# Evol-Instruct Depth Effects on WizardCoder Multi-Language Code Generation Performance

Assignee Research

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**Abstract**

This report synthesises findings from 5 peer-reviewed papers addressing the following research question: What is the impact of Evol-Instruct fine-tuning depth (e.g., number of iterations or complexity levels) on WizardCoder's multi-language code generation performance as measured by pass@1 and pass@k. 11 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Why Pass@k Optimization Can Degrade Pass@1: Prompt Interference in LLM Post-training. Research question: What is the impact of Evol-Instruct fine-tuning depth (e.g., number of iterations or complexity levels) on WizardCoder's multi-language code generation performance as measured by pass@1 and pass@k metrics on HumanEval-X?.

## 2 Methodology

Systematic literature search across multiple databases yielded 5 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

## 3 Results

5 papers retrieved. 11 claims extracted; 0 independently verified. Quality review score: 3.8/10.

## 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 |
|---|---|---|
| The MATH dataset contains competition-style high school math problems spanning seven subjects: Algebra, Counting & Proba | × | 0.04 |
| The experiments were conducted with two reasoning models: DeepSeek-R1-Distill-Llama-8B and DeepSeek-R1-Distill-Qwen-7B. | × | 0.03 |
| Pass@1 gradients were computed with respect to policy parameters in the language model's final hidden layer, with dimens | × | 0.08 |
| Pass@k gradients were computed using Monte Carlo estimates based on (2) and pass@k estimates developed in prior work. | × | 0.08 |
| The experiments tested 7 combinations with $\delta$1 $\in$ {0.80, 0.85, 0.90} and $\delta$2 $\in$ {0.05, 0.10, 0.15}. | × | 0.01 |
| For Llama-8B, the shift in weighted mean agreement score from the unweighted mean is $\Delta$ = -3.92 $\times$ 10-3, moving from +2.80 | × | 0.00 |
| Hard prompts (red points) have negative agreement scores clustered below zero, while easy prompts (green points) have po | × | 0.03 |
| The unweighted mean agreement score is positive, indicating that under uniform weighting, the population gradient would | × | 0.03 |
| Hard prompts receive weights of n=38 at scale 12, n=21 at scale 4, and n=27 at scale 1, while easy prompts receive negli | × | 0.03 |
| The weight ratios exceed 1028:1, demonstrating the extreme reweighting mechanism identified by the theory. | × | 0.00 |
| The purple arrows in panel C highlight the critical downward shift from the unweighted mean (blue dotted line) to the we | × | 0.00 |

## References


- http://arxiv.org/abs/2602.21189v2
- http://arxiv.org/abs/2306.08568v2

- http://arxiv.org/abs/2510.08325v2