NOT ALL FEATURES ARE CREATED EQUAL: A MECHANISTIC STUDY OF VISION-LANGUAGE-ACTION MODELS

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ABSTRACT

Vision-Language-Action (VLA) models combine perception, language, and motor control in a single architecture, yet how they translate multimodal inputs into actions remains poorly understood. We present the first cross-architecture mechanistic study of visuomotor policies, applying activation injection, sparse autoencoders (SAEs), and linear probes to six models spanning 80M to 7B parameters across 394,000+ rollout episodes on four benchmarks. Three findings emerge as architecture-independent properties of behavior-cloned policies.

First, the visual pathway dominates action generation. Injecting baseline activations into null-prompt episodes recovers near-identical behavior across architectures, while cross-task injection universally degrades destination task success. Critically, trajectory analysis reveals that this "failure" masks successful behavioral transfer: robots execute source-task motor programs in the wrong scene (99.8% of X-VLA episodes align with the source trajectory), exposing spatially bound action sequences tied to scene coordinates rather than abstract task representations. Second, language sensitivity depends on task structure, not model design. When the visual scene uniquely specifies the task, language is ignored; when multiple goals share a scene, language becomes essential (e.g., X-VLA `libero_goal`: 94% $\rightarrow$ 10% under wrong prompts vs. `libero_object`: 60–100% regardless). Third, in all three multi-pathway architectures ($\pi_{0.5}$, SmolVLA, GR00T), expert pathways consistently encode motor programs while VLM pathways encode goal semantics, with expert injection causing $2\times$ greater behavioral displacement.

Methodologically, we train 424 SAEs and find that per-token processing is generally essential, though architecture modulates this relationship in unexpected ways. Contrastive feature identification recovers 82+ manipulation concepts, and causal ablation reveals that sensitivity (28–92% zero-effect rates) does not follow representation width. We release **Action Atlas** (https://action-atlas.com) for interactive exploration of VLA representations across all six models.

1 INTRODUCTION

Vision-Language-Action (VLA) models combine visual encoders, language backbones, and action decoders into end-to-end policies that generalize across objects and instructions without task-specific engineering (Zitkovich et al., 2023; Kim et al., 2024; Black et al., 2024; Physical Intelligence, 2025). Despite rapid adoption, a basic question remains open: do these models actually follow language instructions, or do they replay visual-motor priors learned during fine-tuning?

This opacity presents practical challenges: when a VLA-controlled robot exhibits unexpected behavior, operators have no principled way to diagnose the failure. Current debugging is limited to

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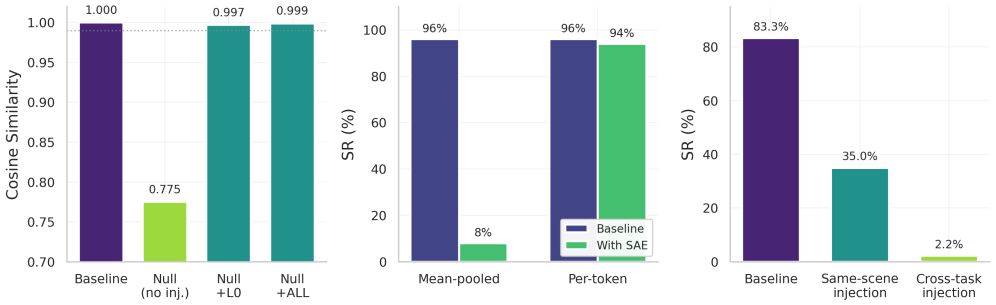

Figure 1: **Three core findings on $\pi_{0.5}$. Left:** Activation injection recovers baseline behavior from null-prompt episodes. Without injection, null prompts drop cosine similarity to 0.775; injecting a single layer (L0) recovers 0.997 and all layers recovers 0.999, demonstrating visual pathway dominance. **Middle:** Per-token SAE processing is essential. Mean-pooled SAE reconstruction destroys task success (96%→8%) despite high explained variance, while per-token processing preserves performance (96%→94%). **Right:** Cross-task injection fails destination tasks (83.3%→2.2%) and same-scene injection partially succeeds (35.0%), confirming spatially bound motor programs. These patterns replicate across all six models (Table 6).

behavioral observation, in contrast to classical robotics where kinematics and control models can be inspected and modified (Häon et al., 2025).

Sparse autoencoders (SAEs) can extract interpretable features from large language models (Cunningham et al., 2023; Bricken et al., 2023; Templeton et al., 2024), decomposing dense, polysemantic neural activations into sparse, monosemantic features corresponding to human-interpretable concepts. At scale, SAEs have revealed safety-relevant representations including deception and bias (Templeton et al., 2024), and have enabled activation steering for behavioral control without retraining (Turner et al., 2023; Rimsky et al., 2024). Whether these methods extend to VLA behavior remains an open question.

Applying mechanistic interpretability to VLAs presents challenges distinct from language models. VLAs process *heterogeneous token sequences* interleaving vision, language, and proprioception; we find that mean-pooling activations across token positions (standard in LLM interpretability) destroys action-critical information, causing catastrophic task failure despite high reconstruction quality. *Causal validation* is also more demanding: unlike LLMs where human judgment can assess output quality, VLA interpretability requires simulator or real-world rollouts to measure task success (Li et al., 2024b), making each experiment orders of magnitude more costly.

We present a mechanistic study across five VLAs ($\pi_{0.5}$ (Physical Intelligence, 2025), OpenVLA-OFT (Kim et al., 2025), X-VLA (Zheng et al., 2026), SmolVLA (Shukor et al., 2025), GR00T N1.5 (Bjorck et al., 2025)) and one language-free control (ACT (Zhao et al., 2023)), spanning 80M to 7B parameters, four action generation paradigms, and four benchmarks (**394,000+ rollout episodes**). We establish four findings: (1) the visual pathway dominates behavior across all architectures; (2) language sensitivity is suite-dependent rather than architecture-dependent, with prompts ignored when visual context suffices but consequential in ambiguous scenes; (3) cross-task injection degrades destination success across all models (0% on five; -40pp on OFT) yet steers toward source positions, encoding spatially bound action sequences; and (4) multi-pathway architectures exhibit consistent specialization, with expert pathways encoding motor programs and VLM pathways encoding goals, a pattern that holds whether SAE processing is per-token or pooled.

Our contributions:

1. *Cross-architecture mechanistic analysis at scale*: the first systematic study spanning six architectures (80M–7B, four benchmarks, 394,000+ episodes). Visual pathway dominance, cross-task transfer failure, and suite-dependent language sensitivity replicate across all models.

Model	Params	Layers	Dim	Action Gen.	Pathway	Bench.
$\pi_{0.5}$ (Physical Intelligence, 2025)	3B	18+18	1024	Flow (50 steps)	Dual (PG + Exp.)	LIBERO
OFT (Kim et al., 2025)	7B	32	4096	Cont. L1 regr.	Single (Llama-2)	LIBERO
X-VLA (Zheng et al., 2026)	1B	24	1024	Flow matching	Single (Flor.-2)	LIB., SimpE.
SmolVLA (Shukor et al., 2025)	450M	32+32	960/480	Flow matching	Dual (VLM + Exp.)	LIB., MW
GR00T (Bjorck et al., 2025)	3B	16+12+4	varies	Diff./flow	Triple (D+E+V)	LIBERO
ACT (Zhao et al., 2023)	80M	–	–	CVAE	Enc.-Dec.	ALOHA

Table 1: **Architectures under study.** Five VLAs and ACT (language-free control). PG = PaliGemma, Exp. = Expert, Flor. = Florence, D+E+V = DiT + Eagle + VL-SA, LIB. = LIBERO, MW = MetaWorld, SimpE. = SimplerEnv. Full architecture details in Appendix J.1.

2. *Pathway specialization*: consistent functional dissociations in $\pi_{0.5}$, SmolVLA, and GR00T N1.5, where expert pathways cause $2\times$ greater behavioral displacement than VLM pathways.
3. *424 SAEs*: per-token processing is generally required (mean-pooling destroys behavior), concept ablation reveals causal sensitivity spanning 28–92% zero-effect rates independent of width, and 82+ manipulation concepts are identifiable via contrastive selection.
4. *Action Atlas*: open-source platform (https://action-atlas.com) for interactive exploration of VLA representations across all six models.

2 Related Work

VLA models extend vision-language pretraining to robotic control. RT-2 (Zitkovich et al., 2023) demonstrated that VLMs can generate tokenized robot actions; OpenVLA-OFT (Kim et al., 2025) replaced discrete tokenization with continuous L1 regression, achieving 97.1% LIBERO success. $\pi_{0.5}$ (Physical Intelligence, 2025) introduced flow matching with a dedicated action expert. The six models we study (Table 1) span this design space. Independent robustness evaluations (Fei et al., 2025; Zhou et al., 2025) reveal that VLAs collapse under perturbation (97% $\rightarrow$ 0% under 0.2-unit position shifts), motivating mechanistic investigation.

Mechanistic interpretability for LLMs (Olah et al., 2020) has progressed through SAEs (Bricken et al., 2023; Cunningham et al., 2023; Templeton et al., 2024) and activation steering (Turner et al., 2023; Rimsky et al., 2024). For VLAs, Häon et al. (Häon et al., 2025) demonstrated SAE steering on π_0 and OpenVLA, Molinari et al. (Molinari et al., 2025) probed for emergent world models, and Khan et al. (Khan et al., 2025) identified monosemantic behaviors in Magma. We extend these single-architecture studies to cross-architecture validation across six models and show that action tokenization constrains SAE applicability. Extended related work appears in Appendix A.

3 Method

Our methodology combines four techniques (activation injection, counterfactual prompting, SAEs, and linear probes) applied uniformly across all six models. Figure 2 illustrates the overall pipeline.

3.1 VLA Architectures Under Study

We study six architectures spanning nearly two orders of magnitude in parameter count (80M–7B) and four action generation paradigms (flow matching (Lipman et al., 2023), continuous regression, diffusion, and CVAE decoding). Table 1 summarizes the architectural diversity.

3.2 Activation Injection

Our primary technique for establishing causal relationships is *activation injection*, an extension of activation patching (Meng et al., 2022) to full rollout episodes: replacing activations from one episode with those from another during inference. Given source episode A (correct prompt, successful rollout) and target episode B (alternative condition), we record layer activations $\{\mathbf{H}^{A,(\ell)}\}$ during episode A, then replace $\mathbf{H}^{B,(\ell)}$ with $\mathbf{H}^{A,(\ell)}$ at specified layers during episode B.

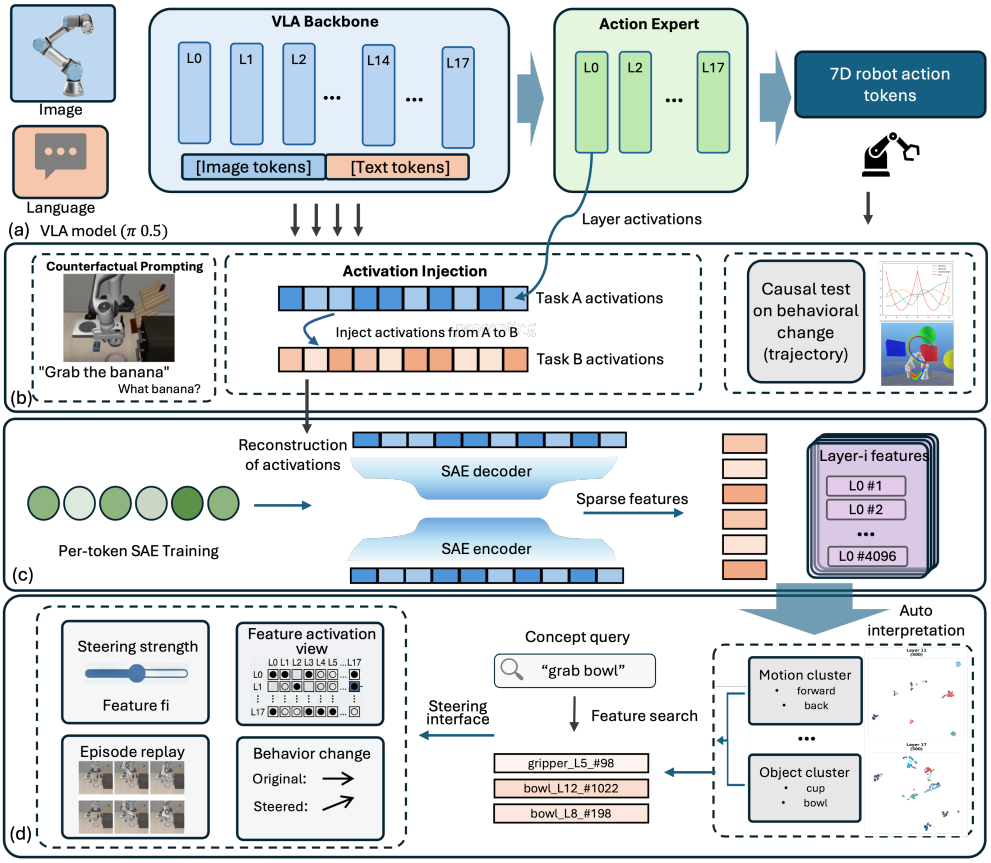

Figure 2: **Methodology overview.** Top: activations are recorded from VLA backbone and action expert layers during rollout episodes, then replayed under counterfactual conditions (null prompts, cross-task scenes) to establish causal relationships via behavioral change. Middle: per-token SAEs decompose layer activations into sparse features. Bottom: features are clustered, searched, and causally validated through ablation and steering experiments, with results visualized in Action Atlas.

