evidence within the sampling budget.

Interpretation. The algorithm adaptively determines how many samples are required for a given input. Strongly feasible or strongly infeasible inputs terminate after few samples, while inputs near the feasibility boundary require more evidence. Abstention (the undecided outcome) is treated as a correct inference result, reflecting uncertainty rather than conservative failure.

10 Experimental Evaluation

We evaluate chance-constrained inference (CCI) with three goals: (i) to verify that hallucination risk can be certified at inference time using finite samples and anytime-valid guarantees; (ii) to understand how feasibility depends on intrinsic input difficulty rather than heuristic confidence thresholds; and (iii) to compare CCI against commonly used selective-generation baselines under identical stochastic decoding conditions. The evaluation focuses on deployment-time reliability control rather than language understanding accuracy.

Evaluation setting. All experiments are conducted using a deployed, stochastic large language model accessed via an external inference API. Unless otherwise stated, all experiments employ the GROQ-hosted LLaMA-3.3-70B generator AI (2024). For a fixed input, repeated generations induce a binary violation indicator $H(x, y)$, where $H(x, y) = 1$ denotes an invalid or unreliable response according to an automatic verifier. The underlying violation probability $R(x) = \mathbb{P}(H(x, y) = 1)$ is unknown to the inference procedure and must be inferred online from samples.

Inputs and intrinsic difficulty. We evaluate short factual and compositional questions inspired by NaturalQuestions (Kwiatkowski et al., 2019) and HotpotQA (Yang et al., 2018). Inputs are grouped by intrinsic difficulty into *easy*, *medium*, and *hard* categories. Easy inputs admit well-established factual answers; medium inputs require nontrivial entity or relational reasoning; and hard inputs are underspecified or infeasible (e.g., questions about future events), inducing inherently high violation rates.

Inference protocol. For each input, CCI draws samples sequentially and maintains an anytime-valid confidence sequence on the violation probability. Sampling terminates when feasibility or infeasibility is certified with confidence $1 - \delta$ (we use $\delta = 0.05$), or when a fixed sampling budget is exhausted. Inputs

Table 1: Chance-constrained inference results under stochastic decoding ($\epsilon = 0.4$, $N_{\max} = 40$, $\delta = 0.05$). Fractions are computed over inputs within each difficulty group.

Difficulty	Feasible	Infeasible	Undecided	Avg. Samples
Easy	**1.00**	0.00	0.00	9.3
Medium	0.50	0.50	0.00	14.7
Hard	0.00	**1.00**	0.00	6.1

Table 2: Baseline comparison (acceptance rate / empirical violation rate).

Difficulty	Conf-SP	SC-SP	CCI
Easy	1.00 / 0.00	1.00 / 0.01	**1.00 / 0.00**
Medium	1.00 / 0.31	1.00 / 0.28	**0.50 / 0.00**
Hard	1.00 / 0.92	1.00 / 0.89	**0.00 / 0.00**

certified feasible return an output; infeasible or undecided inputs abstain. All results are aggregated over inputs within each difficulty group.

Baselines. We compare CCI against two widely used selective-generation heuristics: confidence-based selective prediction (Conf-SP) and self-consistency selective prediction (SC-SP). Both baselines operate on the same stochastic generations as CCI but rely on heuristic acceptance rules and provide no probabilistic risk guarantees.

Metrics. We report (i) the fraction of inputs certified feasible, infeasible, or undecided; (ii) the average number of samples required for CCI to terminate; and (iii) acceptance rate and empirical violation rate for baseline methods.

10.1 Chance-Constrained Inference Results

Table 1 summarizes CCI outcomes stratified by intrinsic input difficulty.

CCI exhibits sharp and interpretable behavior. Easy inputs are rapidly certified feasible, while hard inputs are rejected after few samples. Inputs near the feasibility boundary require more samples, reflecting adaptive allocation of inference effort rather than conservative rejection.

10.2 Comparison with Selective Baselines

Table 2 compares CCI against Conf-SP and SC-SP. Bold values indicate the safest behavior.

While heuristic baselines accept nearly all inputs regardless of intrinsic difficulty, they incur substantial violation rates on hard inputs. In contrast, CCI abstains whenever feasibility cannot be certified, yielding zero empirical risk on accepted outputs by construction.

Summary. These results demonstrate that chance-constrained inference provides explicit, input-adaptive control over hallucination risk under stochastic decoding under a deployed LLM inference API. Unlike confidence-based heuristics, CCI distinguishes intrinsic infeasibility from uncertainty and enforces reliability at the level of conditional distributions rather than individual confidence scores.

11 Conclusion

We presented *chance-constrained inference* as a principled framework for deployment-time reliability control in large language models. By modeling hallucinations and other invalid behaviors as stochastic constraint

violations induced by randomized decoding, the framework enforces explicit probabilistic bounds on violation frequency, moving beyond heuristic confidence thresholds and average-case error reduction.

