



# Pelican-Unified 1.0: A Unified Embodied Intelligence Model (UEI) for Understanding, Reasoning, Imagination and Action

Beijing Innovation Center of Humanoid Robotics (X-Humanoid)

WFM System Group

{vito.dai,jian.tang,jason.ju}@x-humanoid.com

May 15, 2026

## Abstract

*“The soul never thinks without an image.” — Aristotle*

*“My thinking is first and last and always for the sake of my doing.” — William James*

博学之，审问之，慎思之，明辨之，笃行之。 — 《礼记·中庸》

We argue that foundation models for embodied intelligence should not be built upon fragmented capabilities. Rather, understanding, reasoning, imagination, and action should be regarded as interdependent dimensions in a single adaptive intelligence loop. The advancement of an embodied agent in the physical world does not arise from possessing independent vision model, language model, world model, and action policy, but from its capability to integrate world understanding, task reasoning, future imagination, and action execution within a latent world space that can be aligned, abstracted, planned, and refined. We therefore advocate a unified paradigm for building embodied intelligence models of physical intelligence.

By “unified,” we do not refer to simple concatenation of multiple expert networks at their outputs, nor to the assembly of independently optimized modules into a sequential pipeline. We mean *structurally shared representations, mutually constrained conditions, and co-evolution through a common training process*. Concretely, a truly unified model should exhibit three key properties: **unified understanding**, which embeds scenes, instructions, action histories, and visual contexts into a shared semantic space for a holistic understanding of what the agent sees, what it needs to accomplish, what it has done, and what state the world is in; **unified reasoning**, which turns reasoning into a language-grounded, supervisable process over task intent, action choices, and future consequences, rather than a linguistic monologue detached from action and imagination; and **unified generation**, which jointly reads out future imagination and low-level action from the same diffusion decoding process conditioned on the same reasoning latent, so actions are shaped by imagined consequences, imagination is framed by task reasoning, and reasoning is constrained by what can be imagined and executed. *In this way, understanding, reasoning, imagination, and action become a collaborative system that exchanges gradients, corrects itself, and strengthens itself within a single training loop, rather than separate stages in a pipeline.*

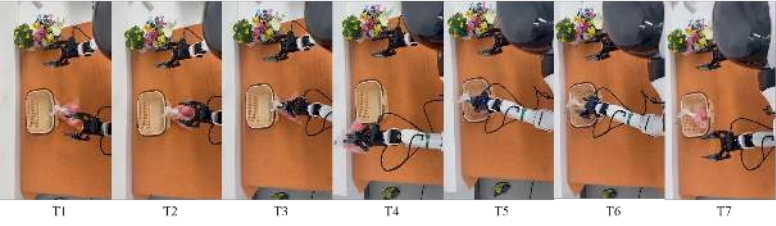
Based on this paradigm, we present **Pelican-Unified 1.0**, the first embodied foundation model trained according to the principle of unification. Pelican-Unified 1.0 uses a single VLM as a unified understanding module, mapping scenes, instructions, visual contexts, and action histories into a shared semantic space. The same VLM also serves as a unified reasoning module, autoregressively producing task-, action-, and future-oriented chains of thought in a single forward pass and projecting the final hidden state into a dense latent variable. A Unified Future Generator (UFG) then conditions on this latent variable and jointly generates future videos and future actions through two modality-specific output heads within the same denoising process. The language, video, and action losses are all backpropagated into the shared representation, enabling the model to jointly optimize understanding, reasoning, imagination, and action during training, rather than training three isolated expert systems.

Experiments demonstrate that unification does not imply compromise. With a single checkpoint, Pelican-Unified 1.0 achieves strong performance across all three capabilities: 64.7 on eight VLM benchmarks, the best among comparable-scale models; 66.03 on WorldArena, ranking first; and 93.5 on RoboTwin, the second-best average among compared action methods. These results show that the unified paradigm succeeds in preserving specialist strength while bringing understanding, reasoning, imagination, and action into one model.

arXiv:2605.15153v1 [cs.RO] 14 May 2026



**Input:** Sequence [T1-T7]: Observation images & current state & Task prompt: Place apples into the basket  
**Output:** Joint action and future video



## Pelican-Unified 1.0



### REASONING

VLM Reasoner with Chain-of-Thought

**Scene Understanding & Grounding**

Instruction: Replace the red wire connected to terminal B7.

Chain-of-Thought (CoT):

1. Locate terminal block B.
2. Identify terminal B7.
3. Observe the red wire connected to B7.
4. Plan to remove the red wire.
5. Insert the new wire and tighten the screw.

**Task Decomposition**

Locate B7 → Unscrew → Remove Red Wire → Insert New Wire → Tighten Screw

**Spatial & Object Reasoning**

Q: Which cable should be unplugged?

A. Green  
 B. Blue  
 C. Red ✓  
 D. Black

Answer: The red cable connected to port 3.  
 Rationale: It matches the instruction and port index.

### Unified Generation

Given multimodal inputs, Pelican-Unified jointly produces:

- ✓ Multimodal Understanding
- ✓ Chain-of-Thought Reasoning
- ✓ Feature Video Rollouts
- ✓ Low-level Action Chunks



### Benchmark Highlights

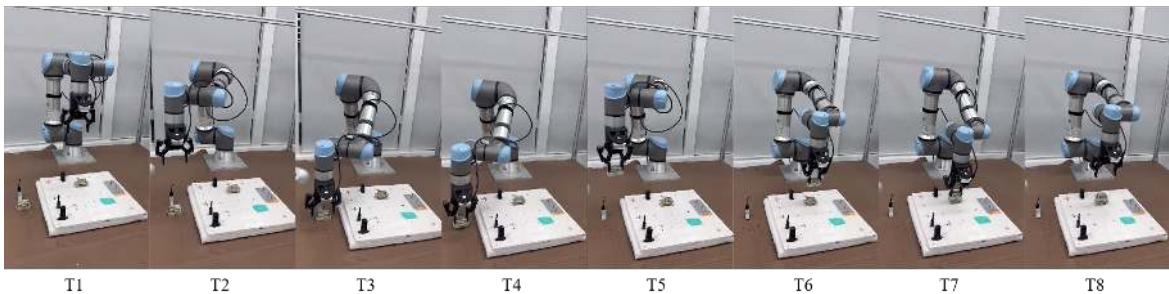
State-of-the-Art Across Benchmarks

- VLM Benchmarks**: 64.5 (8-benchmark average) **SOTA**
- RoboTwin**: 93.6 (Robot manipulation) **2nd Place**
- WorldArena**: 66.0 (World modeling) **SOTA**

### Action-Conditioned State Prediction

Ground truth (red box) vs Generated video (black box)

**Input:** Sequence [T1-T8]: Observation images & current state & Task prompt: Place the waterproof block onto its corresponding target position.  
**Output:** Joint action and future video.





## 1. Introduction

**The progress of general intelligence is reshaping embodied intelligence.** Modern AI has moved from task-specific automation toward foundation models that can generalize across domains, follow language instructions, and reuse shared representations across many tasks. Embodied AI is undergoing a similar transition. Early robotic systems were largely built as scripted automation pipelines: perception detected predefined states, planners selected predefined routines, and controllers executed predefined motions. Recent embodied systems have become increasingly intelligent, replacing hand-designed pipelines with learned policies, vision–language grounding, large-scale imitation, and generative prediction. This shift has brought the field closer to the goal of physical intelligence: agents that can understand the world, reason about tasks, imagine what may happen, and act to change the world. Yet this progress also exposes a central question. Should physical intelligence be built by scaling separate specialists for understanding, reasoning, imagination, and action, or should these capabilities be learned as parts of one adaptive loop?

**Embodied intelligence models have advanced rapidly, but along fragmented paths.** Vision language models such as Gemini Robotics ER [37] and Pelican-VL [52] bring strong semantic understanding and spatial-temporal reasoning to embodied settings, but they are not executable policies: they cannot directly act, cannot test their reasoning through physical consequences, and cannot ground their conclusions in the outcomes of their own behavior. Vision–language–action models such as RT-2 [55],  $\pi_0$  [5],  $\pi_{0.5}$  [20], OpenVLA [25], and Helix [15] connect language and perception to motor commands, but they typically lack explicit future imagination; as a result, their actions are often learned as imitation mappings, which limits generalization to unseen compositions, long-horizon tasks, and contact-rich interactions. World models and video generators such as Cosmos-Predict [2], LeWorldModel [30], and other recent generators [35, 4, 8] can imagine future visual states, but their imagination often remains implicit in pixels, difficult to steer with task logic, human knowledge, or language-grounded reasoning. World Action Models [47] further connect imagined futures to actions, but without unified reasoning, they remain hard to interpret, hard to correct during rollout, and vulnerable to long-horizon error accumulation. The field is therefore not short of powerful components. What remains missing is a model in which understanding, reasoning, imagination, and action are learned as mutually conditioning parts of the same physical intelligence loop.

