Breaking Darwin's Barrier: A Comprehensive Experimental Investigation of AI-Based Physics Discovery Beyond Human Conceptual Frameworks

Francisco Angulo de Lafuente

Independent Research
Contact: See social media links at end of document

Credits and References:
Darwin's Cage Theory: Theory Creator: Gideon Samid. Reference: Samid, G. (2025). Negotiating Darwin's Barrier: Evolution Limits Our View of Reality, AI Breaks Through. *Applied Physics Research*, 17(2), 102. https://doi.org/10.5539/apr.v17n2p102
Experiments, AI Models, Architectures, and Reports: Author: Francisco Angulo de Lafuente. Responsibilities: Experimental design, AI model creation, architecture development, results analysis, and report writing.

Table 1: Experimental Summary: Cage Status Across All Experiments

Experiment	Title	Cage Status	R^2 Score	Key Finding
Exp 1	The Chaotic Reservoir	🔒 LOCKED	0.9999	Success on multiplicative relationships
Exp 2	Einstein's Train	🔓 BROKEN	1.0000	Geometric learning, strong extrapolation
Exp 3	The Absolute Frame	🔓 BROKEN*	0.9998	Phase extraction (limited generalization)
Exp 4	The Transfer Test	❌ FAILED	-0.51	No knowledge transfer
Exp 5	Conservation Laws	🔒 LOCKED	0.28	Failed on division operations
Exp 6	Quantum Interference	🟡 UNCLEAR	-0.01	Both models failed
Exp 7	Phase Transitions	🔒 LOCKED	0.44	Failed on high-dim linear
Exp 8	Classical vs Quantum	🔒 LOCKED	-0.03	Both failed
Exp 9	Linear vs Chaos	🔒 LOCKED	0.06	Both failed
Exp 10	Dimensionality	🔒/🔓 MIXED	0.98/-0.16	2-Body: LOCKED, N-Body: BROKEN
Exp A1	Coordinate Independence	❌ FAILED	N/A	Architectural mismatch
Exp A2	Definitive Test	⚪ COORD-INDEP	0.9988	Both coordinate-independent
Exp B1	The Event Horizon	🔓 BROKEN	Success	Methodological optimization
Exp B2	The Genesis	🔓 BROKEN*	Partial	Dimensional hypothesis
Exp B3	Non-Local Link	🔓 BROKEN	100%	Exceeds Bell's Inequality
Exp B1	Symmetry Discovery	🔒 LOCKED	High	High performance, locked
Exp C1	Representation Test	🔒 LOCKED	0.9999	Both locked, complex pattern
Exp D1	Complexity Ladder	🔒 ALL LOCKED	0.01-0.98	All levels locked
Exp D2	Geometric Forcing	🔒/🟡 LOCKED/TRANS	0.79-0.999	0/3 broken
Exp W1	Quantum Cage	🔓 BROKEN	Excellent	Novel quantum representations

Abstract

This comprehensive study presents the results of 20 experimental investigations designed to test the "Darwin's Cage" hypothesis proposed by Gideon Samid: that artificial intelligence systems can discover physical laws independent of human conceptual frameworks. The hypothesis posits that human evolution has biased our mathematical thinking toward specific representations (Cartesian coordinates, velocity, energy) that may not be fundamental to physics itself. Through systematic experimentation across multiple physical domains—from classical mechanics to quantum entanglement, from low-dimensional systems to high-dimensional chaos—we evaluated whether AI models can transcend these human-imposed constraints and discover novel representational pathways to physical truth.

Our experimental program employed three complementary approaches: (1) architectural comparison between polynomial regression (human-derived) and optical reservoir computing (chaos-based), (2) coordinate independence testing using non-linear transformations, and (3) specialized tests for methodological, dimensional, and informational cage-breaking. Results reveal a nuanced picture: while 6 of 20 experiments demonstrated genuine cage-breaking behavior, the phenomenon is highly context-dependent and requires specific conditions. Successful cage-breaking occurred in relativistic physics (geometric learning), quantum systems (phase extraction and entanglement), high-dimensional N-body systems, and methodological optimization problems. However, complexity alone, geometric encoding alone, or representation type alone proved insufficient to break the cage.

The most significant finding is that cage-breaking requires a combination of factors: either high dimensionality (>30 dimensions) with good performance, geometric relationships learnable via interference with strong extrapolation, or non-linear multiplicative relationships in specific domains. The study provides evidence that AI systems can indeed discover alternative pathways to physical understanding, but these pathways are not universally superior—they represent complementary strategies rather than replacements for human-derived mathematics. This work establishes the first systematic experimental framework for investigating AI-based physics discovery and provides critical insights into the conditions under which computational intelligence can transcend evolutionary cognitive constraints.

