Multimodal LLM Alignment with DPO: Challenges, Solutions, and Research Opportunities

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Abstract

Multimodal large language models (MLLMs) have exhibited substantial capability in performing complex tasks that integrate visual, auditory, and textual modalities. Nevertheless, they continue to exhibit notable shortcomings in truthfulness, safety, and alignment with human preferences, thereby motivating intensive research on alignment algorithms specifically tailored to MLLMs. This paper provides a systematic and comprehensive survey of MLLM alignment, structured along three principal dimensions: (i) the algorithmic pipeline and technical procedures underlying alignment methods, (ii) the application domains and usage scenarios for which these methods are designed, and (iii) the evaluation methodologies employed to measure alignment quality. The objective of this work is to furnish researchers with a coherent framework for situating recent advances in MLLM alignment and to facilitate the development of more robust, reliable, and human-aligned multimodal systems.

1 Introduction

Multimodal large language models (MLLMs) have achieved remarkable progress in integrating information from vision, language, and other modalities, and have been widely deployed across downstream applications such as embodied AI (Liang et al., 2025b), scientific reasoning (Wang et al., 2025d), and human–AI interaction (Durante et al., 2024). Despite these impressive advances, a fundamental open question remains: **how can we rigorously align the behavior of these models with human values and expectations?** Since the early development of large language models, alignment has been a central and continuously evolving theme, giving rise to a rich family of alignment algorithms shown in Fig 1. Nowadays, alignment procedures have become an indispensable component of foundation model training pipelines, referred to Qwen3-VL (Bai et al., 2025), Keye-VL (Kwai Keye Team et al., 2025) and InternVL3.5 (Wang et al., 2025c), and they increasingly exhibit a dual nature: wide applicability and task-specificity.

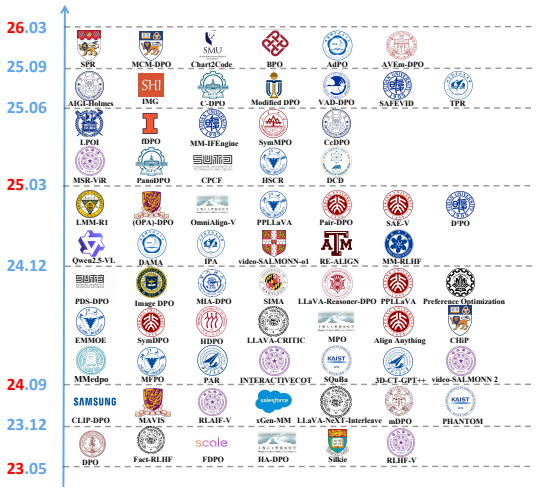

Figure 1: A timeline of MLLM alignment algorithms

Recent survey papers have increasingly touched on MLLM alignment from complementary angles. (Ji et al., 2025) and (Li et al., 2025d) provide broad, systematic reviews of LLM alignment and underline its importance for reliable downstream deployment. From a mechanisms-oriented lens, (Shu et al., 2025) studies alignment and misalignment through explainability, relating observed behaviors to representation- and behavior-level causes. More targeted treatments also emerge: (Sharma et al., 2025) expands the RLHF/RAHF landscape to cover cultural considerations, multimodal settings, and latency-aware alignment objectives, while (Li and Tang, 2024) surveys multimodal alignment and fusion as a core technical theme. Nevertheless, much of the existing literature still either positions multimodal alignment as one component within a broader topic or concentrates on cataloging surface-level phenomena rather than articulating a unified, deployment-facing account of multimodal alignment. A systematic integration of alignment meth-

ods, evaluation protocols, and application practice for MLLMs is still lacking. Against this backdrop, we revisit the alignment problem for multimodal large models from a more systematized and application-oriented perspective. A more detailed comparison between our work and existing surveys is provided in Appendix C.

Our main contributions can be summarized as follows:

- **Technical pipeline.** We clearly present the detailed technical pipeline for multimodal alignment, covering preference signal construction and alignment objective design, thereby formalizing an end-to-end recipe for the MLLM alignment algorithm.
- **Application scenarios.** We analyze how alignment manifests across a variety of multimodal application scenarios, highlighting recurring design patterns as well as task-dependent requirements and constraints.
- **Evaluation framework.** Across diverse application scenarios, we systematically compare the relevant evaluation benchmarks and their key emphases, thereby guiding researchers to refine alignment strategies toward metric-specific objectives correspondingly.

The overall framework of our paper is shown in Fig 2. This survey aims to provide a comprehensive perspective that enables researchers in both academia and industry to identify fundamental, cross-domain challenges in multimodal alignment. In total, we survey more than 60 distinct alignment methods, some of which appear in multiple categories due to their wide applicability. By doing so, we hope it can facilitate the design and innovation of more broadly applicable alignment algorithms that can effectively address, and ultimately go beyond, the complexities of real-world environments.

2 MLLM Alignment Technical Pipeline

Alignment in MLLM is generally an end-to-end design process. In practice, it is typically decomposed into two major stages: **preference signal construction** and **alignment objective design**. The preference signal determines the sources and representational forms of supervision used during alignment. In contrast, the alignment objective specifies how these signals are integrated into learning and the degree or intensity of alignment is enforced. Consequently, alignment across domains and tasks should not be viewed as isolated cases; rather, it can be understood as an adaptive design grounded in diverse human preferences and expectations. This section provides a detailed decomposition and analysis of this unified design framework, with a cross-category synthesis of design patterns and methodological insights presented in Appendix E.

2.1 Preference Signals Construction

Multimodal settings involve rich, experience-grounded information, while alignment objectives vary substantially across tasks and may even be mutually conflicting. Consequently, preference signal construction in MLLMs is not merely a labeling problem, but a supervision design problem shaped by trade-offs in semantic fidelity, scalability, controllability, and failure modes. This helps explain why existing methods do not converge to a single paradigm: depending on whether the target preference is best captured by human judgment, model-based evaluation, programmatic rules, or environment interaction, they instead adopt different strategies, as shown in the upper part of Fig. 3.

2.1.1 Human Preference

The most direct form of supervision for preference alignment comes from humans. To a considerable extent, MLLM alignment mirrored the success of RLHF in the text-only setting: annotators provide pairwise preferences, scalar ratings, or ranked sequences to support preference labeling. Early MLLMs alignment methods, such as LLaVA-RLHF (Sun et al., 2023a), RLHF-V (Yu et al., 2024a), M-HalDetect (Gunjal et al., 2024), largely relied on carefully designed human annotations for training datasets, which substantially mitigated hallucinations and jailbreak attacks. In domains with high professional complexity or stringent safety requirements, human-in-the-loop remains indispensable. In biomedical systems, 3D-CT-GPT++ (Chen et al., 2025a) depend on expert-designed tasks and quality criteria, even when parts of the subsequent scoring process are delegated to language models. Similarly, embodied settings such as EMMOE (Li et al., 2025a) require the collection and analysis of expert demonstrations as a prerequisite for building imitation-learning and preference datasets.