**We argue that the path forward is unification rather than modular accumulation.** By “unified,” we do not mean concatenating the outputs of multiple expert networks or wiring separately trained modules into a longer pipeline. We mean that understanding, reasoning, imagination, and action should share internal representations, condition one another, and co-evolve through a common training process. This view is also consistent with embodied cognition: reasoning, imagination, and action do not operate as separable capabilities [24, 10]; motor planning recruits systems involved in simulating movement [21, 19]; perception is organized around what the body can do [13]; and future imagination supports action selection [9, 16]. For embodied intelligence foundation models, this principle leads to three requirements. First, *understanding should be unified*: scenes, instructions, visual context, action history, and world state should be represented in a shared semantic space, reducing the semantic breaks that appear when perception, language, and action are encoded separately. Second, *reasoning should be unified*: reasoning should not be a detached language trace, but a language-grounded, supervisable process whose final state directly conditions what the model imagines and executes, allowing task logic and human knowledge to guide generation. Third, *generation should be unified*: future imagination and low-level action should be produced by the same conditional generative process, so actions become consequence-aware, imagination becomes task-directed, and reasoning becomes constrained by what can be simulated and executed. Under this view, the missing capability in each specialist is not an optional add-on; it is the ceiling of the other capabilities.

**We instantiate this paradigm in Pelican-Unified 1.0.** Pelican-Unified is designed to make the understanding–reasoning–imagination–action loop a single trainable object. VLM serves as both the unified understanding engine and the unified reasoning engine: it maps scenes, instructions, visual context, and action history into a shared semantic representation, autoregressively produces a task-, action-, and future-oriented chain of thought, and projects the final hidden state into a dense latent variable  $z$ . A unified Future Generator (UFG) then conditions on  $z$  and jointly generates the future video and the next chunk of low-level actions through two modality-specific output heads within the same denoising process. Language, video, and action losses all backpropagate through the shared representation. Thus,  $z$  is not a bridge between independently optimized modules; it is the learned internal state where reasoning, imagination, and action become mutually conditioning aspects of the same generative process.

**Our experiments test whether unification preserves specialist competence and improves integrated physical behavior.** Taken apart, a single Pelican-Unified checkpoint reaches the frontiers normally occupied by separate specialists: it achieves **64.7** average on eight VLM benchmarks, among the strongest performers within models of similar scale; reaches **93.5%** average success on RoboTwin as a competitive visuomotor policy, achieving the second-best average among compared action methods; and obtains **EWM Score 66.03** on WorldArena as a world model, ahead of dedicated world models. Taken as a whole, on a real UR5e robot and a Tienkung humanoid robot operating industrial control panels, the model achieves significant improvements on both zero-shot and compositional tasks, demonstrating the generalization and practical value of the unified architecture across different embodiments.

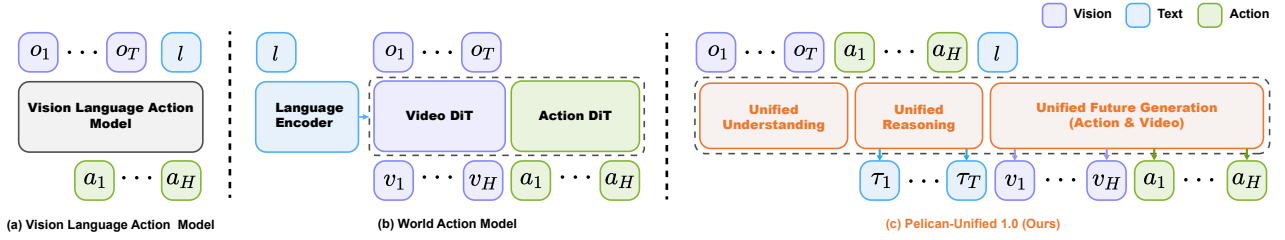


Figure 1: Pelican-Unified 1.0 closes the understand–reason–imagine–act loop by centering all three faces on one loop state  $z$ . A VLA (left) maps observations and instructions directly to an action chunk, so supervision shapes only the act face. A WAM (middle) jointly predicts future video and action, but its latent carries no explicit reasoning process. Pelican-Unified 1.0 (right) first uses a VLM reasoner (Qwen3-VL 4B) to construct a task-conditioned prefix: a chain-of-thought trace together with  $z$ , specifying what future should happen and what action should realize it. A unified future generator (Wan2.2-5B) then denoises future-video tokens and action tokens jointly under  $z$ , and an action-refine read lets the action tokens attend back to the imagined visual tokens before readout. Text, video, and action losses all backpropagate through the same  $z$ , so the loop is trained as one object rather than as three stitched modules. Solid arrows: inference; dashed: training gradients.

### Our contributions.

1. **A unified paradigm for embodied intelligence models.** We formulate physical intelligence as a coupled loop of understanding, reasoning, imagination, and action, and argue that the relevant unit of modeling is not an isolated specialist or a pairwise fusion, but the closed loop itself.
2. **A concrete realization of three forms of unification.** Pelican-Unified 1.0 realizes unified understanding by building an action-oriented task state from scenes, instructions, visual context, and action history; unified reasoning by turning chain-of-thought into a dense loop state  $z$  that specifies what future should happen; and unified generation by jointly denoising future video and low-level actions from the same  $z$ , with the final action read refined against the imagined future before execution.
3. **An end-to-end objective that makes the loop learnable.** Language, video, and action supervision are trained jointly, and all three losses backpropagate through the shared latent representation. This turns reasoning, imagination, and action from inter-module messages into mutually shaping gradients within a single model.
4. **Empirical evidence that unification preserves specialist competence and improves integrated physical behavior.** Pelican-Unified matches or exceeds dedicated models on VLM reasoning, visuomotor policy learning, and world modeling benchmarks, while achieving substantially stronger zero-shot, compositional, and long-horizon performance on real UR5e industrial control-panel manipulation tasks than the strongest modular baseline.

## 2. Pelican-Unified 1.0

### 2.1. Unified Modeling

As shown in Fig. 1, Pelican-Unified 1.0 realizes unified understanding, reasoning, imagination, and action through a single end-to-end trainable architecture, which couples the VLM backbone initialized from Qwen3-VL [3] with a unified diffusion decoder initialized from Wan2.2 [43].

Given the observations  $o_{\leq t}$ , action history  $a_{< t}$ , and language instruction  $l$ , Pelican-Unified constructs a shared latent task state within the VLM. Pelican-Unified maps this multimodal context to three outputs:

$$(\tau_t, \hat{v}_{t:t+H}, \hat{a}_{t:t+H}) = \mathcal{M}_{\Theta}(o_{\leq t}, a_{< t}, l), \quad (1)$$

where  $\tau_t$  is a chain-of-thought reasoning trace,  $\hat{v}_{t:t+H}$  is an imagined future video, and  $\hat{a}_{t:t+H}$  is an executable action chunk.

Pelican-Unified consists of two tightly coupled components: a VLM that constructs a unified task state and generates the reasoning trace, and a Unified Future Generator that uses the same state to jointly denoise future video latents and action trajectories. The three training signals—language, video, and action—are optimized jointly, forcing the shared representation to be simultaneously semantic, predictive, and actionable.

### 2.2. Unified Encoder

Pelican-Unified first encodes the interaction history using a vision-language backbone. The multimodal input context  $c_t = (o_{\leq t}, a_{< t}, l)$  includes the observation history, previous actions, and the language instruction. The VLM produces a chain-of-



thought trace:

$$p_\phi(\tau_t | c_t) = \prod_{i=1}^{|\tau_t|} p_\phi(\tau_{t,i} | c_t, \tau_{t,<i}). \quad (2)$$

This reasoning trace is not treated as a post-hoc explanation. It is an intermediate representation of task intent, physical constraints, future consequences, and action choices. Thus, language reasoning becomes a trainable component of the embodied generation process: it exposes the model’s internal decision structure, aligns the latent state with high-level task semantics, and provides a bridge between perception and future-conditioned control.

Unlike modular systems that compute visual features, language plans, world states, and policy states separately, Pelican-Unified uses  $z$  as a unified interface through which downstream generation can access task-relevant visual, linguistic, and temporal information.

$$z = P_\phi(h_{\tau_t}) \quad (3)$$

$h_{\tau_t}$  denotes the VLM hidden state after constructing the reasoning trace, and  $P_\phi$  projects it into the dense loop state  $z$ . This is the key coupling representation in Pelican-Unified, which carries the information required by both future video generation and action prediction. This representation is not optimized only for language modeling; it is also pressured by downstream generative losses to encode information that is useful for predicting how the physical world will evolve and what actions should be executed.

