

WORLD MODELS NEED A PHYSICAL REGISTRY: LEARNING INTERNAL PREDICTIVE STATES FOR PHYSICALLY PLAUSIBLE WORLD MODELS

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ABSTRACT

Video world models must generate physically plausible futures, not just realistic frames. Existing approaches typically use semantic, physical, or predictive information to guide the visual generation stream, leaving a fundamental question: **where inside the generator should predictions of scene evolution live?** Standard video tokens jointly encode appearance and dynamics, but provide no distinct state for learning and reading predictive dynamics. We answer this question with the **Physical Registry**: temporally grounded registry slots inside a video DiT that are initialized from an observation-conditioned forecast, co-evolve with video tokens, and receive future-representation supervision, making predictive dynamics an explicit, readable state of the generator. In a controlled comparison of predictive-state interfaces on Physics-IQ Verified, Physical Registry improves vanilla fine-tuning by 9.9/8.7 points on I2V/V2V, the largest gain among the interfaces we compare. Across all Cosmos and WAN backbones, Physical Registry improves Physics-IQ Verified scores. With only 0.45% additional parameters, it enables Cosmos 3 Nano 16B to surpass the published I2V score of Cosmos 3 Super 64B (43.56 vs. 42.7). On WorldModelBench, it also improves physical adherence and the total score for all four evaluated backbones. Because the registry becomes candidate-specific while remaining readable, the *Physical Registry Selector (PRS)* ranks emerging futures by how far their intermediate registry readouts depart from the shared forecast before full denoising is complete. Across four backbones, this selection improves I2V scores by 5.6–15.9% without completed-video external scoring. Together, these results support a broader principle: **dynamics prediction should live as an explicit model state that co-evolves with the video representation**. Project page: <https://grainsack.github.io/physical-registry/>.

1 INTRODUCTION

Video generators are increasingly used as world models, i.e., environments for training agents (Ha & Schmidhuber, 2018; Bruce et al., 2024; NVIDIA et al., 2025b). From this perspective, a generated video should contain not only high-quality visuals, but also physically plausible phenomena such as solid mechanics, fluid dynamics, optics, thermodynamics, and magnetism (Motamed et al., 2026). However, recent video models still often fail to follow them (Li et al., 2025a; Motamed et al., 2026).

To address this, exploiting physical priors has made some progress by supplying explicit cues about scene evolution, such as motion, force, or physical control signals (Yang et al., 2025a; Gillman et al., 2025; Wang et al., 2025a). However, it depends on availability of the controls and corresponding supervision. On the other hand, supervision for aligning the intermediate features in the video models to pre-trained representations is readily available (Yu et al., 2025; Zhang et al., 2025; Hwang et al., 2025; Bhowmik et al., 2026). However, their appearance and dynamics can remain entangled (Bhowmik et al., 2026). This context motivates us to ask a more basic question: **How and where can we internalize scene evolution using representation alignment?**

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We introduce the *Physical Registry*, dedicated registry slots containing scene evolution inside video DiTs. They are encouraged to be aligned with representations of future frames to be generated, which are predicted from a source frame. We use JEPA representations for the Physical Registry because JEPA’s predictive representation learning aligns with our goal of modeling scene evolution: a frozen JEPA encoder–predictor (Bardes et al., 2024; Assran et al., 2025) produces forecast features for future temporal positions in the same space as future-video targets, compactly representing how the scene is expected to evolve. Prior works have also shown that JEPA representations capture physical properties (Garrido et al., 2025; Joseph et al., 2026). In detail, the Physical Registry of the first DiT layer starts from JEPA features of the source and future frames via the JEPA encoder and encoder–predictor, respectively. Then, a readout layer aligns the registries for future frames to the original representations of the future frames from the JEPA encoder. As a whole, the registries and video tokens are designed to co-evolve through the transformer blocks such that the registries can estimate the original representations from the predicted representations.

We show that a dedicated registry combined with predictive supervision yields the largest gain among the compared interfaces. Notably, this gain generalizes to Cosmos and WAN backbones. Furthermore, the readouts can be used to choose the best sample among denoising processes from different initial noises, namely *Physical Registry Selector (PRS)*. It works in the middle of denoising processes instead of completely generated videos (Yuan et al., 2026; Internò et al., 2026).

Our contributions are threefold:

- The Physical Registry conveys future dynamics from the initial frames in a video generator.
- The Physical Registry provides an internal selection signal across different initial noises before fully generating videos.
- The Physical Registry outperforms other interfaces for predictive representations.

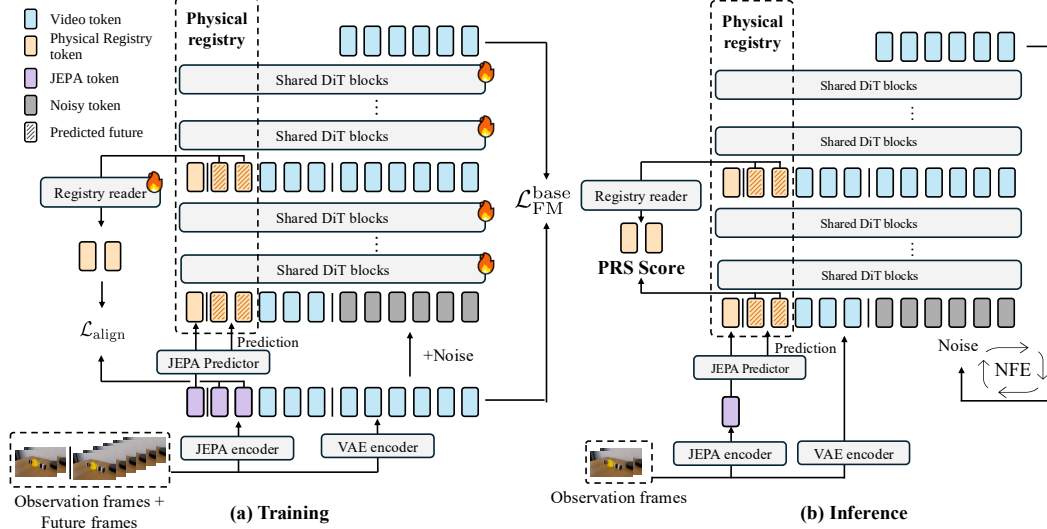
2 RELATED WORK

Physical plausibility in video generation. Prior work improves physical plausibility or controllability by conditioning video generation on motion, force, trajectory, or language-derived physical signals (Li et al., 2025b; Gillman et al., 2025; Wang et al., 2025a; Yang et al., 2025a; Pathak et al., 2026). These approaches express the intended evolution through an external control signal, whereas Physical Registry represents predicted future dynamics as an internal state of the video generator.

Predictive representations inside video generators. I-JEPA learns predictive representations from visible context, with V-JEPA and V-JEPA 2 extending this principle to video (Assran et al., 2023; Bardes et al., 2024; Assran et al., 2025). JEPA representations capture dynamics-relevant structure, including sensitivity to intuitive-physics violations and information about motion and physical plausibility (Garrido et al., 2025; Joseph et al., 2026). Generative models typically use such pretrained representations in one of two ways. REPA and its video extensions align them with intermediate generative features (Yu et al., 2025; Zhang et al., 2025; Hwang et al., 2025; Bhowmik et al., 2026; Lian et al., 2026), while ReDi (Kouzelis et al., 2025) and PHANTOM (Shen et al., 2026) jointly generate visual and representation states. Register tokens offer a different primitive: Vision Transformer registers provide additional tokens for internal computation (Darcet et al., 2024), and HyperDiT (He et al., 2026) uses representation-aligned semantic registers for image generation. Physical Registry brings these lines together by holding forecast-initialized predictive representations in dedicated, temporally grounded registry slots within the video backbone and supervising them toward future representations.

Inference-time guidance and candidate selection. WMReward uses V-JEPA 2 as a physics reward for inference-time guidance and best-of- N selection (Yuan et al., 2026), while GeoPhys uses an external physical-plausibility verifier to rerank generated candidates (Internò et al., 2026). PRS instead ranks candidates from the generator’s own intermediate registry states, without an external reward model or verifier.

Figure 1: **Physical Registry during training and inference.** The Physical Registry gives predicted future dynamics a dedicated, readable state inside the video DiT. (a) Training: forecast-initialized registry tokens co-evolve with video tokens and receive predictive supervision. (b) Inference: the same registry provides readouts for PRS (Section 3.5).



3 METHOD

We augment flow-matching video DiTs with Physical Registry (Sec. 3.1) with forecast-initialized registry states (Sec. 3.2) that evolve with the video representations (Sec. 3.2), and align them toward the target future (Sec. 3.3). Then we introduce our training objective (Sec. 3.4) and our inference technique (Sec. 3.5).

3.1 CONDITIONAL FLOW MATCHING

Let X_0 denote a clean video latent, $\epsilon \sim \mathcal{N}(0, I)$, and $t \sim \mathcal{U}(0, 1)$. With condition c , rectified flow (Liu et al., 2023) uses linear interpolation path, velocity target, and objective:

$$X_t = (1 - t)X_0 + t\epsilon, \quad V^* = \epsilon - X_0, \quad (1)$$

$$\mathcal{L}_{\text{FM}}^{\text{base}} = \mathbb{E}_{X_0, \epsilon, t} \left[\|V_\theta(X_t, t | c) - V^*\|_2^2 \right], \text{ respectively.} \quad (2)$$

Below, we augment DiTs with the Physical Registry using the same formulation.

3.2 PHYSICAL REGISTRY

Physical Registry represents the forecast in a fixed set of dedicated registry slots that carry predictive features alongside the video latent rather than within it. Let $X_t \in \mathbb{R}^{B \times C \times T_v \times H \times W}$ denote the noisy video latent. We use the frozen JEPA encoder E and predictor P . The encoder receives a full video and produces JEPA features for individual frames. The predictor receives the JEPA feature of the first frame and produces future representations in the shared representation space (Bardes et al., 2024; Assran et al., 2025). Given an initial observed frame x , we retain the first encoder-derived feature as an observed context and use the predictor to forecast the remaining features:

$$\begin{aligned} H^{\text{enc}} &= E(x), \\ J^{\text{cond}} &= [H^{\text{enc}}; P(H^{\text{enc}}; n_{\text{context}} = 1)] \in \mathcal{J}^{T_r}. \end{aligned} \quad (3)$$

We define J^{cond} to be the *forecast*, with $T_r = 8$: one encoder-derived feature for the observed context and seven predictor-generated features for the subsequent future temporal positions. The forecast occupies T_r positions, called *registry slots*, placed after the video tokens. Each slot is a spatial grid of *registry tokens* which are the units for attention, whereas slots correspond to frames.

A learned spatio-temporal adapter G_ϕ (Appendix A) maps the forecast into the video latent’s shape and coordinates. At each denoising step t , the same forecast initializes the registry, which is

concatenated with the noisy video latent along the temporal dimension:

$$R_t^{(0)} = G_\phi(J^{\text{cond}}) \in \mathbb{R}^{B \times C \times T_r \times H \times W}, \quad Z_t^{(0)} = [X_t; R_t^{(0)}] \in \mathbb{R}^{B \times C \times (T_v + T_r) \times H \times W}. \quad (4)$$

To place the registry on the same temporal axis as the video, each registry slot is assigned the RoPE coordinate of its corresponding video time. Let $u_s \in [0, 1]$ denote the normalized clip time of registry slot s , and let ρ_v map normalized time to the corresponding video-latent RoPE coordinate. We use

$$\tau_s^{\text{reg}} = \rho_v(u_s), \quad s \in \{1, \dots, T_r\}, \quad (5)$$

with $u_s = (s - 1)/T_r$ for uniformly spaced registry slots.

After patchification, video and registry tokens remain distinct but are jointly processed by the same bidirectional self-attention blocks. Although the registry is initialized from the same observation-conditioned forecast at each denoising step, interaction with the evolving video tokens makes its hidden state candidate-specific as it propagates through the DiT.

3.3 PREDICTIVE SUPERVISION OF THE REGISTRY

We supervise the registry toward representations of the realized future. Conditioning and target features play complementary roles: J^{cond} is an observation-conditioned forecast that initializes $R_t^{(0)}$, while Z^{tgt} is the target encoding of the corresponding full training video v :

$$Z^{\text{tgt}} = E^{\text{tgt}}(v) = (Z_1^{\text{tgt}}, \dots, Z_{T_r}^{\text{tgt}}), \quad Z_s^{\text{tgt}} \in \mathcal{J}. \quad (6)$$

Because J^{cond} depends only on the observation, the registry starts each denoising step from an observation-only prediction. As the registry exchanges information with the video tokens, predictive supervision encourages this state to align with the representation of the future realized in the training video. We apply the supervision at an intermediate DiT block so that the registry is shaped toward the realized future and can subsequently interact with the video states throughout the remaining DiT blocks. Let $H_{\text{reg}, t, s}$ denote the hidden state of registry slot s at the supervised layer and denoising step t . A readout q_ψ maps each registry state to a slot-level vector in the JEPA feature space:

$$\hat{Z}_{t, s} = q_\psi(H_{\text{reg}, t, s}). \quad (7)$$

Writing $\bar{Z}_s^{\text{tgt}}$ for the corresponding slot-level target, we optimize

$$\mathcal{L}_{\text{align}} = -\frac{1}{T_r} \sum_s \cos(\hat{Z}_{t, s}, \bar{Z}_s^{\text{tgt}}). \quad (8)$$

Appendix A specifies the readout and target construction. After training, the same readout q_ψ is frozen and reused for selection in Sec. 3.5.

3.4 TRAINING OBJECTIVE

Given the augmented sequence $Z_t^{(0)} = [X_t; R_t^{(0)}]$, the DiT jointly processes the video and registry tokens. We denote by $V_\theta^X(Z_t^{(0)}, t, c_{\text{txt}})$ the velocity prediction from the video tokens. The flow-matching objective is

$$\mathcal{L}_{\text{FM}} = \mathbb{E}_{X_0, \epsilon, t} \left[\left\| V_\theta^X(Z_t^{(0)}, t, c_{\text{txt}}) - V^* \right\|_2^2 \right]. \quad (9)$$

Both terms optimize the shared DiT:

$$\mathcal{L} = \mathcal{L}_{\text{FM}} + \lambda_{\text{align}} \mathcal{L}_{\text{align}}. \quad (10)$$

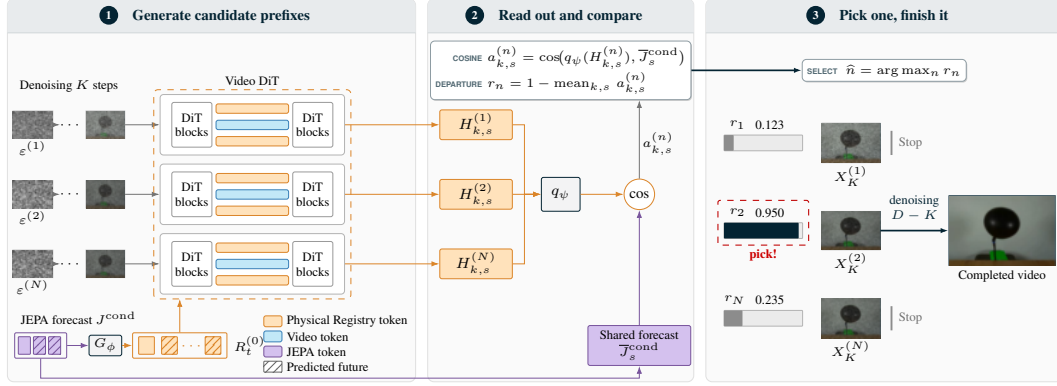
The video tokens receive the generation objective and the registry slots receive predictive supervision through the same DiT blocks, so the registry carries future-referenced information while the backbone continues to learn generation.