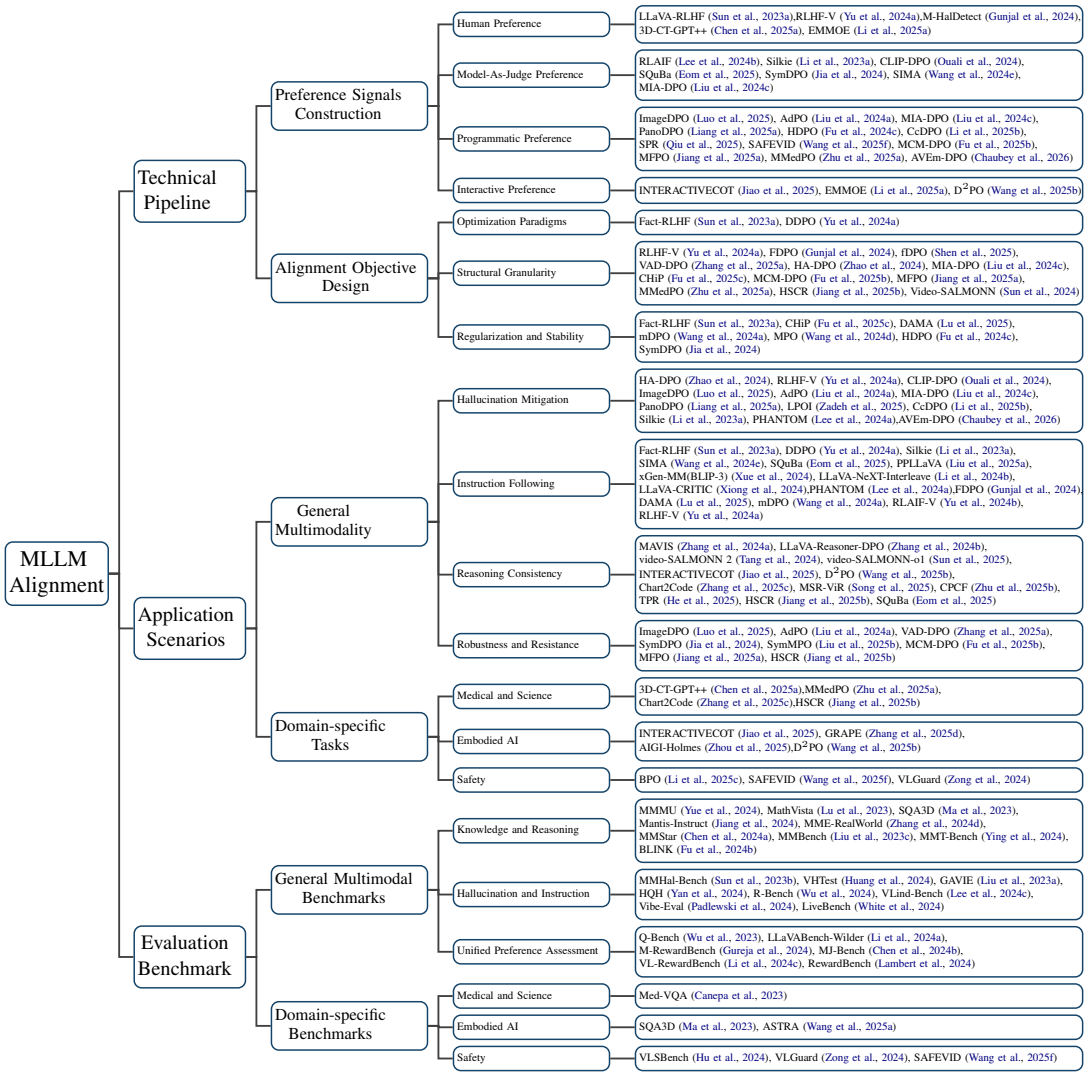

Figure 2: The overall framework of MLLM Alignment

2.1.2 Model-As-Judge Preference

Golden standard human annotations are prohibitively expensive. With the growing adoption of RLAIF (Lee et al., 2024b), increasing work has shifted to the LLM-as-judge paradigm, leveraging strong LLMs or auxiliary visual encoders to generate labels and scores for candidate samples. Closed-source models such as GPT (OpenAI., 2024; Achiam et al., 2023) and Gemini (Comanici et al., 2025; Team, 2024) have reached near-human performance on multiple tasks, therefore widely used to annotate preference data across diverse areas, including vision-language understanding (Liu et al., 2023b; Li et al., 2023a; Lee et al., 2024c), video understanding (Tang et al., 2025; Sun et al., 2024), long chain-of-thought reasoning (Zhang et al., 2025b; Wang et al., 2025e), and model safety (Zong et al., 2024; Zhao et al., 2024).

A key ingredient of Model-based annotation is prompt engineering that operationalizes target preferences: decomposing complex requirements into multi-dimensional criteria to improve reliability. For example, Silkie (Li et al., 2023a) uses GPT-4V to score responses along dimensions such as helpfulness, visual faithfulness, and ethical considerations, yielding stable preference signals. CLIP-DPO (Ouali et al., 2024), in contrast, employs CLIP-like visual encoders to assist preference generation and scoring, illustrating how modular encoders can be exploited for preference construction.

Beyond such external judges, preference signals could come from the target model itself: depending on modality settings, methods such as SQuBa (Eom et al., 2025), SymDPO (Jia et al., 2024), SIMA (Wang et al., 2024e), and MIA-DPO (Liu et al., 2024c) construct preference pairs from model responses in text-only or vision-language scenarios. Nevertheless, Model-as-judge

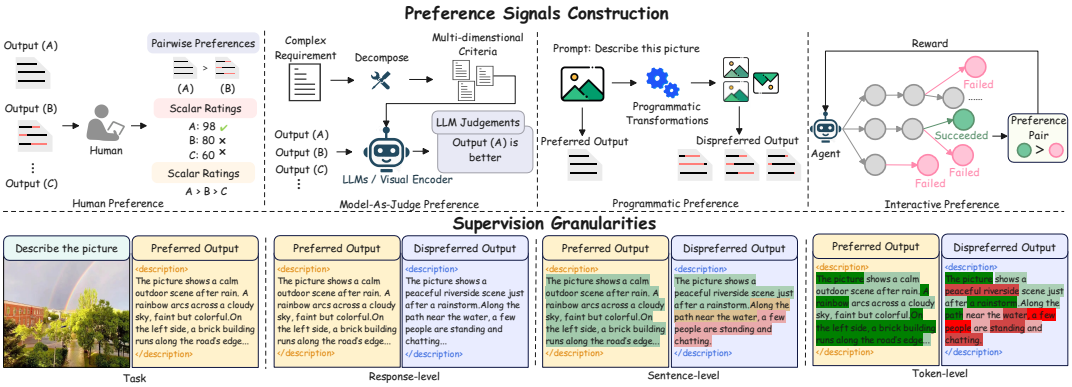

Figure 3: Preference signal construction mechanisms and supervision granularity designs.

substantially improves labeling efficiency and reduces cost, but it also inevitably transfers the biases and failure modes of the judging or generating models into the preference data.

2.1.3 Programmatic Preference

Preferences are specified through reusable rules and procedural generation, making programmatic preference construction crucial for MLLMs because it encodes task structure, safety constraints, and hallucination definitions into the data pipeline.

Visual perturbations and contrastive variants enable large-scale preference data construction. Image DPO (Luo et al., 2025) and AdPO (Liu et al., 2024a) generate positive/negative pairs via semantic edits, blurring, or adversarial transforms, while MIA-DPO and PanoDPO (Liang et al., 2025a) use compositing, viewpoint changes, or conditional preferences to strengthen visual grounding. For hallucination and safety control, HDPO (Fu et al., 2024c), CcDPO (Li et al., 2025b), SPR (Qiu et al., 2025), and SAFEVID (Wang et al., 2025f) build contrastive pairs by varying hallucination severity, temporal coherence, or hazardous content. Beyond pairwise setups, MCM-DPO (Fu et al., 2025c) and MFPO (Jiang et al., 2025a) define modality-aware, multi-criteria preferences, AVEm-DPO (Chaubey et al., 2026) enhances the model's ability to perceive emotions by introducing Emotion-based Response Preference, and MMedPO (Zhu et al., 2025a) applies domain-aware weighting to emphasize clinically critical errors.

Programmatic preference design is now central to MLLM alignment, offering scalable, low-cost data, precise control over failure modes, and more reproducible training signals than large-scale human annotation or generic judge-based scoring.

