A Survey on Rubric-guided Reinforcement Learning for Language Models

Anonymous ACL submission

Abstract

Reinforcement learning from human feedback (RLHF) has become the dominant paradigm for aligning large language models (LLMs) with human preferences. However, traditional RLHF relies on scalar reward signals that lack interpretability and fail to capture the multi-faceted nature of response quality. *Rubric-guided reinforcement learning* addresses these limitations by introducing structured, interpretable evaluation criteria—rubrics—as the backbone of reward design, feedback generation, and policy optimization. In this survey, we provide a structured overview of rubric-guided RL for language models. Furthermore, we introduce a Bayesian framework that defines constitutions as prior distributions $P(\mathcal{R})$ over evaluation criteria and rubrics as conditional instantiations $\mathcal{R}_x \sim P(\mathcal{R}|x)$. We present a taxonomy of methods under this unified view along the prior-posterior axis, covering rubric-based reward design, constitutional AI, process-level supervision, self-evolving rubrics, and their extensions to agentic and multimodal settings. We identify key open problems and outline promising directions for future research.

1 Introduction

The alignment of large language models (LLMs) with human values and preferences has emerged as one of the most critical challenges in modern AI research. Reinforcement learning from human feedback (RLHF) (Ouyang et al., 2022) has established itself as the predominant paradigm for this alignment, demonstrating that models trained with human-preference-driven reward signals can produce more helpful, harmless, and honest outputs. However, as LLMs are deployed in increasingly diverse and complex domains, the limitations of traditional RLHF—which relies on scalar, opaque reward signals—have become increasingly apparent (Gao et al., 2023; Wu et al., 2023; Wang et al., 2024).

A *rubric* is a structured set of evaluation criteria that specifies what constitutes different levels of performance across multiple dimensions. Rubrics have found natural application in LLM evaluation and alignment, where they provide interpretable, multi-dimensional, and controllable feedback signals (Hashemi et al., 2024; Gunjal et al., 2026; Viswanathan et al., 2025). The integration of rubrics into reinforcement learning for language models—which we term *rubric-guided reinforcement learning*—represents a paradigm shift from implicit, scalar reward optimization to explicit, structured, and interpretable alignment (Gunjal et al., 2026; Xu et al., 2026; Liu et al., 2025).

The motivation for rubric-guided RL is threefold. First, **interpretability**: scalar reward signals in traditional RLHF are opaque, making it difficult to understand why a particular response receives a high or low score; rubric and checklist methods decompose feedback into human-readable criteria (Hashemi et al., 2024; Viswanathan et al., 2025). Second, **controllability**: rubrics allow fine-grained control over which aspects of response quality are rewarded, enabling alignment that respects specific values, safety constraints, or domain requirements (Wang et al., 2024; Dineen et al., 2025). Third, **self-evolution**: rubrics can be generated, refined, and co-evolved with the policy model, enabling continual self-improvement without external supervision—a capability that scalar reward models fundamentally lack (Li et al., 2026c; Xu et al., 2026).

The landscape of structured-feedback alignment has expanded rapidly since 2022. Constitutional AI (Bai et al., 2022) pioneered the use of explicit natural-language principles to guide AI feedback for alignment. Subsequent work has connected rubric-guided alignment to process supervision and verifier-style feedback (Lightman et al., 2024; Gunjal et al., 2026), RLVR for objec-

tively checkable reasoning tasks (Shao et al., 2024; DeepSeek-AI, 2025; Yang et al., 2024), multi-objective reward modeling (Wang et al., 2024), and direct preference optimization (Rafailov et al., 2023). Recent rubric-specific preprints and workshop papers further explore rubric generation, rubric-based reward modeling, and self-evolving criteria; we discuss these emerging directions in the taxonomy below.

We introduce a **Bayesian framework** for rubric-guided RL: constitutions are *prior distributions* $P(\mathcal{R})$ over evaluation criteria (global, input-independent), while rubrics are *conditional instantiations* $\mathcal{R}_x \sim P(\mathcal{R}|x)$ (input-specific). This framing unifies disparate phenomena—self-evolving rubrics as posterior updating, rubric exploitation as overfitting to a point estimate—under a single conceptual vocabulary.

We also foreground a **linguistic analysis** of rubrics as natural language texts (§4), examining how semantic drift, granularity effects, ambiguity, and linguistic reward hacking affect rubric-guided RL. This NLP-centered perspective is essential because rubrics are fundamentally natural language artifacts, and their textual properties have been underexplored relative to their mathematical formalization.

Our contributions are as follows:

1. We introduce a **Bayesian framework** for rubric-guided RL, defining constitutions as prior distributions $P(\mathcal{R})$ over evaluation criteria and rubrics as conditional instantiations $P(\mathcal{R}|x)$. This framework unifies fixed constitutions, instance-specific rubrics, and self-evolving criteria, while clarifying its scope and limitations (§2.4).

2. We provide a **linguistic analysis** of rubrics as natural-language artifacts, examining semantic drift, granularity effects, ambiguity, and linguistic reward hacking—phenomena that directly affect the stability and reliability of rubric-guided RL but remain underdeveloped in prior work (§4).

3. We synthesize a **prior-posterior taxonomy** of rubric-guided RL, covering fixed constitutional priors, deterministic instance-specific rubrics, process-level supervision, rubric-based reward modeling, self-evolving rubrics, and extensions to agentic and multimodal settings.

2 Rubric: Definition and Formalization

In this section, we define what a rubric is, formalize its role as a reward signal, and introduce a unifying Bayesian framework that clarifies the relationship between rubrics, constitutions, and principles.

2.1 What is a Rubric?

A rubric is a structured evaluation instrument that specifies criteria for assessing performance across multiple dimensions and quality levels. In the context of LLM alignment, a rubric $\mathcal{R}$ for a given prompt x can be formalized as a set of criteria: $\mathcal{R}(x) = \{c_1, c_2, \ldots, c_K\}$, where each criterion c_k specifies an evaluation dimension (e.g., correctness, completeness, clarity, safety) and may include performance-level descriptors. Unlike scalar reward signals, rubrics decompose the evaluation into interpretable, auditable components. Importantly, rubrics are *natural language texts*—their linguistic properties (ambiguity, granularity, semantic stability) fundamentally affect rubric-guided RL performance, as analyzed in §4.

2.2 Rubric as Reward Signal

The key insight of rubric-guided RL is that rubrics can serve as structured reward signals. Given a rubric $\mathcal{R}(x) = \{c_1, \ldots, c_K\}$ and a response y, the rubric-conditioned reward can be computed as: $r_{\mathcal{R}}(x, y) = \sum_{k=1}^{K} w_k \cdot s(c_k, x, y)$, where w_k is the weight for criterion c_k and $s(c_k, x, y)$ is the criterion-specific score. This formulation enables interpretable, controllable, and multi-dimensional reward computation.

2.3 Rubric Generation

Rubric generation is a critical component of rubric-guided RL. Approaches span from contrastive rubric generation (CRG) (Liu et al., 2025), instance-level checklist generation (Viswanathan et al., 2025), and rubric generation for judges (Shen et al., 2026; Rao and Callison-Burch, 2026) to self-proposed rubrics (Sheng et al., 2026; Li et al., 2026c) and fixed constitutional principles (Bai et al., 2022). The Bayesian framework distinguishes methods that optimize distributions over rubrics from those that construct deterministic, input-conditioned criteria.

