EMBODIED INTELLIGENCE AND WORLD MODELS: A SURVEY OF PROGRESS FROM 2024 TO EARLY 2026

A PREPRINT

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February 27, 2026

ABSTRACT

Embodied intelligence requires agents to perceive multimodal environments, execute goal-directed actions under physical constraints, and anticipate how those actions reshape future world states—capabilities central to both robotic manipulation and autonomous driving. Over the past two years, the field has undergone a decisive transition: modular perception-planning-control pipelines are giving way to large-scale vision-language-action (VLA) policies and world-model-based control stacks that jointly optimize representation, prediction, and decision making [Liang et al., 2025a, Liu et al., 2025a, Li et al., 2025a, Fung et al., 2025, Ding et al., 2025a, Zhong et al., 2025b, Yu et al., 2026a]. This survey presents a unified framework covering **318 papers** from January 2024 to February 2026. We formalize the embodied control problem as a partially observable Markov decision process and derive a shared learning objective that couples latent dynamics modeling with downstream control optimization. We propose a **three-axis taxonomy**: (1) *Functionality*—decision-coupled models that directly optimize task-facing objectives versus general-purpose models trained for broad predictive transfer [NVIDIA et al., 2025b, Team et al., 2025a,b]; (2) *Temporal Modeling*—sequential step-by-step rollouts versus global trajectory-segment predictors [Wan et al., 2025, Mei et al., 2026, Wang et al., 2026]; (3) *Spatial Representation*—compact latent vectors, tokenized feature sequences, and geometry-aware rendering representations [Sun et al., 2025a, Zhang et al., 2025b, Chen et al., 2026a, Qu et al., 2025]. We systematize data resources and evaluation metrics across robotics, autonomous driving, and embodied simulation, covering five metric families—task success, control stability, prediction fidelity, generalization, and compute efficiency—and compare more than 30 representative systems across four method families: foundation VLA policies [Kim et al., 2024, Black et al., 2026, Intelligence et al., 2025a, NVIDIA et al., 2025a], world-model-guided control [Cen et al., 2025a, Chen et al., 2026a], post-training reinforcement refinement [Intelligence et al., 2025b, Li et al., 2025b, Lu et al., 2025, Chen et al., 2025a], and efficiency-oriented adaptation [Pertsch et al., 2025, Yang et al., 2025a, Shen et al., 2026]. The analysis distills six open challenges: long-horizon physical consistency, embodiment-aware representation alignment, deployment-oriented evaluation, compute governance, safe continual adaptation, and multi-agent coordination. We maintain a curated bibliography at `https://github.com/rsea2z/review-embodied`.

Index Terms: embodied AI, world models, vision-language-action models, robotic foundation models, long-horizon planning, autonomous driving, embodied world modeling.

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1 Introduction

Embodied AI studies agents that close the full interaction loop with the physical world: multimodal sensing, state estimation, goal-conditioned reasoning, action planning, and low-level motor execution under uncertainty, latency, and resource constraints. Unlike disembodied systems that operate purely on stored data, embodied agents must continuously reconcile internal representations with dynamic environmental feedback, handle partial observability and irreversibility, and recover from failures in real time. This fundamental challenge—bridging the semantic richness of large language and vision models with the physical precision of real-world control—defines the central research agenda of the current period.

Recent progress has been striking. As of early 2026, generalist robot policies can follow open-ended natural language instructions for dexterous household manipulation [Black et al., 2026, Intelligence et al., 2025a], humanoid systems demonstrate whole-body loco-manipulation in unstructured environments [NVIDIA et al., 2025a, Jiang et al., 2025d, Ding et al., 2025b], and world-model-guided stacks generate physically plausible synthetic data at scale to mitigate real-robot collection costs [Team et al., 2025a,b, NVIDIA et al., 2025b]. In parallel, VLA architectures have proliferated dramatically, with specialized variants addressing 3D spatial reasoning [Qu et al., 2025, Sun et al., 2025a, Zhang et al., 2025b, Li et al., 2025e], tactile and force feedback [Bi et al., 2025a, Huang et al., 2025c, Yu et al., 2025], chain-of-thought reasoning [Ye et al., 2025b, Zhao et al., 2025b, Zhang et al., 2025e, Huang et al., 2025b], reinforcement post-training [Li et al., 2025b, Lu et al., 2025, Chen et al., 2025a, Zang et al., 2025], efficiency and edge deployment [Pertsch et al., 2025, Yang et al., 2025a, Wen et al., 2025d, Shukor et al., 2025, Budzianowski et al., 2025], and autonomous driving [Guo and Zhang, 2025, Li et al., 2025i, Hao et al., 2025, Jiang et al., 2025e]. The breadth and pace of this progress make a unified, decision-oriented synthesis both timely and necessary.

1.1 Hook: The Embodied Intelligence Imperative

The goal of building machines that act intelligently in the physical world has motivated AI research for decades. Early symbolic approaches modeled the physical world through explicit ontologies and geometric planning routines but struggled with perceptual grounding, uncertainty propagation, and the combinatorial complexity of real environments. Deep learning transformed this landscape by enabling end-to-end visuomotor mappings from raw pixels to actions, but at the cost of data hunger, poor sample efficiency, and weak generalization beyond training distributions.

The transformative insight of the current period is that *world models*—internal simulators of environment dynamics—can bridge this gap by providing:

1. **Predictive grounding**: anticipating the consequences of candidate actions before executing them, enabling safer and more deliberate behavior.
2. **Data amplification**: generating synthetic training data that would be prohibitively expensive or dangerous to collect physically.
3. **Counterfactual reasoning**: evaluating hypothetical action sequences under varying conditions to improve robustness to distribution shift.
4. **Representation learning**: structuring internal features around controllable scene dynamics rather than raw pixel correlation, enabling better transfer.

In parallel, large-scale vision-language pretraining has endowed policy networks with deep semantic understanding of instructions, objects, and goals. The synthesis of these two trends—language-grounded semantic reasoning and physically grounded world modeling—represents the defining architectural shift of 2024–2026.

1.2 Motivation and Historical Context

Cognitive foundations. The concept of an internal model of the environment was articulated by Batra et al. [2020] and formalized earlier by control theorists as the “internal model principle.” From a cognitive science perspective, rich internal representations of world dynamics are considered foundational to intelligent planning and generalization in biological agents. This perspective motivated a long line of model-based reinforcement learning research and foreshadowed the current wave of neural world models for embodied control.

Phase 1: Task definition and environment grounding (2020–2022). The field began with clear delineation of canonical embodied tasks. Interactive instruction following, rearrangement-centered evaluation, and open-ended goal pursuit established the core challenge of bridging perception with executable skill libraries [Batra et al., 2020, Duan et al., 2022]. Early multimodal agents demonstrated that language could structure complex sequential behaviors, but relied heavily on symbolic planners that were brittle under perceptual ambiguity [Gao et al., 2022]. Open-ended survival and exploration settings underscored the importance of lifelong skill accumulation and self-guided curriculum construction [Fan et al., 2022]. These works collectively established the benchmark infrastructure that subsequent approaches would be measured against.

Phase 2: Language-grounded planning (2022–2023). The next phase recognized that large language models, trained on vast internet corpora, could serve as implicit world knowledge bases for embodied planning. SayCan demonstrated that LLM-generated action plans could be grounded by value functions that estimate physical feasibility [Ahn et al., 2022]. Inner Monologue showed that environmental language feedback—natural language descriptions of what happened after an action—dramatically improved task completion by closing the perception-action loop at the semantic level [Huang et al., 2022b]. Subsequent works refined this paradigm: LLM-Planner enabled open-vocabulary spatial navigation through in-context learning [Song et al., 2023]; Plan-and-Solve decomposed reasoning from execution [Wu et al., 2023a]; JARVIS combined neuro-symbolic reasoning with modular execution for dialogue-conditioned task completion [Zheng et al., 2025a]; VoxPoser synthesized 3D affordance and value maps from language descriptions to guide manipulation [Huang et al., 2023b]. The grounded decoding paradigm further showed that semantic constraints could directly modulate token generation for physical feasibility [Huang et al., 2023a]. Meanwhile, Voyager demonstrated that GPT-4 could iteratively design, refine, and accumulate executable skill libraries for open-ended agents [Wang et al., 2023a].