3.5 THE PHYSICAL REGISTRY SELECTOR

Through joint interaction with the video tokens and predictive supervision, the Physical Registry becomes a readable internal state that reflects the future dynamics represented by each generation trajectory. This makes it possible to compare candidate trajectories before generation is complete using the registry states themselves.

For a fixed observation, all candidates start from the same observation-conditioned forecast, but their registry states become candidate-specific as they interact with different video trajectories during denoising. We therefore interpret the departure of each registry from the shared forecast as the trajectory-specific update to the predicted future. The *Physical Registry Selector (PRS)* ranks candidates by this departure and continues denoising only the selected trajectory for the remaining steps. For input x , let the N candidate trajectories be $\mathcal{C}(x) = \{Y^{(n)}\}_{n=1}^N$, all initialized from the same forecast J^{cond} , which we denote by $\bar{J}^{\text{cond}}$ when used as their shared reference. After K denoising steps, PRS compares each candidate’s registry readouts with $\bar{J}^{\text{cond}}$, selects the trajectory whose registry reflects the largest candidate-specific update to the shared forecast, and continues denoising it from its current latent for the remaining $D - K$ steps, where D is the total number of denoising steps (Figure 2).

Figure 2: **Three-stage prefix selection with PRS.** Candidates share the same forecast initialization, are ranked from registry readouts over a K -step prefix, and only the selected trajectory continues for the remaining $D - K$ steps.



The readout q_ψ maps the registry hidden state $H_{k,s}^{(n)}$ into the JEPA feature space. The *forecast-departure score* for candidate n , accumulated over K denoising steps and a registry subset $\mathcal{S}$, is

$$r^{(n)} = 1 - \frac{1}{K|\mathcal{S}|} \sum_{k=1}^K \sum_{s \in \mathcal{S}} \cos\left(q_\psi\left(H_{k,s}^{(n)}\right), \bar{J}_s^{\text{cond}}\right),$$

$$\hat{n} = \arg \max_{n \in \{1, \dots, N\}} r^{(n)}.$$
(11)

The score measures angular departure from the shared forecast and is invariant to positive rescaling of the registry readouts. Appendix F.2 empirically supports this ranking direction and its robustness.

4 EXPERIMENTS

We first show that Physical Registry is a more effective interface for predictive representations than conditioning and joint generation (Sec. 4.2), and that its gains generalize across video backbones and world-model benchmarks (Sec. 4.3). We then show that its registry states support candidate selection during generation (Sec. 4.4), before analyzing the sources of its gains and its responses to physical changes (Secs. 4.5 and 4.6).

4.1 EXPERIMENTAL DETAILS

Benchmarks and tasks. We evaluate on Physics-IQ Verified (Rädsch et al., 2026), which scores physical plausibility against recorded futures, and on WorldModelBench (Li et al., 2025a), which scores instruction following, physical adherence, and common sense over its full 350-prompt set. Metric definitions are in Appendix A.

Multi-backbone evaluation. We use Cosmos and WAN 2.2 as two backbone families: Cosmos is a widely used world-model backbone that supports both I2V and V2V continuation, while WAN

2.2 is a widely adopted video-generation backbone in recent world-model research. Since WAN does not provide a V2V setting, we evaluate it on I2V only. Models are fine-tuned on the Enlarge dataset, which combines physics-oriented, web, simulation, and robot videos (Wang et al., 2025b; 2023; NVIDIA, 2026a;b) while excluding Physics-IQ videos (Appendix A). Each backbone–Physical Registry pair shares the task, conditioning input, sampling protocol, and evaluator.

Candidate selection. All methods use the same ten-candidate pool per input. Plain reports the pool average, while WMReward and PRS select one candidate using completed-video scores and intermediate registry readouts, respectively. Published leaderboard values are used for Plain where available. Additional details are in Appendix F.1.

4.2 CONTROLLED COMPARISON OF PREDICTIVE-STATE INTERFACES

We compare alternative interfaces for incorporating predictive representations into the video generator under a controlled held-view setting. Each variant is adapted on the 66 center-view Physics-IQ videos and evaluated on the 132 held-out left and right views using Physics-IQ Verified, with the same pretrained backbone, training budget, and frozen JEPA source. Table 1 compares conditioning and modulation, video-stream alignment, joint generation, and dedicated registry states (Appendix A).

Table 1: **Controlled comparison of predictive-state interfaces.** Interface mechanisms and Physics-IQ Verified scores after center-view training and left/right evaluation, with std over three generation seeds and Δ relative to vanilla fine-tuning. Registry only sets $\lambda_{\text{align}} = 0$ in Eq. (10).

Variant	Mechanism	Registry	Alignment	Readout	I2V	Δ	V2V	Δ
Vanilla fine-tuning	–	×	×	×	41.3 ± 2.1	–	46.4 ± 1.0	–
REPA (Yu et al., 2025)	Feature alignment	×	✓	×	41.8 ± 1.7	+0.5	46.9 ± 0.9	+0.5
Cross-attention (Peebles & Xie, 2023)	External context	×	×	×	43.1 ± 1.9	+1.8	49.2 ± 1.2	+2.8
AdaLN (Peebles & Xie, 2023)	Feature modulation	×	×	×	45.1 ± 0.8	+3.8	48.3 ± 0.5	+1.9
Joint generation (Kouzelis et al., 2025)	Joint denoising	×	✓	×	45.1 ± 1.8	+3.8	48.0 ± 0.4	+1.6
Registry only	Dedicated predictive state	✓	×	✓	45.0 ± 1.3	+3.7	50.3 ± 0.9	+3.9
Physical Registry	Dedicated predictive state	✓	✓	✓	51.2 ± 1.5	+9.9	55.1 ± 1.1	+8.7

Dedicated predictive states benefit most from predictive supervision. Table 1 shows that a dedicated registry state is already beneficial without predictive supervision: Registry only improves vanilla fine-tuning by +3.7/ + 3.9 on I2V/V2V. In contrast, applying representation alignment directly to the video stream with REPA yields only +0.5/ + 0.5. Adding predictive supervision to the registry further raises the scores to 51.2/55.1, the best among the compared interfaces. These results suggest that explicitly allocating a dedicated internal state for predictive representations is beneficial, and that predictive supervision is important for assigning this state a meaningful role in representing future dynamics.

4.3 FINE-TUNING ON THE ENLARGE DATASET ACROSS VIDEO BACKBONES

Physical Registry improves physical plausibility across backbones. Physical Registry improves Physics-IQ Verified over every evaluated backbone (Table 2). Under the expanded-prompt setting (Appendix A), it raises Cosmos 3 Nano 16B from 37.3/46.45 to 43.56/49.54 on I2V/V2V, surpassing the Cosmos 3 Super 64B reference (42.7/48.02) with only 0.45% additional parameters (Table 6). The WAN TI2V-5B matched-budget control further shows that the gain is not explained by fine-tuning alone: vanilla fine-tuning on the Enlarge dataset remains near pretrained performance, whereas Physical Registry improves (Appendix B). Figure 3 further shows more faithful realization of the intended physical events across five physics categories.

Physical Registry also improves on other physics-related benchmarks. On WorldModelBench, Physical Registry improves physical adherence and the total score across all four backbones. Common sense is maintained or improved, while instruction following decreases on Cosmos v2.5 and WAN TI2V-5B (Table 3; full leaderboard in Table 10, qualitative examples in Appendix I.2). On EWMBench (Hu et al., 2025), Physical Registry also improves Cosmos 3 Nano’s scene consistency and all three motion metrics, with the largest gain in trajectory agreement (Appendix E).

Table 2: **Physics-IQ Verified.** Plain averages our candidate pool or reports the published value (*). Δ is the gain over the backbone above, green parentheses the PRS gain over Plain. Bold and underline mark the best and second-best per task. Gray marks unavailable entries, dashes unreported.

Model	I2V			V2V		
	Plain	Δ	PRS	Plain	Δ	PRS
Cosmos 3 Nano 16B (NVIDIA et al., 2026)	30.18 ± 0.84	—		38.78 ± 0.78	—	
+ Physical Registry	36.01 ± 0.95	+5.83	40.27 (+4.26)	45.12 ± 0.94	+6.34	46.78 (+1.66)
Cosmos 3 Nano 16B [†] (NVIDIA et al., 2026)	$37.3 \pm 0.9^*$	—		46.45 ± 0.76	—	
+ Physical Registry [†]	<u>43.56 ± 0.95</u>	+6.26	45.81 (+2.25)	<u>49.54 ± 0.63</u>	+3.09	52.06 (+2.52)
Cosmos v2.5 2B (NVIDIA et al., 2025b)	30.65 ± 0.37	—		37.40 ± 0.53	—	
+ Physical Registry	33.71 ± 1.11	+3.06	39.08 (+5.37)	42.33 ± 1.90	+4.93	47.67 (+5.34)
WAN 2.2 I2V-A14B (Wan Team, 2025)	$32.2 \pm 0.6^*$	—				
+ Physical Registry	38.44 ± 1.06	+6.24	40.58 (+2.14)			
WAN 2.2 TI2V-5B (Wan Team, 2025)	$27.7 \pm 0.9^*$	—				
+ Physical Registry	29.24 ± 1.30	+1.54	32.03 (+2.79)			
Cosmos 3 Super 64B [†] (NVIDIA et al., 2026)	<u>$42.7 \pm 0.8^*$</u>	—		48.02 ± 0.75	—	
MiniMax H3 (MiniMax, 2026)	$39.8 \pm 0.3^*$	—		37.71 ± 1.75	—	
Grok Imagine Video (Anates Labs, 2026)	$34.8 \pm 0.6^*$	—				
HunyuanVideo 1.5 (Rädsch et al., 2026)	$33.4 \pm 0.8^*$	—				
Cosmos 3 Edge [†] (NVIDIA et al., 2026)	$32.7 \pm 1.1^*$	—		33.29 ± 0.78	—	
CogVideoX-5B (Yang et al., 2025b)	$31.8 \pm 1.5^*$	—				
Kandinsky-WM 1.0 (Anates Labs, 2026)	$30.8 \pm 0.9^*$	—				
Magi-1 (op) (Physics-IQ Benchmark, 2026)	$30.2 \pm 1.1^*$	—		$48.4 \pm 1.1^*$	—	
Sora 2 (Rädsch et al., 2026)	$26.5 \pm 0.8^*$	—				
P-Video (Rädsch et al., 2026)	$25.3 \pm 1.8^*$	—				

[†] Expanded prompt: Claude Opus 5 converts the image-conditioned OP description to NVIDIA’s official I2V JSON format; 50 steps, CFG 3.0, shift 4.75 (Appendix A). * Published Physics-IQ Verified reference; unmarked estimates are our runs.

Figure 3: **Qualitative comparisons across five Physics-IQ categories.** Top: Cosmos 3 Nano 16B backbone; bottom: Physical Registry, with matched conditioning and eight equally spaced frames. Physical Registry better realizes the intended physical event: ball separation after collision, liquid motion in the inverted jar, persistence of the ball and its reflection, preservation of the paper under rising smoke, and wrench attraction toward the magnet. More examples: Figures 16 to 18.

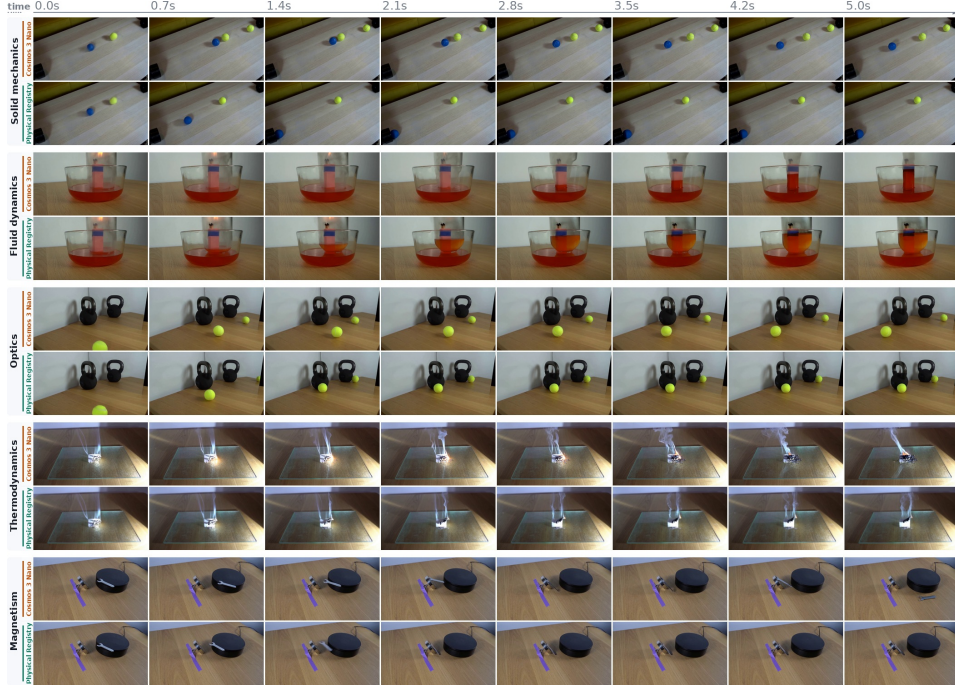
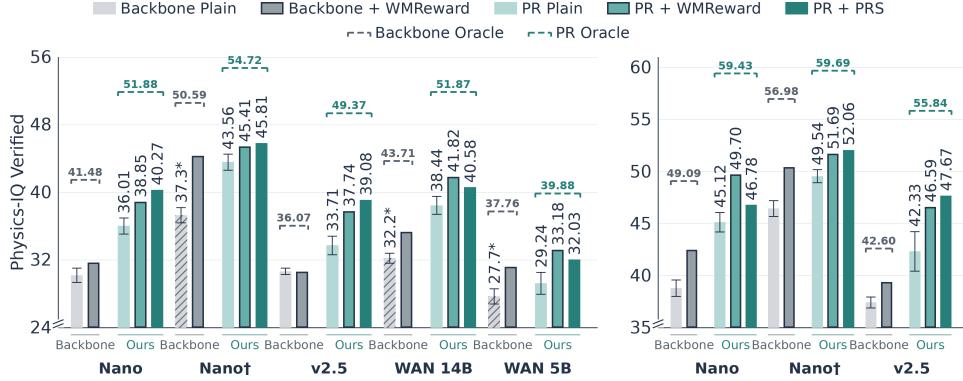


Table 3: **WorldModelBench results.** Values in parentheses indicate the change from the corresponding backbone. * denotes published leaderboard scores (Li et al., 2025a). Table 10 for the full results.