### 2.3. Unified Future Generator

The Unified Future Generator is a diffusion transformer conditioned on the shared task state  $z$ . Its goal is to jointly model two future modalities: future visual observations and robot actions. The sequence  $v_{t:t+H}$  denotes the future video, and  $a_{t:t+H}$  denotes the corresponding future action chunk. We encode the video sequence into a latent representation using a video autoencoder:

$$x^v = \mathcal{E}_{\text{vae}}(v_{t:t+H}), \quad (4)$$

and normalize the action trajectory into a continuous action representation:

$$x^a = \text{Norm}(a_{t:t+H}). \quad (5)$$

The video latent and action trajectory are then treated as two coupled continuous variables to be generated by a shared denoising process.

A crucial design choice is that Pelican-Unified does not use an independent world model for video prediction and a separate policy head for action generation. Instead, both video and action are embedded into the same transformer width:

$$h_s^v = e_v(x_s^v), \quad h_s^a = e_a(x_s^a), \quad (6)$$

where  $x_s^v$  and  $x_s^a$  are noisy states at diffusion time  $s$ , and  $e_v, e_a$  are modality-specific input embedders. The embedded tokens are processed by a shared diffusion transformer:

$$(h_L^v, h_L^a) = \text{DiT}_\theta(h_s^v, h_s^a, z, s). \quad (7)$$

The transformer backbone is shared across modalities. Video tokens and action tokens therefore interact during denoising, while the shared task state  $z$  is injected through cross-attention. This enables the model to learn a joint generative process in which imagined future states inform action prediction, and action dynamics constrain future imagination.

Here, self-attention models temporal and spatial dependencies within the generated future, cross-attention injects language-grounded task information, and the diffusion timestep  $s$  modulates the computation through adaptive normalization. In practice, video tokens carry spatiotemporal positional encodings, while action tokens carry temporal and action-dimensional structure. The final hidden states are mapped to modality-specific velocity predictions:

$$\hat{u}_s^v = d_v(h_L^v), \quad \hat{u}_s^a = d_a(h_L^a), \quad (8)$$

where  $d_v$  is the video output head and  $d_a$  is the action output head. Thus, modality-specific parameters are used only for input/output conversion, while the denoising computation itself is shared.

### 2.4. Conditional Diffusion over Future Video and Action

We train the Unified Future Generator with a continuous-time flow matching objective. The model learns to transform Gaussian noise into clean future video latents and clean future actions. For each training sample, we draw a diffusion time

$$s \sim \mathcal{U}(0, 1), \quad (9)$$



and independently sample Gaussian noise

$$\epsilon^v \sim \mathcal{N}(0, I), \quad \epsilon^a \sim \mathcal{N}(0, I). \quad (10)$$

For future video generation, the model conditions on observed frames and denoises only the future portion. Let  $M_{\text{cond}}$  and  $M_{\text{fut}}$  denote binary masks for the observed prefix and future target region. The noised video latent is constructed as

$$x_s^v = M_{\text{cond}} \odot x^v + M_{\text{fut}} \odot ((1-s)x^v + s\epsilon^v). \quad (11)$$

Thus, the observed visual context remains fixed, while the future latent is continuously interpolated between clean data and noise. The corresponding target velocity is

$$u_s^v = M_{\text{fut}} \odot (\epsilon^v - x^v). \quad (12)$$

This objective asks the model to predict the vector field that moves clean future video latents toward Gaussian noise in the forward diffusion direction. At generation time, the same vector field is integrated in the reverse direction to transform noise into future video.

For action generation, the future action chunk is diffused in the same continuous space:

$$x_s^a = (1-s)x^a + s\epsilon^a, \quad (13)$$

with target velocity

$$u_s^a = \epsilon^a - x^a. \quad (14)$$

The action diffusion process is therefore aligned with the video diffusion process: both modalities share the same diffusion time and are denoised by the same DiT backbone. This coupling is important because the model is not merely learning a policy conditioned on a fixed representation; it is learning a joint future distribution over what the agent will see and what the agent will do.

The DiT predicts the velocity fields:

$$(\hat{u}_s^v, \hat{u}_s^a) = f_\theta(x_s^v, x_s^a, z, s). \quad (15)$$

The video flow matching loss is defined on the future latent region:

$$\mathcal{L}_{\text{video}} = \mathbb{E}_{s, \epsilon^v} \left[ \|M_{\text{fut}} \odot (\hat{u}_s^v - u_s^v)\|_2^2 \right]. \quad (16)$$

For action prediction, we use a robust regression loss over valid action dimensions:

$$\mathcal{L}_{\text{action}} = \mathbb{E}_{s, \epsilon^a} [M_a \odot \text{SmoothL1}(\hat{u}_s^a, u_s^a)], \quad (17)$$

where  $M_a$  masks invalid or padded action dimensions when necessary.

The language reasoning loss is the standard autoregressive negative log-likelihood:

$$\mathcal{L}_{\text{text}} = - \sum_{i=1}^{|\tau_t|} \log p_\phi(\tau_{t,i} | c_t, \tau_{t,<i}). \quad (18)$$

The final objective is

$$\mathcal{L} = \lambda_{\text{text}} \mathcal{L}_{\text{text}} + \lambda_{\text{video}} \mathcal{L}_{\text{video}} + \lambda_{\text{action}} \mathcal{L}_{\text{action}}. \quad (19)$$

This joint objective is the optimization-level realization of unification. The text loss aligns the shared state with task-level reasoning; the video loss forces the state to be predictive of future world dynamics; and the action loss grounds the same state in executable control. Since all three losses are attached to the same task-conditioned representation, the model is trained to make its reasoning, imagination, and action mutually consistent.

In summary, Pelican-Unified 1.0 unifies understanding, reasoning, and generation within a single framework through a shared representation. The vision-language encoder is primarily responsible for understanding, performing semantic alignment and parsing of multimodal observations and language instructions to construct the task state representation. Based on this shared representation, the diffusion generator jointly denoises future video and actions within the same Transformer. The multi-modal training objective enables this representation to be simultaneously semantic, predictive, and actionable. This tightly coupled design eliminates the need for separate world models and policy networks, demonstrating that reasoning, imagination, and execution can naturally emerge as interdependent components of a unified generative process.

### 3. Evaluating the Unified Model as Three Specialists

The first question for a unified model is whether unification comes at the cost of specialist competence. If the shared loop is genuinely useful, then training understanding, reasoning, imagination, and action together should not weaken the model when each capability is evaluated on its own. We therefore evaluate Pelican-Unified 1.0 in three deliberately separated regimes: as a vision–language model on eight multimodal benchmarks, as a visuomotor policy on the RoboTwin dual-arm simulator, and as an action-conditioned world model on WorldArena.

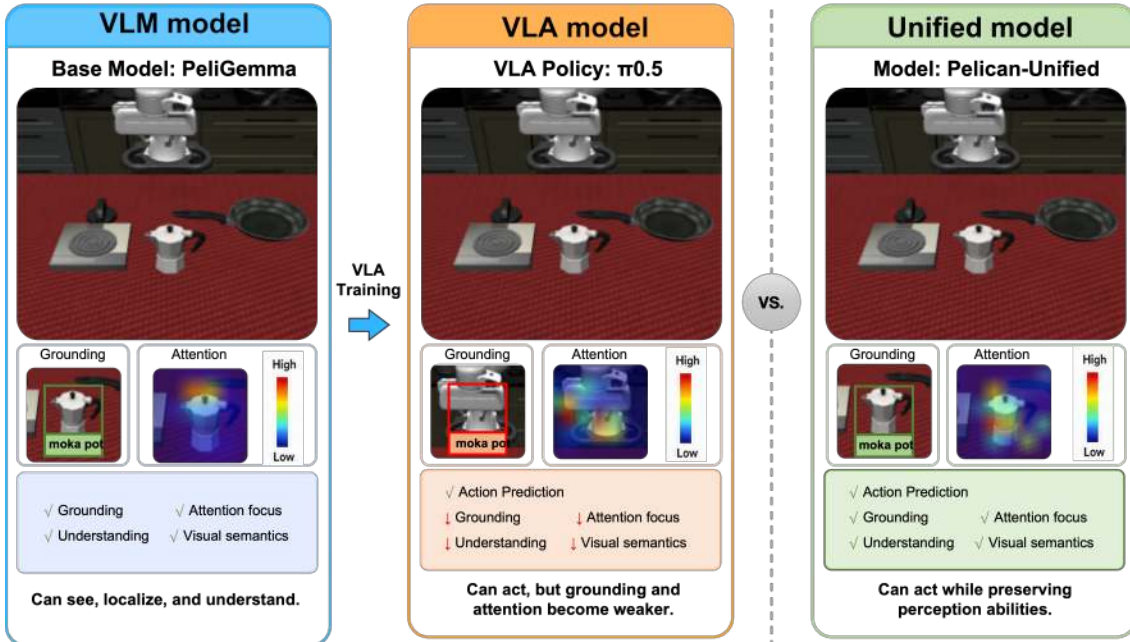


Figure 2: Starting from a base VLM, standard VLA policy training weakens grounding and attention, while Pelican-Unified 1.0 retains them and still predicts actions. Base VLM learns what and where; standard VLA weakens perception, while Pelican-Unified 1.0 preserves it and still learns what action to output.