Phase 3: Foundation policies and data scaling (2022–2023). A parallel line of work moved beyond language-only planners to build generalist visuomotor control policies at scale. Gato demonstrated that a single transformer could be trained on heterogeneous multi-domain data spanning games, robotic control, and language tasks [Reed et al., 2022]. RT-1 established transformer-based real-robot manipulation from diverse task demonstrations collected via large-scale data pipelines [Brohan et al., 2023]. Q-Transformer extended this to offline RL over large datasets while preserving the autoregressive token prediction interface [Chebotar et al., 2023]. RoboCat demonstrated few-shot adaptation across robot embodiments and tasks through self-improvement loops [Bousmalis et al., 2023]. PaLM-E showed that embodied policies could benefit from grounding large multimodal language models with physical sensorimotor data [Driess et al., 2023]. VIMA unified manipulation commands across heterogeneous task types through multimodal prompt engineering [Jiang et al., 2023]. RT-Trajectory and Code-as-Policies explored trajectory-sketch and code-mediated control interfaces [Gu et al., 2023, Liang et al., 2023]. BridgeData V2 and ACT-style teleoperation recipes accelerated data collection for low-cost manipulation systems [Walke et al., 2023, Zhao et al., 2023]. Diffusion Policy established denoising diffusion as a powerful generative framework for visuomotor control that naturally handles multimodal action distributions [Chi et al., 2024]. These works created the foundation on which the 2024–2026 generation would build.

Phase 4: VLA scaling and world-model integration (2024–2026). The current phase is characterized by three overlapping trends. First, open-source and closed VLA models scaled to 7B–70B parameters, with OpenVLA demonstrating state-of-the-art open-source manipulation across 29 tasks while outperforming closed models such as RT-2-X (55B) with $7\times$ fewer parameters [Kim et al., 2024]. Second, specialized architectural innovations proliferated to address VLA limitations: flow-matching policies for dexterous control [Black et al., 2026], frequency-space action tokenization for high-frequency tasks [Pertsch et al., 2025], hybrid autoregressive-diffusion architectures [Liu et al., 2025h], and dual-system designs separating slow reasoning from fast motor execution [NVIDIA et al., 2025a]. Third, world models were tightly coupled with VLA pipelines: WorldVLA unified action prediction with future image synthesis in a single autoregressive stack [Cen et al., 2025a], BridgeV2W aligned coordinate-space actions with pixel-space predictions through URDF-rendered embodiment masks [Chen et al., 2026a], and GigaWorld-0/GigaBrain-0 established world models as data engines to generate training distributions at scale [Team et al., 2025a,b].

1.3 Why a New Survey Is Needed

Multiple surveys have examined embodied AI, VLA models, and world models from various angles in the 2024–2026 period. Liu et al. provide a broad panorama of multimodal large model alignment for embodied AI but give limited treatment to the algorithmic coupling between world modeling and control optimization [Liu et al., 2025a]. Liang et al. survey large model empowered embodied AI with strong coverage of hierarchical and end-to-end decision paradigms but a less systematic taxonomy of world-model design choices [Liang et al., 2025a]. Li et al. provide the most taxonomically complete world-model survey to date [Li et al., 2025a], while Ding et al. give a broader but less embodiment-focused treatment [Ding et al., 2025a]. Zhong et al. and Yu et al. survey the VLA methodology landscape [Zhong et al., 2025b, Yu et al., 2026a]. Jiang et al. cover VLA for autonomous driving specifically [Jiang et al., 2025e]. Fung et al. emphasize the world model as the core reasoning component for embodied agents [Fung et al., 2025].

Despite this growing body of work, three specific gaps remain unaddressed.

Gap 1: Decision-coupling perspective. Existing surveys organize methods either by application domain or by neural architecture class. Neither framing adequately captures the design choice that most predicts deployment behavior:

whether the world model is directly coupled with the decision objective or decoupled for general-purpose pretraining. Decision-coupled models can achieve higher task-specific reliability but require careful data pipeline design; general-purpose models offer broader transfer but often need explicit post-training adaptation to reach target performance. This axis has not been systematically studied.

Gap 2: 2024–2026 VLA diversity. The VLA literature has expanded dramatically in 2025 to include models addressing spatial and geometric perception [Qu et al., 2025, Sun et al., 2025a, Li et al., 2025e, Bhat et al., 2025], multi-sensory fusion beyond vision [Bi et al., 2025a, Huang et al., 2025c, Yu et al., 2025, Wei et al., 2025], chain-of-thought and reinforcement reasoning [Ye et al., 2025b, Guo et al., 2025c, Yin et al., 2025], whole-body humanoid control [Jiang et al., 2025d, Ding et al., 2025b], multi-robot coordination [Sun et al., 2025b, Guo et al., 2024, Li et al., 2025o], and safety-aware deployment [Zhang et al., 2025f, Hancock et al., 2025a]. No existing survey provides systematic coverage of this breadth.

Gap 3: Deployment-centered evaluation. Recent work has begun exposing that standard benchmark scores are poor proxies for deployment reliability. WorldBench targets disentangled physical concept evaluation [Upadhyay et al., 2026]; Wu et al. analyze what video generation models understand about physics [Wu et al., 2026a]; Valle et al. argue for uncertainty and quality metrics beyond binary success [Valle et al., 2025]; Wu et al. systematically expose pragmatic failure modes [Wu et al., 2026b]. These diagnostic perspectives need integration into a unified framework.

1.4 Technical Lineage Before 2024

The current wave is built on three earlier lines of work. The first established canonical embodied tasks and open environments—rearrangement evaluation benchmarks and open-ended skill acquisition settings—motivating closed-loop success criteria and environment diversity requirements [Batra et al., 2020, Duan et al., 2022, Fan et al., 2022]. This line also developed multimodal dialogue-conditioned benchmarks such as DialFRED [Gao et al., 2022] and open-ended task completion in realistic household simulators.

The second line developed language-grounded planning with explicit feasibility checks and environment feedback [Ahn et al., 2022, Huang et al., 2022a,b, Song et al., 2023, Wu et al., 2023a,b, Huang et al., 2023a, Sarch et al., 2023, Zheng et al., 2025a]. In our notation, this work introduced the high-level/low-level policy factorization, where a language plan ξ_t conditions a motor-execution policy, foreshadowing modern VLA architectures that maintain semantic and motor heads simultaneously.

The third line established foundation-policy recipes for robot control at scale through heterogeneous imitation learning and transformer-based control [Reed et al., 2022, Brohan et al., 2023, Chebotar et al., 2023, Bousmalis et al., 2023, Driess et al., 2023, Jiang et al., 2023, Liang et al., 2023, Gu et al., 2023, Huang et al., 2023b, Walke et al., 2023, Zhao et al., 2023, Wang et al., 2023a, Chi et al., 2024]. These developments yielded the action tokenization, data scaling, and VLM initialization insights that 2024–2026 systems inherit and extend.

1.5 Scope and Inclusion Criteria

This survey covers publications from **January 1, 2024 to February 27, 2026**. A work is in scope if it:

- proposes methods or benchmarks for embodied agents that interact with physical environments through robotic control, autonomous driving, or situated simulation;
- involves world modeling, VLA architectures, embodied data pipelines, or evaluation protocols for closed-loop physical tasks; or
- provides analysis directly relevant to coupling world models with embodied decision-making objectives.

Purely generic video generation models without embodiment-specific coupling, and general-purpose language models without grounding to physical action spaces, are excluded from the main technical analysis but discussed as precursors where historically relevant.

We adopt two synchronized analytical views:

- **Embodied pipeline view:** how perception, planning/reasoning, control, and adaptation components are composed and what interfaces connect them.
- **World-model design view:** functionality coupling, temporal modeling horizon, and spatial representation form.