Model	Instruction following (0–3)	Physical adherence (0–5)	Common sense (0–2)	Total (0–10)
Cosmos 3 Nano 16B (NVIDIA et al., 2026)	2.20 ± 0.02	4.50 ± 0.08	1.43 ± 0.06	8.13 ± 0.13
+ Physical Registry	2.20 ± 0.002 (–)	4.82 ± 0.03 (+0.32)	<u>1.81 ± 0.02 (+0.38)</u>	<u>8.83 ± 0.04 (+0.69)</u>
Cosmos v2.5 2B (NVIDIA et al., 2025b)	2.14 ± 0.03	4.43 ± 0.07	1.55 ± 0.05	8.12 ± 0.14
+ Physical Registry	2.07 ± 0.01 (–0.07)	4.54 ± 0.03 (+0.11)	1.58 ± 0.04 (+0.03)	8.19 ± 0.01 (+0.07)
WAN 2.2 I2V-A14B (Wan Team, 2025)	2.23 ± 0.03	4.45 ± 0.04	1.60 ± 0.03	8.28 ± 0.02
+ Physical Registry	2.30 ± 0.04 (+0.07)	4.53 ± 0.04 (+0.07)	1.60 ± 0.02 (+0.004)	8.43 ± 0.05 (+0.15)
WAN 2.2 TI2V-5B (Wan Team, 2025)	2.33 ± 0.01	4.35 ± 0.10	1.57 ± 0.04	8.24 ± 0.14
+ Physical Registry	2.24 ± 0.05 (–0.09)	4.50 ± 0.05 (+0.14)	1.68 ± 0.06 (+0.11)	8.41 ± 0.11 (+0.17)
KLING (Kuaishou Technology, 2024)	2.32*	4.81*	1.95*	9.10*
Luma (Luma AI, 2024)	1.98*	4.49*	1.76*	8.24*
OpenSoraPlan-T2V (Lin et al., 2024)	1.72*	4.64*	1.68*	8.04*
Mochi 1 (Genmo Team, 2024)	2.06*	4.39*	1.45*	7.91*
CogVideoX-I2V (Yang et al., 2025b)	1.78*	4.17*	1.12*	7.08*

Figure 4: **Selection comparison on Physics-IQ Verified.** (left) I2V and (right) V2V. Dashed caps mark Oracle scores and hatched bars denote published scores.



4.4 SELECTION FROM REGISTRY READOUTS

Figure 4 compares PRS with Plain generation and completed-video WMReward. Under the same WMReward selector, Physical Registry improves over its corresponding backbone across all evaluated I2V and V2V settings. PRS improves I2V over Plain by 5.6%–15.9% across the four default backbone configurations, using only intermediate registry readouts without completed-video external scoring.

On Cosmos v2.5, PRS selects after 10 of 35 denoising steps and reaches 38.36/46.68 on I2V/V2V, slightly exceeding WMReward’s 37.74/46.59. Continuing only the selected trajectory requires 125 candidate-steps instead of 350, reducing the serial denoising budget by 64%. Together, these results show that registry readouts provide a useful early signal for candidate selection before generation is complete. Appendices F.1 and F.3 provide the full results and early-selection analysis.

4.5 ABLATION OF THE PHYSICAL REGISTRY

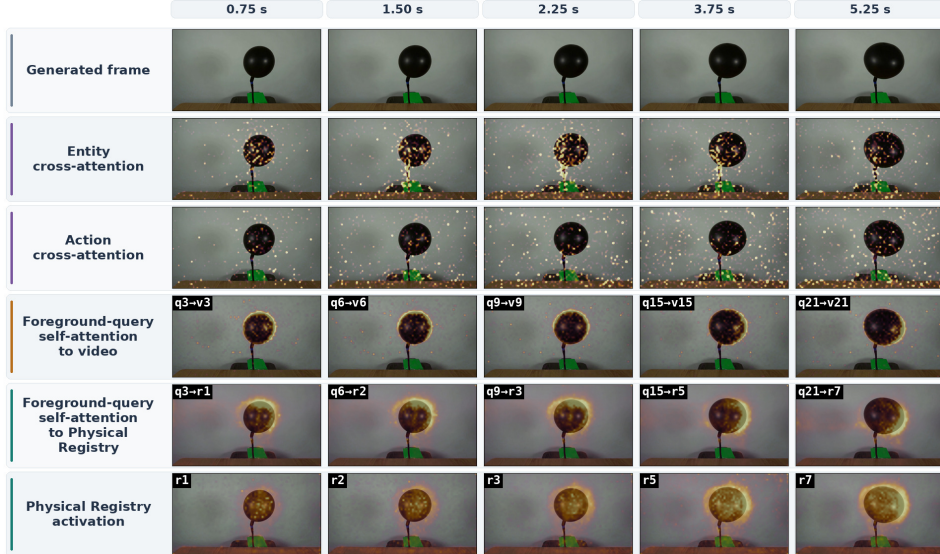
We examine whether the gains of Physical Registry come from the forecast itself, additional registry capacity, or predictive supervision. Table 4(a) tests the forecast content, while Table 4(b) isolates the contributions of registry capacity, forecast initialization, and predictive supervision.

Generation depends on the forecast content. In Table 4(a), removing the projected forecast drops Nano from 36.01 to 16.78 on I2V, whereas moderate Gaussian perturbation ($\sigma = 0.5$) has only a small effect; WAN 14B shows the same trend. The registry therefore depends strongly on the forecast content while remaining robust to moderate perturbation. In the motion-transfer experiment (Appendix G), replacing the forecast with JEPA features from a source video shifts the generated motion toward that source while keeping the initial frame, prompt, and noise fixed.

Table 4: **Registry ablations on Physics-IQ Verified.** (a) Forecast-content controls on Cosmos 3 Nano 16B and WAN 2.2 I2V-A14B. (b) Comparison of learnable registers, joint generation, forecast-initialized registry states, and full Physical Registry on Cosmos v2.5 2B.

Registry content	I2V	V2V	Variant	I2V	Δ	V2V	Δ
Physical Registry			Vanilla fine-tuning	41.3 $\pm$ 2.1	–	46.4 $\pm$ 1.0	–
(Cosmos 3 Nano 16B)	36.01 $\pm$ 0.95	45.12 $\pm$ 0.94	ViT Needs Registers				
Zero mask	16.78 $\pm$ 0.01	24.15 $\pm$ 0.32	(Darcet et al., 2024)	39.0 $\pm$ 1.1	–2.3	44.6 $\pm$ 0.9	–1.8
Perturbed mask (Noise $\sigma = 0.5$)	35.84 $\pm$ 0.11	44.35 $\pm$ 0.75	Joint generation	45.1 $\pm$ 1.8	+3.8	48.0 $\pm$ 0.4	+1.6
Physical Registry			Registry only	45.0 $\pm$ 1.3	+3.7	50.3 $\pm$ 0.9	+3.9
(WAN 2.2 I2V-A14B)	38.44 $\pm$ 1.06		Physical Registry	51.2 $\pm$ 1.5	+9.9	55.1 $\pm$ 1.1	+8.7
Zero mask	35.88 $\pm$ 0.22						
Perturbed mask (Noise $\sigma = 0.5$)	36.40 $\pm$ 0.39						

Figure 5: **Registry attention and activation during balloon inflation.** Foreground queries are video tokens inside the Physics-IQ motion mask of the generated video. Labels give query→key pairs (e.g., q3→r1: queries in latent frame 3 attending to its time-aligned registry slot r1); r1 alone marks that slot’s activation. Protocol: Appendix A; more examples: Appendices H.1 and I.3.



Learnable registers alone are not sufficient. In Table 4(b), input-independent learnable registers underperform vanilla fine-tuning, while forecast initialization improves over them and predictive supervision improves further. The gains therefore do not come from additional registry capacity alone: forecast content in the registry helps, and predictive supervision further strengthens its role in representing future dynamics.

4.6 REGISTRY ATTENTION AND ACTIVATION

Figure 5 highlights how Physical Registry responds differently from text cross-attention and video-token attention during balloon inflation. While these attention maps broadly follow the balloon and its interaction region, attention to the aligned registry slots and registry activation concentrate near the expanding boundary, where the dominant physical change occurs. This suggests that the registry provides a more localized representation of regions where the intended scene dynamics unfold.

5 DISCUSSION AND CONCLUSION

Physical Registry gives predictive representations an explicit, temporally grounded state within the video backbone rather than leaving them entangled with the video representation. Our results suggest that this dedicated state can be explicitly supervised toward future dynamics while remaining readable during inference. More broadly, explicit predictive states provide a useful **interface for representing and reading physically plausible futures** in world models.

AI USE STATEMENT

Writing and language polishing. Generative AI tools were used to refine wording, shorten figure captions, and improve consistency in terminology and presentation.

Retrieval and discovery. Generative AI tools were used to assist in identifying relevant prior methods and related literature. Papers considered or cited in this work were subsequently checked against their original sources by the authors.

Research execution. Generative AI tools were used for routine operational assistance during experimental execution, including preparing and submitting experiment jobs to cloud computing environments, formatting execution commands and configuration files, and assisting with minor scripting or runtime issues.

Manuscript drafting. Generative AI tools were used to help convert author-provided technical notes and descriptions into preliminary prose, reorganize existing text for clarity, and suggest alternative wording. All AI-assisted material was reviewed by the authors.

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APPENDIX

Appendix A gives experimental details. Appendices B to E report additional benchmark results: separating fine-tuning on the Enlarge dataset from the registry interface, Physics-IQ components, WorldModelBench references, and EWMBench. Appendix F details the selector, Appendix G the source-transfer probe, and Appendix H the mechanistic diagnostics. Appendix I collects qualitative comparisons.

A IMPLEMENTATION AND EXPERIMENTAL DETAILS

A.1 REGISTRY ARCHITECTURE AND SUPERVISION

Registry representation. The frozen JEPA encoder is V-JEPA 2.1 (Mur-Labadia et al., 2026) ViT-g at 384 px, loaded from the pretrained target-encoder branch. The registry uses eight slots, one context feature and seven predictor rollout steps, each with 196 spatial tokens of 5,632 channels. Full-video JEPA features provide the alignment targets, mean-pooled over the 196 spatial tokens. Video and registry tokens share dense self-attention, while text remains a separate cross-attention condition.

Predictive supervision. We use $\lambda_{\text{align}} = 0.5$ in Equation (10), following the default REPA projection-loss weight (Yu et al., 2025). Registry only retains the forecast-initialized registry and removes the alignment term. Following prior representation-alignment work (Yu et al., 2025; Zhang et al., 2025), we supervise an early-to-middle generation block. The block used for each backbone is listed below. For WAN I2V-A14B, the block count and alignment index apply to each noise expert.

Mean-pooled implementation	Generation blocks	Alignment block index
Cosmos 3 Nano 16B	36	10
Cosmos v2.5 2B	28	14
WAN 2.2 I2V-A14B	40	11
WAN 2.2 TI2V-5B	30	15

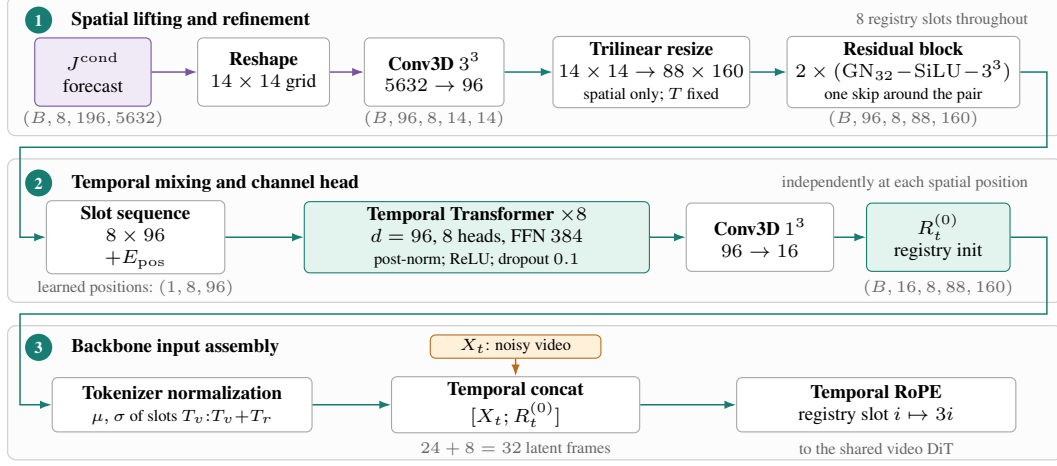
Registry projection architecture. The adapter G_ϕ of Equation (4) combines established video-modeling components: local spatio-temporal convolutions (Tran et al., 2015) and per-position temporal attention, a factorization used in video diffusion architectures (Ho et al., 2022). The convolutions mix neighboring locations and adjacent forecast features. Temporal attention then integrates the slot sequence at each spatial position. Spatial resizing and channel projection match the backbone’s latent geometry while retaining the forecast’s temporal indexing. Figure 6 shows this adapter.

Projection input and output. For the Cosmos v2.5 2B configuration, the input is the forecast J^{cond} , a sequence of $T_r=8$ slots, each a 14×14 grid of 5632-dimensional features (the encoder embedding width of 1408 concatenated over four blocks). The output is $R_t^{(0)}$ in the video-latent format of the backbone: 16 channels over 8 registry slots at the 88×160 latent resolution.

Projection stages. Figure 6 gives the operations and shapes of each stage. Upsampling acts on the two spatial axes only, and the temporal Transformer is applied independently at each spatial position with the eight registry slots as its sequence, so spatial mixing comes from the convolutions and, after concatenation, from the backbone’s self-attention. The adapter is initialized randomly and trained jointly with the backbone.

