

# DeepSeek-R1 and Claude Token Efficiency and Latency in Iterative Code Repair with Repository Context

Assignee Research

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## Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: What is the difference in token efficiency and inference latency between DeepSeek-R1 and Claude when performing iterative code repair on FeedbackEval with full repository context. Recent generations of frontier language models have introduced Large Reasoning Models (LRMs) that generate detailed thinking processes before providing answers. While these models demonstrate improved performance on reasoning benchmarks, their fundamental capabilities, scaling. 8 claims were extracted from source literature; 8 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.7/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: The Illusion of Thinking. Research question: What is the difference in token efficiency and inference latency between DeepSeek-R1 and Claude when performing iterative code repair on FeedbackEval with full repository context?.

## 2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.7/10.

### 3 Results

10 papers retrieved. 8 claims extracted; 8 independently verified. Quality review score: 8.7/10.

### 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
Recent generations of frontier language models have introduced Large Reasoning Models (LRMs) that generate detailed thin	✓	0.35
These models demonstrate improved performance on reasoning benchmarks.	✓	0.21
Current evaluations primarily focus on established mathematical and coding benchmarks, emphasizing final answer accuracy	✓	0.30
This evaluation paradigm often suffers from data contamination.	✓	0.17
Current evaluations do not provide insights into the reasoning traces' structure and quality.	✓	0.24
Frontier LRMs face a complete accuracy collapse beyond certain complexities.	✓	0.25
Frontier LRMs exhibit a counterintuitive scaling limit: their reasoning effort increases with problem complexity up to a	✓	0.36
Standard LLM counterparts outperform LRMs in low-complexity tasks under equivalent inference compute.	✓	0.18

### References

- <https://doi.org/10.48550/arxiv.2507.00699>
- <https://doi.org/10.70777/si.v2i3.15161>

- <https://doi.org/10.70777/si.v2i6.15919>