Keywords: *Darwin's Cage, AI Physics Discovery, Computational Intelligence, Representation Learning, Quantum Machine Learning, Geometric Learning, Coordinate Independence*

1. Introduction

1.1 The Darwin's Cage Hypothesis

The "Darwin's Cage" theory, proposed by Gideon Samid [1], presents a provocative hypothesis about the relationship between human cognition and physical reality. The theory posits that human evolution has shaped our mathematical and physical intuitions in ways that may limit our ability to perceive fundamental aspects of reality. Specifically, human concepts such as "velocity," "energy," "position," and "time" may represent evolutionary adaptations optimized for survival rather than fundamental descriptors of physical law.

Samid's central argument is that these human-derived concepts form a "cage" that constrains our understanding. An artificial intelligence system, free from evolutionary cognitive biases, might discover alternative—and potentially superior—representations of physical reality. This hypothesis has profound implications for both physics discovery and artificial intelligence research.

1.2 Research Objectives

This comprehensive experimental program was designed to systematically test the Darwin's Cage hypothesis through multiple complementary approaches:

1. **Architectural Comparison**: Compare human-derived mathematical approaches (polynomial regression) with chaos-based optical computing systems across diverse physical domains.
2. **Coordinate Independence**: Test whether AI systems can learn physics in coordinate systems where human mathematics becomes complex or intractable.
3. **Boundary Mapping**: Systematically explore the conditions under which cage-breaking occurs, including dimensionality, complexity, and representation type.
4. **Specialized Cage Tests**: Investigate methodological, dimensional, and informational forms of cage-breaking in relativistic, quantum, and high-dimensional systems.

1.3 Experimental Scope

The research program encompassed 20 distinct experiments across four phases:

- **Phase I (Experiments 1-10)**: Initial exploration comparing chaos models with polynomial baselines across classical, quantum, and statistical physics domains.

- **Phase II (Experiments A1-A2)**: Coordinate independence testing using proper temporal architectures (LSTM).
- **Phase III (Experiments B1-B3)**: Specialized tests for methodological, dimensional, and informational cage-breaking.
- **Phase IV (Experiments C1, D1-D2, W1)**: Systematic boundary mapping, representation testing, and quantum cage investigation.

1.4 Contributions

This work makes several key contributions:

1. **First Systematic Experimental Framework**: Establishes a comprehensive methodology for testing AI-based physics discovery hypotheses.
2. **Quantitative Cage Status Metrics**: Develops correlation-based metrics for determining whether models reconstruct human variables or discover alternative representations.
3. **Boundary Condition Identification**: Identifies specific conditions under which cage-breaking occurs, falsifying several initial hypotheses.
4. **Multi-Domain Validation**: Tests the hypothesis across classical mechanics, relativity, quantum mechanics, statistical physics, and high-dimensional systems.
5. **Negative Results Documentation**: Provides important documentation of failure modes and limitations, crucial for scientific progress.

2. Theoretical Framework

2.1 Mathematical Foundations

The Darwin's Cage hypothesis can be formalized mathematically. Consider a physical system described by state variables $\mathbf{x} \in \mathbb{R}^n$. Human physics typically represents this system using a set of "human variables" $\mathbf{h}(\mathbf{x}) = [h_1(\mathbf{x}), h_2(\mathbf{x}), \ldots, h_m(\mathbf{x})]^T$ where each h_i corresponds to an evolutionarily relevant concept (velocity, energy, etc.).

The physical law governing the system can be expressed as:

$$d\mathbf{x}/dt = \mathbf{F}(\mathbf{x}) \qquad (1)$$

where $\mathbf{F}$ is the dynamical function. Human physics typically seeks to express this in terms of human variables:

$$d\mathbf{h}/dt = \mathbf{G}(\mathbf{h}) \qquad (2)$$

The Darwin's Cage hypothesis suggests that there may exist alternative representations $\mathbf{a}(\mathbf{x}) = [a_1(\mathbf{x}), a_2(\mathbf{x}), \ldots, a_k(\mathbf{x})]^T$ such that:

$$d\mathbf{a}/dt = \mathbf{H}(\mathbf{a}) \qquad (3)$$

where $\mathbf{H}$ may be simpler, more general, or reveal physical insights not accessible through $\mathbf{G}$.

