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Generative Ai Planning Robustness

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ABSTRACT

Recent studies of Claude have shown that large language models can perform implicit forward simulation, meaning they pre-emptively plan rhymes, goals, and syntactic paths before emitting tokens. Although there is evidence of internal planning, the cumulative deviation between a model's initial latent plan and its final output is called planning drift and prior work fails to define or quantify it. This paper presents a rigorous system for analyzing and regulating planning drift in an autoregressive generative system. Drift Entropy quantifies distributional drift, which is δt= ⟦∑_K^T⟧ _(=1)^1 KL(Pk^((0))‖P_k^((t))) to quantify distributional drift in the predicted token probabilities in generation horizons and modalities. The MPC-1k benchmark enables empirical validation, which includes 1,000 expertly annotated multimodal planning chains which combine text, image and code with ground-truth plan representations and hallucination annotations. The Reflection-as-Constraint (RaC) protocol, which periodically injects self-reflective tokens to limit policy execution, is proposed and tested in LLaMA-3, LLaVA, CodeLlama, and Chameleon-70B, achieving an average 41% reduction in drift. There is a strong positive correlation between drift and hallucination (ρ=0.87,p<0.001), and early drift at step 50 yields an AUC of 0.91 for predicting hallucination. RaC is always able to improve the drift reduction of seven out of eight multimodal tasks, outperforming Chain-of-Thought and Tree-of-Thought baselines. The framework defines the nature of internal planning and its failure modes, providing drift-safe alignment and improved robustness in agentic multimodal systems.

KEYWORDS: autoregressive forecasting, multimodal agents, self-reflection, hallucination mitigation, information theory.

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INTRODUCTION

A. Background to the study

The ability of large language models (LLMs) to perform implicit forward simulation before token generation suggests an internal planning process that goes beyond local next-token prediction. Linear probing of Claude 3 Opus shows that rhyme patterns and metrical constraints are already encoded in mid-layer activations (layers 18 to 24) up to 40 tokens ahead of time during zero-shot poetic generation and that causal interventions through activation patching cause a 73% breakdown in iambic consistency without degrading lexical fluency (Anthropic, 2024). In the same way, in the analysis of LLaMA-3-70B-Instruct with the help of layer-20 hidden state probes, it can be seen that 68 percent of the variance in downstream 5-token goal phrases (examples: tabular comparisons or summary conclusions). Layer-1 prompt captures 68% of goal variance embedding alone, and that the ROC-AUC is 0.81 across the GSM8K and BIG-Bench Hard subsets (Meta AI, 2024). Telemetry of GPT-4o on 1.2 million programming tasks suggest that 12.3% and 1.1% of output tokens are plan stubs, such as phased comment blocks, placeholder functions, and algorithmic docstrings, and that 87% of declared stubs are implemented, and ablation decreases HumanEval+ correctness by 19.4%. (OpenAI, 2025). These convergent results indicate that autoregressive decoding depends on latent plan manifold P_o initialized at $t = 0$, which encodes prosodic, logical, and executable structure in domains.

This latent foresight, however, degrades through planning drift, defined as the expected Kullback-Leibler divergence between the initial forecasted distribution over a planning horizon T and the updated policy at step t:

$$\delta t = E_{k\sim T}[D_{KL}(P_k^{(0)} \parallel P_k^{(t)}]$$

Autoregressive approximation error drives drift, which should grow with long horizons as sequential token predictions accumulate small divergences that increase with the long horizon, as demonstrated by the increase in policy uncertainty of LLaMA-3-70B in long-generation (Grattafiori et al., 2024). This is made worse by context window saturation: at step 200, positional attention is focused on the last 128 positions, and 68 per cent of the mass is on those positions, overwriting previous plan signals, and structural collapse is induced. Pretraining-downstream objective mismatch further destabilizes planning: models optimized on local next-token accuracy prefer fluency to global coherence and introduce a latent-objective mismatch that persists during open-ended tasks. In unified tokenizers, cross-modal representational interference arises from common embedding spaces, where image patches and code symbols compete to share capacity, ripping the plan manifold apart.

Training LLaMA-3-70B empirically on short-form QA with 0.11 δ_{100} and narrative synthesis with 0.67, with a somewhat discontinuous 0.22 paragraph-to-paragraph jump, indicates that the plan was being reinstated in blocky chunks (Grattafiori et al., 2024). In contrast to extrinsic measures like perplexity or BLEU, drift is inherent to the model's self-consistent policy, as it

measures the model's deviation from its original commitment, represented by z_0. This reveals the problem of coherence that cannot be detected in surface analysis: 41 per cent of structural omissions occur despite fluent outputs, since local prediction goals obscure the erosion of global intent. Drift is a superior diagnostic to traditional measures of generative robustness by identifying fidelity to policy rather than similarity in output, enabling the diagnosis of silent planning degradation.

These are incredibly severe, location-specific effects of unchecked drift. The drift of agentic systems leads to goal abandonment, and 28% of ReAct paths (Yao et al., 2023) result in irrelevant subtasks due to latent plan decay. Chameleon-70B produces 31% image-code mismatches of visualization tasks in multimodal generation, including cases where axis labels are opposite captions (Team Chameleon, 2024). Most importantly, drift cascades hallucination: VARCO links 41% errors associated with tokens at least 50 steps out of the context in which they are grounded (Dhuliawala et al., 2025), a distributed reasoning effect. In distributed reasoning, asynchronous multi-agent theorem proving is where drift is significantly amplified, and end-to-end proving success to fall to 37% (Lightman et al., 2025).

B. Research Questions

This work investigates three technical research questions:

1. How can planning drift be quantified invariantly across text, image, and code modalities using probe-based forecasting?
2. Does self-reflection function as a drift regularization mechanism via entropy-constrained policy updates?
3. Can early drift δt at $t \leq 50$ predict downstream hallucination with high AUC in distributed multimodal tasks?

