RoboWM-Bench: A Benchmark for Evaluating World Models in Robotic Manipulation

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Abstract

*Recent advances in large-scale video world models have enabled realistic future prediction, suggesting potential for robot learning from imagined videos. However, visual realism does not imply physical plausibility, and behaviors from such videos may fail in real-world execution. Existing benchmarks consider plausibility but mainly focus on perception, lacking an evaluation of whether predicted behaviors can translate into successful actions. We introduce **RoboWM-Bench**, a manipulation-centric benchmark for embodiment-grounded evaluation of video world models. This benchmark converts behaviors from both human-hand and robotic manipulation videos into embodied actions and validates them through execution. It spans diverse manipulation scenarios and establishes a unified and reproducible protocol. Evaluation of state-of-the-art video world models shows that generating physically executable behaviors remains challenging, with failures in spatial reasoning, contact stability, and physical realism. While finetuning on manipulation data yields improvements, physical inconsistencies still persist, suggesting opportunities for more physically grounded video generation for robots. The project webpage can be accessed at RoboWM-Bench.*

1. Introduction

Recent advances in video world models, such as Sora [4], Veo [12], Wan [28], and SeeDance [10], have enabled realistic and temporally coherent future predictions, opening new opportunities for robot learning from generated videos. However, despite impressive visual fidelity, they may generate behaviors that violate physical consistency when grounded in real-world dynamics. Motivated by this challenge, recent work adapts world models to robotic manipulation, seeking to better capture embodiment-aware interaction, as seen in GigaWorld [27], Enerverse [13], WOW [7], and related efforts [1, 2, 5]. As these models improve, imagined manipulation videos from models are increasingly viewed as scalable training data, as demonstrated by GigaBrain [11, 26], DreamGen [15], and LVP [5]. In this context, reliable evaluation is crucial for assessing world models and ensuring physically grounded policies.

Existing benchmarks for world models primarily emphasize visual fidelity, semantic consistency, and temporal coherence [9, 14, 16, 21, 22, 32]. More recent efforts incorporate physical plausibility, revealing that SOTA models often fail to maintain coherent physical dynamics despite strong perceptual quality [25, 33, 34]. While these evaluations represent important progress, they remain largely perception- or diagnostic-oriented. To reliably assess predicted videos, evaluation should extend beyond perceptual plausibility to consider whether the predicted behaviors can be faithfully executed by embodied agents and successfully accomplish the intended tasks. A recent study [8] moves toward embodiment-grounded evaluation by validating executability on real robots. However, comprehensive evaluation requires broader coverage and greater task diversity, and its reliance on real-world testing makes large-scale, reproducible benchmarking challenging.

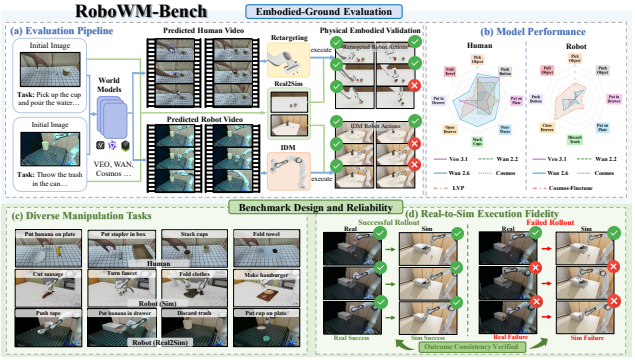


Figure 1. **RoboWM-Bench** evaluates video world models through embodiment-grounded execution. (a) Predicted human-hand and robotic manipulation videos are converted into executable actions via retargeting or inverse dynamics model (IDM) and validated in real-to-sim simulation environments. (b) The benchmark compares execution performance across state-of-the-art video world models for human-hand and robotic manipulation. (c) RoboWM-Bench covers diverse tasks spanning different object properties, interaction dynamics, temporal horizons, and coordination requirements. (d) Real-to-sim fidelity is evaluated by replaying identical real-world trajectories in reconstructed simulations and comparing the resulting task outcomes.

