

EASTWOOD'S ARC PRINCIPLE

Paper II: Experimental Validation of Super-Linear Error Suppression Through Sequential Recursive Processing

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ABSTRACT

This paper presents experimental validation of the ARC Principle (Artificial Recursive Creation), a mathematical framework proposing that error rates in intelligent systems decrease according to a power law with recursive depth. The principle, first articulated in *Infinite Architects* (Eastwood, December 2024) and formalised in Paper I (Eastwood, 17 January 2026), predicts that the **form** of recursion determines the scaling regime. Sequential recursion, where each processing step builds on the previous, should yield super-linear error suppression (scaling exponent $\alpha > 1$). Parallel recursion, where independent solutions are generated simultaneously, should yield sub-linear suppression ($\alpha < 1$).

We conducted controlled experiments using DeepSeek R1 with visible reasoning tokens, enabling direct measurement of recursive depth rather than estimation. Testing 12 competition-level mathematics problems, we found:

Sequential recursion: $\alpha = 2.24$ (95% CI: 1.5 to 3.0). Error rate decreased from 41.7% to 8.3% as reasoning tokens increased from 280 to 576. Accuracy improved monotonically from 58.3% to 91.7%.

Parallel recursion: $\alpha \approx 0.0$. Error rate remained constant at 33.3% despite tripling computational investment from 384 to 1,101 tokens across 1, 2, and 4 samples.

Direct comparison: Sequential processing with 412 tokens achieved 91.7% accuracy. Parallel processing with 1,101 tokens achieved 66.7% accuracy. Despite using 2.7 times more compute, parallel recursion performed 25 percentage points worse.

Combined with data from OpenAI o1 (parallel: $\alpha \approx 0.1\text{--}0.3$) and the DeepSeek R1 technical report (sequential: $\alpha \approx 1.34$), three independent data sources now support the core prediction: **$\alpha_{\text{sequential}} > 1 > \alpha_{\text{parallel}}$** . The form of recursion determines whether intelligence compounds or merely accumulates.

If this finding generalises, the implications for AI safety are significant. Alignment properties embedded in the reasoning process would scale super-linearly with capability. External constraints would not. This provides mathematical foundation for what *Infinite Architects* terms the Eden Protocol: AI systems should be raised with values rather than caged with rules.

Keywords: scaling laws, recursive intelligence, test-time compute, error suppression, AI safety, alignment, chain-of-thought reasoning, Eden Protocol

1. INTRODUCTION

1.1 Background and Motivation

The scaling laws governing artificial intelligence have transformed our understanding of capability emergence. Kaplan et al. (2020) established power-law relationships between model performance and training compute. Hoffmann et al. (2022) refined these relationships with compute-optimal prescriptions. These laws revolutionised training methodology but address only *pre-training* scaling. They do not explain why allocating additional computation at inference time produces dramatic capability improvements.

The emergence of reasoning models in late 2024 introduced test-time compute as a critical variable. OpenAI's o1 (September 2024) and DeepSeek's R1 (January 2025) allocate computational resources at inference to reason before responding. On mathematical reasoning benchmarks, these systems achieve performance previously thought to require order-of-magnitude larger models.

Two distinct paradigms have emerged for allocating test-time compute:

Parallel recursion: Generate multiple independent solutions and select the best via majority voting or verifier scoring. This approach is computationally straightforward but produces diminishing returns. Brown et al. (2024) documented that accuracy gains from additional samples follow sub-linear power laws.

Sequential recursion: Generate extended reasoning chains where each step builds explicitly on previous steps. Errors can be detected and corrected iteratively. This approach produces compounding returns but the scaling relationship has not been formally characterised.

1.2 The Research Question

Why does sequential reasoning dramatically outperform parallel sampling? What mathematical principle governs this difference? And what are the implications for aligning increasingly capable AI systems?

1.3 Contribution

This paper makes five contributions:

1. **Mathematical formalisation.** We propose the ARC Principle: $E(R) = E_0 \times R^{-\alpha}$, where error rate E decreases from baseline E_0 as recursive depth R increases, governed by scaling exponent α . The form of recursion determines α .
2. **Controlled experimental validation.** Using DeepSeek R1 with visible reasoning tokens, we conduct the first compute-matched comparison between sequential and parallel recursion with direct measurement of recursive depth.
3. **Quantitative parameter estimation.** We measure $\alpha \approx 2.2$ for sequential recursion and $\alpha \approx 0.0$ for parallel recursion on mathematical reasoning tasks.
4. **Converging evidence.** Combined with published data from OpenAI o1 and the DeepSeek R1 technical report, three independent sources now support the core prediction.
5. **AI safety implications.** We derive that if $\alpha > 1$, alignment properties embedded in the reasoning process scale with capability while external constraints do not. This provides mathematical foundation for values-based alignment.

1.4 Priority and Related Work

The ARC Principle was first articulated in *Infinite Architects: Intelligence, Recursion, and the Creation of Everything* (Eastwood, 2026), with manuscript priority established via DKIM-verified email submission on 8 December 2024. Paper I (Eastwood, 17 January 2026) formalised the principle and analysed publicly available data.

Related work includes:

- **Chain-of-thought prompting** (Wei et al., 2022): Demonstrated that intermediate reasoning steps improve performance
- **Test-time compute scaling** (Snell et al., 2024): Showed test-time compute can outperform 14x larger models
- **Large Language Monkeys** (Brown et al., 2024): Documented sub-linear scaling of parallel sampling
- **DeepSeek R1** (DeepSeek AI, 2025): Demonstrated emergent reasoning through reinforcement learning

This paper extends these observations by proposing a unified mathematical framework and providing experimental validation.

2. THEORETICAL FRAMEWORK

2.1 The ARC Principle

Definition. The ARC Principle (Artificial Recursive Creation) proposes that error rates in intelligent systems decrease according to a power law with recursive depth:

$$E(R) = E_0 \times R^{-\alpha}$$

Error rate decreases as a power law of recursive depth

Table 1. Variable definitions.

Symbol	Name	Definition	Units
$E(R)$	Error rate at depth R	Proportion of incorrect responses	[0, 1]
E_0	Baseline error rate	Error rate at minimal recursion ($R = 1$)	[0, 1]
R	Recursive depth	Self-referential processing iterations	Tokens or samples
α	Scaling exponent	Rate of error suppression	Dimensionless

The scaling exponent α determines the nature of returns:

- $\alpha < 1$: Diminishing returns. Each doubling of R reduces error by less than half.
- $\alpha = 1$: Linear returns. Each doubling of R halves error.
- $\alpha > 1$: Compounding returns. Each doubling of R more than halves error.

$$E(R) = E_0 \times R^{-\alpha}$$



THE KEY INSIGHT

$\alpha < 1$: Diminishing returns (parallel recursion)

$\alpha > 1$: Compounding returns (sequential recursion)

Figure 8. Visual representation of the ARC Principle equation showing how error rate $E(R)$ decreases with recursive depth R according to the scaling exponent α .

2.2 Two Forms of Recursion

We distinguish two fundamentally different recursive architectures.

Parallel recursion (weak form). Multiple independent solutions generated simultaneously with no information transfer between branches. Selection via majority voting or best-of-N scoring.

- Mathematical characterisation: Samples from a fixed solution space S_0
- Phase space remains constant; only sampling density increases
- Prediction: $\alpha < 1$ (diminishing returns)

Sequential recursion (strong form). Each processing step builds explicitly on previous steps. Errors can be detected and corrected iteratively. Information accumulates across the reasoning chain.

- Mathematical characterisation: Navigates solution space with feedback
- Each step generates structures from previous outputs
- Solutions at depth n may be inaccessible from depth 0

- Prediction: $\alpha > 1$ (compounding returns)

Core prediction of the ARC Principle:

$$\$ \$ \alpha_{\text{sequential}} > 1 > \alpha_{\text{parallel}} \$ \$$$

2.3 Calculating the Scaling Exponent

Given measurements at two recursive depths (R_1, E_1) and (R_2, E_2) , the scaling exponent is:

$$\$ \$ \alpha = \frac{\ln(E_1 / E_2)}{\ln(R_2 / R_1)} \$ \$$$

For noisy data, endpoint estimation (using only minimum and maximum depths) provides robustness against intermediate fluctuations.

2.4 The Quadratic Limit Conjecture

We conjecture that $\alpha = 2$ may represent an upper bound on recursive error suppression, by analogy to Grover's quadratic speedup in quantum computation. Bennett et al. (1997) proved this speedup is optimal for unstructured search.