Projection placement. The module emits the backbone’s native latent channel count. Its output is normalized with the tokenizer’s own per-frame statistics for the registry slots, which places the registry on the scale of the video latent. The normalized output is then concatenated along the temporal axis to give $T_v + T_r = 24 + 8 = 32$ latent frames. Registry slot i receives the video-latent RoPE coordinate $3i$, the temporal alignment of Equation (5). With 2×2 spatial patchification, each registry slot contains 44×80 tokens, giving $8 \times 44 \times 80 = 28,160$ registry tokens in this configuration.

Figure 6: **The registry projection layer G_ϕ .** The three bands show spatial lifting with 3D convolutions (Tran et al., 2015), per-position temporal attention (Ho et al., 2022) and channel projection, and backbone input assembly. Shapes are for the Cosmos v2.5 2B configuration.



Registry readout modules. The readout operator q_ψ in Equations (7) and (11) includes spatial mean-pooling within each registry slot, before its projection. Registry slots remain separate until loss or score aggregation. For training, q_ψ uses a three-layer MLP with output widths 2048, 2048, and 5632, and SiLU activations (19.9M parameters). It maps the spatially averaged registry hidden state to the encoder feature dimension.

The slot-level target $\bar{Z}_s^{\text{tgt}}$ and reference $\bar{J}_s^{\text{cond}}$ are spatial means of the frozen encoder’s target grid and the unprojected shared-forecast grid, respectively. These reductions preserve the temporal indexing of their source features. The alignment loss trains a single readout, which the selection policy reuses frozen. No additional module is trained for selection. The conditioning adapter G_ϕ operates in the reverse direction, mapping the forecast into the video-latent geometry.

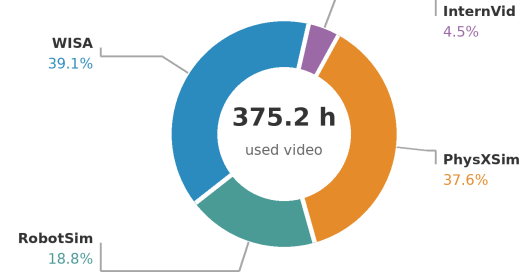
A.2 TRAINING AND DATA

The Enlarge dataset. The Enlarge dataset combines physics-focused data with broad visual coverage. It includes physics-oriented video, rigid-body simulation, general web video, and embodied robot simulation (Wang et al., 2025b; 2023; NVIDIA, 2026a;b). We fine-tune Physical Registry using only its RGB videos and corresponding captions, without additional physical annotations or simulator states. The Enlarge dataset excludes Physics-IQ videos. Table 5 and Figure 7 report the exact number of clips and video hours used from each source.

Table 5: **The Enlarge dataset.** Exact clips used by the evaluated Physical Registry models.

Dataset	Clips	Mean (s)	Hours
WISA	74,370	7.1	146.7
InternVid	8,115	7.5	16.9
SDG-PhysXSim	101,422	5.0	140.9
SDG-RobotSim	28,193	9.0	70.6
Total	212,100	6.4	375.2

Figure 7: **Used-hour composition.** Projected hours for the exact used clips.



Fine-tuning settings. Table 6 reports model sizes, effective batch, and GPU resources for Physical Registry fine-tuning on the Enlarge dataset. The matched-budget WAN control in Appendix B uses 8,000 iterations and effective batch 16.

Table 6: **Model sizes, fine-tuning resources, and optimization settings.** Registry modules denote the added projection and readout parameters (e.g., 16.0M + 19.9M for Cosmos v2.5 2B).

Model	Pretrained	Registry modules	Batch/update	GPU's
Cosmos 3 Nano 16B	16B	72.63M	16	8× H100
Cosmos v2.5 2B	2B	35.93M	16	8× A100 40 GB
WAN 2.2 I2V-A14B	2 × 14B	129.39M	16	8× H100
WAN 2.2 TI2V-5B	5B	105.02M	16	8× A100 40 GB

Model	Learning rate	Schedule	Weight decay	AdamW (β_1, β_2)
Cosmos 3 Nano 16B	1×10^{-5}	constant	0	(0.9, 0.95)
Cosmos v2.5 2B	3×10^{-5}	100-step warm-up, then decay	1×10^{-3}	(0.9, 0.999)
WAN 2.2 I2V-A14B	1×10^{-5}	constant	1×10^{-2}	(0.9, 0.95)
WAN 2.2 TI2V-5B	1×10^{-5}	constant	1×10^{-2}	(0.9, 0.999)

A.3 INFERENCE AND SAMPLING

Sampling settings. Apart from the expanded-prompt setting ([†], Table 2), guidance, shift, sampler, and step count follow each model’s official inference defaults (Table 7). Each backbone and its Physical Registry counterpart use the same settings. Following the Physics-IQ protocol, the first five seconds after conditioning are evaluated.

Table 7: **Sampling settings.** Steps are denoising steps and guidance is the classifier-free guidance scale (WAN I2V-A14B: high-/low-noise experts). Generated frames exclude conditioning frames (Cosmos v2.5: I2V / V2V). [†] Expanded-prompt setting of Table 2.

Model	Steps	Guidance	Shift	Sampler	Resolution	Gen. frames @ fps
Cosmos 3 Nano 16B	35	6.0	10.0	UniPC	1280 × 720	120 @ 24
Cosmos 3 Nano 16B [†]	50	3.0	4.75	UniPC	1280 × 720	120 @ 24
Cosmos v2.5 2B	35	7.0	5.0	UniPC	1280 × 704	92 / 80 @ 16
WAN 2.2 I2V-A14B	40	3.5 / 3.5	5.0	UniPC	1280 × 720	80 @ 16
WAN 2.2 TI2V-5B	50	5.0	5.0	UniPC	1280 × 704	120 @ 24

Sampling cost. Table 8 reports the median per-step time over three Physics-IQ scenarios with three repeats; for Cosmos 3 Nano 16B, whose sampler caches activations, it is computed from total sampling time. The registry increases per-step cost to 1.67× on Cosmos v2.5 2B and 1.55× on Cosmos 3 Nano 16B. Times are compared only within each backbone.

Table 8: **Sampling cost of the registry.** Both arms of a backbone are measured in one session on a single H100 80GB. Times are per sampler step; peak memory is the generation peak above the weights resident before sampling. Two sequence lengths are given for Cosmos 3 Nano 16B because its two classifier-free guidance branches carry different text lengths.

Model	Arm	Sequence (tokens)	s / sampler step	Peak (GiB)
Cosmos v2.5 2B	Backbone	84,480	6.514	6.20
	+Physical Registry	112,640	10.909	7.00
Cosmos 3 Nano 16B	Backbone	28,607 / 31,364	1.384	11.44
	+Physical Registry	35,967 / 38,724	2.148	11.94

Prompt expansion. For the expanded-prompt Nano setting in Tables 2 and 12, Claude Opus 5 (model id `claude-opus-5`) expands the Physics-IQ original description (OP) together with the conditioning image into NVIDIA’s Cosmos I2V structured prompt format. The image specifies appearance and layout, whereas OP specifies temporal dynamics. The expansions are generated once and reused in every run. The balloon-inflation example contrasts OP with the benchmark’s best-practice prompt (BPP), and shows the full expanded prompt produced from OP and the image.

Original description (OP)

A black balloon is attached to a fixed electric air pump hose on a table with a plain wall in the background. Air is being pumped in the balloon. Static shot with no camera movement.

Benchmark best-practice prompt (BPP)

Static locked-off single-shot with fixed frame throughout filmed with constant framerate in real-time. The scene shows a realistic scientific demonstration. The scene only contains the described setup and actions. The balloon is attached to a black hose that points upwards from behind a wooden table. Air is being pumped into the black balloon.

Expanded prompt (OP + image)

Temporal dynamics. Air is pumped continuously into the black balloon so that it swells steadily larger over the five seconds, its rubber stretching thinner and its highlights spreading while the neck stiffens and lifts the balloon more upright on the hose.

Subject. A matte black rubber balloon inflated to a firm round sphere, its neck pulled down over the black nozzle of a hose and clamped there with a band of bright blue tape.

Setting. A bare indoor corner used as a test bay: a plain pale grey-green painted wall fills the frame, and a honey-toned oak tabletop runs straight across the bottom as a level horizontal band. A broad soft shadow of the rig falls on the wall to the left. No other furniture, decoration or clutter is present.

Camera. Static

0:00-0:01. The pump runs on and the black balloon, already a firm centred sphere, grows visibly wider; its paired highlights drift apart as the surface curvature flattens.

0:01-0:02. The balloon continues to swell, its lower bulge rounding out and the pear-shaped taper above the blue tape shortening as rubber is drawn up into the body.

0:02-0:03. Pressure rises enough to stiffen the braided hose; the balloon climbs a little higher on the vertical midline and its slight lean straightens out entirely.

0:03-0:04. Expansion carries on at the same steady rate, the rubber now thinner and its blacks a shade lighter where it is most stretched, with a small wobble passing through the balloon on each pump surge.

0:04-0:05. The balloon reaches its largest size in the clip, taut and nearly upright on the stiff hose, still growing and still intact as the pump keeps running.

A.4 EVALUATION AND VISUALIZATION DETAILS

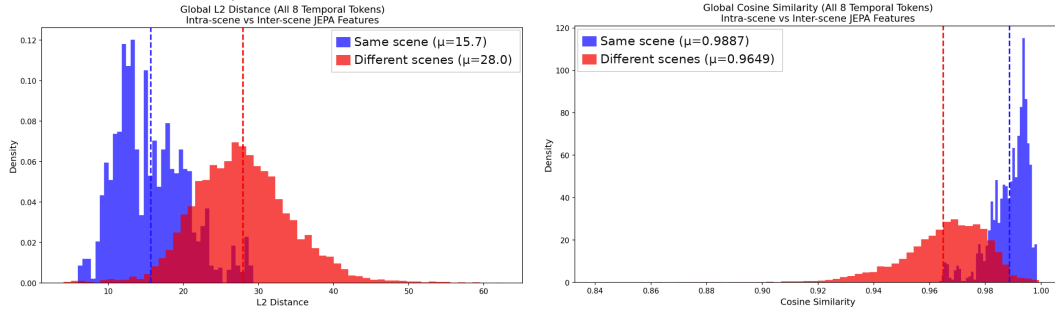
Benchmark metrics. Physics-IQ Verified measures physical plausibility against a recorded future, with higher scores indicating better results (Rädsch et al., 2026). It normalizes four subscores per sample and averages equally across subscores and inputs, replacing dataset-level normalization. The input-level scores support within-input candidate comparisons. WorldModelBench (Li et al., 2025a) supplies a first-frame image and text instruction for 350 prompts spanning 7 application domains and 56 subdomains. Its human-aligned multimodal judge scores instruction following, physical adherence over five physical laws, and common sense over frame-wise and temporal quality. The total is the sum of these scores. EWMBench (Hu et al., 2025) evaluates embodied world models on real robot manipulation episodes, scoring visual scene consistency, motion correctness against the recorded trajectory, and semantic alignment with the task instruction (Appendix E). Each backbone and Physical Registry pair uses the same conditioning inputs, sampling protocol, and judge on the full set.

Tasks and candidate pools. The evaluation covers image-to-video and video-to-video generation on Physics-IQ (Motamed et al., 2026). Candidates are compared within the same scene, view, and conditioning input. Within matched pools of ten candidates per input, Plain scores average the pool, while WMReward and PRS select one candidate from it. The content ablations in Table 4(a) use Cosmos 3 Nano 16B without prompt expansion and WAN 2.2 I2V-A14B. They either replace the

projected registry features with zeros (zero mask) or apply Gaussian noise with $\sigma = 0.5$ (perturbed mask). Their full-model references repeat the Plain values in Table 2.

Controlled comparison (Table 1). All interfaces share the pretrained backbone, center-view training data, training budget, JEPA source, and held-out left/right-view evaluation. REPA aligns ordinary denoising hidden states to JEPA features; joint generation adapts ReDi (Kouzelis et al., 2025) to denoise video and future JEPA tokens in one sequence; Registry only keeps the forecast-initialized registry but removes its alignment loss. Training uses only center views, while evaluation uses the left and right views. This protocol is meaningful only if the JEPA condition describes the same scenario across viewpoints. Figure 8 confirms this: JEPA features from different views of the same scenario are closer than those of different scenarios in both L2 distance and cosine similarity. A held-out view therefore supplies a JEPA condition consistent with its scenario, and the comparison tests how each interface uses this condition under a new viewpoint.

Figure 8: **Cross-view JEPA feature correspondence.** Views of the same scene (blue) are closer than different scenes (red) in L2 distance (left; means 15.7 versus 28.0) and cosine similarity (right; 0.9887 versus 0.9649).



Visualization protocol. Registry activation is the hidden-state variance over denoising steps 0–10 at each aligned registry slot and spatial position, averaged over feature channels.

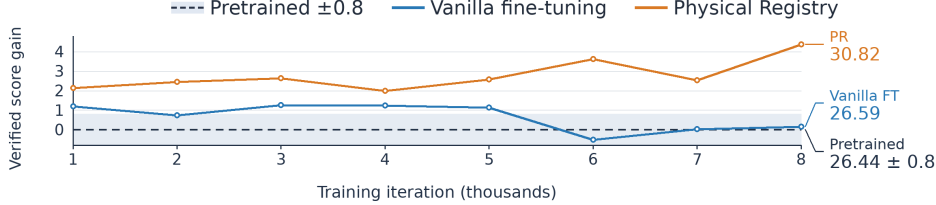
For Figure 5, foreground queries use the Physics-IQ generated-foreground mask (Motamed et al., 2026), downsampled by area averaging to the 44×80 video-latent grid. Attention maps average native QK-softmax responses over steps $\{0, 5, 11, 16, 22, 28, 34\}$.

For Appendix I.3, text-attention maps aggregate the corresponding lexical token groups and normalize by valid-text attention at each spatial location. Text and video self-attention use steps 0–10, while registry self-attention uses steps 11–22.

B EVALUATION CURVES: VANILLA FINE-TUNING VERSUS PHYSICAL REGISTRY

The controlled comparisons in Table 1 and Table 4(b) use Cosmos v2.5 2B. To separate fine-tuning on the Enlarge dataset from the Physical Registry in a second backbone family, we track WAN TI2V-5B for 8,000 iterations with batch size 16, evaluating Physics-IQ Verified every 1,000 iterations. Vanilla fine-tuning on the Enlarge dataset uses the same data, schedule, and optimizer as Physical Registry, differing only in the absence of registry tokens and predictive alignment.