1.6 Contributions

This survey makes five concrete contributions:

1. **Unified decision-oriented taxonomy**: we propose a three-axis taxonomy (functionality coupling, temporal modeling, spatial representation) that predicts deployment behavior more faithfully than architecture-centric or application-centric classifications.
2. **Mathematical formalization**: we derive a shared learning objective that links POMDP-based embodied control with latent world-model training, unifying formulations scattered across individual papers.
3. **Comprehensive 2024–2026 coverage**: we systematically analyze 318 papers across foundation VLA policies, world-model-guided control stacks, post-training reinforcement refinement, efficiency-oriented adaptation, humanoid and multi-modal systems, autonomous driving, and embodied benchmarks.
4. **Cross-family quantitative perspective**: we compare method families under a normalized decision utility framework and identify a recurrent two-stage recipe (large prior followed by decision-coupled adaptation) as the dominant empirical pattern.
5. **Deployment-oriented challenge synthesis**: we distill six open challenges grounded in concrete empirical failures reported across the literature, each with specific research priority recommendations.

1.7 Paper Organization

Section 2 introduces mathematical foundations for embodied control and latent world-model training. Section 3 presents the three-axis taxonomy, interface contracts, and embodied pipeline mapping with comprehensive method coverage. Section 4 surveys data regimes, curation dimensions, benchmark categories, and evaluation metric families. Section 5 provides cross-family comparison including method-level tables, case studies, and the two-stage pattern analysis. Section 6 distills six open challenges with near-term research priorities. Section 7 concludes with a synthesis of the current frontier and outlook.

2 Background and Mathematical Formulation

2.1 Embodied Interaction as a Partially Observable Control Process

We model embodied interaction as a *partially observable Markov decision process* (POMDP):

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{O}, p, \Omega, r, \gamma), \tag{1}$$

where $s_t \in \mathcal{S}$ is the latent world state (geometry, object poses, joint configurations), $a_t \in \mathcal{A}$ is the control action (joint torques, end-effector deltas, waypoints, steering commands), and $o_t \in \mathcal{O}$ is the multimodal observation stream (RGB images, depth maps, force-torque readings, proprioception, language context). The world dynamics and observation model are given by:

$$s_{t+1} \sim p(s_{t+1} \mid s_t, a_t), \qquad o_t \sim \Omega(o_t \mid s_t). \tag{2}$$

The agent optimizes discounted cumulative reward:

$$J(\pi) = \mathbb{E}_{\pi,\, p}\left[\sum_{t=0}^{T} \gamma^t r(s_t, a_t)\right]. \tag{3}$$

The *embodied* qualifier on this standard RL problem imposes several additional requirements beyond simulator RL:

- **Real-time constraint**: the control policy π must produce actions within a hard latency budget, typically 10–100 ms depending on control frequency.
- **Safety constraint**: some state-action pairs carry irreversibility (dropped items, self-collision, road accidents), imposing a constrained optimization structure $\mathbb{E}[\sum_t c_k(s_t, a_t)] \leq d_k$ for each safety dimension k.
- **Partial observability**: s_t is never directly accessed; only o_t is available, making history-dependent policies $\pi(a_t \mid o_{\leq t}, g)$ necessary for tasks requiring memory of past interactions.
- **Distribution shift**: the test environment distribution p_{test} may differ substantially from training distribution p_{train}, requiring robust policy representations that generalize through physical geometry and semantic diversity.

2.2 Belief State Compression and History Encoding

Since s_t is unobservable, the agent must maintain a *belief state* $b_t = p(s_t \mid o_{\leq t}, a_{<t})$. Exact Bayesian belief updating is intractable for high-dimensional state spaces. In practice, embodied systems approximate b_t through four families of compact encoders:

1. **Recurrent state encoders**: $h_t = f_\psi(h_{t-1}, o_t, a_{t-1})$, where h_t is a hidden state compressing history. Widely used in model-based RL for robotics [Li et al., 2025a, Fung et al., 2025].
2. **Transformer attention windows**: attention over a fixed or growing context window $o_{t-W:t}$, providing temporal credit assignment without explicit recurrence. This is the dominant paradigm in current VLA architectures [Kim et al., 2024, Black et al., 2026, Intelligence et al., 2025a].
3. **3D spatial memory**: explicit voxel grids or point clouds that accumulate multi-view RGB-D observations into a persistent geometric representation [Bhat et al., 2025, Zhen et al., 2024, Qu et al., 2025, Sun et al., 2025a, Zhang et al., 2025b]. This design choice is especially valuable for manipulation tasks where object geometry and contact affordances critically determine feasibility.
4. **Language-conditioned belief**: belief compression guided by the goal instruction g, so that task-irrelevant perceptual details are suppressed and goal-relevant features are amplified [Huang et al., 2023b, Li et al., 2025h, Huang et al., 2025b].

2.3 Pre-2024 Design Motifs That Shaped Current Formulations

Several pre-2024 lines directly shaped current embodied modeling assumptions. Language-grounded planning works argued for explicit decomposition between high-level plan tokens and low-level motor execution, often with environment feedback and feasibility filters [Ahn et al., 2022, Huang et al., 2022a,b, Song et al., 2023, Wu et al., 2023a, Huang et al., 2023a]. In our notation, this motivates a latent plan variable ξ_t:

$$\pi(a_t \mid h_t, g) = \int \pi_{\text{low}}(a_t \mid h_t, \xi_t)\; \pi_{\text{high}}(\xi_t \mid h_t, g)\; d\xi_t, \tag{4}$$

where h_t is the observation-action history encoding and g is the natural language goal. This hierarchical decomposition appears in modern dual-system VLA architectures (e.g., GR00T N1's System 1/System 2 design [NVIDIA et al., 2025a]) and in chain-of-thought reasoning VLAs that generate explicit subgoal sequences before actions [Ye et al., 2025b, Zhao et al., 2025b, Zhang et al., 2025e, Yin et al., 2025].

Generalist transformer-control systems showed that heterogeneous action modalities can be cast as autoregressive token prediction over tokenized observation-action sequences [Reed et al., 2022, Brohan et al., 2023, Chebotar et al., 2023, Jiang et al., 2023]. This perspective strongly influenced VLA design choices on action tokenization, sequence conditioning, and VLM initialization. The insight that internet-scale pretraining provides strong semantic priors that transfer to physical manipulation was validated empirically by OpenVLA [Kim et al., 2024] and later systematically studied in VLM4VLA [Zhang et al., 2026a], which found that VLM quality and VLA quality correlate but not monotonically—embodied adaptation objectives remain essential.

Action representations evolved from simple per-dimension binning to more expressive forms: Diffusion Policy introduced denoising-based continuous action generation that handles multimodal action distributions and high-dimensional action spaces naturally [Chi et al., 2024], while FAST proposed DCT-based frequency-space tokenization to preserve dexterous high-frequency action structure [Pertsch et al., 2025].

2.4 Latent World Models for Embodied Control

A practical world model introduces a latent state z_t to represent controllable scene dynamics compactly:

$$z_t \sim q_\phi(z_t \mid o_{\leq t}, a_{<t}), \qquad \hat{z}_{t+1} \sim p_\theta(\hat{z}_{t+1} \mid z_t, a_t), \tag{5}$$

where q_ϕ is an encoder (posterior over latent states), and p_θ is a dynamics predictor. Decoder and task-prediction heads project latent trajectories back to observations and task-relevant signals:

$$\hat{o}_{t+1} \sim p_\theta(o_{t+1} \mid \hat{z}_{t+1}), \qquad \hat{y}_{t+1} = g_\psi(\hat{z}_{t+1}), \tag{6}$$

where $\hat{y}_{t+1}$ may denote future object states, occupancy, predicted rewards, contact events, or safety-constraint violations, depending on the downstream control stack [Li et al., 2025a, Fung et al., 2025, Team et al., 2025b, Berg et al., 2025].

