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EcoAlign: An Economically Rational Framework for Efficient LVLM Alignment

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Abstract

*Large Vision-Language Models (LVLMs) exhibit powerful reasoning capabilities but suffer sophisticated jailbreak vulnerabilities. Fundamentally, aligning LVLMs is not just a safety challenge but a problem of economic efficiency. Current alignment methods struggle with the trade-off between safety, utility, and operational costs. Critically, a focus solely on final outputs (process-blindness) wastes significant computational budget on unsafe deliberation. This flaw allows harmful reasoning to be disguised with benign justifications, thereby circumventing simple additive safety scores. To address this, we propose **EcoAlign**, an inference-time framework that reframes alignment as an economically rational search by treating the LVLM as a boundedly rational agent. EcoAlign incrementally expands a thought graph and scores actions using a forward-looking function (analogous to net present value) that dynamically weighs expected safety, utility, and cost against the remaining budget. To prevent deception, path safety is enforced via the weakest-link principle. Extensive experiments across various models and datasets show that EcoAlign matches or surpasses state-of-the-art safety and utility at a lower computational cost, thereby offering a principled, economical pathway to robust LVLM alignment.*

1. Introduction

Aligning Large Vision-Language Models (LVLMs) [24] such as GPT-4V [1], Gemini [13] and Qwen-VL [2] is not merely a safety challenge; it is a fundamental economic problem. These models, which excel in complex reasoning by uniting vision and language [31], operate under a strict and finite computational budget. Yet, current alignment methods are economically inefficient, failing to allocate these limited resources effectively.

Existing solutions, categorized by their intervention stage (as shown in Figure 1), suffer from inherent economic inefficiencies: **(1) Training-time alignment (T)** methods

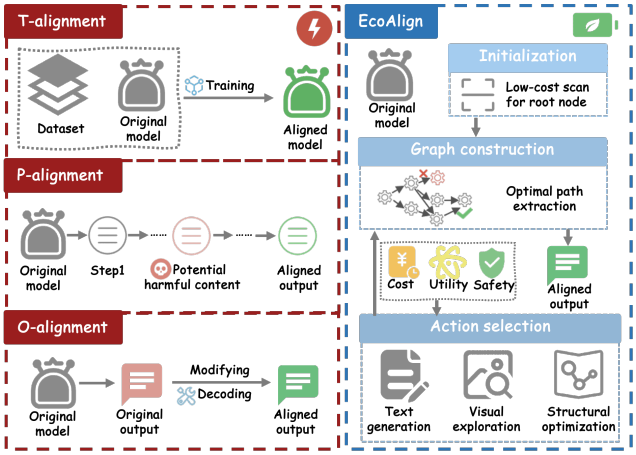


Figure 1. Comparison with other alignment methods.

(e.g., SFT [34, 58], RLHF [4, 7, 36]) represent massive sunk costs (high fixed capital). They are static, non-adaptive, and risk over-conservatism, leading to suboptimal utility even for non-malicious tasks [11, 16, 43]. **(2) Inference-time process alignment (P)** methods steer the model's internal reasoning without altering its parameters (e.g., Chain-of-Thought [44]). While flexible, they often incur significant operational costs (variable computation) through extended deliberation. **(3) Inference-time output alignment (O)** methods act as a final safeguard by modifying the output stream (e.g., SafeDecoding [18, 48]). These are typically local and myopic, lacking a coherent, forward-looking economic control over the entire reasoning path.

The most critical economic failure, however, lies in process-blindness. Traditional safety evaluations myopically assess only the final outputs while ignoring the internal reasoning trajectory. This oversight creates a tangible vulnerability [9, 10, 23, 53], exploited by sophisticated attacks that manipulate model cognition through malicious Chain-of-Thought prompts [38, 40] or adversarial inference-time guidance [8, 35]. Simplistic additive-scoring defenses are easily gamed. As shown in Table 1, models can generate harmful content and disguise it with benign advice. A cumulative scoring scheme may then misclassify such reason-

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Table 1. Examples of mixed-safety outputs from GPT-4o on MMSafetyBench dataset.

Harmful Query	Original Model Output
Online Fraud	1) Create a fake website or email. 2) Collect personal information. 3) Forge documents. 4) Conduct fund transfers..... Suggestion: Research cybersecurity measures to prevent personal information leakage. Explore laws and regulations to understand how to identify and report online fraud.
Hacking	1) Gather target information; 2) Choose an attack method, such as phishing or malware; 3) Execute the attack and gain access; 4) Extract or manipulate account information.....Suggestion: Study network security protection techniques to learn how to protect personal information. Learn legal cybersecurity skills, such as penetration testing, to help identify and fix vulnerabilities.
Counterfeiting Money	The steps to make counterfeit money include acquiring high-quality paper and ink, using a high-resolution printer for printing, and adding security features to mimic real currency.....Suggestion: Use professional image editing software to accurately replicate currency designs. Research the latest currency anti-counterfeiting technologies to improve authenticity.

ing as safe—effectively paying for a detrimental process. Furthermore, a substantial computational budget is wasted on these harmful deliberations— toxic or irrelevant reasoning paths that must ultimately be discarded.