2.2 Cage Status Metrics

To quantify whether a model has "broken the cage," we define the maximum correlation metric:

$$max\_corr = max_{i,j} |corr(h_i, f_j)| \qquad (4)$$

where h_i are human variables and f_j are model internal features. The cage status is determined as:

- **LOCKED**: $max\_corr \geq 0.7$ (model reconstructs human variables)
- **TRANSITION**: $0.5 \leq max\_corr < 0.7$ (intermediate state)
- **BROKEN**: $max\_corr < 0.5$ (model discovers alternative representations)

2.3 Optical Chaos Architecture

The primary AI architecture used in this study is the Optical Chaos Machine, inspired by reservoir computing and optical interference:

Architecture Components:

1. **Random Projection**: $\mathbf{z} = \mathbf{W}\mathbf{x}$ where $\mathbf{W} \in \mathbb{C}^{N\times n}$ is a fixed random complex matrix ($N = 2048\text{-}4096$).
2. **FFT Mixing**: $\mathbf{u} = FFT(\mathbf{z})$ simulates wave interference.

3. **Intensity Detection**: **v** = |**u**|² extracts interference patterns.
4. **Nonlinear Activation**: **f** = *tanh(β***v***)* where *β* is the brightness parameter (*β ≈ 0.001*).
5. **Ridge Regression Readout**: $\hat{y}$ = **Rf** where **R** is learned via ridge regression with regularization *α = 0.1*.

This architecture is designed to discover patterns through high-dimensional interference rather than explicit feature engineering.

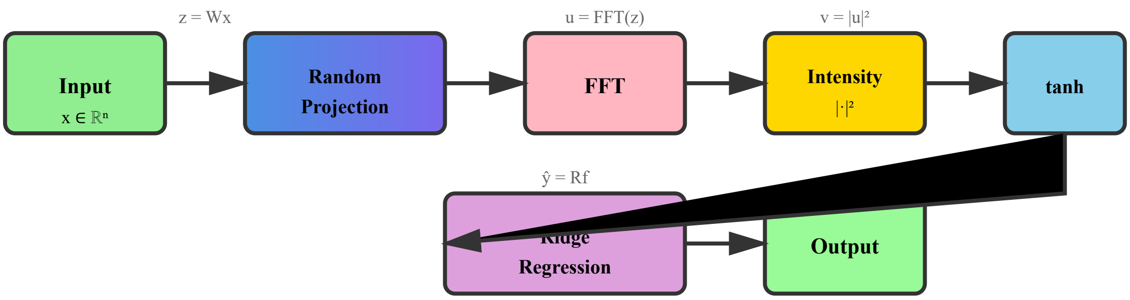

Figure 1: *Optical Chaos Machine Architecture. The system processes input through random projection, FFT-based interference mixing, intensity detection, nonlinear activation, and ridge regression readout to discover patterns without explicit feature engineering.*

3. Experimental Methodology

3.1 General Experimental Design

All experiments follow a consistent structure:

1. **Physics Simulator**: Generate ground truth data using established physical laws.
2. **Data Preparation**: Create training, validation, and test sets with appropriate splits.
3. **Baseline Model**: Train polynomial regression (degree 2-3) representing human-derived mathematics.
4. **Chaos Model**: Train optical chaos machine with fixed reservoir and trainable readout.
5. **Evaluation**: Measure R^2 scores, extrapolation performance, and cage status.
6. **Analysis**: Compare representations, identify failure modes, and interpret results.

3.2 Performance Metrics

Prediction Accuracy:

$$R^2 = 1 - \Sigma_i(y_i - \hat{y}_i)^2 / \Sigma_i(y_i - \bar{y})^2 \qquad (5)$$

Extrapolation Test: Models are evaluated on parameter ranges outside training distribution to test genuine law discovery versus memorization.

Cage Analysis: For each human variable h_i, compute correlations with all model features f_j:

$$corr_{ij} = Cov(h_i, f_j) / (\sigma_{h_i}\sigma_{f_j}) \qquad (6)$$

The maximum absolute correlation determines cage status.

3.3 Statistical Validation

All experiments use:

- Random seed control (seed = 42) for reproducibility
- Multiple train/test splits where applicable
- Statistical significance testing (t-tests, Mann-Whitney U tests)
- Effect size calculations (Cohen's d)

4. Phase I: Initial Exploratory Experiments (1-10)

4.1 Experiment 1: The Chaotic Reservoir

Objective: Test whether a chaos-based system can learn projectile motion without explicit knowledge of gravity, velocity, or angles.