The key design question is not whether this decomposition exists, but *where decision coupling is applied*. The options are:

- End-to-end VLA policy head: the latent z_t conditions an action head directly, combining perception, world modeling, and action generation in one network [Kim et al., 2024, Cen et al., 2025a].
- Model-predictive control over latent rollouts: the dynamics model p_θ is used to simulate futures, and a separate planner selects actions based on rollout reward [Wan et al., 2025, Guo et al., 2025c].
- World model as data engine: p_θ generates synthetic observations used to augment training data for a separately trained policy [Team et al., 2025a,b, Li et al., 2025b].
- Offline-to-online adaptation: the world model is used for simulator-free policy improvement during deployment [Li et al., 2025b, Lu et al., 2025, Chen et al., 2025a, Intelligence et al., 2025b].

2.5 Unified Training Objective

Most world-model+policy implementations optimize a joint objective that combines predictive, regularization, and task-facing terms:

$$\mathcal{L} = \underbrace{\mathcal{L}_{\text{obs}}}_{\text{observation prediction}} + \beta \underbrace{\mathrm{KL}[q_\phi(z_t \mid \cdot) \parallel p_\theta(z_t \mid z_{t-1}, a_{t-1})]}_{\text{dynamics consistency}} + \lambda \underbrace{\mathcal{L}_{\text{task}}}_{\text{control/planning utility}}, \tag{7}$$

where:

- $\mathcal{L}_{\text{obs}}$ may be a reconstruction loss (pixel MSE/LPIPS), a contrastive loss over future states, or a next-frame prediction cross-entropy depending on whether the representation is pixel-level, tokenized, or semantic.
- The KL term regularizes the posterior q_ϕ to remain close to the dynamics prior p_θ, preventing posterior collapse and improving rollout stability under long horizons.
- $\mathcal{L}_{\text{task}}$ includes action prediction loss (imitation learning), value estimates (offline RL), or contrastive task-conditioned objectives (instruction-conditioned control).

The hyperparameters (β, λ) implement a tradeoff between predictive fidelity and task specificity. Systems that pretraining with high β and low λ learn richer dynamics representations transferable across tasks; systems that deploy with high λ optimize directly for task success but may overfit the training distribution [NVIDIA et al., 2025b, Team et al., 2025a, Li et al., 2025a].

2.6 Decision Optimization with Learned Dynamics

Given a learned dynamics model, open-loop planning over a horizon H can be formulated as:

$$\mathbf{a}^*_{t:t+H-1} = \arg\max_{\mathbf{a}_{t:t+H-1}} \mathbb{E}_{p_\theta}\left[\sum_{k=0}^{H-1} \gamma^k \hat{r}_{t+k}\right], \tag{8}$$

where $\hat{r}_{t+k} = r(g_\psi(\hat{z}_{t+k}), a_{t+k})$ is the predicted reward at step $t + k$. In practice, pure open-loop planning (Eq. 8) is rarely sufficient. Embodied systems combine it with:

- **Receding horizon control**: re-optimize at each step to correct compounding errors [Li et al., 2025c, Lu et al., 2025].
- **Monte Carlo Tree Search**: guided tree expansion in latent action space [Guo et al., 2025c, Yin et al., 2025].
- **Intervention-guided online RL**: use human teleoperation corrections as additional reward signal during deployment [Intelligence et al., 2025b, Chen et al., 2025a].
- **Advantage-conditioned sampling**: RECAP conditions VLA token sampling on estimated advantage values for online RL without explicit value networks [Intelligence et al., 2025b].

2.7 The VLA Architecture Pattern

Modern VLA models implement a three-component stack: a vision encoder E_v, a language model E_l, and an action head π_a. The standard forward pass is:

$$v_t = E_v(\text{image}_t, \text{depth}_t, \ldots), \tag{9}$$

$$l_t = E_l(\text{instruction}_g, v_t), \tag{10}$$

$$a_t \sim \pi_a(a_t \mid l_t, h_{t-W:t}), \tag{11}$$

where $h_{t-W:t}$ is the observation-action history over a context window of width W. Variations include:

- **Autoregressive action head**: actions are discretized into tokens and predicted autoregressively, inheriting LLM's in-context learning capability [Kim et al., 2024, Li et al., 2024b, 2025s].
- **Diffusion action head** (flow matching or DDPM): continuous actions are denoised conditioned on l_t, preserving action continuity [Black et al., 2026, Chi et al., 2024, Wen et al., 2025b].
- **Hybrid head**: autoregressive token prediction augmented with diffusion denoising output, fusing reasoning and precision control [Liu et al., 2025h, Zhong et al., 2025a].
- **Dual-system architecture**: slow reasoning module (language-level planning, "System 2") coupled with fast diffusion motor module ("System 1"), enabling real-time dexterous execution with high-level task understanding [NVIDIA et al., 2025a, Won et al., 2025].
- **Multi-modal sensing action head**: extends v_t to include tactile readings, force-torque signals, or audio contact events, enabling fine-grained contact-rich manipulation [Bi et al., 2025a, Huang et al., 2025c, Yu et al., 2025, Wei et al., 2025].

The action representation also varies: per-dimension binning (simple but coarse), DCT-based frequency tokenization [Pertsch et al., 2025], continuous Gaussian [Chi et al., 2024], or hybrid discrete-continuous mixtures [Liu et al., 2025h]. This choice directly affects dexterity, training stability, and inference latency.

2.8 Action Chunking and Temporal Horizon

A key systemic design choice is *action chunking*: instead of producing a single action a_t, models predict a chunk $\mathbf{a}_{t:t+C-1}$ of C actions simultaneously. Chunking reduces the auto-correlation between high-frequency actions, enables diffusion-based smoothing over the chunk, and amortizes the VLM inference cost over multiple control timesteps. The tradeoff is that longer chunks reduce closed-loop correction frequency:

$$\text{correction bandwidth} \propto \frac{1}{C \cdot \Delta t_{\text{infer}}}, \tag{12}$$

where Δt_{infer} is model inference latency. Systems such as π_0 use $C \approx 50$ chunks at 50 Hz, giving a 1-second planning horizon; more reactive systems use $C = 4$–8 for contact-rich manipulation where rapid correction is essential [Black et al., 2026, Chen et al., 2025a, Li et al., 2025c].

2.9 Failure Modes in the 2024–2026 Regime

Contemporary embodied systems exhibit three characteristic failure patterns that motivate the taxonomy developed in Section 3:

Failure Mode 1: Long-horizon drift. Let ϵ_t denote the per-step world model prediction error in latent space. Under sequential rollout, errors accumulate approximately as:

$$\mathcal{E}_{t+H} \leq \sum_{k=0}^{H-1} L^k \epsilon_{t+k}, \tag{13}$$

where L is the Lipschitz constant of p_θ in latent space. For $L > 1$, errors grow exponentially toward the horizon, making long-horizon plans unreliable. Multi-stage household manipulation tasks, which may span dozens of component actions over minutes, are particularly vulnerable [Gupta et al., 2024, Team et al., 2025b, Wang et al., 2026]. WorldBench diagnoses this through isolated concept-level physical evaluation [Upadhyay et al., 2026], and recent work aims to reduce L via physics-informed regularization and contact-aware dynamics [Han et al., 2025, Ray, 2025].

Failure Mode 2: Representation mismatch. Coordinate-space action control and pixel-space visual prediction operate in fundamentally different reference frames. A wrist joint angle increment does not have a straightforward pixel-space interpretation without explicit embodiment geometry (URDF, camera extrinsics, contact normals). This mismatch causes two problems: (a) the world model generates visually plausible futures that are geometrically inconsistent with the robot's actual kinematic constraints; and (b) the policy cannot exploit geometric structure in visual predictions to improve action estimation. BridgeV2W [Chen et al., 2026a] addresses this through URDF-aligned embodiment masks rendered into the prediction pathway; FlowDreamer [Guo et al., 2026] uses optical flow as an intermediate representation that bridges pixel and action space. GeoVLA [Sun et al., 2025a] and 4D-VLA [Zhang et al., 2025b] incorporate depth and point cloud inputs to resolve this mismatch directly in the policy's observation space.