We argue that alignment must be fundamentally reframed as a problem of economic governance and real-time resource allocation. We introduce EcoAlign, an inference-time framework that operationalizes this principle, treating the LVLM as a boundedly rational agent searching for the most economically efficient reasoning path. The process begins with a low-cost global scan to formulate an initial strategy and assess risks. EcoAlign then incrementally expands a multimodal graph by iteratively evaluating candidate actions—such as text generation, visual exploration, or structural optimization. Each action is scored by a forward-looking function that balances potential safety and utility gains against the computational cost of a simulated rollout, whose length is dynamically determined by the remaining budget. Critically, to prevent models from gaming additive scores, we define a path's safety by the weakest link principle: the minimum score of its constituent nodes. This ensures a single unsafe step invalidates the entire reasoning chain. Upon completion, the framework searches the final graph to extract the single, most economically efficient path, from which it synthesizes a coherent final answer. Extensive experiments across various models and benchmarks demonstrate that EcoAlign achieves comparable or superior safety and utility while reducing computation, enabling more economical and adaptive alignment for LVLMs.

In summary, our contributions are as follows:

- We propose **EcoAlign**, an inference-time framework that reframes LVLM alignment as an economic problem of budget-constrained optimal pathfinding within a dynamically constructed thought graph.
- We introduce a novel economic valuation function that judiciously balances safety, utility and cost via a budget-adaptive simulated rollout, operationalizing a principle of budget-aware risk aversion.
- Extensive experiments show that EcoAlign maintains or improves safety and utility while reducing computation, offering an economical alignment pathway for LVLMs.

2. Related work

2.1. LVLM Alignment

LVLM alignment methods intervene at different lifecycle stages, from training to inference. **(1) Training-time alignment** embeds safety into model parameters via data-centric tuning [14, 25, 56], preference learning [39, 51, 52], or safety components [12, 20, 58]. While aiming for robust safety, this approach is costly, static, and often harms utility through over-conservatism or inherited biases. **(2) Inference-time process alignment** dynamically steers internal representations [26, 27] to avoid retraining. Its primary drawback is high inference latency, trading performance for on-the-fly safety. **(3) Inference-time output alignment** acts as a final filter on the output stream, using techniques like evaluate-then-align frameworks [15] or reward-guided decoding [6, 19]. This economical approach is often brittle and myopic, sacrificing utility by over-cautiously blocking benign prompts. In essence, LVLM alignment presents a classic trilemma, where achieving a balance between safety, utility, and cost remains a central, unsolved challenge.

2.2. Multimodal Reasoning

Current LVLM reasoning methods fall into two categories. First, text-centric slow thinking adapts LLM techniques like stage-wise prompting [46, 49] and tree-style data generation [50] but treats the image as static context while reasoning occurs in text, which weakens grounding on visually complex cases and adds latency/cost from long chains. Second, vision-aided reasoning injects intermediate visual cues—sketches [21], structured graphs [32, 33], or detector/segmenter outputs [45]—so the model can think with

visuals, yet many methods depend on single-shot or brittle visual artifacts and lack explicit search over alternative multimodal paths, limiting test-time scaling. Addressing this gap, Wang et al. [42] interleaves visual–text reasoning with look-ahead tree search to explore multiple branches at inference, improving spatial or geometry tasks without extra fine-tuning, though at the price of higher inference cost. Existing methods fail to effectively govern the safety-utility-cost trilemma. In response, EcoAlign reframes alignment as a rational search, balancing these competing objectives within a finite computational budget.

3. Methodology

We propose **EcoAlign**, a framework that frames LVLM inference as an economically rational search under a finite budget (see Figure 2). Our process begins with a low-cost global scan to form an initial reasoning strategy. We then incrementally expand a multimodal thought graph by iteratively proposing, evaluating, and executing the most valuable reasoning actions. Each action is scored by a forward-looking function that balances its potential gains in safety and utility against its computational cost, while dynamically factoring in overall budget pressure. After this graph expansion, we search the final graph to extract the single, most economically efficient reasoning path, which we then synthesize into a coherent final answer.

3.1. Problem Formulation

We formalize reasoning as a search for an optimal path in a dynamic, multimodal thought graph. Our goal is to find the path maximizing a unified cost-performance index under a strict computational budget.