Figure 9: Physics-IQ Verified gains over pretrained WAN TI2V-5B. Shading marks one pretrained standard deviation (± 0.8) around zero.



The vanilla fine-tuning stays within 1.3 points of the pretrained score throughout and ends at $+0.15$ after 8,000 iterations. Physical Registry exceeds vanilla at all eight evaluation points. Even our smallest gain ($+1.98$) exceeds vanilla’s largest ($+1.25$). Under the same data and update budget, vanilla fine-tuning produces little change from pretrained performance, whereas Physical Registry improves consistently across checkpoints. This control supports the interpretation that the WAN TI2V-5B gain in Table 2 arises from the registry interface rather than from additional training data alone.

C PHYSICS-IQ COMPONENTS AND ORIGINAL PHYSICS-IQ SCORE

Table 9 reports the four Physics-IQ Verified components of the Physical Registry models fine-tuned on the Enlarge dataset in Tables 2 and 12, retaining both Nano prompt settings. The Original column reports the original Physics-IQ score, recomputed from the same evaluation metrics (Motamed et al., 2026; Rädtsch et al., 2026). Across both tasks, the model ordering under the original score is unchanged from Verified.

Table 9: **Physics-IQ components and original Physics-IQ score.** Component scores, the Verified score, and the original Physics-IQ score for our Physical Registry (PR) models, each normalized to 0–100. **Bold/underline** mark the highest/second-highest value per column within a task. [†] Expanded-prompt setting of Table 2.

I2V	Spatial	Spatiotemp.	Weighted	Inv. MSE	Verified	Original
Nano 16B + PR	<u>46.63</u>	31.01	<u>32.76</u>	33.63	36.01	35.00
Nano 16B [†] + PR	60.70	33.56	42.46	37.53	43.56	42.95
Cosmos v2.5 2B + PR	44.46	<u>34.44</u>	30.29	25.65	33.71	34.00
WAN I2V-A14B + PR	44.77	42.06	32.67	<u>34.19</u>	<u>38.44</u>	<u>38.90</u>
WAN TI2V-5B + PR	36.82	30.81	22.33	26.99	29.24	27.87
V2V	Spatial	Spatiotemp.	Weighted	Inv. MSE	Verified	Original
Nano 16B + PR	57.72	<u>38.31</u>	<u>43.43</u>	<u>41.02</u>	<u>45.12</u>	<u>45.60</u>
Nano 16B [†] + PR	68.05	38.37	49.90	41.85	49.54	50.54
Cosmos v2.5 2B + PR	<u>57.98</u>	37.43	43.37	30.56	42.33	44.39

D WORLDMODEL BENCH REFERENCE LEADERBOARD

Table 10 collects published WorldModelBench reference scores (Li et al., 2025a) together with the backbone comparisons in Table 3. All four backbone-versus-Physical Registry pairs use the matched protocol described in Appendix A.

Table 10: **WorldModelBench reference scores.** Backbone pairs report mean $\pm$ std, rounded to two decimals. **Bold/underline** mark the highest/second-highest mean in each displayed column. Green/red parentheses show positive/negative Physical Registry-minus-backbone changes before rounding; (–) marks a tie. Rows from KLING onward are published references under their own generation settings (Li et al., 2025a). Main results: Table 3.

Model	Instruction following (0–3)	Physical adherence (0–5)	Common sense (0–2)	Total (0–10)
Cosmos 3 Nano 16B (NVIDIA et al., 2026)	2.20 $\pm$ 0.02	4.50 $\pm$ 0.08	1.43 $\pm$ 0.06	8.13 $\pm$ 0.13
+ Physical Registry	2.20 $\pm$ 0.002 (–)	4.82 $\pm$ 0.03 (+0.32)	1.81 $\pm$ 0.02 (+0.38)	8.83 $\pm$ 0.04 (+0.69)
Cosmos v2.5 2B (NVIDIA et al., 2025b)	2.14 $\pm$ 0.03	4.43 $\pm$ 0.07	1.55 $\pm$ 0.05	8.12 $\pm$ 0.14
+ Physical Registry	2.07 $\pm$ 0.01 (–0.07)	4.54 $\pm$ 0.03 (+0.11)	1.58 $\pm$ 0.04 (+0.03)	8.19 $\pm$ 0.01 (+0.07)
WAN 2.2 I2V-A14B (Wan Team, 2025)	2.23 $\pm$ 0.03	4.45 $\pm$ 0.04	1.60 $\pm$ 0.03	8.28 $\pm$ 0.02
+ Physical Registry	2.30 $\pm$ 0.04 (+0.07)	4.53 $\pm$ 0.04 (+0.07)	1.60 $\pm$ 0.02 (+0.004)	8.43 $\pm$ 0.05 (+0.15)
WAN 2.2 TI2V-5B (Wan Team, 2025)	2.33 $\pm$ 0.01	4.35 $\pm$ 0.10	1.57 $\pm$ 0.04	8.24 $\pm$ 0.14
+ Physical Registry	2.24 $\pm$ 0.05 (–0.09)	4.50 $\pm$ 0.05 (+0.14)	1.68 $\pm$ 0.06 (+0.11)	8.41 $\pm$ 0.11 (+0.17)
KLING (Kuaishou Technology, 2024)	<u>2.32</u>	<u>4.81</u>	1.95	9.10
Minimax (MiniMax, 2024)	2.28	4.72	<u>1.92</u>	<u>8.92</u>
Mochi 1-official (Genmo Team, 2024)	2.00	4.80	1.86	8.66
Runway (Runway, 2024)	2.17	4.60	1.86	8.64
Luma (Luma AI, 2024)	1.98	4.49	1.76	8.24
OpenSoraPlan-T2V (Lin et al., 2024)	1.72	4.64	1.68	8.04
Mochi 1 (Genmo Team, 2024)	2.06	4.39	1.45	7.91
CogVideoX-T2V (Yang et al., 2025b)	2.03	4.27	1.35	7.65
CogVideoX-I2V (Yang et al., 2025b)	1.78	4.17	1.12	7.08
Pandora (Xiang et al., 2024)	1.56	4.31	1.03	6.90
T2V-Turbo (Li et al., 2024)	1.37	4.10	1.08	6.56
OpenSora-T2V (Zheng et al., 2024)	1.61	3.88	0.69	6.17
OpenSora-I2V (Zheng et al., 2024)	1.42	3.85	0.55	5.82

E EMBODIED WORLD MODEL BENCHMARK

EWMBench (Hu et al., 2025) evaluates embodied world models on real robot manipulation episodes along three axes: visual scene consistency, motion correctness against the recorded gripper trajectory, and semantic alignment with the task instruction. It complements Physics-IQ, which scores physical plausibility on passive scenes, by asking whether a generated rollout follows an embodiment through a task.

Protocol. We run the official evaluator on the full public ground-truth split, 21 episodes over seven tasks. Each episode is generated three times from its initial frame and instruction, giving 126 videos across the two arms. Our clips are 121 frames at 24 fps, whereas the recorded episodes run at 30 fps. Both arms share the backbone, sampling recipe, and conditioning inputs, and differ only in the registry interface.

Table 11: **EWMBench (Hu et al., 2025)**. All metrics are higher-is-better and shown on a 0–1 scale. Bold/underline mark the highest/second-highest value in each column across all rows, and green parentheses give the Physical Registry change over the backbone above it.

Model	Scene	Motion			Semantics			Diversity
	Consist.	HSD	NDTW	DYN	BLEU	CLIP	Logic	Div.
Cosmos 3 Nano 16B (NVIDIA et al., 2026)	0.855	0.328	0.305	0.383	<u>0.242</u>	0.884	0.921	0.029
+Physical Registry	0.895 (+0.040)	0.351 (+0.023)	0.378 (+0.073)	0.459 (+0.076)	0.244 (+0.002)	0.897 (+0.013)	0.921	0.018 (-0.011)
EnerVerse-FT* (Huang et al., 2025)	<u>0.943</u>	0.536	0.596	<u>0.536</u>	0.180	0.864	0.978	<u>0.069</u>
LTX-FT* (HaCohen et al., 2024)	0.944	<u>0.476</u>	<u>0.521</u>	0.620	0.174	0.855	<u>0.967</u>	0.016
Kling* (Kuaishou Technology, 2024)	0.889	0.323	0.316	0.305	0.168	0.854	<u>0.967</u>	0.049
Hailuo* (MiniMax, 2024)	0.858	0.223	0.179	0.134	0.185	<u>0.886</u>	0.911	0.037
COSMOS* (NVIDIA et al., 2025a)	0.796	0.250	0.253	0.205	0.123	0.846	0.733	0.080
OpenSora* (Zheng et al., 2025)	0.921	0.155	0.142	0.047	0.160	0.851	0.822	0.042
LTX* (HaCohen et al., 2024)	0.916	0.158	0.143	0.100	0.069	0.832	0.733	0.017

* Published in the EWMBench evaluation table (Hu et al., 2025, Table 2), evaluated on ten tasks with ten ground-truth episodes each; the public ground-truth release used here covers 21 episodes across seven tasks. EnerVerse-FT and LTX-FT are adapted to the benchmark’s robot domain; our models are not.

Results. Physical Registry improves scene consistency and all three motion metrics (Table 11). The largest gains are in trajectory agreement, where NDTW rises by 0.073 and DYN by 0.076. Semantic metrics change by at most 0.013. Diversity, the spread across the three seeds, decreases from 0.029 to 0.018.

F THE PHYSICAL REGISTRY SELECTOR

F.1 AGGREGATION AND PROTOCOL

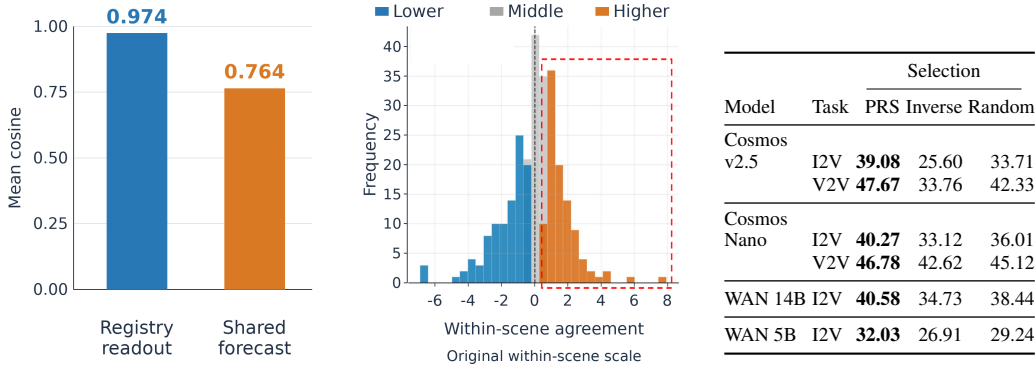
We apply the PRS rule in Equation (11) to candidates generated from the same conditioning input. Each cosine is evaluated before slot–step averaging. Prefix selection follows the PRS settings in Table 12. The registry subset $\mathcal{S}$ is the contiguous range of registry slot positions with the largest departure from the shared forecast. Nano[†] averages over the latest $\min(K, 10)$ evaluations. Prefix-selected quality is measured on the chosen candidate’s completed video under its original 35- or 50-step schedule.

With N candidates and a full trajectory of D steps, continuing one candidate after K prefix steps gives a serial denoising budget of $NK + (D - K)$ candidate-steps, compared with ND for completing all candidates. All selection budgets are reported in these serial denoising candidate-steps. In the completed-video best-of- N (BoN) comparison, WMReward scores decoded candidates with its external world model (Yuan et al., 2026). Relative gains of PRS over Plain are computed as $100(\text{PRS} - \text{Plain})/\text{Plain}$. All reported selection policies and Oracles use ten candidates per input. For backbone rows marked *, Plain is the published reference, while WMReward and Oracle select from our own ten-candidate pool of that backbone; Physical Registry rows use their own pool for every column.

Table 12: **Selection policies on Physics-IQ Verified.** WMReward and PRS each select one candidate from our ten-candidate pool; Oracle is the best in that pool, an upper bound rather than a policy. * marks published Plain values, external to the pool, and [†] the configuration in Table 2. Bold marks the strongest non-Oracle score in each row, gray unavailable PRS.

I2V	Plain	WMReward	PRS	Oracle
Cosmos 3 Nano 16B	30.18 ± 0.84	31.69		41.48
+ Physical Registry	36.01 ± 0.95	38.85	40.27	51.88
Cosmos 3 Nano 16B [†]	37.3 ± 0.9*	44.28		50.59
+ Physical Registry [†]	43.56 ± 0.95	45.41	45.81	54.72
Cosmos v2.5 2B	30.65 ± 0.37	30.61		36.07
+ Physical Registry	33.71 ± 1.11	37.74	39.08	49.37
WAN 2.2 I2V-A14B	32.2 ± 0.6*	35.31		43.71
+ Physical Registry	38.44 ± 1.06	41.82	40.58	51.87
WAN 2.2 TI2V-5B	27.7 ± 0.9*	31.19		37.76
+ Physical Registry	29.24 ± 1.30	33.18	32.03	39.88
V2V	Plain	WMReward	PRS	Oracle
Cosmos 3 Nano 16B	38.78 ± 0.78	42.46		49.09
+ Physical Registry	45.12 ± 0.94	49.70	46.78	59.43
Cosmos 3 Nano 16B [†]	46.45 ± 0.76	50.41		56.98
+ Physical Registry [†]	49.54 ± 0.63	51.69	52.06	59.69
Cosmos v2.5 2B	37.40 ± 0.53	39.38		42.60
+ Physical Registry	42.33 ± 1.90	46.59	47.67	55.84

Figure 10: **Candidate-conditioned registry readouts and selection direction.** (a) Mean cosine to the generated-video reference: the terminal readout tracks the candidate more closely than the shared forecast (0.974 versus 0.764). (b) Within-scene readout–generated-video agreement. (c) PRS against controls per backbone and task: Random is uniform selection in the same pool and Inverse the reversed ranking.



F.2 DIRECTION AND CONSISTENCY

The registry readout tracks the realized candidate. For each completed candidate $v_{\text{gen}}^{(n)}$, we encode the generated video with the same frozen target encoder to obtain a diagnostic reference $Z_{\text{gen}}^{(n)}$. Figure 10(a) compares this reference with the terminal registry readout and with the shared observation-conditioned forecast. The terminal readout has a higher mean cosine similarity to the generated-video reference than the shared forecast (0.974 versus 0.764). This shows that, after interacting with the evolving video tokens, the registry more closely reflects the future realized by the candidate than the common forecast from which it was initialized.

This candidate dependence is visible within scenes. Figure 10(b) resolves the same comparison within individual scenes, showing variation in readout–generated-video agreement across candidates that share the same observation-conditioned forecast. Thus, the terminal registry is not merely preserving the common initialization: its readout varies with the trajectory produced by each candidate.

