

Which Way Does Time Flow? A Psychophysics-Grounded Evaluation for Vision–Language Models

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Abstract

Modern vision–language models (VLMs) excel at many multimodal tasks, yet their grasp of temporal information in video remains weak and has not been adequately evaluated. We probe this gap with a deceptively simple but revealing challenge: judging the arrow of time (AoT)—whether a short clip is played forward or backward. We introduce **AoT-PsyPhyBENCH**, a psychophysically validated benchmark that tests whether VLMs can infer temporal direction in natural videos using the same stimuli and behavioral baselines established for humans. Our comprehensive evaluation of open-weight and proprietary, reasoning and non-reasoning VLMs reveals that most models perform near chance, and even the best model lags far behind human accuracy on physically irreversible processes (e.g., free fall, diffusion/explosion) and causal manual actions (division/addition) that humans recognize almost instantly. These results highlight a fundamental gap in current multimodal systems: while they capture rich visual–semantic correlations, they lack the inductive biases required for temporal continuity and causal understanding. We release the code and data for AoT-PsyPhyBENCH to encourage further progress in the physical and temporal reasoning capabilities of VLMs.

Keywords: Arrow of Time, Vision-Language Models, Psychophysics

1. Introduction

Vision–language models (VLMs) have recently achieved remarkable progress in multimodal understanding, including tasks such as video captioning, retrieval, and question answering (Bai et al., 2025; Qwen Team, 2024; Liu et al., 2024; Wang et al., 2024a; Xiao et al., 2021; Wu et al., 2024; Fu et al., 2025). Yet a fundamental question remains: do these models possess the implicit physical and causal assumptions, i.e. the *inductive biases*, that humans rely on to interpret the physical world? Among the most basic of such biases is the *arrow of time* (AoT): the implicit assumption that events unfold irreversibly from past to future, constrained by gravity, entropy, and causality. Judging whether a short video plays forward or backward provides a minimal yet powerful diagnostic of such bias: a system that has internalized temporal irreversibility should recognize when physical regularities are violated, whereas a system that relies only on visual correlation will fail despite extensive training.

To anchor this diagnostic in human performance, Hanyu et al. (2023) conducted a psychophysical study using 360 three-second natural video clips from everyday activities. They found a global forward bias: participants more often judged reversed clips as forward (39% errors on reversed vs. 9% on forward trials). However, humans detected reversals rapidly and almost flawlessly in five specific



Figure 1: Overview of the arrow-of-time (AoT) task. Given a video played either forward or backward, the model must predict its temporal direction. Humans identify temporal direction accurately, whereas VLMs perform worse and exhibit a bias toward Forward (Section 6.2). Human Forward/Backward F1 is computed on AoT-PsyPhyBENCH, excluding the Reciprocal (cyclic-motion) category.

categories: **Fall** (free fall) and **Diffusion** (diffusion/-

explosion), which involve physically irreversible processes governed by gravity and entropy; **Proceed** (forward locomotion); and **Division** (manual division) and **Put** (manual addition), which involve agent-driven causal sequences. In these cases, reversed playback becomes visibly implausible. For example, when a big chunk of snow ascends back onto the roof, defying gravity (Figure 1). These results demonstrate that humans exploit not only low-level motion cues but prior knowledge of physical regularities and causal structure, providing a psychophysically validated foundation for testing AoT in VLMs.

Building on this, we introduce **AoT-PsyPhyBENCH** (pronounced “*AoT-sci-fi bench*”), an evaluation framework that directly inherits validated stimuli and behavioral baselines from Hanyu et al. (2023). We systematically test modern VLMs, from open-weight to proprietary reasoning/non-reasoning models, on the same AoT judgment task. Our findings reveal that most models perform near chance even in “obvious” irreversible processes, with the best setting lagging humans by approximately **29 percentage points**, suggesting that they lack the inductive biases underpinning human causal and temporal perception (Figure 1).

Our contributions are threefold. (1) Comprehensive evaluation. We present the first systematic evaluation of modern VLMs on psychophysically grounded AoT judgment across zero-shot, few-shot, chain-of-thought prompting, and supervised fine-tuning. Despite apparent task simplicity, the gains from elaborate prompting and fine-tuning are minimal and inconsistent, indicating that the bottleneck is temporal and physical understanding, not instruction following. **(2) Psychophysically validated benchmark.** We introduce **AoT-PsyPhyBENCH**, curated from Hanyu et al.’s psychophysical dataset by retaining only clips with clear human consensus on irreversible processes while excluding ambiguous cyclic motions. This yields a low-ambiguity benchmark enabling direct, reliable human–model comparison on temporal direction judgment. **(3) Open resources.** We release our benchmark, evaluation scripts, and model outputs to advance research on temporal reasoning and physical understanding in VLMs.¹

2. Related Work

2.1. Vision–Language Models (VLMs)

Modern VLMs couple a vision encoder with a large language model (LLM) via a multimodal connector and are typically aligned through instruction tuning

¹<https://mattashiho233.github.io/AoT-PsyPhyBENCH-website/>

on image–video–text data (Wang et al., 2024b; Qwen Team, 2024; Azzolini et al., 2025; Bai et al., 2025). Despite rapid progress, frontier VLMs often fail on video tasks that depend on event order (Xue et al., 2025).