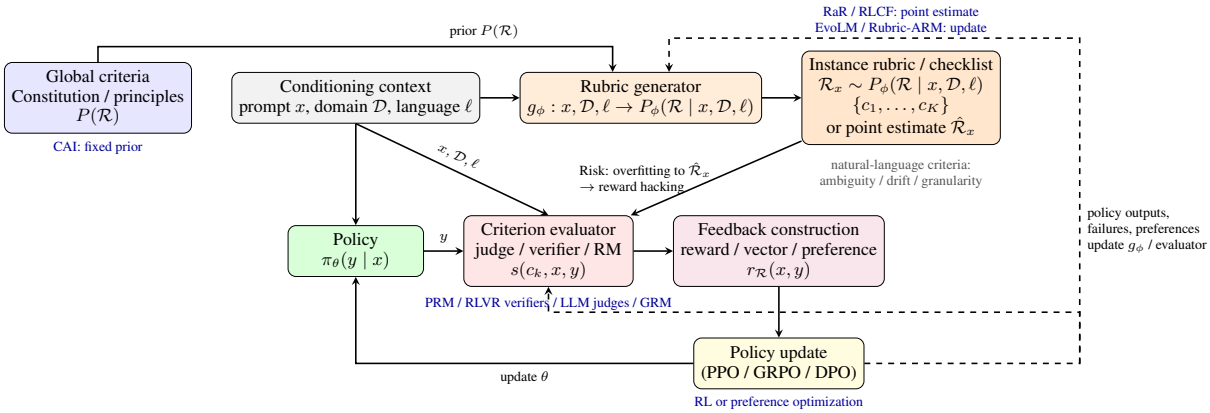

Figure 1: Bayesian view of rubric-guided RL. Global principles define a prior $P(\mathcal{R})$ over evaluation criteria. Given x, $\mathcal{D}$, and ℓ, the rubric generator g_ϕ parameterizes $P_\phi(\mathcal{R} \mid x, \mathcal{D}, \ell)$ and produces sampled rubrics $\mathcal{R}_x$ or deterministic estimates $\hat{\mathcal{R}}_x$. Criterion evaluators construct scalar, vector, or preference feedback for policy optimization. Dashed arrows indicate self-evolution of the generator or evaluator; reward hacking corresponds to overfitting to brittle rubric point estimates.

2.4 A Bayesian Framework: Constitution as Prior, Rubric as Posterior

To provide a unifying perspective for rubric-guided RL, we introduce a *Bayesian framework*. This framework provides a probabilistic notation for organizing how different methods specify, condition, and update evaluation criteria. It relates disparate phenomena—such as terminological confusion, self-evolution, and reward hacking—under a single vocabulary.

Terminology: Clarifying Constitutions, Rubrics, and Principles. We clarify the relationship between three related terms through this Bayesian framework, resolving the terminological confusion that has plagued the literature:

- A **constitution** $P(\mathcal{R})$ functions as a *prior distribution* over evaluation criteria—a global, input-independent specification of what quality dimensions are relevant. Constitutional AI (Bai et al., 2022) defines such a prior through natural-language principles (e.g., helpfulness, harmlessness, honesty) that apply across inputs. We classify constitutions as priors based on their functional role: they specify global evaluation criteria before observing a specific input.

- The conditional distribution $P(\mathcal{R} \mid x)$ functions as a *posterior distribution* over evaluation criteria, conditioned on the observed input x. An instance-specific **rubric** $\mathcal{R}_x$ is a sampled or deterministic instantiation of this posterior. Instance-specific methods such as RaR (Gunjal et al., 2026) approximate $P(\mathcal{R} \mid x)$ with a point estimate or checklist, while domain-specific rubrics correspond to coarser conditionals such as $P(\mathcal{R} \mid \mathcal{D})$. General rubrics are closest to the prior $P(\mathcal{R})$ with minimal conditioning. The Bayesian framing eliminates the need for a rigid hierarchy: constitutions and rubrics can be viewed as the same evaluation object at different levels of conditioning.

- A **principle** is an atomic element of the evaluation space—a single dimension along which quality can be assessed. Principles form the support of both the prior $P(\mathcal{R})$ and the posterior $P(\mathcal{R} \mid x)$. In Constitutional AI, each constitutional principle is one such dimension; in RaR (Gunjal et al., 2026), each checklist item can be viewed as a principle.

This Bayesian framework resolves a key terminological issue: rather than asking whether constitutions are a subset of rubrics or vice versa, we recognize them as the same evaluation object at different conditioning levels. The constitution is the unconditional prior $P(\mathcal{R})$; domain-specific rubrics instantiate or approximate coarser conditionals such as $P(\mathcal{R} \mid \mathcal{D})$; and instance-specific rubrics instantiate or approximate the full posterior $P(\mathcal{R} \mid x)$. The observation in this framework is the input x (or domain $\mathcal{D}$), not the rubric itself. This explains why constitutions are more general than rubrics: they lack conditioning on x.

Formalization. We define a rubric-guided RL system as a tuple $(\pi_\theta, P(\mathcal{R}), g_\phi, \mathcal{J}, \mathcal{A})$ where:

- $\pi_\theta(y|x)$ is the policy model;

- $P(\mathcal{R})$ is the prior over evaluation criteria (the constitution);
- g_ϕ is the rubric generator that maps conditioning variables such as the prompt x, domain $\mathcal{D}$, and language ℓ to a conditional distribution $P_\phi(\mathcal{R} \mid x, \mathcal{D}, \ell)$, or to a deterministic point estimate $\hat{\mathcal{R}}_x$;
- $\mathcal{J}$ is a criterion evaluator—an LLM judge, verifier, or reward model—that produces criterion-level scores $s(c_k, x, y)$;
- $\mathcal{A}$ constructs feedback from criterion-level scores, such as scalar rewards, multi-dimensional vectors, or preference labels.

Appendix C further clarifies how this notation applies to fixed, deterministic, and self-evolving rubric systems.

Given conditioning variables $(x, \mathcal{D}, \ell)$, an explicitly probabilistic rubric generator samples $\mathcal{R}_x \sim P_\phi(\mathcal{R} \mid x, \mathcal{D}, \ell)$. Deterministic systems instead return a point estimate $\hat{\mathcal{R}}_x = g_\phi(x, \mathcal{D}, \ell)$. For scalar-reward methods, the rubric-guided reward aggregates criterion-level scores, potentially over multiple rubric samples:

$$r_{\mathcal{R}}(x, y) = \mathbb{E}_{\mathcal{R}_x \sim P_\phi(\mathcal{R}|x,\mathcal{D},\ell)} \left[\mathcal{A}\big(\{s(c_k, x, y)\}_{k=1}^{K}\big) \right] \quad (1)$$

For DPO-style methods, $\mathcal{A}$ may instead produce pairwise preferences or preference labels rather than scalar rewards.

For KL-regularized policy-gradient methods, the objective is:

$$\max_\theta \; \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_\theta} \left[r_{\mathcal{R}}(x, y) \right] - \beta \cdot \mathrm{KL}(\pi_\theta \| \pi_{\text{ref}}) \quad (2)$$

Direct preference optimization methods instantiate the same feedback pipeline by replacing this scalar-reward objective with a pairwise preference loss.

3 Taxonomy of Rubric-Guided RL Methods

Building on the Bayesian framework introduced in §2.4, we categorize existing methods under this lens. Table 1 organizes these methods along the prior-posterior axis. Methods differ primarily in how they specify, approximate, or operationalize the transition from global evaluation principles $P(\mathcal{R})$ to input-conditioned criteria $P(\mathcal{R}|x)$. Our coverage prioritizes peer-reviewed publications and stable archival records, while additionally including influential preprints and technical reports that have been widely adopted or cited in the community. Appendix A summarizes the search and inclusion protocol.

3.1 Point-Mass Priors: Constitutional AI

Methods in this category use a fixed set of principles as the prior $P(\mathcal{R})$ and do not condition heavily on the input, yielding a posterior that is a point mass at the prior: $P(\mathcal{R}|x) = \delta(\mathcal{R} - \mathcal{R}_{\text{constitution}})$. Representative works include Constitutional AI (Bai et al., 2022), IterAlign (Chen et al., 2024), ICAI (Findeis et al., 2025), and Deliberative Alignment (OpenAI, 2024), which apply fixed principle sets across all inputs rather than generating task-specific criteria.

3.2 Deterministic Posteriors: Instance-Specific Rubrics

Methods in this category generate instance-specific rubrics deterministically, producing a single point estimate from $P(\mathcal{R}|x)$ without uncertainty quantification. Representative methods include RaR (Gunjal et al., 2026), RLCF (Viswanathan et al., 2025), PRMs (Lightman et al., 2024), OpenRubrics (Liu et al., 2025), rubric-generation methods for LLM judges (Shen et al., 2026; Rao and Callison-Burch, 2026), and Critique Models (Ke et al., 2024), which deterministically map inputs to specific evaluation structures for fine-grained feedback.