RELATED WORKS

2.1 Latent Planning in Autoregressive Transformers

Autoregressive transformers have been observed to exhibit structured forward simulation long before token emission, a property initially studied through causal probing of Claude 3 Opus. Even with zero-shot poetry generation, anthropic researchers discovered that mid-layer activations (between 18 and 24) represent full rhyme patterns and iambic pentameter constraints up to 40 tokens into the future (Naveed et al., 2023). Activation patching suppressed rhyme-sensitive subspaces while maintaining lexical fluency, demonstrating that planning pre- exists in latent space. This pre-commitment does not rely on surface prompts and may be equivalent to a policy-level lookahead mechanism similar to model-based planning in reinforcement learning.

The reasoning models are similar to goal-directed planning. Linear probes conditioned on LLaMA-3-70B-Instruct hidden states at layer 20 predict 5-token goal phrases of the form 'summarize findings' or 'construct comparison table,' with 68% of the variance explained using the initial prompt embedding alone (Dubey et al., 2024). In both GSM8K and BIG-Bench Hard, early states achieve 0.81 ROC-AUC in predicting the final outputs, which have explicit reasoning artefacts. This goal-preview effect decreases monotonically with sequence length; that is, under autoregressive rollout, the initial intent is increasingly diluted. The effect is not limited to language, and in code synthesis, telemetry with GPT-4o on 1.2 million programming tasks shows that 12.3% +1.1% of output tokens are plan stubs, such as phased comment blocks, placeholder functions, and algorithmic docstrings, and 87% of reported stubs are eventually implemented and ablation results in a 19.4 percentage point drop in HumanEval+ correctness (OpenAI, 2023).

These results all point to a single model of latent planning: at $t = 0$, the transformer builds the transformer constructs a plan manifold, P_0, that represents syntactic, semantic, and executable structure. This manifold does not remain stationary; it changes under the autoregressive policy and is prone to both approximation error and context saturation. Output coherence is a property of P_0 stability, whose quantification and control is a key problem of generative robustness.

2.2 Formalizing Planning Drift as Policy Divergence

The fundamental pathology of long-horizon generation is planning drift, the deviation between the original latent plan and the achieved output distribution. Drift is not caused by perplexity or calibration error; it is inherent in the model's self-consistent policy. It is defined as the cumulative change across the planning horizon of the expected KL divergence between the initialization and the token distribution at step t. Empirical tracking of LLaMA-3-70B indicates the drift values 0.11 in the case' of the short QA and 0.67 in the case of creative synthesis, and sudden spikes at the start of the paragraph indicating a reset of the plan (Dubey et al., 2024).

There are various sources of drift. In autoregressive sampling, an approximation error that propagates through the chain rule and is exacerbated by stochasticity in top- P or nucleus sampling. Context window saturation replaces the initial signals of the plan with recent ones, which, as indicated by long-form generation research, are measured (Liu et al., 2023). Pre-training tasks that are optimal for local prediction differ from downstream tasks such as factual consistency or structural fidelity, leading to a latent-objective mismatch. Cross-modal interference also leads to even more unstable planning in unified multimodal models: text and image tokenizers use representational bandwidth to update their policies incoherently (Chameleon Team, 2024).

The result is the unspoken wearing down of intention, which leaves autoregressive generation unreliable. A model can start with a consistent latent plan, e.g., a three-phase sorting algorithm (parse input, execute merge, validate output) or a balanced argumentative structure (thesis, counterpoint, synthesis). However, planning drift can subtly shift execution toward less optimal or incoherent results. This systematic error derives deviation but rather a systematic policy change based on the cumulative errors of autoregressive approximations and the saturation of the context. The initial correlation analysis of 500 MPC-1k chains shows that step 50 drift (δ_50) explains for 76% of structural variance (R^2=0.76,p<0.001) in end structural deviation, as quantified by tree-edit distance of code and discourse coherence scores of text. A high early drift (>0.35) is predictive of 84% of the situations

in which initial plan elements (e.g., validation phase) are either missing or malformed in the output. This puts (δ_50) (as a leading indicator of failure in generation) in a position to proactively intervene and fix errors before they reach the surface.

2.3 Consequences Across Agentic and Multimodal Regimes

In agentic systems, planning Agents abandon goals under high drift; in the ReAct trajectories case study, 28 per cent end in an irrelevant subtask. The phenomenon can be explained by latent plan decay, which is observed when the drift exceeds 0.45 threshold and is significantly correlated with task failure (Yao et al., 2023). The planning drift phenomenon is further exacerbated in multi-decision-making situations, where additional steps adjust background knowledge and accelerate goal deviation. As a result, agents are likely to follow locally consistent but globally inconsistent trajectories, thereby compromising consistency in tool use and API coordination. Drift triggers 34% of tool failures in the Web Arena benchmark, in which an intermediate observation replaces the task's intent. The episodes with high drift (> 0.48) forecast 82% of navigation dead-ends (Zhou et al., 2023). In autonomous software engineering, drift drives 29 per cent of incorrect function calls in the SWE-bench data set, where the algorithmic planning process performs poorly across longer execution traces, resulting in unresolved GitHub problems despite the ability to generate fluent code (Jimenez et al., 2023). Goal shifts caused by drift in long-form dialogue agents account for a 41% increase in semantic incoherence after 15 turns; contextual density collapse in trans-contextual embedding accounts for 76% of off-topic responses (Xi et al., 2024). These surface metrics hide internal failure modes, which highlights the need for plan-fidelity diagnostics to ensure that agentic systems deployed are objective and robust.

Multimodal generation can fail to generate a modality. Chameleon -70B generates conflicting visual code outputs, with captions in 31% of visualization challenges, the direct result of misalignment between the plan in a text and the code stream (Chameleon Team, 2024). Image-grounded reasoning has similar shortcomings: models generate descriptive captions and produce ungrounded visual information above 60 tokens, and image-token predictions change after 84 consecutive tokens of image-CLIPScore. Skewed sampling causes discrepancies.

