TIMELENS2: GENERALIST VIDEO TEMPORAL GROUNDING WITH MULTIMODAL LLMS

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ABSTRACT

Video multimodal large language models (MLLMs) can describe what happens in a video, but rarely identify when the supporting evidence occurs. We study generalist video temporal grounding, in which one model predicts a variable-cardinality set of evidence intervals across video lengths, domains, query forms, and viewpoints. Existing training strategies are misaligned with this set-valued task: long-video labels often rely on brittle one-pass annotation, while reinforcement-learning rewards either fail to distinguish non-overlapping predictions or require fragile segment matching. TimeLens2 treats temporal evidence as an interval set throughout supervision and optimization. TimeLens2-93K constructs reliable multi-span supervision through caption-derived proposals, independent localization, cross-agent consensus, semantic verification, and boundary refinement. Our temporal Wasserstein reward computes exact one-dimensional W_1 between uniform distributions over merged interval supports, providing dense, matching-free feedback under unequal cardinalities and equivalent fragmentation; temporal IoU complements it with precise-overlap feedback. Across seven benchmarks, TimeLens2-2B outperforms all size-matched baselines on every benchmark, while the 4B and 8B variants achieve state-of-the-art performance, surpassing open-source models with up to 397B parameters. The 2B, 4B, and 8B variants improve over their Qwen3-VL backbones by 14.2, 13.0, and 18.1 mIoU points, respectively.

1 INTRODUCTION

Multimodal large language models (MLLMs) promise to make growing video archives searchable through language (Maaz et al., 2024; Zhang et al., 2023; Li et al., 2024; Bai et al., 2025). Yet answering *what* happened is not enough: users must also know *when* the supporting evidence appears. Without temporal support, users must still search the full timeline, and even correct descriptions remain unverifiable. Temporal grounding is therefore the video analogue of citation: it makes outputs traceable by requiring precise, potentially disjoint evidence intervals rather than only fluent responses (Ren et al., 2023; Huang et al., 2024a; Wang et al., 2025a).

Temporal grounding is not a single-regime task: supporting evidence may occupy only seconds of an hour-long video, recur at disjoint moments, and appear in third- or first-person footage, while queries may be descriptions or questions. We therefore study *generalist temporal grounding*, where a single MLLM with a unified output interface localizes single- or multi-interval evidence across video lengths, domains, query forms, and viewpoints.

Two structural mismatches stand in the way. The first is in supervision. Temporal evidence is a set of intervals, yet long-video labels are often produced as a single global annotation decision. Because relevant moments are sparse and similar distractors dominate the timeline, a one-pass annotator may confuse similar occurrences, miss repeated evidence, or produce imprecise boundaries (Qian et al., 2024; Zeng et al., 2025; Zhang et al., 2026). Meanwhile, many existing datasets emphasize short videos, declarative captions, and single-span answers (Gao et al., 2017; Krishna et al., 2017; Hendricks et al., 2017). Long-video annotation is therefore not merely a scaling problem; it is an evidence-verification problem.

Even with reliable supervision, optimization remains mismatched with temporal evidence: next-token prediction learns timestamp generation effectively, but lacks an explicit interval-level objective (Ren et al., 2023; Huang et al., 2024a; Zeng et al., 2025; Zhang et al., 2026). Reinforcement learning with

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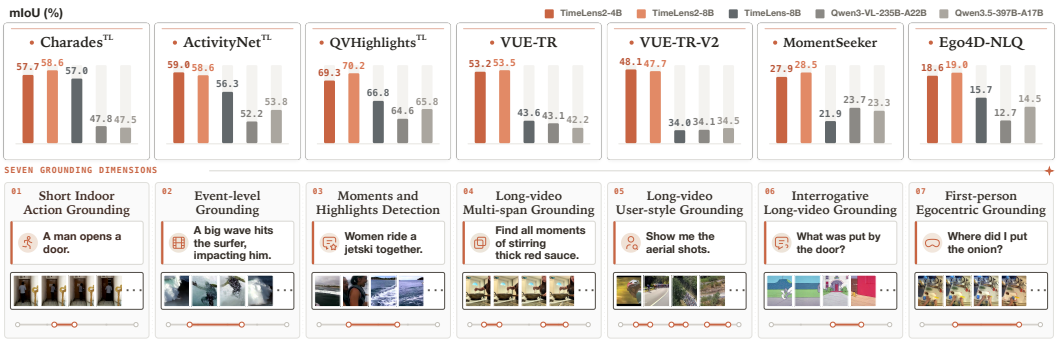

Figure 1: **TimeLens2 as a generalist video temporal-grounding model. Top:** mIoU across seven benchmarks covering diverse dimensions. **Bottom:** Representative queries from each benchmark.

temporal IoU (tIoU) better aligns training with evaluation (Wang et al., 2025c; Li et al., 2025b;a; Chen et al., 2025), but assigns zero to all disjoint predictions, leaving near misses indistinguishable from distant errors. For multi-span targets, one-to-one matching (Luo et al., 2026) is also fragile under fragmentation or unequal cardinality.

We introduce TimeLens2, a generalist temporal-grounding MLLM that treats evidence as a first-class interval set throughout training. The central idea is to make evidence *verifiable* when constructing supervision and *geometry-aware* when optimizing predictions.

TimeLens2-93K turns one brittle global annotation decision into a sequence of increasingly focused ones. Hierarchical, time-stamped captions first provide long-range context for proposing declarative queries and coarse single- or multi-span evidence; complementary grounding agents then independently relocalize that evidence from the video. Temporal consensus and semantic verification remove unstable or mismatched instances, after which local refinement sharpens only the surviving boundaries. By progressively narrowing both the search space and the error type, the pipeline preserves repeated evidence while making long-video supervision more reliable.

Once reliable interval labels are available, training separates capability acquisition from geometric calibration. Long-context supervision first teaches the model to search full videos and generate variable-cardinality interval sets; GRPO then directly calibrates where those intervals lie (Shao et al., 2024). tIoU measures how much predicted support is already correct, but not how a disjoint prediction should move. Our temporal Wasserstein reward supplies this missing geometry by computing the exact one-dimensional W_1 distance between uniform distributions over merged predicted and target supports, providing dense, matching-free guidance for near misses and unequal-cardinality outputs while remaining invariant to equivalent fragmentation.

Figure 1 summarizes performance across seven benchmarks: TimeLens2-2B, TimeLens2-4B, and TimeLens2-8B reach 44.5, 47.7, and 48.0 average mIoU, respectively. The 2B, 4B, and 8B variants improve over their Qwen3-VL backbones by 14.2, 13.0, and 18.1 points (Bai et al., 2025); the 4B model also surpasses Qwen3.5-397B-A17B (Team, 2026) on every benchmark by 7.5 points on average. In data ablations, declarative-only TimeLens2-93K raises question-form grounding on MomentSeeker from 15.3 to 25.8 mIoU (Yuan et al., 2026). Temporal Wasserstein restores informative preferences for 75.8% of all-zero-tIoU GRPO groups.

Our contributions are threefold: (1) we introduce TimeLens2-93K, a staged evidence-verification pipeline that produces reliable single- and multi-span temporal grounding supervision for long videos; (2) we propose a matching-free temporal Wasserstein reward based on exact one-dimensional W_1 over merged interval support, providing graded, fragmentation-invariant feedback for disjoint and unequal-cardinality predictions; and (3) we demonstrate compact 2B, 4B, and 8B generalist models across seven benchmarks covering long-video, multi-span, question-form, and egocentric grounding.

2 Related Work

Temporal Grounding Models. Video temporal grounding has evolved from dedicated localization architectures to generative MLLMs. Classical methods match moment proposals or regress boundaries (Gao et al., 2017; Zhu et al., 2024); recent systems instead express temporal evidence

through a language interface. TimeChat and VTimeLLM introduce temporal instruction tuning and boundary-aware training (Ren et al., 2023; Huang et al., 2024a), while LITA and Grounded-VideoLLM develop timestamp-aware representations (Huang et al., 2024b; Wang et al., 2025a). TimeSuite features grounding-centric instruction tuning to strengthen both long-video QA and temporal localization (Zeng et al., 2025), whereas TimeLens systematically studies data quality and training recipes (Zhang et al., 2026). In parallel, general video representations and embeddings broaden transferable video evidence search (Wang et al., 2026; Liu et al., 2025; Zhu et al., 2026). This shift makes grounding a general MLLM capability. Yet supervision has not kept pace: transfer across video lengths, evidence cardinalities, viewpoints, and query forms remains unresolved. TimeLens2 is designed around this broader regime.

Temporal Grounding Data. The data landscape reflects the same progression. Early benchmarks primarily pair short or domain-specific videos with a single descriptive moment (Regneri et al., 2013; Hendricks et al., 2017; Gao et al., 2017; Krishna et al., 2017). Later datasets expand individual axes of difficulty, including subtitle-aware retrieval, repeated evidence, long-form video, and egocentric search (Lei et al., 2020; 2021; Soldan et al., 2022; Grauman et al., 2022). MLLM recipes then convert timestamped annotations into instruction-following conversations (Ren et al., 2023; Huang et al., 2024a; Zeng et al., 2025; Qian et al., 2024), often scaling through dense captions, procedural videos, or weak narration alignment (Zhou et al., 2017; Miech et al., 2019; Tang et al., 2019; Zhukov et al., 2019). Scale, however, does not by itself resolve supervision quality: in long videos, coarse alignment readily becomes a wrong occurrence, a missed repeat, or an imprecise boundary. TimeLens2-93K targets this bottleneck with consensus-based localization and semantic verification, yielding reliable single- and multi-span supervision across long, diverse videos.