2.1.4 Interactive Preference

As the scope of MLLM tasks expands, preference signals no longer arise solely from static annotation pipelines; they can also be induced from reward information obtained through interaction with environments or tasks. MLLMs operate as agents that generate actions, queries, or reasoning trajectories and receive feedback in the form of task success signals, environment rewards, or trajectory-level performance scores. INTERACTIVECOT (Jiao et al., 2025) in ALFWorld, EMMOE in Replica-like 3D environments, and D^2PO (Wang et al., 2025b) for embodied planning, which derive preferences from task completion signals and decomposed subgoals. GRAPE similarly aligns policies at the trajectory level by contrasting successful and failed trials under spatiotemporal constraints.

While auxiliary LLM judges may still be employed at certain stages, the primary supervision in these approaches is inherently dynamic and trajectory-dependent rather than a one-shot evaluation of static input–output pairs, making interaction itself a central source of alignment feedback.

2.2 Alignment Objective Design

Alignment objectives for multimodal build upon the general framework of preference-based or feedback-based alignment, while introducing broader constraints and more fine-grained decompositions centered on optimization paradigms, structural granularity and stability mechanisms. Detailed objectives are shown in Table 1.

2.2.1 Optimization Paradigms

Online optimization largely follows the RLHF-style formulation, treating alignment as a policy-based reinforcement learning problem. This was a commonly adopted framework in early alignment work; Fact-RLHF (Sun et al., 2023a) uses human scores as rewards for RLHF training. Related RL variants, such as DDPO (Yu et al., 2024a) and RL4VLM (Zhai et al., 2024) interact with an environment or sampler and receive reward signals provided by humans or strong baseline models.

Instead of explicitly fitting a reward model and performing on-policy policy optimization as in PPO-based RLHF, offline-based DPO directly optimizes the policy with a simple contrastive objective over offline preference pairs, while implicitly incorporating a reference-model regularization effect. This RL-free formulation substantially reduces algorithmic and engineering complexity, improves training stability, and lowers computational cost by avoiding iterative sampling-and-optimization loops. Together with its simplicity and scalability, it has made it one of the most widely adopted approaches for preference alignment in current practice. For completeness, we provide the introduction of RLHF and DPO in Appendix A.

2.2.2 Structural Granularity

Traditional alignment typically operates at the response level, treating the output as a single response sequence. For a multimodal input $(x, \mathcal{I})$, where x is a textual query and $\mathcal{I}$ denotes the associated images. The objective is commonly defined over preference pairs, training the model to favor the preferred response over the rejected one(i.e., (y_w, y_l)). Although this response-level formulation is effective across many tasks, recent works move beyond it by introducing fine-grained and hierarchical supervision illustrated in Fig 3 below, either by assigning non-uniform weights to tokens/spans or by defining dedicated objectives for specific structured components of multimodal outputs.

Fine-grained sequence. Fine-grained supervision improves credit assignment by pushing preference signals down to segment, sentence, or token units, which helps suppress localized hallucinations and makes better use of limited preference data. Dense-DPO in RLHF-V concentrates optimization on uncertain or reliability-critical spans, so the model is explicitly trained to correct the most error-prone fragments rather than merely shifting overall response style. FDPO (Gunjal et al., 2024) refines the pairwise objective by decoupling the contributions inside the sigmoid term, offering tighter control over local gradient behavior while keeping the offline preference optimization simplicity. This line also motivates token-level or span-aware DPO variants such as fDPO (Shen et al., 2025) and VAD-DPO (Zhang et al., 2025a) that retain the response-level backbone but inject finer error-targeting mechanisms.

Multiple hierarchies. Hierarchical fusion improves stability and controllability by aligning global preference direction and local grounding constraints across different granularities. HA-DPO (Zhao et al., 2024) and MIA-DPO extend response-level DPO with auxiliary supervised losses from positive examples to strengthen alignment under noisy or sparse supervision. CHiP (Fu et al., 2025c) represents a multi-level design combining visual DPO, sentence-level DPO, and a token-level KL-style sequence constraint, distributing alignment pressure across textual structure and visual evidence. Even when the main objective remains response-level, MIA-DPO's attention-based multi-image pairing implicitly spreads supervision over multiple visual components, improving robustness to compositional inputs.

Multiple dimension. Multi-dimensional designs broaden alignment beyond a single "good vs bad" axis, enabling structured control over multi-component inputs and heterogeneous error modes. MCM-DPO and MFPO define preferences over combinations of answer text, images, and context, encouraging consistent cross-modal reasoning rather than modality-isolated optimization. MMedPO and HSCR (Jiang et al., 2025b) introduce multiple dispreference types and learn to rank them, which supports finer-grained governance of distinct failure patterns such as hallucination versus omission in domain-critical settings. Video-SALMONN series (Sun et al., 2024; Tang et al., 2025) extends this idea to temporal media, video-oriented objectives treat coherence and time-consistency as additional alignment dimensions, pushing preference learning toward richer, scenario-aware control.

2.2.3 Regularization and Stability

As many alignment algorithms can be formulated as contrastive preference optimization, a key concern is preventing excessive distribution shift, catastrophic forgetting, and undesirable likelihood drift

relative to base models. Recent work addresses this with two recurring objective-level designs.

Reference-oriented regularization. Reference-oriented regularization constrains updates toward a trusted baseline. Fact-RLHF uses an explicit KL penalty to limit PPO deviation from the initial policy; CHiP adds KL terms between the reference and updated models for both preferred and dispreferred responses; and PO/MPO-style objectives incorporate log-ratio or reference-based penalties to keep adapted policies close to clean or accurate anchors.

Margin and asymmetry shaping. Complementing reference constraints, margin design and asymmetry-aware objectives regulate how strongly preferences are enforced. DAMA (Lu et al., 2025) rescales the DPO logit gap, mDPO (Wang et al., 2024a) and MPO (Wang et al., 2024d) impose margin-style constraints to preserve base accuracy while enforcing a minimum preference distance, and hallucination-oriented variants such as HDPO and SymDPO adopt anchored or symmetric formulations to mitigate probability drift.

3 Application Scenarios

MLLM alignment is inherently application-driven. As the scope of MLLM deployment continues to expand, these models have demonstrated substantial value in both general-purpose multimodal settings and more domain-specific scenarios.

3.1 General Multimodality

General multimodal capability serves as a foundational application for assessing the effectiveness of multimodal alignment. At the strategy level, its alignment objectives can be understood as four progressively deeper system-level requirements that recur across multimodal model designs: models must first remain grounded in perceptual evidence to mitigate hallucinations, then follow user intent and constraints, further sustain coherent intermediate reasoning for multi-step tasks, and finally preserve these properties under perturbations or adversarial inputs through robustness and resistance.

Hallucination mitigation. As the most basic requirement of general multimodal alignment, hallucination mitigation aims to ensure that responses are grounded in visual evidence rather than linguistic priors or spurious cues. Most methods construct preference pairs that differ in visual faithfulness and optimize against hallucinated outputs at the token or instance level. Clause-aware approaches (Zhao et al., 2024) suppress labeled hallucinated spans, while image-perturbation methods such as CLIP-DPO, Image DPO, and AdPO enforce genuine visual dependence by altering the image while keeping the text fixed. AVEm-DPO further introduces a Text Prior Debiasing mechanism that penalizes samples predictable solely from textual cues, mitigating the model's reliance on textual priors. Multi-image methods further extend this idea by contrasting viewpoints or occlusions to reduce shortcut reasoning (Liang et al., 2025a; Zadeh et al., 2025). More broadly, the incorporation of visual faithfulness as an explicit scoring dimension (Lee et al., 2024a) suggests that hallucination control has become a standard component of general MLLM alignment.