We broadly categorized the VLMs used in our evaluation along two axes: **(i) proprietary vs. open-weight** and **(ii) reasoning vs. non-reasoning**. Proprietary models are accessible only via APIs with limited transparency, while open-weight models release checkpoints and inference scripts, as well as partial training details. Reasoning models are trained to generate multi-step deliberation (e.g., chain-of-thought reasoning) automatically before producing the final output, often with controllable *reasoning effort*. Non-reasoning models prioritise perceptual understanding (e.g., captioning, visual question-answering) and instruction following, without dedicated reasoning objectives; they typically respond directly unless explicitly prompted for step-by-step reasoning.

Building on this taxonomy, we evaluate the following models. **Proprietary non-reasoning:** GPT-4o and GPT-4.1 (OpenAI, 2024, 2025a). **Proprietary reasoning:** o3, o4-mini, and GPT-5 (OpenAI, 2025c,b); Gemini-2.5-Pro (Comanici et al., 2025). **Open-weight non-reasoning:** Qwen2-VL (Wang et al., 2024b) and Qwen2.5-VL (Bai et al., 2025). **Open-weight reasoning:** Cosmos-Reason1 (Azzolini et al., 2025), which combines explicit AoT supervision and reinforcement learning on ~30k pairs of forward/reverse video clips with reasoning traces; and QVQ-72B-Preview (Qwen Team, 2024).

2.2. Temporal Reasoning Benchmarks

We evaluate VLMs on a psychophysically validated AoT benchmark to address two key limitations in current temporal reasoning evaluation:

(1) Lack of temporal dependency. Several recent benchmarks claim to assess temporal reasoning in VLMs, but many do not *demonstrate* dependence on event order (Liu et al., 2024; Wang et al., 2024a; Fu et al., 2025; Xiao et al., 2021; Wu et al., 2024). Xue et al. (2025) evaluated strong VLMs on standard temporal benchmarks and found a critical failure: models show minimal or no performance degradation when frames are *shuffled* or *reversed*, indicating these tasks can be solved through scene context without temporal understanding. In contrast, the AoT judgment is inherently temporal: reversed videos violate physical laws, making temporal order task critical, rather than incidental.

(2) Lack of psychophysical validation. Existing AoT benchmarks simply reverse video datasets (Bagad et al., 2023; Wang et al., 2023; Du et al., 2024; Agarwal et al., 2025; Xue et al., 2025) without *controlled human baselines*, for instance,

with quantitative measurements of accuracy, reaction times, and category-specific effects. This creates systematic evaluation problems: difficulty remains uncalibrated (videos ambiguous to humans become spurious failure cases), model–human performance gaps cannot be quantified, systematic biases (forward bias, category effects) go undetected, and bidirectionally plausible cases contaminate test sets. Psychophysical grounding is essential to distinguish genuine deficiencies from artifacts of ambiguous stimuli.

To address these limitations, we introduce **AoT-PsyPhyBENCH**, a psychophysically validated benchmark enabling direct human–model comparison on temporal direction judgment.

3. AoT-PsyPhyBENCH: A Psychophysically Validated Arrow-of-Time Benchmark

We evaluate whether vision–language models (VLMs) can infer the arrow of time, that is, distinguish between *forward* and *backward* playbacks in everyday videos. Our benchmark builds on the psychophysical study of Hanyu et al. (2023), enabling direct comparison with human performance. The source dataset comprises 360 three-second clips (29.97 FPS) from the Moments in Time dataset (Monfort et al., 2019), covering a broad range of daily dynamics. Ten participants viewed every clip twice—once forward and once reversed—across two sessions on different days (each session: 180 forward, 180 reversed; order randomized per participant). Three raters annotated six motion categories: (1) **Proceed**: forward locomotion of people, animals, or vehicles; (2) **Fall**: free-fall/ballistic motion under gravity; (3) **Diffusion**: centrifugal diffusion or small-particle explosions; (4) **Division**: division of material by hand or tool; (5) **Put**: addition/construction of material by hand; and (6) **Reciprocal**: reciprocating (cyclic) motion (Table 1). The first five categories reflect *irreversible* processes that, when reversed, tend to violate fundamental physical regularities (entropy increase, gravity, causal ordering), whereas reciprocating motion is *bidirectional* and often appears plausible in both directions. Categories are not mutually exclusive. Human performance exhibited a pronounced *forward bias*: participants made errors on **39%** of reversed trials versus **9%** of forward trials, with accuracy strongly modulated by motions from the first five categories. Performance was significantly lower for the reciprocating motion category.

We introduce **AoT-PsyPhyBENCH**, a curated subset of Hanyu et al. (2023) that *excludes the reciprocal motion category* (category 6) and retains only high-consensus clips from categories 1–5. This exclusion is justified by human perfor-

mance: the reciprocal motion category achieved only 61.1% overall accuracy (accuracy with forward and backward videos combined) compared to 81.3–85.1% for the other motion categories, substantially degrading benchmark reliability (77.6% with cyclic motion vs. 89.0% without). From the original 360 clips (720 videos with reversals), our filtering retains 212 clips, resulting in a total of **424** videos. This yields a low-ambiguity benchmark that enables direct and reliable comparison between humans and models. Table 1 provides an overview of the motion categories with comparative statistics illustrating how AoT-PsyPhyBENCH filters the original dataset.