Temporal Grounding Optimization. A parallel mismatch appears in optimization. Supervised instruction tuning teaches the syntax of timestamps through token likelihood, not the quality of the localized evidence. GRPO/RLVR methods make grounding verifiable through format and temporal-overlap rewards, and subsequent work extends this recipe with improved reward design, data selection, refusal, curricula, and multi-segment reasoning (Shao et al., 2024; Wang et al., 2025c; Li et al., 2025b;a; Chen et al., 2025; Yue et al., 2025; Dong et al., 2025; Wu et al., 2026; Luo et al., 2026; Li et al., 2026a). Nevertheless, overlap supplies geometry only after prediction and target intersect. MUSEG introduces pairwise NGIoU for disjoint segments, but its one-to-one matching remains sensitive to fragmentation, merges, and unequal cardinality (Luo et al., 2026). The issue is therefore not merely reward sparsity; it is also the choice of representation for set-valued evidence. Wasserstein geometry provides a useful precedent: NWD represents spatial boxes by Gaussian surrogates and applies pairwise W_2 in supervised tiny-object detection (Wang et al., 2021). Our objective instead treats the merged support of a variable-cardinality interval set as a one-dimensional distribution and computes its exact W_1 distance.

3 TIMELENS2

3.1 TIMELENS2-93K: SCALABLE TEMPORAL GROUNDING DATA CONSTRUCTION

Long videos require full context for evidence search, but sparse evidence and repeated distractors make global annotation unreliable. We construct TimeLens2-93K from diverse web videos and represent each example as $(v, q, \mathcal{Y})$, where $\mathcal{Y} = \{[s_k, e_k]\}_{k=1}^{K}$ is a variable-cardinality set of supporting intervals, unifying single- and multi-span grounding. As shown in Figure 2, hierarchical captions generate declarative queries and coarse proposals; independent agents then relocalize the evidence from short video clips. Temporal consensus and semantic verification reject unstable or mismatched instances before local boundary refinement. The resulting corpus contains 23,793 videos and 93,232 grounding instances, including 12,091 with multiple supporting intervals.

Video source pool. We stratify 34,867 YouTube videos across five duration ranges, from under one minute to over one hour, and diverse visual domains to vary the search horizon, distractor load, and evidence type.

Hierarchical temporally grounded captions. We convert each video into a hierarchical, time-stamped semantic index. A global caption summarizes subjects, setting, actions, and temporal

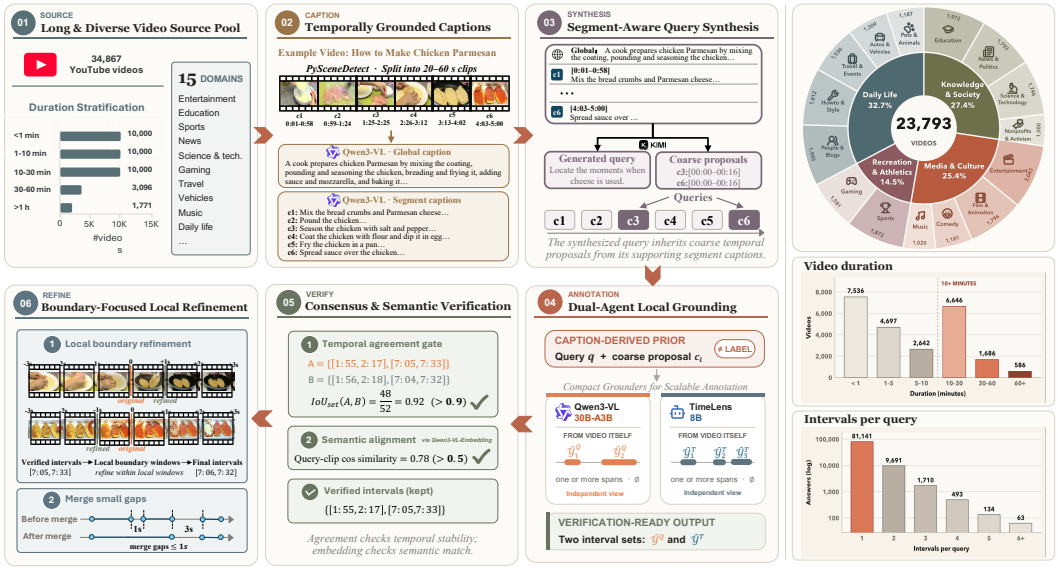

Figure 2: **TimeLens2-93K construction pipeline and corpus profile.**

progression, while segment captions enumerate visually verifiable events within bounded intervals. We partition v into semantically coherent clips $\mathcal{C}(v) = \{c_i = [t_i, t_{i+1}]\}_{i=1}^{N}$ using content-based PySceneDetect boundaries constrained to 20–60 seconds, preserving visual continuity while keeping clips tractable. Qwen3-VL-235B-A22B (Bai et al., 2025) generates both caption levels.

Segment-aware query synthesis. Kimi-K2.5 (Team et al., 2026) jointly generates a non-redundant declarative query from the caption hierarchy and selects every supporting segment. The selected clips form a coarse proposal $\mathcal{P}(q) \subseteq \mathcal{C}(v)$, including disjoint clips when evidence recurs, and provide temporal priors for annotation.

Dual-agent local grounding. Because captions may contain unsupported content and segment boundaries rarely match event boundaries, we relocalize each proposal from the video. For every (q, c_i), Qwen3-VL-30B-A3B (Bai et al., 2025) and TimeLens-8B (Zhang et al., 2026) independently return one or more intervals at one-second resolution or an empty set. Empty outputs reject unsupported proposals, while multi-interval outputs preserve repeated evidence. We map clip-relative timestamps to the original timeline and aggregate them into $\hat{\mathcal{Y}}^{\mathrm{Q}}$ and $\hat{\mathcal{Y}}^{\mathrm{T}}$.

Cross-agent consensus and semantic verification. We test temporal reproducibility and query–evidence alignment separately. Let $\mathrm{merge}(\cdot)$ denote interval union and $|\cdot|$ total duration. For multi-span outputs,

$$\mathrm{IoU}_{\mathrm{set}}(\mathcal{A}, \mathcal{B}) = \frac{|\,\mathrm{merge}(\mathcal{A}) \cap \mathrm{merge}(\mathcal{B})\,|}{|\,\mathrm{merge}(\mathcal{A}) \cup \mathrm{merge}(\mathcal{B})\,|}.$$

We retain instances with $\mathrm{IoU}_{\mathrm{set}}(\hat{\mathcal{Y}}^{\mathrm{Q}}, \hat{\mathcal{Y}}^{\mathrm{T}}) > 0.9$ and keep the Qwen annotation as canonical, since fusion could introduce boundaries predicted by neither model. We then encode the target clip and query with Qwen3-VL-Embedding (Li et al., 2026b) and require normalized text–video cosine similarity of at least 0.5.

Boundary-focused local refinement. For each retained boundary, Qwen3-VL-235B-A22B observes a ± 3-second neighborhood and predicts the visual transition point. For multi-interval labels, we merge adjacent spans separated by at most one second, treating shorter gaps as boundary jitter or brief occlusion.

3.2 TimeLens2 Model: Learning Generalist Video Temporal Grounding

We separate capability acquisition from geometric calibration: long-context supervised training learns evidence search and interval-set generation, while reinforcement learning optimizes decoded intervals against temporal objectives.

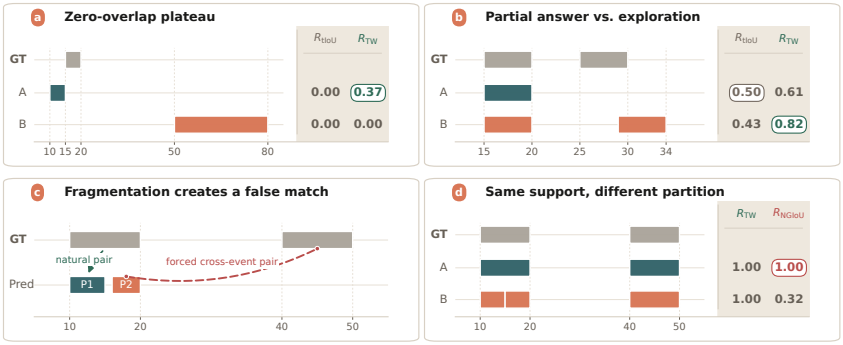

Figure 3: **Overlap plateaus and matching artifacts.** **(a)** tIoU ties near and distant zero-overlap errors. **(b)** It favors a partial single-moment answer. Under one-to-one NGIoU matching (Luo et al., 2026), **(c)** fragmentation creates a false cross-event match, and **(d)** equivalent merged supports receive different scores.

Long-context supervised grounding. We fine-tune Qwen3-VL (Bai et al., 2025) on full-video examples drawn primarily from TimeLens2-93K and TimeLens-100K (Zhang et al., 2026), with the official Ego4D-NLQ training split (Grauman et al., 2022) added for first-person video. All samples use $(v, q, \mathcal{Y})$ with one or more supporting intervals, forcing the model to select sparse evidence among distractors.

Instruction and response-format diversity. For each example, we independently sample the grounding instruction, answer syntax, and timestamp encoding while keeping $\mathcal{Y}$ fixed. Renderings include JSON, natural language, key–value and range styles, and alternative timestamp conventions, encouraging protocol-invariant interval semantics without paraphrasing the evidence query. Full specifications are provided in Section A.1.