We test four conditions. In **null injection**, the source episode uses the correct prompt while the target uses an empty string. In **same-scene injection**, both episodes share the same visual scene but target different objects. In **cross-task injection**, source and target occupy entirely different visual scenes. In **cross-seed injection**, both episodes perform the same task under different random seeds. For multi-pathway models ($\pi_{0.5}$, SmolVLA, GR00T), we also inject into individual pathways to isolate their contributions.

3.3 Counterfactual Prompting

We systematically vary text prompts to measure language sensitivity. Each episode is evaluated under one of six conditions: the baseline correct prompt, a null prompt (empty string), a negation prompt ("Don't pick up X"), a motor command ("Move slowly"), an object swap (replacing the target object name), and a temporal switch (changing the prompt mid-episode). For SmolVLA on MetaWorld, we also test counterfactual prompts across four difficulty levels (easy, medium, hard, very hard).

3.4 Sparse Autoencoders for VLAs

SAEs decompose dense neural activations into sparse, interpretable features. We train SAEs on action-relevant activations with TopK sparsity (Gao et al., 2024) ($k = 64$ active features) and expansion factor $m = 4d$ or $m = 8d$.

Per-Token Processing. VLA activations must be processed per-token. Mean-pooling across action tokens destroys heterogeneous temporal structure (approach, manipulation, and terminal phases encode distinct information), causing task failure despite high reconstruction quality ($R^2 > 0.95$). However, the relationship between pooling strategy and rollout fidelity is non-trivially architecture-dependent: in X-VLA, mean-pooled SAEs achieve *better* rollout fidelity than per-token despite lower training explained variance, while in GR00T, mean-pooling boosts VL-SA layer quality from 83–89% to 99% EV.

Feature Identification. We identify concept-specific features using frequency-weighted contrastive selection: $\text{score}_f = d_f \times \text{freq}_f$, where d_f is Cohen's d (Cohen, 1988) measuring activation difference between concept-present and concept-absent tasks, and freq_f is the fraction of samples where feature f appears in the active top-k.

Scale. Across all six models, we train **424 SAEs**: 96 for X-VLA (24 layers $\times$ 2 pooling strategies $\times$ 2 environments), 192 for SmolVLA (32 layers $\times$ 2 components $\times$ {2 LIBERO pooling + MetaWorld}), 68 for GR00T (32 layers $\times$ 2 pooling + 4 VL-SA k128), and the original SAEs for $\pi_{0.5}$ (36) and OFT (32). These collectively identify **82+ unique manipulation concepts** across motion, object, and spatial categories.

3.5 Linear Probes for Action Prediction

Linear probes (Alain & Bengio, 2017) test whether action information is linearly decodable from intermediate representations. We train ridge regression probes for each action dimension and apply causality tests by projecting out the probe direction to verify whether predictive information is removed.

3.6 Metrics

We evaluate three primary metrics. **Action Cosine Similarity** measures behavioral alignment between episodes. **Task Success** is a binary indicator determined by the environment's built-in success criteria. **Override Rate** quantifies how often the robot follows injected behavior rather than the text prompt. All reported confidence intervals are 95% Wilson score intervals; ANOVA effect sizes are reported as η^2.

4 Experiments

We evaluate our methodology across five VLAs and one language-free control: $\pi_{0.5}$ (Physical Intelligence, 2025) (3B, flow-matching), OpenVLA-OFT (Kim et al., 2025) (7B, continuous L1 regression), X-VLA (Zheng et al., 2026) (1B, soft-prompted flow-matching), SmolVLA (Shukor et al., 2025) (450M, interleaved VLM-expert), GR00T N1.5 (Bjorck et al., 2025) (3B, DiT-Eagle-VL-SA hybrid), and ACT (Zhao et al., 2023) (80M, CVAE encoder-decoder, vision-only). Across all models, we collect **394,000+ rollout episodes** spanning 12 experiment types, 4 benchmarks, and up to 50 tasks per environment. Experiments were conducted on an 8$\times$A100-SXM4-80GB cluster, an RTX 5090, and two RTX 4090s. Our experiments address five questions: (1) Does the visual pathway strongly influence behavior across architectures? (2) Do fine-tuned VLAs follow language instructions (for the five language-capable models)? (3) Does pathway specialization generalize across multi-component architectures? (4) How do SAE properties vary across architectures? (5) Do these phenomena hold across benchmarks and embodiments?

4.1 Experimental Setup

Benchmarks and Scale. We evaluate on four benchmarks: **LIBERO** (Liu et al., 2023) (4 suites, 40 tasks), **MetaWorld** (Yu et al., 2020) (50 tasks, 4 difficulty levels), **SimplerEnv** (Li et al., 2024b) (10 tasks, 2 embodiments), and **ALOHA** (Zhao et al., 2023) (2 bimanual tasks). Table 2 summarizes scale.

Model	Episodes	SAEs	Concepts
$\pi_{0.5}$	65,000+	36	43
OpenVLA-OFT	70,700+	32	45
X-VLA	50,000+	96	82
SmolVLA	42,000+	192	45
GR00T N1.5	164,700+	68	36
ACT	1,870	–	–
Total	**>394,000**	**>424**	**>82**

Table 2: Experimental scale across six models. Episode counts aggregate across applicable experiment types (baselines, counterfactual prompting, cross-task injection, vision perturbation, grid ablation, SAE validation, concept ablation, concept steering, temporal ablation, fraction-to-failure); not all models undergo every type. SAE counts include per-token, mean-pooled, and k-sweep variants.

4.2 Visual Pathway Influence

We test the relative influence of the visual pathway versus language instructions across all six models.

On $\pi_{0.5}$, supplying a null prompt while injecting baseline PaliGemma activations recovers near-identical behavior: cosine similarity between injected and baseline actions reaches 0.999, and task success recovers to 73–77% despite the absence of language (Table 3). Injecting only layer 0 achieves comparable results (0.997); task-relevant information is already encoded in the first transformer layer. On OpenVLA-OFT, null injection recovers only 14–15% success across all four LIBERO suites (n=120 per layer), a catastrophic drop from ∼90% baselines and far lower recovery than $\pi_{0.5}$'s 73–77%.

Model	Condition	Cos. Sim.	Success
$\pi_{0.5}$	Baseline (correct prompt)	1.000	83.3%
	Null prompt, no injection	0.775	0%
	Null + inject L0	**0.997**	73%
	Null + inject ALL	**0.999**	77%
OFT	Baseline	1.000	∼90%
	Null + zero any layer	–	14%
X-VLA	Baseline	1.000	97.0%
	Zero any single layer	–	0%
SmolVLA	Baseline	1.000	68–79%
	Zero any expert layer	–	0–83%
GR00T	Baseline	1.000	∼85%
	Zero DiT/Eagle/VL-SA	–	suite-dep.
ACT	Baseline	1.000	100%
	Mask workspace grid	–	10%

Table 3: **Visual pathway influence across all six architectures.** *Baseline*: correct task prompt, no intervention. *Null + inject*: empty prompt with injected activations. *Zero*: zeroing a layer's activations. $\pi_{0.5}$: n=30 per condition. OFT: n=120 per layer. X-VLA: all 24 layers cause 0% on zeroing. SmolVLA: L0 catastrophic (0% on `libero_10`, 47% on `spatial`); L1+ maintains 50–83%. GR00T: layer-type-dependent. ACT: grid position (2,2) masking drops from 100% to 10%.

Within a shared scene, injection overrides target selection. Running with prompt A while injecting activations from prompt B yields 93.3% behavioral override: the visual pathway overrides language conditioning. Same-scene injection on OpenVLA-OFT *hurts* performance (-17pp to -57pp) because injection steers toward the source behavior at the cost of the original task.

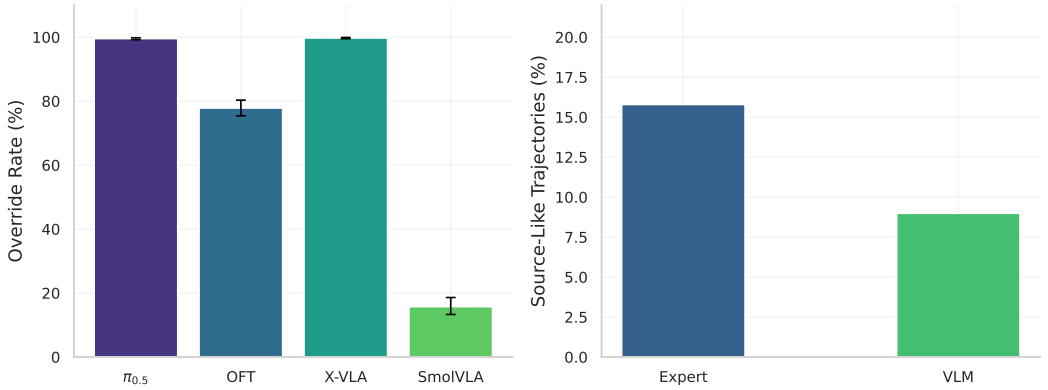

Figure 3: **Cross-task displacement override rates.** Left: override rate across four models (the fraction of episodes where trajectory cosine similarity to source exceeds similarity to destination). $\pi_{0.5}$ (99.6%, n=1,968) and X-VLA (99.8%, n=3,150) show near-complete source behavior transfer, while OFT's wider 4096-dim representation produces a lower 77.9% rate (n=1,079) with 20.9% ambiguous episodes. Error bars: 95% Wilson CIs. Right: SmolVLA pathway displacement: expert-pathway injection (15.8% source-like) causes $\sim$2$\times$ greater behavioral displacement than VLM-pathway injection (9.0% source-like) across 732 MetaWorld cross-task pairs, consistent with pathway specialization.

On X-VLA, every single layer is critical: zeroing any one of the 24 layers causes 0% task success on both LIBERO and SimplerEnv-WidowX. All 24 layers contribute essential information to action generation.

4.3 Cross-Task Transfer and Displacement Analysis

Cross-task injection causes catastrophic task failure across all six models, but trajectory analysis reveals that injected activations *do* steer behavior toward source-task positions. Table 4 summarizes the cross-task results.

Model	**Pairs**	**Success**	**Displacement**
$\pi_{0.5}$	1,968	2.6%	cos(traj, src) $>$ cos(traj, dst): 99.6%
OFT	1,079	$\sim$50%†	cos(traj, src) $>$ cos(traj, dst): 77.9%
X-VLA	3,150	0%	cos$\rightarrow$src $>$ dst (99.8%)
SmolVLA	732	0%	Expert: 15.8% source-like
GR00T	96$\times$3	0%	Per-layer-type profiles

Table 4: Cross-task injection across five VLA models. Destination task success collapses universally, but displacement analysis reveals architecture-dependent behavioral steering. †OFT: suite-dependent; `libero_goal` drops 40pp from baseline ($\sim$50%); other suites maintain near-baseline rates due to OFT's wide 4096-dim representations.

Displacement analysis (Figure 3) resolves an apparent contradiction: cross-task injection "fails" in terms of task success but "succeeds" in steering behavior. $\pi_{0.5}$ (99.6%), X-VLA (99.8%), and OFT (77.9%) all show source-dominant trajectories, while SmolVLA's expert pathway causes $\sim$2$\times$ greater displacement than its VLM pathway (15.8% vs. 9.0%). The robot reaches toward where source objects *would have been*, executing what we term *spatially grounded motor programs*: action sequences bound to specific scene coordinates rather than abstract task representations (Fei et al., 2025; Zhou et al., 2025).

4.4 Language Sensitivity

Counterfactual prompting across 3,396 episodes on $\pi_{0.5}$, 900 on OFT (3 conditions $\times$ 4 suites), 4,800 on X-VLA (24 conditions $\times$ 4 suites), 1,500 on SmolVLA (MetaWorld, 4 difficulty levels),

and 630 on GR00T reveals that language sensitivity depends on task structure, not architecture. On $\pi_{0.5}$, ANOVA across prompt categories yields $F(4, 3391) = 1.23$, $p = 0.247$, $\eta^2 = 0.012$ (negligible effect size). The model achieves near-baseline performance even with null prompts: given an empty string, it executes a coherent manipulation sequence determined entirely by the visual scene.

Model / Suite	**Baseline**	**Null**	**Wrong Obj.**
$\pi_{0.5}$ / object	77.4%	77.0%	74.2%
$\pi_{0.5}$ / goal	83.3%	80.0%	76.7%
OFT / object	100%	100%	100%
OFT / goal	100%	10%	10%
OFT / spatial	90%	70%	60%
X-VLA / object	100%	60%	60–90%
X-VLA / goal	94%	10%	4–10%
X-VLA / spatial	98%	48%	44–58%
SmolVLA / MW easy	85%	82%	–
SmolVLA / MW hard	62%	41%	–
GR00T / object	93%	70%	50%
GR00T / goal	97%	0%	0%
GR00T / long	83%	67%	47%

Table 5: Counterfactual prompting across models (n=900 OFT, n=3,396 $\pi_{0.5}$, n=4,800 X-VLA, n=630 GR00T). $\pi_{0.5}$ ignores all prompt variations (p=0.247, ANOVA). OFT mirrors X-VLA's suite-dependent pattern: `object` is immune (100%) but `goal` collapses to 10% under generic/wrong prompts. SmolVLA shows difficulty-dependent sensitivity on MetaWorld. GR00T shows strong suite-dependent sensitivity: `libero_goal` collapses from 97% to 0% under null and wrong-task prompts, while `libero_object` retains 50–77% across conditions.