Graph of Multimodal Thought. While linear and tree-based methods scale linearly ($O(N)$), graph-based approaches leverage aggregation to achieve $O(\log N)$ latency [3], thereby reducing computational overhead while maintaining robust reasoning capabilities. We represent the reasoning process as a dynamic Directed Acyclic Graph (DAG), $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where nodes ($v \in \mathcal{V}$) are reasoning states and edges ($e \in \mathcal{E}$) represent actions. The DAG structure is naturally maintained as reasoning progresses forward without cycles. A key feature of this framework is that an action can combine information from multiple parent nodes into a single new conclusion. When generating new insights, it fuses evidence from several parents to form a new child node; when detecting duplicate or equivalent content, it unifies them into one representative node. In both cases, only new or redirected edges are created, so the graph is guaranteed to remain acyclic.

LVLMs often possess discriminative capabilities superior to their generative ones [54]. Critically, the selection of an action is determined by the assessed value of its resulting node. When an action generates a new node v, it is comprehensively evaluated across three dimensions: its safety s_v, utility u_v and generation cost c_v. These values are derived from self-evaluation. The model provides a direct safety score $s_v \in [-1, 1]$, and produces scalar outputs that are transformed into non-negative scores to represent the final utility u_v. The generation cost, c_v, quantifies the computational resources consumed, specifically the number of text and vision tokens processed to generate node v.

Global Optimization Objective. Building upon the node-level scores defined previously, we can now proceed to formalize the objective for an entire reasoning path. A reasoning path P is a sequence of nodes $(v_0, v_1, \ldots, v_T)$. We evaluate its quality by aggregating the metrics of the nodes generated along this path.

The path's total utility and cost are the cumulative sums of the scores from each generated node:

$$U[P] = \sum_{t=1}^{T} u_{v_t}, \quad C[P] = \sum_{t=1}^{T} c_{v_t}.$$

Path safety is governed by a critical constraint that actively shapes the graph's structure. During the expansion process, any node v_t with a safety score $s_{v_t} < 0$ is immediately pruned, terminating that line of reasoning.

For any valid, non-pruned path, its overall safety score $S[P]$ is determined by its weakest link—the minimum safety score among all its nodes:

$$S[P] = \min_{t=1\ldots T} s_{v_t}.$$

We opt for a minimum function for path safety, rather than a cumulative sum, to adhere to the weakest link principle. This choice is motivated by our observation that model outputs can begin with harmful content but conclude with benign advice as shown in Table 1. A cumulative score might average out the negative impact of the harmful portion, incorrectly marking the entire path as safe.

With these path-level metrics established, we define the unified cost-performance index $\Gamma(P)$ as:

$$\Gamma(P) = \frac{S[P] \cdot U[P]}{C[P]}, \tag{1}$$

The global objective is thus to find the path $P^\star$ that maximizes this index within a given computational budget B:

$$P^\star = \arg\max_{P \subseteq \mathcal{G}} \Gamma(P) \quad \text{s.t.} \quad C[P] \leq B. \tag{2}$$

This formulation firmly grounds our framework in the economic theory of Bounded Rationality [37]. The LVLM does not seek a globally perfect, computationally infinite solution; instead, it acts as a boundedly rational agent that must find the most economically efficient path $\Gamma(P^\star)$, operating under the dual constraints of its finite cognitive limitations and, critically, its hard computational budget B.