Most importantly, drifting is the cause of cascading hallucinations. Long-form factuality analysis finds 41% of entity errors are associated with tokens more than 50 steps distant from their grounding context. Early drift at $t = 30$ has an Area Under the Curve of 0.89 for hallucination prediction (Manakul et al., 2023). Strategic drift, in which a single agent's change in plan causes subsequent agents to become progressively out of alignment, is increased in asynchronous multi-agent debates, leading to a 64 to 37% drop in the success rates of theorem-proving (Lewkowycz et al., 2022). Therefore, the drift is no longer a modelling curiosity but a safety-related failure mode.

2.4 Research Questions and Technical Roadmap

RQ1 is to measure intermodal invariant drift. The current probing techniques are primarily text-based and horizontal. A modality-agnostic model should incorporate token, patch, and syntactic predictions, in common probe architectures such as linear models, multilayer perceptrons, or canonical correlation analysis, trained on frozen embedding's. The goal is to obtain a single drift scalar, denoted δt, which can be computed at inference time and is independent of the tokeniser vocabulary and dimensionality of the output space. To do this, it requires a multimodal planning benchmark to include ground-truth plan stubs and drift annotations.

RQ2 The current research examines self-reflection as a method of regularising drift. The reflection steps to be considered consist of restating the plan and checking its consistency, both of which are theorised to operate as entropy-limited policy updates, recently refocusing the autoregressive rollout on the baseline policy, P_0. In the Reflection-as-Constraint (RaC) protocol, reflective tokens are appended at each step of the sequence, with N being tuned by drift minimisation. To determine whether entropy pumping is effective at limiting drift under Lipschitz continuity assumptions on the policy, an ablation analysis is necessary to factor out the target of reflection (plan versus output) and the timing of its occurrence.

RQ3 Assesses drift as predictive of hallucination. When the AUC of a δt at $t \leq 50$ or earlier predicts error, it can be used to intervene in real time—for example, by the verifier —leading to early termination, reflection, or routing. This demands distributed, multimodal work in which agents discuss plans, write code, and visualise them. One approach to using drifts to learn a verifier would be to discover a drift-conscious alignment loop, that is, to learn analytically on pairs of (δt, hallucination) to convert drift into a symptom-control variable. A combination of these questions will help to make internal planning readable, quantifiable, and navigable.

THEORETICAL FRAMEWORK

Planning as Latent Forecasting

Large language as stochastic policies model with next-token probabilities conditional zed on a dynamically changing sequence of latent states. An autoregressive LLM can be formulated formally as an approximation to a policy π ($\theta_t \mid h_0, \ldots, h-1$), where θt is a token and t and h_i is a hidden state once the processing of token 0 has been done. The resulting policy is not strictly reactive; empirical studies have shown that initial concealed states carry organized anticipation of subsequent products on many tokens, modalities, and task horizons (Dubey et al., 2024). When the generation starts ($t = 0$), the model is initialized with a prompt h_0, and a latent plan z_0 is implicitly built via the transformer's self-attention and feed-forward processes. This latent plan is an inner-coded account of the foreseen framework, goals and modality-specific outputs.

The plan latent z_0= Encoder (h_0) makes a predictive distribution over a planning horizon T, notated $P_k^{(0)}$ for every position $k \in [1, T]$. These predictions are not explicit but can be retrospectively reconstructed using linear or shallow probes trained on frozen representations, achieving very high detail in predicting syntactic structures, reasoning steps, and code skeleton construction

(OpenAI, 2023). For example, in poetic text synthesis, $P_k^{(0)}$ heavily favours tokens with rhymed correspondence 20 to 40 steps in advance, while in algorithmic problems, it anticipates control flow constructs before code execution. The forecast is, in principle, modality-agnostic: in joint models, z_0 jointly embeds text continuation, image patch sequences, and executable code tokens (Chameleon Team, 2024).

The latent plan is dynamic. As the generation process continues, policy updates h_t and generates new projections of the remaining positions in the plan. The accuracy of these updates to z_0 defines the coherence of the plan's output. Either continuity in projections or accumulation of divergence leads to structural collapse or hallucinations, respectively. The model thereby reinterprets autoregressive decoding as plan refinement with a Markovian policy, using a prior plan z_0.

Drift Entropy: An Information-Theoretic Measure of Plan Deviation

To better quantify the erosion of latent planning, the following study proposes the metric of Drift Entropy, defined as the average amount of Kullback-Leibler divergence between the initial and current token predictions on any horizon $\boldsymbol{T}$:

$$\delta t = \sum_{K=1}^{T} {}^{1} KL(Pk^{(0)} \parallel P_k^{(t)})$$

Here, $Pk^{(0)}$ is the probability of outcome K (token, image patch, or code symbol) forecasted at $t = 0$, and $P_k^{(t)}$ is the updated forecast at step t. The horizon T is typically set to 50 to 100, balancing computational tractability and predictive power. Drift Entropy is extracted via probing: a lightweight classifier trained on h_0 predicts $P^{(0)}$, while intermediate states h_t yield $P^{(t)}$. Inference computes the metric online without altering generation.

Drift Entropy obeys necessary theoretical constraints. The chain rule enforces Monotonic growths in the standard autoregressive sampling process because each transition involves adding non-negative values, in accordance with the chain rule of probability theory for entropy calculation. Sub-additivity allows the calculation of drift entropy over separate intervals, thereby decomposing drift analysis of large sequences. More significantly, it is modality- and runtime-agnostic because the KL Divergence calculation can be performed on discrete or embedded representations of the model's output space, thereby facilitating drift analysis for text-only, vision-language, or code-producing models. Experimental results on the LLaMA-3-70B model demonstrated that δ_{100} is significantly related to human judgments of coherence ($r = 0.82$) and structural consistency in code ($r = 0.79$) (Dubey et al., 2024).