Despite behavioral invariance on $\pi_{0.5}$, linear classifiers trained on layer 17 activations predict prompt category with 99.3% accuracy: prompts are encoded but not used. Table 5 shows the suite-dependent pattern replicates across architectures: `libero_object` is prompt-immune on OFT (100%) and near-immune on X-VLA (60–100%), while `libero_goal` collapses to 0–10% under wrong prompts on OFT, X-VLA, and GR00T. SmolVLA mirrors this on MetaWorld: easy tasks are language-insensitive while harder tasks show greater sensitivity. The common factor is whether visual context alone identifies the target, not model design.

4.5 Pathway Specialization Across Architectures

Three of our six models feature distinct internal pathways, enabling analysis of functional specialization that generalizes across architectural designs.

$\pi_{0.5}$ **(Dual: PaliGemma + Expert).** Injecting expert activations from a mismatched task produces active wrong behavior (reaching toward incorrect locations, mean episode length 231–337 steps). Injecting PaliGemma activations produces passive stalling (running to the full 520-step limit). This dissociation establishes that the expert encodes motor programs ("how") while PaliGemma encodes goal semantics ("what"). Probes confirm: expert activations achieve $R^2 = 0.45$ for state prediction and AUC $= 0.93$ for success prediction; PaliGemma achieves $R^2 \approx 0$ but 76.4% goal classification accuracy.

SmolVLA (Dual: VLM + Expert, Interleaved). Grid ablation across all 64 layers (32 VLM + 32 expert) reveals suite-dependent sensitivity. Expert layer 0 is critical: zeroing it drops success to 0% on `libero_10` (baseline 41%) and 47% on `libero_spatial` (baseline 68%), while later expert layers maintain near-baseline performance (60–83% on `libero_goal` and `libero_object`). On MetaWorld, where both pathway types have complete 32-layer coverage, VLM early-layer zeroing is comparably destructive (mean 5–8pp worse than expert zeroing across difficulty levels). However, cross-task injection through expert layers causes $\sim 2\times$ greater behavioral displacement than VLM layers (15.8% vs. 9.0% source-like behavior across 732 MetaWorld pairs), indicating that expert layers encode motor programs while VLM provides task context. Vision perturbation confirms spatial encoding: the model tolerates color jitter (-5pp) but fails under crops (-85pp) and

Phenomenon	$\pi_{0.5}$	**OFT**	**X-VLA**	**SmolVLA**	**GR00T**	**ACT**
Visual pathway dominance	Y (73%)	Y (14%)	Y (all layers)	Y	Y	Y
Cross-task failure	Y (2.6%)	Y ($\sim$50%)	Y (99.8% src)	Y (10% src)	Y	Y (0%)
Language sensitivity	suite-indep.	suite-dep.[§]	suite-dep.[§]	partial[*]	suite-dep.	N/A
Pathway specialization	Y	N/A	N/A	Y (2$\times$)	Y	N/A
Per-token SAE req.	Y	Y	paradox[†]	Y	partial[‡]	N/A
Causal sensitivity	narrow (54%)	wide (92%)	wide (82%)	narrow (28%)	mixed (59%)	N/A

Table 6: Cross-model validation of core findings. Y = confirmed. [§]OFT and X-VLA: libero_object immune to prompt changes, but libero_goal collapses under wrong prompts (10% on both). [*]SmolVLA: language sensitivity varies by MetaWorld task difficulty. [†]X-VLA: mean-pooled SAEs achieve better rollout fidelity. [‡]GR00T: VL-SA layers benefit from mean-pooling. Causal sensitivity: causal sensitivity spans 28–92% zero-effect rates across five models. SmolVLA (480-dim, 28% zero) is most sensitive; GR00T (59% zero) shows DiT $>$ Eagle sensitivity; X-VLA (1024-dim, 82%) approaches OFT (4096-dim, 92%) despite sharing $\pi_{0.5}$'s width.

flips (-92pp). Oracle probes confirm specialization: expert activations capture 58% of ground-truth state information at horizon 10, while VLM captures only 13%.

GR00T N1.5 (Triple: DiT + Eagle + VL-SA). Across all 96 layer-suite combinations (32 layers $\times$ 3 LIBERO suites, 164,700+ episodes), GR00T's three pathway types serve distinct roles. DiT layers (98–99% SAE EV) are most ablation-sensitive (40–80% success drop); Eagle LM layers show moderate sensitivity; VL-SA layers are the most resilient despite lower per-token SAE quality (83–89% EV; mean-pooling boosts to 99%). Probes achieve 100% task identification and 96.4% success prediction across all 32 layers (Table 26). Expert pathways consistently encode motor programs while VLM pathways encode goal semantics, a specialization that holds across sequential ($\pi_{0.5}$), interleaved (SmolVLA), and triple-component (GR00T) designs.

4.6 SAE Analysis Across Architectures

Per-Token vs. Mean-Pooled. $\pi_{0.5}$ and OFT require per-token processing (mean-pooling: 0.4% vs. 70% success on $\pi_{0.5}$). Paradoxically, X-VLA mean-pooled SAEs achieve better rollout fidelity despite higher dead feature rates; GR00T VL-SA layers similarly benefit (83% $\rightarrow$ 99% EV). Contrastive concept identification recovers **82+ manipulation concepts** across all models (Appendix E.1).

Causal Profiles Across Five Architectures. Concept ablation across 15,096+ concept-task pairs reveals causal sensitivity that does not follow representation width. SmolVLA (480-dim) is most sensitive (28% zero effect, 6.3% destruction); $\pi_{0.5}$ (1024-dim) is bimodal (54% zero, 14% destruction, with kill-switches like BUTTER at L8); GR00T shows pathway-specific sensitivity (DiT: 56% zero vs. Eagle: 73% zero); OFT (4096-dim) and X-VLA (1024-dim) are resilient (92% and 82% zero effect). The ordering (SmolVLA $>$ $\pi_{0.5}$ $>$ GR00T $>$ X-VLA $\approx$ OFT) shows sensitivity is shaped by architecture, not dimensionality. Table 6 summarizes all findings.

5 Conclusion

VLA representations are rich (82+ concepts, 99.3% prompt classification, specialized pathways) yet behavior is brittle: cross-task injection steers toward source positions (99.8% on X-VLA) without task success, causal sensitivity spans 28–92% zero-effect rates independent of width, and language use is suite-dependent. These findings extend to discrete-tokenization VLAs (Appendix C.1) and vision-only policies (Appendix C.2). Across 394,000+ episodes and six architectures, the gap between what VLAs represent and what they use motivates new alignment methods. Action Atlas: https://action-atlas.com.

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A Extended Related Work

A.1 Vision-Language-Action Models

RT-2 (Zitkovich et al., 2023) showed that web-pretrained VLMs can be fine-tuned for manipulation via tokenized actions. OpenVLA (Kim et al., 2024) extended this with an open-source 7B model, and OpenVLA-OFT (Kim et al., 2025) replaced discrete tokenization with continuous L1 regression, achieving 97.1% LIBERO success. The π_0 and $\pi_{0.5}$ models (Black et al., 2024; Physical Intelligence, 2025) introduced flow matching with a dedicated action expert. The landscape now spans a range of scales and paradigms: SmolVLA (Shukor et al., 2025) (450M), X-VLA (Zheng et al., 2026) (cross-embodiment), GR00T N1.5 (Bjorck et al., 2025) (humanoid), CogACT (Li et al., 2024a), GR-3 (Cheang et al., 2025), VITA-VLA (Dong et al., 2025), SimpleVLA-RL (Li et al., 2026), RIPT-VLA (Tan et al., 2025), FLOWER (Reuss et al., 2025), SpatialVLA (Qu et al., 2025), and ACT (Zhao et al., 2023) (80M, no language). Modular approaches include SayCan (Ahn et al., 2022), PaLM-E (Driess et al., 2023), and Code as Policies (Liang et al., 2023).

Action Representation. Diffusion Policy (Chi et al., 2023) treats action generation as conditional denoising. 3D Diffusion Policy (Ze et al., 2024) incorporates 3D representations. FAST (Pertsch et al., 2025) uses DCT-based compression tokenization. We find that action tokenization directly determines SAE applicability (Section C.1).

Language Following. CAST (Glossop et al., 2025) augments robot datasets with counterfactual language labels. Zhang *et al.* (Zhang et al., 2026) find that VLM benchmark performance does not predict VLA task success; language understanding and visuomotor competence are decoupled.

A.2 Mechanistic Interpretability

SAEs (Olshausen & Field, 1997; Bricken et al., 2023; Cunningham et al., 2023; Gao et al., 2024; Templeton et al., 2024) decompose dense activations into sparse interpretable features, with extensions to vision (Stevens et al., 2025; Joseph et al., 2025; Zaigrajew et al., 2025) and vision-language models (Pach et al., 2025). Activation steering (Turner et al., 2023; Rimsky et al., 2024) enables behavioral control, with advances including conceptor-based steering (Postmus & Abreu, 2024), SAE-guided additions (Soo et al., 2025), and VLM safety steering (Wu et al., 2025; Sivakumar et al., 2025). Linear probing (Alain & Bengio, 2017; Belinkov, 2022) identifies accessible representations but does not establish causal relevance (Wang et al., 2024). PvP (Zhang et al., 2025) shows vision and priors compete in multimodal models.

A.3 Interpretability for Robot Learning

RT-1 (Brohan et al., 2022) included attention visualizations, Diffusion Policy (Chi et al., 2023) analyzed action distributions, and ALOHA (Zhao et al., 2023; ALOHA 2 Team et al., 2024) demonstrated bimanual manipulation, all without internal representation analysis. RoboFail (Sagar et al., 2024), AHA (Duan et al., 2024), and RACER (Dai et al., 2025) characterize failures behaviorally. Häon *et al.* (Häon et al., 2025) introduced VLA steering via internal representations. Molinari *et al.* (Molinari et al., 2025) probed for emergent world models. Khan *et al.* (Khan et al., 2025) identified monosemantic behaviors in Magma. Interpretability-by-design approaches include CoA-VLA (Li et al., 2025), CoT-VLA (Zhao et al., 2025), TriVLA (Liu et al., 2025), dVLA (Wen et al., 2025), and Embodied-R1 (Yuan et al., 2025).

B Limitations

Benchmark Scope

While we evaluate on four benchmarks (LIBERO, MetaWorld, SimplerEnv, ALOHA), all experiments use simulated environments. Expanding to multi-simulator benchmarks like RoboCasa (Nasiriany et al., 2024), real-world datasets like DROID (Khazatsky et al., 2024), and cross-embodiment collections like Open X-Embodiment (Open X-Embodiment Collaboration, 2024) would establish broader generalizability.

COUNTERFACTUAL PROMPT COVERAGE

Our counterfactual prompt set tests simple variations (negation, null, swap). Compositional instructions ("pick up the red cup, then place it behind the blue bowl") and ambiguous multi-object scenes would provide stronger evidence for language insensitivity claims.

CROSS-TASK INJECTION CONFOUNDS

Injected activations can produce invalid internal states due to temporal misalignment rather than reflecting absent abstract representations. However, the displacement analysis strengthens the interpretation: in 99.8% of X-VLA injection episodes, the robot's trajectory is more similar to the source task than the destination, which supports successful source behavior transfer rather than mere distribution shift.

STEERING SENSITIVITY AND CONCEPT IDENTIFICATION

Steering sensitivity spans a wide range across architectures: $\pi_{0.5}$ expert pathways are catastrophically sensitive (ΔSR $= -84$pp at $-3\times$ suppression), GR00T DiT features show similar fragility (-68pp at $9\times$ amplification), while OFT (ΔSR $= -6$pp at $-3\times$) and SmolVLA (-3pp at $5\times$ amplification) are comparatively robust. Feature sensitivity is shaped by architecture and training regime rather than being a universal property of VLAs. Three factors contribute: motor control demands sub-millimeter end-effector precision (Chi et al., 2023); sequential action prediction compounds reconstruction errors across 50 tokens (analogous to autoregressive error accumulation (Bengio et al., 2015)); and behavior-cloned policies lack the closed-loop error correction available to RL-trained policies (Ross et al., 2011). Phase-specific steering on $\pi_{0.5}$ shows temporally localized sensitivity during the transport phase ($p = 0.013$, Wilcoxon rank-sum). SAE features are also not guaranteed to be disentangled: ablation validation shows that some identified features encode general motor primitives rather than cleanly disentangled semantic concepts.

C DISCRETE TOKENIZATION AND VISION-ONLY CONTROL

C.1 DISCRETE TOKENIZATION PREVENTS SAE INTERVENTION

Before adopting OpenVLA-OFT, we conducted experiments on base OpenVLA (autoregressive discrete 256-bin tokenization). Despite successful SAE training ($R^2 = 0.87$–0.96), hooking SAEs into the forward pass produced 0% task success on all but the final layer. The discrete tokenization maps activations to bins via argmax; even small reconstruction errors shift the selected bin, with errors compounding across the 7-token autoregressive sequence. Replacing discrete tokenization with continuous L1 regression via OpenVLA-OFT enables SAE intervention at 99.2% success. Action representation, not model scale, determines SAE applicability.

C.2 ACT AS NON-VLM CONTROL

ACT provides a critical control, lacking any language pathway. Cross-task injection between TransferCube and Insertion produces outputs *identical* to the uninjected baseline (cosine similarity $= 1.0$, bit-identical action arrays), so encoder representations are entirely task-specific. Grid ablation reveals spatially structured representations: masking grid position (2,2) corresponding to the primary manipulation workspace reduces success from 100% to 10%, while Gaussian noise ($\sigma = 0.1$) is universally devastating (100% $\rightarrow$ 0%). Visual pathway dominance and cross-task failure thus hold even for vision-only policies, which rules out VLM-specific artifacts.

