# Diffusion Trajectory Guidance vs Distilled Action Baselines in RoboBench Compounding Errors

Assignee Research

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**Abstract**

This report synthesises findings from 9 peer-reviewed papers addressing the following research question: How do compounding error rates in multimodal alignment differ between diffusion trajectory guidance and distilled action baselines on unseen RoboBench scenarios. 14 claims were extracted from source literature; 3 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Enhancing Diffusion Policy with Classifier-Free Guidance for Temporal Robotic Tasks. Research question: How do compounding error rates in multimodal alignment differ between diffusion trajectory guidance and distilled action baselines on unseen RoboBench scenarios?.

## 2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.2/10.

## 3 Results

9 papers retrieved. 14 claims extracted; 3 independently verified. Quality review score: 5.2/10.

## 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 |
|---|---|---|
| Diffusion-based policies, such as Diffusion Policy (DP) and Action Chunking with Transformers (ACT), have shown remarkab | ✓ | 0.18 |
| These methods excel in tasks requiring multi-modal action distributions, such as pushing or pouring, achieving significan | × | 0.05 |
| Temporal sequential tasks with repetitive cycles and precise termination requirements pose significant challenges for ex | × | 0.12 |
| DP and ACT struggle to accurately judge when to terminate a task, especially in dynamic environments, due to their relia | × | 0.04 |
| DP and ACT employ diffusion models with implicit action distributions, lacking explicit probability outputs, which intro | × | 0.06 |
| In practical applications, such as robotic imitation of human screw-tightening motions, robots may persist in redundant | × | 0.04 |
| The proposed framework enhances termination judgment by integrating Classifier-Free Guidance (CFG), training conditional | ✓ | 0.25 |
| The model's design draws inspiration from human intuition in repetitive tasks, where individuals naturally monitor cycle | × | 0.04 |
| The framework incorporates timestep counts as a temporal cue, mirroring human-like awareness of task progression to prev | × | 0.08 |
| The approach simplifies the model for cyclic manipulation by relying on lightweight step-based guidance, achieving robus | × | 0.05 |
| The proposed framework significantly enhances deterministic control and execution reliability for sequential robotic tas | ✓ | 0.27 |
| CFG-DP (Ours) achieves a success rate of 83.2%, with 0.3 repetitive actions and a completion time of 24.2 seconds in the | × | 0.14 |
| DP achieves a success rate of 55.6%, with 2.6 repetitive actions and a completion time of 32.0 seconds in the real-world | × | 0.11 |
| ACT achieves a success rate of 50.3%, with 3.2 repetitive actions and a completion time of 41.0 seconds in the real-worl | × | 0.11 |

## References


- http://arxiv.org/abs/2503.14504v2
- http://arxiv.org/abs/2510.09786v1
- http://arxiv.org/abs/2309.03452v2