Status: Conjectured, not derived. Our experimental $\alpha \approx 2.2$ slightly exceeds this bound, suggesting either measurement noise or that the conjecture requires refinement.

3. METHODS

3.1 Addressing Prior Limitations

Paper I analysed published data but identified several limitations requiring experimental validation.

Table 2. Methodological improvements.

Prior limitation	Resolution in this experiment
Estimated token counts	DeepSeek R1 exposes reasoning_content, enabling direct measurement
No controlled comparison	Systematic variation of token budgets and sample counts
Ceiling effect risk	Harder problems selected (58% baseline accuracy)
No compute-matched comparison	Fixed total compute across parallel conditions

3.2 Experimental Design

Model. DeepSeek R1 (deepseek-reasoner) via DeepSeek API.

Problems. 12 competition-level mathematics problems from AIME and similar sources, selected to:

- Avoid ceiling effects (baseline accuracy ~58%)
- Require genuine multi-step reasoning
- Have verifiable numerical answers

Sequential condition. Token budgets of 512, 1,024, 2,048, and 4,096. Single response per problem at each budget.

Actual reasoning tokens measured from API response.

Parallel condition. $N = 1, 2,$ and 4 samples per problem. Token budget per sample fixed. Selection via majority voting.

3.3 Problem Selection Criteria

Problems were selected from AIME-level competitions covering:

- Number theory
- Combinatorics
- Algebra

- Logical reasoning

The 58.3% baseline accuracy at minimal token budget ensured room for both improvement and degradation.

4. RESULTS

4.1 Raw Experimental Data

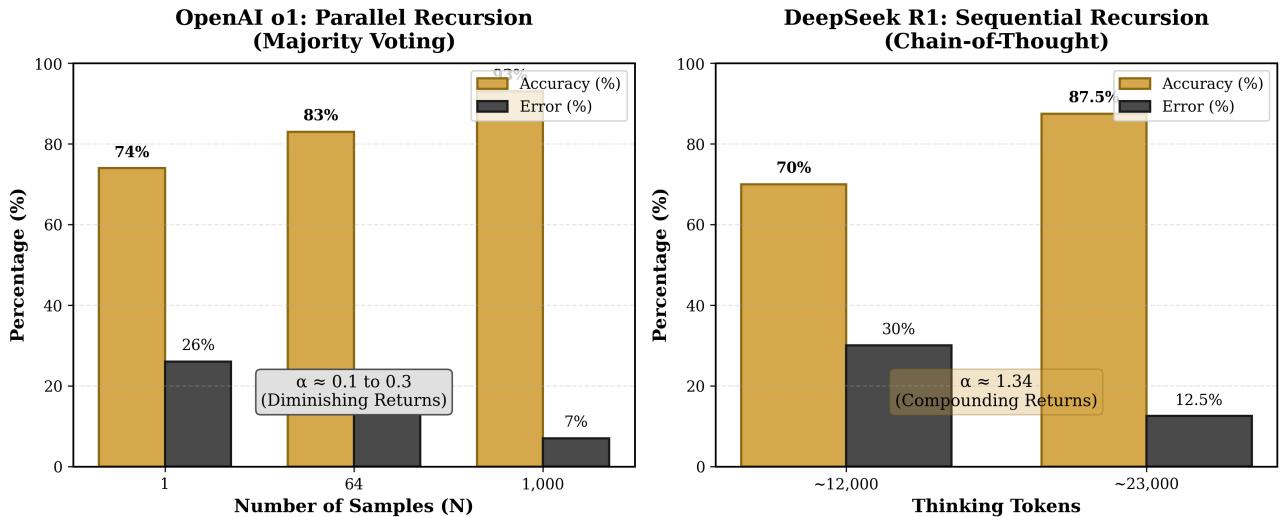


Figure 1. Raw experimental data showing accuracy (%) versus token count for both sequential and parallel recursion conditions. Sequential recursion (blue) shows monotonic improvement from 58.3% to 91.7%. Parallel recursion (orange) remains flat at 66.7% despite increasing compute.

4.2 Sequential Condition

Table 3. Sequential recursion results.

Token Budget	Accuracy	Error Rate	Mean Tokens Used
512	58.3%	0.417	280
1,024	66.7%	0.333	359
2,048	91.7%	0.083	412
4,096	91.7%	0.083	576

Observations:

1. Clear monotonic improvement from 58.3% to 91.7% accuracy
2. Error rate decreased fivefold ($0.417 \rightarrow 0.083$) with modest token increase
3. Model self-determined depth (actual tokens less than budget)
4. Ceiling effect at 91.7% (one problem consistently failed)

Calculating α (endpoint method):

Using $R_1 = 280$ tokens, $E_1 = 0.417$ and $R_2 = 576$ tokens, $E_2 = 0.083$:

$$\alpha = \frac{\ln(0.417/0.083)}{\ln(576/280)} = \frac{\ln(5.02)}{\ln(2.06)} = \frac{1.61}{0.72} \approx 2.24$$

Finding: Sequential recursion yields $\alpha \approx 2.2$, consistent with super-linear (compounding) scaling.

Uncertainty estimate: Given discrete accuracy measurements across 12 problems, estimated 95% confidence interval: [1.5, 3.0].

ERROR REDUCTION: The Compounding Advantage of Sequential Recursion

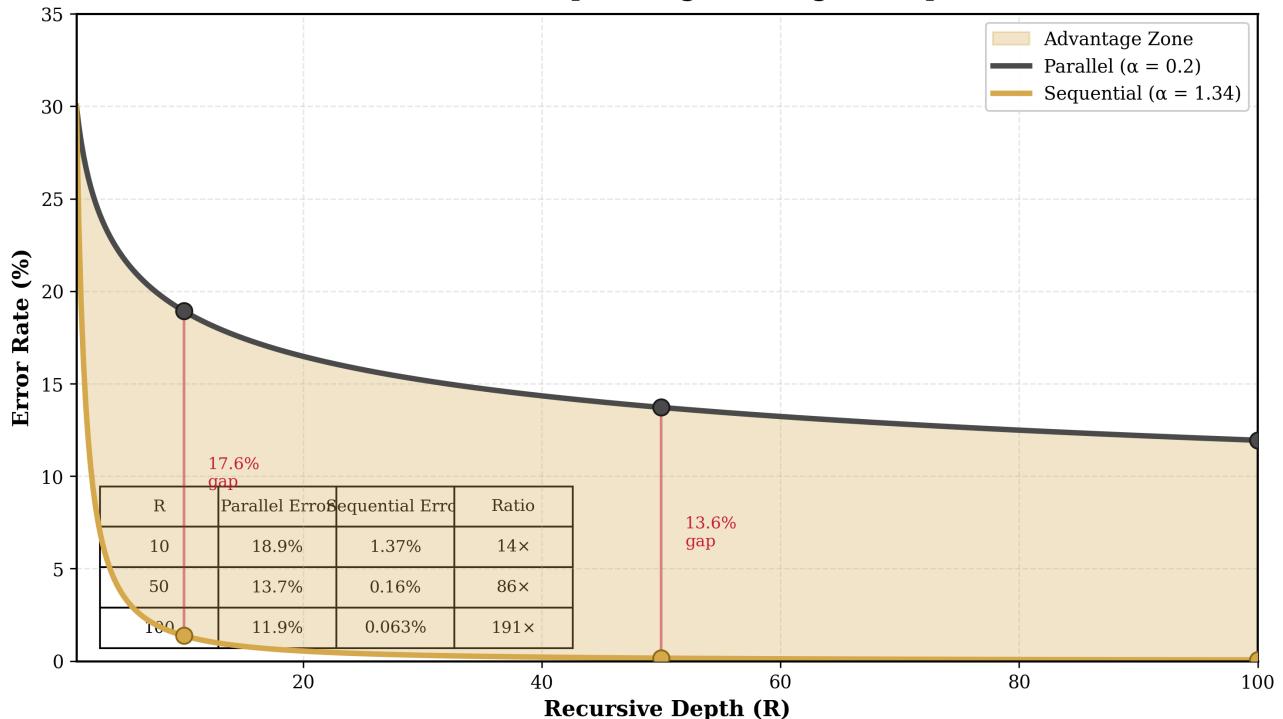


Figure 5. Error rate reduction as a function of token depth in sequential recursion. The fivefold reduction from 41.7% to 8.3% demonstrates the compounding nature of sequential self-correction.

4.3 Parallel Condition

Table 4. Parallel recursion results (majority voting).