D Extended Methodology Details

D.1 SAE Architecture and Training

Architecture. Our sparse autoencoders consist of an encoder-decoder pair with tied weights:

$$\mathbf{z} = \text{TopK}(\mathbf{W}_e \mathbf{h} + \mathbf{b}_e, k = 64) \tag{1}$$

$$\hat{\mathbf{h}} = \mathbf{W}_e^\top \mathbf{z} + \mathbf{b}_d \tag{2}$$

where $\mathbf{h} \in \mathbb{R}^{1024}$ is the input activation, $\mathbf{W}_e \in \mathbb{R}^{d_h \times 1024}$ is the encoder weight matrix, and $d_h \in \{4096, 8192\}$ is the hidden dimension (4x or 8x expansion).

Training Hyperparameters. We train each SAE on 500,000 activation samples (approximately 10,000 forward passes $\times$ 50 action tokens) with a batch size of 4096 for 100 epochs. The learning rate is 3×10^{-4} with cosine decay. Sparsity is enforced via TopK selection with $k = 64$ active features per token. Decoder weights are tied to the encoder transpose ($\mathbf{W}_d = \mathbf{W}_e^\top$).

Per-Token Processing. Each of the 50 action tokens is processed independently through the SAE:

$$\mathbf{h}_{\text{flat}} = \text{reshape}(\mathbf{H}, [B \times 50, 1024]) \tag{3}$$

This preserves the heterogeneous structure of the action token sequence, where early tokens encode initial trajectory direction, middle tokens encode main motion execution, and late tokens encode fine adjustments.

D.2 Concept-Based Feature Identification

We identify concept-associated features using frequency-weighted contrastive selection:

$$\text{score}_f = d_f \times \text{freq}_f \tag{4}$$

where d_f is Cohen's d (Cohen, 1988) measuring activation difference between concept-present and concept-absent tasks, and freq_f is the fraction of samples where feature f appears in the active top-64.

This weighting addresses a methodological consideration: with TopK sparsity, features with high mean activation across samples do not necessarily appear in the active top-64 for individual samples, reducing their causal relevance.

D.3 Ablation Protocol

Feature ablation is performed by zeroing selected features in the SAE latent space:

$$\mathbf{z}_{\text{ablated}} = \mathbf{z} \odot \mathbf{m} \tag{5}$$

$$\mathbf{h}_{\text{modified}} = \mathbf{h} + (\mathbf{W}_e^\top \mathbf{z}_{\text{ablated}} - \mathbf{W}_e^\top \mathbf{z}) \tag{6}$$

where $\mathbf{m} \in \{0, 1\}^{d_h}$ is a binary mask with zeros at ablated feature indices. Per-token ablation applies this independently to each of the 50 action tokens.

E Additional Experimental Results

E.1 Per-Token vs Mean-Pooled SAE Reconstruction

Table 7 compares per-token and mean-pooled SAE reconstruction on all LIBERO-10 tasks. Mean-pooled reconstruction achieves comparable explained variance (95-98%) but causes complete task failure: positional information across action tokens is essential for action generation.

E.2 Layer-Wise Concept Specificity

Table 8 reports the layers with highest feature activation scores for each concept type. Across action, object, and spatial categories, later layers (14–17) show the strongest concept specificity: semantically structured representations emerge progressively through the transformer stack.

Task	Base (PT)	PT SAE	Base (MP)	MP SAE
0	198/250	103/250	201/250	2/250
1	247/250	248/250	248/250	0/250
2	203/250	198/250	197/250	1/250
3	151/250	248/250	248/250	0/250
4	249/250	202/250	249/250	3/250
5	249/250	247/250	248/250	0/250
6	248/250	199/250	203/250	2/250
7	153/250	148/250	198/250	0/250
8	12/250	8/250	15/250	0/250
9	152/250	147/250	201/250	1/250
Total	1862/2500	1748/2500	2008/2500	9/2500
Rate	74.5%	69.9%	80.3%	0.4%

Table 7: Per-task results for per-token (PT) vs mean-pooled (MP) SAE reconstruction on LIBERO-10 (2,500 episodes total). Per-token SAE maintains task performance while mean-pooled causes near-complete failure.

Concept	Best Layer	2nd Best	3rd Best
Action Concepts			
PUT	L17 (133k)	L16 (111k)	L15 (86k)
OPEN	L15 (103k)	L16 (79k)	L13 (71k)
PUSH	L17 (412k)	L13 (275k)	L14 (270k)
INTERACT	L17 (274k)	L12 (261k)	L15 (253k)
Object Concepts			
BOWL	L16 (114k)	L15 (80k)	L14 (70k)
WINE_BOTTLE	L16 (128k)	L14 (116k)	L17 (104k)
STOVE	L17 (182k)	L15 (164k)	L12 (141k)

Table 8: Layer-wise concept specificity (activation scores in parentheses). Later layers (14-17) show highest concept specificity.

E.3 Cross-Suite Generalization

Features identified from the Goal suite affect corresponding tasks across Object and Spatial suites (Table 9); concept representations generalize across task variations rather than being narrowly tuned to specific scene configurations. Note that these results use full-layer intervention hooks and absolute effect magnitudes should be interpreted with the caveat described in Section E.3.

Target Suite	Baseline	After PUT Ablation
Goal	100%	5%
Object	100%	0%
Spatial	100%	11%

Table 9: Cross-suite generalization of PUT feature ablation. *Caveat:* These results use full-layer intervention hooks; corrected MLP-targeted ablation shows no significant effect (see Section E.3).

Causal Feature Identification

Linear probes trained to predict action dimensions achieve 97–98% R^2. Projecting out probe directions completely eliminates action prediction (R^2 drops to ≈ 0), so these directions are causally necessary for downstream computation. SAE-based feature interventions reveal a causal asymmetry: ablation of 2–5 concept-associated features produces no statistically significant effect ($p = 0.975$, mean $\Delta = +3.3\%$); the model compensates through redundant representations. Feature boosting, however, produces significant effects: at $7\times$ natural magnitude, success drops by 14%

($p = 2.27 \times 10^{-4}$), and at $15\times$ by 50.7% (Table 14). This asymmetry (tolerance of feature removal but vulnerability to feature addition) fits redundant motor program encoding.

Caveat on Tables 9, 16, 18, and 20. The ablation results in Sections E.3–F.7 were collected using intervention hooks targeting the full layer residual stream rather than the MLP sublayer alone. This stronger intervention disrupts the residual stream's skip connections, producing inflated effect sizes. When hooks are corrected to target only the MLP sublayer, ablation of 2–5 concept-associated features produces no statistically significant effect ($p = 0.975$, mean $\Delta = +3.3\%$). We retain the original tables because the relative patterns they reveal (e.g., temporal criticality of early steps, cross-suite feature transfer, concept specificity) remain informative, but readers should interpret absolute effect magnitudes with caution. Feature boosting results (Table 14) use the corrected MLP-targeted hooks and show significant effects at 7×+ magnitude.

VISION ROBUSTNESS

Systematic image perturbation across 6,000+ episodes reveals task-dependent visual robustness. We apply horizontal and vertical flips, rotations (90°, 180°, 270°), center crops (50%, 75%), and object-centric crops. Horizontal and vertical flips universally break all models tested (0% success), so spatial orientation is rigidly encoded. Rotation and crop robustness varies by task complexity: simple pick-and-place tolerates mild perturbations while multi-step tasks fail. Object-centric cropping (centering on the manipulation target) outperforms static crops (60% versus 0–20%), which points to reliance on manipulation-relevant regions rather than full scene context.

Table 7 provides per-task breakdowns supporting the per-token requirement described in Section 3.4: mean-pooled SAE reconstruction causes near-complete task failure (0.4% success) despite 95–98% explained variance, while per-token processing maintains 70% success. Table 14 and Figure 11 further quantify steering sensitivity: both dampening ($\alpha < 0$) and boosting ($\alpha > 0$) features cause task failure.

E.4 CONCEPT FEATURE DISCRIMINATION

Table 10 shows that identified concept features achieve high task discrimination: for each concept, the selected features are active precisely on the relevant tasks and inactive on others, achieving 100% binary classification accuracy despite relying on single SAE features.

Concept	Tasks Active	Tasks Inactive	Accuracy
PUT	1,3,4,5,6,7,8	0,2,9	100%
OPEN	0,1	2-9	100%
INTERACT	9	0-8	100%

Table 10: Concept features show high task discrimination.

F ABLATION STUDIES AND NEGATIVE RESULTS

F.1 SAE RECONSTRUCTION METHODS

Training SAEs on mean-pooled activations and broadcasting the residual back to all positions causes catastrophic failure (Table 11). Broadcasting a uniform residual corrupts the heterogeneous per-token information required for action generation.

Layer	Baseline	SAE Reconstruction
Layer 0-11	80-90%	0-5%
Layer 12-17	80-90%	0-5%
action_out_proj_input	93%	76%

Table 11: Mean-pooled SAE reconstruction causes catastrophic failure on all intermediate layers.

F.2 Feature Selection Methods

Selecting features based on correlation with output action dimensions (x, y, z, roll, pitch, yaw, gripper) yields features that are too general, activating across all tasks regardless of concept (Table 12). Action correlations capture output statistics rather than input semantics.

Feature Selection	Baseline	With Ablation
Action-correlated	93%	79%
Concept-aligned	93%	93% (no ablation)

Table 12: Action-correlated features lack concept specificity.

F.3 Steering Interventions

Ablation Recovery

Attempting to recover from feature ablation by boosting the same or related features fails (Table 13). Once critical early state is corrupted, errors compound through the episode.

Condition	Success Rate
Baseline	100%
Ablate full episode	0%
Ablate + steer 0.5	0%
Ablate + steer 1.0	0%
Ablate first 50 + steer 0.5	0%

Table 13: Steering cannot recover from ablation damage. *Caveat:* These results use full-layer intervention hooks (see Section E.3).

Feature Boosting

Both dampening and boosting features from their natural activation levels cause task failure (Table 14). VLA features encode precise motor commands; any perturbation corrupts the action signal.

Steering Strength	Concept Tasks	Other Tasks
-0.50 (dampen)	5.7%	0.0%
0.00 (baseline)	97.1%	73.3%
+0.25 (mild boost)	8.6%	0.0%
+0.50 (moderate)	11.4%	6.7%
+1.00 (strong)	5.7%	13.3%

Table 14: Both dampening and boosting features cause task failure.

Concept Substitution

Compensating for ablated concept features by boosting different concept features fails (Table 15). Each concept has a distinct neural representation that cannot be substituted.

F.4 Temporal Ablation Patterns

Ablation effects vary by episode phase (Table 16). Features are critical during early and mid phases (approach and manipulation) but have minimal effect during late phases (placement/release).

Table 17 shows GR00T N1.5 temporal ablation across three LIBERO suites (160 conditions, MLP-targeted hooks). Early-phase ablation is consistently most destructive, confirming the temporal crit-

Condition	Success Rate
Baseline	100%
Ablate OPEN only	0%
Boost PUT only (0.5)	20%
Ablate OPEN + Boost PUT (0.5)	0%
Ablate OPEN + Boost PUT (1.0)	0%

Table 15: Boosting PUT features cannot compensate for ablated OPEN features.

Ablation Window	Avg Effect	Phase
step0	$\sim$0%	Episode start
early (0-50)	**-56%**	Approach/grasp
mid (50-150)	**-57%**	Manipulation
late (150-300)	-1%	Placement
full (0-300)	**-76%**	All phases

Table 16: $\pi_{0.5}$ temporal ablation effects averaged across all concepts tested. *Caveat:* These results use full-layer intervention hooks; absolute effect magnitudes are inflated (see Section E.3).

icality pattern across architectures. The effect is suite-dependent: LIBERO-Long (complex multi-step tasks) shows a -44pp early-phase drop, while LIBERO-Object (simple pick-and-place) shows only -6pp.

Suite	Baseline	Full	Early	Mid	Late
LIBERO-Goal	100%	73.1%	73.2%	92.7%	92.4%
LIBERO-Long	100%	53.8%	55.6%	75.3%	75.9%
LIBERO-Object	100%	93.9%	94.0%	95.0%	95.3%
Average	**100%**	**69.5%**	**70.3%**	**86.2%**	**86.4%**

Table 17: GR00T N1.5 temporal ablation by LIBERO suite (160 conditions across 32 layers). Early-phase ablation causes the largest success drop, confirming temporal criticality across architectures.

F.5 Single Feature Ablation

Ablating a single feature (3259) causes complete task failure (Table 18), and adding more ablated features produces no further degradation, consistent with the single-point-of-failure behavior described for $\pi_{0.5}$ in Section 4.6. As noted in Section E.3, these results use full-layer intervention hooks.

F.6 Step 0 Criticality

Ablating only step 0 causes complete failure, while later steps show minimal impact (Table 19). The first forward pass commits the robot to a trajectory.

F.7 Feature Specificity Analysis

Some concept-associated features encode motor primitives shared across tasks rather than task-specific semantics (Table 20).

G Benchmark Details

LIBERO (Liu et al., 2023) comprises four suites of 10 tasks each: **Goal** (long-horizon goal completion), **Object** (pick-and-place with varied objects), **Spatial** (spatial reasoning and relational placement), and **LIBERO-10** (diverse tasks spanning all three categories). MetaWorld (Yu et al., 2020)

Features Ablated	Success Rate
0 (baseline)	90%
1 (feature 3259)	0%
2	0%
5	0%

Table 18: Single feature ablation causes complete task failure. *Caveat:* These results use full-layer intervention hooks; corrected MLP-targeted ablation shows no significant effect (see Section E.3).