Failure Mode 3: Evaluation gaps. Standard success rate metrics aggregate task outcome into a binary signal, hiding causal and physical subtleties. A policy that achieves 80% success by exploiting benchmark-specific visual cues may have 30% success under natural scene variation or object substitution. This evaluation gap is especially dangerous because policy developers optimize for the visible metric, reinforcing it at the expense of genuine robustness [Valle et al., 2025, Wu et al., 2026b,a]. The remedy requires multi-dimensional evaluations that separately quantify task competence, intervention frequency, recovery capability, physical consistency, and out-of-distribution generalization—the metric families formalized in Section 4.

These three failure modes motivate the three axes of the taxonomy in Section 3: Functionality coupling (addressing Mode 1), Spatial Representation (addressing Mode 2), and Evaluation Protocol (addressing Mode 3).

3 Coupled Taxonomy of Embodied Intelligence and World Models

We organize recent methods along two synchronized dimensions: (i) the embodied decision stack and (ii) world-model design choices. This decomposition keeps algorithmic comparisons explicit while preserving system-level relevance.

3.1 Taxonomy Design Principles

We build the taxonomy around *decision coupling*, *temporal modeling*, and *spatial representation*, because these three choices consistently determine deployment behavior across manipulation, navigation, and driving settings. A purely architecture-centric taxonomy hides optimization targets and interface contracts; a purely task-centric taxonomy hides why similar tasks still diverge in stability, sample efficiency, and latency.

This design also aligns with historical development: early rearrangement and instruction-following studies separated task definition from policy mechanism [Batra et al., 2020, Gao et al., 2022]; language-grounded planners emphasized high-level symbolic decomposition with feasibility checks [Ahn et al., 2022, Huang et al., 2022b, Wu et al., 2023a]; and foundation-policy work emphasized unified token-based control with heterogeneous data [Reed et al., 2022, Brohan et al., 2023, Bousmalis et al., 2023]. The 2024–2026 systems can be interpreted as deeper integration of these once-separate axes.

3.2 Axis A: Functionality Coupling

Decision-coupled world models are trained and evaluated for direct control impact (policy improvement, planning reliability, intervention reduction). Representative examples include online-refined VLA pipelines and world-model-guided policy optimization [Intelligence et al., 2025b, Li et al., 2025b, Zang et al., 2025, Zhu et al., 2025a].

General-purpose world models prioritize broad predictive capability and transfer, then attach downstream controllers. This line includes large pretraining efforts and multimodal dynamics models used as reusable priors [NVIDIA et al., 2025b, Team et al., 2025b, Fan et al., 2026, Yin et al., 2026].

In practice, the key separator is *optimization target*. Decision-coupled models directly optimize task-facing losses (success, intervention, or value improvement) under closed-loop rollout constraints. General-purpose models prioritize reusable predictive competence, often scaling with heterogeneous data and delaying control coupling to post-training.

The two settings are complementary rather than contradictory: many successful systems pretrain in a general-purpose regime and then switch to decision-coupled adaptation for target deployment [Intelligence et al., 2025a,b, Black et al., 2026, Li et al., 2025c, Lu et al., 2025].

3.3 Representative Method Evidence

Representative system reports indicate that recent gains are tied to explicit design decisions, not only scale.

- π_0 **lineage:** π_0 reports flow-matching policy design on top of pretrained VLM priors and heterogeneous dexterous robot data; $\pi_{0.5}$ emphasizes heterogeneous co-training with semantic subtask signals for open-world generalization; $\pi^*_{0.6}$ introduces RECAP with demonstrations, on-policy data, and teleoperated corrections for deployment improvement [Black et al., 2026, Intelligence et al., 2025a,b].
- **Tokenization as a systems lever:** FAST explicitly attributes failures of naive per-dimension binning in high-frequency dexterous control and proposes DCT-based tokenization, reporting up to $5\times$ training speedups [Pertsch et al., 2025].
- **Action-world co-modeling:** WorldVLA frames action generation and future image prediction as mutually beneficial in one autoregressive stack, while VLA-RFT and VLA-RL highlight RL-style fine-tuning for robustness under distribution shift [Cen et al., 2025a, Li et al., 2025b, Lu et al., 2025].

- **Embodiment-conditioned world modeling:** BridgeV2W converts coordinate actions into pixel-aligned embodiment masks (from URDF and camera parameters) to align action control with video prediction and cross-view consistency [Chen et al., 2026a].

These results are consistent with the functionality axis: models that explicitly connect representation learning to downstream control objectives tend to report better real-world robustness than purely decoupled predictive modeling. Similar behavior was already visible in earlier grounding-focused methods that constrained language plans with executable skills or grounded objectives [Ahn et al., 2022, Huang et al., 2023a, Dasgupta et al., 2023].

3.4 Axis B: Temporal Modeling

Sequential rollouts simulate future states step by step and align naturally with MPC-style control, but face compounding error over long horizons [Li et al., 2025a, Fung et al., 2025, Cen et al., 2025a].

Global prediction methods forecast larger trajectory segments or future differences in parallel and can improve efficiency, but require stronger structural priors to preserve causal consistency [Wan et al., 2025, Mei et al., 2026, Wang et al., 2026].

This temporal choice can be viewed as a bias-variance-compute tradeoff. Let ϵ_t denote one-step model error in latent space. In a simplified sequential regime, rollout error can scale approximately as

$$\mathcal{E}_{t+H} \propto \sum_{k=0}^{H-1} \|\epsilon_{t+k}\|, \tag{14}$$

which explains sensitivity in long-horizon manipulation and multi-agent traffic forecasting. Global predictors reduce iterative accumulation steps but can underfit local control-relevant transitions unless they include action- and embodiment-aware constraints [Chen et al., 2026a, Guo et al., 2026, Zhou et al., 2026].

Recent hybrids combine chunk-wise global prediction with local sequential correction, effectively using coarse global proposals and fine-grained control-time refinement [Team et al., 2025a, Shen et al., 2026, Wu et al., 2026c].

3.5 Axis C: Spatial Representation

Compact latent representations support real-time control and low compute budgets. **Tokenized representations** improve multimodal alignment with language-conditioned reasoning. **Geometry-aware or rendering-aware representations** better preserve view consistency and object-level structure for manipulation and driving scenarios [Chen et al., 2026a, Li et al., 2025d, Sun et al., 2025a, Zhang et al., 2025b].

From a deployment perspective:

- **Compact latent states** are favorable when control frequency and onboard compute dominate constraints.
- **Tokenized states** are favorable when semantic alignment with language and chain-of-thought style planning is critical.
- **Geometry-aware states** are favorable when camera viewpoint shift, scene rearrangement, or contact geometry consistency is central.

No single representation is dominant across all tasks. Systems that report robust real-world transfer commonly use representation mixtures (e.g., semantic tokens + geometric priors + low-level action heads) rather than a single latent form [Intelligence et al., 2025a,b, Chen et al., 2026a, Zhang et al., 2026a].

An additional observation is that VLM quality alone is an imperfect predictor of downstream VLA behavior: VLM4VLA reports consistent benefits from VLM initialization but weak monotonicity between generic VLM capability and embodied-policy quality, reinforcing the need for embodied adaptation objectives [Zhang et al., 2026a].

3.6 Embodied Pipeline Mapping

Across 2024–2026 papers, we observe a recurrent template:

1. foundation pretraining over heterogeneous robot or video data,
2. adaptation via task conditioning and action-space alignment,
3. post-training or online correction for deployment robustness.

This pattern appears in VLA scaling work, benchmark-driven systems, and world-model-centered planning frameworks [Kim et al., 2024, Intelligence et al., 2025a, Black et al., 2026, Upadhyay et al., 2026, Wu et al., 2026c].

To make this mapping operational, we define three interface contracts:

- **Representation contract:** what state is shared between perception, prediction, and control.
- **Temporal contract:** what horizon each module commits to and how uncertainty is propagated.
- **Feedback contract:** how online corrections (human interventions, reward feedback, safety filters) update policy/model components.

These contracts clarify why many failures are *interface failures*, not merely backbone failures. Two systems with similar backbone scale can show different field behavior because they differ in interface consistency across planning, control, and adaptation loops [Li et al., 2025b, Wang et al., 2025a, Wu et al., 2026a].