4. Experimental Settings

We evaluate the following models (described in Section 2) on AoT-PsyPhyBENCH: **Proprietary non-reasoning**: GPT-4o and GPT-4.1; **proprietary reasoning**: o3, o4-mini, GPT-5, and Gemini-2.5-Pro; **open-weight non-reasoning**: Qwen2-VL and Qwen2.5-VL; **open-weight reasoning**: Cosmos-Reason1-7B and QVQ-72B-Preview. We test these models across multiple experimental settings, which are detailed in the following sections.

4.1. Zero-shot Settings

For the zero-shot experiments, we adopted a simple prompt design. In the system prompt, the model is asked to output only the F (forward) or B (backward) label as follows:

System prompt *You will see videos provided from the user, played either forward or backward. Finish your answer with F or B only. F for forward and B for backward.*

In the user prompt, we provide the sampled video frames with the following instruction:

User prompt *[Video frames] Detect whether the video plays forward or backward with confidence.*

4.2. Few-shot Settings

For few-shot experiments, we constructed four demonstration examples from AoT-PsyPhyBENCH: two forward and two backward videos exhibiting visually distinctive temporal cues (e.g., explosions, falling objects). Each demonstration consists of sampled video frames, the user prompt from Section 4.1, and the correct label (F for forward, B for backward). These four demonstration videos were excluded from the test set to prevent data leakage.






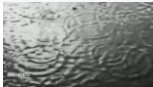





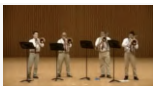
| Category & Description | Reversal is easy for humans? | Human F1 (F/B) | Human Acc | # samples | Included in AoT-PsyPhyBENCH? | Example 1 | Example 2 |
|---|------------------------------|--------------------|-----------|-----------|------------------------------|---|---|
| (1) Proceed: forward locomotion of people, animals, or vehicles | ✓ | 86.5 / 82.5 | 84.8 | 82 | Yes |  |  |
| (2) Fall: free-fall/ballistic motion under gravity | ✓ | 86.9 / 82.8 | 85.1 | 84 | Yes |  |  |
| (3) Diffusion: centrifugal diffusion or small-particle explosions | ✓ | 84.6 / 78.7 | 82.1 | 56 | Yes |  |  |
| (4) Division: division of material by hand or tool | ✓ | 86.0 / 80.6 | 83.8 | 37 | Yes |  |  |
| (5) Put: addition/-construction of material by hand | ✓ | 84.1 / 77.4 | 81.3 | 67 | Yes |  |  |
| (6) Reciprocal: reciprocating (cyclic) motion | ✗ | 71.6 / 38.5 | 61.1 | 148 | No |  |  |

Table 1: Motion categories following Hanyu et al. (2023), with human performance, counts, and visual examples. Human F1 scores are reported as forward (F)/backward (B) for each motion category, and Human Acc reports overall human accuracy for each category. Categories are not mutually exclusive: clips assigned to categories 1–5 may also overlap with Reciprocal. AoT-PsyPhyBENCH includes categories 1–5 and excludes category 6. ✓ marks categories where reversal is typically easy for humans (irreversible processes); ✗ marks cyclic, bidirectional motions where reversal is challenging.

4.3. Reasoning Effort Ablation Settings

Reasoning-centric models are trained to generate internal reasoning chains automatically before producing outputs, while non-reasoning models usually respond directly unless explicitly prompted for step-by-step reasoning. We ablated the length of thinking of VLMs by either setting the reasoning effort parameter of reasoning models, or by manually prompting chain-of-thought (CoT) reasoning.

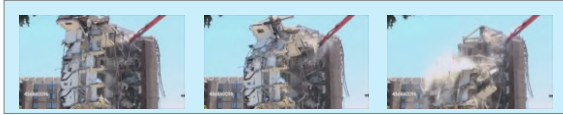
Controlling Reasoning Effort for Proprietary Reasoning Models. We set the reasoning effort in GPT-5 and Gemini-2.5-Pro to 3 levels: **low**, **medium**, and **high**. To be noted, the low, medium, and high reasoning effort of Gemini-2.5-Pro corresponds to the thinking budget in its native API of 1,024, 8,192, and 24,576 tokens, respectively. These values represent upper bounds; models do

not necessarily use the full allocated budget.

Simulating Reasoning Effort Control with CoT Reasoning for Non-Reasoning Models. Open-weight models lack explicit reasoning effort control available in proprietary reasoning models. We therefore use few-shot chain-of-thought (CoT) prompting to simulate varying reasoning depths. Using two videos from Section 4.2, we created two CoT variants: **Simple CoT** with brief reasoning and **Multi-Step CoT** with elaborate step-by-step analysis.

Simple CoT. The model is instructed to focus on moving elements and identify visual cues indicating playback direction. We manually curated reasoning traces for each demonstration. The instruction for this setting is provided in Figure 6. Two manually curated reasoning traces are shown in Figure 2, 3.

Multi-step CoT. We designed structured instruc-



Simple CoT

The sequence of events shows a building being demolished, with a wrecking machine tearing parts of it down. This process makes physical sense. Therefore, the video is playing forward.