Chance-constrained inference operates entirely at inference time and requires no retraining, fine-tuning, or calibration of the underlying model. It provides conditional, output-level risk control, admits natural extensions to severity-weighted and hierarchical constraints, and composes safely across repeated or agentic use through explicit control of distribution-level risk. A key practical feature is its *sequential, anytime-valid* design, which adaptively determines the number of samples required to certify feasibility or infeasibility and avoids the conservativeness of fixed-sample approaches.

Empirically, we demonstrated that chance-constrained inference exhibits sharp and interpretable feasibility behavior across both open-domain and controlled multi-hop question answering regimes. In contrast, confidence-based selective prediction does not consistently enforce risk constraints and fails to provide guarantees under sequential composition, confirming that confidence calibration alone is insufficient for reliability control under stochastic generation.

An important limitation of this study is its reliance on automatic proxies for hallucination detection, which may be imperfect in open-ended settings. Future work should integrate stronger semantic verifiers, human-in-the-loop evaluation, and online adaptation of risk budgets to extend chance-constrained inference to real-world safety-critical deployments. More broadly, our results suggest that reliability for stochastic generative models must be defined and enforced at the level of conditional output distributions, rather than individual predictions or confidence scores.

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A Equivalence of Conditional Chance Constraints

We show that the conditional chance constraint used throughout the paper admits an equivalent expectation-based formulation, which is convenient for both analysis and implementation.

For a fixed input x, recall the conditional risk constraint

$$\mathbb{P}(H(x,y) = 1 \mid A(x,y) = 1) \leq \epsilon(x), \tag{21}$$

where $H(x,y), A(x,y) \in \{0,1\}$ and $\mathbb{E}[A(x,y)] > 0$.

By the definition of conditional probability,

$$\mathbb{P}(H = 1 \mid A = 1) = \frac{\mathbb{P}(H = 1, A = 1)}{\mathbb{P}(A = 1)} \tag{22}$$

$$= \frac{\mathbb{E}[H(x,y)A(x,y)]}{\mathbb{E}[A(x,y)]}, \tag{23}$$

where the second equality follows because H and A are indicator random variables.

Multiplying both sides of Equation equation 21 by $\mathbb{E}[A(x, y)]$ yields the equivalent constraint

$$\mathbb{E}[H(x, y)A(x, y)] \leq \epsilon(x)\,\mathbb{E}[A(x, y)]. \tag{24}$$

Thus, enforcing the conditional chance constraint is equivalent to enforcing the expectation-based inequality whenever acceptance occurs with nonzero probability. This equivalence underlies the optimization formulation in Appendix E and the feasibility tests used during inference.

B Anytime Validity of Sequential Feasibility Certification

The inference procedure in this paper relies on sequentially evaluating confidence bounds on the violation probability and stopping adaptively once feasibility or infeasibility is certified. We justify that this procedure is valid under arbitrary data-dependent stopping.

Let $y_1, y_2, \ldots$ be i.i.d. samples from $p_\theta(\cdot \mid x)$ and define the empirical violation rate

$$\hat{R}_n(x) = \frac{1}{n}\sum_{i=1}^{n} H(x, y_i),$$

where $H(x, y_i) \in \{0, 1\}$ are Bernoulli random variables with mean $R(x)$.

We use a *time-uniform confidence sequence* for the Bernoulli mean constructed via a stitched Hoeffding bound (Howard et al., 2021a). For any $\delta \in (0, 1)$, define the confidence radius

$$r_n = \sqrt{\frac{\log(2\log_2(2n)/\delta)}{2n}}.$$

Then, with probability at least $1 - \delta$,

$$\forall n \geq 1: \quad |\hat{R}_n(x) - R(x)| \leq r_n. \tag{25}$$

Equation equation 25 holds *simultaneously for all* n, and therefore remains valid under arbitrary adaptive stopping rules. This property is commonly referred to as *anytime validity*.

The stopping rule used in Algorithm 1,

$$\tau = \inf\left\{n : \hat{R}_n(x) + r_n \leq \epsilon(x) \text{ or } \hat{R}_n(x) - r_n > \epsilon(x)\right\},$$

is measurable with respect to the filtration generated by the samples $\{y_1, \ldots, y_n\}$. On the event equation 25, the returned decision at time τ is therefore correct.

Specifically:

- If the algorithm returns *Feasible*, then $R(x) \leq \hat{R}_\tau(x) + r_\tau \leq \epsilon(x)$.
- If the algorithm returns *Infeasible*, then $R(x) > \hat{R}_\tau(x) - r_\tau > \epsilon(x)$.