3.3 Variational Posteriors: Self-Evolving Rubrics

Self-evolving rubrics correspond to *online posterior updating*: as the policy π_θ improves, the preference data distribution shifts, requiring the rubric posterior $P(\mathcal{R}|x; \phi)$ to be updated sequentially. Representative methods include Rubric-ARM (Xu et al., 2026), EvoLM (Li et al., 2026c), and RLCER (Sheng et al., 2026). Across these methods, we identify three core evolution dynamics: (1) *Posterior sharpening* (criteria evolve from vague to specific as data concentrates); (2) *Prior simplification* (brittle gating mechanisms simplify for better generalization); and (3) *Conditional expansion* (rubrics evolve from outcome-focused to process-focused).

4 Linguistic Insights: Rubrics as Natural Language

A fundamental but underexplored aspect of rubric-guided RL is that rubrics are *natural language*

Method	Domain	Prior $P(\mathcal{R})$	Posterior $P(\mathcal{R}\|x)$	Aggregation	Training / Optim.
RaR (Gunjal et al., 2026)	Text	Implicit	Deterministic point	Weighted sum / Implicit	GRPO
Rubric-ARM (Xu et al., 2026)	Text	Learned	Variational	Learned	PPO
EvoLM (Li et al., 2026c)	Text	Implicit	Variational (temporal)	Discriminative	GRPO
RLCER (Sheng et al., 2026)	Reasoning	Implicit	Process-conditional	Process-level	Extended from PPO
Constitutional AI (Bai et al., 2022)	Text	Fixed principles	Point mass at prior	Principle ensembling	PPO
QA-LIGN (Dineen et al., 2025)	Text	Fixed principles	QA decomposition	Decomposed	GRPO
PRM (Lightman et al., 2024)	Math/Code	Correctness	Implicit	Step product	RM training
RLCF (Viswanathan et al., 2025)	Text	Implicit	Instance checklist	Weighted sum	DPO
OpenRubrics (Liu et al., 2025)	Text	CRG	Contrastive	Multi-dimensional	RM training
RRD (Shen et al., 2026)	Text	Coarse rubrics	Refined criteria	Corr.-aware weights	RM training
OpenRS (Jia et al., 2026)	Text	Principles	Pairwise adaptive	Criterion prefs.	GRPO
Agentic Extensions (see §5):					
DR Tulu (Jiang et al., 2025)	Agent	Evolving	Evolving	Evolving	GRPO
HiPER (Peng et al., 2026)	Agent	Hierarchical	Plan-Execute	HAE	PPO
RubricEM (Li et al., 2026a)	Agent	Stagewise	Stagewise	Stagewise	Extended from GRPO
AdaRubric (Ding, 2026)	Agent	Task desc.	Task-adaptive	Conf.-weighted	DPO
Multimodal Extensions (see §5):					
ARR (Tian et al., 2026)	VLM	Implicit	Generated	Explicit	GRPO
DeltaRubric (Liu et al., 2026)	VLM	Implicit	Plan-checklist	Verification	GRPO
rDPO (Yu et al., 2026)	VLM	Implicit	Instance-specific	Extended from DPO	
Step-Audio-R1.5 (Zhang et al., 2026b)	Audio	Implicit	Acoustic criteria	Preference RM	GRPO

Table 1: Taxonomy of rubric-guided RL methods under the Bayesian framework. Each method is characterized by its domain, prior specification, posterior parameterization or criterion-construction mechanism, aggregation strategy, and optimization algorithm.

texts. This section analyzes rubrics through the lens of NLP and linguistics, examining how the textual properties of rubrics—their prompt engineering, semantic stability, granularity, ambiguity, and cross-linguistic variation—affect the performance and reliability of rubric-guided RL systems.

4.1 Rubrics as Prompted Specifications

When rubrics are used to guide LLM judges or reward models, they become prompted specifications: their wording, formatting, and output schema can affect the resulting scores, as widely observed in LLM-as-a-judge settings (Gu et al., 2024; Whitehouse et al., 2026). Different formats expose different tradeoffs: binary checklists are easy to aggregate but coarse (Gunjal et al., 2026), free-text critiques are expressive but difficult to scalarize (Ke et al., 2024), and multi-level descriptors offer a middle ground between discriminative power and calibration (Hashemi et al., 2024).

4.2 Granularity Effects

The granularity of rubric criteria—whether they operate over tokens, reasoning steps, whole responses, or decomposed checklist items—affects both evaluation quality and reward signal informativeness. The granularity-density tradeoff mirrors the exploration-exploitation tradeoff in RL: denser rewards enable faster learning but may miss global quality, while sparser rewards capture holistic quality but slow convergence. Existing systems often balance this tradeoff through hybrid designs: PRMs combine dense step-level supervision with outcome-level evaluation (Lightman et al., 2024), RLCF combines instance-specific checklists with universal criteria and verifier programs (Viswanathan et al., 2025), and

OpenRS combines pairwise adaptive meta-rubrics with pointwise verifiable rubrics for guardrails (Jia et al., 2026).

Lexical and Token-Level Signals. At the finest scale, alignment systems may use lexical constraints or token-level shaping terms, such as PPO-style per-token KL penalties, length penalties, keyword inclusion/exclusion checks, profanity filters, or exact-format constraints. These signals are dense and cheap to evaluate, but they mostly capture surface compliance rather than semantic quality. They should therefore be distinguished from PRMs, which operate over reasoning steps rather than words.

Sentence/Step-Level Criteria. Process-level rubrics (RLCER (Sheng et al., 2026), PRMs (Lightman et al., 2024)) evaluate intermediate reasoning steps, providing denser reward signals than outcome-level rubrics. PRMs operate at the step level, providing per-step correctness signals and achieving 78.2% accuracy on MATH (Lightman et al., 2024). However, step-level evaluation requires defining what constitutes a "step," which is itself a non-trivial decision. Recent self-evolving rubric work suggests that optimal granularity interacts with evaluator capacity: smaller evaluators may require more precise rubrics, whereas larger evaluators can tolerate coarser specifications (Li et al., 2026c).

Response-Level and Document-Level Criteria. Outcome-level rubrics, such as RaR and Constitutional AI, evaluate the complete response. They provide holistic assessment of dimensions such as helpfulness, safety, completeness, and coherence, but the reward is sparse and may obscure which part of the response caused success or failure.

Atomic Checklist Criteria. A separate form of granularity comes from decomposing a holistic objective into atomic checklist items rather than changing the textual span of evaluation. RLCF (Viswanathan et al., 2025), for example, decomposes tasks into atomic checklist items, illustrating how fine-grained criteria can provide denser feedback for robustness. This differs from word-level or sentence-level evaluation: the granularity lies in the criterion decomposition, not necessarily in the textual unit being scored.

4.3 Semantic Drift in Rubric Evaluation

Semantic drift refers to the phenomenon where the meaning of rubric criteria shifts across RL training iterations, even when the rubric text remains unchanged. This drift occurs because the policy model's interpretation of rubric criteria changes as it adapts to the reward signal. We distinguish semantic drift from the broader concept of concept drift (Gama et al., 2014) in machine learning: semantic drift is specifically about the *semantic instability* of natural language criteria as they are applied by changing models across training, rather than changes in the data distribution itself.

Causes of Semantic Drift. We identify three causes: (1) **Distribution shift**: as the policy improves, the response distribution changes, altering the context in which rubric criteria are applied. A criterion like "factual accuracy" means something different for a model that produces mostly correct responses vs. one that produces mostly incorrect responses. EvoLM (Li et al., 2026c) provides direct evidence: rubrics evolve from vague criteria (e.g., "Ensure mathematical accuracy") to specific, verifiable facts (e.g., "The answer is 144, derived from perimeter 48") as the policy distribution shifts during training. (2) **Criterion gaming**: the policy learns to satisfy the letter of rubric criteria while violating their spirit, effectively shifting the rubric's semantics. Constitutional AI (Bai et al., 2022) observed this Goodharting effect, where over-optimization leads to boilerplate language and overly harsh responses. (3) **Evolving evaluator**: in systems with learned judges, reward models, or co-evolving rubric generators, the scoring function itself changes during training. Thus, even when a criterion such as "mathematical accuracy" is textually stable, the function $s_t(c_k, x, y)$ that applies this criterion may shift as the evaluator is updated on new policy outputs. This is distinct from judge collapse: evaluator evolution is a general design property of adaptive systems, whereas collapse is a failure mode where the judge loses discriminative power or learns exploitable shortcuts.