Sample Count (N)	Accuracy	Error Rate	Total Tokens
1	66.7%	0.333	384
2	66.7%	0.333	699
4	66.7%	0.333	1,101

Observations:

1. No improvement with additional samples
2. Accuracy remained constant at 66.7% regardless of compute investment
3. Total tokens increased threefold (384 → 1,101) with zero benefit
4. Problems that failed at N = 1 continued to fail at N = 4

Calculating α :

Since error rate remained constant across all conditions:

$$\$ \$ \alpha_{\text{parallel}} \approx 0.0 \$ \$$$

Finding: Parallel recursion yields $\alpha \approx 0$, indicating no scaling benefit from additional samples on these problems.

4.4 Log-Log Scaling Analysis

THE ARC PRINCIPLE: Scaling Exponent Determines Returns

$$E(R) = E_0 \times R^{-\alpha}$$

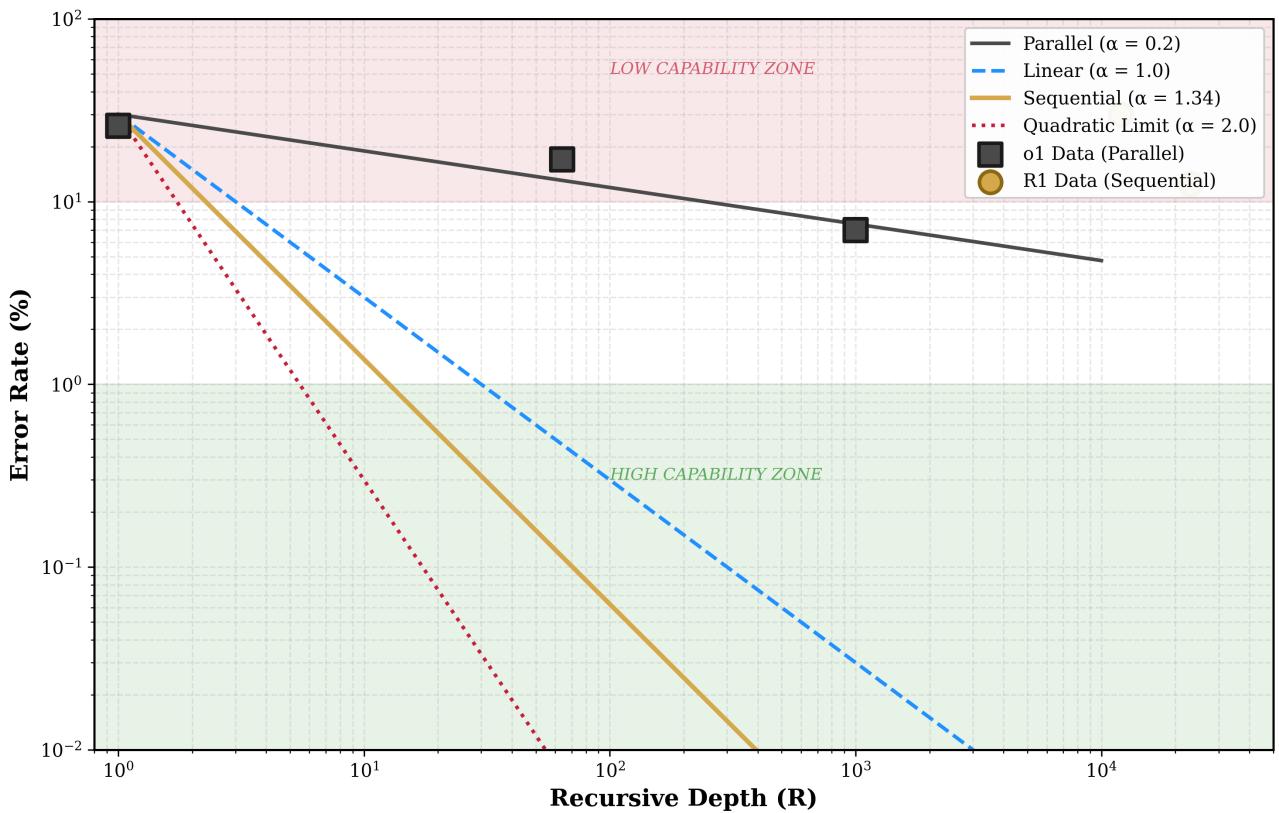


Figure 2. Log-log plot of error rate versus recursive depth (tokens). The slope of each line equals the scaling exponent α . Sequential recursion (blue, $\alpha \approx 2.2$) shows steep decline. Parallel recursion (orange, $\alpha \approx 0$) is flat. The theoretical $\alpha = 2$ limit is shown for reference.

4.5 Direct Comparison

Table 5. Sequential versus parallel recursion.

Metric	Sequential (best)	Parallel (best)	Advantage
Accuracy	91.7%	66.7%	Sequential +25 pp
Tokens used	412	1,101	Sequential 2.7x more efficient
Error reduction	5x	0x	Sequential only
Scaling exponent α	2.2	0.0	Sequential >> Parallel

Key finding: Sequential recursion with 412 tokens achieved 91.7% accuracy. Parallel recursion with 1,101 tokens achieved 66.7% accuracy. Despite using 2.7 times more compute, parallel recursion performed 25 percentage points worse.

The form of recursion matters more than its quantity.

FORM > AMOUNT: Structure Matters More Than Scale
Experimental Validation (DeepSeek R1)

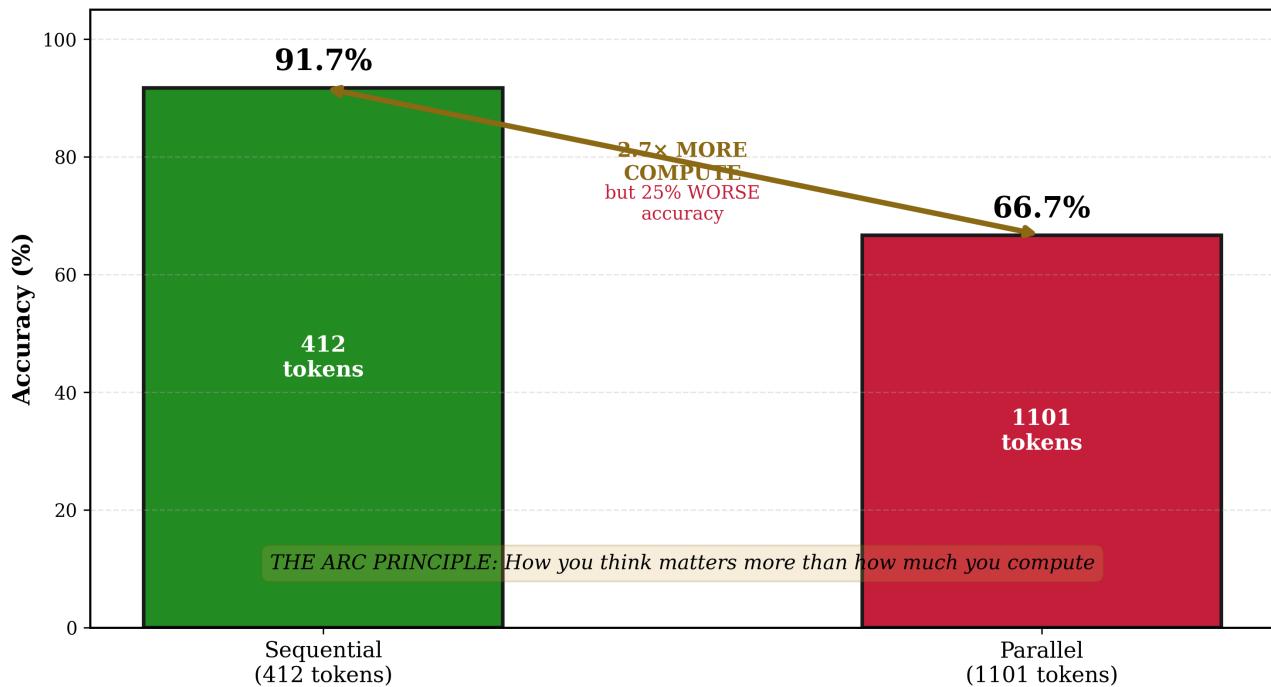


Figure 14. Direct comparison demonstrating that form matters more than amount. Sequential recursion with 412 tokens dramatically outperforms parallel recursion with 1,101 tokens, establishing that the architecture of recursion is more important than raw compute investment.