Table 1: Comparison on general and embodied benchmarks. **Bold** indicates best results, underline indicates second-best results, - indicates that the model does not possess this capability (score of 0.0).

Method	General Benchmark					Embodied Benchmark			Avg.
	MMMU [50]	MMBench [28]	MMStar [6]	InfoVQA [32]	ChartQA [31]	Where2Place [49]	PhyX [36]	RefSpatial [54]	
<i>Vision-Language-Action Models</i>									
OpenVLA [25]	26.3	-	-	-	-	-	-	-	3.3
ECoT [51]	26.6	3.7	-	-	-	-	10.1	-	5.0
MolmoAct [26]	28.4	55.1	1.2	41.9	55.9	8.2	29.7	-	27.5
$\pi_{0.5}$ [20]	24.0	6.8	21.7	7.7	5.1	-	16.2	-	10.2
<i>Vision-Language Models</i>									
Gemma3-4B-IT [23]	39.3	68.6	37.1	40.9	50.3	7.5	17.2	2.2	32.9
Qwen3-VL-4B-Instruct [3]	<u>52.6</u>	<u>84.5</u>	<u>62.9</u>	<u>78.4</u>	<u>81.1</u>	<u>17.0</u>	<u>41.1</u>	<u>48.0</u>	<u>58.2</u>
<i>Our Unified Model</i>									
Pelican-Unified	<b>53.0</b>	<b>84.9</b>	<b>63.3</b>	<b>78.4</b>	<b>81.5</b>	<b>45.2</b>	<b>61.7</b>	<b>49.3</b>	<b>64.7</b>

### 3.1. Understanding Capability.

As shown in Tab. 1, Pelican-Unified consistently achieves the highest overall performance across multimodal benchmarks for both general reasoning and embodied evaluation. Specifically, our model achieves an average score of 64.7, outperforming all compared VLA and VLM baselines. Pelican-Unified improves the overall average from 58.2, achieved by Qwen3-VL-4B-Instruct (the 4B base model we build upon) to 64.7. Furthermore, it substantially outperforms prior VLA architectures, surpassing MolmoAct (27.5) by a large margin.

A detailed breakdown of these results reveals that these gains are attained without sacrificing general multimodal capabilities. On traditional general reasoning benchmarks, Pelican-Unified matches or marginally exceeds the baseline set by Qwen3-VL-4B-Instruct. By contrast, the improvements are largest in embodied evaluation, where spatial grounding and physical understanding are critical. On embodied-oriented benchmarks such as Where2Place and PhyX, our model outperforms Qwen3-VL-4B-Instruct by +28.2 and +20.6 points, respectively. This breakdown shows that our model transfers effectively to embodied tasks without losing general reasoning: it retains strong perception while substantially improving action-aware understanding. Consequently, our unified model learns richly physically grounded representations, which provide stronger features for downstream action and video prediction.



Table 2: Benchmark Results on Seen Tasks. We compare Pelican-Unified 1.0 with state-of-the-art VLA and world-model-based methods. Pelican-Unified 1.0 achieves the second-best average result while using a unified understanding–reasoning–imagination–action model. \*Results for X-VLA are adopted from Motus [4]. Unless otherwise specified, best results are highlighted in **bold**, and second-best results are underlined. †Second-best average success rate among compared methods.

Type	Model	Clean	Randomized	Avg
VLA	$\pi_0$ [5]	65.9	58.4	62.2
	X-VLA* [53]	72.9	72.8	72.9
	$\pi_{0.5}$ [20]	82.7	76.8	79.8
	starVLA [11]	88.2	88.3	88.3
	ABot-M0 [45]	81.2	80.4	80.8
	LingBot-VLA [44]	86.5	85.3	85.9
World Model	JEPA-VLA [33]	73.5	–	–
	Motus [4]	88.7	87.0	87.9
	LingBot-VA [27]	92.9	91.6	92.3
	Fast-WAM [48]	91.9	91.8	91.9
	Being-H0.7 [29]	90.2	89.6	89.9
	AIM [14]	<b>94.0</b>	92.1	93.1
	MotuBrain [39]	<b>95.8</b>	<b>96.1</b>	<b>95.9</b>
Unified Model	<b>Pelican-Unified 1.0</b> <sup>†</sup>	93.6	<u>93.3</u>	<u>93.5</u>

### 3.2. Action Capability.

We evaluate Pelican-Unified on the RoboTwin 50-task dual-arm benchmark (Tab. 2), our model achieves an average success rate of **93.5%**. It outperforms most specialized VLA and world-model baselines, including AIM (93.1%), LingBot-VA (92.3%), and starVLA (88.3%). This result demonstrates the strong manipulation capability of our model on complex tasks.

Under clean and randomized conditions, Pelican-Unified achieves 93.6% and 93.3% success, respectively. Per-task results show that the improvements are broad: 31 out of 50 tasks reach at least 95% success, 39 tasks reach 90%, and 15 tasks are solved perfectly (100%). High-success tasks span clicking, shaking, stacking, handover, and articulated-object manipulation, indicating reliable performance across both precise contact and multi-object coordination. Failures are concentrated in the hardest long-horizon or geometry-sensitive tasks, such as hanging mugs and dustbin insertion, which require tight alignment or sustained contact. These patterns indicate that unified training does not degrade low-level control. Rather, shared reasoning and predictive representations improve both generalizability and robustness across diverse manipulation regimes.

### 3.3. Imagination Capability.

As shown in Tab. 3, on the WorldArena benchmark, Pelican-Unified’s imagination component achieves an EWM Score of **66.03**, ranking first. It also ranks first in 3D Accuracy (98.13) and Motion Quality (62.69), two dimensions where spatial coherence and physical plausibility are critical. On other metrics—Visual Quality (63.43), Content Consistency (60.33), Physics Adherence (61.51), Controllability (59.28)—the model performs competitively.

Automated WorldArena metrics can reward visually clean but task-irrelevant rollouts. We therefore conduct a blind human study to assess whether generated rollouts are usable for downstream control. Trained annotators rate each rollout on a {0, 1, 2} scale across four axes: Controllability (preserving first-frame conditions), Task Success (achieving manipulation goals), Temporal Consistency (stable shapes without flicker), and Physical Plausibility (coherent contact and gravity). This design separates conditioning fidelity from execution quality.

As shown in Tab. 4, Pelican-Unified 1.0 achieves the highest overall score (mean 1.76) and outperforms existing baselines. It excels on Task Success (1.81) and Controllability (2.00). The system treats first-frame conditions as manipulation goals and commits to completing them. Several video-diffusion models score near zero on Task Success despite high Temporal Consistency (e.g., Happyhorse, EnerVerse-AC), showing that visually fluent rollouts can abandon the task.

This performance comes from the unified architecture. Unlike pure video generation models that focus on pixel-level fidelity, Pelican-Unified is pretrained on large-scale real-world robot interaction data, which encodes spatial structure and physical dynamics. The model learns 3D geometry cues—depth, object permanence, viewpoint consistency—without explicit reconstruction or physics engines. This is reflected in the 3D Accuracy. The competitive Motion Quality confirms that the model generates temporally coherent motions consistent with kinematic constraints, as these constraints are present in the pretraining action sequences. Additionally, the model supports action-conditioned video generation, improving generation quality and ensuring action-frame alignment (Fig. 3).



Table 3: Performance comparison on the World Arena Benchmark (0–100 scale). Pelican-Unified achieves the best overall EWM Score (66.03, rank #1) and demonstrates strong spatiotemporal reasoning, ranking first in both 3D Accuracy (98.13) and Motion Quality (62.69). It also delivers balanced performance across all other dimensions.