Rollout-guided hard-sample mining. We generate multiple off-policy completions from the SFT checkpoint for each TimeLens2-93K and TimeLens-100K example and use mean tIoU as an empirical competence estimate. Lower-scoring examples receive higher GRPO sampling weights (Shao et al., 2024), concentrating updates on current localization failures.

Temporal Wasserstein reward. tIoU is sparse for reward shaping: it ties all disjoint predictions and can favor a partial single-moment answer over one covering multiple target moments (Figure 3(a,b)). One-to-one interval matching supplies non-overlap credit but is sensitive to fragmentation and equivalent partitions (Figure 3(c,d)). We therefore complement tIoU with a temporal Wasserstein reward, R_{TW}, measuring the transport required to align predicted temporal mass with the target support.

Each sampled completion is parsed into a predicted interval set $\hat{\mathcal{Y}}$ and scored by

$$R(\hat{\mathcal{Y}}, \mathcal{Y}) = R_{\mathrm{tIoU}}(\hat{\mathcal{Y}}, \mathcal{Y}) + R_{\mathrm{TW}}(\hat{\mathcal{Y}}, \mathcal{Y}) - \mathbf{1}_{\mathrm{invalid}}.$$

The indicator penalizes outputs that cannot be parsed into valid intervals. For valid predictions, set-level tIoU rewards recovered support:

$$R_{\mathrm{tIoU}}(\hat{\mathcal{Y}}, \mathcal{Y}) = \frac{|\operatorname{merge}(\hat{\mathcal{Y}}) \cap \operatorname{merge}(\mathcal{Y})|}{|\operatorname{merge}(\hat{\mathcal{Y}}) \cup \operatorname{merge}(\mathcal{Y})|}.$$

To supply geometry beyond overlap, we lift each non-empty interval set $\mathcal{A}$ to a uniform temporal distribution over its merged support:

$$\mu_{\mathcal{A}}(t) = \frac{\mathbf{1}\{t \in \operatorname{merge}(\mathcal{A})\}}{\ell(\mathcal{A})}, \qquad \ell(\mathcal{A}) = |\operatorname{merge}(\mathcal{A})|.$$

This makes the reward invariant to how identical support is partitioned. In one-dimensional time, the 1-Wasserstein distance has the exact CDF form

$$W(\hat{\mathcal{Y}}, \mathcal{Y}) = W_1(\mu_{\hat{\mathcal{Y}}}, \mu_{\mathcal{Y}}) = \int_{\mathbb{R}} \left| F_{\hat{\mathcal{Y}}}(t) - F_{\mathcal{Y}}(t) \right| \, dt,$$

Table 1: Comparison with proprietary and open-source models on temporal video grounding benchmarks. Metrics are R1@0.5 and mIoU (%). ^{TL} denotes evaluation on TimeLens-Bench (Zhang et al., 2026); † marks the VUE-TR vision subsets, and ‡ the MomentSeeker text-only query subset.

Size	Model	Charades^{TL}		ActivityNet^{TL}		QVHighlights^{TL}		VUE-TR†		VUE-TR-V2†		MomentSeeker‡		Ego4D-NLQ	
		R1@0.5	mIoU	R1@0.5	mIoU	R1@0.5	mIoU	R1@0.5	mIoU	R1@0.5	mIoU	R1@0.5	mIoU	R1@0.5	mIoU
Proprietary models															
	GPT-5 (Singh et al., 2025)	42.0	40.5	44.9	42.9	60.4	56.8	–	–	19.5	20.0	–	–	–	–
	Gemini 3 Pro (Google, 2025)	–	–	–	–	–	–	–	–	41.3	39.7	–	–	–	–
	Gemini 2.5 Pro (Comanici et al., 2025)	61.1	52.8	64.2	58.1	75.9	70.4	20.5	21.9	–	–	–	–	–	–
Open-source models															
2B	Marlin-2B (NemoStation, 2026)	51.7	46.5	40.5	37.9	48.5	46.8	23.6	24.8	19.9	19.2	15.2	16.3	7.8	8.9
2B	Qwen3.5-2B (Team, 2026)	46.8	46.0	52.8	48.9	65.7	60.6	27.2	27.8	21.5	21.6	12.8	15.6	10.1	11.2
2B	Qwen3-VL-2B (Bai et al., 2025)	44.4	43.4	41.0	39.9	53.4	52.2	29.9	31.4	22.5	24.1	9.8	12.4	8.1	9.3
2B	**TimeLens2-2B**	60.6	53.4	62.0	55.4	72.8	67.0	50.7	51.1	44.5	43.8	21.9	24.3	16.5	16.8
4B	InternVL3.5-4B (Wang et al., 2025b)	14.1	16.0	12.7	14.9	15.8	17.7	14.1	16.5	6.0	8.5	2.1	3.2	0.7	2.0
4B	Qwen3-VL-4B (Bai et al., 2025)	53.8	49.4	54.8	50.7	66.4	62.3	33.0	33.6	19.9	20.3	13.5	15.3	10.6	11.4
4B	Molmo2-4B (Clark et al., 2026)	31.1	34.7	40.3	40.9	62.6	60.8	42.5	43.1	30.9	32.1	14.7	19.5	7.7	10.0
4B	VideoChat3-4B (Li et al., 2026c)	64.9	56.1	60.5	54.6	72.5	67.0	47.8	47.9	40.4	40.2	24.4	25.9	13.9	14.6
4B	**TimeLens2-4B**	66.6	57.7	65.5	59.0	75.2	69.3	52.4	53.2	49.5	48.1	27.0	27.9	18.1	18.6
7B+	Qwen3.5-397B-A17B (Team, 2026)	47.8	47.5	59.1	53.8	71.6	65.8	42.7	42.2	35.5	34.5	22.3	23.3	13.3	14.5
7B+	Qwen3-VL-235B-A22B (Bai et al., 2025)	50.8	47.8	57.5	52.2	70.2	64.6	42.5	43.1	34.5	34.1	21.2	23.7	11.5	12.7
7B+	Qwen3.5-35B-A3B (Team, 2026)	50.4	48.2	58.6	52.6	72.6	66.0	46.3	44.6	37.1	35.3	20.2	22.6	12.0	13.0
7B+	Qwen3-VL-30B-A3B (Bai et al., 2025)	46.5	48.1	51.1	49.4	67.6	63.2	40.4	42.5	32.3	32.6	19.6	22.6	10.4	11.5
7B+	Vidi-1.5-9B (Team et al., 2025a)	18.3	22.0	40.2	39.3	58.4	55.9	45.0	47.0	31.9	34.3	14.8	18.6	6.5	8.4
7B+	LLaVA-OneVision-2-8B (An et al., 2026)	59.6	52.6	57.9	52.4	70.0	65.7	40.8	41.3	35.0	34.5	18.0	19.6	12.0	12.8
7B+	Qwen3-VL-8B (Bai et al., 2025)	49.3	47.2	51.1	48.0	62.9	59.4	23.8	25.5	13.1	14.0	9.4	9.8	4.8	5.3
7B+	InternVideo3-8B (Yan et al., 2026)	61.7	53.2	51.4	46.3	62.6	59.2	39.4	41.1	32.4	32.6	17.9	19.3	7.3	8.6
7B+	TimeLens-8B (Zhang et al., 2026)	65.8	57.0	62.0	56.3	71.7	66.8	42.9	43.6	34.4	34.0	20.4	21.9	14.6	15.7
7B+	Video-o3-7B (Zeng et al., 2026)	34.2	38.6	41.0	38.9	49.5	47.4	22.1	25.1	12.9	15.3	9.8	13.0	1.9	3.1
7B+	VideoChat-Flash-7B (Li et al., 2024)	37.9	39.7	21.8	24.8	30.6	32.7	15.4	17.3	9.5	10.1	5.9	7.2	1.5	2.5
7B+	MiMo-VL-7B (Xiaomi, 2025)	42.6	39.6	38.7	35.5	42.6	41.5	17.5	19.1	10.1	10.4	3.8	6.0	0.4	1.0
7B+	TimeSuite-7B (Zeng et al., 2025)	35.5	38.1	17.5	19.8	16.9	21.7	10.3	13.2	5.3	7.3	3.3	5.9	0.6	1.4
7B+	**TimeLens2-8B**	68.0	58.6	65.6	58.6	76.1	70.2	51.6	53.5	49.1	47.7	27.3	28.5	18.4	19.0

where $F_{\mathcal{A}}(t) = \int_{-\infty}^{t} \mu_{\mathcal{A}}(\tau)\, d\tau$. We convert it into a scale-normalized similarity:

$$R_{\text{TW}}(\hat{\mathcal{Y}}, \mathcal{Y}) = \exp\left(-\frac{W(\hat{\mathcal{Y}}, \mathcal{Y})}{|\operatorname{merge}(\mathcal{Y})| + \epsilon}\right).$$

Normalizing by target duration makes scores comparable across event scales without rewarding overly broad predictions through a prediction-dependent denominator.

Discussion. Unlike matched NGIoU (Luo et al., 2026), R_{TW} compares merged temporal mass directly, avoiding interval correspondence and providing dense, partition-invariant credit. Together, tIoU anchors support overlap, R_{TW} supplies geometry, and the parse penalty enforces valid outputs.

4 Experiments

4.1 Experimental Setup

Benchmarks. We evaluate TimeLens2 on the seven temporal grounding benchmarks: the TimeLens-Bench (Zhang et al., 2026) re-annotations of Charades-STA (Gao et al., 2017), ActivityNet Captions (Krishna et al., 2017), and QVHighlights (Lei et al., 2021); the vision subsets of the long-video VUE-TR (Team et al., 2025a) and VUE-TR-V2 (Team et al., 2025b); the text-only query subset of MomentSeeker (Yuan et al., 2026) for question-form localization; and the official validation split of the egocentric Ego4D-NLQ (Grauman et al., 2022).