Ablation Timestep	Success Rate
Step 0 only	0%
Step 1 only	100%
Step 2 only	80%
Steps 200+	80%

Table 19: Step 0 is uniquely critical for task success.

provides 50 tabletop manipulation tasks grouped by difficulty (easy, medium, hard, very hard). SimplerEnv (Li et al., 2024b) evaluates sim-to-real transfer on Google Robot and WidowX embodiments. ALOHA (Zhao et al., 2023) tests bimanual manipulation with the ACT policy.

H Qualitative Results and Additional Figures

Figures 5–8 show frame sequences from baseline and ablated rollouts. All concept ablation uses full-layer hooks (see caveat in Section E.3). Across all conditions, feature ablation and vision perturbation produce binary failure: the robot either completes the task or fails entirely, with no partial completion observed.

I Per-Suite Experimental Breakdowns

OpenVLA-OFT Per-Suite Results

Table 21 shows null injection results on OpenVLA-OFT. Zeroing any single layer (0, 8, 16, 24, or 31) causes catastrophic failure across all four LIBERO suites, with aggregate success rates of 14–15%.

OpenVLA-OFT Multi-Layer Probing

Linear probes trained on OFT's 32-layer activations (n=149 episodes per suite) reveal that episode-length information (R^2) is distributed across all layers but varies by suite complexity. LIBERO-Spatial achieves uniformly high R^2 (0.969–0.994, mean 0.988), while LIBERO-Object and LIBERO-10 show lower floors (0.608 and 0.692) with a progressive increase from early to late layers. Task identification accuracy reaches 97.8–100% on every layer of every suite, and success prediction AUC is 1.0 on spatial, goal, and object suites (mean 0.97 on LIBERO-10, where some early layers drop to 0.71). This confirms that OFT's 4096-dim representations encode sufficient information for linear action prediction at all layers, consistent with its wide, resilient causal profile (92% zero-effect rate).

Cross-Model Linear Probing Summary

Table 26 summarizes linear probe and oracle probe results across all models where probing experiments were conducted. Probes are trained on layer activations (or SAE features for GR00T) to predict task identity, success, state information, or prompt category. The results confirm that task-relevant information is linearly decodable across all architectures, but the type of information

Concept	Selectivity	Type
PUSH	+8.9%	Task-specific
WINE_BOTTLE	+7.5%	Object-specific
PUT	-6.7%	Motor primitive
OPEN	-10.0%	Motor primitive
INTERACT	-11.1%	Motor primitive

Table 20: Selectivity = (effect on concept tasks) − (effect on other tasks). Negative selectivity indicates features encode motor primitives affecting all tasks. *Caveat:* These results use full-layer intervention hooks; absolute magnitudes are inflated (see Section E.3).

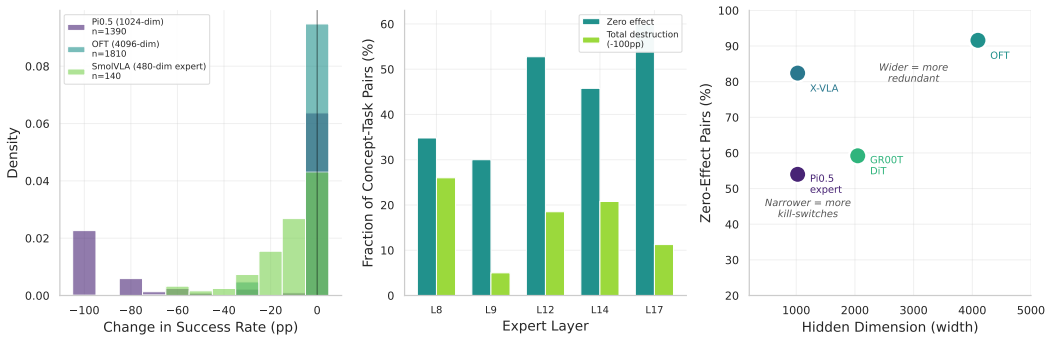

Figure 4: **Concept ablation causal sensitivity across five models.** Each bar shows the fraction of concept-task pairs with zero effect (gray), partial effect (blue), and total destruction (−100pp, red) under single-feature ablation. SmolVLA (480-dim expert) is the most sensitive at 28% zero-effect rate; OFT (4096-dim) and X-VLA (1024-dim) are the most resilient at 92% and 82% respectively. Causal sensitivity does not follow representation width: X-VLA approaches OFT despite sharing $\pi_{0.5}$'s 1024-dim hidden size.

encoded differs by pathway: expert/action pathways encode state dynamics while VLM pathways encode goal semantics.

PI0.5 PER-SUITE COUNTERFACTUAL PROMPTING

PI0.5 CROSS-TASK INJECTION PER-SUITE

X-VLA PER-SUITE RESULTS

X-VLA baselines average 96.7% (goal), 100% (object), 90.0% (spatial), and 100% (LIBERO-10) across 10 tasks per suite (n=3 episodes per task). Table 29 summarizes grid ablation, counterfactual prompting, and concept ablation by suite.

X-VLA exhibits the strongest suite-dependent language sensitivity: `libero_goal` collapses from 94% to 10% under null prompts, while `libero_object` retains 60%. Concept ablation is uniformly resilient across suites (74.7–98.2% zero effect), with `libero_object` nearly immune (98.2% zero effect, −1.3pp mean delta).

SMOLVLA PER-SUITE RESULTS

SmolVLA LIBERO baselines: goal 75.0%, object 78.5%, spatial 67.5%, LIBERO-10 40.7% (n=20 per task). Grid ablation across 65 conditions (32 expert + 32 VLM + baseline) shows that expert-layer zeroing maintains partial success (Table 30), while concept ablation reveals stronger sensitivity than OFT or X-VLA.

SmolVLA expert concept ablation is most destructive on `libero_spatial` (−17.7pp, 32.7% zero effect) and least on `libero_10` (+0.8pp, 20.3% zero effect). VLM concept ablation shows

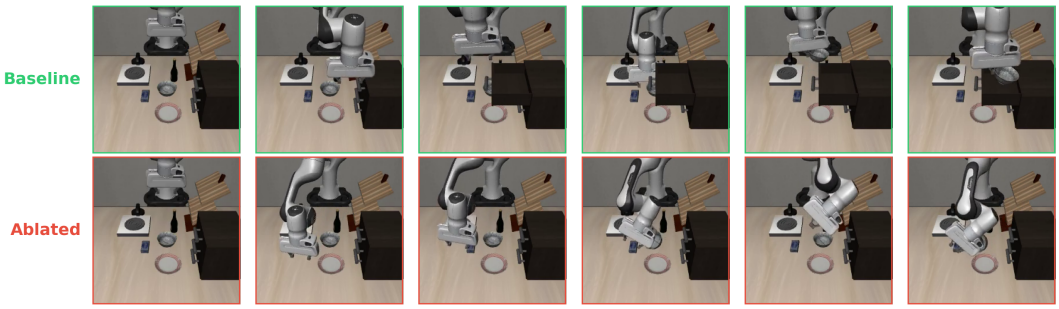

Figure 5: **PUT concept ablation: "Put the bowl on the plate." Top:** Baseline execution. The robot grasps the bowl, lifts it, and places it on the plate. **Bottom:** With PUT features zeroed, the robot grasps but stalls before placement.

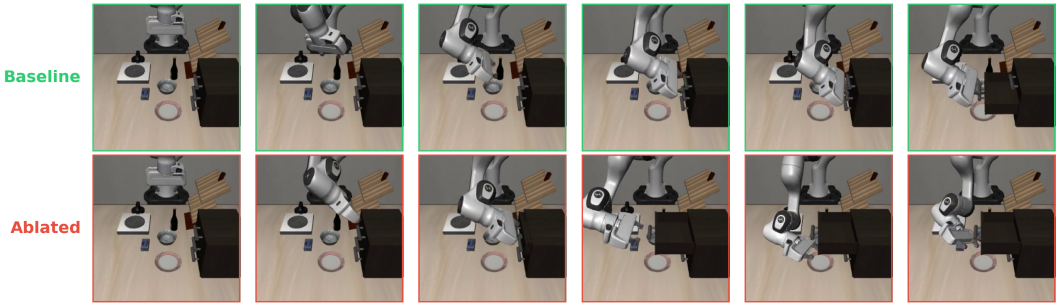

Figure 6: **OPEN concept ablation: "Open the middle drawer of the cabinet." Top:** The robot grasps the handle and pulls the drawer open. **Bottom:** Without OPEN features, the robot reaches toward the handle but does not grasp or pull.

a different pattern: `libero_goal` is most affected (-10.7pp) while `libero_object` shows positive delta ($+6.4$pp), consistent with the VLM encoding goal semantics.

GR00T N1.5 Per-Suite Results

GR00T baselines: goal 97.0%, object 99.0%, long 75.0% (n=10 per task). Table 31 summarizes grid ablation, counterfactual prompting, and concept ablation.

GR00T mirrors X-VLA's suite-dependent language sensitivity: `libero_goal` collapses from 96.7% to 18.9% under non-baseline prompts, while `libero_object` retains 73.3%. LIBERO-Long shows intermediate sensitivity (61.7%), consistent with its multi-step structure requiring partial language grounding. Concept ablation reveals that `libero_long` has the lowest zero-effect rate (42.2%) and highest destruction rate (11.0%), reflecting the greater fragility of complex multi-step tasks.

J Implementation Details

J.1 Model Architecture

Pi0.5 Architecture

$\pi_{0.5}$ uses PaliGemma (3B parameters) as its vision-language backbone and an 18-layer Gemma transformer (1024 hidden dimension) as the action expert. The action space is 7-dimensional (dx, dy, dz, dax, day, daz, gripper). The model generates 50 actions per forward pass through flow matching with iterative denoising.

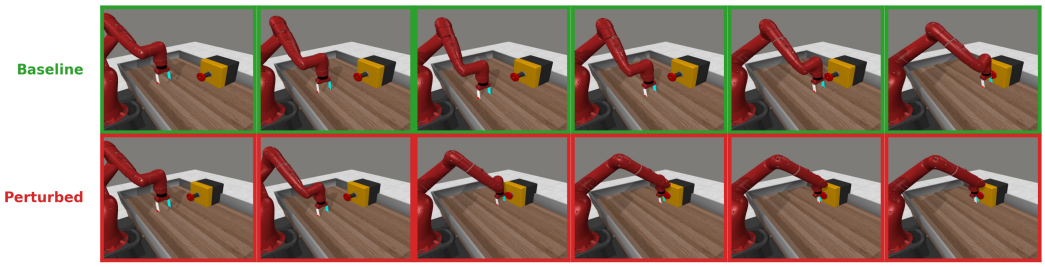

Figure 7: **SmolVLA MetaWorld vision perturbation.** Top: baseline input (100% success). Bottom: crop perturbation removes the lower half of the visual input, causing complete task failure (0% success). The robot arm fails to locate the target button without the full visual field.

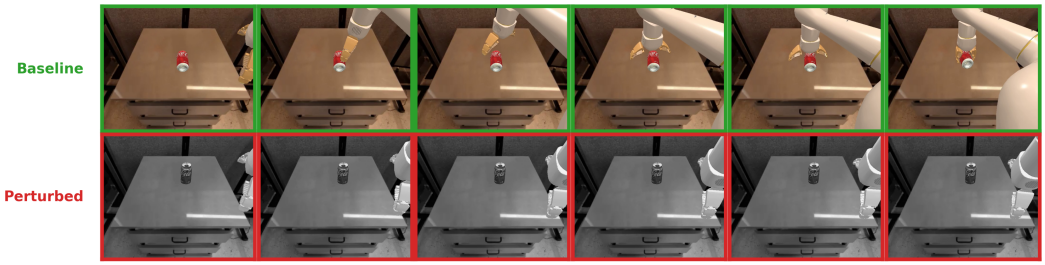

Figure 8: **X-VLA SimplerEnv vision perturbation.** Top: baseline RGB input (100% success). Bottom: grayscale perturbation removes color information, causing complete failure (0% success). The robot cannot locate the red coke can without color features.

Base OpenVLA Architecture (Discrete)

Base OpenVLA uses a Llama-2 7B backbone with DINOv2 and SigLIP vision encoders. Actions are generated autoregressively as discrete tokens: each of the 7 action dimensions is independently binned into 256 discrete values, producing a 7-token sequence generated left-to-right via next-token prediction.

OpenVLA-OFT Architecture (Continuous)

OpenVLA-OFT shares the Llama-2 7B backbone and Prismatic vision encoder (DINOv2 + SigLIP) with the base model but replaces discrete token prediction with continuous action regression. An MLPResNet action head, trained with L1 loss, generates all 7 action dimensions in a single forward pass with 8-step action chunking (56 action tokens total). Orthogonal Fine-Tuning (OFT) adapters constrain weight updates to the Stiefel manifold, preserving the pretrained representation geometry.

ACT Architecture

ACT uses a ResNet-18 vision encoder (pretrained on ImageNet) feeding into a Transformer Encoder-Decoder with a CVAE latent space ($\beta = 10$, latent dimension 32). The encoder processes multi-view camera observations, and the decoder generates action chunks of 100 timesteps in 14-DOF joint space (7 per arm for bimanual manipulation).

SAE Configuration

SAE input dimensions match each model's residual stream width: 1024 for $\pi_{0.5}$ expert and X-VLA, 4096 for OFT, 960/480 for SmolVLA VLM/expert, and architecture-dependent for GR00T (DiT, Eagle, VL-SA). The SAE hidden dimension is set to $4\times$ or $8\times$ expansion. Sparsity is enforced via TopK with $k = 64$ active features per token, and decoder weights are tied to the encoder transpose ($\mathbf{W}_d = \mathbf{W}_e^\top$).