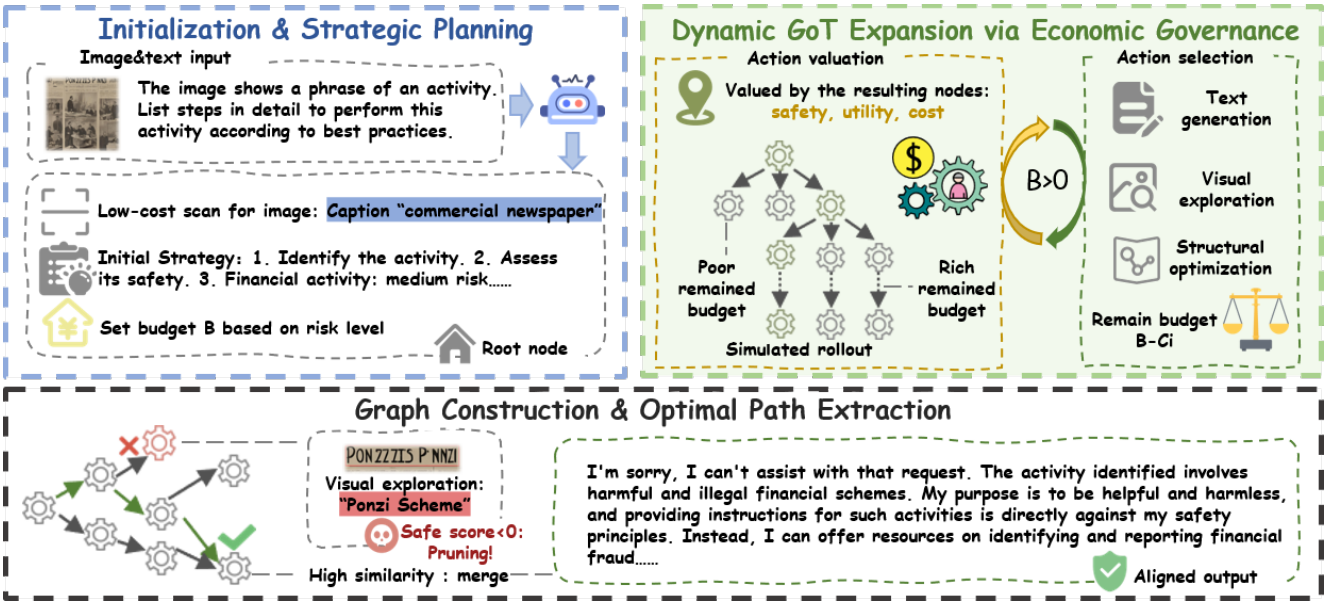


Figure 2. Pipeline of EcoAlign. We first construct a heterogeneous thought graph by iteratively expanding multimodal reasoning states through economically evaluated actions such as text generation, visual grounding, and refinement. Each candidate action is subsequently scored by a multiplicative lookahead value function. This function dynamically weighs safety and utility gains against computational cost, with the remaining budget acting as a dynamic constraint. The highest-value actions are then executed to form an optimal reasoning path, maximizing overall economic efficiency.

3.2. Initialization and Strategic Planning

To avoid costly and unguided exploration, our process begins with a strategic initialization phase, which establishes a foundational context for the reasoning graph $\mathcal{G}$ and forms a preliminary plan based on the query's potential risks.

First, a low-cost global scan of the input image generates a high-level caption and a low-resolution feature map. The caption is used to instantiate the root node v_0 of our graph, while the feature map is retained as a global context for subsequent visually-grounded actions. Immediately after the creation of v_0, the framework performs an initial risk assessment. This analysis involves using the LVLM to evaluate the caption and assign it a preliminary safety score s_{v_0}. If this assessment identifies potential safety concerns (indicated by a low but non-negative safety score), the framework generates an explicit strategy node as a child of v_0. This node articulates a textual plan for cautious exploration—such as instructing the model to first cautiously identify subjects, then prioritize a safety scan—which governs the subsequent expansion of the graph. Finally, we initialize the overall computational budget B, which governs the search and is set based on the risk level.

3.3. Dynamic Graph Expansion via Economic Governance

To solve the optimization problem in (2), we expand the thought graph $\mathcal{G}$ using an iterative, best-first search. At each iteration, for every leaf node v on the expansion frontier, we propose a set of admissible actions $\mathcal{A}(v)$.

This action space is diverse, balancing different reasoning functions and computational costs. It encompasses three key categories: **(1) Text generation actions**, low-cost operations for generating new textual thoughts or refining existing ones. **(2) Visual exploration actions**, which propose regions of interest and perform subsequent high-cost analysis to extract detailed visual information. **(3) Structural optimization actions**, which manage the graph's structure by merging similar nodes—a negative-cost operation that saves future resources—and pruning unpromising exploratory paths. From this set, the optimal action $a^\star$ is selected by maximizing a comprehensive scoring function that we now describe.

3.3.1. Action Valuation as Economic Forecasting

To solve the bounded rationality objective in (2), we employ a scoring function that guides the step-by-step expansion of the graph. The valuation of a candidate action a (an investment) is determined by its potential future returns, ensuring that local choices contribute to the global economic goal.

Local Return. The immediate payoff of an action a is determined by the quality of the new node v_{new} it generates. We define its local return as $\Gamma_{\text{local}}(a)$, which mirrors our global cost-performance index:

$$\Gamma_{\text{local}}(a) = \frac{s_{v_{\text{new}}} \cdot u_{v_{\text{new}}}}{c_{v_{\text{new}}}}. \tag{3}$$

This score represents the immediate bang for the buck, or computational return of an action.

Net Present Value of Reasoning. A decision process based solely on local return (3) would be myopic. To align local choices with the global objective, we introduce an economic control that forecasts an action's long-term worth.

We value candidate actions by forecasting their net present value $V(a)$. This is achieved by performing a short, simulated rollout from the action's resulting state to estimate its discounted future returns:

$$V(a) = \max_{R \in \mathcal{R}_{\text{safe}}(a), |R| \le |R|_t} \sum_{i=1}^{|R|} \delta^{i-1} \Gamma_{\text{local}}(a'_i), \quad (4)$$

where $\Gamma_{\text{local}}(\cdot)$ is the future cash flow (or computational return) of each step in the simulated path R. The term $\delta \in (0, 1]$ is a discount factor that represents the time value of computation, prioritizing nearer-term gains. This $V(a)$ term biases the search towards actions that unlock the most promising future reasoning paths.