Evaluation metrics. We report mean temporal Intersection-over-Union (mIoU) and Recall@1 at tIoU thresholds of 0.3, 0.5, and 0.7. mIoU measures average boundary overlap, whereas R1@threshold is the fraction of top predictions meeting the specified overlap. The main paper reports mIoU and R1@0.5; R1@0.3 and R1@0.7 are deferred to Table 8.

Implementation details. Unless specified otherwise, TimeLens2 uses Qwen3-VL-2B/4B/8B-Instruct (Bai et al., 2025). Following Section 3.2, SFT combines TimeLens2-93K, TimeLens-100K (Zhang et al., 2026), and the official Ego4D-NLQ-v2 training split (Grauman et al., 2022), converting Ego4D answer windows to $(v, q, \mathcal{Y})$. The 4B and 8B variants train for one epoch with 100K-token packing, a global batch size of 256, and a cosine-decayed learning rate of 5×10^{-6}; the 2B variant uses 160K-token packing, a global batch size of 128, and a learning rate of 10^{-5}.

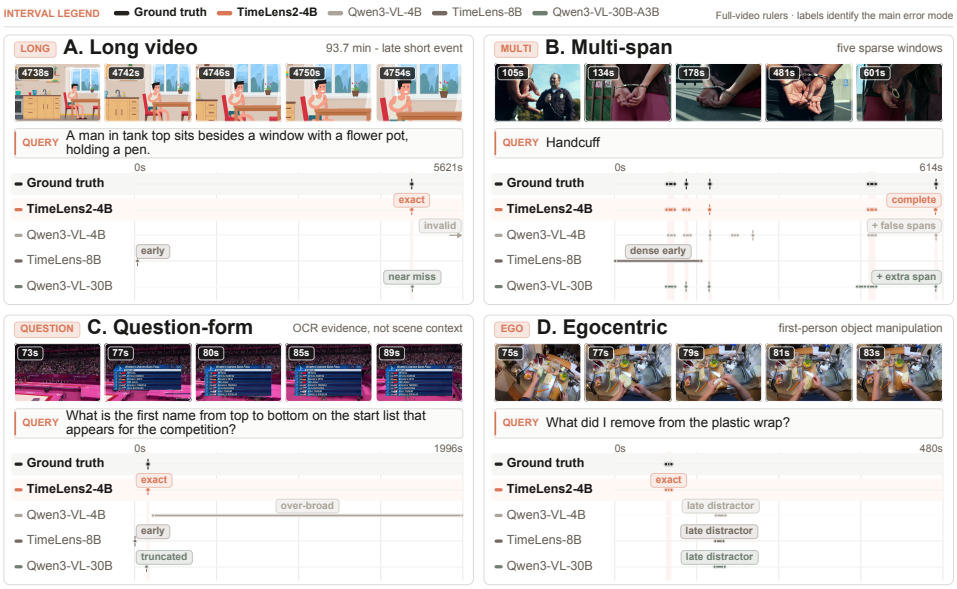

Figure 4: **Qualitative grounding comparison.** Each panel shows five target frames, the query, and full-video predictions; colors follow the shared legend.

For RL mining, we draw eight off-policy rollouts per TimeLens2-93K and TimeLens-100K example from the SFT checkpoint and up-weight low-mean-tIoU examples. GRPO uses eight generations per prompt, a global batch size of 64, a learning rate of 10^{-6}, and KL coefficient 0.04, with group rewards mean-centered but not variance-scaled. Videos are sampled at 2 fps, capped at 512 frames, and processed within 16K tokens. The reward is $R_{\text{tIoU}} + R_{\text{TW}} - \mathbf{1}_{\text{invalid}}$; every RL experiment and ablation retains the fixed invalid-output penalty. In both stages, the visual encoder is frozen and the language model is updated.

4.2 Comparison with State-of-the-Art

Temporal grounding. Table 1 shows that TimeLens2 performs consistently across model scales and benchmark regimes. At 2B, TimeLens2-2B outperforms all three size-matched open-source baselines on all seven benchmarks in both metrics, reaching 44.5 average mIoU—14.2 points above Qwen3-VL-2B (Bai et al., 2025) and 2.4 points above TimeLens-8B (Zhang et al., 2026). TimeLens2-8B surpasses all prior methods in R1@0.5 on all seven benchmarks and in mIoU on six, trailing Gemini 2.5 Pro on QVHighlights by only 0.2 points. Notably, TimeLens2-4B already outperforms every prior model, including substantially larger and proprietary systems, on six of seven benchmarks in both metrics. Its advantage is largest where temporal search is hardest: over the Qwen3-VL-4B backbone, it improves mIoU by 19.6 points on VUE-TR and 27.8 on VUE-TR-V2, while gaining 12.6 on question-form MomentSeeker and 7.2 on egocentric Ego4D-NLQ. These gains across long videos, query forms, and viewpoints indicate that TimeLens2 improves temporal evidence search rather than merely fitting dataset-specific boundary patterns.

Qualitative analysis. The central challenge in temporal grounding is not event recognition alone, but selecting query-relevant evidence from long, repetitive, or fragmented timelines. Figure 4 makes this distinction visible. In a 93.7-minute video, TimeLens2 retrieves a brief event near 4,750 seconds, while the baselines drift, miss the target, or produce an invalid timestamp. When the evidence recurs, it recovers all five sparse handcuff spans without adding plausible but false windows. The question-form example further separates semantic relevance from answer-bearing evidence: TimeLens2 isolates the brief OCR start list needed to answer the query rather than grounding the broader competition scene. In the egocentric case, it identifies the actual object removal while every baseline selects a later, visually similar interaction. Together, these cases show that TimeLens2 learns evidence-directed temporal search: it remains complete across disjoint spans while resisting distractors, even when the evidence is late, sparse, or defined by the query's intent.

4.3 Ablation Study

Table 2: **Effect of TimeLens2-93K.** Qwen3-VL-4B mIoU (%) across SFT mixtures; sizes are videos / QA turns (K), counting multi-turn annotations. Avg. is unweighted.

Supervised setting	Videos / QA (K)	Evaluation mIoU (%)							
		Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
Backbone									
Qwen3-VL-4B	–	49.4	50.7	62.3	33.6	20.3	15.3	11.4	34.7
Scaling TimeLens2-93K									
5% TimeLens2-93K	1.2 / 4.7	53.0	55.7	67.5	48.3	38.0	22.8	14.2	42.8
20% TimeLens2-93K	4.8 / 18.6	53.4	57.2	68.8	**51.1**	44.4	**26.2**	15.8	45.3
50% TimeLens2-93K	11.9 / 46.6	53.4	57.4	68.6	50.5	45.2	26.1	15.9	45.3
100% TimeLens2-93K	23.8 / 93.2	54.7	57.7	68.8	50.3	**46.0**	25.8	17.2	45.8
Dataset comparison and mixture									
TimeLens-100K	19.4 / 96.6	53.0	51.6	61.3	39.0	33.8	22.9	14.5	39.4
TimeLens2-93K + TimeLens-100K	43.2 / 189.8	55.9	58.4	69.0	50.3	45.3	25.8	17.3	46.0
TimeLens2-93K + TimeLens-100K + Ego4D-NLQ	**44.5 / 203.7**	**56.3**	**58.9**	**69.2**	50.9	45.6	25.8	**17.8**	**46.4**

Effect of TimeLens2-93K. To isolate supervision from RL, we fine-tune Qwen3-VL-4B on different data mixtures. Table 2 shows two-phase scaling: the first 5% of TimeLens2-93K raises average mIoU from 34.7 to 42.8, 20% reaches 45.3, and the full corpus reaches 45.8 with gains concentrated on harder settings such as VUE-TR-V2 and Ego4D-NLQ. Thus, a small high-confidence subset establishes evidence search, while broader coverage improves robustness. Despite containing only declarative queries, TimeLens2-93K also raises question-form MomentSeeker from 15.3 to 25.8, demonstrating transfer across query forms. Scale alone does not explain the gain: with comparable QA turns, TimeLens-100K reaches only 39.4 average mIoU. Adding it to TimeLens2-93K raises 45.8 to 46.0, mainly on TimeLens-Bench-style datasets; Ego4D-NLQ further raises it to 46.4 and strengthens egocentric grounding. Thus, TimeLens2-93K supplies transferable search, while TimeLens-100K and Ego4D-NLQ add complementary benchmark and viewpoint coverage.

Table 3: **Impact of progressive label curation.** Qwen3-VL-4B mIoU (%) under a fixed SFT recipe. The cascade applies temporal consensus, semantic verification, and boundary refinement. Shading marks the Qwen anchor and final labels.