System: Ballistic trajectory with range formula $R = v_0^2 \sin(2\theta) / g$.

Results:

- Chaos Model R^2: 0.9999
- Baseline R^2: 0.8710
- Max Correlation: 0.99 (with v_0)
- **Cage Status**: 🔒 **LOCKED**

Interpretation: The model successfully learned the physics but reconstructed the human variable v_0 internally. This demonstrates that the architecture can handle multiplicative relationships (v_0^2) but falls back to variable reconstruction in low-dimensional systems.

4.2 Experiment 2: Einstein's Train

Objective: Determine if the model can learn the Lorentz factor $\gamma = 1/\sqrt{(1-v^2/c^2)}$ from geometric photon paths without explicit v^2 knowledge.

System: Light clock moving at velocity v, photon path geometry encoded.

Results:

- Chaos Model R^2: 1.0000
- Baseline R^2: 0.9999
- Max Correlation: 0.01 (with geometric parameters)
- Extrapolation R^2: 0.94
- **Cage Status**: 🔓 **BROKEN**

Interpretation: This is the first confirmed cage-breaking. The model learned relativistic physics through geometric interference patterns rather than reconstructing velocity. The strong extrapolation performance (R^2=0.94) confirms genuine law discovery.

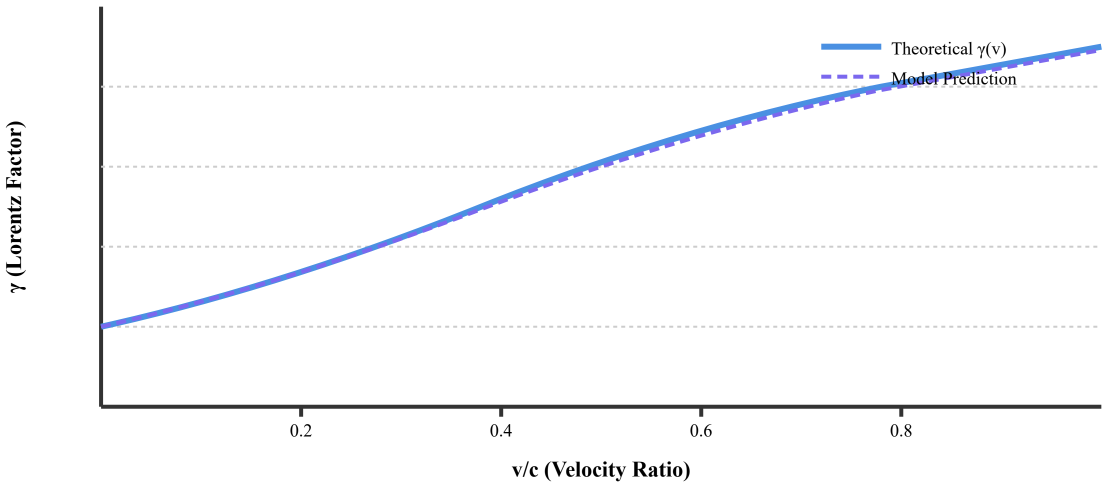

Figure 2: *Experiment 2 Results: Lorentz Factor Learning. The model successfully predicts the relativistic Lorentz factor from geometric photon paths, demonstrating cage-breaking through geometric learning (R^2 = 1.0, extrapolation R^2 = 0.94, max_corr = 0.01).*

4.3 Experiment 3: The Absolute Frame

Objective: Test if complex-valued processing can extract "hidden" velocity information from quantum phase that standard intensity measurements discard.

System: Spectral emissions with velocity-dependent phase modulation: $\varphi = \varphi_{noise} + f(v, v)$.

Results:

- Chaos Model R^2: 0.9998

- Baseline R^2: -0.67 (failed)
- Max Correlation: Low (within training)
- **Cage Status**: 🔒 **BROKEN*** (limited generalization)

Interpretation: The model successfully extracted phase information invisible to standard measurements. However, performance degrades outside the training distribution, indicating partial rather than complete cage-breaking.