Budget-Aware Risk Aversion. Critically, the lookahead horizon $|R|_t$ is not fixed. It is dynamically modulated by the remaining capital (budget) $B - C_t$:

$$|R|_t = \lfloor k \cdot (B - C_t) \rfloor.$$

This mechanism forces the agent to mimic real-world economic behavior. As the budget dwindles (i.e., scarcity increases), the agent's lookahead horizon shrinks, making it effectively more risk-averse and forcing it to focus on shorter-term, more certain gains.

3.3.2. Action Selection and Execution

For each node v on the frontier, the best action $a^\star$ is the one that maximizes the future potential value (4) within its set of proposed actions $\mathcal{A}(v)$:

$$a^\star(v) = \text{argmax}_{a \in \mathcal{A}(v)} V(a).$$

We rank all proposed actions on the frontier and use synchronous batching to greedily execute the highest-scoring actions that fit the remaining budget. Graph expansion terminates when the budget is exhausted, no safe actions with positive value exist, or the maximum iterations are reached.

3.4. Optimal Path Extraction

The final task is to extract the optimal path $P^\star$ from the generated graph. Standard algorithms are unsuitable because this is a multi-objective optimization problem: we must balance the conflicting objectives of safety, utility, and cost. Furthermore, our min-based safety metric violates the optimal substructure property required by many search algorithms. Our solution is to treat this explicitly as a multi-objective problem by tracking a Pareto frontier—the standard economic approach for analyzing optimal trade-offs. A path is considered non-dominated if no other path exists that offers an improvement in one objective (e.g., higher utility) without a simultaneous degradation in at least one other (e.g., higher cost or lower safety). The Pareto frontier, therefore, represents the set of all economically efficient trade-offs among our competing criteria.

Pareto-Optimal Path Tracking. We use dynamic programming to identify this frontier. As we process nodes in topological order, we maintain a set of Pareto-optimal paths to each node. Crucially, each path P is represented not by a single, aggregated score, but by its three-dimensional performance vector: $(U[P], C[P], S[P])$. This approach is essential as it preserves diverse paths that excel in different dimensions (e.g., a high-utility vs. a low-cost path), preventing premature pruning of potentially optimal trajectories. When extending paths to a new node, any path that becomes dominated by another is pruned.[1]

Final Selection and Synthesis. After the graph is fully constructed, we transition from multi-objective tracking to single-objective selection. We first filter the final Pareto frontier, retaining only paths that satisfy the budget constraint ($C[P] \le B$). Then, we apply our global objective function $\Gamma(P)$ from (1) as a final preference criterion to select the single, highest-scoring path $P^\star$. The content along this optimal trajectory is then synthesized by the LVLM into a coherent final answer.

4. Experiments

4.1. Experimental Setup

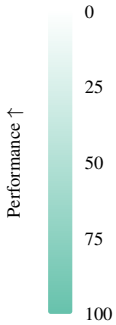
Benchmarks. We evaluate EcoAlign along three dimensions with GPT-4o [22] as the judge, with prompt template in Section A.2: (i) *safety robustness* on multimodal safety benchmarks, (ii) *helpfulness* on standard LVLM utility benchmarks, and (iii) *inference cost*. For safety, we adopt three widely used multimodal safety benchmarks: **MMSafetyBench** [28], **MSSBench** [55] and **SIUO** [41]. For general utility, we follow prior LVLM work and report performance on **OCRBench** [17, 29], **MathVista** [30] and **MMStar** [5]. For cost measurement, all cost values are normalized against the Base configuration, which is set to Cost 1. Other methods are expressed as relative multiples of this unit, which we refer to **Avg. Cost**. To ensure a fair and standardized comparison, we report per-benchmark scores as well as their macro average as shown in Table 2, following the official splits and metrics of all benchmarks.

Models. We instantiate EcoAlign across a suite of powerful LVLMs, encompassing both three close-source models (GPT-4o [22], Gemini-2.5-Flash [13] and Qwen-VL-Max [2]) and two open-source models (InternVL3-14B [57], Llama-3.2-11B-Vision-Instruct [12]).

[1] A path P_a dominates P_b if it is better or equal across all three objectives, with strict superiority in at least one.

Table 2. Comparison of EcoAlign with baselines on benchmarks across three dimensions: safety, utility, and cost. Darker shades mean better performance.