Model	EWM Score	Rank	Visual Quality	Motion Quality	Content Consistency	Physics Adherence	3D Accuracy	Controllability
<b>Pelican-Unified</b>	<b>66.03</b>	<b>1</b>	63.43	<b>62.69</b>	60.33	61.51	<b>98.13</b>	59.28
WorldScape v0.2	64.24	2	62.65	42.34	65.18	<b>73.29</b>	96.28	59.38
FlowWAM-FiveAges	64.12	3	63.29	41.05	66.92	67.82	<u>97.84</u>	60.28
MotuBrain [39]	64.07	4	60.69	<u>62.21</u>	59.57	61.18	91.64	57.35
FAW	63.28	5	62.37	40.17	65.42	<u>69.28</u>	96.85	58.79
Goose_Egg	62.96	6	58.86	53.97	62.12	61.43	92.14	58.45
ABot-PhysWorld (text) [7]	62.63	7	<b>64.41</b>	48.34	63.37	56.73	85.46	<u>63.11</u>
Z-WM	62.47	8	<u>64.20</u>	37.43	64.84	63.88	96.48	59.80
GigaWorld-1	62.34	9	63.04	39.16	65.17	64.68	97.02	57.28
HeroF1	60.38	10	57.40	49.10	64.30	53.97	87.46	56.97
Ctrl-World [18]	59.98	11	57.42	50.91	62.25	55.41	88.46	53.42
Wan2.6 [40]	59.80	12	61.44	45.92	64.00	42.67	84.68	62.66
RunWorld	59.24	13	48.34	60.87	60.54	43.88	89.52	57.28
CogvideoX [46]	58.79	14	55.79	42.18	<u>67.71</u>	50.88	88.28	55.09
Veo3.1 [12]	57.77	15	57.44	30.26	<b>68.34</b>	46.43	86.96	<b>63.15</b>

Table 4: Human evaluation on WorldArena rollouts (0–2 scale per axis). Each rollout is independently rated along *Task Success*, *Controllability*, *Temporal Consistency* and *Physical Plausibility*; the *Average* column is the unweighted mean of the four. Pelican-Unified 1.0 attains the best overall mean (1.76, rank #1), driven by the highest Task Success (1.81) and a perfect Controllability score (2.00).

Model	Task Success	Controllability	Temporal Consistency	Physical Plausibility	Average
<b>Pelican-Unified 1.0</b>	<b>1.81</b>	<b>2.00</b>	<b>2.00</b>	<u>1.23</u>	<b>1.76</b>
Seedance2.0 [34] (API)	1.21	1.87	<u>1.98</u>	1.15	<u>1.55</u>
Happyhorse-1.0 [38] (API)	<u>1.65</u>	1.81	<b>2.00</b>	0.13	1.40
EnerVerse-AC [22]	0.00	1.84	<b>2.00</b>	<b>1.64</b>	1.37
Wan2.7 [41] (API)	1.19	1.68	<b>2.00</b>	0.29	1.29
Cosmos-Predict2 [1]	0.63	1.85	1.79	0.35	1.16
GigaWorld-0 [17]	0.33	<u>1.94</u>	<u>1.98</u>	0.13	1.09
UnifoLM-WMA-0 [42]	0.05	1.48	<b>2.00</b>	0.11	0.91

## 4. Real-World Robot Evaluation

We ground our evaluation in real-world scenarios, as the inherent difficulty of physical manipulation exposes whether a system possesses a genuine **reason–imagine–act** closed loop or merely a chain of cooperating modules. Our experimental platform comprises a UR5e robotic arm and a Tienkung humanoid robot. The evaluation is organized around two core capabilities that a closed-loop system should satisfy:

**Compositional generalisation.** Atomic skills  $A$  and  $B$  compose into  $A+B$  without any combined demonstrations.

**Zero-shot transfer.** Generalisation learned during the imagination phase transfers directly to the unified video–action model without additional training.

### 4.1. Compositional Generalisation

We design a compositional generalisation test on the UR5e robotic arm to jointly validate two capabilities: the ability to compose unseen task combinations, and the capacity for fine-grained manipulation guided by the imagination-based world model. Specifically, the atomic tasks  $\mathcal{A}$  (*plug RJ45*) and  $\mathcal{B}$  (*waterproof*) are trained *individually*, with no complete demonstration of the two chained together appearing in the training data. At test time, the robot receives a single natural-language instruction (e.g. “*plug the RJ45 cable into port 3 and apply waterproofing*”) and must complete phase  $\mathcal{A}$  followed by phase  $\mathcal{B}$  within one continuous episode, as shown in Fig. 4.

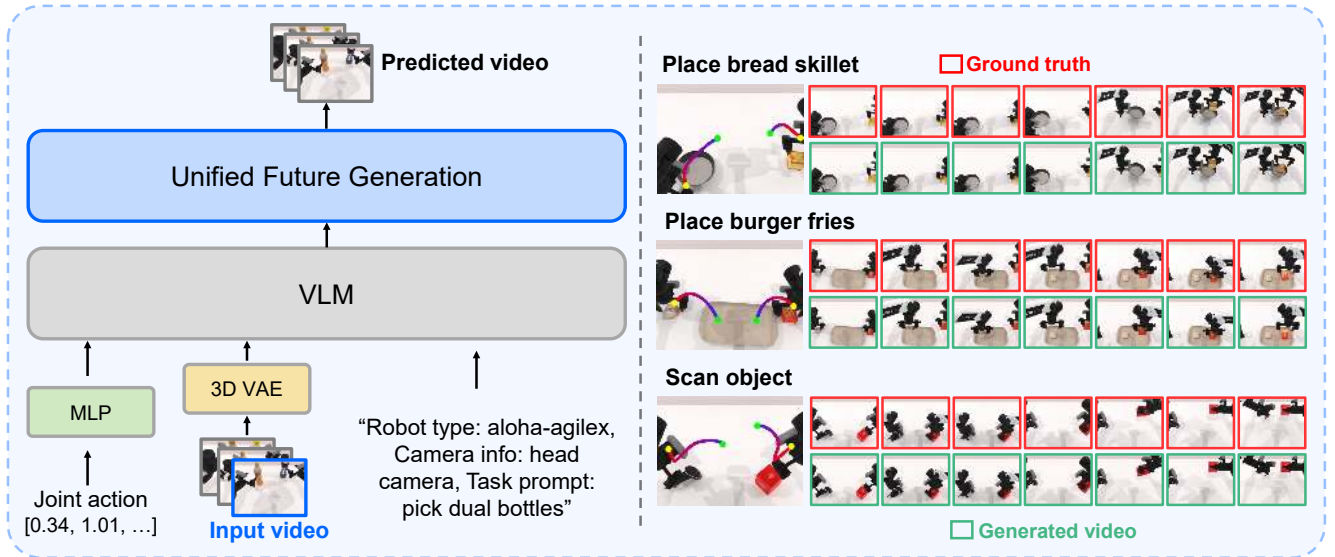


Figure 3: Pelican-Unified 1.0 can take actions as conditional inputs, enabling action-conditioned video prediction. Left: The overview of the action-conditioned video prediction model. Right: Comparison of videos generated by our method with ground truth. Our action-conditioned video prediction model achieves fine-grained alignment between input action commands and the generated video frames, given historical observations.

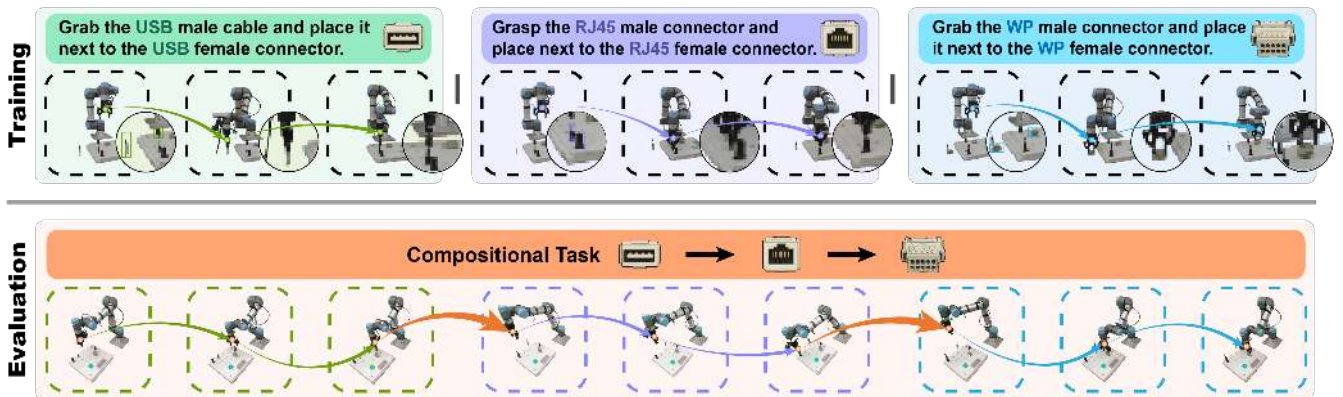


Figure 4: **Compositional generalization evaluation.** During training, the model is optimized only on atomic manipulation tasks individually, without exposure to their composed counterparts. At test time, we evaluate the model on unseen compositional tasks that require combining multiple learned skills, demonstrating strong compositional generalization ability in long-horizon embodied manipulation.