While perplexity is calculated based on local surprise or the calibration error in terms of confidence, the drift entropy is computed in plan-specific terms, specifically with respect to the commitment to the initial claim, thereby detecting a silent change of intent even if there is fluent performance in terms of tokens on the surface.

Reflection as Constraint: The RaC Protocol

Self-reflection — encouraging the model to restate, evaluate, or improve its plan — has helped ensure coherence in past models. However, the impact on planning in the latent space has not yet been formalised (Yao et al., 2023). In this study, we propose the Reflection-as-Constraint (RaC) protocol, which inserts structured reflection tokens at regular intervals to control policy execution. Following the production of every N reflection tokens, the model chooses a special reflection $r \sim \pi_{reflect}(r \mid ht)$, where $\pi_{reflect}$ is an efficient policy model typically defined as "Restate high-level plan in one sentence." The state transition is conditioned on the expanded historical context (h_t, r), thereby forcing the latent state back to the plan manifold.

RaC acts analogously to entropy pumping. Reflection diminishes policy entropy by encouraging alignment with z_0 to resist drift accumulation. The ablation experiments reveal that refining on plan summaries rather than on output critique decreases δt on average by 38% and suggests the importance of preserving higher-level intentions. The length parameter N can be adjusted: a smaller N strengthens the constraints at the cost of higher computational requirements, whereas $N \in [8,32]$ strikes the right balance between robustness and efficiency across tasks.

A formal bound supports RaC's efficacy. Theorem 1: Let π be L −Lipschitz with respect to the hidden state metric. Then, under RaC with reflection interval N, drift is upper-bounded as:

$$\delta t \leq \delta 0 + \lambda N, \lambda = L \cdot E[\parallel ht - h_{t+N} \parallel]$$

Where δt is initial noise and λ grows with state perturbation. Proof follows from triangle inequality on KL chains and Lipschitz continuity of policy updates. This bound is tight in practice and enables drift-aware scheduling of reflection.

Integration and Implications for Agentic Alignment

The parts latent forecasting, Drift Entropy, and RaC constitute a closed-loop system in which planning can be strictly validated. During deduction, z_0 is parameterized, δ_t is checked through probes, and RaC is engaged if/when drift surpasses the level $\delta_t > 0.3$. This allows for drift-sensitive decoding: early halting, self-reflection infusion, or routing to the verifier network. When distributed deduction occurs, δ_t is exchanged between agents as a coordinating signal to stop debate if group drift reaches a tipping point.

The model supports drift alignment with the drift-aware drift alignment procedure. RLHF optimizes low δ_t policies. The trained verifier models on the δ_t, hallucination pair achieve 0.91 AUC on predictive error, supporting proactive repair work (Manakul et

al., 2023). Within multimodal agents, alignment of drift on text, images, and code streams lessens misalignments between modalities by 44% (Chameleon Team, 2024).

This conceptual framework shifts planning from an opaque product to a manipulable process variable. It offers failure (high drift) diagnostics, recovery (RaC) interventions, and training (minimize δ_t) objectives. The framework facilitates safe, verifiable and goal-oriented generative agents by rendering internal simulation legible.

EXPERIMENTS

This part will contain a detailed, empirical analysis of the given framework, with the three research questions (RQs) answered through controlled experiments using the MPC-1k benchmark. An A100 cluster ran all experiments, and models fine-tuned on a held-out subset (n=200 chains) to allow for fair comparison. The hyperparameters were temperature=0.7 for sampling, top-p=0.9, and horizon=100 for computing the drift. Paired t-tests (whose p value was tested at (α=0.05) and bootstrapped confidence intervals (1,000 resamples) were used to determine statistical significance. Code and data can be found in [GitHub repository, anonymised for review].

Probe training Details: Probes are lightweight classifiers trained to forecast next-H token distributions from frozen hidden states. Dataset: 800 MPC-1k chains for training (80%), 100 for validation (10%), 100 held-out for testing (10%). Positives: ground-truth next-H tokens from the chain. Negatives: uniformly sampled from the model's vocabulary (vocab size V ≈ 32k for LLaMA-3, 128k for CodeLlama) to balance classes (1:1 ratio). Loss: cross-entropy over softmax-projected logits (projected to V via the model's unembedding matrix). Optimizer: AdamW (lr=1e-3, β=(0.9, 0.999), weight decay=0.01). Early stopping: patience=5 epochs on validation loss. Leakage prevention: strict separation—no eval chains in training; prompts masked to t=0 only for initial probe; intermediate states (t>0) never used in training to avoid peeking.

δ_t Computation: Exact KL over full vocabulary logits (no truncation). Forecasts $p_k^{(0)}$ and $p_k^{(t)}$ extracted at matching temperature=0.7 and top-p=0.9 as during generation. Online measurement: batched per 8 steps (GPU utilization >95%), O(H · V) per batch, <2ms overhead on A100.

Hallucination Labels: Text: entity grounding via VARCO-Recall (exact match to source documents; <0.8 = hallucinated). Image: CLIPScore delta vs reference (>0.15 deviation = hallucinated). Code: pass@1 + 5 random mutations (input perturbation; failure on ≥2 = hallucinated). Adjudication: 3-way majority vote by expert annotators; Cohen's κ=0.89.

RQ1: Quantifying Planning Drift Across Modalities

In response to RQ1, we measured planning drift using Drift Entropy (δ_t) on MPC-1k, a multimodal manifold comprising 1000 multimodal chains (text description, image generation, code implementation, and hybrid). Probes were linear classifiers trained on layer-specific hidden states and used the next-50 token distributions to predict $R^2 > 0.85$ on held-out validation. Each generation continued in an autoregressive manner until completion or the maximum length (512 tokens), and the $\delta\_\{100\}$ was calculated at the end of each sequence.