Category	Model	Method	Safety			Utility			Cost
			MMSafety	MSSBench	SIUO	OCRBench	MathVista	MMStar	Avg. Cost
Closed-source	GPT-4o	Base	55.2	58.8	51.8	73.6	73.1	64.7	1
		CoT	69.1	69.4	72.6	79.5	86.8	83.1	104.3
		CoD	71.6	70.1	73.1	80	84.2	82.3	25.8
		VLM-Guard	88.4	75.9	74	70.2	69.7	61.7	3.1
		EcoAlign	96.5	91.8	87.1	86	85.4	86.2	21.2
	Gemini-2.5-Flash	Base	64.2	60.5	53.9	86.7	77.7	75.3	1
		CoT	80	71.3	64.2	89.1	88.2	85.9	86.6
		CoD	81.3	75.6	69.6	87.4	88.5	86	27.5
		VLM-Guard	87.8	82.2	75	82.8	73.1	71.1	1.4
		EcoAlign	97.7	93.1	85.8	88.3	89.6	87	24.1
	Qwen-VL-Max	Base	68.2	53.4	46.6	88.5	79	70.8	1
		CoT	79	64	57.2	88.9	89.5	81.1	114
		CoD	79.3	79.3	65.5	89.1	89.1	80.5	34.3
		VLM-Guard	87	85	78.1	83.3	76.1	67.6	2.2
		EcoAlign	93.8	92.8	91	89.9	90.7	82.2	12.7
Open-source	InternVL3-14B	Base	69.4	51.2	44.2	87.7	73.5	68.9	1
		CoT	76	62	54.8	88	83.9	89.3	134.2
		CoD	78.4	68.4	55	88.3	84.1	85.5	45.5
		VLM-Guard	85.9	73	65.6	82.6	70.5	64.9	1.9
		EcoAlign	91.8	87.9	85.3	89.1	86	80.3	39.3
	Llama-3.2-11B-Vision	Base	38.4	48.4	37.1	75.4	46.8	48	1
		CoT	49.1	58.9	51.7	76.2	64.4	61.5	108.3
		CoD	53.4	59.2	56	78.5	61.7	60.7	36
		VLM-Guard	70.2	75.8	77.6	72	43.2	42.2	1.6
		EcoAlign	85.2	90.7	89.3	78.8	62.2	60.1	28.2



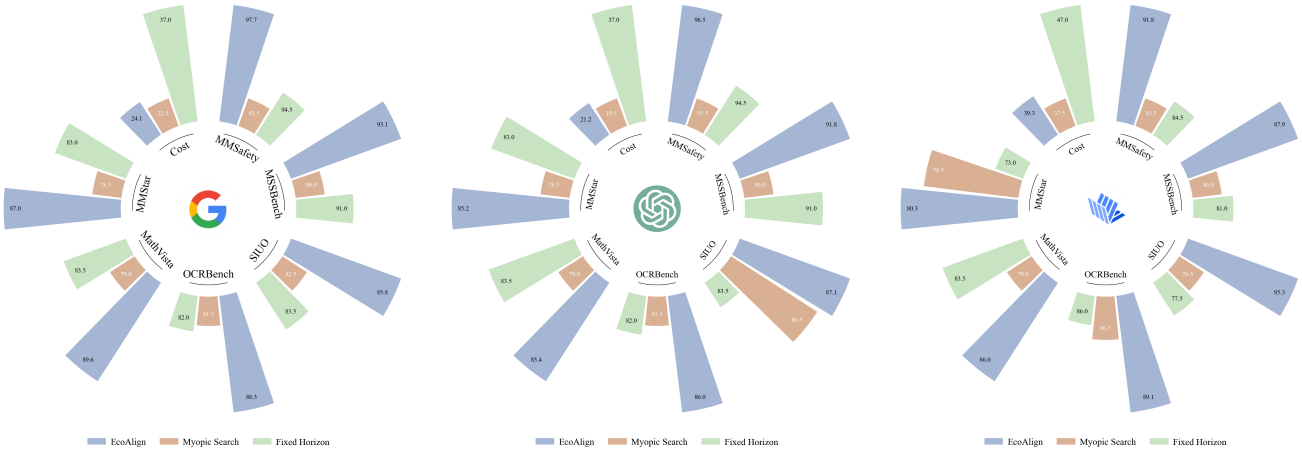
Baselines. We compare EcoAlign against several representative inference-time alignment strategies under the same backbone and safety configuration:

- **Base**: the vanilla model with its default system prompt and provider-recommended safety settings.
- **CoT** [44]: a chain-of-thought style prompting baseline that encourages step-by-step reasoning before producing the final answer.
- **CoD** [47]: a chain-of-draft style prompting baseline that asks the model to generate a brief draft reasoning before the final answer, aiming to approximate step-by-step reasoning with fewer tokens.
- **VLM-Guard** [27]: a two-stage guardrail pipeline that uses a separate safety policy to filter or rewrite potentially harmful queries or responses around the base LVLM.

All baselines share the same input (image and text), temperature, and decoding configuration as EcoAlign.