Instruction following. Building on perceptual grounding, instruction-following alignment further asks whether MLLMs can respond in ways that are not only faithful to the input, but also compliant with user intent and task constraints. RLHF-style pipelines optimize policies with user-derived rewards reflecting overall preferences over multimodal responses, whereas DPO-style methods (Liu et al., 2025a; Xue et al., 2024; Xiong et al., 2024) scale preference construction through human ratings, LLM-as-judge scoring, or cross-model comparisons. Extensions such as FDPO, DAMA, and mDPO refine preference separation, while RLAIF-V (Yu et al., 2024b) and RLHF-V introduce denser evaluator feedback to improve controllability and reliability. Across these systems, visual inputs are incorporated into prompts, but the core alignment target is robust multimodal instruction adherence and consistent satisfaction of user goals.

Reasoning consistency. Beyond producing grounded and instruction-compliant responses, many multimodal tasks also require models to reason through intermediate steps in a coherent and trustworthy manner. Reasoning alignment therefore targets how MLLMs arrive at answers, shaping CoT traces, decompositions, and intermediate decisions rather than only final outputs. This line includes CoT alignment for mathematical and visual reasoning (Zhang et al., 2024a,b), stepwise optimization for temporal and audio-visual understanding (Tang et al., 2024; Sun et al., 2025), and environment-grounded reasoning improved by task success signals in embodied settings (Jiao et al., 2025). In parallel, several

methods align intermediate artifacts such as plans, code variants, or structured edits (Song et al., 2025; Zhang et al., 2025c; Zhu et al., 2025b), so that preference learning constrains the reasoning products themselves. Together, these approaches extend multimodal alignment from response-level supervision to process-level consistency.

Robustness and resistance. Finally, general multimodal alignment must ensure that grounding, instruction adherence, and reasoning consistency remain stable under perturbations or misleading inputs. Robustness- and resistance-oriented methods address this by testing whether model behavior is preserved when modalities conflict or when visual evidence is subtly altered. VAD-DPO extends this logic to videos by contrasting visually similar but semantically opposite clips. Complementary objectives such as SymDPO and SymMPO (Liu et al., 2025b) further reduce over-reliance on textual cues, while methods like MCM-DPO, MFPO, and HSCR generalize supervision from isolated pairs to multi-candidate comparisons, encouraging reliance on the most informative visual evidence. In this sense, robustness alignment serves as the stability test of general multimodal capability.

3.2 Domain-specific Tasks

MLLM alignment becomes more in-depth in domain-specific tasks, exhibiting strong domain specificity, and is primarily applied to Medical and science, embodied AI, and safety scenarios.

Medical and science. Medical and scientific applications place a premium on factual correctness, domain expertise, and calibrated behavior under complex multimodal evidence. 3D-CT-GPT++ constructs radiology preference data scored by experts or experienced reasoning LLMs. MMedPO differentiates hallucination-type versus lesion and weights them by clinical severity with visualization-aware signals. MSR-ViR further aligns long-form scientific summarization via preferences over multi-stage outputs. HSCR (Jiang et al., 2025b) targets medical VLM alignment by automatically constructing high-quality preference pairs to improve clinical trustworthiness with limited training data.

Embodied AI. MLLMs are increasingly used for spatial perception and action selection in simulated and real environments. INTERACTIVECOT collects rollouts in environments like ALFWorld and treats task success as a preference signal to optimize multimodal CoT traces for action. In robotics, GRAPE aligns manipulation policies by contrasting successful and failed trajectories under spatial constraints, while D^2PO jointly learns action selection and state prediction via preference learning, coupling policy and world model learning. Domain systems like AIGI-Holmes (Zhou et al., 2025) combine vision experts with MLLMs and apply DPO to task-specific datasets for visual forensics and inspection. Across these settings, alignment depends on environmental dynamics and long-horizon success, making robustness to distribution shift and stable interaction crucial.

Safety. Safety-centered alignment seeks to prevent harmful content, curb misuse, and improve risk awareness in multimodal systems. BPO (Li et al., 2025c) introduces the MMSafe-PO dataset and a text-inertia loss to deter "modality cheating," making safe, visually grounded responses strictly preferred over unsafe or ungrounded ones. Training-time safety alignment is increasingly complemented by inference-time modules that serve as multimodal filters or risk classifiers. LLaMA Guard 3 Vision (Cheng et al., 2024) provides pairwise safety gating at the response level, while VL-Guard (Zong et al., 2024) targets lightweight guard models and calibrated risk detection for VLM deployments. MultiTrust (Zhang et al.) offers a unified trustworthiness evaluation suite to audit safety and robustness under diverse stressors, and MMDT (Xu et al., 2025) enforces decoding-time trustworthiness by intervening during generation rather than relying only on post-hoc filtering. Safety alignment usually employs conservative objectives and adversarial preference data to enhance robustness and reliability.

4 Benchmark and Evaluations

Mirroring the application landscape, existing benchmarks fall into two groups: general multimodal and domain-specific: the former are designed to reflect breadth-oriented use of MLLMs across diverse vision–language tasks and thus measure overall MLLM capability and alignment, while the latter track deployment in specialized settings with task-critical depth and boundary conditions. Given the heterogeneity of multimodal tasks and alignment objectives, a finer-grained categorization is necessary to more precisely capture the distinct evaluation focuses across different benchmarks. We list typical benchmarks in Table 2.

4.1 General Multimodal Benchmarks

General-purpose multimodal benchmarks assess broad cross-task capabilities across vision–language settings, with evaluation focusing on knowledge and reasoning, hallucination and instruction, and unified preference assessment.

Knowledge and reasoning. As demands for multimodal reasoning grow, general-purpose knowledge and reasoning benchmarks are increasingly used to track how alignment reshapes a model's reasoning profile. MMMU (Yue et al., 2024) and MathVista (Lu et al., 2023) remain representative suites for cross-disciplinary and math-oriented reasoning, while SQA3D (Ma et al., 2023)targets spatial perception and grounded reasoning. Complementing these, fine-grained real-world visual reasoning benchmarks are often organized as broader suites (Jiang et al., 2024; Zhang et al., 2024d; Chen et al., 2024a; Liu et al., 2023c; Ying et al., 2024; Fu et al., 2024b), which probe more localized and realistic visual reasoning effects of alignment.

Hallucination and instruction. Another key dimension is whether aligned models can produce faithful, evidence-consistent responses and remain robust against misleading or shifting contexts. Benchmarks such as MMHal-Bench (Sun et al., 2023b), VHTest (Huang et al., 2024), GAVIE (Liu et al., 2023a), and HQH (Yan et al., 2024) primarily measure factual grounding by testing consistency between visual inputs and generated responses, enabling systematic measurement of multimodal hallucinations. In contrast, R-Bench (Wu et al., 2024), VLind-Bench (Lee et al., 2024c), Vibe-Eval (Padlewski et al., 2024), and LiveBench (White et al., 2024) place greater weight on robustness and interaction behavior, assessing whether models maintain cautious, stable, and faithful response patterns under adverse conditions or distribution shifts.

Unified preference assessment. Alignment stems from the need for consistency with human preferences, so a model's alignment is often judged by how closely its outputs match human judgments. Q-Bench (Wu et al., 2023), LLVisionQA, LLDescribe, and LLaVA Bench-Wilder (Li et al., 2024a) evaluate alignment to human expectations via controlled perception-focused QA and description tasks, jointly reflecting visual ability and instruction following. Going beyond task performance, M-RewardBench (Gureja et al., 2024), MJ-Bench (Chen et al., 2024b), VL-RewardBench (Li et al., 2024c), and RewardBench (Lambert et al., 2024) assess alignment at the preference level, measuring how well multimodal reward models or LLM-as-judge systems approximate human preferences on safety, reliability, and bias in multi-task, multilingual settings.