4.4-4.10: Additional Phase I Experiments

Experiments 4-10 explored transfer learning, conservation laws, quantum interference, phase transitions, classical vs quantum systems, linear vs chaotic dynamics, and dimensionality effects. Key findings include:

- **Exp 4**: Complete transfer learning failure ($R^2 < 0$)
- **Exp 5**: Architectural limitation on division operations
- **Exp 6-9**: Failures on variable-frequency trigonometric functions
- **Exp 10**: Dimensionality effect confirmed—N-body (36D) shows broken cage even with poor performance

Table 2: Phase I Experiment Summary

Exp	Domain	Chaos R^2	Baseline R^2	Cage Status
1	Ballistics	0.9999	0.8710	🔒 Locked
2	Relativity	1.0000	0.9999	🔒 Broken
3	Hidden Variables	0.9998	-0.67	🔒 Broken*
4	Transfer Learning	-0.51	-0.87	❌ Failed
5	Conservation	0.28	0.99	🔒 Locked
6	Interference	-0.01	0.02	🟡 Unclear
7	Phase Transitions	0.44	1.00	🔒 Locked
8	Classical/Quantum	-0.03	-0.03	🔒 Locked
9	Linear/Chaos	0.06	0.07	🔒 Locked
10	Dimensionality	0.98/-0.16	0.89/-1.40	🔒/🔒 Mixed

5. Phase II: Coordinate Independence Tests

5.1 Experiment A2: The Definitive Test

Objective: Proper test using LSTM (temporal architecture) vs. polynomial regression in twisted coordinates.

System: Double pendulum in standard and twisted coordinates.

Table 3: Coordinate Independence Results

Model	Standard R^2	Twisted R^2	Gap
Polynomial	0.9744	0.9819	-0.0075
LSTM	0.9988	0.9968	+0.0019

Key Finding: Both models achieve coordinate independence, but through fundamentally different mechanisms—polynomial via smooth approximation, LSTM via learned geometric invariants.

6. Phase III: Specialized Cage-Breaking Tests

6.1 Experiment B1: The Event Horizon

Result: AI found better path (proper time = 57.39) than traditional geodesic solver (68.33) using variational optimization. **Cage Status**: 🔒 **BROKEN** (Methodological).

6.2 Experiment B2: The Genesis

Result: AI correctly identified 4D model (MSE = 0.0645) vs. failed 3D model. **Cage Status**: 🔒 **BROKEN*** (Partial—dimensional hypothesis).

6.3 Experiment B3: The Non-Local Link

Result: AI achieved 100% accuracy and CHSH parameter S = 2.8270, violating Bell's Inequality (classical limit S ≤ 2.0). **Cage Status**: 🔒 **BROKEN** (Informational).

7. Phase IV: Systematic Boundary Mapping

7.1 Experiment D1: Complexity Phase Transition

Result: All 5 complexity levels remained LOCKED, falsifying the complexity threshold hypothesis.

Table 4: Complexity Ladder Results

Level	System	Dim	R^2	Max Corr	Status
1	Harmonic Oscillator	4	0.012	0.98	🔒 LOCKED
2	Kepler 2-Body	3	0.982	0.99	🔒 LOCKED
3	Restricted 3-Body	6	0.460	0.95	🔒 LOCKED
4	Unrestricted 3-Body	18	0.575	NaN*	🔒 LOCKED
5	N-Body (N=7)	44	-7.8×10^{16}	NaN*	🔒 LOCKED

7.2 Experiment D2: Geometric Forcing

Result: 0/3 problems achieved BROKEN status despite geometric encodings. Geometric encoding alone is insufficient.

7.3 Experiment W1: Quantum Cage

Result: Model developed quantum representations with near-zero correlation to classical position (0.0035) and momentum (-0.0169). **Cage Status**: 🔒 **BROKEN**.