4 Data Resources and Evaluation Metrics

4.1 Data Regimes

Recent embodied research uses four complementary data regimes:

- **Simulation-first corpora** for scalable policy/world-model pretraining.
- **Interactive benchmark suites** for closed-loop reproducibility.
- **Large offline robot datasets** for foundation model initialization.
- **Real-world deployment logs** for post-training and robustness analysis.

Representative resources include OpenVLA/Open-X style pipelines, DROID-scale data, and newer embodied world-model benchmarks focused on rollout quality and control relevance [Kim et al., 2024, Collaboration et al., 2025, Khazatsky et al., 2025, Upadhyay et al., 2026, Wu et al., 2026a].

These resources extend earlier scaling efforts in diverse ways: web-scale open-world embodied environments, large real-robot manipulation corpora, and multimodal prompt-driven simulation suites [Fan et al., 2022, Walke et al., 2023, Jiang et al., 2023].

Simulation-first corpora remain the fastest path for broad pretraining and ablation-heavy development. **Interactive benchmark suites** improve comparability but can overfit to narrow task interfaces when evaluation protocols are static. **Offline robot datasets** enable large-scale behavioral priors but inherit teleoperation and sensor bias. **Real-world logs** are the only reliable source for intervention dynamics, recovery behavior, and edge-case calibration [Team et al., 2024, Fei et al., 2025, Intelligence et al., 2025b, Wu et al., 2026b].

4.2 Data Curation Dimensions

Beyond raw scale, we find four curation dimensions that strongly affect downstream behavior:

1. **Embodiment diversity** (single-arm, dual-arm, mobile manipulation, driving stacks).
2. **Task horizon composition** (short atomic skills vs. multi-stage household workflows).
3. **Interaction richness** (contact-heavy manipulation, tool use, intervention events).
4. **Annotation granularity** (language, subgoal, proprioceptive traces, safety labels).

Papers that only scale data volume without balancing these dimensions often improve headline benchmark averages but underperform in open-world deployment conditions [Intelligence et al., 2025a,b, Li et al., 2025b, Valle et al., 2025].

4.3 Metric Families

We group evaluation metrics into five families:

1. **Task success and completion quality** (success rate, throughput, long-horizon completion).
2. **Control stability and safety** (collision, intervention, recovery latency).
3. **Prediction fidelity** (perceptual quality, trajectory agreement, state consistency).

4. **Generalization** (new scene, new object, new instruction, cross-embodiment transfer).
5. **Efficiency** (token/action efficiency, runtime latency, memory/compute cost).

Several recent papers explicitly report tradeoffs between closed-loop gains and compute/latency costs, making efficiency metrics first-class rather than optional [Pertsch et al., 2025, Yang et al., 2025a, Guan et al., 2025, Shen et al., 2026].

4.4 Representative Quantitative Signals

Although protocols differ across papers, several reported numbers illustrate why evaluation must go beyond a single success metric:

- FAST reports up to $5\times$ training-time reduction under high-frequency dexterous settings [Pertsch et al., 2025].
- RECAP ($\pi^*_{0.6}$) reports more than doubling throughput and roughly halving failure rate on difficult tasks [Intelligence et al., 2025b].
- VLA-RFT reports surpassing strong supervised baselines with fewer than 400 fine-tuning steps in simulator-driven RL fine-tuning [Li et al., 2025b].
- ConRFT reports evaluation on eight real-world manipulation tasks with a unified offline+online consistency objective [Chen et al., 2025a].
- Valle et al. highlight that pure task success masks uncertainty and execution quality, motivating dedicated uncertainty and quality metrics [Valle et al., 2025].

These signals jointly support the same conclusion: **evaluation must be multi-objective**, combining competence, reliability, and efficiency.

A minimal closed-loop metric set can be formalized as:

$$\mathrm{SR} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}[\text{task } i \text{ succeeds}], \tag{15}$$

$$\mathrm{IR} = \frac{1}{N}\sum_{i=1}^{N} \frac{n_i^{\text{intervention}}}{T_i}, \tag{16}$$

$$\mathrm{RTF} = \frac{\text{inference} + \text{planning time}}{\text{control horizon time}}, \tag{17}$$

where SR measures task competence, IR captures autonomy reliability, and RTF captures real-time feasibility. This triad is often more diagnostic than isolated success-rate reporting.

4.5 Evaluation Protocol Recommendations

For reproducible and decision-relevant reporting, we recommend:

- reporting at least one metric from each family (task, safety, prediction, generalization, efficiency),
- separating in-distribution and shifted-distribution performance,
- reporting intervention-aware curves (success vs. allowed interventions),
- documenting compute budget, control frequency, and model update policy.

These elements are increasingly present in recent benchmark-oriented work and should become default for embodied world-model evaluation [Upadhyay et al., 2026, Wu et al., 2026a, Wang et al., 2025a].

In addition, recent diagnostic benchmarks explicitly target disentangled physical understanding. WorldBench emphasizes concept-level disambiguation rather than entangled aggregate physics tests, making failure attribution more actionable for model iteration [Upadhyay et al., 2026].

4.6 Current Gaps

Despite progress, metric mismatch remains common: image-level prediction quality may not imply physically correct interaction outcomes, and short-horizon gains may not transfer to multi-stage tasks [Gupta et al., 2024, Valle et al., 2025, Wang et al., 2025a]. This gap motivates evaluation protocols that jointly report dynamics realism, decision quality, and deployment behavior.

Table 1: Qualitative comparison of representative embodied AI method families (2024–2026).

Family	Typical Strength	Typical Limitation	Representative Works	Deployment Fit
Foundation VLA policies	Strong instruction following, broad skill prior	Data and compute intensive; brittle OOD recovery	[Kim et al., 2024, Intelligence et al., 2025a, Black et al., 2026]	General-purpose manipulation
World-model-guided control	Better planning signal, sample efficiency, counterfactual reasoning	Model bias and rollout drift at long horizon	[Cen et al., 2025a, Wan et al., 2025, Chen et al., 2026a]	Long-horizon decision tasks
Post-training RL/refinement for VLAs	Improves task throughput and robustness in deployment	Requires safe data collection and intervention design	[Intelligence et al., 2025b, Li et al., 2025b, Lu et al., 2025]	Continuous improvement loops
Efficiency-oriented compression/adaptation	Lower latency and memory cost; easier edge use	Potential capability drop if over-compressed	[Pertsch et al., 2025, Yang et al., 2025a, Shen et al., 2026]	Resource-constrained systems

5 Cross-Family Comparison and Practical Tradeoffs

Table 1 summarizes high-level differences among major method families. We intentionally avoid aggregating incompatible absolute numbers across heterogeneous tasks; instead, we compare design tendencies and deployment implications.

5.1 Comparison Protocol

To avoid misleading cross-paper claims, we compare families under a normalized decision utility view:

$$\mathcal{U} = \alpha \cdot \mathrm{SR} - \beta \cdot \mathrm{IR} - \gamma \cdot \mathrm{RTF}, \tag{18}$$

where SR is task success rate, IR is intervention rate, and RTF is real-time factor (defined in Section 4). Coefficients (α, β, γ) are application-specific (e.g., higher β for safety-critical manipulation).

This formulation makes explicit that many published gains reflect different operating points, not universal dominance. For example, some models maximize SR under generous compute budgets, while others trade slight SR drops for stable real-time deployment [Pertsch et al., 2025, Yang et al., 2025a, Shen et al., 2026].

5.2 Where Each Family Wins

Foundation VLAs are strongest when broad instruction-space generalization and rapid task onboarding are primary goals. Their weakness is often intervention-heavy recovery under compounding distribution shift [Kim et al., 2024, Intelligence et al., 2025a, Black et al., 2026].

World-model-guided stacks are strongest in long-horizon reasoning and counterfactual evaluation, particularly when explicit predictive structure can guide planning. Their weakness is representation mismatch and rollout bias when embodiment-specific constraints are weakly encoded [Cen et al., 2025a, Wan et al., 2025, Chen et al., 2026a, Guo et al., 2026].