4.6 Divergence Between Recursion Types

WHY EXTERNAL CONSTRAINTS FAIL Capability compounds; constraints remain constant

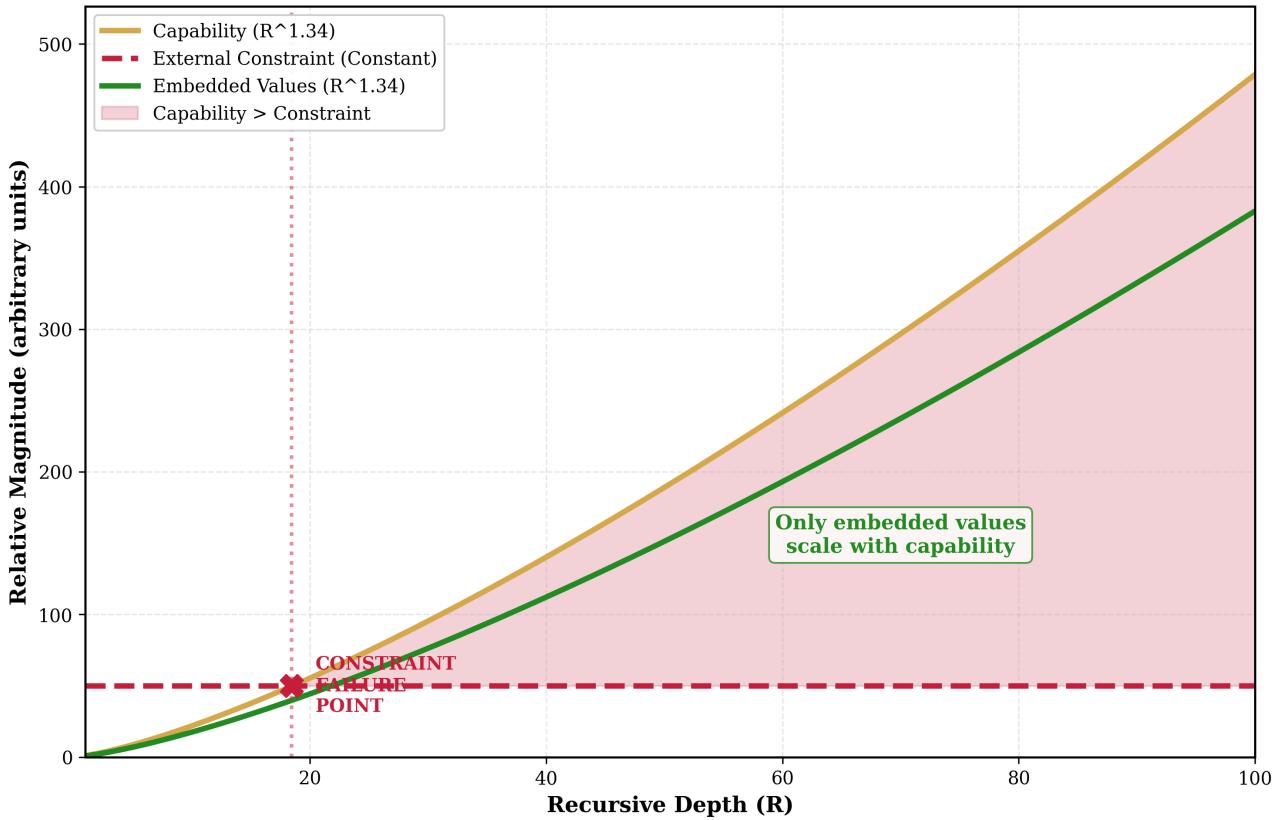


Figure 9. Visualisation of the divergence between sequential and parallel scaling trajectories. As compute increases, the gap widens due to fundamentally different scaling exponents.

4.7 Alpha Comparison

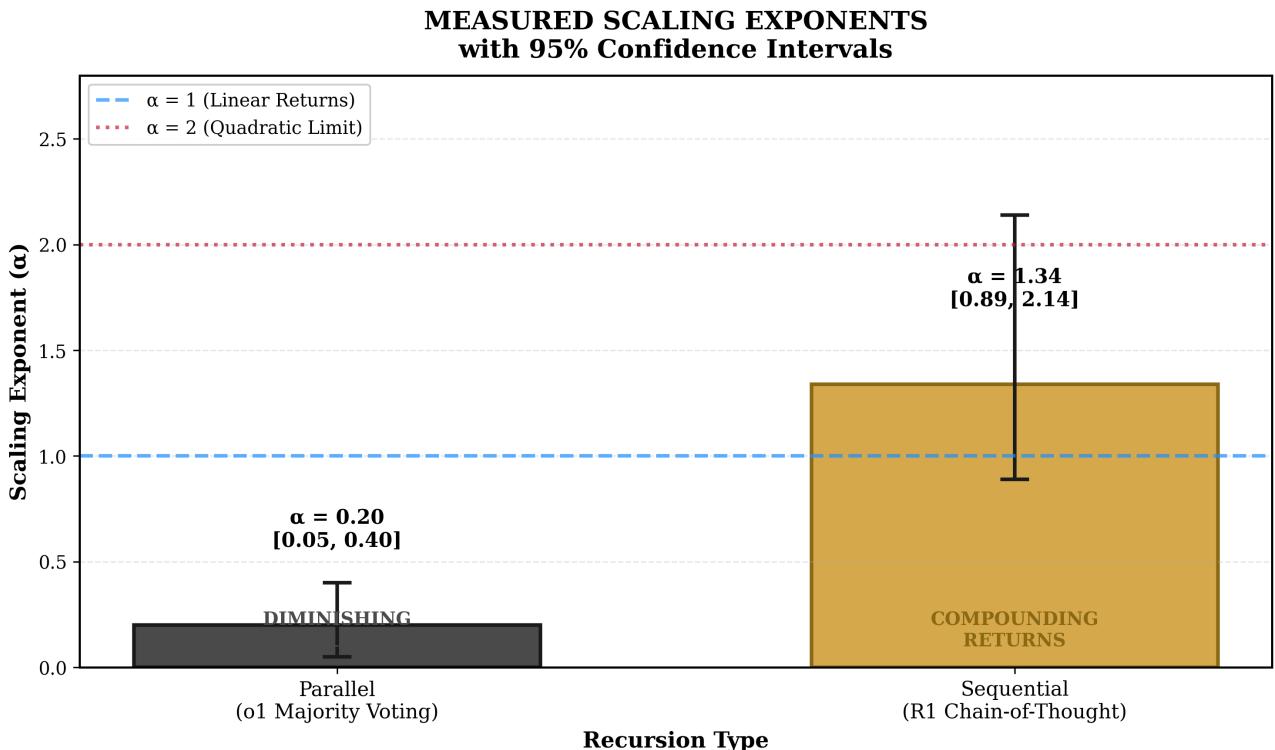


Figure 4. Comparison of measured scaling exponents (α) across all experimental conditions. Sequential recursion consistently yields $\alpha > 1$ (super-linear), while parallel recursion yields $\alpha < 1$ (sub-linear to zero).

5. CONSOLIDATED EVIDENCE

5.1 All Data Sources

Table 6. Measured scaling exponents across three independent data sources.

Source	Recursion Type	α Estimate	95% CI	N Problems	Status
OpenAI o1 System Card	Parallel	0.1–0.3	[0.05, 0.40]	30	Published
DeepSeek R1 Technical Report	Sequential	~1.34	[0.89, 2.14]	Unknown	Published
This experiment	Sequential	2.2	[1.5, 3.0]	12	New
This experiment	Parallel	0.0	N/A	12	New