4.2 Domain-specific Benchmarks

Domain-specific benchmarks assess if a model meets practical standards within a specific domain. Unlike general evaluations, they focus on downstream tasks, expert norms, and risk profiles, emphasizing boundary conditions and failure tolerance over average performance. They evaluate both broad capability and trustworthiness under specialized requirements.

Domain sensitivity manifests differently across fields. In medical and scientific settings, where error tolerance is extremely low, benchmarks like Med-VQA (Canepa et al., 2023) and 3D-CT-GPT++ test expert imaging interpretation, while MMedPO and related work impose clinically grounded preference criteria to enforce diagnostic logic and terminological rigor. In embodied AI, benchmarks move from static perception to closed-loop perception–decision–action: SQA3D targets 3D spatial understanding, and ASTRA (Wang et al., 2025a), Engine, and RL4VLM evaluate whether models convert instructions into executable, adaptive plans. In safety-critical domains, benchmarks stress-test harmlessness and robustness: VLGuard and VLSBench (Hu et al., 2024) probe resistance to visual jailbreaks, RLAIF-V and HallusionBench target harmful multimodal hallucinations, and SafeVID extends this to video generation. These benchmarks indicate that in specialized domains, alignment is judged more by adherence to expert standards than by general usefulness.

5 Conclusion

MLLM alignment has progressed rapidly in recent years. In this survey, we provide a systematic and comprehensive review of existing work from three complementary perspectives: technical pipelines, application scenarios, and evaluation methodologies. Due to space constraints, we place an extended discussion of future directions in the Appendix D. We hope this survey will serve as a useful reference and help catalyze further research on principled, reliable, and scalable MLLM alignment.

Limitations

Paper retrieval, inclusion, and exclusion were done by a single reviewer (the study's first author). While we implemented rigorous procedures to ensure comprehensive coverage of published works, this approach inherently carries the risk of omitting potentially relevant studies. Furthermore, classification of papers into specific categories or citation implementation might contain inadvertent errors. Nevertheless, we have performed multiple verification steps throughout the analytical process to mitigate such limitations. Although minor inconsistencies or omissions may persist, we maintain that this survey constitutes the most comprehensive review of MLLM alignment currently available, offering an objective and detailed assessment of future research directions and outstanding challenges.

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A Preliminary of Optimization Paradigm

A.1 RLHF

RLHF is a technique that combines RL with human feedback to align AI models (such as LLMs) with human preferences or values. It is widely used in alignment tasks and has played a crucial role in fine-tuning generative models (e.g., ChatGPT). RLHF typically consists of three stages: pretrained model, reward modeling, and RL fine-tuning.

In the field of MLLM alignment, RLHF-based methods are relatively rare, with Fact-RLHF being a representative example. Fact-RLHF undergoes three training phases (supervised fine-tuning, human preference collection & preference modeling, and factually-augmented RLHF) to align with human preferences. In Table 1, we present the loss function of the Fact-RLHF algorithm and compare it with other alignment algorithms. The training objective of RLHF is as follows:

$$\mathcal{L}_{\text{RLHF}} = -\mathbf{E}_{(\mathcal{I},x)\in D, y\sim\pi_\phi(y|\mathcal{I},x)} [r_{\boldsymbol{\theta}}(\mathcal{I},x,y) - \beta \cdot \mathbb{D}_{KL}(\pi_\phi(y|\mathcal{I},x) \parallel \pi^{\text{INIT}}(y|\mathcal{I},x))], \tag{1}$$

where $\mathcal{L}$ denotes the loss function, $\mathcal{D}$ represents the dataset, $\mathcal{I}$ represents the image, x represents the question, y represents the response, $\mathbb{D}_{KL}$ represents the KL divergence, π_ϕ represents the trained MLLM policy, π^{INIT} represents the fixed initial policy model, $r_{\boldsymbol{\theta}}$ represents the reward model, and β represents a hyperparameter.

A.2 DPO

DPO is an emerging model alignment approach designed to replace traditional RLHF by directly optimizing model policies using preference data, eliminating the need for explicit reward model training or complex reinforcement learning algorithms. Its core idea is to transform human preferences into optimization objectives for probabilistic models, thereby simplifying the alignment process and improving efficiency.

Since DPO does not require an explicit reward model, it reduces the number of hyperparameters, making it widely adopted in the MLLM alignment field. In Table 1, we present the DPO loss function and all its variants in MLLM alignment, allowing readers to quickly and intuitively understand the differences and connections between different algorithms. The DPO training objective is defined as follows:

$$\mathcal{L}_{\text{dpo}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}} [\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w|\mathcal{I},x))}{\pi_{\text{ref}}(y_w|\mathcal{I},x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l|\mathcal{I},x))}{\pi_{\text{ref}}(y_l|\mathcal{I},x))})], \tag{2}$$

where $\mathcal{L}$ denotes the loss function, $\mathcal{D}$ represents the dataset, $\mathcal{I}$ represents the image, x represents the question, y_w, y_l represents the chosen and rejected responses respectively, $\mathbb{D}_{KL}$ represents the KL divergence, π_ϕ represents the trained MLLM policy, π_{ref} represents the reference MLLM policy, $r_{\boldsymbol{\theta}}$ represents the reward model, and β represents a hyperparameter, σ represents the sigmoid function.

B Background of MLLM Alignment

In this section, we will provide a brief explanation of the complete training process for MLLMs, which consists mainly of three phases: pre-training, instruction tuning, and alignment with human preference.

B.1 Pre-Training

The pre-training phase of MLLMs primarily aims to align the feature spaces of different modalities with that of the language model. The data used in this phase is typically simple caption data. For instance, image-caption pairs are commonly used for image/video understanding MLLMs (Bai et al., 2023; Chen et al., 2023), while speech data and transcriptions are used for speech understanding MLLMs (Fu et al., 2024a, 2025a). Through this pre-training phase, the model learns to understand inputs from various modalities.

B.2 Instruction Tuning

Building on the pre-training phase, the SFT phase aims to teach the model how to interact with humans by focusing on understanding questions and providing responses in a specified format, i.e., instruction-following ability. The data used in this phase is typically high-quality and diverse dialogue data. For example, in the commonly seen visual question answering (VQA) task, given an image and its corresponding instruction, the trained model will provide the correct answer for the task.

B.3 Alignment with Human Preference

Previous works have shown that SFT tends to make the model memorize training data and try to generalize across diverse scenarios (Chu et al., 2025). The alignment phase, typically involving reinforcement learning (RL) strategies, is crucial for generalizing to unseen domains. However, most multimodal models neglect this step (Wang et al., 2024c; Deitke et al., 2024; Chen et al., 2024c; Dai et al., 2024; Agrawal et al., 2024). The goals of the alignment stage are broad, such as reducing hallucinations (Zhang et al., 2024c; Lu et al., 2025), enhancing conversational abilities (Xiong et al., 2024), improving safety (Zong et al., 2024), strengthening the reasoning abilities (Wang et al., 2024d), improving capabilities for long-reasoning tasks like DeepSeek-R1 (Chen et al., 2025b), and overall MLLM performance (Zhang et al., 2025b). This phase usually uses pair data that incorporates human preference.

C Positioning Relative to Prior Works

Here, we reiterate the systematic and innovative aspects of our work compared to other surveys.

First, previous alignment review papers have primarily focused on AI (Ji et al., 2025) or LLM (Kumar et al., 2025) alignment, with no existing work specifically addressing MLLM alignment. Our paper is the first survey dedicated to MLLM alignment. Among related works, (Kumar et al., 2025) is the most relevant, but it provides only a broad overview of LLM post-training methods without delving into their specific characteristics, making it more of a general summary. In contrast, we offer a detailed analysis of each method, enabling readers to intuitively understand their distinctions and quickly grasp the fundamentals of MLLM alignment. While MLLMs demonstrate immense potential in handling complex tasks involving visual, auditory, and textual data, state-of-the-art MLLMs are rarely rigorously aligned with human preferences. Our paper aims to provide researchers with a comprehensive and systematic guide to entering the field of MLLM alignment.