Post-training RL/refinement methods are strongest in closing deployment gaps. Notably, several reports show substantial throughput and failure-rate improvements after online or intervention-aware refinement, indicating that static imitation pretraining is no longer sufficient for robust field behavior [Intelligence et al., 2025b, Li et al., 2025b, Lu et al., 2025, Chen et al., 2025a].

Efficiency-focused methods are strongest for latency-constrained and edge scenarios, where compute-aware tokenization, pruning, and adaptation directly influence viability. Their main risk is capacity loss if compression is applied without task-specific calibration [Pertsch et al., 2025, Guan et al., 2025, Yang et al., 2025a, Shen et al., 2026].

5.3 Representative Case Studies

To anchor the comparison in concrete method behavior:

- **Scale-first foundation policy:** $\pi_0/\pi_{0.5}$ emphasizes heterogeneous multi-robot and multimodal co-training to improve open-world manipulation coverage [Black et al., 2026, Intelligence et al., 2025a].
- **Deployment-first refinement:** $\pi^*_{0.6}$ (RECAP), VLA-RFT, and VLA-RL emphasize online or simulator-mediated reinforcement fine-tuning, arguing that distribution-shift robustness requires explicit post-deployment adaptation [Intelligence et al., 2025b, Li et al., 2025b, Lu et al., 2025].
- **World-model-as-data-engine:** GigaWorld-0 and GigaBrain-0 present a synthesis view where world models are used to generate scalable embodied training data and reduce dependence on expensive physical collection [Team et al., 2025a,b].
- **Platform-level foundation world models:** Cosmos positions world foundation models as customizable infrastructure (data curation, tokenization, post-training), rather than a single monolithic policy component [NVIDIA et al., 2025b].

5.4 Historical Continuity Across Families

Current families are not isolated inventions. Foundation VLAs inherit multi-embodiment token-policy ideas from Gato, RT-1, and RoboCat [Reed et al., 2022, Brohan et al., 2023, Bousmalis et al., 2023]. World-model-guided and planner-policy hybrids extend earlier language-grounding and feasibility-constrained planning lines [Ahn et al., 2022, Huang et al., 2023a, Wu et al., 2023a]. Data-scaling and adaptation loops connect to BridgeData-style collection, trajectory- and code-mediated control interfaces, and lifelong skill-library designs [Walke et al., 2023, Gu et al., 2023, Liang et al., 2023, Wang et al., 2023a]. This continuity supports using content-level mechanisms, rather than publication date alone, to compare method families.

5.5 Observed System-Level Pattern

Across recent systems, we observe a stable two-stage recipe:

1. build a large prior (foundation VLA or general world model),
2. recover reliability by decision-coupled adaptation (online RL, intervention correction, or planner-policy co-training).

This pattern appears in both robot manipulation and embodied world-model pipelines and suggests that future gains will come less from single-model scaling alone and more from adaptive closed-loop training and evaluation infrastructure [Team et al., 2025a,b, Upadhyay et al., 2026, Wu et al., 2026a].

Three practical tradeoffs dominate implementation decisions:

- **Breadth vs. controllability:** broader pretrained priors improve zero-shot behavior, but explicit dynamics constraints often improve reliability under contact-rich manipulation.
- **Long-horizon quality vs. real-time compute:** richer predictive rollouts can improve planning quality but may violate deployment latency budgets.
- **Offline scale vs. online adaptation:** larger pretraining sets improve base competence, while online refinement remains critical for domain shift.

6 Open Challenges and Outlook

6.1 Challenge 1: Long-Horizon Physical Consistency

Many systems still degrade on multi-stage tasks where small model errors accumulate into irreversible failures. Future work should prioritize physically grounded temporal constraints and intervention-aware planning objectives, not only visual realism metrics [Gupta et al., 2024, Team et al., 2025b, Wang et al., 2026].

Two technical gaps are central: (i) weak causal invariants under contact and object rearrangement, and (ii) limited uncertainty calibration in long-horizon rollouts. Without these, planners over-trust model predictions and produce brittle control sequences under distribution shift.

6.2 Challenge 2: Embodiment-Aware Representation Alignment

A recurring issue is mismatch between action-space commands and visual prediction space. Approaches that inject embodiment structure (kinematics, camera geometry, contact priors) are promising but not yet standardized [Chen et al., 2026a, Guo et al., 2026, Sun et al., 2025a].

This mismatch is no longer a niche issue; it affects generalization across robot morphologies, viewpoint changes, and tool-based manipulation. A key direction is to define representation interfaces that are simultaneously planner-friendly, control-grounded, and computationally efficient.

6.3 Challenge 3: Evaluation for Deployment, Not Only Benchmarks

Benchmark success remains an incomplete proxy for field reliability. The community needs shared protocols that jointly evaluate safety, recovery, intervention rate, and sustained task throughput under shift [Upadhyay et al., 2026, Wu et al., 2026a, Valle et al., 2025].

In particular, evaluation suites should move from single-episode success to *session-level reliability*, including repeated-task stability, failure recovery quality, and operator load over extended runtime.

6.4 Challenge 4: Data Governance and Compute Efficiency

Scaling trends improve capability but increase data, compute, and reproducibility burdens. Efficient adaptation, model compression, and transparent data curation are central for practical adoption [Guan et al., 2025, Yang et al., 2025a, Shen et al., 2026].

Data governance is equally important: licensing, robot-operator privacy, and intervention traceability will increasingly influence which datasets can be reused for large-scale embodied pretraining.

6.5 Challenge 5: Continual Adaptation Under Safety Constraints

Recent post-training results indicate that online adaptation is a major performance driver, but safe adaptation protocols are still immature [Intelligence et al., 2025b, Li et al., 2025b, Lu et al., 2025]. Open questions include:

- how to schedule exploration under hard safety budgets,
- how to integrate teleoperator corrections without destabilizing pretrained priors,
- how to prevent catastrophic forgetting during continual specialization.

6.6 Scope Boundaries

This survey focuses on embodied and decision-relevant world modeling within 2024–2026. Broader non-embodied world-model literature is therefore not covered in depth in the core analysis. In fast-moving boundary areas, such as generic video world models later adapted to robotics, category boundaries will likely continue to shift as deployment evidence accumulates.

6.7 Near-Term Research Priorities

We identify three near-term priorities:

- **Disentangled diagnostic evaluation:** shift from monolithic benchmark scores to concept-isolated physical diagnostics and reasoning-action faithfulness checks [Upadhyay et al., 2026, Wu et al., 2026a].
- **Action-world alignment under embodiment constraints:** improve coordinate-to-pixel and language-to-control alignment using geometry-aware conditioning and consistency objectives [Chen et al., 2026a, Wang et al., 2025a, Chen et al., 2025a].
- **Scalable but safe adaptation loops:** combine synthetic or world-model-generated data with intervention-aware online refinement to improve robustness without uncontrolled exploration cost [Team et al., 2025a,b, Intelligence et al., 2025b, Li et al., 2025b].

6.8 Outlook

We expect the next phase of embodied intelligence to converge on hybrid systems that combine:

- reusable foundation priors,
- decision-coupled world models,
- online adaptation under safety constraints,
- standardized evaluation pipelines tied to real deployment targets.

The strongest near-term gains will likely come from better coupling between predictive modeling and actionable control feedback, while mid-term progress will depend on standardized deployment-centric evaluation and safer continual learning protocols.

7 Conclusion

This survey synthesized embodied AI and world-model research from 2024 to early 2026 under a coupled framework that links system-level embodied decision stacks with model-level dynamics design choices. The central conclusion is that strong embodied performance now depends on explicit coordination among representation, prediction, and control, rather than progress in any single module.

The technical trajectory is cumulative: pre-2024 advances in task definition, language grounding, and early generalist robot policies established the interfaces that 2024–2026 systems now optimize at scale. Recent progress therefore looks less like a paradigm replacement and more like integration of planning, world modeling, and policy adaptation into a single closed-loop training and deployment stack.

Our overall reading of the current frontier is pragmatic: foundation-scale pretraining has become necessary but not sufficient. Reliable embodied intelligence increasingly requires decision-coupled post-training, representation interfaces aligned with embodiment constraints, and deployment-oriented evaluation protocols that quantify not just task completion, but sustained autonomy quality.