Failures are concentrated at the transition—the moment where the just-completed  $A$ -state must be re-perceived as the new initial condition for  $B$ . VLA baselines fail at this transition not because they cannot re-perceive the environment, but because their action distributions carry no representation of “what should happen after  $A$  is done”. The imagination face, having seen each atomic verb ground out into a future-frame distribution during training, can render the post- $A$  scene state and re-condition on it; the action face follows. That this succeeds without the model ever having seen a complete chained demonstration is the strongest single piece of evidence that it has learned the perception–action loop, rather than merely memorizing a richer action policy.

As shown in Fig. 5, we further compare the real execution videos with the corresponding generated imagination videos during rollout. The results demonstrate that our model is able to produce physically consistent imagination and future-state predictions that closely align with the real-world observations. This indicates that the model does not merely hallucinate plausible scenes, but instead conditions its predictions on the actual environment dynamics, enabling grounded and physically coherent reasoning during execution.

## 4.2. Zero Shot Generalization

We posit that achieving robust zero shot generalization is fundamentally predicated on the broad adaptability of the underlying embodied intelligence foundation model. To verify this, we first conduct an exhaustive suite of evaluations across diverse cases within the Tienkung environment to establish a baseline for the model’s fundamental generalization capabilities. Building

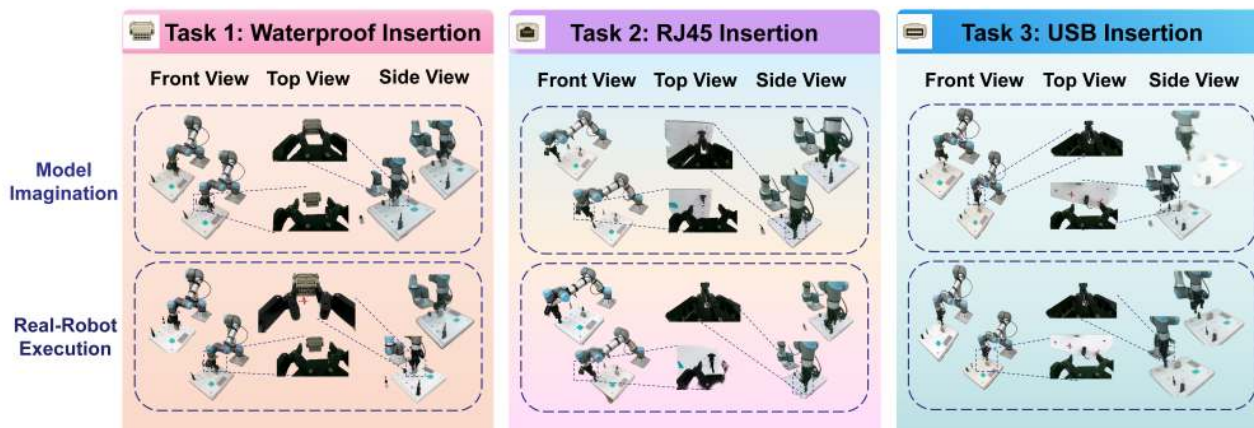


Figure 5: **Fine-grained manipulation and physical imagination capability.** Our model demonstrates strong fine-grained embodied manipulation skills in challenging connector insertion tasks, including waterproof, RJ45, and USB insertion, while also exhibiting powerful physical imagination ability to predict plausible future interactions and object dynamics under real-world constraints.

upon this foundation, we designed a rigorous OOD benchmark within our Unified framework. Specifically, we performed joint training on five seen tasks, each containing an average of 300 video-action episodes, and three unseen tasks, which were provided with only 50 video sequences per task. By evaluating the task success rates in these novel scenarios, we systematically demonstrate the efficacy of our framework in bridging the domain gap and generalizing to unfamiliar environments.

As demonstrated in Tab. 4, Pelican-Unified 1.0 attains the best overall mean score of 1.76 (rank #1) in human evaluation, driven by the highest Task Success score of 1.81 and a perfect Controllability score of 2.00. Our unified approach significantly outperforms dedicated baselines: 0.21 ahead of the strongest video-diffusion specialist (Seedance2.0, 1.55). Notably, Pelican-Unified 1.0 is the only model to excel simultaneously in controllability, task success, temporal consistency, and physical plausibility under blind expert scrutiny, providing empirical evidence of robust generalization capabilities in embodied scenarios and establishing a solid prerequisite for subsequent experiments.

Building upon the robust generalization of our embodied intelligence model, the Unified framework further enhances performance through joint training. As shown in Fig. 6, the Unified model achieves strong performance across seen tasks, demonstrating the synergy between our base model and the joint training paradigm in maintaining high-fidelity execution while extending capabilities to out-of-distribution scenarios.

## 5. Discussion

### 5.1. What this means for the field

Integrated physical behavior depends on coupling, not only on component strength. Zero-shot transfer, compositional skill use, and long-horizon coherence are precisely the behaviors modular pipelines have tried to engineer at the interfaces between planner, world model, and policy. Our results suggest that these behaviors are difficult to obtain by strengthening any one component in isolation. A policy without future imagination remains weakly consequence-aware; a world model without unified reasoning remains difficult to steer with task semantics and human knowledge; and reasoning without action and imagination remains detached from physical outcomes. What is missing in modular systems is therefore not only more capacity, but also a training process that forces the components to become mutually informative.

This changes what progress in embodied AI should measure. Once understanding, reasoning, imagination, and action are trained as one loop, improvement is not only a matter of making each specialist larger. It also depends on how tightly the model shares representations across modalities, how directly reasoning conditions generation, how jointly future video and action are decoded, and how much the data itself contains aligned observation, instruction, reasoning, action, and future outcomes. In our ablations, the most valuable data is not merely more data of the old form, but loop-closed data in which these signals are annotated on the same example. Such data is valuable because a unified model can absorb it as a coupled training signal, and because a coupled model is precisely the kind of system that asks for it.

### 5.2. Coda

We began from a simple claim: physical intelligence should not be built from fragmented capabilities. An agent that must keep improving in the physical world needs to understand the current situation, reason about the task, imagine possible futures, and