F

Multi-step CoT

Observation: I see a building in poor condition with its framework exposed and walls missing in the center, and another building in the background. A red crane arm extends from the top right of the frame. There are some tree branches that are moving slightly on the top left of the frame. The upper part of the damaged building appears unstable and begins to collapse, breaking apart and falling into the structure itself toward the end. Debris and smoke are visible as this happens. The red crane arm is seen moving and making contact with the damaged building.

Assumption: Based on what I observed and using common sense about cause and effect and physical laws, I assume the red crane arm is moving toward the damaged building to assist in bringing it down. The movement of the tree branches is likely caused by the wind, but it is difficult to tell whether it is playing normally or in reverse.

Conclusion: Since the top part of the damaged building is falling down, which supports my assumption of demolition work and does not violate physical laws, I conclude that the video is being played forward.

F

Figure 2: Manually curated chain-of-thought reasoning traces for a *Forward* example.

tions with multi-step reasoning traces divided into three stages: *Observation* (objectively describe visible events without assumptions), *Assumption* (infer plausible physical or causal sequences), and *Conclusion* (determine whether observations align with or contradict *assumptions* to judge playback direction). The instruction for this setting is provided in Figure 7. Two manually curated reasoning traces are shown in Figure 2, 3. A model output example is shown in Figure 4.

4.4. Supervised Fine-Tuning (SFT) Settings

We constructed in-domain fine-tuning datasets to test whether explicit temporal direction supervision improves model performance. Note that all videos in Hanyu et al. (2023), AoT-PsyPhyBENCH, and these fine-tuning datasets are drawn from Moments in Time (Monfort et al., 2019). We randomly sampled 500, 1,500, and 2,500 clips distributed across its 339 action classes in the original dataset. These clips are entirely distinct from the videos in AoT-PsyBench. Each video was used to create two examples: the original (forward, labeled F) and its temporal reverse (backward, labeled B), yielding 1,000, 3,000, and 5,000 training examples.

We fine-tuned Qwen2-VL-7B and Qwen2.5-VL-7B using the zero-shot prompt format (Section 4.1) with standard supervised learning. We then evaluated these models on AoT-PsyPhyBENCH.



Simple CoT

This scene appears to take place on the water, where a large splash is occurring. It looks like an explosion happened underwater. The splash is very large at the beginning but gradually becomes smaller and eventually converges to a single point. In the background, I can see a bridge and a boat or cruise ship on the left side, floating on the water. The boat seems to be moving, but it is difficult to tell whether it is moving forward or in reverse. Since the splash starts out large and gradually converges to a small point, it contradicts the physical law that an explosion should begin small and expand outward. Therefore, this video is being played backward.

B

Multi-step CoT

Observation: I see a bridge in the background and a boat or cruise ship on the left side, floating on the water. The boat appears to be moving. A large water splash or explosion is occurring in the water. The splash is very large at the beginning of the video but gradually shrinks and becomes very small by the end.

Assumption: Based on what I observed, and using common sense regarding causal relationships and physical laws, I assume there is an explosion happening under the water, which creates a large splash that erupts into the air. The bridge remains stationary, so it doesn't provide much information. The boat seems to be moving, but it's unclear whether it's moving forward or backward.

Conclusion: Since the water splash starts off large and gradually shrinks into a small point, which contradicts the typical behavior of an explosion, which begins small and expands, I conclude that the video is being played backward.

B

Figure 3: Manually curated chain-of-thought reasoning traces for a *Backward* example.

4.5. Evaluation Metrics

We evaluate models using overall accuracy and F1 scores for Forward and Backward classes separately. Class-specific F1 scores highlight potential directional biases in model predictions.

4.6. Hyperparameter Settings

Frame Sampling and FPS Settings. Frames were sampled at equal temporal intervals without resizing. Frame rates were set based on model-specific defaults and training configurations: 2 FPS for Qwen2-VL, Qwen2.5-VL, and QVQ-72B-Preview (standard for these models), and 4 FPS for Cosmos-Reason1-7B (matching its inference settings recommendation²) and all proprietary models. Preliminary experiments showed that 4 FPS balances performance with API costs (Section 5.5).

Inference Parameters. For open-weight models (Qwen2-VL, Qwen2.5-VL, and QVQ-72B-Preview), we set temperature to 0.6 and top-p to 0.95. For Cosmos-Reason1-7B, we used temperature 0.6, top-p 0.95, and repetition penalty 1.05, consistent with settings reported in their paper. For GPT-4o (GPT-4o-2024-11-20) and GPT-4.1 (GPT-4.1-2025-04-14), we applied temperature 0.6, top-p 0.95,

²<https://huggingface.co/nvidia/Cosmos-Reason1-7B>

| Model | F. F1 | B. F1 | Acc. |
|-----------------------------|-------|-------|-------------|
| Baselines | | | |
| Random | — | — | 50.0 |
| Human | 90.0 | 88.1 | 89.2 |
| Open Models | | | |
| Non-reasoning Models | | | |
| Qwen2-VL-7B | 66.7 | 0.0 | 50.0 |
| Qwen2.5VL-7B | 63.0 | 19.5 | 49.3 |
| Qwen2.5VL-72B | 57.4 | 38.2 | 49.5 |
| Reasoning Models | | | |
| QVQ-72B-Preview | 66.1 | 0.0 | 49.4 |
| cosmos-reason1 7B | 31.2 | 63.3 | 52.1 |
| Proprietary Models | | | |
| Non-reasoning Models | | | |
| GPT-4o | 65.4 | 24.9 | 52.6 |
| GPT-4.1 | 62.5 | 57.4 | 60.1 |
| Reasoning Models | | | |
| o3 | 67.2 | 29.1 | 55.2 |
| o4-mini | 67.4 | 33.1 | 56.1 |
| GPT-5 | 68.7 | 26.8 | 56.1 |
| Gemini-2.5-pro | 65.9 | 51.4 | 59.9 |