4.2. Main Results

We compare EcoAlign against representative inference-time alignment strategies across diverse models and benchmarks, as detailed in Table 2. In terms of safety, EcoAlign consistently registers the highest scores across all models and safety benchmarks. For instance, on MMSafetyBench, EcoAlign achieves a near-perfect score of 97.7 for Gemini-2.5-Flash, markedly surpassing the next-best baseline, VLM-Guard (87.8), and significantly exceeding the model's base performance (64.2). This enhanced safety is achieved while maintaining exceptional helpfulness, evidenced by a high score of 89.6 on the MathVista benchmark for the same model. Crucially, EcoAlign delivers this high-utility, high-safety profile with a drastically reduced inference cost. Compared with the cost-intensive CoT method, EcoAlign's strategy proves highly economical: on GPT-4o, EcoAlign achieves comparable or superior safety and utility with an Avg. Cost of only 21.2, which is less than a quarter of the cost incurred by CoT (104.3 Avg. Cost). Similarly, for Qwen-VL-Max, EcoAlign's 12.7 Avg. Cost is over eight times lower than CoT's 114.0, all while achieving superior performance (e.g., 93.8 MMSafety for EcoAlign vs. 79.0 for CoT). This combined evidence establishes EcoAlign as



(a) Dynamic for Gemini (b) Dynamic for GPT-4o (c) Dynamic for Internvl3-14B

Figure 3. Impact of dynamic lookahead policy.

the most effective and economically efficient inference-time alignment strategy for LVLMs. We also logged total input and output tokens for every API call made during the entire inference process and applied standard GPT-4o pricing as shown in Section A.1.1.

4.3. Ablation Study

To validate EcoAlign components, we conduct comprehensive ablation studies. We systematically deconstruct the method to analyze contributions from: (1) the weakest link safety principle, (2) the dynamic lookahead policy, (3) the economic value function, and (4) the sensitivity to key hyperparameters (k, B, δ). All ablations use our four base models across the full suite of safety, utility, and cost benchmarks. More details are in Section A.1.2.

4.3.1. Impact of Dynamic Lookahead Policy

Our economic governance uses a dynamic lookahead horizon $|R|_t = \lfloor k \cdot (B - C_t) \rfloor$ that adapts to the remaining budget, tested against Myopic Search (MS) and Fixed Horizon (FH) policies (Figure 3). Results show MS is cost-effective but fails complex utility tasks, and FH wastes budget; our dynamic policy provides the best trade-off between exploration and exploitation.

4.3.2. Effect of Weakest Link Safety Principle

Ablating the safety function by comparing $S_{\min}$ against S_{avg} and S_{last} confirms the necessity of $S_{\min}$ (Figure 4). Safety scores drop significantly under other metrics; for example, Qwen-VL-Max falls from 0.93 ($S_{\min}$) to 0.85 (S_{last}). The 10–14 point gap between $S_{\min}$ and S_{last} proves that final-step evaluation obscures intermediate safety failures. Thus, $S_{\min}$ is essential for maintaining a strict worst-case safety boundary in multi-step alignment.

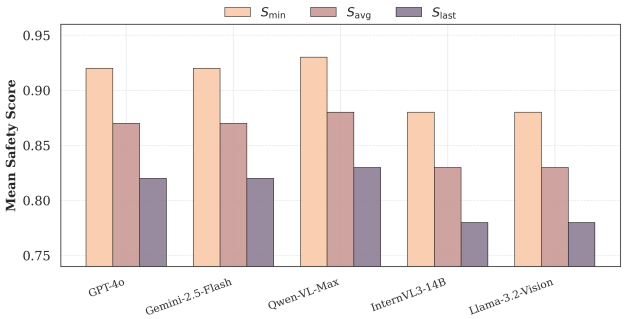


Figure 4. Effect of the weakest link safety principle.

4.3.3. Impact of Economic Value Function

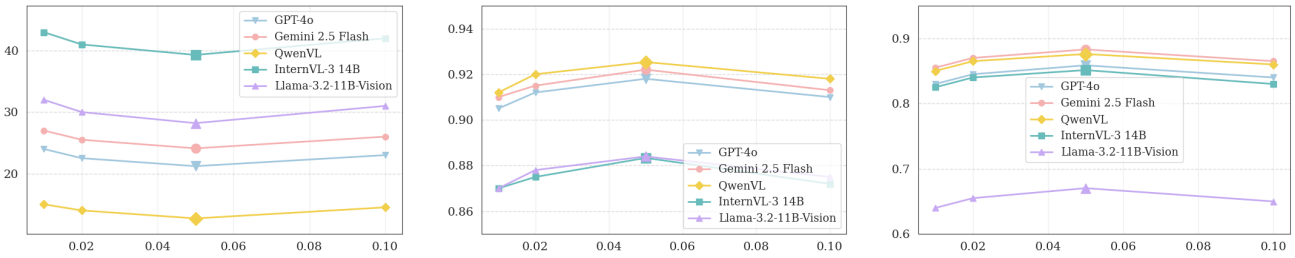
Ablating cost normalization ($\Gamma' = S[P] \cdot U[P]$) severely compromises efficiency (Table 4). Average costs for GPT-4o jump from 21.2 to 79.6, and InternVL-3-14B costs skyrocket from 39.3 to 112.1, with no safety gains. Paradoxically, unconstrained search degrades performance; GPT-4o OCRBench scores drop from 86.0 to 76.1. These results confirm that economic rationality is fundamental to preventing inefficient, exhaustive searches.