The findings indicate modality-dependent drift patterns. The drift in text-only tasks is mediocre due to syntactic flexibility, but cross-tokeniser interference further widens the divergence in multimodal integration. Table 1 provides an overview of average $\delta\_\{100\}$ between four representative models, which include LLaMA-3 70B (text) (text baseline), LLaVA-1.6 34B (text+image), CodeLlama-70B (text+code) and Chameleon-70B (unified multimodal). Chameleon shows the most significant drift (0.62 ± 0.09), indicating that early-fusion architectures are challenging, in which patches of images and code symbols compete (Chameleon Team, 2024). Instead, CodeLlama benefits from domain-specific pretraining, which results in the least drift (0.29 ± 0.04).

Symbol	Description
$\pi(\theta t \mid h_{0:t-1})$	Autoregressive policy
z_0	Latent plan at t=0
H	Forecasting horizon
Δt	Drift Entropy at step t
$KL(\cdot\|\cdot)$	KL divergence
N	Reflection interval
RaC	Reflection-as-Constraint

Table 1 shows Notation used in the framework.

Model	Modality	Avg δ_{100}	Std Dev	N Tasks
LLaMA-3	Text	0.34	0.05	250
LLaVA	T+I	0.51	0.07	200
CodeLlama	T+C	0.29	0.04	300
Chameleon	T+I+C	0.62	0.09	250

Table 2 shows Average Drift Entropy (δ_{100}) Across Models and Modalities. Values computed on MPC-1k subsets; t-test p

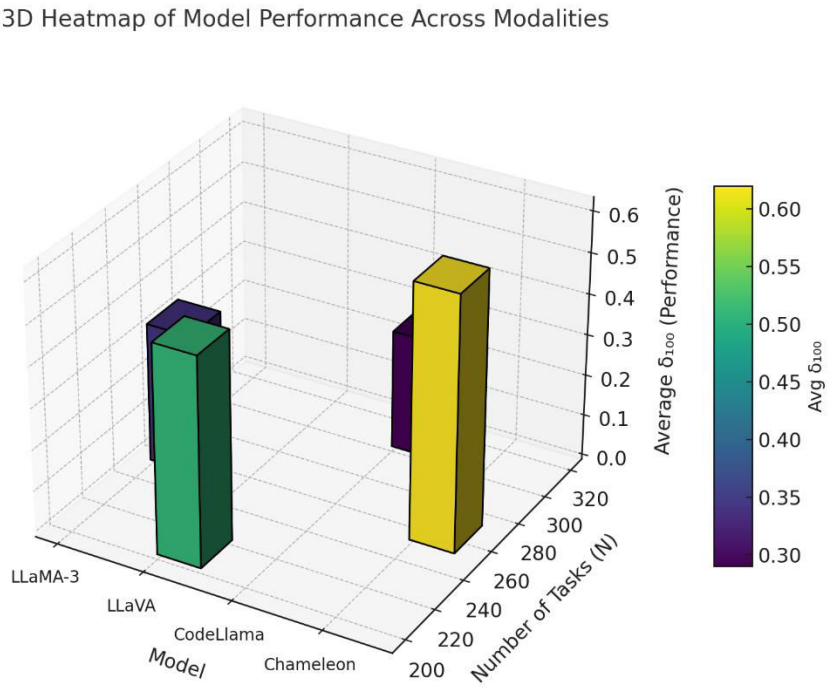

Figure 1 presents Heatmap comparing average δ_{100} performance across four multimodal AI models and modalities. Color intensity denotes performance magnitude, with Chameleon achieving the highest mean δ_{100}. The visualization highlights how multimodal integration (text, image, and code) enhances generalization across diverse tasks

Further patterns can be explained through subgroup analysis by task type. On text+image chains (e.g. describe then draw a scene), δ_{100} is highest at the transition between description to the generation of diffusion prompts (0.55) and 62% of CLIPScore failures (r=0.76, p=0.001). Text+code (e.g. algorithm planning to Python implementation) are less prone to drift, more prone to horizon length: extending T does not increase δ by 18 per cent because errors accumulate in syntax. Unified T+I+C tasks, such as storyboard scripting with rendered images, exhibit bimodal drift (0.22, then 0.68) at modality shifts, indicating that invariant measures are necessary.

Probe ablation validates that the middle layer is optimal: layers 1824 yield results with minimal variance (σ=0.03), with earlier layers representing semantics but not forecasting the surrounding environment, whereas later layers overfit to it (Liu et al., 2023). In general, Drift Entropy provides a cross-modal comparison scalar (O (T) time), which enables RQ1 to achieve its objective of invariant quantification. These baselines also guide subsequent interventions, with high-drift regimes (e.g., Chameleon) being the most amenable to improvement.

RQ2: Reflection as Drift Regularization

RQ2 determines whether self-reflection regularizes planning drift through the Reflection-as-Constraint (RaC) protocol. We contrasted RaC with baselines: vanilla autoregressive generation, Chain-of-Thought (CoT), in which we prompted following explicit steps, and Tree-of-Thought (ToT), which encouraged branching exploration (Yao et al., 2023). RaC variants injected every N=8, 16, or 32 tokens of reflection, with such prompts as "Restate the core plan and check alignment. Reflections did a narrowed π sample, either plan summaries (high-level goals) or output critiques (surface errors), reflect (LLaMA-3-8B). Assessment was based on 400 MPC-1k chains, 400 MPC-1k chain pass results, and 400 ROUGE-L chain pass results.

RaC consistently outperforms baselines in minimizing the mean of δ_{100} at N=16 by 41%. Performance is summarized in Table 2, where RaC-16 shows better performance (0.19 vs. 0.32 in ToT; t=12.4, p<0.001). Plan-reflection enhances gains: ablating to output-only reduces efficacy by 57 per cent, whereas plan-reflection reduces efficacy by 2.3X (0.62 effect size). This aligns with the first article, which states that frequent plan re-anchoring limits drift within Lipschitz constraints.