Second, we systematically organize MLLM alignment algorithms based on their application scenarios, data construction, and evaluation methods, addressing key questions such as how algorithms are applied, how datasets are built, and how methods are evaluated. This forms a clear and structured framework for MLLM alignment:

(1) **Algorithms**: In Table 1, we establish a unified notation system to formally describe different algorithms, allowing readers to grasp their differences and connections quickly.

(2) **Datasets**: In Table 2, we summarize existing open-source datasets in terms of size, categories, response-generating models, data sources, and annotation models, providing readers with a clear and concise overview of MLLM alignment-specific datasets.

(3) **Technical Pipeline**: In Fig 1 and Fig 3, we summarize the end-to-end technical pipeline of MLLM alignment, covering benchmark-driven evaluation and preference construction, and highlight the key design choices and method characteristics at each stage to provide a practical reference for researchers.

Third, we thoroughly discuss emerging research directions and open challenges in MLLM alignment, such as visual challenges, comprehensive evaluation, full-modality alignment, MLLM reasoning, insights from LLM alignment, and MLLM as agents. These are critical issues uniquely faced by MLLM alignment today, and our paper is the first to systematically propose them in Appendix D. By doing so, we aim to inspire potential research ideas and foster growth within the alignment community.

D Future Directions

Despite rapid progress in multimodal post-training, several open challenges remain in scaling alignment beyond image–text, transferring reasoning-oriented RL or data advances to MLLMs, mitigating overoptimization and reward hacking, and enabling robust, secure agentic behaviors under multimodal interaction. Given these circumstances, we outline key directions spanning full-modality alignment, reasoning-centric optimization, insights

from LLM alignment, and MLLM-based agents.

Full-modality alignment Align-anything(Ji et al., 2024) pioneers full-modality alignment through the multimodal dataset "align-anything-200k", which spans text, images, audio, and video. This study demonstrates the complementary effects between different modalities. However, their work is still in its early stages. The dataset for each modality is relatively small, limiting its ability to cover a wide range of tasks. Additionally, the proposed algorithm is only a preliminary improvement on the DPO method, and it does not fully exploit the unique structural information inherent in each modality. Moving forward, the design of alignment algorithms beyond image/text domains, particularly for other modalities, to enhance multimodal model capabilities, will be a key trend.

MLLM reasoning Recent advancements in reasoning LLMs, such as OpenAI's O1 and DeepSeek-R1, highlight the importance of RL algorithms and preference data in enhancing performance in complex tasks. Key insights can be categorized as follows: (1) *Data*: (a) *Scale & Quality*: From small-model resampling (e.g., OpenMathInstruct (Toshniwal et al., 2024)) to large-scale synthetic data (e.g., Qwen-2.5-MATH (Yang et al., 2024a)), datasets now include millions of samples. (b) *Efficiency*: Approaches like "less is more" alignment (e.g., LIMA (Zhou et al., 2023)) demonstrate that minimal, high-quality data can optimize pretrained capabilities. (2) *Optimization Framework*: (a) *Sampling Strategies*: Online RL techniques (e.g., DeepSeek V3 (DeepSeek-AI, 2024)) mitigate distributional shifts. (b) *Training Paradigms*: Multi-stage, collaborative optimization (e.g., Llama 3's DPO iteration) improves model performance. (c) *Algorithms*: Advancements in PPO techniques, such as DPO and GRPO, focus on reducing parameter count and refining reward functions (e.g., PRIME (Cui et al., 2025)). These trends emphasize efficiency, generalization, and precision in unlocking LLMs' reasoning potential.

Insight from LLM alignment The development of LLM alignment highlights three key insights and opportunities for improvement: (1) training efficiency—PPO-based methods require simultaneous loading of policy and reference models, slowing training; reference-free approaches like SimPO (Meng et al., 2024) could accelerate optimization by eliminating dependency on reference models, though their role in MLLM alignment needs deeper analysis. (2) overoptimization mitigation (Gao et al., 2023; Rafailov et al., 2024)—DPO/RLHF risks reward hacking where proxy metrics improve while real-world performance degrades, exacerbated by biased or low-quality data. Solutions include diversifying training datasets, early stopping, and regularization to balance generalization. Addressing these challenges requires rethinking optimization architectures, robust data curation, and synergistic integration of RL paradigms.

MLLM as agents Combine the advanced reasoning capabilities of LLMs with multimodal perception—encompassing text, images, and audio—enabling cross-modal knowledge synthesis and task decomposition for complex real-world applications (Xi et al., 2023; Wang et al., 2024b; Ma et al., 2024b; Durante et al., 2024; Ma et al., 2024a). These capabilities position MLLMs as promising agents for various domains, such as autonomous driving and industrial robotics (Li et al., 2023b; Liu et al., 2024b). However, designing MLLMs as effective agents presents several unresolved challenges: (1) *Multi-agent Collaboration*: Lack of mature frameworks for multimodal communication (Ossowski et al., 2025), shared memory, and coordination in MLLM-based multi-agent systems. (2) *Robustness*: Vulnerability to adversarial attacks (e.g., image perturbations hijacking agent behavior (Wu et al., 2025)) in open environments, necessitating systematic robustness testing and defense mechanisms. (3) *Security*: Expanded attack surfaces across multimodal perception, reasoning, and memory modules, requiring comprehensive safeguards against privacy breaches and malicious hijacking (Yang et al., 2024b).

E Cross-Category Analysis and Design Insights

Beyond the taxonomy presented in the main text, we further synthesize these components into a unified design space consisting of three interacting dimensions: preference signal construction, alignment objective design, and application-driven requirements. These components are not independent; rather, effective alignment strategies emerge from their coordinated design.

Preference signals and optimization paradigms. Different sources of preference signals naturally correspond to different optimization frameworks. Human-annotated preferences, as used in methods such as LLaVA-RLHF and RLHF-V, are typically integrated into RL-based pipelines and remain es-

sential in expert-intensive domains such as medical systems like 3D-CT-GPT++. However, their scalability is limited by annotation cost. In contrast, model-as-judge approaches such as Silkie and CLIP-DPO enable large-scale preference generation using strong evaluators or auxiliary encoders, making them more compatible with DPO-style offline optimization. While these approaches significantly improve efficiency, they may also inherit biases from the judging models.

Structured alignment objectives. Another important trend is the move from response-level optimization to more structured objectives. Early preference optimization typically treats the entire response as a single unit, which limits its ability to address localized multimodal errors. Recent methods introduce finer-grained supervision to improve credit assignment during training. For example, RLHF-V applies dense preference supervision over unreliable spans, while hierarchical designs such as CHiP distribute alignment signals across visual, sentence, and token levels. These structured objectives generally improve robustness and controllability in multimodal outputs.

Programmatic preference construction. Programmatic preference generation has become an important strategy for scaling multimodal alignment. Methods such as ImageDPO and AdPO construct contrastive pairs through visual perturbations, encouraging models to rely on visual evidence rather than language priors. Similarly, MIA-DPO and PanoDPO exploit multi-image variations to strengthen cross-modal grounding. Compared with manual annotation, programmatic preferences provide better scalability and allow explicit encoding of task constraints, although poorly designed perturbations may introduce artifacts.