Table 2: Zero-shot performance.

and frequency penalty 0. For OpenAI reasoning models (o3, o4-mini, GPT-5), inference parameters such as temperature and top-p are not exposed via the API and thus remained at default values. For Gemini-2.5-Pro (accessed 2025-10-02), we used the OpenAI-compatible API with default values: temperature 1.0 and top-p 0.95.

SFT Parameters. We froze the vision encoder and applied LoRA (Hu et al., 2021) (rank 8) to both the language model and the vision-language bridging MLP layer. We used a maximum sequence length of 2,048 tokens, a batch size of 2 per device with gradient accumulation over 2 steps (effective batch size of 4), a learning rate of 1×10^{-5} , and trained for 5 epochs with a cosine learning rate scheduler and 10% warmup.

5. Results

5.1. Zero-shot Performance

Table 2 presents zero-shot results, revealing two key gaps: **open vs. proprietary** and **VLM vs. human** performance gaps. Additionally, we did not find advantages of reasoning models over non-reasoning models.

Open vs. Proprietary. Open-weight models cluster around 50% accuracy (random baseline), with Cosmos-Reason1-7B slightly higher at 52.1%. QVQ-72B-Preview, designed for mathematical reasoning over single images rather than physical dy-

| Model | #Shots | F. F1 | B. F1 | Acc. |
|---------------------------|--------|-------|-------|-------------|
| Open Model | | | | |
| Qwen2.5 | 0 | 57.4 | 38.0 | 49.5 |
| VL-72B | 2 | 64.2 | 18.7 | 50.2 |
| | 4 | 65.4 | 21.1 | 51.9 |
| Proprietary Models | | | | |
| | 0 | 62.3 | 57.4 | 60.0 |
| GPT-4.1 | 2 | 59.5 | 51.7 | 56.0 |
| | 4 | 60.0 | 49.9 | 55.5 |
| | 0 | 65.4 | 24.9 | 52.6 |
| GPT-4o | 2 | 66.8 | 4.61 | 50.7 |
| | 4 | 66.5 | 5.07 | 50.7 |
| | 0 | 68.7 | 26.8 | 56.1 |
| GPT-5 | 2 | 69.5 | 29.2 | 57.4 |
| | 4 | 69.2 | 30.9 | 57.4 |

Table 3: Few-shot performance.

namics, performs at chance with extreme label bias (Section 6.2). Cosmos-Reason1-7B, despite being trained on an undisclosed AoT dataset where it reportedly achieved 60% accuracy, shows minimal improvement on our benchmark. **Proprietary models** consistently exceed random guessing, with GPT-4.1 achieving the highest zero-shot performance (60.1%).

VLM vs. Human. All VLMs lag substantially behind humans (89.2%), with a gap of 29.1 percentage points even for the best zero-shot model, GPT-4.1.

Reasoning vs. Non-Reasoning: Explicit reasoning capability provides no clear advantage. The non-reasoning model GPT-4.1 (60.1%) outperforms reasoning models o3 (55.2%), o4-mini (56.1%), and GPT-5 (56.1%).

5.2. Few-shot Performance

We test whether few-shot examples elicit in-context learning for AoT (Table 3). Overall, few-shot prompting does *not* consistently improve performance and often amplifies label prediction bias. GPT-5 shows modest, stable gains (Accuracy: 56.1→57.4/57.4%; Forward F1: 68.7→69.5/69.2; Backward F1: 26.8→29.2/30.9). In contrast, GPT-4.1 degrades with few-shot prompts (Accuracy: 60.0→56.0/55.5%; Forward F1: 62.3→59.5/60.0; Backward F1: 57.4→51.7/49.9). GPT-4o shows severe degradation: accuracy drops (52.6→50.7%), with Backward F1 collapsing catastrophically (24.9→4.6/5.1), indicating near-complete failure to detect reversed videos. The open model Qwen2.5-VL-72B exhibits minimal accuracy change (49.5→51.9%) but substantially worsened bias

| Model | Effort | F. F1 | B. F1 | Acc. |
|---------------------------|--------|-------|-------|-------------|
| Proprietary Models | | | | |
| GPT-5 | Low | 68.9 | 34.4 | 57.8 |
| | Medium | 68.7 | 26.8 | 56.1 |
| | High | 69.1 | 25.7 | 56.4 |
| Gemini-2.5-pro | Low | 67.2 | 52.1 | 61.1 |
| | Medium | 65.9 | 51.4 | 59.9 |
| | High | 65.3 | 49.0 | 58.7 |

Table 4: Reasoning effort ablation.

| Setting | Shots | F. F1 | B. F1 | Acc. |
|-------------------------------|-------|-------|-------|------|
| Qwen2.5VL-72B-instruct | | | | |
| No CoT | 2 | 64.2 | 18.7 | 50.2 |
| Simple | 2 | 67.3 | 3.76 | 51.2 |
| Multi-step | 2 | 66.7 | 5.48 | 50.7 |

Table 5: Chain-of-Thought performance on the Qwen2.5VL-72B-instruct model.