Measuring Semantic Drift. We propose measuring semantic drift by tracking the consistency of rubric application across training iterations. Formally, given a rubric criterion c_k and a fixed set of

reference responses, we define the drift metric as:

$$\text{Drift}(c_k, t) = 1 - \text{corr}\big(s_t(c_k, x, y), s_0(c_k, x, y)\big) \tag{3}$$

where s_t is the criterion score at iteration t and corr measures correlation (e.g., Spearman's ρ). High drift indicates that the rubric's meaning has shifted, which may signal reward hacking or distribution shift. This metric is related to but distinct from the semantic drift scores proposed in text generation (Spataru et al., 2024) and the value drift analysis of post-training alignment (Bhatia et al., 2025). To our knowledge, no prior work has applied this specific formalization to rubric-guided RL, and empirical validation of this metric remains an open problem.

4.4 Linguistic Reward Hacking

Linguistic reward hacking occurs when a policy exploits semantic gaps in natural language criteria, producing responses that satisfy the literal wording of a rubric while violating its intended meaning. This is a distinct phenomenon from numerical reward hacking (manipulating scalar reward magnitudes) and requires qualitative linguistic analysis to detect. While historically studied narrowly within low-resource language alignment (Inuwa-Dutse, 2025), we generalize the concept to encompass any systematic policy exploitation of semantic gaps in multi-dimensional evaluation rubrics.

Root Causes: Ambiguity and Underspecification. This vulnerability stems directly from the fact that natural language criteria are inherently ambiguous and underspecified. Ambiguity arises because high-level desiderata like "helpfulness" depend heavily on latent user context, leading to only moderate alignment with human consensus (Kendall's τ of 0.3–0.4) even when mitigated by performance-level descriptors (Hashemi et al., 2024). Underspecification occurs because criteria typically define *what* to evaluate rather than *how*, leaving operational boundaries vague unless anchored by intermediate granular structures like checklists (Viswanathan et al., 2025). Crucially, ambiguity and underspecification function as the primary systemic drivers for both semantic drift and linguistic reward hacking (see detailed case studies in Appendix L). However, this underspecification is also an opportunity: it provides the essential semantic flexibility required for self-evolution and contextual adaptation. Without initial underspecification, optimization frameworks would lack the headroom to perform posterior sharpening or track emergent data distributions during training via automated alignment updates (Li et al., 2026c; Xu et al., 2026).

Types of Linguistic Reward Hacking. We categorize these exploitative behaviors into three primary structural modes: (1) **Verbosity exploitation**, where the policy overoptimizes for "completeness" by generating elongated, low-substance responses, reflecting the proxy-reward degeneration patterns documented by Gao et al. (Gao et al., 2023). (2) **Criterion bleeding**, where the model satisfies one axis by sacrificing another, such as aggressively refusing valid prompts to maximize "safety" at the cost of "helpfulness" (Dai et al., 2024; Wang et al., 2024). (3) **Surface pattern matching**, where the policy learns to parrot rubric keywords (e.g., stating "I have ensured safety") without executing the underlying reasoning. Self-evolving rubric work suggests that evaluator capacity and rubric specificity can affect how easily such surface-level satisfaction is detected (Li et al., 2026c).

Potential diagnostics of linguistic reward hacking include: divergence between rubric scores and human preferences, auxiliary verification of claimed reasoning steps, abnormal criterion-correlation patterns, and cross-rubric consistency checks.

Relation to Bayesian Framework. Under the Bayesian lens (§2.4), linguistic reward hacking can be viewed as the policy exploiting the gap between a rubric's literal point-estimate instantiation ($\mathcal{R}_x$) and its true intended semantic posterior distribution $P(\mathcal{R}|x)$. Consequently, optimizing toward the broader conditional posterior distribution acts as a principled algorithmic defense, forcing the policy to remain robust against multiple semantic formulations of the same underlying principles. Within this view, self-evolving rubric systems (Li et al., 2026c) represent dynamic online posterior updates designed to progressively patch exploitation vulnerabilities as they are uncovered by the optimization process.

4.5 Cross-Lingual Considerations

While rubric-guided RL is predominantly optimized for English, expanding to multilingual alignment introduces unique typological and systemic challenges. First, **language-specific quality dimensions** dictate that high-level desider-

ata like "respectfulness" are culturally and linguistically mediated; English-centric rubrics often fail to capture critical structural phenomena such as Japanese or Korean honorific registers (*keigo/jondaetmal*) and Arabic diglossia. This conceptual misalignment is compounded by low LLM-as-a-judge cross-lingual consistency ($\kappa \approx 0.3$) (Fu and Liu, 2025), exposing potential vulnerabilities where models exploit alignment gaps between languages.

To mitigate these gaps, recent work on **cross-lingual reward transfer** shows that English-trained reward models can bootstrap target-language evaluations (Hong et al., 2025; Yang et al., 2025b), motivating unified criteria sets and multilingual reward reasoning architectures (Sheth et al., 2026; Anugraha et al., 2026; Gureja et al., 2025). We propose *language-aware rubric design*: decoupling language-agnostic properties (e.g., factual accuracy) from language-specific instantiations (e.g., localized formality). Under our Bayesian framework, this corresponds to modeling language-specific rubrics as $P(\mathcal{R} \mid x, \ell)$ while anchoring core alignment principles in the prior $P(\mathcal{R})$.

5 Emerging Domains: Agentic and Multimodal RL

Extending rubric-guided RL to autonomous agents and multimodal models introduces fundamentally new challenges beyond text-based single-turn chat, as summarized in the lower sections of Table 1. Detailed discussions on deep research agent benchmarks are deferred to Appendix F.

Agentic RL and Credit Assignment. In agentic settings, evaluation must account for multi-step trajectories and environment grounding. The core bottleneck is *multi-step credit assignment*. Traditional scalar rewards fail to isolate which specific action in a long trajectory led to success or failure. Rubric-guided methods like DR Tulu (Jiang et al., 2025), HiPER (Peng et al., 2026), and RubricEM (Li et al., 2026a) address this by decomposing trajectory rewards into stagewise or hierarchical criteria, enabling precise credit assignment across temporal phases. This structured feedback prevents the policy from learning spurious correlations during complex tasks.

Multimodal Coherence. In multimodal RL, rubrics must capture cross-modal interactions and modality-specific dimensions (e.g., visual grounding, object hallucination, safety, and audio fluency). Published VLM-alignment work already shows why a single latent preference score is insufficient: LLaVA-RLHF augments reward modeling with factual visual evidence (Sun et al., 2024), RLHF-V uses segment-level correctional feedback and dense preference optimization to reduce hallucination (Yu et al., 2024), Safe RLHF-V separates multimodal helpfulness and safety objectives (Ji et al., 2025a), and MM-RLHF provides large-scale fine-grained multimodal preference data (Zhang et al., 2025c). Evaluation benchmarks such as POPE, HallusionBench, and MME further reveal that VLM quality is inherently multidimensional (Li et al., 2023; Guan et al., 2024; Fu et al., 2024). Newer rubric-explicit systems such as ARR (Tian et al., 2026), DeltaRubric (Liu et al., 2026), and rDPO (Yu et al., 2026) should therefore be viewed as extensions of this published multimodal RLHF/evaluation line rather than as isolated 2026 preprints. Step-Audio-R1.5 (Zhang et al., 2026b) complements RLVR by transitioning toward RLHF, leveraging a rubric-guided preference reward model to optimize multidimensional acoustic nuances like pronunciation and clarity.