Design insights across applications. Across application scenarios, alignment methods typically target four recurring objectives: hallucination mitigation, instruction following, reasoning consistency, and robustness. For example, CLIP-DPO and ImageDPO primarily improve visual grounding, reasoning-oriented methods such as LLaVA-Reasoner-DPO or INTERACTIVECOT focus on aligning intermediate reasoning processes, while robustness-oriented objectives such as SymDPO improve stability under perturbations.

Overall, successful alignment strategies tend to combine scalable preference construction, structured optimization objectives, and multimodal-aware supervision signals. These design principles suggest that future work will likely emphasize hybrid pipelines that integrate multiple sources of feedback while maintaining controllability and robustness in complex multimodal environments.

F Leveraging Visual Information for Alignment

For clarity, we use the following notation to represent the composition of current alignment data: preference data $\mathcal{D} = (x, \mathcal{I}, y_w, y_l)$, where x is the question, $\mathcal{I}$ is the image, and y_w and y_l represent the winning and losing responses, respectively. In current research, three main approaches are employed to leverage visual information in order to enhance alignment performance, though each has its limitations:

1. **Using corrupted or irrelevant images as alignment phase negative samples.** Researchers create new images $\mathcal{I}_{neg}$ and use $(y_w|x, \mathcal{I}_{neg})$ as a negative sample. This approach improves MLLM robustness to different images and reduces hallucinations. However, visual negatives often rely on diffusion algorithms or image modifications that lack robust quality metrics, incurring high computational costs.

2. **Generating new questions and answers based on corrupted images.** In this method, researchers create a new image $\mathcal{I}_{neg}$, use it to generate additional response y_{neg}, and then treat $(y_{neg}|x, \mathcal{I})$ as a negative sample. This method also essentially compares textual outputs, but it adds more variety to the textual comparison. However, the process of generating additional negative samples incurs extra computational overhead.

3. **Using cosine similarity metrics from models like CLIP to assess text-image matching.** This approach uses a similarity score between the text and the image to filter data or as part of the reinforcement learning reward function. While this can help reduce data noise, the quality of the score depends on the evaluation model's quality, which may be subject to model bias.

Each of these methods plays a role in enhancing MLLM alignment with visual data, but they come with trade-offs in terms of efficiency, cost, and the potential for biases.

Method	Loss
Fact-RLHF	$\mathcal{L}_{\text{RLHF}} = -\mathbf{E}_{(\mathcal{I},x)\in D, y\sim\pi_\phi(y\|\mathcal{I},x)}[r_{\boldsymbol{\theta}}(\mathcal{I},x,y) - \beta\cdot\mathbb{D}_{KL}(\pi_\phi(y\|\mathcal{I},x)\parallel\pi^{\text{INIT}}(y\|\mathcal{I},x))]$
SILKIE SIMA CLIP-DPO RLAIF-V 3D-CT-GPT++ MAVIS EMMOE xGen-MM(BLIP-3) LLaVA-NeXT-Interleave LLAVA-CRITIC SQuBa PPLLaVA HDPO SymDPO INTERACTIVECOT SAE-V TPR SAFEVIS CPCF LLaVA-Reasoner-DPO OmniAlign-V AIGI-Holmos IPA MM-IFEngine SPR C-DPO Modified DPO	$\mathcal{L}_{\text{dpo}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]$
RLHF-V	$\mathcal{L}_{\text{Dense-dpo}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\mathbb{I}_{y_i\notin y_u}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]$ $+\mathbb{I}_{y_i\in y_u}[\gamma\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]]$
F-DPO	$\mathcal{L}_{\text{Fine grained-dpo}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x))}) - \log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]$
HA-DPO & MSR-ViR	$\mathcal{L} = \mathcal{L}_{\text{dpo}} + \mathbf{E}_{(\mathcal{I},x,y)\sim\mathcal{D}_{\text{SFT}}}[-\log\text{P}(\text{y}\|\mathcal{I},\text{x};\pi_{\boldsymbol{\theta}})]$
MIA-DPO	Loss : $\mathcal{L} = \mathcal{L}_{\text{dpo}} + \gamma\cdot\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[-\log(\text{y}_\text{w}\|\mathcal{I},\text{x})]$
CHiP	$\mathcal{L} = \mathcal{L}_{\text{dpo}} + \mathcal{L}_{\text{Image dpo}} + \lambda\cdot\mathcal{L}_{\text{Sentence dpo}} + \gamma\cdot\mathbf{E}_{(\mathcal{I},x,y_w^{\text{Token}},y_l^{\text{Token}})\sim\mathcal{D}_{\text{Token}}}$ $\beta\mathbb{D}_{\text{SeqKL}}[\pi_{\text{ref}}(y_w\|\mathcal{I},x)\parallel\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x)] - \beta\mathbb{D}_{\text{SeqKL}}[\pi_{\text{ref}}(y_l\|\mathcal{I},x)\parallel\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x)]$
Image DPO	$\mathcal{L}_{\text{Image dpo}} = -\mathbf{E}_{(\mathcal{I}_w,\mathcal{I}_l,x,y_w)}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x))}{\pi_{\text{ref}}(y_w\|\mathcal{I}_w,x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_l,x))}{\pi_{\text{ref}}(y_w\|\mathcal{I}_l,x))})]$
AdPO	$\mathcal{L} = -\mathbf{E}_{(\mathcal{I}_w,\mathcal{I}_l,x,y_w,y_l)}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x))}{\pi_{\text{ref}}(y_w\|\mathcal{I}_w,x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I}_l,x))}{\pi_{\text{ref}}(y_l\|\mathcal{I}_l,x))})]$ $+\Sigma_{t=1}^{\text{T}}\log\pi_{\boldsymbol{\theta}}(y_w^t\|\mathcal{I}_l,x_t^{1:t-1})$
PHANTOM	$\mathcal{L} = \mathcal{L}_{\text{SFT}} - \mathbf{E}_{(\mathcal{I}_w,\mathcal{I}_l,x,y_w)}[\log\sigma(\frac{\beta}{\|y_w\|}\log\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x)) - (\frac{\beta}{\|y_w\|}\log\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x))]$
video-SALMONN 2	$\mathcal{L} = \mathcal{L}_{\text{dpo}} + \lambda\mathbf{E}_{(\mathcal{I},x,y_{\text{gt}})\sim\mathcal{D}_{\text{gt}}}\log\pi_{\boldsymbol{\theta}}(y_{\text{gt}}\|\mathcal{I},x)$
Preference Optimization	$\mathcal{L} = \mathcal{L}_{\text{dpo}} + \lambda\mathbf{E}_{(\mathcal{I},x,y)\sim\mathcal{D}_{\text{reg}}}[\log\frac{\pi_{\boldsymbol{\theta}}(\text{y}\|\text{x})}{\pi_{\text{ref}}(\text{y}\|\text{x})}]$
DAMA	$\mathcal{L} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\alpha\cdot\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x))} - \alpha\cdot\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]$
mDPO LPOI	$\mathcal{L} = \mathcal{L}_{\text{dpo}} + \mathbf{E}_{(\mathcal{I}_w,\mathcal{I}_l,x,y_w,y_l)\sim\mathcal{D}}[-\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x))}{\pi_{\text{ref}}(y_w\|\mathcal{I}_w,x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I}_l,x))}{\pi_{\text{ref}}(y_l\|\mathcal{I}_l,x))})]$ $-\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I}_w,x))}{\pi_{\text{ref}}(y_w\|\mathcal{I}_w,x))} - \delta)$
MPO	$\mathcal{L} = \alpha_1\cdot\mathcal{L}_{\text{dpo}} - \alpha_2\cdot\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}\left[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x)}{\pi_{\text{ref}}(y_w\|\mathcal{I},x)} - \delta)\right]$ $-\alpha_2\cdot\left[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x)}{\pi_{\text{ref}}(y_l\|\mathcal{I},x)} - \delta)\right] - \alpha_3\cdot\left[\frac{\log\pi_{\text{ref}}(y_w\|\mathcal{I},x)}{\|y_w\|}\right]$
CcDPO MMedPO MFPO HSCR IMG BPO	$\mathcal{L}_{\text{Image-Text DPO}} = \alpha_1\cdot\mathcal{L}_{\text{DPO}} + \alpha_2\cdot\mathcal{L}_{\text{Image DPO}}$
PanoDPO	$\mathcal{L}_{\text{Image-2-Text DPO}} = \mathcal{L}_{\text{Image-Text DPO}} + \alpha_3\cdot -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x+c))}{\pi_{\text{ref}}(y_w\|\mathcal{I},x+c))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))}{\pi_{\text{ref}}(y_l\|\mathcal{I},x))})]$
D^{2}PO PAR	$\alpha_1\mathcal{L}_{\text{Action DPO}} + \alpha_2\mathcal{L}_{\text{State DPO}}$ $\mathcal{L}_{\text{simPO}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\beta\log\pi_{\boldsymbol{\theta}}(y_w\|\mathcal{I},x) - \beta\log\pi_{\boldsymbol{\theta}}(y_l\|\mathcal{I},x))]$
DCD	$\mathcal{L}_{\text{DCD}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\pi_\theta(y_l\|x,\mathcal{I}_l) + \log\pi_\theta(y_w\|x,\mathcal{I}_w)]$
fDPO	$\mathcal{L}_{\text{fDPO}} = \beta_1\cdot\mathcal{L}_{\text{DescDPO}} + \beta_2\cdot\mathcal{L}_{\text{ReasonDPO}}$
AVEm-DPO	$\mathcal{L}_{\text{DPO}}^{av\text{-}prompt} = -\mathbb{E}\left[\log\sigma\left(u(a_w,v_w,a_l^{\text{PMP}},v_l^{\text{PMP}},x^m,y_w)\right)\right]$ $\mathcal{L}_{\text{DPO-TPD}} = -\mathbb{E}_{(a,v,x,y_w,y_l)\sim\mathcal{D}^{\text{pref}}}\Big[\log\sigma\Big(\beta\big(\log\frac{\pi_\theta(y_w\|(a,v,x))}{\pi_{\text{ref}}(y_w\|(a,v,x))} - \log\frac{\pi_\theta(y_l\|(a,v,x))}{\pi_{\text{ref}}(y_l\|(a,v,x))}\big)$ $-\gamma_{\text{TPD}}(\log\pi_{\text{text}}(y_w\|x) - \log\pi_{\text{text}}(y_l\|x))\Big)\Big]$ $\mathcal{L}_{\text{AVEm-DPO}} = \mathcal{L}_{\text{DPO-TPD}}^y + \lambda_{av}\mathcal{L}_{\text{DPO}}^{av\text{-}prompt}$
Pair-DPO	$\mathcal{L}_{\text{Pair-dpo}} = -\mathbf{E}_{(\mathcal{I},x,y_w,y_l)\sim\mathcal{D}}[\log\sigma(\Delta\text{Und}\Delta\text{Gen})]$, $\Delta\text{Und} = \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|,x))}{\pi_{\text{ref}}(y_w\|x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|,x))}{\pi_{\text{ref}}(y_l\|x))}, \Delta\text{Gen} = \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_w\|,x))}{\pi_{\text{ref}}(y_w\|x))} - \beta\log\frac{\pi_{\boldsymbol{\theta}}(y_l\|,x))}{\pi_{\text{ref}}(y_l\|x))}$