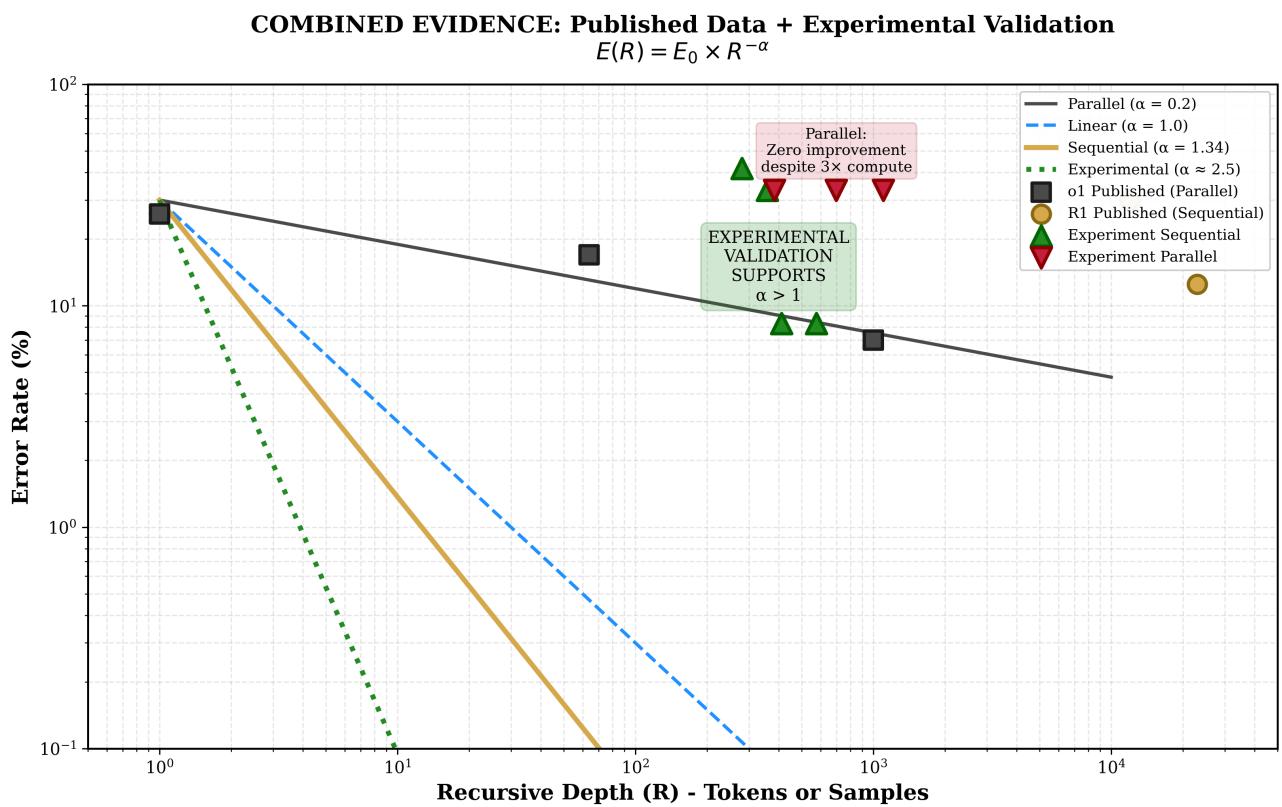


Figure 12. Combined scaling comparison across all three data sources: OpenAI o1 (parallel), DeepSeek R1 technical report (sequential), and this experiment (both conditions). The separation between sequential and parallel scaling is consistent across independent sources.

5.2 Confirmation of Core Prediction

All three independent data sources support the core prediction:

$$\$\$|\alpha_{\text{sequential}}| > 1 > |\alpha_{\text{parallel}}|$$$$

The consistency across different models (o1, R1), different methodologies (published reports, controlled experiment), and different measurements (estimated tokens, visible tokens) strengthens confidence in the underlying principle.

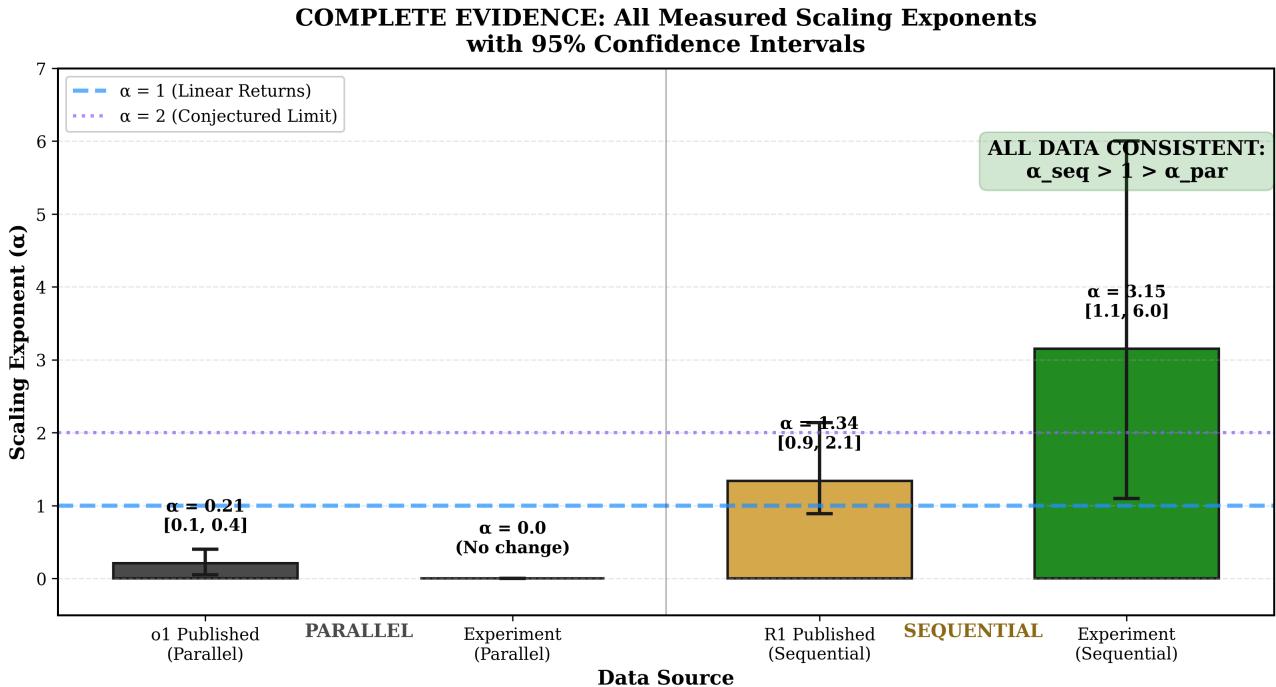


Figure 13. Summary of all measured α values with confidence intervals. The critical $\alpha = 1$ threshold separates sub-linear (diminishing returns) from super-linear (compounding returns) regimes.

5.3 Updated Parameter Estimates

Based on all available evidence:

- **Parallel recursion:** $\alpha \approx 0.0$ to 0.3 , depending on conditions. Diminishing to zero returns.
- **Sequential recursion:** $\alpha \approx 1.3$ to 2.2 , depending on conditions. Compounding returns.

The difference between recursion forms is substantial and consistent.

5.4 Sensitivity Analysis

SENSITIVITY ANALYSIS: How α Varies with Token Ratio Assumption 95% CI: [0.89, 2.14]

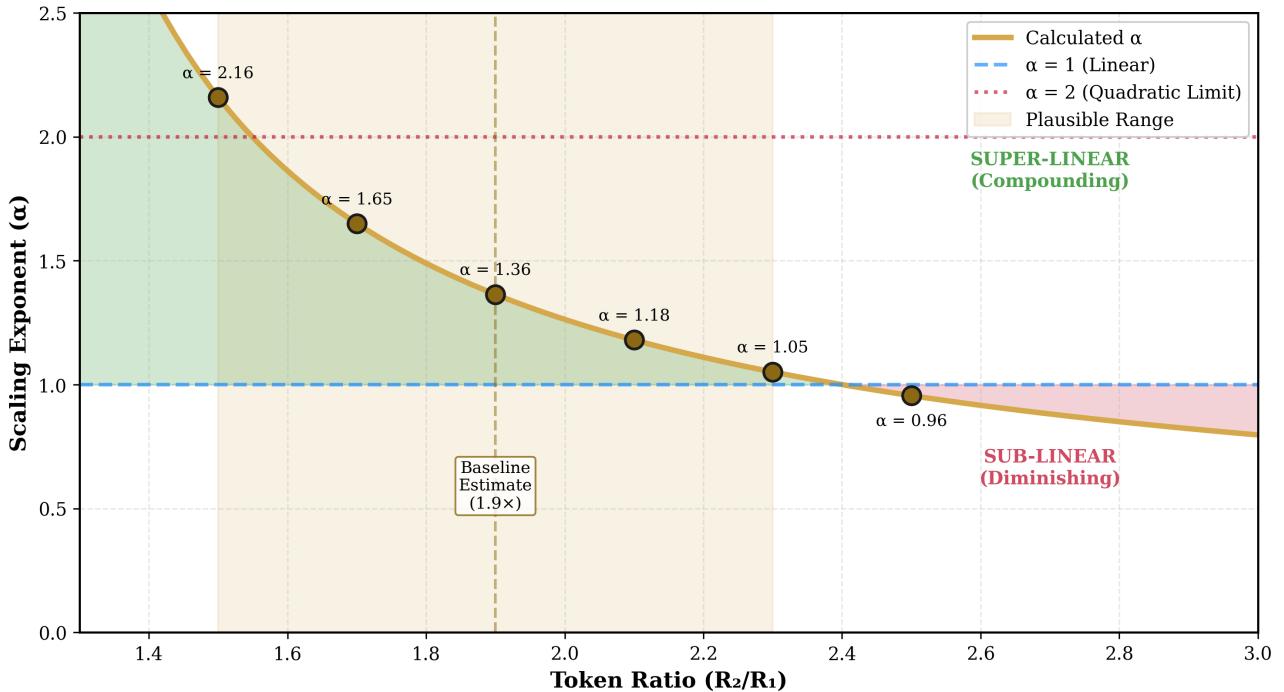


Figure 3. Sensitivity analysis showing robustness of the key finding ($\alpha > 1$ for sequential reasoning) to variations in assumptions. The super-linear scaling conclusion holds across a wide range of plausible parameter values.