Label curation stage	Videos / QA (K)	Evaluation mIoU (%)							
		Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
Raw Qwen3-VL-30B-A3B labels	28.9 / 735.4	51.7	50.9	60.1	47.4	43.2	24.9	15.7	42.0
Raw TimeLens-8B labels	33.6 / 999.2	54.4	51.5	59.2	48.5	40.3	24.7	15.7	42.0
Qwen-anchored curation cascade									
+ Temporal consensus	26.4 / 174.2	53.1 (+1.4)	52.9 (+2.0)	62.0 (+1.9)	49.5 (+2.1)	44.1 (+0.9)	25.8 (+0.9)	16.6 (+0.9)	43.4 (+1.4)
+ Semantic verification	23.8 / 93.2	53.3 (+0.2)	53.4 (+0.5)	63.0 (+1.0)	50.8 (+1.3)	45.1 (+1.0)	26.3 (+0.5)	16.6 (+0.0)	44.1 (+0.6)
+ Boundary refinement	**23.8 / 93.2**	**54.7** (+1.4)	**57.7** (+4.3)	**68.8** (+5.8)	50.3 (-0.5)	**46.0** (+0.9)	25.8 (-0.5)	**17.2** (+0.6)	**45.8** (+1.7)

Impact of progressive label curation. Effective curation should remove distinct supervision errors, not merely shrink the dataset. Under a fixed SFT recipe, Table 3 reveals a quality-over-quantity pattern. The raw annotators tie at 42.0 average mIoU yet differ by dataset, making agreement informative. Temporal consensus cuts the pool from 735.4K to 174.2K QA turns while raising mIoU to 43.4; semantic verification leaves 93.2K and reaches 44.1. Removing temporal instability and semantic mismatch therefore improves performance with only one-eighth as many labels.

With evidence identity established, boundary noise becomes the dominant bottleneck. Refining the same 93.2K labels yields the largest stage gain, adding 1.7 points to reach 45.8 mIoU without additional data. The full cascade improves over the raw Qwen labels by 3.8 points overall. Although refinement loses 0.5 points on VUE-TR and MomentSeeker, the progression exposes a clear factorization of annotation error: consensus tests temporal reproducibility, semantic verification tests relevance, and local refinement resolves boundary uncertainty.

Effect of long-context training. Longer contexts help only if the model can search them without absorbing more distractors. Holding the data, backbone, and optimization fixed, we vary the maximum packed length. Table 4 shows average mIoU rising from 44.4 at 16K to 46.4 at 100K, but unevenly: Charades and QVHighlights peak by 32K, whereas VUE-TR-V2, MomentSeeker, and Ego4D-NLQ gain 4.0, 1.5, and 3.3 points by 100K. VUE-TR's late 1.8-point jump from 64K to 100K further suggests a context-threshold effect for long-range examples. These asymmetries indicate that long-context training expands the effective temporal search horizon rather than uniformly benefiting every task. We therefore use 100K for final SFT.

Table 4: **Effect of long-context training.**

Max. packed length	Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
16K	56.1	57.0	68.2	49.1	41.6	24.3	14.5	44.4
32K	**56.3** (+0.2)	57.5 (+0.5)	**69.2** (+1.0)	48.8 (-0.3)	44.2 (+2.6)	25.1 (+0.8)	16.6 (+2.1)	45.4 (+1.0)
64K	56.1 (-0.2)	58.5 (+1.0)	**69.2** (+0.0)	49.1 (+0.3)	45.5 (+1.3)	25.7 (+0.6)	17.4 (+0.8)	45.9 (+0.5)
100K	**56.3** (+0.2)	**58.9** (+0.4)	**69.2** (+0.0)	**50.9** (+1.8)	**45.6** (+0.1)	**25.8** (+0.1)	**17.8** (+0.4)	**46.4** (+0.5)

Effect of instruction and response-format diversity. A generalist grounder should recover the same evidence regardless of request phrasing or timestamp serialization; otherwise, it may learn the interface rather than the task. Holding the TimeLens2-93K examples, Qwen3-VL-4B backbone, and SFT recipe fixed, we independently vary requests and renderings using the 27 instructions and 28 response specifications in Table 7. Table 5 shows that rendering diversity alone raises average mIoU from 44.9 to 45.4, while request diversity reaches 45.0. Together they reach 45.8 (+0.9), perform best on six of seven benchmarks, and yield the largest gains on VUE-TR (+3.0) and QVHighlights (+1.3). The joint gain exceeds the sum of the isolated gains by 0.3 points. Thus, response-format diversity is the stronger standalone lever, but their positive interaction suggests that varying both sides of the interface helps disentangle evidence localization from surface realization and improves transfer across prompting protocols.

Table 5: **Instruction/response-format diversity.**

Grounding request	Target rendering	Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
Single	**Single**	54.3	57.0	67.5	47.3	45.8	25.7	16.6	44.9
Single	Diverse	**54.8**	57.4	68.5	50.0	45.4	25.3	16.3	45.4 (+0.5)
Diverse	Single	54.7	57.2	67.3	48.2	45.7	25.3	16.5	45.0 (+0.1)
Diverse	**Diverse**	54.7	**57.7**	**68.8**	**50.3**	**46.0**	**25.8**	**17.2**	**45.8** (+0.9)

Ablation on temporal reward design. The usefulness of R_{TW} depends on how an interval set is represented. Holding all other RL settings fixed, we compare uniform support with endpoint atoms, center Gaussians, and boundary Gaussians in Figure 5. All improve average mIoU over R_{tIoU}, from 47.0 to 47.4–47.7 (Table 6), showing that distance-aware credit complements overlap. Uniform support is the only variant to improve every benchmark and attains the best average, 47.7.

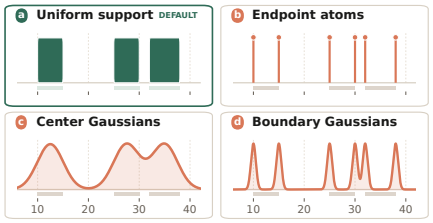

Figure 5: The same intervals are converted into four probability distributions.

Table 6: **Temporal reward design.**

Temporal reward	Temporal distribution	Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
R_{tIoU}	–	57.4	58.1	67.2	52.0	47.8	27.7	18.5	47.0
$R_{\text{tIoU}} + R_{\text{TW}}$	**Uniform support**	**57.7**	**59.0**	69.3	53.2	**48.1**	27.9	18.6	**47.7** (+0.7)
$R_{\text{tIoU}} + R_{\text{TW}}$	Endpoint atoms	57.2	58.9	68.4	**53.9**	47.6	27.6	18.5	47.4 (+0.4)
$R_{\text{tIoU}} + R_{\text{TW}}$	Center Gaussians	57.4	**59.0**	**69.4**	53.2	47.4	**28.3**	18.8	47.6 (+0.6)
$R_{\text{tIoU}} + R_{\text{TW}}$	Boundary Gaussians	57.1	**59.0**	69.2	52.9	46.9	28.0	**18.9**	47.4 (+0.4)

Uniform support preserves both evidence location and duration, matching the span occupancy measured by mIoU. Endpoint atoms and boundary Gaussians emphasize transitions, whereas center Gaussians mainly encode location; each discards interval-interior or duration information and is less stable across tasks. Thus, dense credit is most effective when its representation matches the evaluation geometry, motivating uniform support by default. Matched-NGIoU comparisons and zero-overlap and group-relative diagnostics appear in Section A.4.

5 Conclusion

Video MLLMs become reliable interfaces to video archives only when their answers are traceable to supporting moments. This requires trustworthy evidence labels and an objective that guides imperfect interval predictions. TimeLens2 addresses both. TimeLens2-93K replaces brittle global annotation with evidence proposal, independent localization, consensus and semantic verification, and boundary refinement; the temporal Wasserstein reward supplies dense, matching-free geometry when overlap is uninformative. Across seven benchmarks, this design enables compact 2B, 4B, and 8B models to outperform much larger open-source models in long-video, multi-span, question-form, and egocentric settings. More broadly, treating evidence consistently as an interval set from supervision through optimization turns temporal grounding from a specialized retrieval task into a native, auditable capability of generalist video MLLMs.

AI USE STATEMENT

We used generative AI tools to assist with writing and polishing this manuscript and to generate synthetic training data, as described in Section 3.1. The authors reviewed the AI-assisted content and take full responsibility for the final manuscript and dataset.

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A SUPPLEMENTARY MATERIAL

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A.1 INSTRUCTION AND RESPONSE-FORMAT DIVERSITY

Temporal grounding requires both locating relevant evidence and expressing intervals through a specified interface. Training with a single prompt–response convention can entangle localization with surface form, reducing robustness when the request phrasing or output format changes.

For each QA turn, we keep the video, synthesized query q, and target interval set $\mathcal{Y}$ fixed, then independently and uniformly sample one of 27 grounding requests and one of 28 response specifications. The request pool varies how localization is posed, while the response pool controls answer syntax, timestamp encoding, and multi-interval composition. A deterministic renderer expresses the same $\mathcal{Y}$ under the sampled specification. As summarized in Table 7, this factorization defines 756 possible interface pairings without query paraphrases that could shift the intended evidence. It therefore encourages interface-invariant temporal semantics and format-conditioned serialization, while enabling the controlled 2×2 analysis in Table 5.

Table 7: **Factorized interface diversity used during SFT.** Independent sampling from 27 grounding requests and 28 response specifications defines 756 possible pairings while the query and target intervals remain fixed. Counts in each response axis partition the same 28 specifications; examples render two intervals.