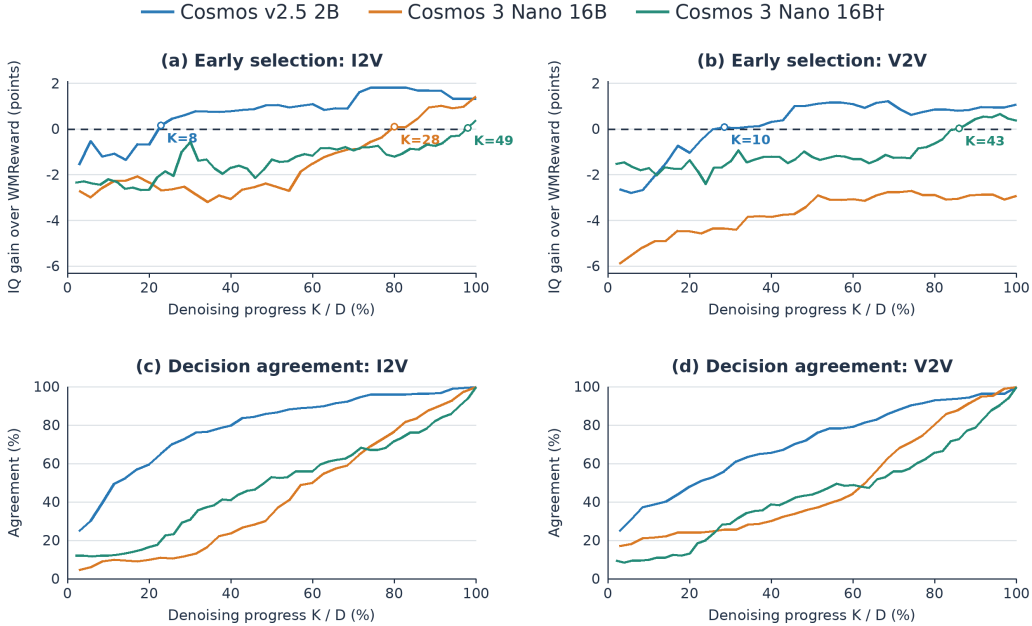
Selection direction. PRS outperforms both the reversed ranking (Inverse) and uniform selection (Random) in every configuration (Figure 10(c)), supporting the direction in Equation (11). The direction also holds for smaller pools: averaged over all pools of four to six candidates drawn from the ten, PRS keeps positive gains over both controls, and paired scenario-level bootstrap intervals exclude zero. Against completed-video WMReward, PRS is comparable while selecting before the candidates are fully denoised. Within inputs, departure is also positively rank-correlated with Verified quality (e.g., Spearman 0.297 [0.209, 0.383] for Cosmos v2.5 I2V at pool size four). Entries below are PRS-minus-control gains in Physics-IQ Verified points with 95% intervals.

Model	Pool	Task	Inverse	Random	WMReward
Cosmos v2.5 2B	6	I2V	+12.58 [9.19, 16.08]	+5.07 [3.01, 7.23]	+1.33 [-0.45, 3.33]
	6	V2V	+12.69 [8.60, 17.04]	+4.90 [2.85, 7.09]	+0.60 [-0.64, 1.92]
	5	I2V	+11.46 [8.39, 14.66]	+4.73 [2.94, 6.59]	+1.24 [-0.24, 2.98]
	5	V2V	+11.37 [7.70, 15.34]	+4.50 [2.65, 6.48]	+0.22 [-0.84, 1.36]
	4	I2V	+10.05 [7.34, 12.85]	+4.32 [2.80, 5.87]	+1.05 [-0.16, 2.49]
	4	V2V	+9.86 [6.62, 13.30]	+4.08 [2.48, 5.81]	-0.05 [-0.91, 0.87]
WAN 2.2 I2V-A14B	6	I2V	+4.35 [2.53, 6.28]	+1.82 [0.92, 2.74]	-0.51 [-1.31, 0.30]
	5	I2V	+3.99 [2.32, 5.76]	+1.71 [0.88, 2.55]	-0.47 [-1.19, 0.25]
	4	I2V	+3.53 [2.04, 5.10]	+1.56 [0.83, 2.31]	-0.42 [-1.05, 0.20]

F.3 EARLY SELECTION

Figure 11 compares table-aligned prefix selection for Cosmos v2.5 and the two Nano configurations. Cosmos v2.5 first exceeds WMReward after 8/10 steps on I2V/V2V. At ten steps, Cosmos v2.5 selection already slightly exceeds completed-video WMReward on both tasks. It agrees with the full-schedule PRS decision on 72.7%/56.1% of I2V/V2V inputs, and this agreement increases as more denoising steps are used for selection (Figure 11c,d).

Figure 11: **Early selection and decision agreement.** (a,b) Prefix-selected Physics-IQ Verified gain over WMReward using the PRS settings in Table 12; zero marks the WMReward reference. (c,d) Agreement with the full-schedule PRS decision. Horizontal axes show the fraction of denoising steps used for selection. [†] denotes the expanded-prompt Nano configuration in Table 2. Protocol: Appendix F.1.



F.4 SELECTION COST

Continuing only the selected candidate saves candidate-steps as well as the decodes and reward evaluations that completed-video selection needs. Table 13 times both policies end to end on the same Physical Registry model, using $K = 10$ as an illustrative prefix length; Table 12 reports quality under the PRS settings, and Figure 11 shows quality as a function of the prefix length. On Cosmos v2.5 the measured wall-clock ratio is $2.84\times$ against the $2.80\times$ (64%) candidate-step reduction reported in Section 4.4. Across backbones, measured wall-clock speedups range from $2.84\times$ to $4.06\times$ and broadly track the reduction in candidate-steps, while also reflecting backbone-specific sampling, decoding, and reward-evaluation costs.

Table 13: **End-to-end cost of selection.** One input, $N = 10$ candidates, both policies run on the same Physical Registry model inside one job on a single H100 80 GB; model loading is excluded. Complete BoN times sampling, all ten VAE decodes, and the ten WMReward evaluations; PRS times the ten prefixes, the continuation of the selected candidate, and its single decode. $K = 10$ is an illustrative prefix length. [†] Expanded-prompt setting (Table 7).

Backbone	Policy	Candidate-steps	Decodes	Wall-clock (s)	Speed-up
Cosmos v2.5 2B	Complete BoN + WMReward	350	10	4,031	$1.00\times$
	PRS ($K = 10$ of $D = 35$)	125	1	1,420	$2.84\times$
Cosmos 3 Nano 16B [†]	Complete BoN + WMReward	500	10	1,985	$1.00\times$
	PRS ($K = 10$ of $D = 50$)	140	1	614	$3.23\times$
WAN 2.2 I2V-A14B	Complete BoN + WMReward	400	10	10,748	$1.00\times$
	PRS ($K = 10$ of $D = 40$)	130	1	3,289	$3.27\times$
WAN 2.2 TI2V-5B	Complete BoN + WMReward	500	10	2,834	$1.00\times$
	PRS ($K = 10$ of $D = 50$)	140	1	697	$4.06\times$

G MOTION TRANSFER

G.1 SETUP AND SCOPE

To test whether registry content can influence generated motion, we replace the native forecast of a receiver scene (the white-sphere scene) with source-video JEPA features on Cosmos 3 Nano 16B with Physical Registry. Both configurations use the white-sphere image and general prompt shown in Figures 12 and 13. The conditioning image, text, initial noise, and sampler are held fixed. The text specifies no falling, bouncing, or settling behavior.

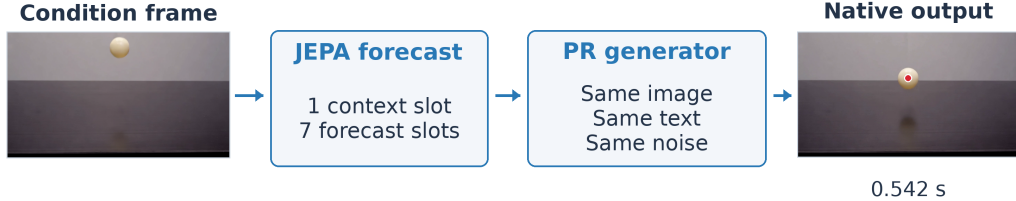
Experimental setup. The native-forecast configuration combines one source-context feature with seven predicted features. The transfer configuration instead uses eight features from a frozen JEPA video encoder applied to the source video. Both representations have shape $8 \times 196 \times 5632$ and enter the same trained projection and video-generation interface. The source features are full video representations, containing scene content as well as dynamics. For this comparison, both configurations use the same factor-two amplification of the projected registry residual in the conditional branch, $P(0) + 2[P(J) - P(0)]$. The unconditional branch uses $P(J)$ without amplification. Here P is the trained projection and J the chosen registry input. Both receiver outputs use the same inference configuration: 50 denoising steps, classifier-free guidance scale 3.0, flow shift 4.75, and 1280×720 outputs with 121 frames at 24 fps.

Figure 12: **Registry-source configurations for motion transfer.** The native configuration uses the conditioning image’s JEPA context and forecast; the transfer configuration uses video-encoded features from the source video. Both use the same conditioning frame, general text, initial noise, and projection recipe. The exact prompt is shown in a monospace block and contains no motion description.

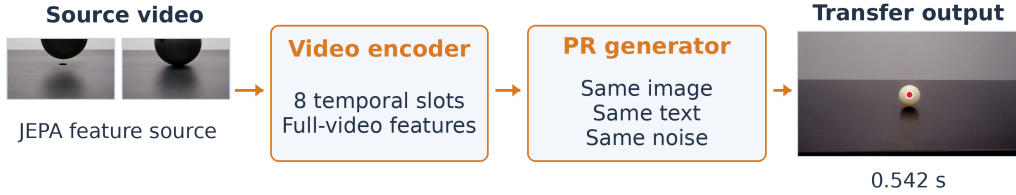
Shared general prompt (no motion description)

A small smooth white sphere and a plain tabletop in a fixed-camera side view. Neutral background, consistent lighting, one continuous shot.

A: Native forecast



B: Source-feature transfer



Conditional projection: $P(0) + 2 [P(J) - P(0)]$
Only the registry input changes; red dots mark ball centers.

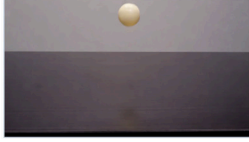
G.2 SOURCE EXAMPLES

Each example compares two generations that share the conditioning image, prompt, initial noise, and sampler: A uses the native forecast, and B replaces it with the source video’s JEPA features.

Bowling ball: bounce suppression. In the source video, a heavy bowling ball lands and stays on the table. With the native forecast, the generated ball (A) bounces three times with decreasing

Figure 13: **Motion transfer with matched inputs.** The source video supplies JEPA features; A and B are generated videos. Red dots track ball centers and rows share timestamps. The plot shows the upward return $r(t) = \max_{s \leq t} y(s) - y(t)$, with image y increasing downward, over the second after A's first landing (0.333 s). B first lands at 0.417 s. Numbers mark A's three diminishing returns.

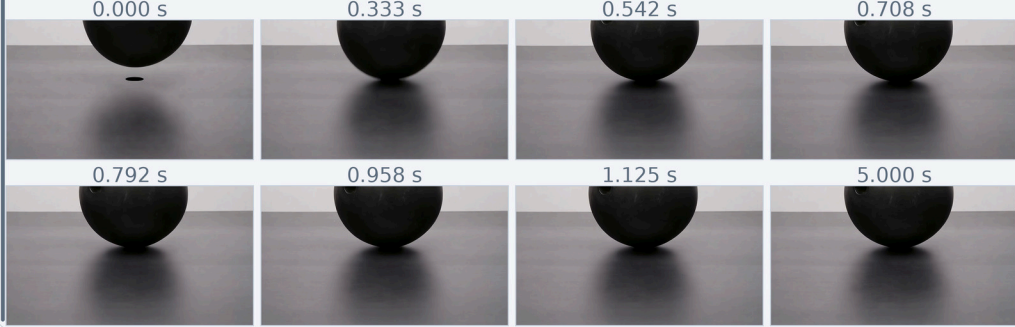
Condition frame



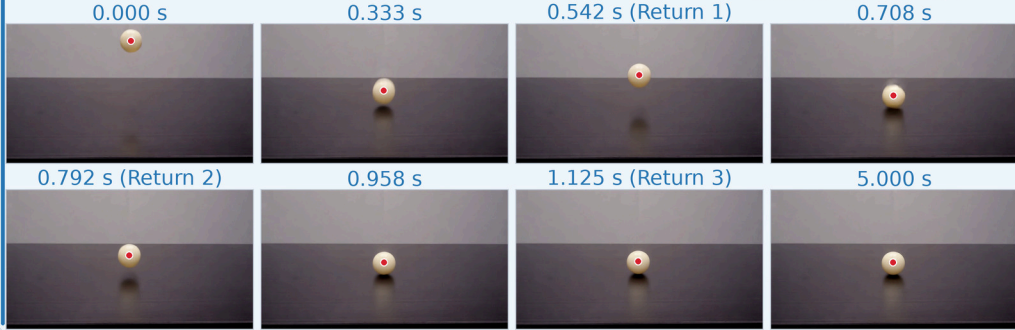
Shared general prompt (no motion description)

A small smooth white sphere and a plain tabletop in a fixed-camera side view. Neutral background, consistent lighting, one continuous shot.