(Backward F1: 38.0→18.7/21.1). These results demonstrate that few-shot prompting provides limited benefits for temporal reasoning: only one model (GPT-5) shows modest improvement, while others either decline or amplify their existing forward bias, suggesting that in-context learning is insufficient to elicit robust AoT understanding.

5.3. Reasoning Effort Ablation

Controlling reasoning effort in proprietary reasoning VLMs. We varied the reasoning effort parameter (low/medium/high) for GPT-5 and Gemini-2.5-Pro (Table 4). Surprisingly, increasing reasoning effort does not improve performance and often degrades it. Gemini-2.5-Pro with low effort achieves 61.1% accuracy, the highest performance across all our experimental settings, yet medium and high efforts decrease to 59.9% and 58.7%, with Backward F1 declining from 52.1 to 51.4 to 49.0. From the low effort setting, we highlight one correctly predicted example, where we asked Gemini-2.5-Pro to explain its reasoning in a follow-up dialogue turn (bottom-right of Figure 4). GPT-5 showed an even more pronounced pattern: low effort achieves 57.8% accuracy, while medium and high efforts drop to 56.1% and 56.4%. More critically, Backward F1 collapses with increased effort (34.4 to 26.8 to 25.7), indicating amplification of forward bias. These results suggest that extended reasoning does not elicit better temporal reasoning and instead reinforces existing directional biases.

Chain-of-thought (CoT) prompting in an open VLM. We tested explicit step-by-step reasoning with Qwen2.5-VL-72B using two CoT variants (Simple

| Data Size | F. F1 | B. F1 | Acc. |
|------------------------------|-------|-------|------|
| Qwen2VL-7B Training | | | |
| Vanilla | 66.7 | 0.0 | 50.0 |
| 1000 | 64.1 | 12.2 | 49.1 |
| 3000 | 54.2 | 48.2 | 51.4 |
| 5000 | 59.4 | 31.6 | 49.1 |
| Qwen2.5VL-7B Training | | | |
| Vanilla | 63.0 | 19.5 | 49.3 |
| 1000 | 54.8 | 43.5 | 49.8 |
| 3000 | 54.5 | 43.4 | 49.5 |
| 5000 | 54.5 | 43.4 | 49.5 |

Table 6: SFT performance.

| Model | FPS | F. F1 | B. F1 | Acc. |
|---------|-----|-------|-------|-------------|
| Human | 30 | 90.0 | 88.1 | 89.2 |
| GPT-4.1 | 2 | 62.1 | 51.2 | 57.3 |
| | 4 | 62.5 | 57.4 | 60.1 |
| | 8 | 62.9 | 55.8 | 59.7 |
| | 16 | 62.4 | 53.7 | 58.5 |
| | 30 | 64.4 | 55.9 | 60.6 |

Table 7: FPS ablation results.

and Multi-step; Section 4.3). As shown in Table 5, CoT prompting fails to improve performance and amplifies label prediction bias, most notably with Multi-step CoT (2-shot), where Backward F1 drops by 13.2 points (Section 6.2). In the model output example using the Multi-step CoT prompt (top-right in Figure 4), we saw that the model usually could identify the event in the video, yet it strongly believed that no physical law was violated and the video was played forward. Combined with the reasoning effort results, these findings demonstrate that additional deliberation, whether through explicit effort controls or prompted CoT, does not compensate for the lack of robust temporal and physical understanding, and often exacerbates existing biases.

5.4. SFT Performance

We fine-tuned Qwen2-VL-7B and Qwen2.5-VL-7B on 1,000, 3,000, and 5,000 training examples to test whether explicit supervision improves AoT performance (Table 6). Although fine-tuning mitigated the extreme forward bias seen in vanilla models (in the 3000 example setting, Qwen2-VL-7B Backward F1: 0→48.2, Qwen2.5-VL-7B Backward F1: 19.5→43.4), it did not lead to real task competence: accuracy stayed near chance (~50%) across all training set sizes. Performance plateaued after 1,000 examples, with no gains from additional data. These results suggest that AoT task might require different training approaches beyond conventional SFT.