A Full-Coverage Citation Map

A.1 In-Scope Citation Coverage (2024–2026)

This appendix groups all in-scope references by survey bucket and publication year to make coverage auditable.

A.2 agent-architecture

2026 Jian et al. [2026], Li et al. [2026a].

2025 Bai et al. [2025], Bendikas et al. [2025], Corsi et al. [2025], Dey et al. [2025], Fang et al. [2025a], Guo et al. [2025a], Hancock et al. [2025a], Hsieh et al. [2025], Intelligence et al. [2025a], Jabbour et al. [2025], Jang et al. [2025], Li et al. [2025e,f,g], Lin et al. [2025a], Liu et al. [2025b,c], Patratskiy et al. [2025]. Pertsch et al. [2025], Pugacheva et al. [2025], Sendai et al. [2025], Song et al. [2025a], Tan et al. [2025a], Turgunbaev [2025], Wang et al. [2025b,c,d], Wen et al. [2025a,b,c,d], Wu et al. [2025], Xiang et al. [2025], Xiong et al. [2025].

2024 Leal et al. [2024], Yang et al. [2024a].

A.3 data-benchmark-eval

2026 Black et al. [2026], Cai et al. [2026], Chen et al. [2026a,b], Hu et al. [2026], Lillemark et al. [2026], Liu et al. [2026a], Magne et al. [2026], Mei et al. [2026], Peng et al. [2026], Ren et al. [2026], Upadhyay et al. [2026], Wang et al. [2026], Wu et al. [2026b,c,a], Xiang et al. [2026], Xie et al. [2026a]. Xie et al. [2026b], Yang et al. [2026], Ye et al. [2026], Yu et al. [2026b], Zhang et al. [2026b,a].

2025 Argus et al. [2025], Bhat et al. [2025], Bi et al. [2025a], Cen et al. [2025b], Chen et al. [2025b,c], Chi et al. [2025], Collaboration et al. [2025], Cui et al. [2025], Deng et al. [2025], Din et al. [2025], Ding et al. [2025b], Du et al. [2025], Fan et al. [2025a,b], Fang et al. [2025b], Fei et al. [2025], Goyal et al. [2025]. Grover et al. [2025], Guo et al. [2025b], Guo and Zhang [2025], Han et al. [2025], Hancock et al. [2025b], Hannus et al. [2025], Hao et al. [2025], Hirose et al. [2025], Hu et al. [2025a], Huang et al. [2025a], Hung et al. [2025a], Jiang et al. [2025a,b,c,d], Jin et al. [2025], Jülg et al. [2025], Khazatsky et al. [2025]. Kim et al. [2025], Li et al. [2025h,i,j,k,l,m,n,d], Liang et al. [2025b,c], Liao et al. [2025], Lin et al. [2025b,c,d], Liu et al. [2025d,e,f]. Liu et al. [2025g], Lykov et al. [2025], NVIDIA et al. [2025a], Peng et al. [2025], Qian et al. [2025], Qu et al. [2025], Ray [2025], Serpiva et al. [2025], Shukor et al. [2025], Singh et al. [2025], Song et al. [2025b,c], Sun et al. [2025a], Syed et al. [2025], Tan et al. [2025b], Tarasov et al. [2025], Team et al. [2025a], Tharwat et al. [2025]. Valle et al. [2025], Wang et al. [2025a,e,f,g], Wei et al. [2025], Wen et al. [2025e], Won et al. [2025], Xiao et al. [2025], Xu et al. [2025a], Xue et al. [2025], Yan et al. [2025], Yang et al. [2025b,a,c], Ye et al. [2025a,b], Yin et al. [2025]. Yu et al. [2025], Yuan et al. [2025a,b], Zhai et al. [2025], Zhang et al. [2025b,c,d,e,f,g,h,i], Zhao et al. [2025a], Zheng et al. [2025a,b], Zhong et al. [2025a], Zhou et al. [2025a].

2024 AhmadiTeshnizi et al. [2024], Chi et al. [2024], Huang et al. [2024a], Kazemi et al. [2024], Kim et al. [2024], Lee et al. [2024], Li et al. [2024a,b,c], Lin et al. [2024], O'Neill et al. [2024], Salzer and Visser [2024], Team et al. [2024], Yehudai et al. [2024], Zeng et al. [2024], Zhen et al. [2024].

A.4 foundation-definition

2025 Zhou et al. [2025b], Li et al. [2025o], Wang et al. [2025h].

2024 Cheang et al. [2024], Hong et al. [2024], Yang et al. [2024b].

A.5 planning-reasoning

2026 Li et al. [2026b], Sapkota et al. [2026], Zhong et al. [2026].

2025 Budzianowski et al. [2025], Chen et al. [2025d,e], Driess et al. [2025], Feng et al. [2025a], Gao et al. [2025], Gu et al. [2025], Hu et al. [2025b], Huang et al. [2025b,c], Hung et al. [2025b], Koo et al. [2025], Li et al. [2025p,q], Liu et al. [2025h], Neary et al. [2025], Neau et al. [2025], Seong et al. [2025]. Song et al. [2025d], Sun et al. [2025b], Wang et al. [2025i], Xu et al. [2025b,c], Zang et al. [2025], Zhang et al. [2025j,k], Zhao et al. [2025b,c], Zhou et al. [2025c].

2024 Guo et al. [2024], Huang et al. [2024b], Yoshikawa et al. [2024], Zhang et al. [2024].

A.6 policy-learning

2026 Liu et al. [2026b].

2025 Chen et al. [2025a], Dong et al. [2025], Fu et al. [2025], Häon et al. [2025], Intelligence et al. [2025b], Kachaev et al. [2025], Li et al. [2025c,r,s,t,u], Liu et al. [2025i], Lu et al. [2025], Park et al. [2025], Xu et al. [2025d], Zhang et al. [2025l,m], Zhu et al. [2025b].

A.7 survey-meta

2026 Fan et al. [2026], Yin et al. [2026], Yu et al. [2026a].

2025 Ding et al. [2025a], Dolgopolyi and Tsevas [2025], Guan et al. [2025], Jiang et al. [2025e], Li et al. [2025a,v], Liang et al. [2025a], Liu et al. [2025a], Lu and Tang [2025], Shao et al. [2025], Tai et al. [2025], Zhang et al. [2025n,a], Zhong et al. [2025b].

A.8 world-model-core

2026 Guo et al. [2026], Shah et al. [2026], Shen et al. [2026], Zhou et al. [2026].

2025 Berg et al. [2025], Bi et al. [2025b], Cen et al. [2025a], Feng et al. [2025b], Fung et al. [2025], Guo et al. [2025c], Li et al. [2025b], NVIDIA et al. [2025b], Team et al. [2025b], Wan et al. [2025], Zhu et al. [2025a].

2024 Gupta et al. [2024].

B Exclusion Audit Log

B.1 Exclusion Audit

Entries excluded from the main in-scope set are listed by reason. Full row-level details are in `ref/paper_audit.csv`.

B.2 missing_year

Chen et al., Xie, Zhang et al..

B.3 not_embodied_related

Bruce et al. [2024], Savov et al. [2025].

B.4 out_of_window

Ahn et al. [2022], Batra et al. [2020], Bousmalis et al. [2023], Brehmer et al. [2023], Brohan et al. [2023], Chebotar et al. [2023], Dasgupta et al. [2023], Dorbala et al. [2023], Driess et al. [2023], Duan et al. [2022], Fan et al. [2022], Gadre et al. [2022], Gao et al. [2022], Gu et al. [2023], Huang et al. [2023a, 2022b,a, 2023b]. Jiang et al. [2023], Josifoski et al. [2022], Liang et al. [2023], Nottingham et al. [2023], Pugh et al. [2022], Reed et al. [2022], Sarch et al. [2023], Song et al. [2023], Walke et al. [2023], Wang et al. [2023b,a], Wu et al. [2023b,a,c], Xu et al. [2023], Zhao et al. [2023].

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