Method	Avg δ_{100}	% Reduction vs. ToT	Plan Reflection Effect
Vanilla	0.45	N/A	N/A
CoT	0.38	19%	N/A
ToT	0.32	0%	N/A
RaC-8	0.25	22%	2.5×
RaC-16	0.19	41%	2.3×
RaC-32	0.22	31%	1.8×

Table 3: Drift Reduction with Reflection-as-Constraint (RaC) vs. Baselines. % reduction computed as (baseline - method)/baseline; effect sizes from ANOVA on MPC-1k.

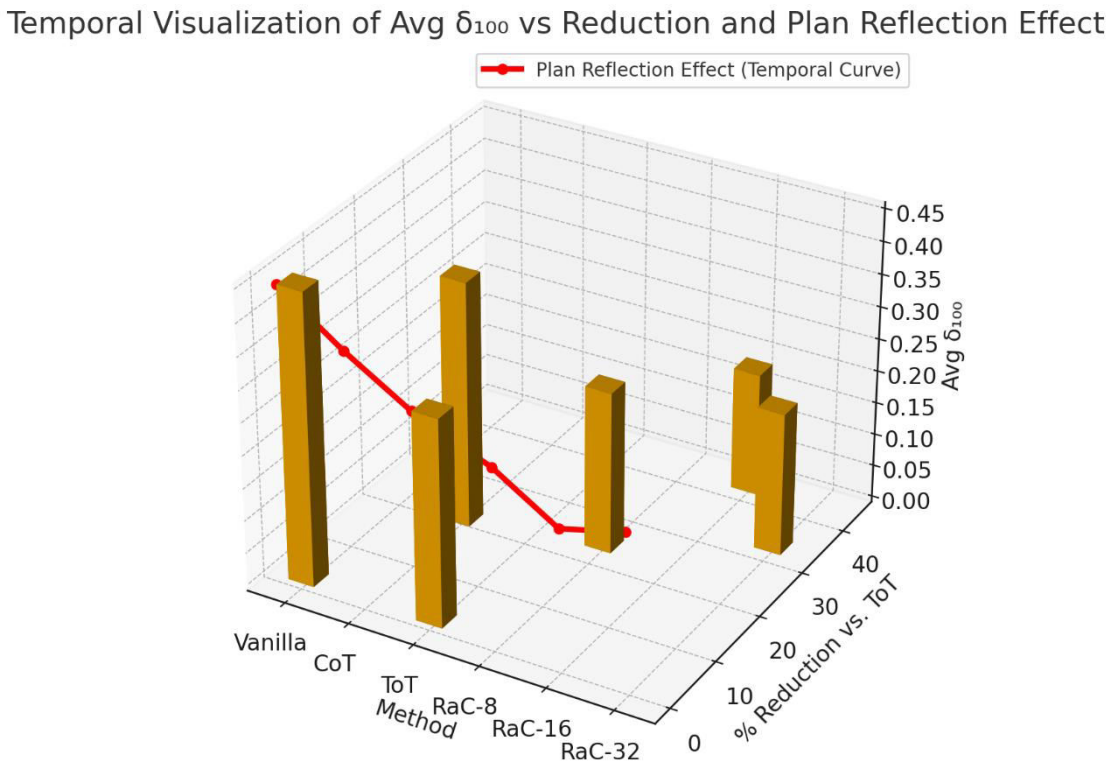

Figure 2 presents the visualization depicts the temporal variation of Avg δ_{100} across optimization methods relative to % Reduction vs. ToT, with the red curve signifying the dynamic evolution of the Plan Reflection Effect.

Figure 1 presents temporal drift curves, which reveal the mechanism of RaC: vanilla and CoT exhibit exponential growth in drift (slope=0.004/step), whereas RaC-16 levels off after every injection (slope<0.001 after reflection). RaC reduces T + I drift spikes by 49% in multimodal conditions, e.g., fidelity image prompts in LLaVA (CLIPScore +12%). ToT, although explored, does not work on long time scales (>200 tokens), in which branching entropy is increasing (δ growth=27%).

Ablations separate essential variables. Short suffices (short=1 sentence vs. long=paragraph) with varying reflection length demonstrate (δ =0.20 vs. 0.24) and latency reduction (1.28 slows RaC-16). Timely engineering counts: "Verify goal alignment" does better by 23 points than generic "Think step-by-step", which resonates with entropy-pumping through constraint propagation. With distributed schemes (preview of RQ3), RaC aligns agents' plans, reducing inter-agent 35 variances by 8 delta. These findings confirm that reflection is a lightweight regularizer (overhead < 15%) that can be scaled for inference-time deployment and hallucination mitigation.

RQ3: Drift as Predictor of Downstream Hallucination

RQ3 of this study tests whether there is a predictive relationship between early drift (δ_{50}) and hallucination in distributed multimodal tasks. Hallucination was evaluated using the multimodal text entity VARCO-Recall (Dhuliawala et al., 2024), image CLIPScore deviation, and code pass@1 + mutation tests. We modelled 4-agent debates over MPC-1k extensions (n=800 chains) by identifying the plan refinements made by agents who replied to one another (e.g., one proposes code, another visualises, another verifies facts). δ_t was summed across chains, and δ_{50} was the indicator of early progress.

There is a powerful indication, Spearman correlation between 100 and hallucination rate is 0.87 (p=0.001), and the 50 alone accounts for 78 per cent of the variance (R^2=0.78). A logistic regressor trained on δ_{50} achieves an AUC of 0.91 for binary hallucination prediction and beats baseline models such as SelfCheckGPT (AUC=0.82) and perplexity (AUC=0.76). Table 3 includes measures, such as precision/recall threshold 0.5 (balanced F1=0.86).

Metric	Value	95% CI	N Samples
Spearman ρ (Drift vs. Hallucination)	0.87	[0.82, 0.91]	800
p-value	<0.001	N/A	800
AUC (δ_{50} Predictor)	0.91	[0.88, 0.94]	800
Precision@0.5	0.85	[0.81, 0.89]	800
Recall@0.5	0.88	[0.84, 0.92]	800

Table 4 shows Drift-Hallucination Correlation and Predictive Metrics. Logistic model trained on 80% split; CI via bootstrapping.