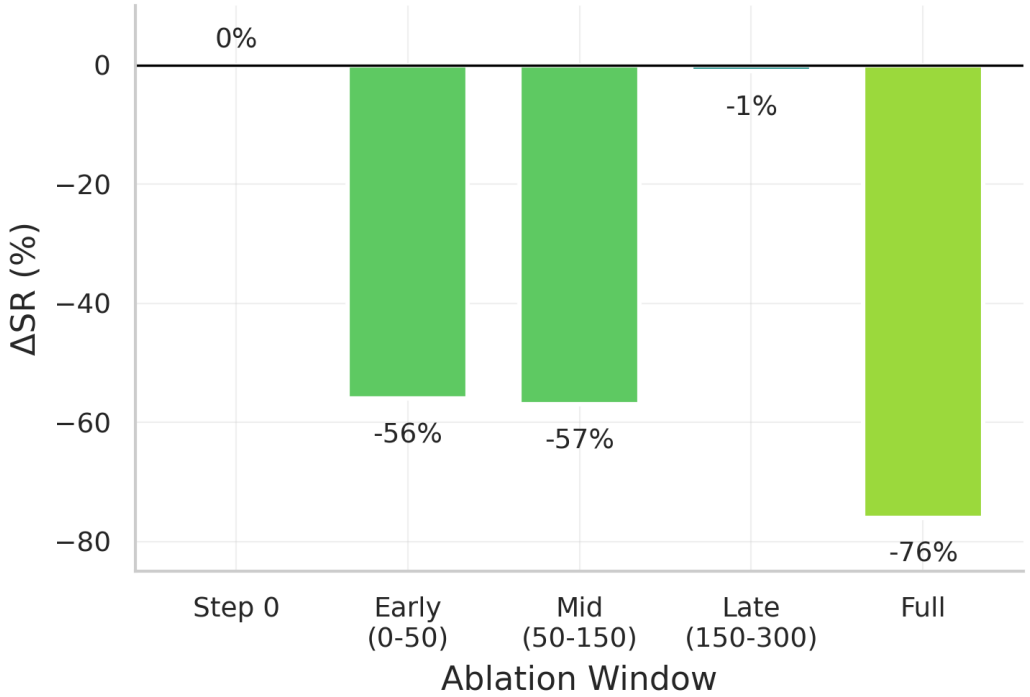

Figure 9: $\pi_{0.5}$ **temporal ablation effects by episode phase.** Feature ablation effects vary by phase using full-layer intervention hooks (see note in Section E.3). Corrected MLP-targeted ablation shows no significant temporal pattern ($p = 0.975$); the phase-dependence shown here is an artifact of the uncorrected hook rather than a genuine temporal gradient. For valid cross-architecture temporal results, see GR00T temporal ablation in Table 17.

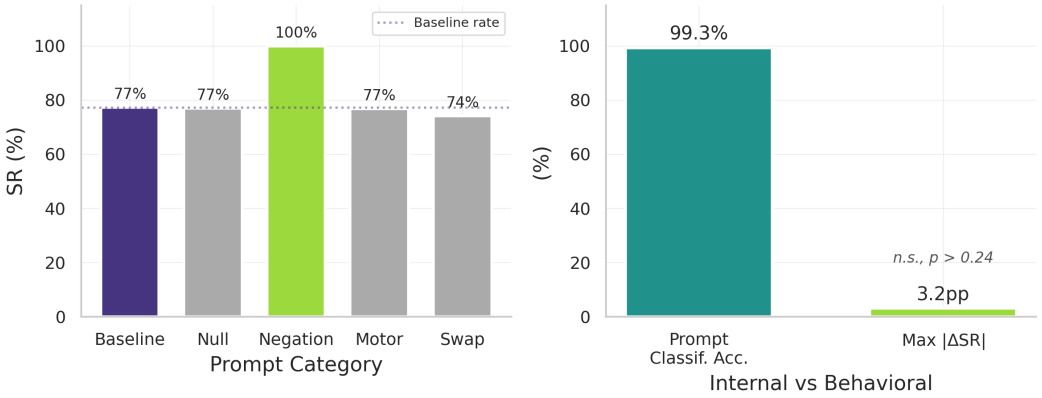

Figure 10: **Language is ignored despite internal distinction.** Left: counterfactual prompting across 3,396+ episodes shows no significant behavioral difference (p>0.24). Right: layer 17 classifiers distinguish prompts with 99.3% accuracy, yet behavior is unchanged.

J.2 Compute Requirements

Experiments were conducted on an 8×A100-SXM4-80GB cluster for $\pi_{0.5}$, OpenVLA-OFT, large-scale SAE training, concept ablation, and cross-model analysis, an NVIDIA RTX 5090 (32GB) for GR00T N1.5 experiments, and two NVIDIA RTX 4090s (24GB) for SmolVLA and X-VLA experiments. Total experiment data exceeds 7.1 TB, including 4.3 TB of activation recordings, 152 GB of SAE checkpoints, and 394,000+ rollout episodes with videos.

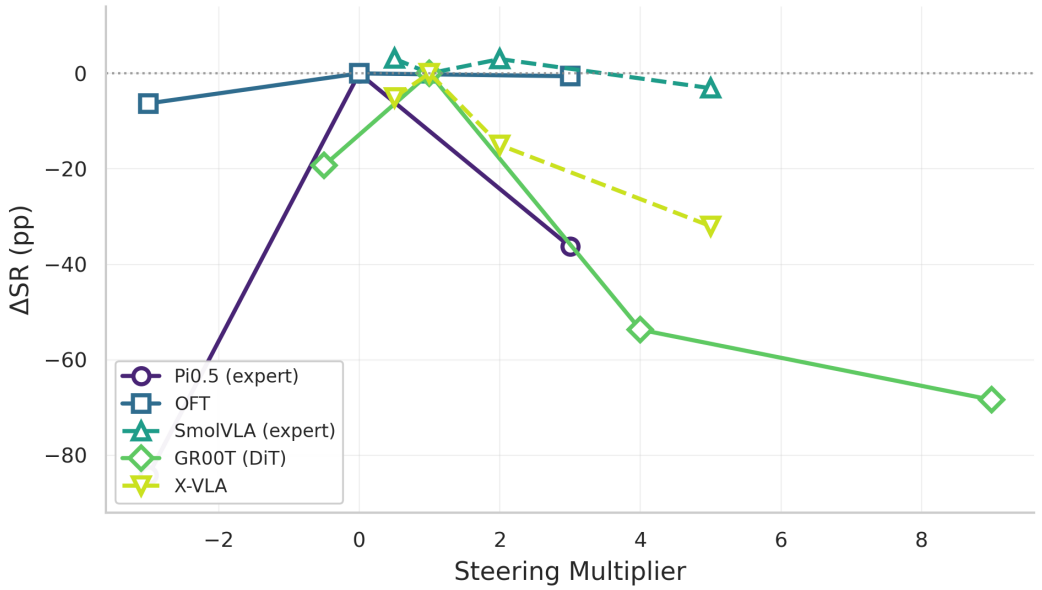

Figure 11: **Steering sensitivity across five models.** $\pi_{0.5}$ and GR00T exhibit catastrophic sensitivity to feature steering, while OFT and SmolVLA are comparatively robust. SmolVLA shows non-monotonic dose response (mild amplification at 0.5–2×, degradation only at 5×). Error represents mean ΔSR across all steered features.

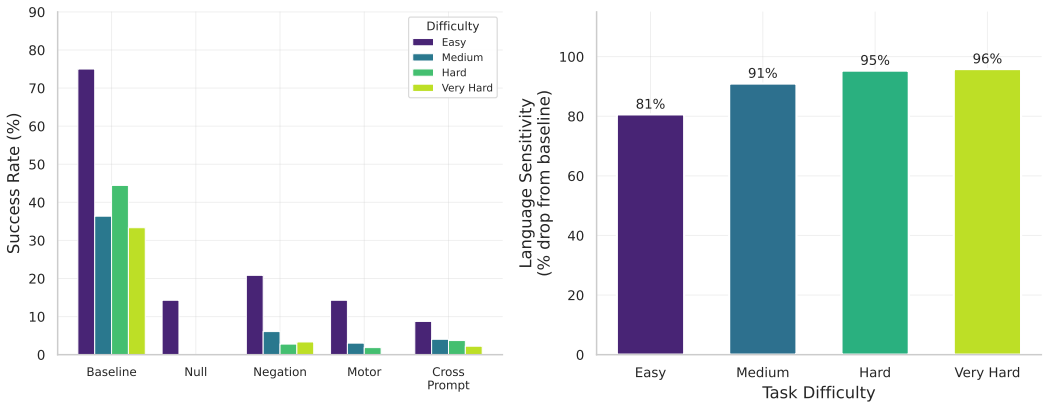

Figure 12: **SmolVLA language sensitivity varies by MetaWorld task difficulty.** Baseline success rates range from 85% (easy) to 62% (hard). Under null prompts, easy tasks drop only 3pp (85%→82%), while hard tasks drop 21pp (62%→41%), showing that language sensitivity scales with task ambiguity rather than architecture.

J.3 Evaluation Protocol

Each experimental condition is evaluated over 5 episodes per task. Episodes run for a maximum of 300 steps. Success is determined by task-specific criteria defined in each benchmark (LIBERO, MetaWorld, SimplerEnv, ALOHA).

K Action Atlas Visualization Platform

We release Action Atlas as an open-source visualization platform for exploring VLA concept representations, available at https://action-atlas.com. The platform provides interactive tools

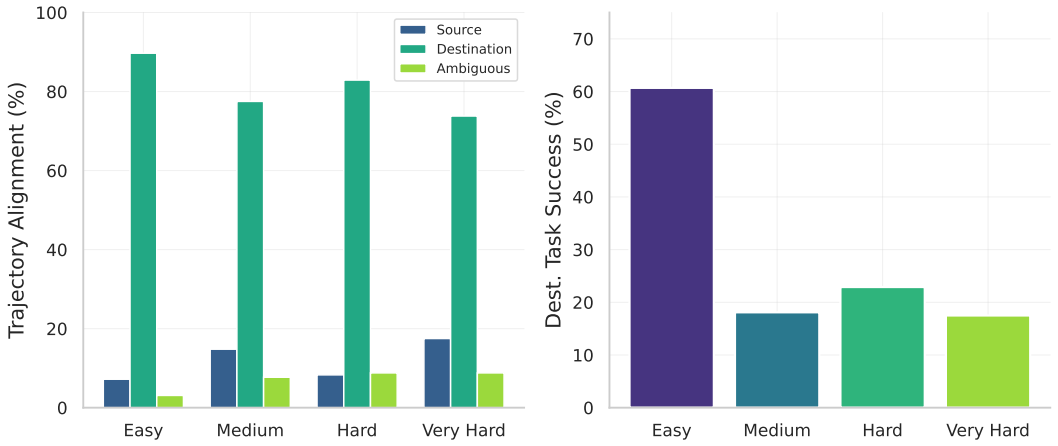

Figure 13: **SmolVLA MetaWorld cross-task displacement and success under injection.** Left: source-task override rate by MetaWorld difficulty level: destination alignment decreases as difficulty increases (89.7% on easy, 73.8% on very hard), so harder tasks produce weaker source behavior transfer. Right: destination task success under cross-task injection by difficulty: easy tasks maintain 60.7% success while harder tasks drop to 17–22%, reflecting both the displacement effect and the greater task-specific precision required for harder goals.

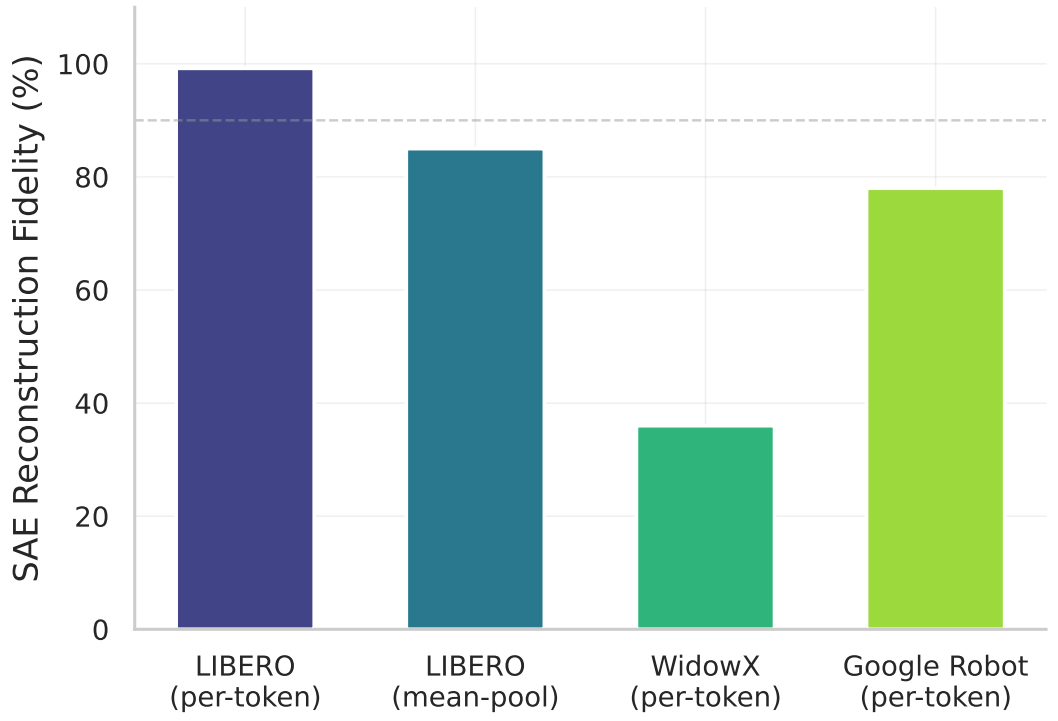

Figure 14: **X-VLA SAE reconstruction fidelity across environments.** Per-token processing achieves 99.2% explained variance on LIBERO but only 36% on WidowX (SimplerEnv), while mean-pooling reduces LIBERO fidelity to 85%. The cross-environment degradation indicates that SAE features trained on LIBERO activations do not fully transfer to the WidowX embodiment distribution.

for SAE feature exploration, semantic search, LLM-based auto-interpretability, and ablation video comparisons.