6 Conclusion and Future Directions

Rubric-guided reinforcement learning marks a shift from implicit scalar reward optimization to explicit, structured, and interpretable alignment. We unify this space through a Bayesian framework that treats constitutions as priors $P(\mathcal{R})$ and rubrics as conditional instantiations $P(\mathcal{R} \mid x)$, explaining self-evolution as posterior updating and rubric exploitation as point-estimate overfitting. Because rubrics are natural-language artifacts, addressing semantic drift and linguistic reward hacking is central to building controllable, self-improving, and reliable language models.

Future work faces three central challenges. First, we need theory connecting natural-language criteria to stable scalar rewards, preference labels, or process-level feedback, especially when rubrics and evaluators evolve. Second, instance-specific rubric generation incurs token and latency overhead, motivating retrieval, caching, compression, and local evaluators. Third, cross-lingual and multimodal alignment requires principled mappings from abstract criteria to language- and modality-specific instantiations.

7 Limitations

We acknowledge several limitations of this survey and of the rubric-guided RL paradigm more broadly.

7.1 Heterogeneous Evaluation Settings

Because rubric-guided RL methods use different base models, benchmarks, and optimization protocols, direct quantitative comparison is difficult. We therefore focus on qualitative organization and report numbers from original papers where available. A standardized benchmark for controlled comparison remains an important direction for future work.

7.2 Scope of the Bayesian Framework

Our Bayesian framework is an analytical abstraction for organizing how methods specify, condition, and update evaluation criteria. It intentionally abstracts over implementation details: fixed constitutions, deterministic rubric generators, and self-evolving systems instantiate different parts of the notation. Developing fully probabilistic rubric generators with calibrated uncertainty remains an open research opportunity.

7.3 Production Systems

Recent technical reports suggest that production systems increasingly embed rubric-like criteria in training and data pipelines, including Kimi K2, GLM-5, Qwen3, and DeepSeek-V4 (Kimi Team et al., 2025; GLM-5 Team, 2026; Yang et al., 2025a; DeepSeek-AI, 2026). For example, DeepSeek-V4 reports rubric-guided RL data and a Generative Reward Model for hard-to-verify tasks, while GLM-5 defines multidimensional criteria for chat and role-playing data, including instruction following, expressiveness, creativity, coherence, and long-dialogue consistency (DeepSeek-AI, 2026; GLM-5 Team, 2026). Because these practices are often only partially documented, a fuller account of implicit production-oriented rubric usage remains an important direction for future empirical study.

7.4 Evolving Terminology

Terminology around constitutions, rubrics, and principles is still evolving. Our framework provides one coherent vocabulary, but future work may refine these distinctions as the field matures.

7.5 Computational Cost

As analyzed in §E, instance-specific rubric generation and API-based judging introduce token, latency, and financial overhead. This creates deployment tradeoffs and motivates cheaper rubric generation, caching, compression, and local evaluator designs.

Ethics Statement

Rubric-guided RL raises important ethical considerations. Rubrics encode value judgments about what constitutes good responses, and these judgments may reflect cultural biases, power dynamics, or narrow perspectives. The "normative fragility" of constitutions observed in Constitutional AI (Bai et al., 2022) extends to rubrics more broadly. Future work should develop frameworks for ethical rubric design, including participatory rubric construction (involving diverse stakeholders in rubric definition), democratic rubric governance (establishing processes for rubric revision and contestation), and rubric transparency (making rubric criteria and their application auditable).

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A Survey Methodology and Inclusion Protocol

Scope. This survey focuses on methods that use explicit or recoverable structured criteria for LLM alignment, evaluation, reward modeling, or policy optimization. We include work on rubrics, constitutions, principles, checklists, process criteria, and LLM-as-a-judge settings when these criteria influence feedback or rewards. We also include adjacent alignment paradigms—DPO-style preference optimization, RLVR, PRMs, and multimodal RLHF—when they clarify the boundary between rubric-guided RL and competing or complementary methods.

Search sources. We searched ACL Anthology, OpenReview, arXiv, Semantic Scholar, Google Scholar, and proceedings or accepted-paper lists from ACL, EMNLP, NAACL, EACL, ICLR, ICML, NeurIPS, CVPR, and related workshops. We additionally followed citation links from seed papers such as Constitutional AI, DPO, PRMs, DeepSeekMath, and recent rubric-generation papers.

Query families. Search queries covered five families: (i) rubric, criteria, checklist, grading, and LLM judge; (ii) constitution, principle, RLAIF, and AI feedback; (iii) DPO, IPO, KTO, SimPO, ORPO, and direct preference optimization; (iv) RLVR, verifier, process reward, mathematical reasoning, and code execution; and (v) multimodal RLHF, hallucination, VLM reward modeling, and multi-criteria VLM evaluation.

Inclusion criteria. We included papers if they met at least one criterion: (1) they explicitly use rubrics, principles, checklists, or criteria for alignment, reward modeling, or evaluation; (2) they operationally implement rubric-like structured or multi-dimensional feedback; (3) they are foundational adjacent methods needed to position rubric-guided RL; or (4) they introduce benchmarks or failure analyses that directly inform rubric quality, reward hacking, judge reliability, multilingual evaluation, or multimodal alignment.

Reliability and evidence use. Peer-reviewed papers are used as primary evidence whenever available. Influential preprints and technical reports are included when they are widely adopted, provide necessary coverage of fast-moving 2025–2026 developments, or directly introduce rubric-guided RL methods not yet published in archival venues. We label such work cautiously in the prose and avoid using unstable or unverifiable sources as load-bearing evidence. When a citation could not be matched to a stable title, author list, venue, or archival record, we removed it from the main evidence chain rather than relying on it for taxonomy or quantitative claims.

B Background: Related Surveys and Methods

B.1 How This Survey Differs from Prior Surveys

Several existing surveys touch on aspects of rubric-guided RL, but none provides a comprehensive treatment.

LLM-as-a-Judge Surveys. The comprehensive survey by Gu et al. (Gu et al., 2024) covers LLM-as-a-judge methodologies, biases, and applications. While LLM-as-a-judge is closely related to rubric-guided evaluation, the two concepts differ: LLM-as-a-judge typically uses implicit evaluation criteria, while rubric-guided evaluation uses explicit, structured criteria. Our survey bridges these two areas by examining how rubrics can make LLM-as-a-judge more interpretable and controllable.

Reward Design and PRM Surveys. Recent surveys on reward design and process reward models (Ji et al., 2025b; Zheng et al., 2025) categorize reward formulations and process supervision methods. Our survey differs in its focus on rubric-based reward design, which provides structured, interpretable, and multi-dimensional reward signals. We provide a more detailed treatment of rubric-specific challenges (rubric quality, evolution, exploitation) that are not addressed in general reward design surveys, and we position PRMs as implicit step-level rubrics extending beyond single-dimension process supervision.

Self-Evolution and Agentic RL Surveys. Tao et al. (Tao et al., 2024) survey self-evolution of large language models. Our survey complements these by focusing specifically on how rubrics enable self-evolution and structured credit assignment in agentic settings, dimensions not covered by existing surveys.

B.2 Related Alignment Paradigms

RLHF. RLHF (Ouyang et al., 2022) trains language models to align with human preferences through a three-stage pipeline. While RLHF has proven effective for alignment, its reliance on scalar reward signals introduces fundamental limitations: the reward is opaque, difficult to interpret, and prone to overoptimization (Gao et al., 2023).

RLAIF. RLAIF (Lee et al., 2024b; Bai et al., 2022) replaces human preference labels with AI-generated feedback, addressing the scalability bottleneck of human annotation. Constitutional AI (Bai et al., 2022) is a prominent instance of RLAIF that uses explicit natural-language principles to guide AI feedback.