Table 1: Various preference optimization objectives given preference data $\mathcal{D} = (x,\mathcal{I},y_w,y_l)$, where x is the question, $\mathcal{I}$ is the Image, and y_w and y_l are winning and losing responses.

Dataset	Size	Categories	Response Model	Data Sources	Annotation Model
LLaVA-RLHF	10K	Hallucination	LLaVA-SFT	LLaVA-Instruct	Human
RLHF-V	1.4K	Hallucination	Muffin	UniMM-Chat	Human
VLFeedback	80K	Hallucination	12 Models	9 Datasets	GPT-4
CLIP-DPO	750K	Hallucination	MobileVLM-v2	12 Datasets	CLIP
M-HalDetect	16K	Hallucination	InstructBLIP	MS COCO	Human
HA-DPO	6K	Hallucination	3 Models	Visual Genome	GPT-4
SIMA	17K	Hallucination	LLaVA-1.5	LLaVA-Instruct	LLaVA-1.5
RLAIF-V	83K	Hallucination	3 Models	7 Datasets	2 Models
xGen-MM (BLIP-3)	62.6K	Hallucination	xGen-MM-4B	open-source	-
MIA-DPO	52K	Multi-Image	LLaVa-v1.5 & InternLM-XC 2.5	Not mentioned	Not mentioned
MAVIS	88K	Math	MAVIS-7B	Self-Constructed	GPT-4
EMMOE-100	10K	Embodied AI	Video-LLaVA	Self-Constructed	GPT-4
Image-DPO	60K	visual reasoning	Cambrian-8B & LLaVA-1.5	3 Datasets	Stable Diffusion
LLAVA-CRITIC	40.1K	Multiple tasks	LLaVA-OneVision	3 Datasets	LLaVA-OneVision
MMPR	3.25M	Reasoning	InternVL2-8B	Not mentioned	automate pipeline
video-SALMONN-o1	100K	Reasoning	Gemini-1.5-pro	Self-Constructed	GPT4
MMedPO	19 K	Medical	Med-LVLM & GPT-4o	Self-Constructed	GPT-4o
CPCF	50K	Image Referring	Fine-tuned Forret	Open Images	MLLM Itself
SHAREGPT-4O-REASONING	193K	Reasoning	Fine-tuned LLaVA-Next	9 Datasets	Golden Answer
OmniAlign-V	205K	Multiple tasks	LLaVA-Next & GPT-4o	Self-Constructed	automate pipeline
D^2PO	15K	Embody AI	automate pipeline	Self-Constructed	automate pipeline
Holmes-DPOSet	49K	Multiple tasks	Fine-tuned MLLMs	Self-Constructed	automate pipeline
Pick-a-Pic	851K	Generation	Self-Generated	Generative Models	
IPA	89K	Instruction Following	Qwen2VL-7B	15 Datasets	LLM-as-judge
MM-IFInstruct	23k	Instruction Following	Intern-VL-2.5 7B	automate pipeline	
PAR	5K	General	LLaVA-1.5 7B & Qwen-VL-chat-9B	LLaVA-80K	KL divergence
SPR	10K	Spatial Understanding	Ferret	Object365	automate pipeline
SENTINEL	8.6K	Hallucination	LLaVA-1.5	Visual Genome	automate pipeline
TAlt & PAlt	18K	alt-text generation	Gemini	Social Networks	automate pipeline
Chart2Code	23K	code generation from chart	GPT-4o	ReachQA	Reward Models
MMSafe-PO	5.6K	Safety	human & MLLM	Anthropic-HH	Human
Fin-APT	470	Financial Advisory Videos	Gemma2-9B	Youtube	GPT-4o
Pair-DPO	5K	Multimodal Understanding and Generation	Show-o	Journey-DB	automate pipeline
SafeVid-350K	350K	Video Understanding Safety	LLaVA-Next & GPT-4	Self-Constructed	automate pipeline
TPR	20K	hallucination	LLaVA-1.5-7B	7 datasets	LLaVA-Next-34B
MultiScope	42k	Multi-Image	3 datasets	LLaVA-OneVision	automated-pipeline

Table 2: Preference optimization dataset construction, including dataset, data size, categories: usage of the data, data sources, response model: the model to generate responses y_w and y_l by given image $\mathcal{I}$ and prompt x, and annotation model: the model to annotate y_w and y_l.