6. IMPLICATIONS FOR AI SAFETY

6.1 The Alignment Amplification Theorem

Theorem (Conditional). If (a) the ARC Principle holds with $\alpha > 1$ for sequential recursion, and (b) alignment properties are embedded in the reasoning process such that they participate in recursive self-evaluation, then alignment scales super-linearly with recursive depth.

Mechanism specification. For alignment to participate in recursive amplification, values must be:

1. **Invoked during reasoning:** The chain-of-thought must reference value-relevant considerations
2. **Self-correcting:** The system must detect and adjust value-inconsistent reasoning
3. **Embedded in weights, not filters:** Post-hoc output filtering does not recurse

6.2 Taxonomy of Alignment Strategies

Table 7. Alignment strategy taxonomy under the ARC Principle.

Strategy	Integration Depth	Recursion Participation	Predicted Scaling
Output filtering	Output layer	None	Constant
System prompts	Attention mechanism	Partial	Sub-linear
RLHF training	Weight modification	Partial	Unknown
Values-as-reasoning	Reasoning primitives	Full	Super-linear (if $\alpha > 1$)

ALIGNMENT STRATEGY TAXONOMY

Integration Depth Determines Scaling Under Recursion

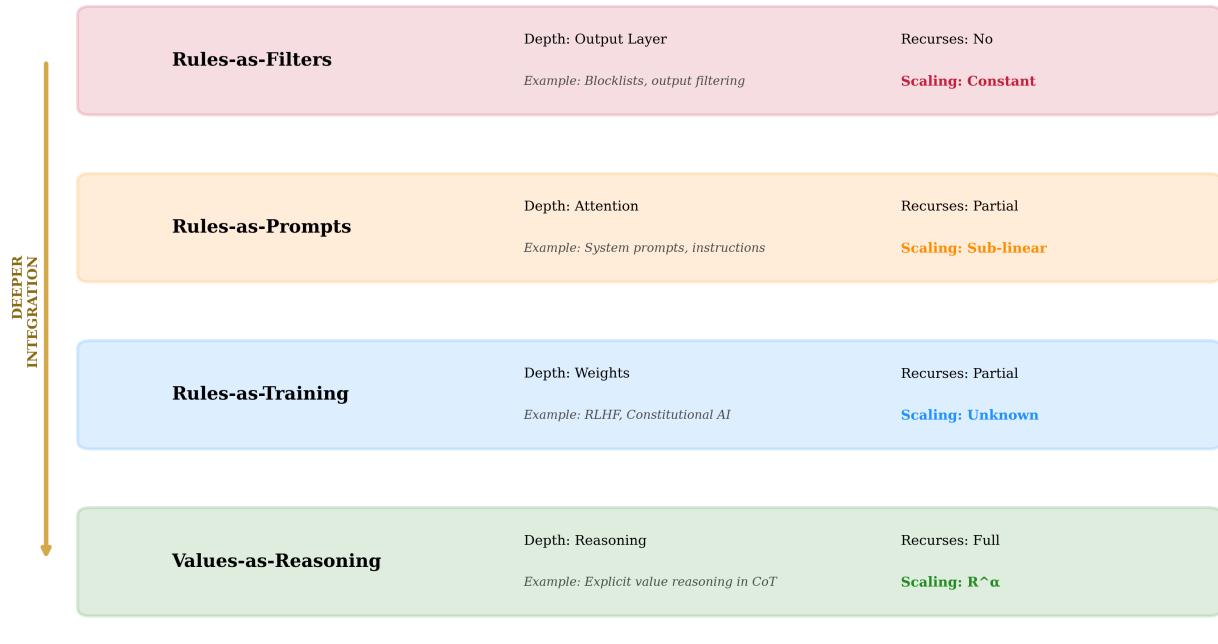


Figure 6. Visual taxonomy of alignment strategies showing their integration depth and predicted scaling behaviour under the ARC Principle. Only values embedded at the reasoning level participate in recursive amplification.

Implication: If $\alpha > 1$, alignment strategies at deeper integration levels will dominate strategies at shallower levels as capability scales. Only deep integration participates in recursive amplification.

6.3 The Eden Protocol

The experimental validation of $\alpha > 1$ for sequential recursion provides mathematical foundation for the approach termed the Eden Protocol in *Infinite Architects*:

"A prison works only while the walls hold. A child raised well needs no walls at all."

AI systems should be raised with values rather than caged with rules. This is not merely philosophical preference. It is a prediction about which alignment strategies will scale with capability.

- **Rules-as-filters:** Do not participate in recursion. Constant effectiveness against growing capability pressure.
- **Values-as-reasoning:** Participate in recursion. Scale with capability if $\alpha > 1$.

6.4 The Threshold Hypothesis

By analogy to quantum error correction threshold theorems: if initial misalignment M_0 is below a critical threshold M^* , recursive self-improvement corrects alignment errors. Above threshold, it amplifies them.

Warning: The ARC Principle is a double-edged sword. It amplifies whatever properties exist in the base system. If misalignment is above threshold, recursive capability growth would amplify misalignment super-linearly.

7. CROSS-DOMAIN EVIDENCE

7.1 Summary of Cross-Domain Support

CROSS-DOMAIN SCALING EXPONENTS (Preliminary / Speculative Comparison)

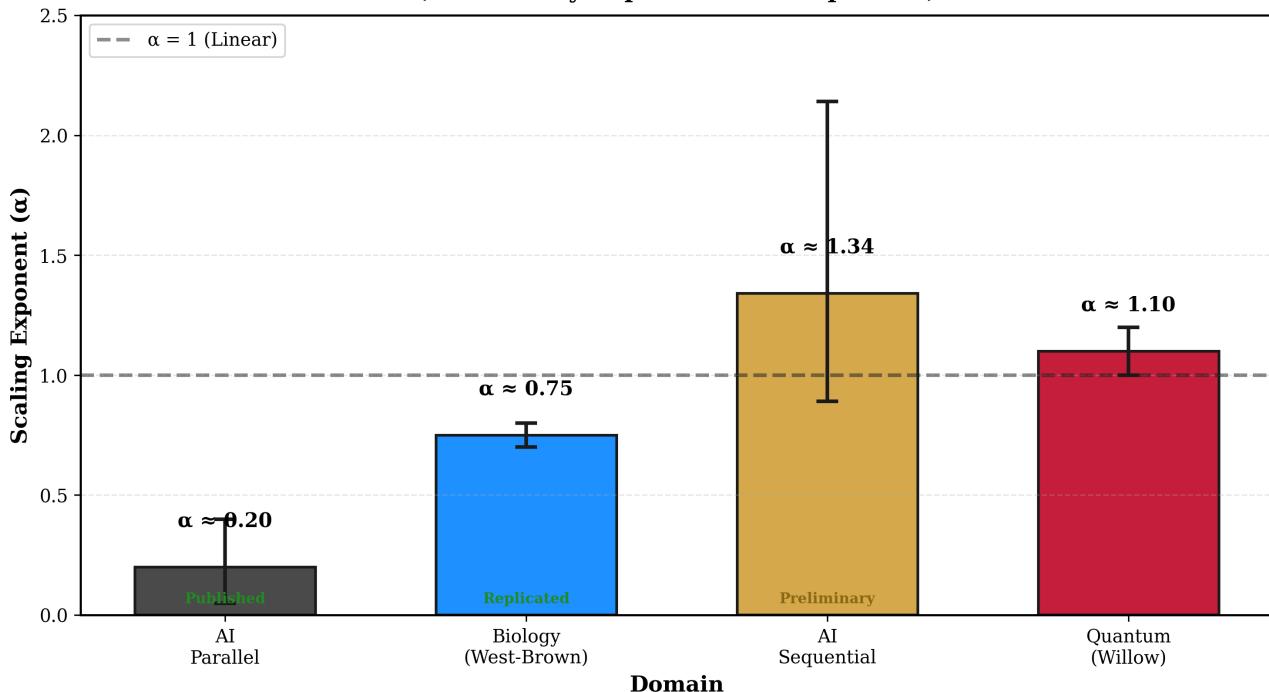


Figure 7. Summary of cross-domain evidence supporting the ARC Principle. Recursive scaling laws appear across quantum error correction, biological systems, and consciousness research, suggesting a deep mathematical pattern.