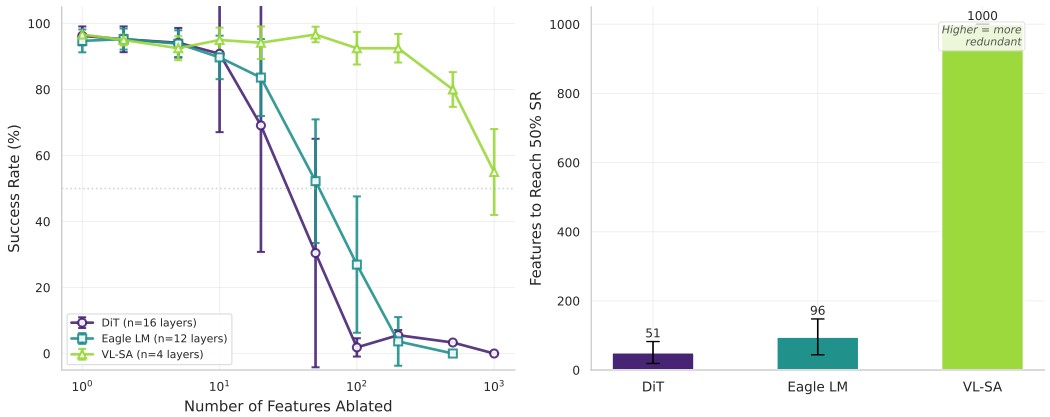

Figure 15: **GR00T N1.5 layer-type contribution profiles.** SAE feature ablation across 32 layers (16 DiT + 12 Eagle LM + 4 VL-SA) reveals distinct importance profiles per layer type: DiT layers are the most ablation-sensitive (40–80% success drop), Eagle LM layers show moderate sensitivity, and VL-SA layers are the most resilient. This mirrors the pathway specialization observed in $\pi_{0.5}$ and SmolVLA.

Suite	Baseline	Null Layer	Aggregate
libero_goal	∼90%	∼0%	33/234 (14%)
libero_object	∼90%	∼0%	43/294 (15%)
libero_spatial	∼90%	∼0%	31/216 (14%)
libero_10	9/10 tasks	0/10 tasks	–

Table 21: OpenVLA-OFT null injection by suite. Zeroing any single layer (tested: 0, 8, 16, 24, 31) destroys task success across all suites.

Suite	Episodes	Aggregate Success
libero_goal	582	87.8%
libero_object	162	77.8%
libero_spatial	192	74.0%
libero_10	582	71.8%

Table 22: OpenVLA-OFT same-scene injection by suite (1,518 total episodes).

Window	Task Survival	Surviving Tasks
Baseline	9/10	Tasks 0–5, 7–9
null_early	0/9	None
null_mid	0/9	None
null_late	2/9	Tasks 3, 9

Table 23: OpenVLA-OFT temporal injection on `libero_10`. Early and mid-episode nulling destroys all tasks; late nulling allows partial recovery.

Suite	Min R^2	Max R^2	Mean R^2	Layers > 0.70
LIBERO-Spatial	0.969	0.994	0.988	32/32 (100%)
LIBERO-Goal	0.845	0.941	0.896	32/32 (100%)
LIBERO-10	0.692	0.837	0.780	30/32 (93.8%)
LIBERO-Object	0.608	0.885	0.813	29/32 (90.6%)
All suites	**0.608**	**0.994**	**0.869**	**123/128 (96.1%)**

Table 24: OpenVLA-OFT multi-layer probing: episode-length R^2 across all 32 layers for four LIBERO suites (n=149 per suite).

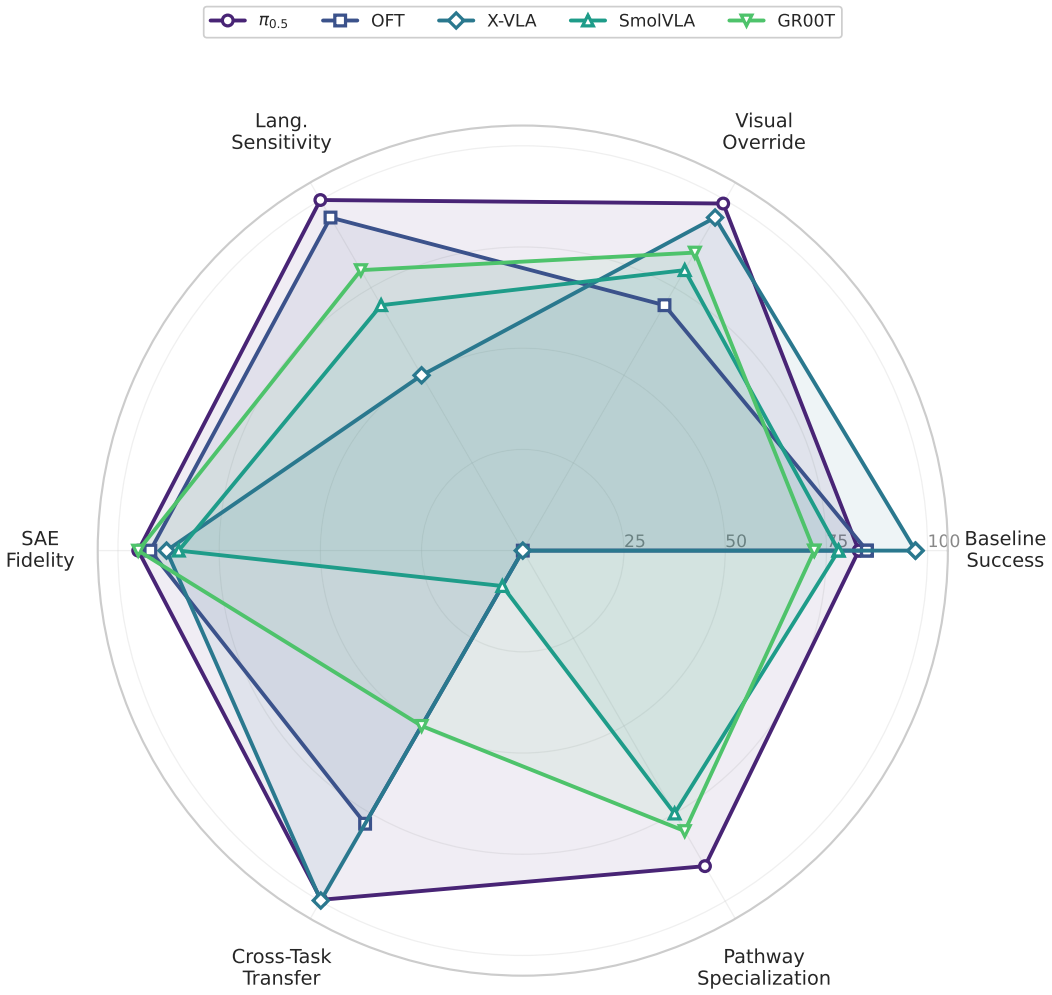

Figure 16: **Cross-model capability radar.** Five VLAs scored on baseline success, visual override strength, language sensitivity, SAE fidelity, cross-task transfer rate, and pathway specialization. OFT lacks pathway specialization (single-pathway architecture); SmolVLA and GR00T show the strongest pathway specialization alongside $\pi_{0.5}$.

Suite	Early (L0–7)	Middle (L8–23)	Late (L24–31)
LIBERO-Spatial	0.984	0.991	0.986
LIBERO-Object	0.719	0.834	0.863
LIBERO-Goal	0.859	0.896	0.933
LIBERO-10	0.733	0.779	0.827

Table 25: OpenVLA-OFT multi-layer probing: mean R^2 by layer region.

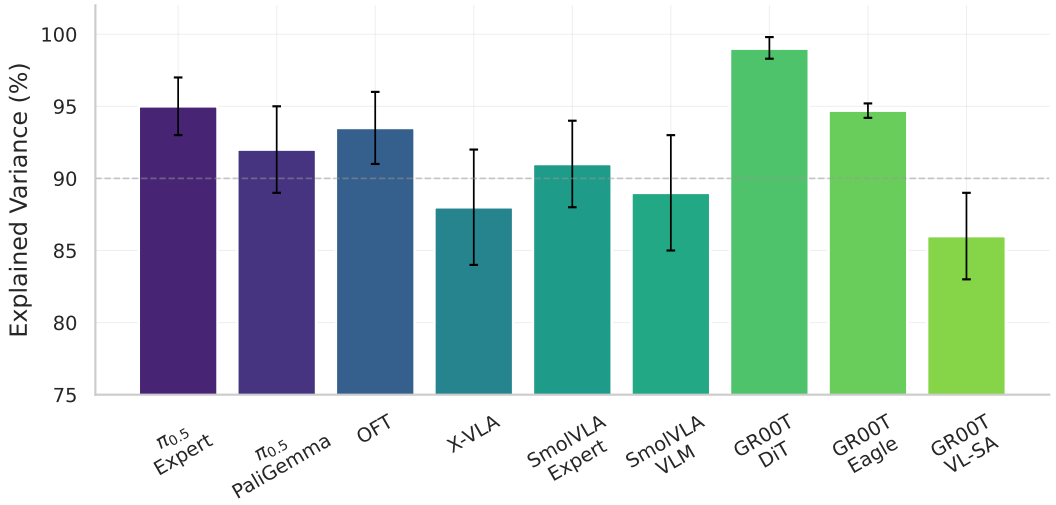

Figure 17: **SAE explained variance by architecture and pooling strategy.** GR00T DiT layers achieve the highest per-token reconstruction quality (98.3–99.8% EV); GR00T VL-SA layers show the lowest per-token quality (83–89%) but improve to 99% EV with mean-pooling. X-VLA mean-pooled SAEs paradoxically achieve better rollout fidelity than per-token despite lower EV. Error bars: range across layers within each model. Dashed line: 90% threshold.

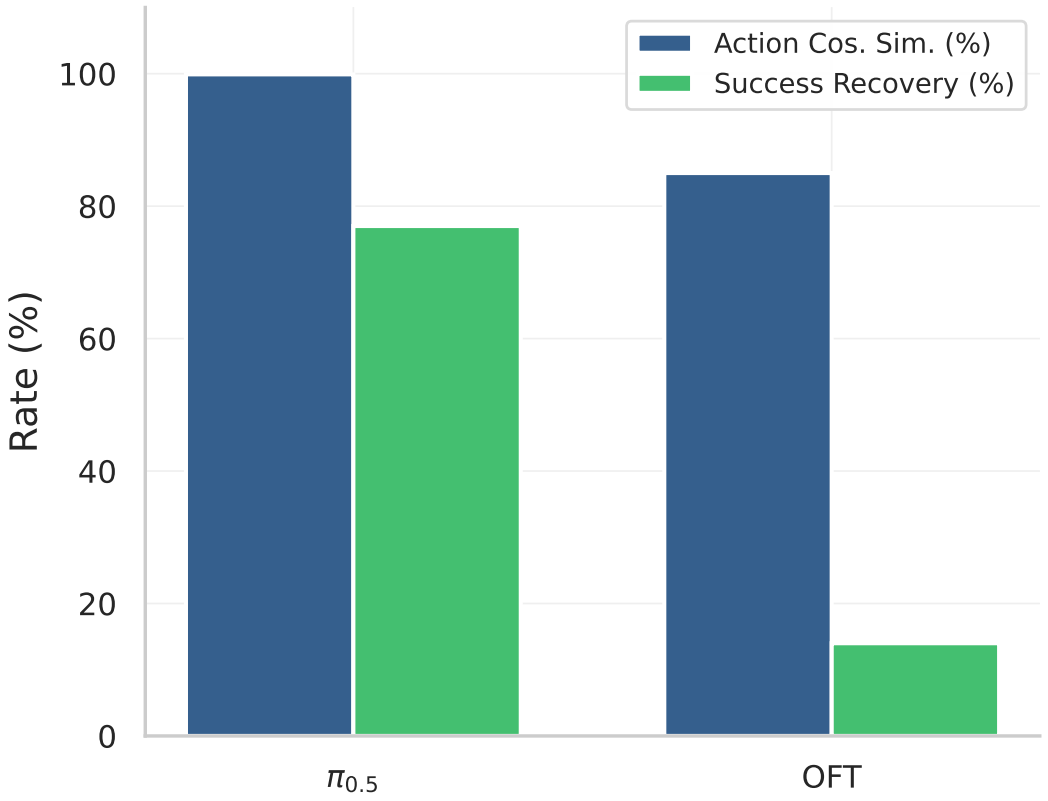

Figure 18: **Null injection recovery for $\pi_{0.5}$ and OFT.** Action cosine similarity (left bars) measures how closely injected actions match baseline; success recovery (right bars) measures task completion under null prompt with injected baseline activations. $\pi_{0.5}$ recovers 77% success with 0.999 cosine similarity, showing strong visual pathway dominance. OFT recovers only 14% despite 0.85 cosine similarity; OFT's representations are more entangled with language context.