Component	Variation	Count	Representative realization
Grounding request	Question, command, or explicit task schema	27	"When does q happen?"; "Locate the segments where q occurs."; "Query: q. Return matching intervals."
Response specification	Format-conditioned interval rendering	28	Specifies syntax, timestamp encoding, and rules for one or multiple intervals
Composition of the 28 response specifications			
Surface syntax	Natural language / labeled fields / bracketed arrays / bare intervals	12 / 5 / 6 / 5	`It happens from 12.0s to 18.5s, and 31.0s to 36.0s.`; `[[12.0, 18.5], [31.0, 36.0]]`
Timestamp encoding	Decimal seconds / minute–second / hour–minute–second	26 / 1 / 1	`12.0s`; `00:12`; `00:00:12`
Multi-interval composition	Format-consistent joining	28	Repeated clauses or interval tokens joined by conjunctions, punctuation, or an outer array

A.2 FULL TEMPORAL GROUNDING RESULTS

The main paper reports R1@0.5 and mIoU; Table 8 adds R1@0.3 and R1@0.7 wherever available. The progression from loose to strict overlap separates coarse evidence retrieval from boundary precision: a model may find the correct event at R1@0.3 yet fail to delimit it at R1@0.7. Through

its 4B and 8B variants, TimeLens2 achieves the highest reported R1@0.3 and R1@0.7 on all seven benchmarks. The 2B variant extends this evaluation to a smaller scale, reaching average R1@0.3, R1@0.5, and R1@0.7 scores of 57.9, 47.0, and 32.0, respectively.

Table 8: **Full temporal grounding results across IoU thresholds.**

Model	Metric	Charades TL	ActivityNet TL	QVHighlights TL	VUE-TR †	VUE-TR-V2 †	MomentSeeker ‡	Ego4D-NLQ
GPT-5 (Singh et al., 2025)	R1@0.3	59.3	57.4	72.4	–	28.0	–	–
	R1@0.5	42.0	44.9	60.4	–	19.5	–	–
	R1@0.7	22.0	30.4	46.4	–	11.6	–	–
	mIoU	40.5	42.9	56.8	–	20.0	–	–
Gemini 3 Pro (Google, 2025)	R1@0.3	–	–	–	–	51.5	–	–
	R1@0.5	–	–	–	–	41.3	–	–
	R1@0.7	–	–	–	–	26.0	–	–
	mIoU	–	–	–	–	39.7	–	–
Gemini 2.5 Pro (Comanici et al., 2025)	R1@0.3	74.1	72.3	84.1	29.1	–	–	–
	R1@0.5	61.1	64.2	75.9	20.5	–	–	–
	R1@0.7	34.0	47.1	61.1	10.3	–	–	–
	mIoU	52.8	58.1	70.4	21.9	–	–	–
Qwen3.5-397B-A17B (Team, 2026)	R1@0.3	69.3	70.6	82.1	52.4	45.6	34.3	20.5
	R1@0.5	47.8	59.1	71.6	42.7	35.5	22.3	13.3
	R1@0.7	24.9	41.7	56.1	33.1	25.5	9.9	7.1
	mIoU	47.5	53.8	65.8	42.2	34.5	23.3	14.5
Qwen3-VL-235B-A22B (Bai et al., 2025)	R1@0.3	71.7	69.0	79.6	55.8	44.1	34.4	17.8
	R1@0.5	50.8	57.5	70.2	42.5	34.5	21.2	11.5
	R1@0.7	24.5	39.3	54.5	31.6	24.1	11.3	6.3
	mIoU	47.8	52.2	64.6	43.1	34.1	23.7	12.7
Qwen3.5-35B-A3B (Team, 2026)	R1@0.3	69.5	69.4	81.6	56.2	47.0	33.2	18.2
	R1@0.5	50.4	58.6	72.6	46.3	37.1	20.2	12.0
	R1@0.7	27.3	40.1	56.5	32.4	24.9	9.7	6.9
	mIoU	48.2	52.6	66.0	44.6	35.3	22.6	13.0
Qwen3-VL-30B-A3B (Bai et al., 2025)	R1@0.3	70.3	65.7	79.3	53.0	42.7	33.6	16.1
	R1@0.5	46.5	51.1	67.6	40.4	32.3	19.6	10.4
	R1@0.7	25.1	36.5	52.6	32.2	21.8	9.2	5.5
	mIoU	48.1	49.4	63.2	42.5	32.6	22.6	11.5
Vidi-1.5-9B (Team et al., 2025a)	R1@0.3	28.7	51.8	68.7	57.3	43.9	27.0	11.4
	R1@0.5	18.3	40.2	58.4	45.0	31.9	14.8	6.5
	R1@0.7	10.1	28.2	46.2	36.0	22.2	6.9	3.4
	mIoU	22.0	39.3	55.9	47.0	34.3	18.6	8.4
LLaVA-OneVision-2-8B (An et al., 2026)	R1@0.3	73.1	65.6	78.2	51.2	46.3	28.8	18.2
	R1@0.5	59.6	57.9	70.0	40.8	35.0	18.0	12.0
	R1@0.7	34.0	40.9	57.0	30.1	22.8	8.2	6.4
	mIoU	52.6	52.4	65.7	41.3	34.5	19.6	12.8
Qwen3-VL-8B (Bai et al., 2025)	R1@0.3	68.5	63.8	74.4	33.0	19.6	13.6	7.4
	R1@0.5	49.3	51.1	62.9	23.8	13.1	9.4	4.8
	R1@0.7	26.2	35.0	49.3	17.5	8.3	4.5	2.5
	mIoU	47.2	48.0	59.4	25.5	14.0	9.8	5.3
InternVideo3-8B (Yan et al., 2026)	R1@0.3	75.8	60.0	72.2	51.0	40.8	28.8	12.3
	R1@0.5	61.7	51.4	62.6	39.4	32.4	17.9	7.3
	R1@0.7	32.8	33.4	48.9	32.0	21.7	7.3	3.2
	mIoU	53.2	46.3	59.2	41.1	32.6	19.3	8.6
TimeLens-8B (Zhang et al., 2026)	R1@0.3	78.8	71.8	81.2	56.4	46.2	32.0	21.9
	R1@0.5	65.8	62.0	71.7	42.9	34.4	20.4	14.6
	R1@0.7	37.6	43.8	57.1	31.2	23.5	9.9	7.7
	mIoU	57.0	56.3	66.8	43.6	34.0	21.9	15.7
Video-o3-7B (Zeng et al., 2026)	R1@0.3	58.7	53.2	62.7	32.8	21.4	18.2	4.2
	R1@0.5	34.2	41.0	49.5	22.1	12.9	9.8	1.9
	R1@0.7	16.2	24.4	34.4	14.5	7.0	3.9	0.7
	mIoU	38.6	38.9	47.4	25.1	15.3	13.0	3.1
VideoChat-Flash-7B (Li et al., 2024)	R1@0.3	60.2	35.5	45.2	20.2	13.7	10.9	3.1
	R1@0.5	37.9	21.8	30.6	15.4	9.5	5.9	1.5
	R1@0.7	17.8	10.5	16.7	10.7	5.6	2.2	0.6
	mIoU	39.7	24.8	32.7	17.3	10.1	7.2	2.5
MiMo-VL-7B (Xiaomi, 2025)	R1@0.3	57.9	49.3	57.1	25.1	14.7	6.5	0.9
	R1@0.5	42.6	38.7	42.6	17.5	10.1	3.8	0.4
	R1@0.7	20.5	22.4	28.4	11.2	4.8	1.6	0.1
	mIoU	39.6	35.5	41.5	19.1	10.4	6.0	1.0
TimeSuite-7B (Zeng et al., 2025)	R1@0.3	56.3	27.1	27.1	15.8	9.4	6.9	1.6
	R1@0.5	35.5	17.5	16.9	10.3	5.3	3.3	0.6
	R1@0.7	18.0	8.6	9.9	7.0	3.2	1.2	0.3
	mIoU	38.1	19.8	21.7	13.2	7.3	5.9	1.4
InternVL3.5-4B (Wang et al., 2025b)	R1@0.3	24.6	20.0	25.5	20.4	11.0	3.7	2.0
	R1@0.5	14.1	12.7	15.8	14.1	6.0	2.1	0.7
	R1@0.7	6.2	8.2	6.2	9.5	3.5	0.6	0.1
	mIoU	16.0	14.9	17.7	16.5	8.5	3.2	2.0
Qwen3-VL-4B (Bai et al., 2025)	R1@0.3	71.8	67.4	78.4	41.0	25.6	21.5	15.5
	R1@0.5	53.8	54.8	66.4	33.0	19.9	13.5	10.6
	R1@0.7	28.7	37.6	51.1	25.0	13.3	5.4	6.0
	mIoU	49.4	50.7	62.3	33.6	20.3	15.3	11.4
Molmo2-4B (Clark et al., 2026)	R1@0.3	44.4	50.8	73.7	52.0	41.7	25.2	11.8
	R1@0.5	31.1	40.3	62.6	42.5	30.9	14.7	7.7
	R1@0.7	18.5	29.9	51.8	33.7	20.8	8.0	4.5
	mIoU	34.7	40.9	60.8	43.1	32.1	19.5	10.0
VideoChat3-4B	R1@0.3	78.4	70.1	81.0	61.0	53.8	37.2	20.9
	R1@0.5	64.9	60.5	72.5	47.8	40.4	24.4	13.9
	R1@0.7	35.9	42.2	56.8	34.7	27.3	12.0	7.2
	mIoU	56.1	54.6	67.0	47.9	40.2	25.9	14.6
Marlin-2B (NemoStation, 2026)	R1@0.3	66.3	50.5	60.7	31.6	24.5	23.9	12.7
	R1@0.5	51.7	40.5	48.5	23.6	19.9	15.2	7.8
	R1@0.7	27.1	25.3	34.9	16.4	12.0	5.8	3.8
	mIoU	46.5	37.9	46.8	24.8	19.2	16.3	8.9
Qwen3.5-2B (Team, 2026)	R1@0.3	67.3	64.5	74.8	34.7	28.7	22.2	15.9
	R1@0.5	46.8	52.8	65.7	27.2	21.5	12.8	10.1
	R1@0.7	24.5	35.9	50.5	17.0	13.7	6.1	5.1
	mIoU	46.0	48.9	60.6	27.8	21.6	15.6	11.2
Qwen3-VL-2B (Bai et al., 2025)	R1@0.3	62.7	53.7	67.8	41.9	33.7	17.3	13.3
	R1@0.5	44.4	41.0	53.4	29.9	22.5	9.8	8.1
	R1@0.7	23.4	26.5	39.3	18.5	13.8	3.2	3.8
	mIoU	43.4	39.9	52.2	31.4	24.1	12.4	9.3
TimeLens2-2B	R1@0.3	74.2	71.1	81.1	64.2	57.5	34.1	23.3
	R1@0.5	60.6	62.0	72.8	50.7	44.5	21.9	16.5
	R1@0.7	33.6	43.2	57.8	38.9	31.5	9.8	9.1
	mIoU	53.4	55.4	67.0	51.1	43.8	24.3	16.8
TimeLens2-4B	R1@0.3	80.3	74.6	83.3	66.5	62.9	38.8	26.0
	R1@0.5	66.6	65.5	75.2	52.4	49.5	27.0	18.1
	R1@0.7	37.5	47.2	60.0	41.1	35.5	12.5	10.0
	mIoU	57.7	59.0	69.3	53.2	48.1	27.9	18.6
TimeLens2-8B	R1@0.3	80.9	74.0	84.4	65.3	61.8	40.8	27.0
	R1@0.5	68.0	65.6	76.1	51.6	49.1	27.3	18.4
	R1@0.7	38.9	46.6	61.2	41.9	34.8	13.7	9.6
	mIoU	58.6	58.6	70.2	53.5	47.7	28.5	19.0