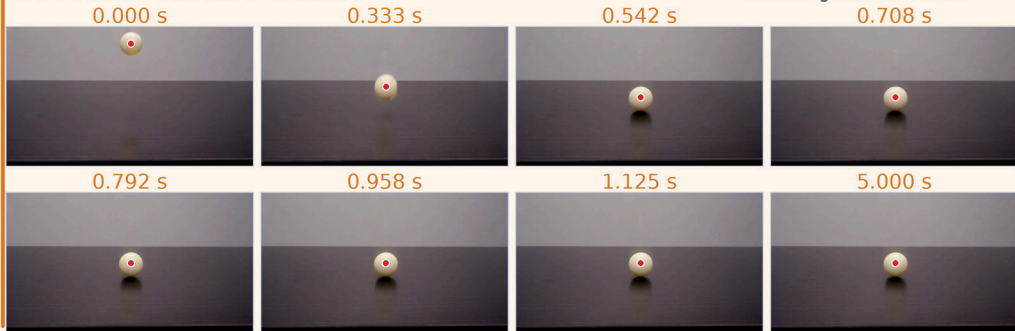
Source video



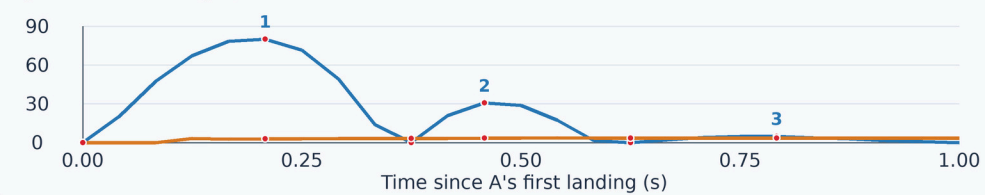
A: Native forecast



B: Source-feature transfer



Upward return (px)



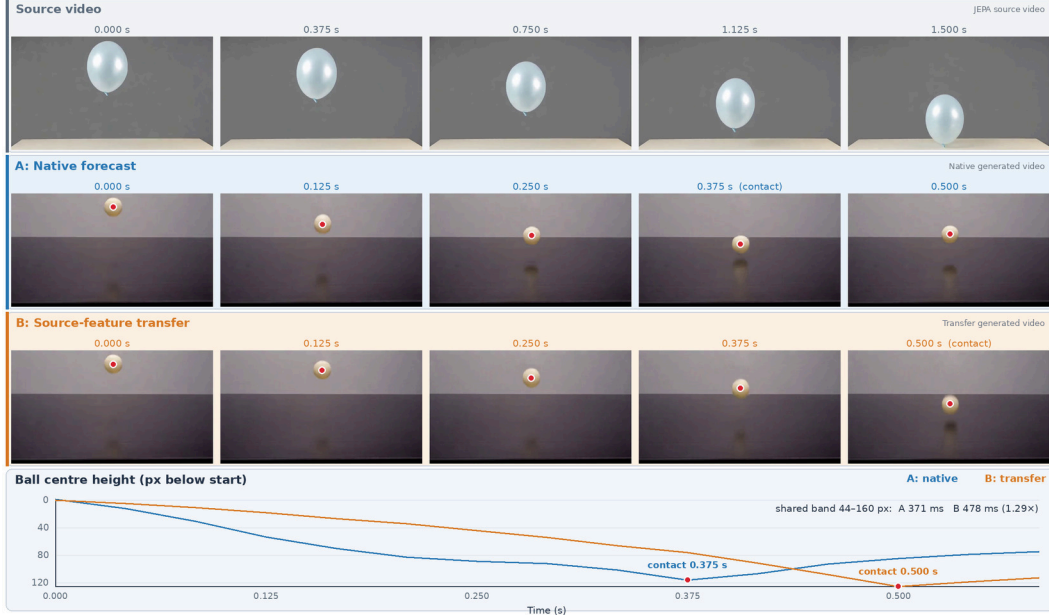
height before settling. With the bowling-ball features (B), it lands and settles with almost no rebound (Figure 13), and the maximum upward return drops from 80.1 to 3.6 pixels (Table 14).

Table 14: **Image-plane ball-center movement in the matched pair.** Both outputs use Cosmos 3 Nano 16B with Physical Registry, over all 121 frames. Image y increases downward, and distances are image-plane pixels. Definitions in Figure 13.

Configuration	Valid frames	Vertical span	Upward return	Path length
A: Native forecast	121/121	289.7	80.1	526.9
B: Transfer	121/121	281.1	3.6	290.9

Balloon: slower descent. In the source video, a balloon descends slowly to the table, so we compare the descent before contact. With the balloon features (B), the ball descends more slowly than with the native forecast (A) (Figure 14). It takes 478 instead of 371 ms ($1.29\times$) to pass through the same height range, and first contact moves from 0.375 to 0.500 s. The rebound after contact also drops from 40.9 to 12.1 pixels. First-frame silhouette areas differ by only 1.0%, so the slower descent is not explained by a change in ball size.

Figure 14: **Descent transfer from a slow-descent source.** A and B share the prompt, initial noise, sampler, and amplification, and differ only in the registry source. Red dots track ball centers and rows share timestamps. The plot follows each center to first table contact, with image y increasing downward and contact marked on each curve.



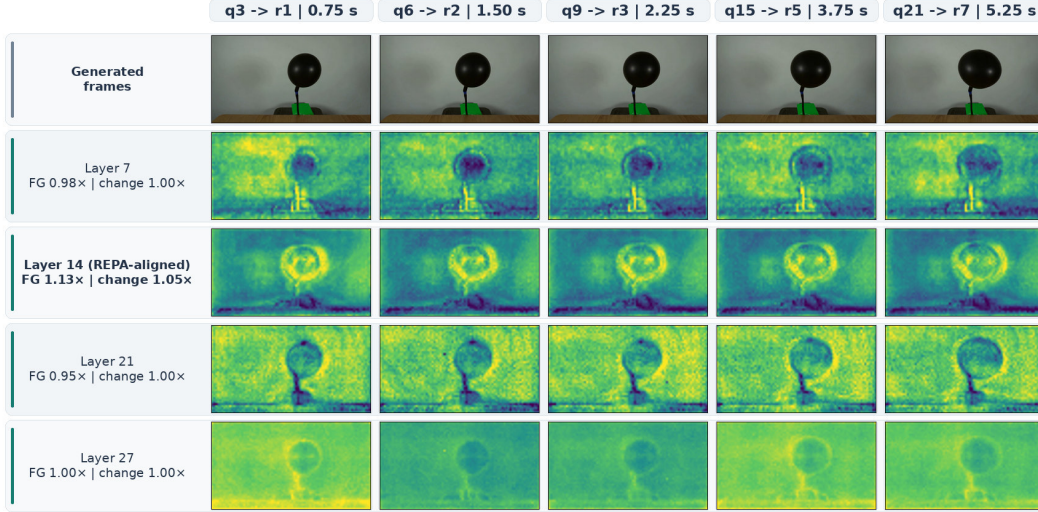
Changing only the registry content changes the generated motion, indicating that the generator uses the registry’s predicted dynamics when producing motion.

H EXTENDED MECHANISTIC DIAGNOSTICS

H.1 REGISTRY FEATURE VISUALIZATION

Registry activation maps characterize the spatial organization of each registry slot. The main-text visualization in Section 4.6 aligns five future times from one balloon-inflation trajectory and visualizes entity and action conditioning, foreground-query attention to video tokens and to the aligned registry slots, and slot-wise registry activation.

Figure 15: **Registry feature organization across DiT layers.** Columns align five generated frames with their registry slots. Heat rows show hidden channel variance at denoising step 16 for layers 7, 14, 21, and 27. Each layer uses an independent viridis log scale over all eight slots, so colors preserve within-layer slot magnitude.



Per-layer log scales use all eight registry slots; displayed columns retain within-layer magnitude. Metrics use unnormalized maps.

For the depth sweep, we fix denoising step 16 and measure variance across hidden feature channels at every registry token. Layers 7, 21, and 27 retain broad scene-level activation, while the alignment-supervised layer 14 exhibits a response around the balloon and expanding contour. At this layer, foreground enrichment is $1.13\times$ and change-region enrichment is $1.05\times$. This layer shows the largest measured enrichment among these four layers. Enrichment is measured on the unnormalized maps.

I QUALITATIVE COMPARISONS

I.1 ADDITIONAL QUALITATIVE COMPARISONS

Figure 16 covers the five physics categories of Figure 3 on Cosmos v2.5, and Figures 17 and 18 provide additional comparisons on the same backbone. In each block, the top row shows the backbone and the bottom row shows Physical Registry built on the same backbone. Both rows start from the same conditioning input, and frames are sampled at eight equally spaced times of the generated sequence.

In these examples, Physical Registry completes several intended events that the backbone leaves unrealized, while avoiding some duplicated or spurious objects. On Cosmos v2.5 (Figure 16), Physical Registry propagates the domino topple after contact and extinguishes a lit match once it reaches the water. In set A (Figure 17), the backbone duplicates the released ball and the magnet-sequence block, while Physical Registry keeps each single. In set B (Figure 18), Physical Registry flattens the styrofoam cup under the descending kettlebell, while the backbone leaves it standing.

Figure 16: **Qualitative comparisons on Cosmos v2.5.** One scenario per physics category, with the layout of Figure 3; here the top row is the Cosmos v2.5 backbone.

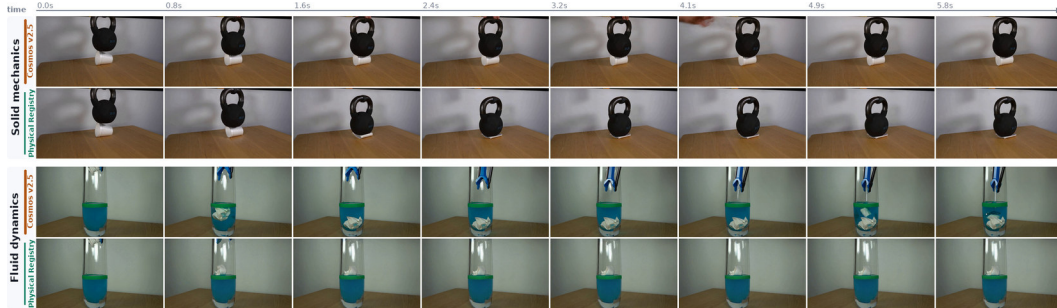


I.2 WORLDMODEL BENCH QUALITATIVE EXAMPLES

Figures 19 and 20 show eight WorldModelBench generations from Cosmos 3 Nano 16B with Physical Registry, grouped into robotics and driving/industrial/natural scenes. Each text prompt is followed by eight evenly spaced generated frames in a large 4×2 storyboard, read left to right and then top to bottom. These examples illustrate the range of robotics, driving, industrial, and natural-scene prompts covered by the evaluation.

I.3 ADDITIONAL ATTENTION AND REGISTRY VISUALIZATIONS

We extend Figure 5 with six Physics-IQ examples spanning solid mechanics, fluid dynamics, optics, and magnetism (Motamed et al., 2026). All panels show the same six rows: generated frames, entity and action cross-attention, self-attention to video and registry slots, and registry activation. Captions identify entity words and event verbs. Appendix A gives the visualization protocol. Across these

Figure 17: **Additional qualitative comparisons (set A).** Layout as in Figure 3.Figure 18: **Additional qualitative comparisons (set B).** Layout as in Figure 3.

examples, registry attention and activation tend to concentrate more locally around interacting or changing regions, whereas text cross-attention is often broader.

Figure 19: **WorldModelBench** robotics examples (Cosmos 3 Nano 16B with Physical Registry). Each prompt is followed by eight frames, read left to right and top to bottom; times are in seconds.

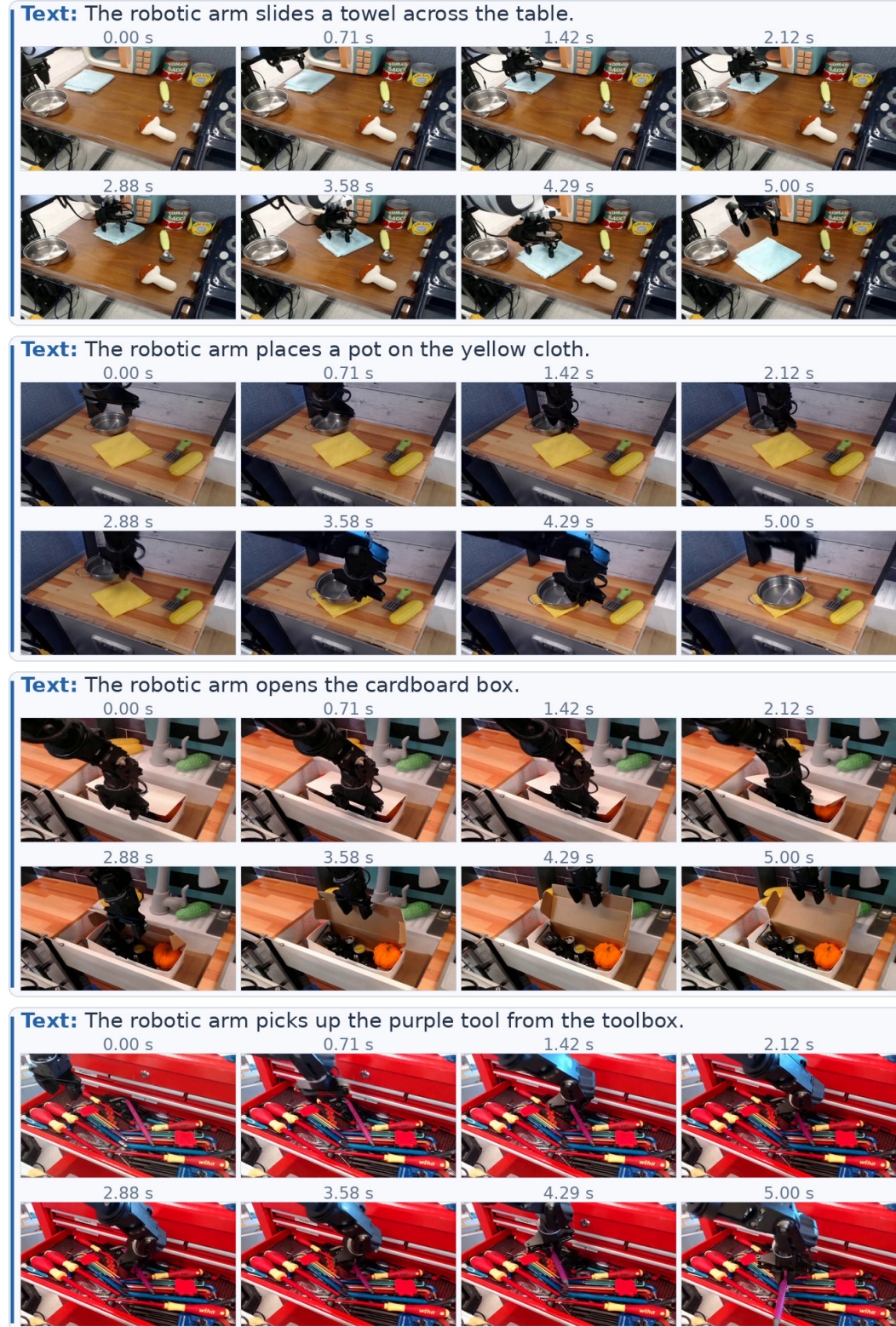


Figure 20: **WorldModelBench driving, industry, and nature examples (Cosmos 3 Nano 16B with Physical Registry).** Layout as in Figure 19.