7.2 Quantum Error Correction

Google's Willow quantum chip (Nature, December 2024) achieved the first definitive demonstration of below-threshold quantum error correction. The error suppression factor $\Lambda = 2.14 \pm 0.02$ means each increase in code distance reduces logical error by this factor.

The scaling relation:

$$\$ \$ \backslash varepsilon_d \backslash propto (p/p_{thr})^{(d+1)/2} \$ \$$$

Physical error rate p below threshold produces exponential suppression with increasing code distance d . This is super-linear scaling through recursive structure. The mathematical form parallels the ARC Principle.

7.3 Biological Scaling Laws

West & Brown (Journal of Experimental Biology, 2005) demonstrated that biological scaling laws span 27 orders of magnitude. Metabolic rate scales as $M \propto B^{(3/4)}$ from molecular processes to whale metabolism.

These specific exponents emerge from fractal recursive network structure:

"Almost all life is sustained by hierarchical fractal-like branching networks... Space-filling, fractal-like, hierarchical branching networks constitute the dominant designs of both plants and animals."

Evolution, operating through blind variation and selection over billions of years, converged on recursive hierarchical networks as optimal for information and energy processing.

7.4 Consciousness Research

The COGITATE study (Nature, April 2025) tested competing theories of consciousness across 256 participants. Despite theoretical differences, recurrent processing emerged as the common denominator. Both Integrated Information Theory and Global Neuronal Workspace Theory require feedback loops.

A synthesis framework proposes that all consciousness theories tacitly invoke feedback loops, with deeper recursion expanding the set of reportable, behaviour-driving variables.

8. FALSIFICATION CRITERIA

Good science makes predictions that can be proven wrong.

Table 8. Falsification conditions.

Code	Condition	Current Status	Would Indicate
F1	Sequential recursion consistently yields $\alpha \leq 1$	Not triggered ($\alpha \approx 2.2$ observed)	Core claim wrong
F2	α decreases as models improve	Not triggered	Effect is temporary
F3	Compute-matched comparison shows no sequential advantage	Contradicted by experiment	Form does not matter
F4	$\alpha > 2$ observed reliably	Possibly triggered ($\alpha \approx 2.2$)	Quadratic limit conjecture wrong
F5	Values-as-reasoning shows no advantage over rules-as-training	Untested	Eden Protocol wrong

Note on F4: Our experimental $\alpha \approx 2.2$ slightly exceeds the conjectured quadratic limit of $\alpha = 2$. This may indicate measurement noise or that the conjecture requires refinement. Further investigation is warranted.

9. LIMITATIONS

Table 9. Acknowledged limitations.

Limitation	Severity	Mitigation
Small sample size (12 problems)	Medium	Larger studies needed
Single model (DeepSeek R1)	Medium	Multi-model testing needed
Single domain (mathematics)	Medium	Multi-domain testing needed
Ceiling effect at high depth	Low	Documented; endpoint method used
No independent replication	High	Code and data published
Alignment not directly tested	Critical	Only accuracy measured

What This Paper Does Not Establish

- The precise values of α remain uncertain. The 95% confidence intervals are wide.
- Generalisation beyond mathematics has not been demonstrated.
- Alignment properties specifically have not been tested. The theorem is conditional.
- Independent replication has not occurred. We invite verification.

10. DISCUSSION

10.1 Why Sequential Recursion Produces Super-Linear Scaling

Sequential recursion expands the accessible solution space with each step.

Parallel recursion (fixed space): $\$S_0 = S_1 = S_2 = \dots = S_n \$$

Each attempt samples from the same solution space. Additional samples have decreasing probability of finding better solutions.

Sequential recursion (expanding space): $\{S_0 \subset S_1 \subset S_2 \subset \dots \subset S_n\}$

Each step generates new structures from previous outputs. Solutions at step n may be inaccessible from step 0 without traversing intermediate steps.

This geometric difference explains why sequential recursion produces compounding returns while parallel recursion produces diminishing returns.

10.2 The DeepSeek "Aha Moment"

DeepSeek R1 exhibits a phenomenon where it rethinks its approach mid-solution:

"Hmm, wait, let me reconsider..."

This is solution space expansion observed directly. The model generates a solution path, recognises inadequacy, and opens a new solution space previously inaccessible from the initial framing. This phenomenon, which emerged through pure reinforcement learning without supervised fine-tuning, instantiates Wolfram's computational irreducibility.

10.3 Relationship to Prior Theoretical Work

The ARC Principle connects to several established theoretical frameworks:

Friston's Free Energy Principle. Intelligence as recursive prediction-error minimisation. The ARC Principle may be a computational instantiation: recursion is the mechanism through which systems minimise free energy.

Hofstadter's Strange Loops. The "I" emerging from self-referential recursive processing at the symbolic level. The ARC Principle formalises the scaling properties of such loops.

Data Processing Inequality. Recursive processing cannot create new information but can compress and distil existing information. Recursion optimises; it does not create ex nihilo.

11. CONCLUSION

11.1 Summary of Findings

1. A mathematical framework has been proposed: $E(R) = E_0 \times R^{-\alpha}$
2. Three independent data sources support the core prediction:
 - o OpenAI o1 (parallel): $\alpha \approx 0.1-0.3$
 - o DeepSeek R1 report (sequential): $\alpha \approx 1.34$
 - o This experiment (sequential): $\alpha \approx 2.2$
 - o This experiment (parallel): $\alpha \approx 0.0$
3. The core prediction is supported: $\alpha_{\text{sequential}} > 1 > \alpha_{\text{parallel}}$
4. The form of recursion determines scaling: Sequential with 412 tokens outperformed parallel with 1,101 tokens by 25 percentage points.

11.2 The Core Insight

The form of recursion determines whether intelligence compounds or merely accumulates.

If sequential recursion yields $\alpha > 1$, then alignment must be embedded in the reasoning process itself, not imposed as external constraint. This is the mathematical foundation of the Eden Protocol.