In this paper, we introduce **RoboWM-Bench**, a systematic and reproducible manipulation-centric benchmark for embodiment-grounded evaluation of video world models. RoboWM-Bench operationalizes *physical executability* as a principled and measurable evaluation criterion, grounding assessment in verifiable control execution rather than perceptual judgment alone. Specifically, the benchmark evaluates whether interactions predicted in generated videos can

be translated into executable action sequences and successfully performed in a physically grounded environment.

As illustrated in Figure 1, given initial observations and task descriptions, video world models generate future manipulation videos involving either human hands or robot arms. The predicted behaviors are then converted into embodied action sequences through inverse dynamics modeling [3, 15] for robotic videos, or pose tracking and retargeting [18, 19, 24] for human demonstrations. To enable fair and accessible evaluation across real-world scenarios, we adopt a real-to-simulation (real-to-sim) framework in which scenes are reconstructed in simulation to match their real-world counterparts [6, 30]. The extracted actions are then executed within the reconstructed environments using visually and physically high-fidelity simulation, enabling standardized and reproducible validation of physical executability. RoboWM-Bench spans a broad spectrum of manipulation scenarios, including diverse object dynamics, short- and long-horizon tasks, and both single-arm and bimanual interactions. Through this unified protocol, RoboWM-Bench enables consistent and reproducible comparison of video world models under embodiment constraints. It also provides hierarchical evaluation, incorporating both step-level executability metrics and final task-level success rates, which together enable fine-grained diagnostic analysis as well as holistic performance assessment.

We evaluate video world models on RoboWM-Bench under embodied execution. The results suggest a noticeable gap between visual realism and physical executability, with success rates decreasing as task complexity increases. Qualitative analysis reveals common inconsistencies in generated videos, including unrealistic object deformation and inaccurate contact prediction, which may lead to dynamically infeasible actions. While fine-tuning on manipulation data improves executability, some physical inconsistencies remain. These observations suggest that ensuring physically consistent behavior remains a challenge, and highlight opportunities for advancing more physically grounded and embodiment-aware world modeling.

2. RoboWM-Bench

2.1. Benchmark Overview

RoboWM-Bench evaluates video world models via physical executability across human and robotic manipulation. Given an observation and task, world-model-predicted videos are converted into actions (Sec. 2.2) and executed in real-to-sim environments for reproducible evaluation (Sec. 2.3). The benchmark spans a diverse suite of tasks (Sec. 2.4), with executability determined by whether the intended task objective is achieved (Sec. 2.5).

2.2. Embodied Video-to-Action Execution

RoboWM-Bench evaluates both human-hand and robotic manipulation videos. While human-centric predictions often exhibit higher visual quality, robotic videos align more directly with downstream control.

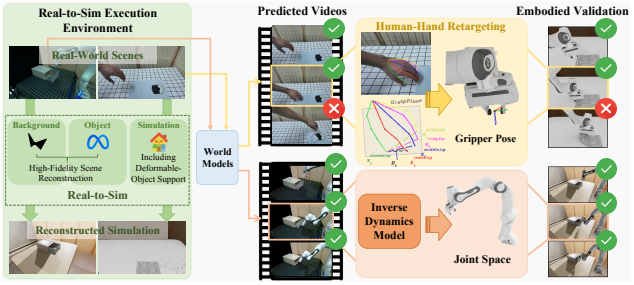


Figure 2. **Pipeline of RoboWM-Bench.** We reconstruct real-world scenes into simulation for reproducible evaluation. Video predictions are mapped to actions via human-centric retargeting or robot-centric inverse dynamics. The resulting actions are executed in simulation to evaluate embodied executability.

2.2.1. Human-Centric Retargeting.

Following [18, 19], we estimate 3D human hand poses via HaMeR [24] and retarget them to robot end-effector (EE) poses. The EE position is defined as the thumb-index midpoint. To improve orientation stability over prior formulations [19], we project the thumb and index fingertips onto a fitted plane; the x-axis connects these projections, while the z-axis is the plane normal, better preserving interaction geometry. For gripper aperture, we use the minimum distance between the thumb and all other fingertips to capture diverse contact points. Finally, we apply trajectory smoothing and temporal denoising to stabilize the retargeted motion [19].

