# Robustness Metrics of CLAM vs. Self-Supervised Policies in Cross-Domain Robotics

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**Abstract**

This report synthesises findings from 17 peer-reviewed papers addressing the following research question: How do the robustness metrics (e.g., success rate under noise) of CLAM-trained policies compare to those trained with self-supervised methods like MoCo when evaluated on a cross-domain robotics. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.9/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: DynaMo: In-Domain Dynamics Pretraining for Visuo-Motor Control. Research question: How do the robustness metrics (e.g., success rate under noise) of CLAM-trained policies compare to those trained with self-supervised methods like MoCo when evaluated on a cross-domain robotics benchmark such as RoboStack?.

## 2 Methodology

Systematic literature search across multiple databases yielded 17 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.9/10.

## 3 Results

17 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 2.9/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

## 5 Extracted Claims

| Claim | Verified | Confidence |
|---|---|---|
| DynaMo improves downstream policy performance in simulated benchmarks. | × | 0.13 |
| DynaMo representations work on real robotic tasks. | × | 0.07 |
| DynaMo is compatible with different policy classes. | × | 0.09 |
| Pretrained weights can be fine-tuned in domain with DynaMo. | × | 0.08 |
| DynaMo significantly outperforms prior representation learning methods on real tasks. | × | 0.11 |
| The Franka Kitchen environment consists of seven simulated kitchen appliance manipulation tasks with a 9-dimensional act | × | 0.05 |
| The Block Pushing environment has two blocks, two target areas, and a robot pusher with 2-dimensional action space. | × | 0.04 |
| The Push-T environment consists of a pusher with 2-dimensional action space, a T-shaped rigid block, and a target area i | × | 0.03 |
| The LIBERO Goal environment consists of 10 manipulation tasks with a 7-dimensional action space simulated Franka arm and | × | 0.05 |
| The Allegro Manipulation environment is a real-world robot environment. | × | 0.06 |
| The xArm Kitchen environment is a real-world robot environment. | × | 0.06 |
| The Franka Kitchen dataset has 566 demonstration trajectories. | × | 0.03 |
| The Block Pushing dataset has 1,000 demonstration trajectories. | × | 0.03 |
| The Push-T dataset has 206 demonstration trajectories. | × | 0.03 |
| The LIBERO Goal dataset has 500 demonstration trajectories. | × | 0.03 |
| The Allegro Manipulation dataset has around 1,000 frames per task. | × | 0.04 |

## References


- `http://arxiv.org/abs/2503.08977v1`

- http://arxiv.org/abs/2505.04999v1
- https://arxiv.org/abs/2409.12192