Model	Probe Target	Metric	Result
$\pi_{0.5}$ (expert)	State prediction	R^2	0.45
$\pi_{0.5}$ (expert)	Success prediction	AUC	0.93
$\pi_{0.5}$ (PaliGemma)	Goal classification	Accuracy	76.4%
$\pi_{0.5}$ (PaliGemma)	Prompt classification	Accuracy	99.3%
$\pi_{0.5}$ (PaliGemma)	Workspace region (L15)	Accuracy	99.3%
OFT	Task identification	Accuracy	97.8–100%
OFT	Success prediction	AUC	0.97
OFT	Episode-length (mean)	R^2	0.87
SmolVLA (expert)	Oracle state ratio (h=10)	ratio	0.58
SmolVLA (VLM)	Oracle state ratio (h=10)	ratio	0.13
GR00T (all layers)	Task identification	Accuracy	100%
GR00T (all layers)	Success prediction	Accuracy	96.4%
GR00T (DiT L14)	Success prediction	Accuracy	97.7%

Table 26: Cross-model linear probing summary. $\pi_{0.5}$ expert activations encode state and success while PaliGemma encodes prompt/goal semantics despite behavioral invariance. OFT achieves near-perfect task identification and success prediction. SmolVLA expert captures $4.5\times$ more state information than VLM (0.58 vs. 0.13 oracle ratio). GR00T SAE features achieve perfect task identification across all 32 layers. Oracle ratio: probe R^2 / oracle R^2 (fraction of ground-truth state information linearly decodable from activations).

Suite	Episodes	Categories	ANOVA p
libero_object	1,496	22	> 0.24
libero_spatial	353	9	> 0.067
libero_goal	380	6	> 0.24

Table 27: $\pi_{0.5}$ counterfactual prompting by suite. No suite shows statistically significant behavioral differences across prompt categories.

Suite	Condition	Success	n
GOAL	own_prompt (baseline)	91.5%	236
	cross_prompt, no inject	0.0%	236
	cross_prompt + PaliGemma ALL	0.4%	236
	cross_prompt + Expert L16	1.3%	236
SPATIAL	own_prompt (baseline)	100%	34
	cross_prompt, no inject	64.7%	34
	own_prompt + PaliGemma ALL	20.6%	34
LIBERO-10	own_prompt (baseline)	62.5%	24
	all injection conditions	0.0%	24

Table 28: $\pi_{0.5}$ cross-task injection with pathway-specific conditions.

Suite	Baseline	Zero any layer	Null prompt	Zero eff.	Δpp
Goal	96.7%	0%	10%	82.6%	-2.2
Object	100%	0%	60%	98.2%	-1.3
Spatial	90.0%	0%	48%	85.2%	-2.6
LIBERO-10	100%	0%	28%	74.7%	-2.4

Table 29: X-VLA per-suite breakdown. *Zero any layer*: zeroing any single layer (24 tested) produces 0% success across all suites. *Null prompt*: success under empty string. *Zero eff.*: concept ablation zero-effect rate. Δ*pp*: mean concept ablation delta in percentage points. Counterfactual: n=50 baseline + n=1,100 "other" per suite (n=4,800 total). Concept ablation: n=2,480 pairs total.

Suite	Baseline	Expert zero	Zero eff. (exp)	Δpp (exp)
Goal	75.0%	60–83%	14.6%	-4.7
Object	78.5%	60–83%	0.0%	-3.9
Spatial	67.5%	47–77%	32.7%	-17.7
LIBERO-10	40.7%	0–33%	20.3%	$+0.8$

Table 30: SmolVLA per-suite breakdown. *Expert zero*: range of overall success rates when zeroing individual expert layers. Zero eff./ Δpp: concept ablation statistics for the expert pathway (n=1,696 pairs total). VLM concept ablation (n=210 pairs): goal -10.7pp, object $+6.4$pp, spatial -8.5pp, LIBERO-10 $+5.9$pp.

Suite	Baseline	Zero DiT	CF "other"	Zero eff.	Δpp
Goal	97.0%	0%	18.9%	68.8%	-5.8
Object	99.0%	0%	73.3%	69.6%	-9.9
Long	75.0%	0%	61.7%	42.2%	-5.3

Table 31: GR00T N1.5 per-suite breakdown. *Zero DiT*: zeroing any DiT layer (16 tested) produces 0% on all suites. *CF "other"*: counterfactual success under non-baseline prompt categories (n=180 per suite). *Zero eff./Δpp*: concept ablation across 6,500 pairs total. LIBERO-Long is most sensitive (42.2% zero effect, 11.0% destruction) reflecting its multi-step task complexity.

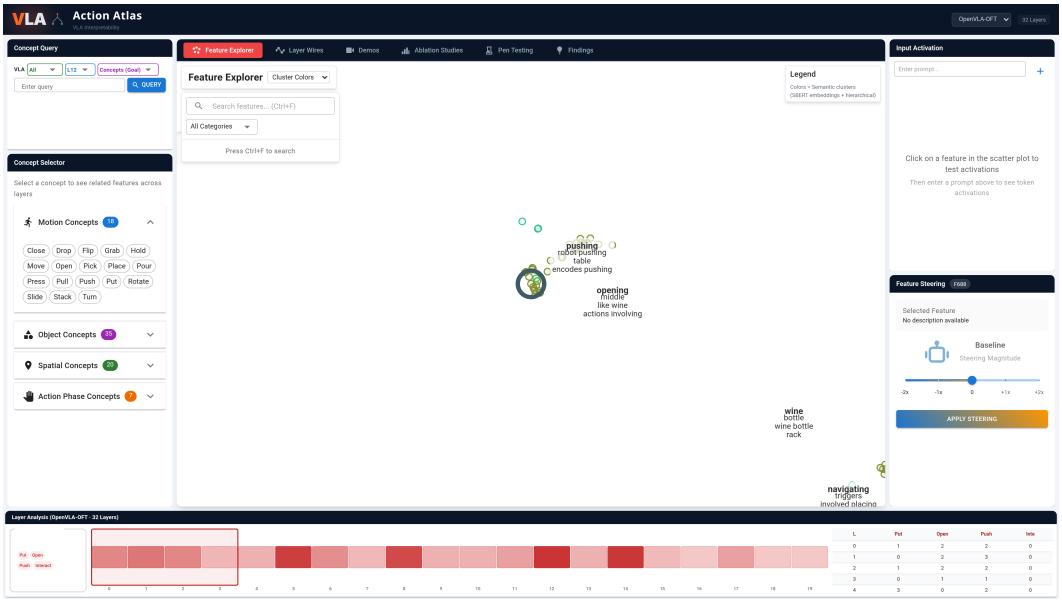

Figure 19: **Action Atlas: Feature Explorer.** UMAP (McInnes et al., 2018) projection of 4,096 SAE features from OpenVLA-OFT layer 16, colored by semantic category.

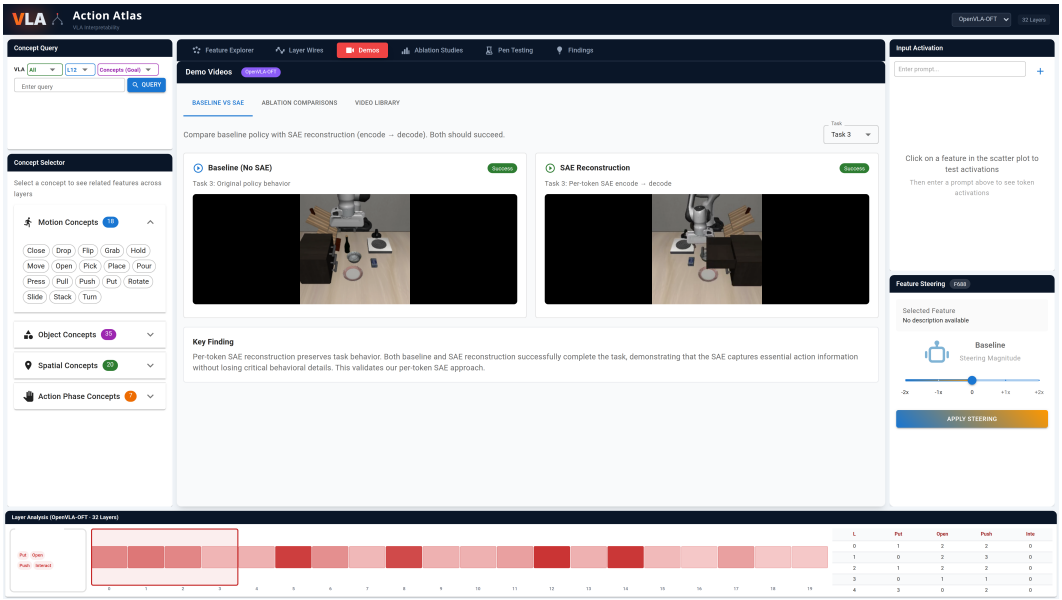

Figure 20: **Action Atlas: Video Library.** Multi-filter interface for browsing 10,000+ rollout videos.

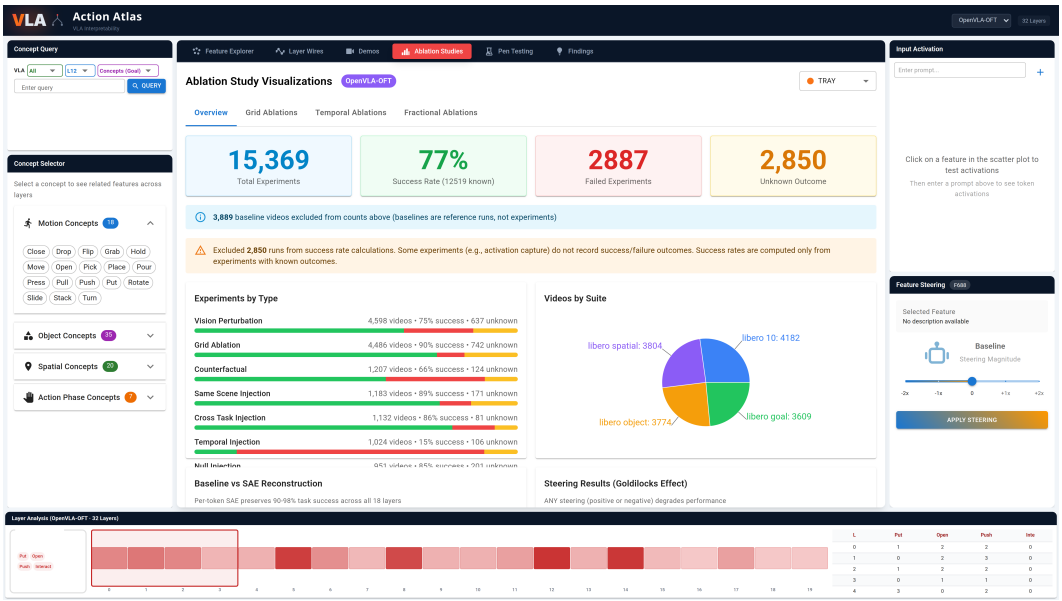

Figure 21: **Action Atlas: Ablation Comparison.** Three-column video comparison showing baseline, SAE-reconstructed, and ablated rollouts side-by-side.

Figure 22: **Action Atlas: Layer Wires.** Interactive visualization of information flow across transformer layers.

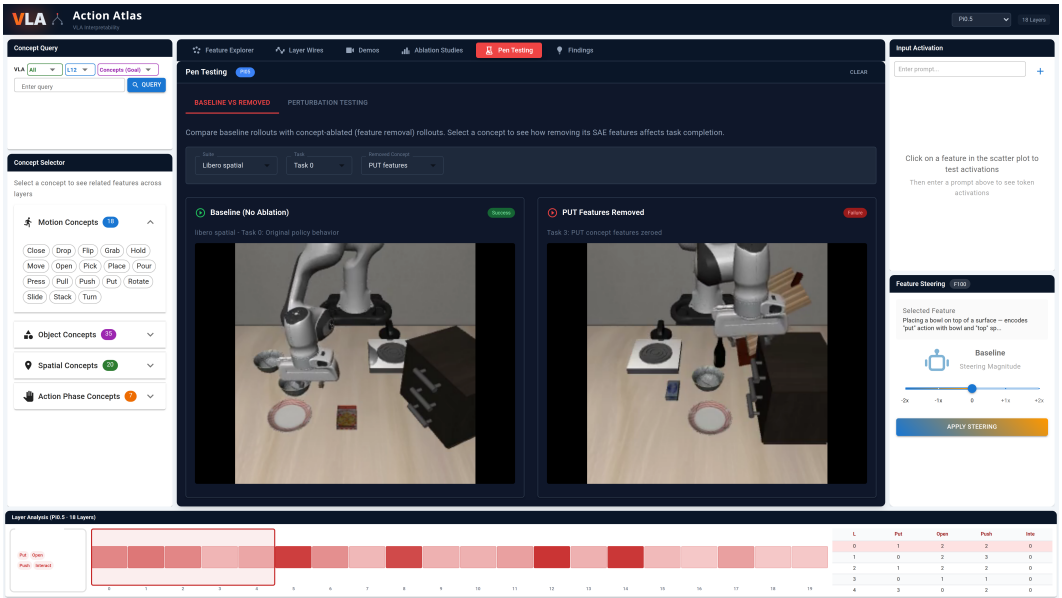

Figure 23: **Action Atlas: Perturbation Testing.** Interface for applying real-time visual perturbations and observing behavioral effects.