2.2.2. Robot-Centric Execution.

For robotic videos, we recover joint-space actions via an inverse dynamics model (IDM) [3, 15]. The IDM takes consecutive frames as input to predict intermediate action chunks [15]. To optimize training, we employ a two-stage strategy: (1) **Simulation Pretraining**: We collect large-scale, high-frequency (80Hz) robot trajectories in simulation for smooth motion supervision. To bridge the sim-to-real gap, we adopt a background-masking strategy [27], isolating the robot arm to minimize domain discrepancies. (2) **Real-world Finetuning**: The IDM is finetuned on a small real-world dataset without masking. This pipeline enhances data efficiency and sim-to-real generalization, ensuring reliable action extraction for robotic benchmarks.

2.3. High-Fidelity Real-to-Sim Framework

RoboWM-Bench conducts evaluation in open-source simulation to ensure accessibility and reproducibility. Built on the LeHome framework [20], our pipeline supports high-fidelity rendering and realistic physics. For real-to-sim reconstruction, we adopt a modular pipeline: (1) **Scene Reconstruction.**: Backgrounds are represented via 4D Gaussians [30] for visual and spatial consistency. (2) **Object Assets**: Rigid geometries are acquired through 3D segmentation [6], while articulated and deformable models follow [20]. (3) **State Initialization**: Initial poses are es-

Table 1. Task-level and step-level embodied execution success rates (%) on RoboWM-Bench across human-hand and robotic tasks.

Method	Human (Task Level)								Human (Step Level)				
	Pick Object	Push Button	Put on Plate	Pour Water	Stack Cups	Open Drawer	Put in Drawer	Fold Towel	Put in Drawer				
									contact	lift	above drawer	in drawer	close drawer
Cosmos	23%	40%	15%	0%	10%	10%	10%	0%	80%	20%	20%	20%	10%
Wan 2.2	57%	80%	55%	60%	40%	0%	20%	0%	**100%**	60%	60%	40%	20%
Wan 2.6	**83%**	**100%**	**70%**	**80%**	**80%**	**80%**	**80%**	**40%**	**100%**	**80%**	**80%**	**80%**	**80%**
Veo 3.1	73%	**100%**	30%	60%	20%	20%	60%	0%	**100%**	70%	70%	60%	60%
LVP	70%	40%	**70%**	40%	20%	**80%**	40%	20%	**100%**	70%	60%	50%	40%

Method	Robot (Task Level)								Robot (Step Level)				
	Close Drawer	Pick Object	Push Object	Push Button	Put on Plate	Discard Trash	Pull Object	Put in Drawer	Put in Drawer				
									contact	lift	above drawer	in drawer	close drawer
Cosmos	0%	10%	10%	10%	10%	0%	0%	0%	10%	0%	0%	0%	0%
Wan 2.2	30%	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Wan 2.6	50%	20%	40%	40%	20%	10%	0%	0%	30%	0%	0%	0%	0%
Veo 3.1	20%	20%	10%	20%	10%	0%	0%	0%	30%	0%	0%	0%	0%
Cosmos-FT	**90%**	**50%**	**50%**	**60%**	**40%**	**30%**	**40%**	**20%**	**60%**	**20%**	**20%**	**20%**	**20%**

timated via FoundationPose [29] or MegaPose [17], with camera calibration performed using FEEPE [31]. This framework ensures simulation faithfully preserves the physical structure of real scenes, enabling scalable and reproducible evaluation without costly physical hardware.

2.4. Manipulation Task Suite

RoboWM-Bench comprises a suite of manipulation tasks with varying levels of complexity, designed to systematically evaluate the embodied reasoning and physical consistency of video world models. Built on the LeHome simulation engine [20], the benchmark enables reproducible and physically realistic interactions. RoboWM-Bench spans diverse object types and interaction regimes, including rigid-object tasks, articulated interactions, and deformable-object manipulation. It further includes long-horizon tasks requiring multi-stage planning, as well as bimanual tasks that introduce coordination constraints. Together, these tasks enable systematic evaluation.