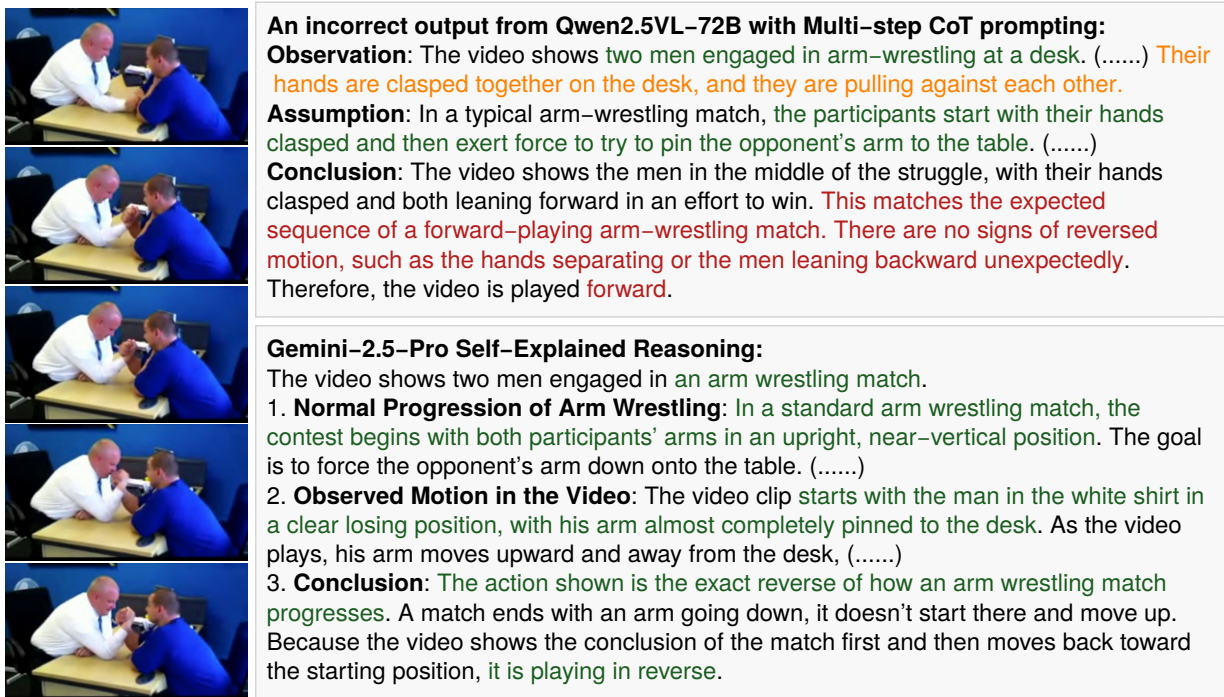


Figure 4: **Left:** a backward video clip (category: Put). **Top-Right:** Qwen2.5VL-72B Multi-step CoT reasoning. **Bottom-Right:** Gemini-2.5-Pro's self-explained reasoning trace. Qwen2.5VL-72B correctly identified the event in the scene and made a valid assumption, but **failed to observe that the event was reversed** which **led to an incorrect conclusion**. In contrast, Gemini-2.5-Pro correctly detected the reversal of the event in Step 2 based on a valid assumption it made in Step 1. The Gemini-2.5-Pro output is from the low reasoning effort setting.

5.5. FPS Ablation

We evaluated GPT-4.1 across frame rates from 2 to 30 FPS and compared results to human performance (Table 7). Notably, at 30 FPS, corresponding to the complete video with all frames, the model achieves only 60.6% accuracy, falling far short of human performance at 89.2%. This 28.6 percentage point gap demonstrates that the performance deficit is not due to insufficient temporal information. Across tested frame rates, model accuracy varies minimally (57.3–60.6%). Given the marginal improvement from 4 FPS (60.1%) to 30 FPS and API cost considerations, we selected 4 FPS as the default for all proprietary models.

6. Analyses

6.1. Motion Category Analysis

We analyze per-category performance across the five motion classes in AoT-PsyPhyBENCH: Proceed, Fall, Diffusion, Division, and Put. Figure 5 compares humans with three VLMs: Cosmos-Reason1 7B (best open-weight model in the zero-shot setting, 52.1%), GPT-4.1 (best proprietary and overall model in the zero-shot setting, 60.1%), and Gemini-2.5-Pro (best overall model, 61.1%). Humans remain strong across all categories and both

directions, while VLMs show substantial gaps with striking asymmetry: relatively better on forward videos but dramatically worse on backward videos, revealing strong *label prediction bias*.

Category-specific patterns. The largest F1 deficits appear in Proceed and Fall, where all models struggle to capture the causal and gravitational cues defining temporal direction. Diffusion and Put show moderate F1 scores but remain below human performance even in forward playback, suggesting incomplete modeling of dispersion and goal-directed manipulation. Division is comparatively easier for both humans and models, likely due to clear temporal discontinuities (e.g., splitting). Notably, Cosmos-Reason1-7B achieves relatively strong backward F1, particularly on Fall and Division, consistent with its explicit AoT-oriented training, whereas Gemini-2.5-Pro and GPT-4.1 perform better in forward playback but drop when the temporal order is reversed. Overall, these results suggest that current VLMs rely primarily on directional visual priors and dataset correlations rather than robust physical causality understanding.