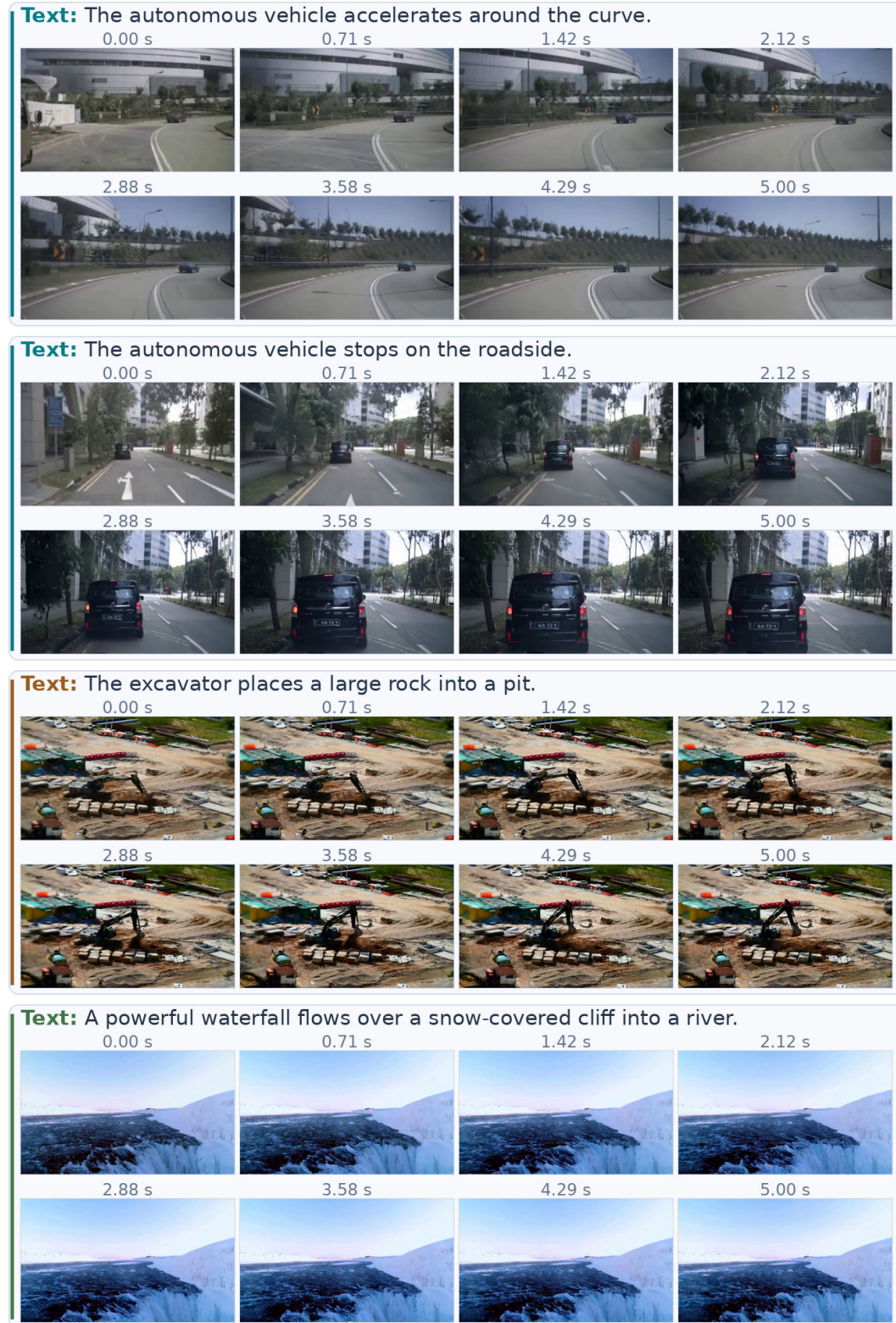


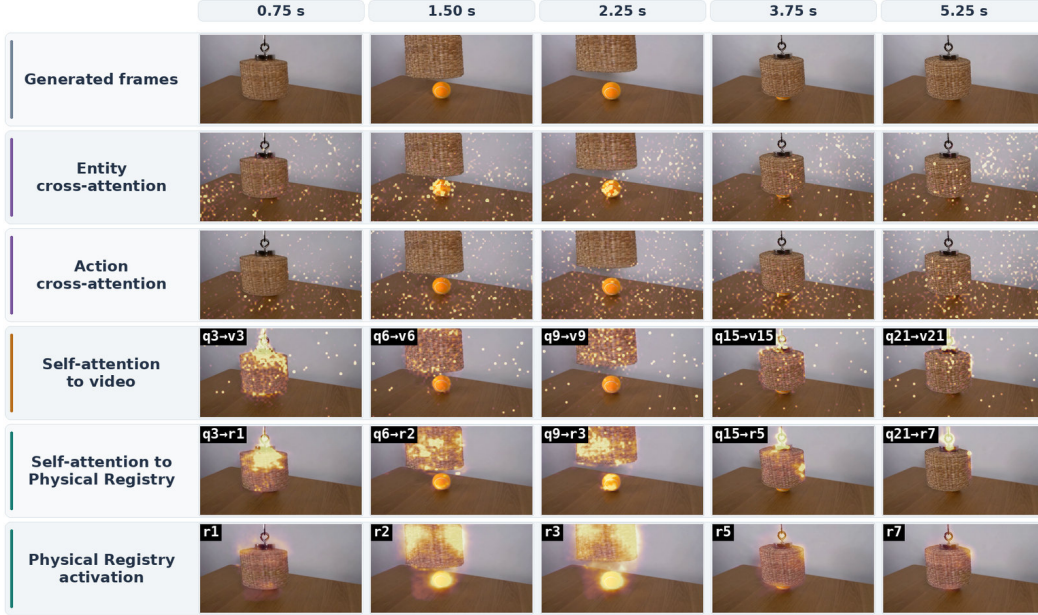
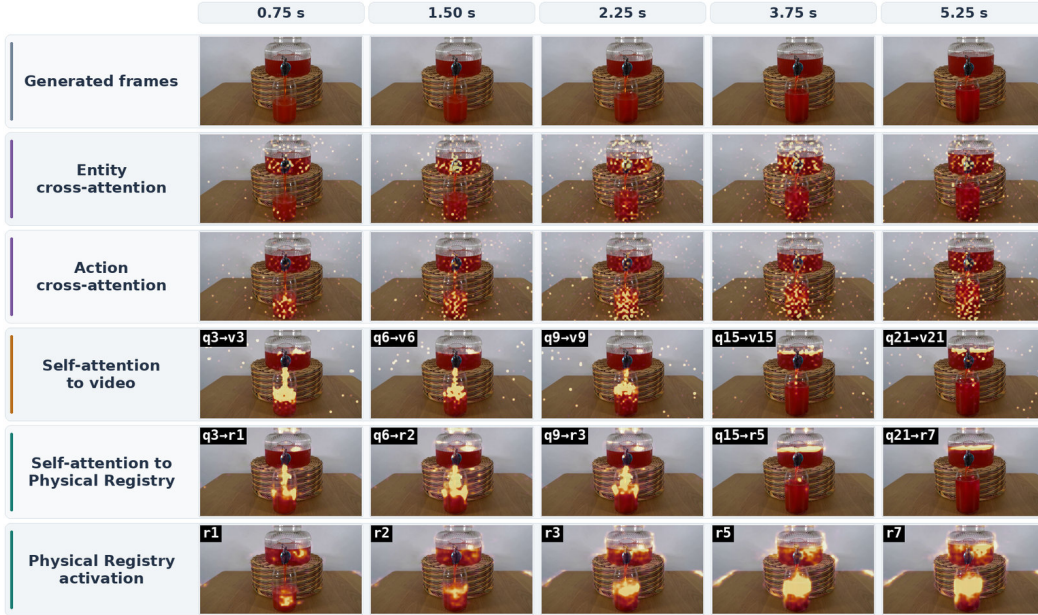
Figure 21: **Solid mechanics: object occlusion.** Entity text: *ball*. Action text: *lowered*.Figure 22: **Fluid dynamics: filling a glass.** Entity text: *glass, red*. Action text: *filled*.

Figure 23: **Optics: a mug and its cast shadow.** Entity text: *mug*. Action text: *placed, rotating, rotates, casting*.

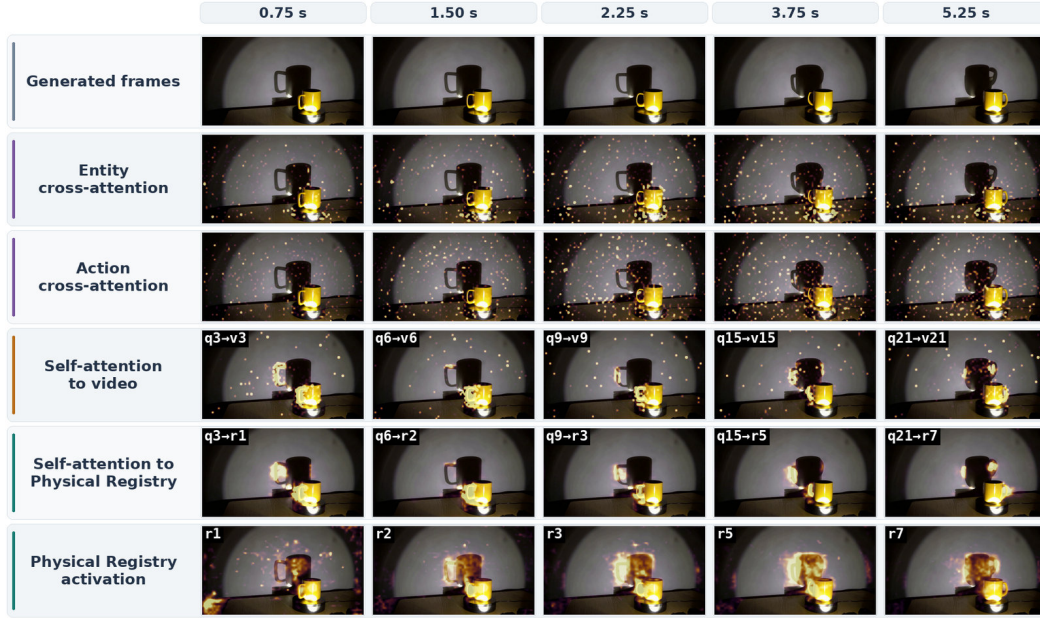


Figure 24: **Magnetism: a magnet–domino interaction.** Entity text: *domino, magnet*. Action text: *placed, rotating*.

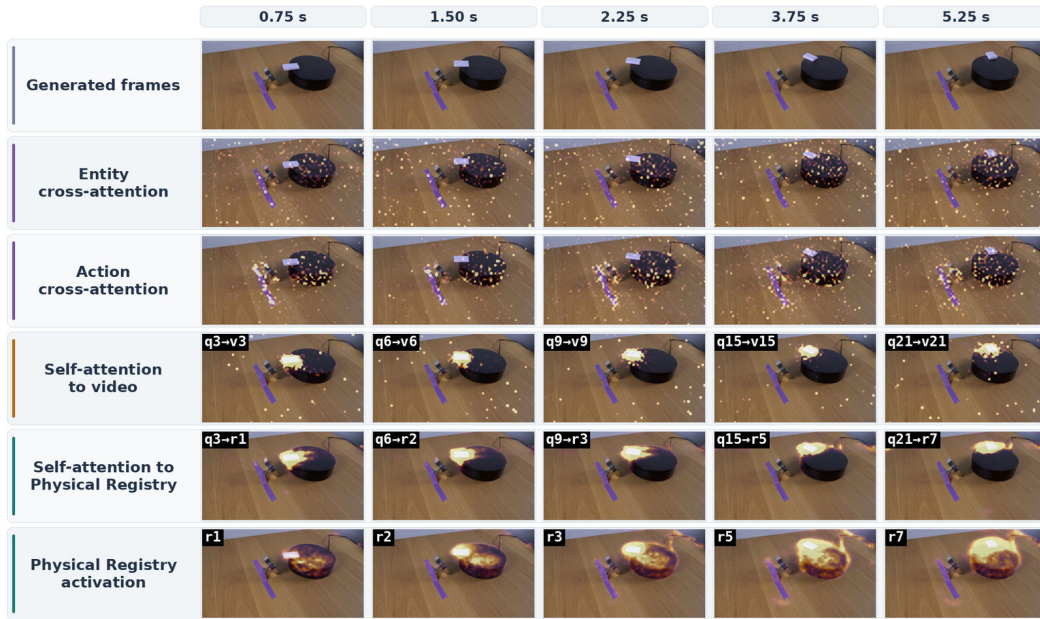
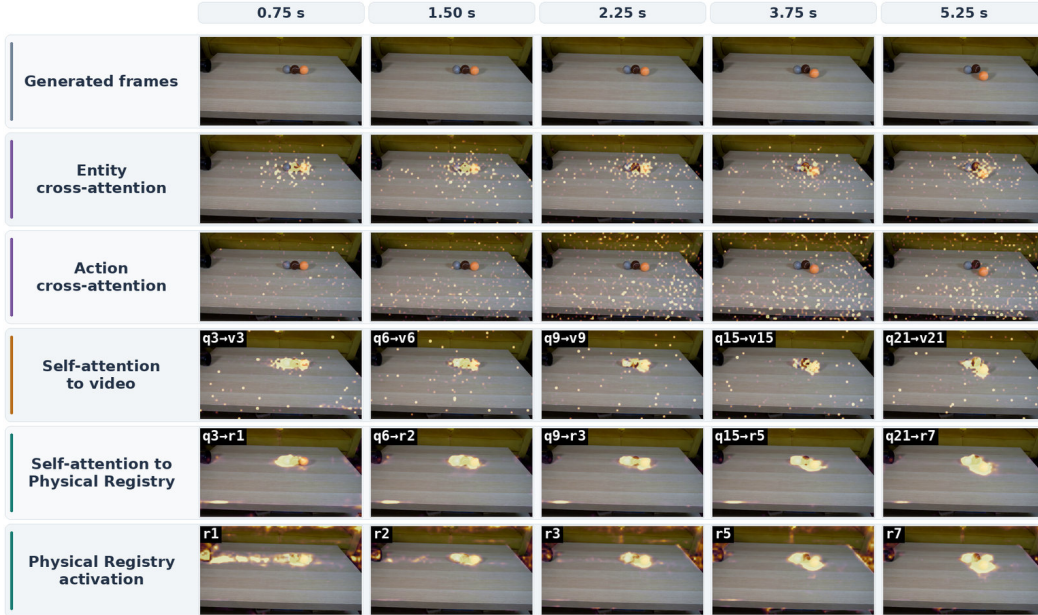


Figure 25: **Solid mechanics: rolling-ball interaction.** Entity text: *ball, balls*. Action text: *rolls*.Figure 26: **Fluid dynamics: pouring liquid over a duck.** Entity text: *liquid, duck*. Action text: *pours*.