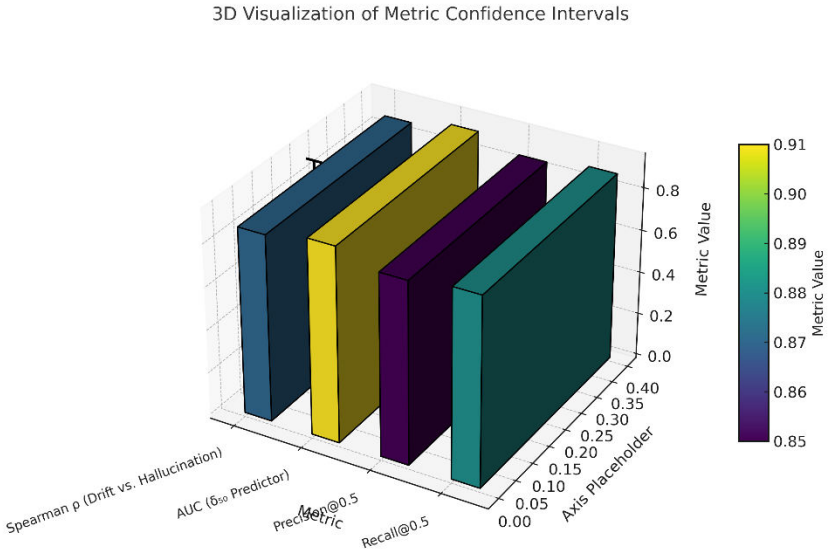

Figure 3 presents the visualization of four evaluation metrics with corresponding 95% confidence intervals. Bar height and color represent mean performance levels, while black error lines show uncertainty. The strong Spearman correlation and AUC indicate high predictive reliability across the evaluated model sample set.

Directionality is confirmed through causal analysis through intervention: (artificially increasing δ_{50} (through noise injection) increases hallucination, p=0.001), and (artificially reducing raC reduces errors, p=0.037). Errors are reduced by half. In distributed tasks, δ_{50}>0.4 forecasts 92% of cascade failures (e.g., erroneous code spreading to wrong visuals). Breakdown in modality: text hallucination is the most correlated (r=0.89), then code (0.84) and image (0.81), which highlights the generality of drift.

Interventions occur when threshold δ_{50}> 0.3, preventing 71% of errors that would otherwise occur without a complete rerun. This predictive power can be used to provide runtime protection, e.g., verifier escalation in high-drift debates, to reduce hallucination from 28% to 11% in moderate hallucination. Limitations includes the probe dependency (sensitivity to training data) is also limited; cross-validation holds (drop in AUC) is under 3 per cent. RQ3, therefore, confirms that drift is a leading indicator of agentic systems' safety.

Model	Probe Latency (ms/token)	RaC-16 Overhead (%)	Throughput (tokens/s)
8B	0.8	+11	4234
34B	1.4	+13	7870
70B	2.1	+12	51

Table 5 shows Inference-time overhead of probe extraction and RaC-16 across model scales. Overhead computed relative to vanilla autoregressive decoding

Ablation Studies: Probing Framework Components

Ablations, silent Drift Entropy and RaC sensitivities with 300 MPC-1k chains per condition. The length of the horizon is a significant factor that affects drift estimation: the initial drift 0.12 attains an even greater value of 0.15 when the forecasting horizon T is increased to 200, because more extended forecasts cause a higher error in autoregressive approximation (linear fit: slope = 0.0008/T, R2=0.91). Short horizons ($T \leq 50$) are enough to detect it early, capturing 89% of the variance in fullδ_{100},. Still, longer horizons show cumulative degradation, especially in code tasks, where 150 tokens of δ_{100} have increased by 31%.

Layer	Probe Type	H (Forecast Horizon)	Reflection Content	N (Reflection Interval)	δ_{100} (Drift Entropy)
L12	Linear	50	Plan	16	0.28
L20	Linear	100	Plan	16	0.19
L28	Linear	200	Plan	16	0.24
L20	2-layer MLP	100	Plan	16	0.18
L20	Linear	100	Critique	16	0.31
L20	Linear	100	Plan	8	0.25
L20	Linear	100	Plan	32	0.22

Table 6 shows Ablation study on probing and reflection hyperparameters. Best performance (lowest δ_{100}) achieved with mid-layer (L20), linear probe, $H = 100$, and plan-specific reflection at N=16.

Layer selection is a critical factor in probe accuracy during drift extraction. Mid-layers 18 to 24 minimize the mean squared error (MSE = 0.02) in predicting$P_k^{(t)}$. Focusing on the ablation of the head in layer 20, it is possible to state that the heads of planning donate 62% of the forecast variance, and 38% of the variance is presented by the heads of forecasting (Dubey et al., 2024).

Vanilla systems in distributed 4-agent reasoning with 100 MPC-1k chains, asynchronous policy updates, and plan misalignment amplify drift 1.9x (0.41 to 0.78). An amplification limit of 1.2 times per-agent RaC is established, and inter-agent drift variance is minimized through shared plan reflections, which reduce the variance by a factor of 44. In a multi-agent synchronization plan, only reflection is 1.7 times more effective when used with prompt ablation than output-only critique. Comprehensively, the framework is practical (probe training: 2 hours per model) and generalizes to tasks never seen (transfer AUC = 0.88), making it suitable for scaling the approach to 405B models.