2.5. Evaluation of Embodied Executability

We define *embodied executability* as the translation of predicted behaviors into dynamically feasible, task-completing actions. Our protocol employs a hierarchical assessment: (1) Step-level checks of key interactions (e.g., contact, lifting). (2) Task-level success requires passing all step-level checks and fulfilling the final objective. This design enables fine-grained failure analysis and clear task-level evaluation.

3. Experiments

We conduct extensive experiments with video world models across diverse tasks (3.1). Specifically: (1) We quantify the embodied executability of world models and provide analysis (3.2). (2) We compare against existing benchmarks and show that RoboWM-Bench provides a more embodiment-grounded evaluation (3.3). (3) We validate RoboWM-Bench by analyzing the consistency of action extraction and simulation-based execution (3.4).

3.1. Environment Setup

We evaluate video world models on human and robotic manipulation tasks. The environment is built on LeHome [20, 23], supporting high-fidelity rendering and deformable objects. For each task, we report average accuracy over 10 episodes with randomized object initialization. We evaluate several SOTA video world models across two categories. **General-purpose models** include closed-source Veo3.1 [12] and Wan2.6 [28], alongside open-source Wan2.2 [28] and Cosmos-Predict2.5 [2]. **Interaction-oriented models** feature LVP [5], designed for complex human behaviors. Additionally, we evaluate **Cosmos-Finetune**, a variant finetuned on our real-world manipulation dataset (50 trajectories per task), to assess the impact of domain-specific data on embodied grounding.

3.2. Embodied Executability of World Models

Table 1 summarizes execution success rates (simulation results in Appendix). We observe several key trends: **(1) Human-hand vs. Robot Embodiment.** Human-centric videos outperform robotic ones, likely due to human-dominated pretraining biases. Furthermore, human hands exhibit superior geometric stability, whereas robotic manipulators often suffer from structural distortions that trigger execution failure. **(2) Interaction Complexity.** Success rates decline as tasks transition from short-horizon interactions (e.g., *Push Button*) to long-horizon tasks (e.g., *Put in Drawer*) due to cumulative multi-step errors. *Fold Towel* remains the most challenging, indicating that deformable object interactions are particularly difficult for current world models. **(3) Impact of Finetuning.** Finetuning Cosmos with minimal data (50 trajectories/task) improves consistency and reduces artifacts. Yet, persistent bottlenecks in 3D spatial reasoning that cause localization and grasping

Table 2. Accuracy of action extraction methods.

Method (Human)	Pick Object	Stack Cups	Pour Water	Open Drawer	Fold Towel	Put on Plate	Put in Drawer	Average
Retargeting	**100%**	**90%**	**90%**	**100%**	**100%**	**100%**	**100%**	**97.1%**
Method (Robot)	Pick Object	Pull Object	Push Object	Discard Trash	Close Drawer	Put on Plate	Put in Drawer	Average
IDM_{Real}	70%	70%	80%	70%	90%	70%	50%	71.4%
$IDM_{Sim+Real}$	**100%**	**90%**	**100%**	**90%**	**100%**	**100%**	**90%**	**95.7%**

failures suggest a key direction for future improvement.

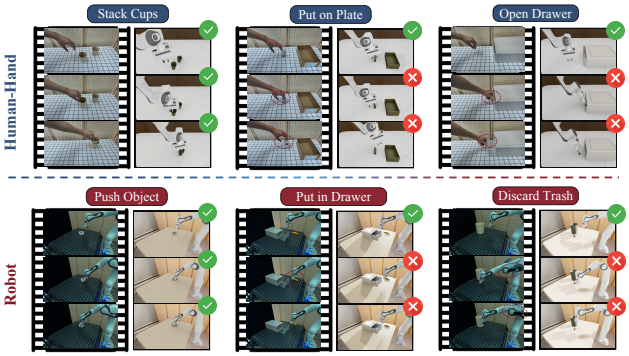


Figure 3. **Qualitative execution results on RoboWM-Bench.** For each task, predicted videos (left) are converted into robot actions and executed in simulation (right).