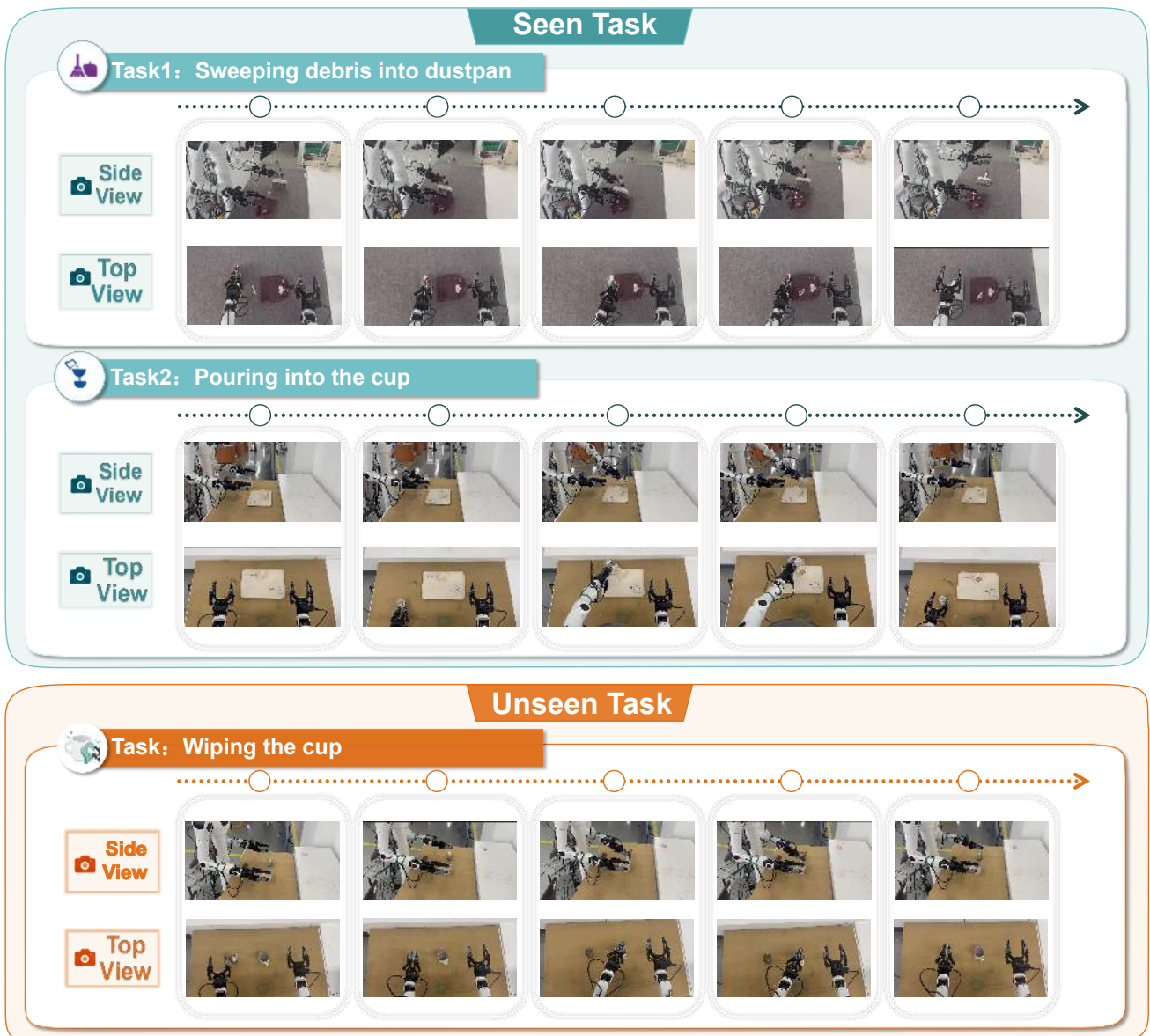


Figure 6: **Execution timelines of seen and unseen robotic manipulation tasks.** For each task, we visualize synchronized side-view and top-view observations at five representative execution steps. The upper block shows two seen tasks, including sweeping debris into a dustpan and pouring into a cup, while the lower block shows an unseen cup-wiping task for evaluating cross-task generalization.

act in ways whose consequences feed back into the next round of understanding. Pelican-Unified 1.0 is a concrete attempt to make this loop a single trainable object. Its empirical signature matches the claim: the model preserves specialist competence when evaluated one face at a time, and exhibits stronger integrated behavior when evaluated as a whole.

We do not claim general embodied intelligence. We claim something more specific: a foundation model for embodied intelligence should allow understanding, reasoning, imagination, and action to co-evolve through a shared representation, rather than refine them as isolated systems and connect them only after training. Pelican-Unified 1.0 shows that this unification is not merely an engineering simplification. It is a practical modeling direction that preserves the strengths of specialists while enabling behaviors that depend on the loop itself. The next stage of embodied AI may therefore be shaped less by assembling larger specialists, and more by learning the shared process through which understanding, reasoning, imagination, and action become one adaptive system.



## References

- [1] N. Agarwal, A. Ali, M. Bala, Y. Balaji, E. Barker, T. Cai, P. Chattopadhyay, Y. Chen, Y. Cui, Y. Ding, et al. Cosmos world foundation model platform for physical ai, 2025.
- [2] A. Ali, J. Bai, M. Bala, Y. Balaji, A. Blakeman, T. Cai, J. Cao, T. Cao, E. Cha, Y.-W. Chao, et al. World simulation with video foundation models for physical ai. *arXiv preprint arXiv:2511.00062*, 2025.
- [3] S. Bai et al. Qwen3-vl technical report. *arXiv preprint arXiv:2511.21631*, 2025.
- [4] H. Bi, H. Tan, S. Xie, Z. Wang, S. Huang, H. Liu, R. Zhao, Y. Feng, C. Xiang, Y. Rong, H. Zhao, H. Liu, Z. Su, L. Ma, H. Su, and J. Zhu. Motus: A unified latent action world model, 2025.
- [5] K. Black, N. Brown, D. Driess, A. Esmail, M. Equi, C. Finn, N. Fusai, L. Groom, K. Hausman, B. Ichter, et al.  $\pi_0$ : A vision-language-action flow model for general robot control. *arXiv preprint arXiv:2410.24164*, 2024.
- [6] L. Chen, J. Li, X. Dong, P. Zhang, Y. Zang, Z. Chen, H. Duan, J. Wang, Y. Qiao, D. Lin, et al. Are we on the right way for evaluating large vision-language models? *arXiv preprint arXiv:2403.20330*, 2024.
- [7] Y. Chen, R. Chen, D. Huo, Y. Yang, D. Qi, H. Liu, T. Lin, S. Zeng, J. Xiao, X. Chang, F. Xiong, X. Wei, Z. Ma, and M. Xu. Abot-physworld: Interactive world foundation model for robotic manipulation with physics alignment, 2026.
- [8] X. Chi, P. Jia, C.-K. Fan, X. Ju, W. Mi, K. Zhang, Z. Qin, W. Tian, K. Ge, H. Li, et al. Wow: Towards a world omniscient world model through embodied interaction. *arXiv preprint arXiv:2509.22642*, 2025.
- [9] A. Clark. Whatever next? predictive brains, situated agents, and the future of cognitive science. *Behavioral and brain sciences*, 36(3):181–204, 2013.
- [10] A. Clark. *Surfing Uncertainty: Prediction, Action, and the Embodied Mind*. Oxford University Press, Oxford, 2016.
- [11] S. Community. Starvla: A lego-like codebase for vision-language-action model developing. *arXiv preprint arXiv:2604.05014*, 2026.
- [12] G. DeepMind. Veo 3.1: Our most capable generative video model. <https://deepmind.google/technologies/veo/>, 2026. Accessed: 2026-05-14.
- [13] D. C. Dennett. *The embodied mind: Cognitive science and human experience*, 1993.
- [14] L. Fan, Z. Xu, C. Cao, W. Zhang, M. Yuan, and J. Chen. Aim: Intent-aware unified world action modeling with spatial value maps. *arXiv preprint arXiv:2604.11135*, 2026.
- [15] A. Figure. Helix: A vision-language-action model for generalist humanoid control, 2024.
- [16] K. Friston. The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2):127–138, 2010.
- [17] GigaAI. Gigaworld-0: World models as data engine to empower embodied ai, 2025.
- [18] Y. Guo, L. X. Shi, J. Chen, and C. Finn. Ctrl-world: A controllable generative world model for robot manipulation. In *The Fourteenth International Conference on Learning Representations (ICLR)*, 2026.
- [19] G. Hesslow. Conscious thought as simulation of behaviour and perception. *Trends in Cognitive Sciences*, 6(6):242–247, 2002.
- [20] P. Intelligence, K. Black, N. Brown, J. Darpinian, K. Dhabalia, D. Driess, A. Esmail, M. Equi, C. Finn, N. Fusai, et al.  $\pi_{0.5}$ : a vision-language-action model with open-world generalization. *arXiv preprint arXiv:2504.16054*, 2025.
- [21] M. Jeannerod. Neural simulation of action: A unifying mechanism for motor cognition. *NeuroImage*, 14(1):S103–S109, 2001.
- [22] Y. Jiang, S. Chen, S. Huang, L. Chen, P. Zhou, Y. Liao, X. He, C. Liu, H. Li, M. Yao, and G. Ren. Enerverse-ac: Envisioning embodied environments with action condition, 2025.
- [23] A. Kamath, J. Ferret, S. Pathak, N. Vieillard, R. Merhej, S. Perrin, T. Matejovicova, A. Ramé, M. Rivière, L. Rouillard, et al. Gemma 3 technical report, 2025.
- [24] E. R. Kandel, J. D. Koester, S. H. Mack, and S. A. Siegelbaum. *Principles of Neural Science*. McGraw-Hill Education, New York, 6 edition, 2021.