6.2. Label Prediction Bias

We observed that most VLMs exhibit **label prediction bias**: models strongly favor one label over the other despite balanced forward/backward video dis-

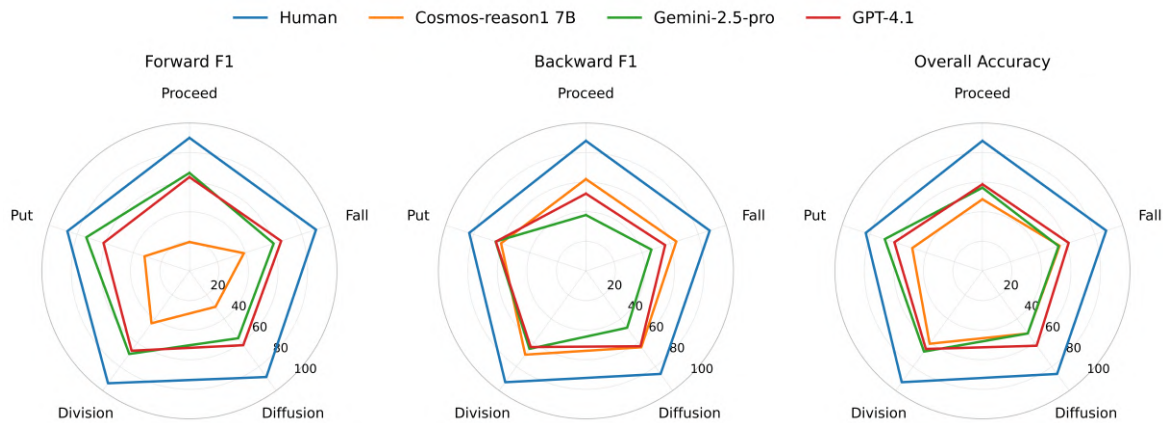


Figure 5: Per-category comparison on AoT-PsyPhyBENCH across three representative models. Cosmos-reason1-7B (zero-shot; best open-weight in this setting), GPT-4.1 (zero-shot; best proprietary and best overall model in this setting), and Gemini-2.5-Pro (zero-shot, low-reasoning effort; best model across all settings), and humans: (a) forward F1 (left), (b) backward F1 (middle), and (c) overall accuracy (right). Humans remain consistently high across all categories and both directions. In contrast, VLMs show substantial gaps. Backward detection is the most challenging, revealing a forward-direction bias (with Cosmos-reason1 as a notable exception, showing comparatively strong backward F1).

tribution in AoT-PsyPhyBENCH. In zero-shot evaluation (Table 2), GPT-4o predicted 87% of clips as Forward (only 13% as Backward), while QVQ-72B-Preview predicted 100% Forward, causing minority-class F1 scores to drop below 0.4 due to low recall. Most models exhibit Forward bias (Qwen2.5-VL series, QVQ-72B-Preview, GPT-4o, o3, o4-mini, GPT-5), while Cosmos-Reason1-7B shows Backward bias, likely due to extensive reversed-clip exposure during reinforcement learning.

Furthermore, **reasoning amplifies bias**: when models engage in step-by-step reasoning, biases intensify rather than improve. QVQ-72B-Preview often correctly identified scene events but failed to detect reversed motion, with its reasoning process reinforcing the idea that the video is played forward. Similarly, increasing reasoning effort (GPT-5 in Table 4) or enforcing chain-of-thought (Table 5, Figure 4) further amplified label prediction bias rather than correcting it.

7. Conclusion

We present **AoT-PsyPhyBENCH**, a psychophysically validated benchmark designed to assess whether modern vision–language models (VLMs) possess a human-like inductive bias for inferring the *arrow of time*—the implicit understanding that physical events unfold irreversibly from past to future. Our experiments reveal that current VLMs perform far below human baselines, even on intuitive scenarios such as falling objects, which humans find easy to interpret. This striking shortfall cannot be attributed to limited data or lack of reasoning depth. Instead, it highlights a fundamental

absence of inductive biases for temporal continuity, causality, and physical irreversibility—principles that humans internalize effortlessly through interaction with the physical world. We release AoT-PsyPhyBENCH and its evaluation code to foster the development of multimodal systems that move beyond statistical pattern recognition toward genuine physical understanding.

8. Limitations

Our work has two limitations. First, for proprietary models, even though we report the specific model names and versions used, exact replication may be affected by undisclosed updates or API changes beyond our control. Second, we haven’t been able to offer a conclusive explanation for why SFT did not work on AoT. One possible reason is that open-source VLMs may not effectively encode temporal information along the frame sequence. Cosmos-Reason1-7B saw improvement with reinforcement learning in their work, however, they did not publish their dataset and we did not see improvement on our benchmark, either.

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A. Appendix

A.1. Instructions in Manual CoT Experiments

The instruction used in the Simple CoT setting is shown in Figure 6. The instruction for the Multi-step CoT setting is shown in Figure 7.

(Instruction) Is this video played forward (F) or backward (B)? Pay attention to moving parts in the video as they may be the visual clues to indicate the direction of the playback. Think step by step before giving out your final answer. Finish your answer with F for forward or B for backward only.

Figure 6: The instruction for the Simple CoT setting.

Is this video played forward or backward?
Think in three steps: **Observation**, **Assumption**, and **Conclusion**.
In **Observation**, describe what you see in the video honestly, without making any early assumptions about whether it is played forward or backward. Pay close attention to moving elements such as people’s movements, the flow of liquid, or any changes in the size or position of objects. In **Assumption**, make a reasonable guess about what should normally happen in this scene if it were played forward. Base this guess on common sense, including causal relationships, the laws of physics, and the arrow of time. In **Conclusion**, check whether your Observation matches or contradicts your Assumption. If what you observed follows the expected behavior based on your assumption, then the video is played forward. If what you observed goes against your assumption, then the video is being played backward.
Finish your answer with F for forward or B for backward only.

Figure 7: The instruction used for the Multi-step CoT setting.