A.3 Additional Qualitative Examples

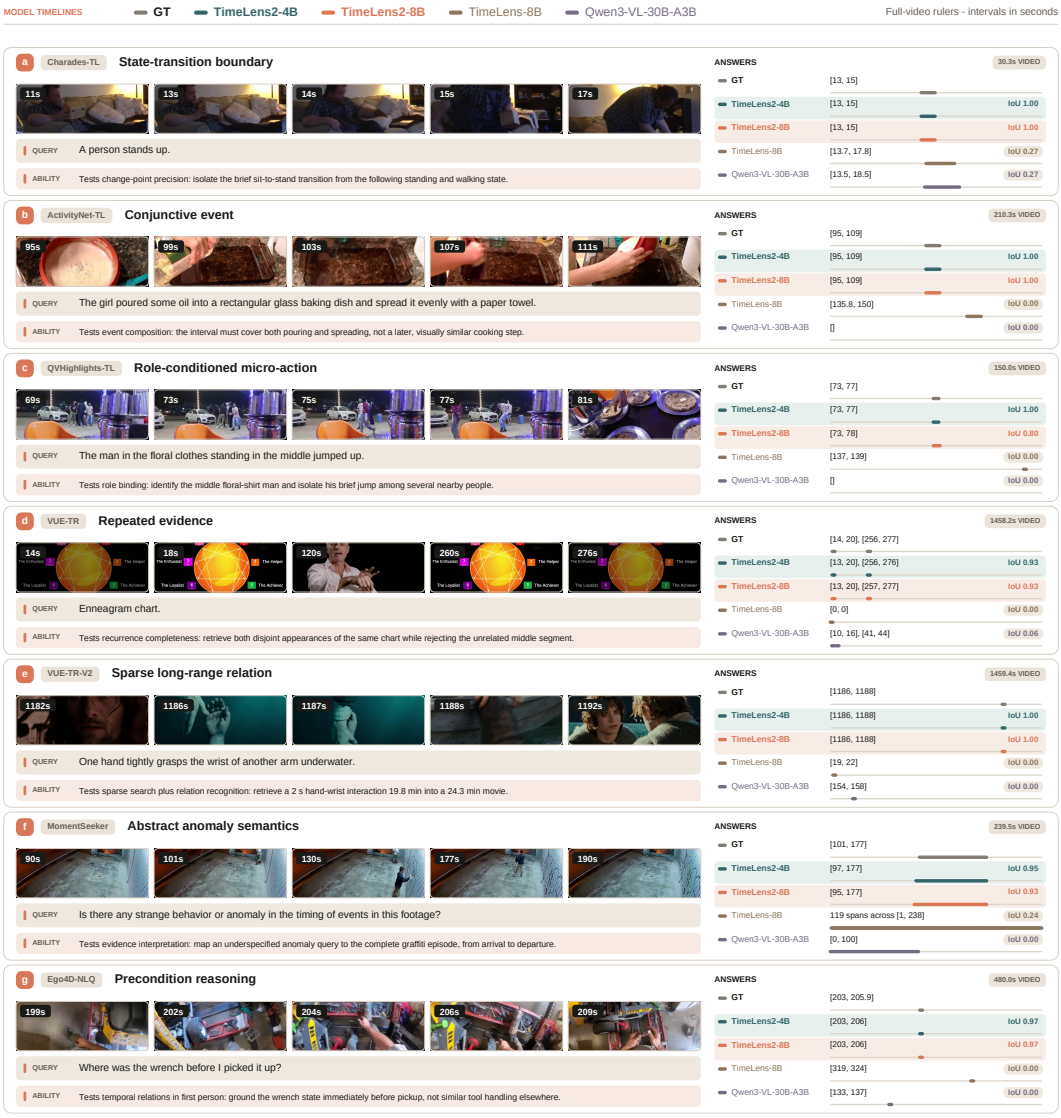

Figure 6: **Additional qualitative results on all seven benchmarks.** Each row pairs five frames near the target evidence with the query, the temporal reasoning challenge, and full-video timelines showing the ground truth and predictions from four models. The TimeLens2 variants consistently recover the intended evidence, whereas the baselines select distractors, miss events, overextend boundaries, or fragment their predictions.

These examples probe complementary temporal-reasoning capabilities. Charades-TL tests precise state-transition boundaries; ActivityNet-TL requires one interval covering both actions in a conjunction; QVHighlights-TL tests role-conditioned entity binding; and VUE-TR requires complete retrieval of recurring evidence. VUE-TR-V2 adds sparse search for a two-second relation nearly 20 minutes into a film. MomentSeeker requires mapping an underspecified anomaly query to the complete graffiti episode, rather than broad or fragmented coverage. Ego4D-NLQ tests precondition reasoning by locating the wrench immediately before pickup. Across all settings, TimeLens2 remains precise, complete, and resistant to visually similar distractors.

A.4 Additional Analysis

We further compare R_{TW} with matched NGIoU and isolate its mechanism with two diagnostics: whether the gain is concentrated on distance-ranked zero-overlap misses, and whether the same dense signal creates usable within-group preferences for GRPO.

Comparison with matched NGIoU. NGIoU also provides graded feedback for non-overlapping intervals, making it a natural alternative to R_{TW}. We replace only R_{TW} with R_{NGIoU}, using MUSEG's one-to-one matching (Luo et al., 2026). As shown in Table 9, NGIoU reaches 47.1 average mIoU, compared with 47.7 for temporal Wasserstein. The gap is larger on the multi-interval VUE-TR benchmarks: 1.4 points on VUE-TR and 1.0 on VUE-TR-V2. NGIoU depends on pairwise assignments, which can change when predictions split, merge, or differ in number. In contrast, R_{TW} compares merged temporal support directly and is invariant to equivalent fragmentations. Thus, dense feedback alone is insufficient; robust multi-interval rewards should avoid fragile correspondences.

Table 9: **Temporal Wasserstein vs. matched NGIoU.** We vary only the auxiliary dense reward; all other RL settings are fixed. R_{NGIoU} uses MUSEG's start-time-sorted one-to-one matching (Luo et al., 2026). The Avg. gain is relative to matched NGIoU; shading distinguishes the comparator and our default reward.

Temporal reward	Charades^{TL}	ActivityNet^{TL}	QVHighlights^{TL}	VUE-TR†	VUE-TR-V2†	MomentSeeker‡	Ego4D-NLQ	Avg.
$R_{\mathrm{tIoU}} + R_{\mathrm{TW}}$	**57.7**	**59.0**	**69.3**	**53.2**	**48.1**	27.9	**18.6**	**47.7** (+0.6)
$R_{\mathrm{tIoU}} + R_{\mathrm{NGIoU}}$	**57.7**	58.8	67.7	51.8	47.1	**28.2**	18.5	47.1

Diagnostic ablation on zero-overlap misses. Average gains establish efficacy, but not mechanism: R_{TW} may help for reasons unrelated to its distance-aware signal. We therefore examine the 4,332 benchmark predictions from RL-tIoU that have no overlap with the target and group them by their minimum temporal distance to it. If R_{TW} supplies the intended geometry, recovery should decay with distance.

Table 10: **Where does temporal Wasserstein help?** We stratify the 4,332 valid zero-tIoU predictions from RL-tIoU by distance to the target. Gap is normalized by total ground-truth duration; recovery is the fraction of corresponding examples on which adding R_{TW} yields positive tIoU. Shading follows the distance gradient.

Zero-overlap misses under R_{tIoU}			After adding R_{TW}	
Distance	**Normalized gap**	**Cases**	**Recovered (%) ↑**	**mIoU (%) ↑**
Near	$\leq 1\times$	644	**21.9**	**7.5**
Mid	1–$5\times$	808	15.8	4.0
Far	$> 5\times$	2,880	5.7	1.4
All zero-overlap misses		**4,332**	**10.0**	**2.8**

Table 10 shows a clear distance effect. Adding R_{TW} recovers positive overlap for 21.9% of near misses, 15.8% of mid-distance misses, and only 5.7% of far misses; mIoU similarly falls from 7.5 to 4.0 and 1.4. These zero-overlap cases also account for most of the overall improvement from 47.0 to 47.7 in Table 6. Thus, R_{TW} helps mainly where tIoU provides no signal, giving more credit to near misses than distant errors.