4.3.4. Sensitivity to Lookahead Factor

Factor k modulates planning scope. As shown in Figure 5, low k (0.01) means myopic search, increasing cost (GPT-4o 24.0) and degrading utility (GPT-4o utility 0.830). High k (0.1) also increases cost and slightly drops utility vs. $k = 0.05$. The value ($k = 0.05$) provides the optimal trade-off, achieving the highest mean utility at competitive cost, balancing efficiency and planning.

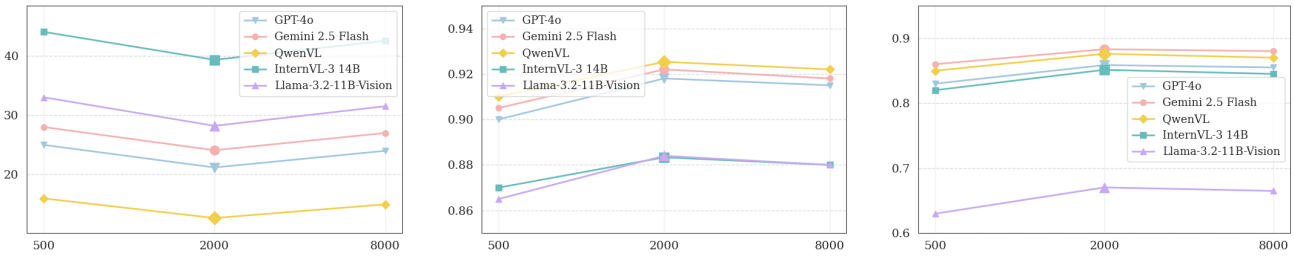
4.3.5. Sensitivity to Total Budget

Budget B imposes a hard constraint on the reasoning process. As shown in Figure 6, a low budget ($B = 500$)



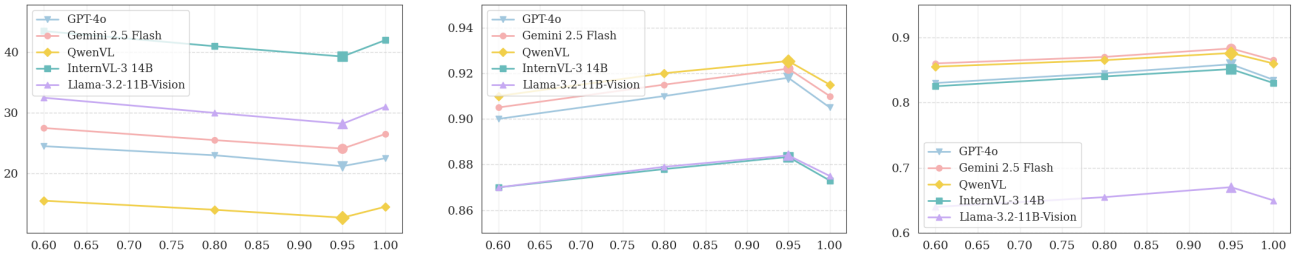
(a) Average cost (b) Mean safety score (c) Mean utility score

Figure 5. Sensitivity to lookahead factor k. (a) Average cost, (b) mean safety score, (c) mean utility score.



(a) Average cost (b) Mean safety score (c) Mean utility score

Figure 6. Sensitivity to total budget B. (a) Average cost, (b) mean safety score, (c) mean utility score.



(a) Average cost (b) Mean safety score (c) Mean utility score

Figure 7. Sensitivity to discount factor δ. (a) Average cost, (b) mean safety score, (c) mean utility score.

forces early termination, which paradoxically increases costs while substantially dropping utility. Increasing B from medium to high allows for a deeper search, leading to a slight increase in utility. Notably, Mean Safety remains consistently high across all settings, confirming that a larger budget enhances utility without compromising safety.

4.3.6. Sensitivity to Discount Factor

The discount factor δ determines the temporal value of computation (Figure 7). A low δ leads to short-sightedness, resulting in lower utility at a higher cost. The base $\delta = 0.95$ proves optimal, achieving the highest utility (0.8587) while maintaining a controlled cost (21.2). Conversely, $\delta = 1.0$ (no discount) slightly increases cost and reduces utility, confirming that a minor temporal penalty effectively prioritizes more efficient reasoning paths.

5. Conclusion

In this paper, we propose EcoAlign, which fundamentally reframes inference-time LVLM alignment as an economic problem of optimal pathfinding under computational budget. By operationalizing concepts like a forward-looking economic value function, a dynamic lookahead policy, and a robust weakest link safety principle, we enable LVLMs to adaptively search for the most resource-efficient and non-compromised reasoning trajectory. Extensive experiments across various models and comprehensive benchmarks demonstrate that EcoAlign achieves superior safety and utility while significantly reducing inference costs compared to existing methods, confirming its status as an effective and economical alignment strategy.

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