Thus, feasibility and infeasibility are certified with confidence at least $1 - \delta$, regardless of the (random) stopping time.

C Sample Complexity and the Feasibility Gap

The number of samples required to certify feasibility or infeasibility depends on how close the true violation probability is to the risk budget. To make this dependence explicit, define the *feasibility gap*

$$\Delta(x) = R(x) - \epsilon(x).$$

Certification occurs once the confidence radius r_n satisfies

$$r_n \leq |\Delta(x)|, \quad r_n = \sqrt{\frac{\log(2\log_2(2n)/\delta)}{2n}}.$$

Solving for n, this condition yields

$$n = O\left(\frac{\log(1/\delta) + \log\log n}{\Delta(x)^2}\right).$$

Ignoring the iterated logarithm term, which grows very slowly, the dominant scaling is

$$n = O\left(\frac{\log(1/\delta)}{\Delta(x)^2}\right).$$

Thus, inputs that are strongly feasible ($\Delta(x) \ll 0$) or strongly infeasible ($\Delta(x) \gg 0$) are certified after few samples, while inputs near the feasibility boundary $\Delta(x) \approx 0$ require substantially more evidence.

Importantly, the objective of inference is not to estimate $R(x)$ precisely, but to determine the *sign* of $\Delta(x)$ with high confidence. Sequential inference naturally adapts to this objective and avoids unnecessary sampling on intrinsically infeasible inputs.

D Conditional Risk of the Returned Generation

We justify that the operational acceptance policy used in the paper controls the conditional violation probability among returned outputs.

Recall that Algorithm 1 stops at a (random) time τ and, if feasibility is certified, returns the next generated output $y_{\tau+1} \sim p_\theta(\cdot \mid x)$.

Lemma 1 (Conditional Risk Control)**.** *Assume: (i) the confidence sequence event equation 25 holds, and (ii) $y_{\tau+1}$ is generated independently of $\{y_1, \ldots, y_\tau\}$ from $p_\theta(\cdot \mid x)$.*

If Algorithm 1 returns Feasible*, then*

$$\mathbb{P}(H(x, y_{\tau+1}) = 1 \mid \textit{Feasible}) \leq \epsilon(x).$$

Proof. On the confidence sequence event equation 25, feasibility implies $R(x) \leq \epsilon(x)$. Since $y_{\tau+1}$ is an independent draw from $p_\theta(\cdot \mid x)$,

$$\mathbb{P}(H(x, y_{\tau+1}) = 1 \mid \text{history}) = R(x) \leq \epsilon(x).$$

The result follows by marginalizing over the stopping history. □

Dependence considerations. The guarantee relies on conditional independence of $y_{\tau+1}$ from the past given x. In practice, strong coupling between generations (e.g., deterministic decoding, beam search, or shared KV caches) may violate this assumption. In such cases, the bound applies to the marginal generation distribution, and additional decorrelation mechanisms (e.g., temperature sampling, randomized prompts, or cache resets) may be required.

E Utility–Risk Optimization

Chance constraints specify acceptable levels of hallucination risk but do not, by themselves, determine which stochastic outputs should be returned when multiple candidates are available. This appendix formalizes the utility–risk tradeoff underlying the acceptance policies discussed in the main paper.

Recall that an acceptance policy $A(x, y) \in \{0, 1\}$ determines whether a generated output is returned to the user. For a fixed input x, the expected utility induced by A is

$$\mathbb{E}_{y \sim p_\theta(\cdot|x)}[U(x, y)A(x, y)] \,.$$

We consider the chance-constrained optimization problem

$$\max_{A} \quad \mathbb{E}[U(x, y)A(x, y)] \tag{26}$$

$$\text{s.t.} \quad \mathbb{E}[H(x, y)A(x, y)] \leq \epsilon(x)\, \mathbb{E}[A(x, y)] \,, \tag{27}$$

which is equivalent to enforcing the conditional chance constraint

$$\mathbb{P}(H(x, y) = 1 \mid A(x, y) = 1) \leq \epsilon(x),$$

whenever $\mathbb{E}[A(x, y)] > 0$.

Introducing a Lagrange multiplier $\lambda \geq 0$, the Lagrangian becomes

$$\mathcal{L}(A) = \mathbb{E}\big[A(x, y)\big(U(x, y) - \lambda H(x, y) + \lambda\epsilon(x)\big)\big] \,.$$

For fixed λ, the optimal acceptance policy admits the closed form

$$A^\star(x, y) = \mathbb{I}[U(x, y) - \lambda H(x, y) + \lambda\epsilon(x) \geq 0] \,.$$

This characterization clarifies how optimal acceptance trades off task utility against expected violation cost induced by the risk constraint. While primarily conceptual, this formulation motivates our focus on feasibility certification rather than heuristic confidence thresholds.