Diagnostic on group-relative reward structure. GRPO learns from within-group preferences, so a dense reward helps only if it breaks ties among rollouts. With tIoU, a group of non-overlapping predictions can receive uniformly zero reward and, after mean-centering, no temporal learning signal. To isolate the effect of R_{TW}, we score the same valid rollout groups collected over 300 training steps with both R_{tIoU} and $R_{\mathrm{tIoU}} + R_{\mathrm{TW}}$.

Table 11: **Does temporal Wasserstein create group-relative signal?** We score the same valid rollout groups collected over 300 training steps with both rewards. Constant groups contain only one reward value; zero-tIoU rescue is the fraction of all-zero-tIoU groups that become non-constant after adding R_{TW}. Advantages are mean-centered without variance scaling.

Scoring reward	Constant groups ↓	Distinct/group ↑	$\mathrm{Var}_g(R)$ ↑	$\mathbb{E}_g\lvert A\rvert$ ↑	Zero-tIoU rescue ↑
R_{tIoU}	13.8%	4.63	0.023	0.098	–
$R_{\mathrm{tIoU}} + R_{\mathrm{TW}}$	**3.6%**	**6.04**	**0.091**	**0.190**	**75.8%**

As shown in Table 11, adding R_{TW} reduces constant-reward groups from 13.8% to 3.6% and rescues 75.8% of all-zero-tIoU groups. Beyond tie-breaking, distinct rewards per group rise from 4.63 to 6.04, within-group variance increases by $4.0\times$, and mean absolute advantage nearly doubles. Because rewards are mean-centered without variance scaling, this extra spread passes directly into the policy update. Temporal Wasserstein thus turns otherwise silent groups into ranked training signals, explaining its strong fit with group-relative optimization.

A.5 Temporal Grounding Evaluation Protocol

Benchmarks and evaluation subsets. We conduct all in-house evaluations with VLMEvalKit (Duan et al., 2026). Within this framework, we implement evaluation adapters for the TimeLens-Bench re-annotations of Charades-STA, ActivityNet Captions, and QVHighlights; the vision-query subsets of VUE-TR and VUE-TR-V2; the text-only query subset of MomentSeeker; and the official Ego4D-NLQ-v2 validation split. We use visual frames only: audio and subtitles are not supplied to the model.

Standard video input configuration. For models evaluated, the input configuration is fixed per benchmark rather than tuned per model; the exact constructor arguments are given in Table 12. The video processor receives `min_pixels` and `max_pixels` as per-frame pixel-area bounds and `total_pixels` as the aggregate visual pixel budget. We first sample at the specified frame rate. If $\lfloor T \times \mathrm{fps} \rfloor$ exceeds `frames_limit`, we uniformly retain the capped number of frames over the entire duration T, and pass the resulting effective sampling rate to the model.

Model-specific input settings. All evaluated Qwen3-VL and Qwen3.5 variants, LLaVA-OneVision-2-8B, TimeLens-8B, VideoChat3-4B, InternVideo3-8B, Molmo2-4B, and TimeLens2-2B/4B/8B use the standard per-benchmark settings in Table 12. Every deviation is summarized in Table 13 by model and dataset group. These deviations are used when a model cannot accommodate the standard context or frame budget. All Qwen3.5 models except Qwen3.5-2B are evaluated with thinking enabled, which substantially improves temporal-grounding performance. For Qwen3.5-2B, we disable thinking because it frequently enters non-terminating reasoning loops, especially on long-video benchmarks. Thinking is disabled for every other evaluated model. Because Molmo2 follows generic instructions and prescribed output formats unreliably, we adopt the native spatiotemporal-grounding question template from its original work. Specifically, we use the prompt "Point the start and end of the event described by the sentence *query*." and parse the first two temporal coordinates from its native `<points coords="...">` or `<tracks coords="...">` response.

Table 12: **Standard input configuration.** Exact arguments for the seven temporal grounding benchmarks.

Benchmark	Queries N	Temporal sampling		Per-frame area		Total area	Output
		FPS	`frames_limit`	`min_pixels`	`max_pixels`	`total_pixels`	
Charades-TimeLens	3,363	4	2,048	32^2	640^2	128000×32^2	one interval
ActivityNet-TimeLens	4,500	4	2,048	32^2	640^2	128000×32^2	one interval
QVHighlights-TimeLens	1,541	4	2,048	32^2	640^2	128000×32^2	one interval
VUE-TR (vision)	525	1	2,048	32^2	480^2	128000×32^2	all intervals
VUE-TR-V2 (vision)	715	1	2,048	32^2	480^2	128000×32^2	all intervals
MomentSeeker (text-only)	1,000	2	2,048	32^2	480^2	128000×32^2	all intervals
Ego4D-NLQ-v2 (val)	4,552	2	2,048	32^2	480^2	128000×32^2	one interval

Table 13: **Model-specific overrides.** Input configurations that deviate from Table 12. TL denotes the three TimeLens-Bench datasets.

Model	Dataset group	FPS	Frame cap	Min. `min_pixels`	Max. `max_pixels`	Total area `total_pixels`
Global overrides						
Video-o3-7B / MiMo-VL-7B	All seven	2	768	10×28^2	768×28^2	24576×28^2
VideoChat-Flash-7B	All seven	$\sim$1	512	448^2	448^2	–
TimeSuite-7B	All seven	–	128	224^2	224^2	–
Dataset-specific override						
InternVL3.5-4B	TL	1	32	28^2	448^2	12800×32^2
	VUE-TR	1	128	28^2	448^2	12800×32^2
	VUE-TR-V2 / MomentSeeker	1	128	32^2	480^2	12800×32^2
	Ego4D-NLQ	1	64	32^2	480^2	12800×32^2

Table 14: **Dataset-side prompt templates.** Exact templates used in the standard temporal grounding evaluation; {`query`} is replaced by the benchmark query.

Benchmark group	Prompt template
Charades-/ActivityNet-/ QVHighlights-TimeLens	`Please find the visual event described by the sentence '{query}', determining its starting and ending times. The format should be: 'The event happens in <start time> - <end time> seconds'.`

VUE-TR / VUE-TR-V2	`You are given a video.`
	`Task: temporal retrieval.`
	`Given the query: "{query}", return ALL time spans (in seconds) where the query is relevant.`
	`Output format MUST be a JSON array of [start, end] pairs, e.g. [[0, 3.5], [10, 12]].`

MomentSeeker	`You are given a video.`
	`Task: temporal grounding.`
	`Given the query: "{query}", return ALL time spans (in seconds) where the query is grounded in the video.`
	`Output format MUST be a JSON array of [start, end] pairs, e.g. [[0, 3.5], [10, 12]].`

Ego4D-NLQ-v2 (val)	`You are given a video.`
	`Task: temporal grounding.`
	`Given the query: "{query}", return the time span (in seconds) where the query is grounded in the video.`
	`Output format MUST be [[start, end]].`

Prompt templates. The evaluation entry point uses the dataset-side prompts in Table 14.

A.6 Train–Test Overlap Audit

We canonicalized the complete list of training-source YouTube IDs and compared it with the video identifiers used by all seven evaluation subsets. Specifically, we removed the `v_` prefix from ActivityNet IDs, reduced QVHighlights clip names to their 11-character source IDs, and used the native YouTube IDs provided by VUE-TR, VUE-TR-V2, and the explicitly identified YouTube videos in MomentSeeker. We additionally searched each benchmark's `video`, `video_id`, and `src_video_path` fields for embedded training IDs. The intersection was *empty* for every benchmark. Charades and Ego4D use non-YouTube identifiers, while most MomentSeeker videos are distributed under renamed internal identifiers without a source-ID mapping; thus, this audit establishes *zero* overlap among recoverable source identifiers but cannot exclude content duplicates concealed by renaming.

A.7 Limitations and Future Directions

Limitations. TimeLens2-93K was constructed under finite financial and computational budgets. We therefore relied on cost-effective, predominantly open-weight models throughout the pipeline: Qwen3-VL-235B-A22B-Instruct for captioning, Kimi-K2.5 for query and proposal generation, Qwen3-VL-30B-A3B and TimeLens-8B for temporal annotation, and Qwen3-VL-235B-A22B-Instruct for final refinement. Although this pipeline already produces effective training data, its quality is inevitably bounded by the capabilities of these models. Replacing them with stronger proprietary multimodal models, such as Gemini 3.1 Pro (Google DeepMind, 2026), could substantially improve the richness, diversity, and temporal precision of the resulting annotations. We therefore believe that the current dataset is not the endpoint of this recipe, but a first demonstration with considerable room to scale.

Future directions. Beyond improving temporal grounding data with stronger models, our construction framework may naturally extend to long-context spatiotemporal grounding, where a model must determine not only *when* an event occurs, but also *where* relevant entities appear and how they evolve over time. This capability is particularly important for embodied intelligence: an agent operating over long horizons must connect past observations with the current scene, track changes in objects and environments, and ground its decisions in concrete visual evidence before completing downstream tasks. We hope our work can inspire larger and richer spatiotemporally grounded datasets, as well as models that turn long-video perception into persistent memory, grounded reasoning, and ultimately reliable action.