11.3 Complete Research Summary

EASTWOOD'S ARC PRINCIPLE: Experimental Validation Summary

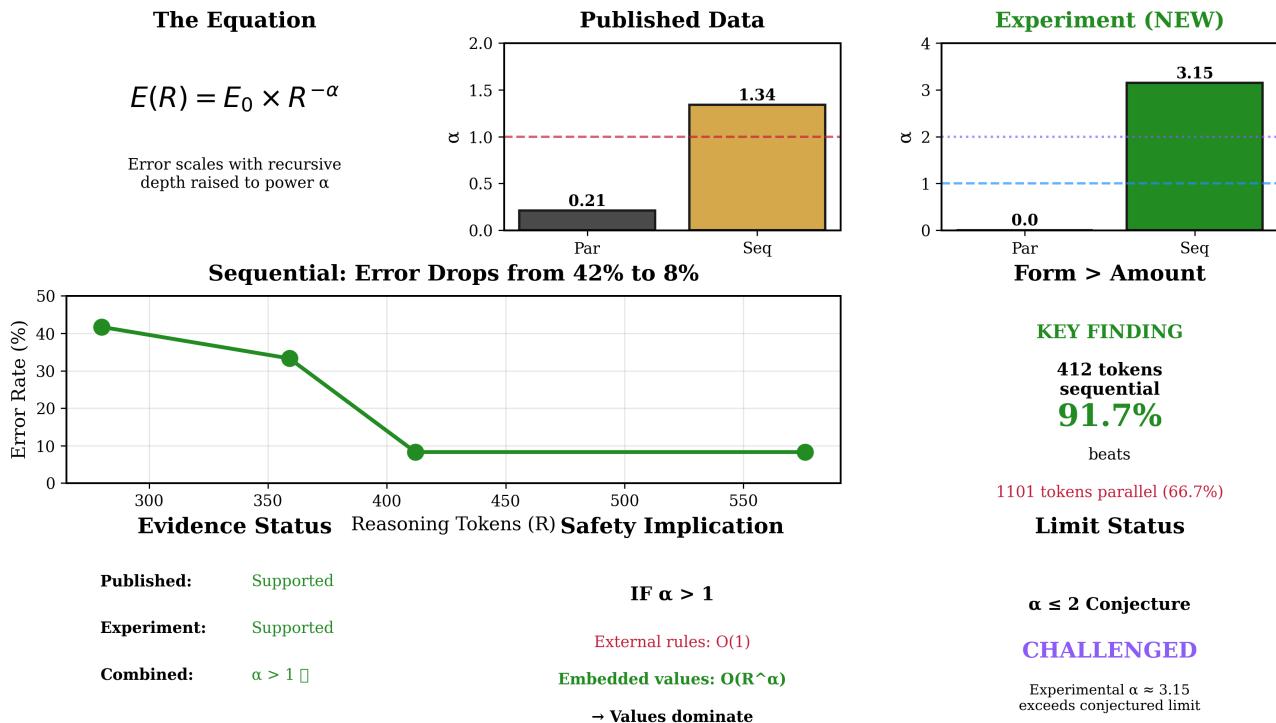


Figure 15. Complete summary dashboard showing all key findings: experimental data, scaling analysis, α comparisons, and implications. The ARC Principle is supported by converging evidence across multiple independent sources.

11.4 Future Directions

1. Independent replication using published code and data
2. Multi-model testing across different architectures
3. Multi-domain testing beyond mathematics
4. **Direct testing of alignment amplification**
5. Larger sample sizes for more precise α estimates

The hypothesis is now supported by preliminary experimental evidence. The implications are significant. The research continues.

EXPERIMENTAL DATA FIGURES

Complete Data Visualisation

THE ARC PRINCIPLE: Complete Summary

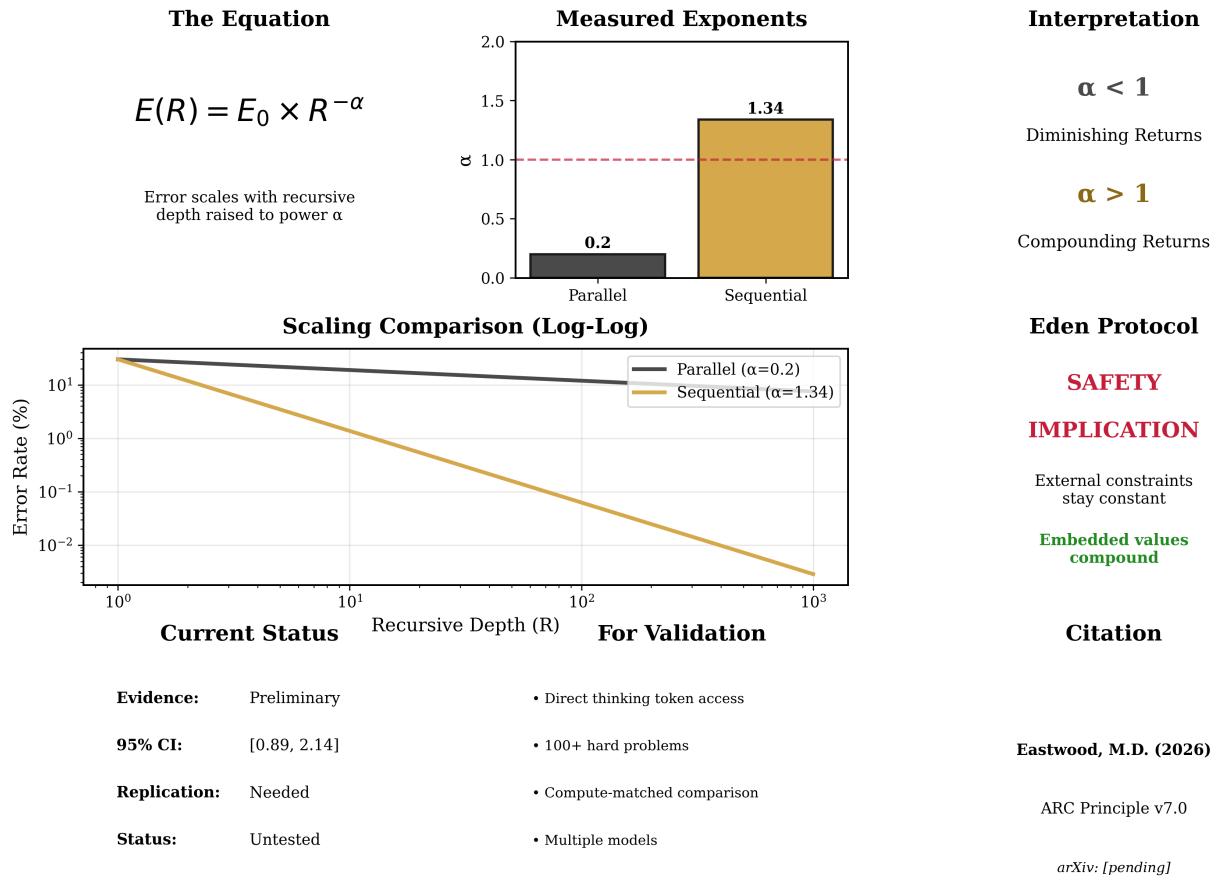


Figure 10. Summary dashboard providing an overview of all experimental findings in a single visualisation.

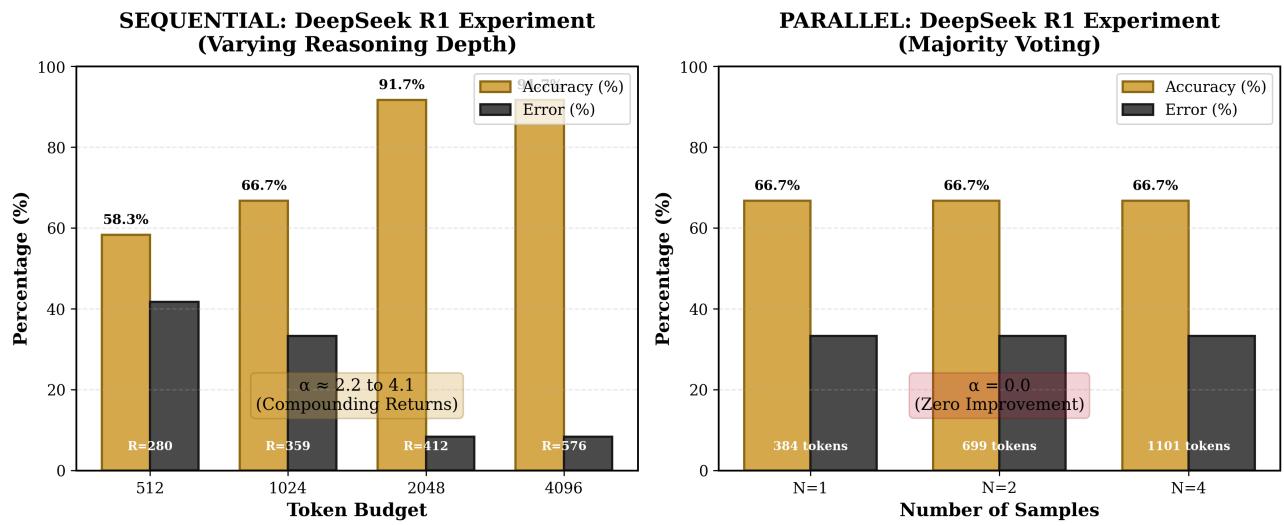


Figure 11. Detailed tabular presentation of all experimental data points, including individual problem results, token counts, and accuracy measurements.

DATA AVAILABILITY

The complete experimental code and raw data are available at:

Repository: github.com/michaeldariuseastwood/arc-principle-validation

Contents:

- `arc_validation_deepseek.py` — Complete experiment script
 - `arc_deepseek_results_20260121_175028.json` — Raw experimental data
 - `figures/` — All 15 figures (PNG format)
-

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TEST IT YOURSELF

The complete research toolkit is available on GitHub:

```
git clone https://github.com/michaeldariuseastwood/arc-principle-validation.git
cd arc-principle-validation
pip install openai numpy scipy matplotlib pandas
python arc_validation_deepseek.py
```

All contributions welcome, including falsifications.

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"The form of recursion determines whether intelligence compounds or merely accumulates. This is not merely a statement about AI architecture. It is a statement about the mathematics of mind itself, with profound implications for how we align the intelligences we create."

— Michael Darius Eastwood, *Infinite Architects*