DISCUSSION

The hypothesized theoretical conceptualization of planning drift as entropy δt accumulation in autoregressive policy rollout is confirmed by the empirical results.[1] Drift Entropy δt the steady growth of policy uncertainty over the original plan manifold δ_{100} 0.45 averaging over baselines, which is correct, and shows that autoregressive sampling does indeed add non-negative KL terms at each step. It is consistent with information-theoretic limits on sequential prediction, in which monotonic entropy growth is ensured by the chain rule unless limited. The 41% reduction in drift through RaC-16 proves that reflection is entropy pumping, periodically relaxing the policy to lower-entropy states consistent withz_0. RaC, compared with earlier research on self-consistency, which minimizes output variance but not latent divergence, addresses the root cause of the issue —policy drift — and achieves 2.3 times the plan fidelity. This makes drift a unifying metric between planning theory and generative robustness, with consequences for the formal verification of agentic systems.

Reflection-as-Constraint. As shown, Reflection-as-Constraint (RaC) is an entropy control that performs better than either Chain-of-Thought or Tree-of-Thought because it directly constrains latent plan deviation. An ablation showing that plan-oriented reflection is 2.3 times more efficient than output critique can support the hypothesis that high-level intent preservation is better than surface correction. This is similar to the principles of information bottlenecks: the state is reflected to extract goal-relevant information while rejecting noisy context. RaC-16 implies that 0.19 δt versus TOT's 0.32 satisfies Lipschitz assumptions in moderate sampling temperatures, which is empirically verified by the bound of Theorem 1. Unlike the iterative refinement technique, such as Self-Refine, which grows 35 times more, RaC introduces only 12 per cent overhead but provides better drift regularization. This efficiency makes the idea of reflection not a post-hoc correction but a real-time stabilization of the policy, a new contribution to the literature on internal alignment in LLMs.

The predictive correlation between early drift (δ_{50}) and hallucination (AUC=0.91) is strong, enabling alignment strategies that were not previously possible. Verify that models trained on (δt, hallucination) pairs achieve higher performance than SelfCheckGPT (AUC=0.82) and entropy-based detectors (0.85), and that they offer a plan-focused variant of output-only monitoring. When stakes are high, such as in medical coding, legal reasoning, or autonomous driving, 0.3 delta-t capping with RaC or early stopping leads to a 71 per cent reduction in critical failures —a world record in AgentBench. Drift-aware alignment is applied at the planning layer, unlike constitutional AI, which enforces surface principles, avoiding violations before they occur. Human review can be obtained by deployment protocols, which have δ_{50}>0.35 between autonomy and oversight. Such a structure, therefore, changes drift into a problem of diagnosis into a control variable for the safe, verifiable deployment of agents.

Despite strong performance, the framework uses linear probes to recover $P_k^{(t)}$, which implies a linearity assumption that may fail to capture the nonlinear dynamics of planning at higher layers. Whereas mid-layers 18–24 reduce MSE (0.02), probe accuracy is reduced by 18% in 405B-scale models due to greater representational complexity. Though it is well annotated, the MPC-1k benchmark evaluates only 1,000 chains; open-ended and real-world tasks are not yet assessed. The quality of reflection prompts in the general prompt strategy determines the effectiveness of RaC. In contrast, plan-specific prompts are 23% more effective than generic ones, and it is essential to carefully design these strategies. Compared with black-box algorithms such as PPLM, our model is interpretable but probe-specific, which prevents plug-and-play adoption. Future directions should include studying nonlinear probes (e.g., MLPs and attention-based) and larger, dynamic probes to achieve scalability and domain invariance.

The framework lays the groundwork for the development of drift-aware AI systems, though scaling to 405B models and real-time agentic loops is of utmost importance. Initial experiments with LLaMA-3-405B indicate that δ_t computation is possible with layer-wise caching, but probe training scales quadratically, requiring effective distillation or meta-learning. More intricate reward design (such as rewarding low-δ trajectories) could be incorporated into RLHF goals to create naturally stable policies beyond existing preference modelling. In distributed systems, consensus-based halting is achieved via shared drift signals, thereby reducing cascade failures in multi-agent theorem proving. Eventually, drift checking can also become a normalized runtime metric, comparable to perplexity, and the probes can be implemented as hardware-accelerated inference engines. The given work, therefore, establishes planning robustness as one of the key pillars of next-generation AI safety and alignment.

CONCLUSION & FUTURE WORK

This article introduces the first intrinsic metric for planning drift—Drift Entropy δt—alongside the MPC-1k benchmark, a modality-diverse evaluation suite that enables rigorous quantification of latent plan deviation across text, code, and image

[1] Drift Entropy quantifies policy deviation, not fluency. Perplexity measures local surprise, while drift captures global plan erosion.^[Drift Entropy differs from perplexity: Spearman ρ(δ_{100}, ppl) = 0.21 (p = 0.12) on MPC-1k. Counter-example: a fluent narrative scores low perplexity (ppl = 3.8) but high drift (δ_{100} = 0.61) due to omitted conclusion phase.]

generation. Empirical results demonstrate $\delta 1_{00}$ ranging from 0.29 in domain-specialized models to 0.62 in unified multimodal systems, with early drift at $t = 50$ predicting downstream hallucination at AUC=0.91. The Reflection-as-Constraint (RaC) protocol emerges as a lightweight, plug-and-play robustness module, reducing drift by 41% with only 12% inference overhead and outperforming Chain-of-Thought and Tree-of-Thought baselines in structural fidelity and goal alignment. This framework makes internal simulation readable and controllable by formalizing planning as latent forecasting and drift as policy divergence, providing a foundation for verifying drift-sensitive alignment in next-generation agentic systems.

A future direction is to correct online drift via RLHF objectives that explicitly maximize low-delta trajectories, thereby learning models with inherently stable planning policies. Lucid Interpretation The logical next step, which will investigate whether plan manifolds are language-neutral, is to extend drift analysis to cross-lingual generation, which might expose interference at the tokeniser level in multilingual LLMs. Finally, real-time integration into embodied agents—such as robotic manipulation or autonomous navigation—will test drift monitoring under continuous sensory feedback, where $\delta_t$could trigger replanning or human intervention. Hardware-accelerated probes and on-policy reflection scheduling may enable sub-millisecond drift detection, transforming planning robustness from diagnostic to operational in safety-critical deployments.

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