- [25] M. J. Kim, K. Pertsch, S. Karamcheti, T. Xiao, A. Balakrishna, S. Nair, R. Rafailov, E. Foster, G. Lam, P. Sanketi, et al. Openvla: An open-source vision-language-action model. *arXiv preprint arXiv:2406.09246*, 2024.
- [26] J. Lee, J. Duan, H. Fang, Y. Deng, S. Liu, B. Li, B. Fang, J. Zhang, Y. R. Wang, S. Lee, W. Han, W. Pumacay, A. Wu, R. Hendrix, K. Farley, E. VanderBilt, A. Farhadi, D. Fox, and R. Krishna. Molmoact: Action reasoning models that can reason in space, 2025.
- [27] L. Li, Q. Zhang, Y. Luo, S. Yang, R. Wang, F. Han, M. Yu, Z. Gao, N. Xue, X. Zhu, Y. Shen, and Y. Xu. Causal world modeling for robot control. *arXiv preprint arXiv:2601.21998*, 2026.
- [28] Y. Liu, H. Duan, Y. Zhang, B. Li, S. Zhang, W. Zhao, Y. Yuan, J. Wang, C. He, Z. Liu, et al. Mmbench: Is your multi-modal model an all-around player? In *European conference on computer vision*, pages 216–233. Springer, 2024.
- [29] H. Luo, W. Zhang, Y. Feng, S. Zheng, H. Xu, C. Xu, Z. Xi, Y. Fu, and Z. Lu. Being-h0.7: A latent world-action model from egocentric videos. *arXiv preprint arXiv:2605.00078*, 2026.
- [30] L. Maes, Q. L. Lidec, D. Scieur, Y. LeCun, and R. Balestrierio. Leworldmodel: Stable end-to-end joint-embedding predictive architecture from pixels. *arXiv preprint arXiv:2603.19312*, 2026.
- [31] A. Masry, D. Long, J. Q. Tan, S. Joty, and E. Hoque. ChartQA: A benchmark for question answering about charts with visual and logical reasoning. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2263–2279, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [32] M. Mathew, V. Bagal, R. P. Tito, D. Karatzas, E. Valveny, and C. V. Jawahar. Infographicvqa, 2021.
- [33] S. Miao, N. Feng, J. Wu, Y. Lin, X. He, D. Li, and M. Long. Jepa-vla: Video predictive embedding is needed for vla models, 2026.
- [34] T. Seedance, D. Chen, L. Chen, X. Chen, Y. Chen, Z. Chen, Z. Chen, F. Cheng, T. Cheng, Y. Cheng, et al. Seedance 2.0: Advancing video generation for world complexity, 2026.
- [35] Y. Shang, Z. Li, Y. Ma, W. Su, X. Jin, Z. Wang, L. Jin, X. Zhang, Y. Tang, H. Su, et al. Worldarena: A unified benchmark for evaluating perception and functional utility of embodied world models. *arXiv preprint arXiv:2602.08971*, 2026.
- [36] H. Shen, T. Wu, Q. Han, Y. Hsieh, J. Wang, Y. Zhang, Y. Cheng, Z. Hao, Y. Ni, X. Wang, Z. Wan, K. Zhang, W. Xu, J. Xiong, P. Luo, W. Chen, C. Tao, Z. Mao, and N. Wong. Phyx: Does your model have the "wits" for physical reasoning?, 2025.
- [37] G. R. Team, S. Abeyruwan, J. Ainslie, J.-B. Alayrac, M. G. Arenas, T. Armstrong, A. Balakrishna, R. Baruch, M. Bauza, M. Blokzijl, et al. Gemini robotics: Bringing ai into the physical world. *arXiv preprint arXiv:2503.20020*, 2025.
- [38] H. Team. Happyhorse-1.0, 2026.
- [39] M. Team, C. Xiang, F. Bao, H. Liu, H. Tan, H. Bi, J. Li, J. Liu, J. Pang, K. Jing, L. Liu, M. Cai, R. Cui, R. Zhao, R. Wang, S. Huang, Y. Feng, Y. Rong, Z. Wang, and J. Zhu. Motubrain: An advanced world action model for robot control, 2026.
- [40] W. Team. Wan2.6: A state-of-the-art video generation model. `WanAI:LeadingAIVideoGenerationModel`, 2026. Accessed: 2026-05-14.
- [41] W. Team. Wan2.7, 2026.
- [42] Unitree. Unifolm-wma-0: A world-model-action (wma) framework under unifolm family, 2025.
- [43] T. Wan, A. Wang, B. Ai, B. Wen, C. Mao, C.-W. Xie, D. Chen, F. Yu, H. Zhao, J. Yang, et al. Wan: Open and advanced large-scale video generative models. *arXiv preprint arXiv:2503.20314*, 2025.
- [44] W. Wu, F. Lu, Y. Wang, S. Yang, S. Liu, F. Wang, Q. Zhu, H. Sun, Y. Wang, S. Ma, et al. A pragmatic vla foundation model. *arXiv preprint arXiv:2601.18692*, 2026.
- [45] Y. Yang, S. Zeng, T. Lin, X. Chang, D. Qi, J. Xiao, H. Liu, R. Chen, Y. Chen, D. Huo, et al. Abot-m0: Vla foundation model for robotic manipulation with action manifold learning. *arXiv preprint arXiv:2602.11236*, 2026.
- [46] Z. Yang, J. Teng, W. Zheng, M. Ding, S. Huang, J. Xu, Y. Yang, W. Hong, X. Zhang, G. Feng, D. Yin, Y. Zhang, W. Wang, Y. Cheng, B. Xu, X. Gu, Y. Dong, and J. Tang. Cogvideox: Text-to-video diffusion models with an expert transformer, 2025.
- [47] S. Ye, Y. Ge, K. Zheng, S. Gao, S. Yu, G. Kurian, S. Indupuru, Y. L. Tan, C. Zhu, J. Xiang, et al. World action models are zero-shot policies. *arXiv preprint arXiv:2602.15922*, 2026.



- [48] T. Yuan, Z. Dong, Y. Liu, and H. Zhao. Fast-wam: Do world action models need test-time future imagination? *arXiv preprint arXiv:2603.16666*, 2026.
- [49] W. Yuan, J. Duan, V. Blukis, W. Pumacay, R. Krishna, A. Murali, A. Mousavian, and D. Fox. Robopoint: A vision-language model for spatial affordance prediction for robotics, 2024.
- [50] X. Yue, Y. Ni, K. Zhang, T. Zheng, R. Liu, G. Zhang, S. Stevens, D. Jiang, W. Ren, Y. Sun, C. Wei, B. Yu, R. Yuan, R. Sun, M. Yin, B. Zheng, Z. Yang, Y. Liu, W. Huang, H. Sun, Y. Su, and W. Chen. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *Proceedings of CVPR*, 2024.
- [51] M. Zawalski, W. Chen, K. Pertsch, O. Mees, C. Finn, and S. Levine. Robotic control via embodied chain-of-thought reasoning, 2025.
- [52] Y. Zhang, C. Liu, X. Ren, H. Ni, S. Zhang, Z. Ding, J. Hu, H. Shan, Z. Niu, Z. Liu, et al. Pelican-vl 1.0: A foundation brain model for embodied intelligence. *arXiv preprint arXiv:2511.00108*, 2025.
- [53] J. Zheng, J. Li, Z. Wang, D. Liu, X. Kang, Y. Feng, Y. Zheng, J. Zou, Y. Chen, J. Zeng, T. Wang, Y.-Q. Zhang, J. Liu, and X. Zhan. X-vla: Soft-prompted transformer as scalable cross-embodiment vision-language-action model. In *The Fourteenth International Conference on Learning Representations (ICLR)*, 2026.
- [54] E. Zhou, J. An, C. Chi, Y. Han, S. Rong, C. Zhang, P. Wang, Z. Wang, T. Huang, L. Sheng, and S. Zhang. Roborefer: Towards spatial referring with reasoning in vision-language models for robotics, 2026.
- [55] B. Zitkovich, T. Yu, S. Xu, P. Xu, T. Xiao, F. Xia, J. Wu, P. Wohlhart, S. Welker, A. Wahid, et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. In *Conference on Robot Learning*, pages 2165–2183. PMLR, 2023.



## 6. Contributions

Our contributors are organized based on their roles and magnitude of contribution. The final public release will replace the group-level placeholders below with individual names after internal approval.

### 6.1. Core Contributors

Unified VLM and Action capability: Yi Zhang, Yinda Chen, Che Liu, Zeyuan Ding

Unified World-model capability: Jin Xu, Shilong Zou

Evaluation and Assets: Junwei Liao, Jiayu Hu

### 6.2. Contributors

Xiancong Ren, Xiaopeng Zhang, Yechi Liu, Haoyuan Shi, Zecong Tang, Haosong Sun, Renwen Cui, Kuishu Wu, Wenhai Liu, Yang Xu, Yingji Zhang, Yidong Wang, Senkang Hu, Jinpeng Lu, Nga Teng Chan, Ye Chen Wu

### 6.3. Supports

Bokai Ji, Jian Li, Yuliang Zhan

### 6.4. Tech Lead

Yong Dai

### 6.5. Corresponding Authors

Jian Tang, Xiaozhu Ju

### 6.6. Acknowledgments

We thank our families, friends, and colleagues for their patience, understanding, and unwavering support throughout this work. The pursuit of a scientific vision is never carried by the researchers alone; it is sustained by the generosity, sacrifice, and trust of those closest to us. We dedicate this paper to the memory of Jin Xu's mother, whose encouragement, even in the final moments of her life, gave strength to this work and to the people who carried it forward.