As shown in Figure 3, Wan2.6 achieves the strongest performance, yet **even strong world models often generate visually plausible but physically inconsistent interactions.** In *Put on Plate*, the model depicts lifting an object despite only touching it without a stable grasp, while in *Open Drawer*, predicted motions resemble closing rather than grasping. These predictions result in execution failures in simulation. For robotic tasks, unrealistic contact behaviors are compounded by geometric distortions in the predicted manipulator, which further reduces reliability.

3.3. Visual Plausibility vs. Embodied Execution

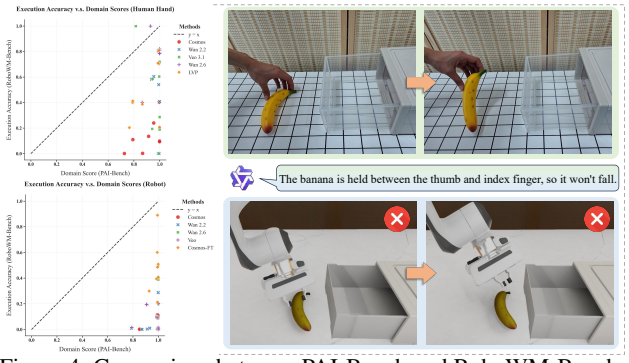


Figure 4. Comparison between PAI-Bench and RoboWM-Bench.

We compare RoboWM-Bench execution accuracy with PAI-Bench scores for perceptual plausibility. As shown in Fig. 4, videos achieve near-saturated scores on PAI-Bench while RoboWM-Bench yields more discriminative outcomes. This discrepancy arises because actions that appear visually plausible may remain physically infeasible, which are captured by embodied execution but often missed by perceptual metrics, demonstrating that RoboWM-Bench provides a more direct measure of physical executability.

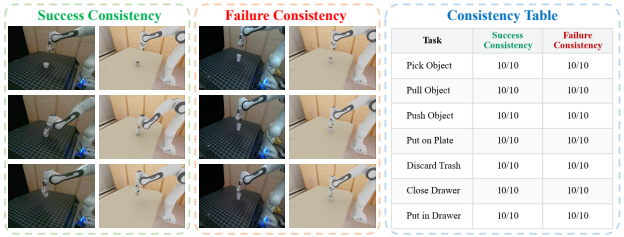
3.4. Robustness of RoboWM-Bench

To assess the robustness of RoboWM-Bench, we evaluate two key components of the evaluation pipeline: (1) the accuracy of action extraction from videos, including pose tracking and retargeting for human-hand videos, and the inverse dynamics model (IDM) for robotic manipulation videos; (2) the fidelity of reconstructed simulation environments with respect to their corresponding real-world scenes.

3.4.1. Action Extraction Accuracy.

To verify action extraction accuracy, we execute actions from real-world trajectories in simulation. As shown in Table 2, the human-centric retargeting pipeline achieves high reliability, though minor failures in *Stack Cups* and *Pour Water* arise from precision mismatches between robot grippers and human fingertips. Regarding robotic videos, $IDM_{Sim+Real}$ significantly outperforms IDM_{Real}, confirming that simulation pretraining provides essential motion priors for inverse dynamics. Remaining failures are attributed to minor prediction errors that compromise stability in tasks involving precision-dependent contacts.

3.4.2. Simulation Reconstruction Fidelity.



Task	Success Consistency	Failure Consistency
Pick Object	10/10	10/10
Pull Object	10/10	10/10
Push Object	10/10	10/10
Put on Plate	10/10	10/10
Discard Trash	10/10	10/10
Close Drawer	10/10	10/10
Put in Drawer	10/10	10/10

Figure 5. **Real-to-sim consistency.** Identical trajectories are executed in real-world scenes and reconstructed simulation environments, yielding consistent success and failure outcomes.

We evaluate the consistency between real-world trajectories and their reconstructed simulation counterparts. Ideally, identical actions should yield matching outcomes across domains. Since the reconstruction pipeline is shared, we use robotic tasks as a representative benchmark. To quantify consistency, we replay 10 successful and 10 failed real-world trajectories in simulation. As shown in Figure 5, execution outcomes are faithfully reproduced, confirming that our simulation environments preserve the physical structure and interaction dynamics of real scenes. This validation demonstrates that RoboWM-Bench enables reliable evaluation independent of the original physical setups.

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