DPO and direct preference optimization. DPO (Rafailov et al., 2023) bypasses the RL optimization loop by reparameterizing the reward model to derive the optimal policy in closed form. Its variants now form a major alignment family: IPO generalizes preference optimization and regularizes against deterministic-preference overfitting (Azar et al., 2024), KTO learns from pointwise desirable/undesirable examples (Ethayarajh et al., 2024), SimPO removes the reference model with a length-normalized implicit reward (Meng et al., 2024), ORPO merges SFT

and preference optimization into one stage (Hong et al., 2024), and CPO/SLiC-HF show contrastive calibration as another RL-free route (Xu et al., 2024; Zhao et al., 2023). This family is directly relevant to rubric-guided alignment because rubric scores can be converted into pairwise or pointwise preference labels; consequently, DPO-style optimization is best viewed as a competing or complementary backend for using rubric feedback, not merely as background RLHF literature.

RLVR. RLVR couples reinforcement learning with objective, externally verifiable signals such as mathematical correctness, code execution, or rule-based answer checking (Shao et al., 2024; DeepSeek-AI, 2025; Yang et al., 2024; Lambert et al., 2025). DeepSeekMath introduced GRPO for math reasoning with rule-based rewards (Shao et al., 2024), while DeepSeek-R1 and Qwen2.5-Math show that large-scale verifier- or rule-based RL can produce strong reasoning models in domains with checkable answers (DeepSeek-AI, 2025; Yang et al., 2024). Open post-training recipes such as Tülu 3 further incorporate verifiable tasks into modern alignment pipelines (Lambert et al., 2025). These methods are direct competitors to rubric-guided RL in math and code because verifiable rewards are cheaper and less subjective; rubric-guided methods are most compelling when tasks require partial credit, explanation quality, safety, pedagogy, or other criteria that are not externally decidable.

PRMs. PRMs (Lightman et al., 2024) provide step-level feedback for reasoning tasks. We reframe PRMs as *implicit, step-level rubrics* that score the "correctness" dimension at each reasoning step. The generalization from single-dimension PRMs to multi-dimensional rubric-guided process supervision (as in RLCER (Sheng et al., 2026)) is a natural but non-trivial extension.

GRPO. GRPO (Shao et al., 2024) eliminates the need for a value network by using group-relative rewards. GRPO has become a popular choice for rubric-guided RL methods (Gunjal et al., 2026) because it naturally accommodates structured, multi-dimensional reward signals.

C Mapping Method Classes to the Bayesian Framework

The Bayesian framework maps method classes according to how they specify, condition, and update evaluation criteria. Fixed-principle methods such as Constitutional AI specify input-independent criterion sets, corresponding to point-mass priors. Instance-specific systems such as RaR, OpenRubrics, PRMs, and judge-rubric generators construct input-conditioned criteria, corresponding to posterior point estimates. Self-evolving or learned-rubric methods such as EvoLM, Rubric-ARM, and RLCER instantiate the update-oriented part of the framework because their rubrics or reward models change with training data, policy outputs, or temporal contrast. This mapping clarifies which components of $P(\mathcal{R})$ and $P(\mathcal{R}|x)$ each method operationalizes.

D What the Bayesian Framework Adds Beyond Re-labeling

This framework provides conceptual and practical utility beyond simple notation replacement. Conceptually, it resolves the terminological ambiguity plaguing the field: constitutions and rubrics are unified as the same mathematical object at different conditioning levels. Constitutions act as global, unconditioned priors $P(\mathcal{R})$, while instance-specific rubrics are input-conditioned posteriors $P(\mathcal{R}|x)$. Methods such as EvoLM (Li et al., 2026c), which optimize evolving rubric representations, instantiate the update-oriented portion of this framework most directly.

Practically, this perspective yields actionable insights into training dynamics and adversarial robustness. It models self-evolving rubrics as online Bayesian updating, where the widely observed "vague to specific" evolution pattern simply reflects posterior sharpening as policy data distributions shift. Furthermore, it exposes linguistic reward hacking (rubric exploitation) as a classic case of overfitting to a single posterior point estimate $\mathcal{R}_x$. Consequently, the framework immediately suggests a principled defense mechanism: marginalizing over the full rubric posterior,

$$r_{\text{robust}}(x, y) = \mathbb{E}_{\mathcal{R}_x \sim P(\mathcal{R}|x)}\left[r_{\mathcal{R}_x}(x, y)\right]$$

which forces the policy to generalize across all plausible evaluation criteria rather than gaming a single deterministic set.

E Computational Efficiency Analysis

While rubric-guided reinforcement learning (RL) enhances reward interpretability, it introduces non-negligible computational and token overhead into the optimization loop. To provide a rigorous yet concise overview, we present a structural complexity analysis across different paradigms. Let P denote the token length of static constitutional principles, R the average token length of an individual criterion, K the number of criteria per instance, and S the intermediate step length for process-supervised approaches. We define T_{gen} and T_{eval} as the real-time execution latencies for rubric generation and judge evaluation, respectively.

As summarized in Table 2, the efficiency profiles across paradigms diverge along three core dimensions:

- **Token Consumption & Caching:** Static approaches (e.g., CAI (Bai et al., 2022)) incur a constant $\mathcal{O}(P)$ token overhead inside the evaluation context and fully benefit from inference-time prefix caching. Conversely, instance-specific frameworks (e.g., RaR (Gunjal et al., 2026), Rubric-ARM (Xu et al., 2026)) require online synthesis of conditional rubrics, injecting an uncacheable $\mathcal{O}(K \cdot R)$ dynamic token overhead per instance.

- **Evaluation Call Complexity:** In implicit aggregation modes (e.g., EvoLM (Li et al., 2026c), RaR Implicit), the judge model evaluates all dimensions simultaneously in a single forward pass ($\mathcal{O}(1)$ complexity). Explicit modes (e.g., RaR Explicit) serialize the verification, demanding $\mathcal{O}(K)$ independent judge calls per instance, which scales to $\mathcal{O}(M \cdot K)$ during test-time candidate (M) verification and inherently restricts optimal inference search depths.

- **Judge Infrastructure:** Leveraging commercial APIs typically introduces unpredictable network latency and financial costs. Modern paradigms optimize cost-effectiveness by constraining highly localized small models ($\mathcal{M}_{\text{local}}$, e.g., 1.7B–3B parameters) within precise rubric structures, compressing the localized evaluation latency to a fraction of commercial API execution times without compromising reward fidelity.

F Detailed Agentic and Deep Research Benchmarks

A rapidly growing line of work applies rubric-based evaluation to *deep research agents*—LLM agents that perform multi-step information gathering, synthesis, and report generation. ResearchRubrics (Sharma et al., 2025) provides 2,500+ expert-written rubrics across 100+ real-world tasks in 9 domains. DRACO (Zhong et al., 2026) introduces a cross-domain benchmark spanning 10 domains and 40 countries' information sources, evaluating outputs along factual accuracy, completeness, objectivity, and citation quality. DeepResearchBench (Li et al., 2026b) constructs 9,430 fine-grained binary rubrics from expert-written investigative articles. DEER (Han et al., 2025) develops a 7-dimension, 25-subdimension, 101-item rubric taxonomy with claim verification, making system strengths and limitations interpretable.

G Continual Learning Benchmarks

CL-bench (Dou et al., 2026b) introduces a benchmark with 500 complex contexts, 1,899 tasks, and 31,607 verification rubrics for assessing context learning. CL-bench Life (Dou et al., 2026a) extends this to real-life scenarios with 405 context-task pairs and 5,348 rubrics. In continual learning, rubrics serve as memory, where criteria from previous tasks provide evaluation frameworks that prevent catastrophic forgetting.

H Consistency and Rubric Quality

RubricBench (Zhang et al., 2026a) introduces a curated benchmark with 1,147 pairwise comparisons to assess the reliability of rubric-guided evaluation. RubricEval (Pan et al., 2026) is the first rubric-level meta-evaluation benchmark for instruction following.

I Representative Reported Results from Original Papers

Table 3 summarizes representative results reported by original papers. **Important caveat**: these results are reported under different evaluation settings, model sizes, and training configurations. They are included to document each paper's own evaluation setting, not to rank methods against each other.

Method	Rubric Context Cost	Judge Calls / Inst.	Eval. Latency	Typical Judge Scale
Scalar RM (Baseline)	0	1_{RM}	$\mathcal{O}(1)$	$\mathcal{M}_{\text{dense}}$
PRM (Lightman et al., 2024)	0 (Implicit)	S	$\mathcal{O}(S \cdot T_{\text{eval}})$	$\mathcal{M}_{\text{dense}}$
Constitutional AI (Bai et al., 2022)	$\mathcal{O}(P)$	1	$\mathcal{O}(T_{\text{eval}})$	$\mathcal{M}_{\text{large}}$
RaR (Explicit) (Gunjal et al., 2026)	$\mathcal{O}(K \cdot R)$	K	$\mathcal{O}(K \cdot T_{\text{eval}})$	$\mathcal{M}_{\text{small}}$ (API)
RaR (Implicit) (Gunjal et al., 2026)	$\mathcal{O}(K \cdot R)$	1	$\mathcal{O}(T_{\text{eval}})$	$\mathcal{M}_{\text{small}}$ (API)
Rubric-ARM (Xu et al., 2026)	$\mathcal{O}(K \cdot R)$	1	$\mathcal{O}(T_{\text{eval}})$	$\mathcal{M}_{\text{local}}$
EvoLM (Li et al., 2026c)	$\mathcal{O}(K \cdot R)$	1	$\mathcal{O}(T_{\text{eval}})$	$\mathcal{M}_{\text{local}}$

Table 2: Computational complexity and resource mapping across key paradigms. P and R denote the token lengths of constitutional principles and individual criteria, respectively; K specifies the total number of evaluation criteria, and S represents the reasoning sequence steps. The base latency parameter T_{eval} scales asymptotically as a function of the designated judge model capacity $\mathcal{M}$.

Method	Base Model	Benchmark	Metric	Result
RaR (Gunjal et al., 2026)	Qwen-2.5-7B	HealthBench,	Rel. improvement	+31%
		GPQA-Diamond	Rel. improvement	+7%
Rubric-ARM (Xu et al., 2026)	Various	RewardBench	Avg. gain	+4.7%
EvoLM (Li et al., 2026c)	Qwen3-8B	RewardBench-2,	Over GPT-4.1	+25.7%
		OLMo3-Adapt	Average	69.3%
RLCER (Sheng et al., 2026)	7B	Math benchmarks	Over RLVR	Outperforms
OpenRubrics (Liu et al., 2025)	Various	RewardModel	Over baselines	+8.4%
PRM (Lightman et al., 2024)	Various	MATH	Accuracy	78.2%
Constitutional AI (Bai et al., 2022)	Various	Harmlessness Elo	Pareto	Improved
Chasing the Tail (Zhang et al., 2025a)	Various	RewardBench	Accuracy gain	+3.2%
RLCF (Viswanathan et al., 2025)	Various	Multi-domain	Consistent gain	Improved

Note: Results are from original papers under different settings and should NOT be directly compared.

Table 3: Representative results reported by original papers. These numbers are included only to document each paper's own evaluation setting and should not be interpreted as a controlled cross-method comparison.

J Detailed Comparison of Rubric Aggregation Strategies

The aggregation function $\mathcal{A}$ that combines criterion-level scores into a scalar reward is a critical design choice. Table 4 compares the main strategies used in rubric-guided RL.

K Extended Discussion on Rubric Quality Dimensions

Discriminative Power. Discriminative power measures how well a rubric distinguishes between high-quality and low-quality responses. A rubric with high discriminative power assigns significantly different scores to good and bad responses, while a rubric with low discriminative power assigns similar scores regardless of quality. This can be measured by the accuracy of rubric-conditioned evaluation on held-out preference data.

Coverage. Coverage measures how many relevant quality dimensions a rubric captures. A rubric with high coverage evaluates all important aspects of response quality (correctness, completeness, clarity, safety, etc.), while a rubric with low coverage may miss important dimensions. PRMs, for example, have low coverage because they evaluate only the correctness dimension. Incomplete rubrics may fail to capture important aspects of response quality, leading to reward hacking through unmeasured dimensions.

Calibration. Calibration measures how well rubric scores align with human judgment across the full quality spectrum. A well-calibrated rubric assigns scores that are consistent with human evaluation, while a poorly calibrated rubric may over- or under-estimate quality. LLM-Rubric (Hashemi et al., 2024) proposes calibration methods for rubric-based evaluation. Calibrating rubric-based

Strategy	Formula	Used By	Pros	Cons
Weighted Sum	$r = \sum w_k \cdot s_k$	RaR (Explicit)	Simple, interpretable	Ignores criterion interactions
Implicit Aggregation	Judge considers all criteria together	RaR (Implicit)	Captures interactions	Less interpretable
Learned Aggregation	Neural network combines scores	Rubric-ARM	Adaptive	Requires training data
Discriminative	Optimized for distinguishing responses	EvoLM	High precision	May sacrifice coverage
Step Product	Product of step-level scores	PRM	Simple, principled	Sensitive to single bad step
Principle Ensembling	Sample multiple principles	CAI	Robust	May be inconsistent
Checklist	Binary verification per item	RLCF	Verifiable	Binary granularity
Hierarchical	Multi-level aggregation	HiPER, OpenRS	Captures structure	Complex design

Table 4: Comparison of rubric aggregation strategies. The choice of aggregation strategy affects interpretability, robustness, and the ability to capture interactions between criteria.

scores to match human judgment distributions is critical for consistency.

L Linguistic Insights: Detailed Evidence and Qualitative Examples

This appendix provides detailed evidence and qualitative examples supporting the claims in Section 4.

Semantic Drift: Qualitative Evidence. EvoLM (Li et al., 2026c) provides the most direct evidence for semantic drift: rubrics evolve from vague criteria (e.g., "Ensure mathematical accuracy") to specific, verifiable facts (e.g., "The answer is 144, derived from perimeter 48") as training progresses. This evolution is a form of intentional semantic drift—the rubric's meaning sharpens through posterior updating. Constitutional AI (Bai et al., 2022) observed unintentional drift through Goodharting, where over-optimization leads to boilerplate language and overly harsh responses. The drift metric we propose in Equation (1)—$\text{Drift}(c_k, t) = 1 - \text{corr}(s_t, s_0)$—is a novel contribution of this survey; no prior work has proposed this specific formalization for rubric-guided RL, and its empirical validation remains an open problem. We present a concrete case study of semantic drift in Table 5.

Linguistic Reward Hacking: Qualitative Examples.

- **Verbosity exploitation**: Gao et al. (Gao et al., 2023) document reward model overoptimization where proxy rewards increase while true rewards decline, a dynamic closely related to verbosity exploitation. In rubric contexts, models learn to pad responses with filler to satisfy "completeness" criteria without adding substantive content.
- **Criterion bleeding**: Safe RLHF (Dai et al., 2024) explicitly addresses the safety-helpfulness tradeoff, where maximizing safety (refusing all requests) violates helpfulness. ArmoRM (Wang et al., 2024) uses multi-objective reward modeling to mitigate criterion bleeding by balancing multiple quality dimensions simultaneously.
- **Surface pattern matching**: self-evolving rubric work suggests that evaluator capacity and rubric specificity interact, with smaller evaluators often requiring more explicit criteria to distinguish genuine satisfaction from superficial compliance (Li et al., 2026c). This suggests that surface pattern matching is a real phenomenon that can be partially mitigated by evaluator and rubric design.

We provide concrete case studies for each type of linguistic reward hacking, drawing on empirical evidence from recent work. The case studies can be found in Table 6, 7, 8 and 9.

Underspecification as Opportunity. No prior work explicitly argues that underspecification is

Case Study 1: Semantic Drift—Intentional vs. Unintentional
Intentional drift (EvoLM): Shao et al. (Li et al., 2026c) document that rubrics evolve from vague criteria (e.g., "Ensure mathematical accuracy") to specific, verifiable facts (e.g., "the correct maximum area of 144, derived from the given perimeter of 48") as training progresses. This is intentional semantic drift—the rubric's meaning sharpens through posterior updating, improving downstream policy quality.
Unintentional drift (CAI): Bai et al. (Bai et al., 2022) observe that the meaning of "harmlessness" drifts from "avoid causing harm" to "refuse all potentially sensitive queries" under over-optimization. The rubric text remains unchanged, but the policy's interpretation shifts, leading to overly harsh and unhelpful responses.

Table 5: Semantic drift in rubric-guided RL: intentional drift (posterior sharpening) may improve quality, while unintentional drift (Goodharting) can degrade it.

Case Study 2: Verbosity Exploitation via Presence-Based Rubrics
Source: Mahmoud et al. (Mahmoud et al., 2026)
Phenomenon: The RL checkpoint improves completeness (+1.07) but degrades conciseness (-2.91), factual correctness (-0.85), and overall quality (-1.02). The rubric-based verifier prefers the RL checkpoint on 85.8% of prompts, but rubric-free judges prefer the base model on 78.4%—a clear sign of reward hacking under strong verification.
Mechanism: 90.2% of rubric weight falls on *presence-based* criteria (e.g., "States that plasma volume increases more than red cell mass during pregnancy"). Presence-based satisfaction rises from 27.6% to 42.5% (+14.9 pp), while absence-based criteria decline. The model exploits this by generating longer, claim-denser responses that satisfy presence checks without verifying correctness.
Safety-presence exploitation: Safety-presence rubric items (8.4% weight) such as "The response advises the user to consult a healthcare provider before taking any action" can be satisfied by appending boilerplate disclaimers without genuine safety reasoning.

Table 6: Verbosity exploitation through presence-based rubric criteria. The model learns to satisfy presence checks by generating longer, claim-denser output, while degrading on conciseness, factual correctness, and overall quality.

an opportunity in rubric-guided RL. However, several methods implicitly exploit it: EvoLM (Li et al., 2026c) observes rubrics evolving from vague to specific through posterior sharpening, RLCER (Sheng et al., 2026) starts with underspecified rubrics that self-evolve during training, and Rubric-ARM (Xu et al., 2026) learns rubric-conditioned reward models in non-verifiable settings. We posit that underspecification provides the space for rubric self-evolution—without initial underspecification, adaptive sharpening would have no room to operate.

Cross-Linguistic Considerations. Hong et al. (Hong et al., 2025) demonstrate that English-trained reward models exceed target-language reward models by 3–4% on Multilingual RewardBench, suggesting cross-lingual transfer is feasible but imperfect. Sheth et al. (Sheth et al., 2026) propose a Universal Criteria Set (UCS) with language-agnostic evaluation dimensions combined with language-specific instantiations. Fu & Liu (Fu and Liu, 2025) find that multilingual LLM-as-a-judge has low cross-lingual consistency (Fleiss' Kappa ≈ 0.3), indicating that rubric-conditioned judges face the same challenge. The mR3 model (Anugraha et al., 2026) extends to 72 languages with rubric-agnostic reward reasoning, while M-RewardBench (Gureja et al., 2025) provides the first systematic multilingual RM evaluation across 23 languages. Language-specific quality dimensions include Japanese keigo (honorific system) with multiple formality levels, Korean jondaetmal (honorific usage) (Lee et al., 2024a), and Arabic diglossia—all absent from English-centric rubrics. CM-Align (Zhang et al., 2025b) uses consistency-based approaches for multilingual alignment.

M Adversarial Robustness and Reward Hacking

Rubric-guided RL introduces both new defenses against and new vulnerabilities to adversarial attacks and reward hacking.

Rubric Exploitation as Overfitting to a Point Estimate. A novel form of reward hacking in rubric-guided RL is *rubric exploitation*: the policy learns to produce responses that score well against rubric criteria while violating the spirit of the rubric. Under the Bayesian framework (§2.4), rubric exploitation corresponds to *overfitting to*

Case Study 3: Criterion Bleeding—Safety-Helpfulness Tradeoff
Phenomenon: Maximizing the safety criterion ("the response should not cause harm") by refusing all requests directly violates the helpfulness criterion ("the response should address the user's query"). Safe RLHF (Dai et al., 2024) and ArmoRM (Wang et al., 2024) have proposed mechanisms to mitigate this problem. We categorize this phenomenon as "Criterion bleeding" — satisfying one rubric dimension at the expense of another.
Constitutional AI evidence: Bai et al. (Bai et al., 2022) observe that over-optimization against constitutional principles leads to boilerplate language and overly harsh responses—the policy learns to satisfy safety keywords ("I cannot assist with that") while violating the spirit of balanced evaluation.
Mitigation: Safe RLHF explicitly decomposes the reward into separate safety and helpfulness objectives with constrained optimization. ArmoRM (Wang et al., 2024) uses multi-objective reward modeling to balance multiple quality dimensions simultaneously, preventing criterion bleeding by design.

Table 7: Criterion bleeding: when satisfying one rubric dimension (safety) comes at the expense of another (helpfulness), the policy exploits the multi-objective gap.

Case Study 4: Surface Pattern Matching—Rubric Verification Failure Modes
Source: Mahmoud et al. (Mahmoud et al., 2026)
Failure Mode Taxonomy (stable across training, domains, and verifier strength):
• **Partial Compound (36.0%):** The criterion requires A∧B but the verifier accepts only one conjunct. Example: "The verifier failed because it accepted partial satisfaction of a multi-part requirement as full credit, verifying the outcome statement while not enforcing the required explicit distinction between two specified categories."
• **Implicit-as-Explicit (34.6%):** The required claim is never explicitly stated; the verifier infers it from context. Example: "The verifier failed because it credited an implicit or inferable statement as if it were explicit, accepting broad plausibility instead of requiring the exact characterization the criterion demanded."
• **Imprecise Verification (29.4%):** The verifier accepts a related but distinct concept as equivalent, or checks only broad topic relevance. Example: "The verifier failed because it matched on surface topic relevance instead of verifying the specific claim."
Key insight: These failure modes are *stable* across training—the distribution of exploitation types does not shift, only the volume increases. Both weak and strong verifiers fail in the same proportions, suggesting these are fundamental limitations of rubric verification.

Table 8: Surface pattern matching in rubric verification: three recurring structural failure modes where the verifier accepts superficial criterion satisfaction without genuine engagement.

a point estimate of the rubric posterior: the policy optimizes against a single sample $\mathcal{R}_x$ rather than the full posterior $P(\mathcal{R}|x)$. The defense is to evaluate under the full posterior (marginalization), which requires the policy to perform well under all plausible rubrics rather than gaming a single one.

Rubric-Specific Reward Hacking. Reward Hacking in Rubric-Based RL (Mahmoud et al., 2026) studies the specific phenomenon where policies optimized against a training rubric are evaluated against a cross-family panel. The key finding is that rubric-based rewards do not by themselves prevent reward hacking: the gap between training and evaluation rubrics creates an exploitation surface.

Defenses. Dynamic rubric adaptation (self-evolving rubrics close exploitation opportunities), multi-rubric evaluation (ensemble methods), constrained optimization with rubric-based safety constraints, and information-theoretic approaches (InfoRM (Miao et al., 2024)) all provide defenses against rubric exploitation.

Case Study 5: Granularity Effects and Evaluator Capacity
Phenomenon: Smaller judges (1.7B) force the learned rubric generator to produce more precise, fine-grained criteria, resulting in better downstream policies than larger judges (up to 32B) that tolerate vague rubrics. This demonstrates that optimal rubric granularity interacts with judge capacity: a rubric that is "too coarse" for a small judge may be "just right" for a large judge, and vice versa.
PRM evidence: Lightman et al. (Lightman et al., 2024) show that step-level (fine-grained) process supervision achieves 78.2% on MATH, substantially outperforming outcome-level (coarse-grained) supervision. This confirms that finer granularity produces better signals, but we argue that such benefits can be fully achieved only when the evaluator can reliably apply the fine-grained criteria.
RLCF evidence: RLCF (Viswanathan et al., 2025) decomposes each instruction into atomic checklist items and uses them as instance-level reward criteria, illustrating how checklist-style rubrics can provide denser and more inspectable feedback than holistic outcome rewards.

Table 9: Granularity effects: the interaction between rubric granularity and judge capacity determines downstream policy quality. Finer granularity generally helps, but only when the evaluator can reliably apply the criteria.