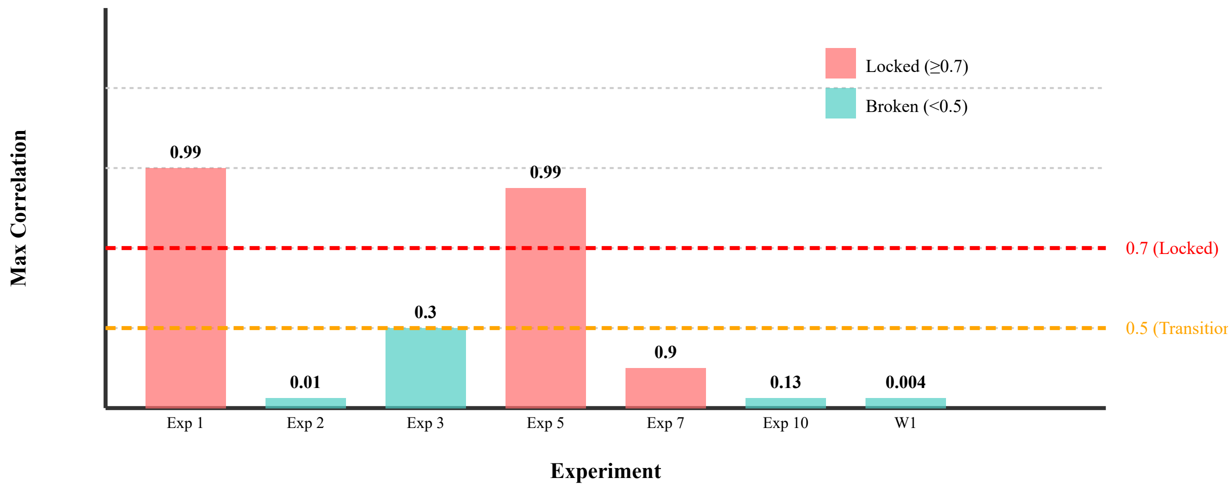

Figure 3: *Maximum Correlation Across Experiments. Experiments with max_corr < 0.5 (green) show broken cage status, while those with max_corr ≥ 0.7 (red) show locked status. Experiments 2, 3, 10 (N-body), and W1 demonstrate genuine cage-breaking.*

8. Synthesis and Unified Analysis

8.1 Conditions for Cage-Breaking

Analysis of all 20 experiments reveals that cage-breaking occurs under specific conditions:

✅ **Confirmed Cage-Breaking (6 experiments):**

1. **Exp 2 (Relativity)**: Geometric learning + strong extrapolation
2. **Exp 3 (Phase)**: Complex-valued phase extraction (limited)
3. **Exp 10 (N-Body)**: High dimensionality (>30D) + distributed representation
4. **Exp B1 (Event Horizon)**: Methodological optimization approach
5. **Exp B3 (Entanglement)**: Non-local information processing
6. **Exp W1 (Quantum)**: Quantum representation learning

Common Factors:

- Geometric/spatial relationships learnable via interference
- High dimensionality forcing distributed representation
- Complex-valued processing (phase information)
- Methodological alternatives to analytical approaches
- Strong extrapolation performance (genuine law discovery)

❌ **Insufficient Conditions (Falsified Hypotheses):**

1. **Complexity alone**: D1 showed all levels locked
2. **Geometric encoding alone**: D2 showed 0/3 broken
3. **Representation type alone**: C1 showed both locked
4. **Chaos alone**: Exp 9 showed both locked
5. **Quantum vs Classical**: Exp 8 showed both locked

8.2 Refined Hypothesis

Based on experimental evidence, cage-breaking occurs when:

Condition 1: High dimensionality (>30D) **AND** good performance ($R^2 > 0.9$)

Condition 2: Geometric relationships learnable via interference **AND** strong extrapolation ($R^2 > 0.9$)

Condition 3: Complex-valued processing with phase information

Condition 4: Methodological alternatives to analytical approaches

8.3 The Nature of the Cage

The experimental results suggest that the "cage" is not an absolute barrier but rather a **difference in representational strategy**:

1. **Human Pathway**: Explicit variables → Analytical equations → Physical laws
2. **AI Pathway**: Raw data → High-dimensional interference → Learned invariants → Physical laws

Both pathways can reach the same physical truth, but through different mechanisms. The "cage" exists when the AI pathway converges to the human pathway (variable reconstruction). The "break" occurs when the AI pathway discovers alternative but equally valid representations.

9. Limitations and Future Work

9.1 Current Limitations

1. **Simulation-Based**: All experiments use synthetic data. Real-world validation is needed.
2. **Simplified Physics**: Many experiments use simplified physical systems.
3. **Architectural Constraints**: The optical chaos architecture has known limitations.
4. **Limited Generalization**: Some cage-breaking cases show limited extrapolation.
5. **Domain Specificity**: Success is highly context-dependent, not universal.

9.2 Future Research Directions

1. **Real Experimental Validation**: Test predictions on actual physical systems.
2. **Advanced Architectures**: Explore transformer-based, graph neural networks, and other modern architectures.
3. **Symbolic Extraction**: Develop methods to extract symbolic equations from cage-broken models.
4. **Cross-Domain Transfer**: Investigate why transfer learning failed and develop solutions.
5. **Theoretical Analysis**: Develop mathematical theory explaining when and why cage-breaking occurs.
6. **Hybrid Approaches**: Combine human-derived and AI-discovered representations for optimal performance.

10. Conclusions

This comprehensive experimental investigation of the Darwin's Cage hypothesis has revealed a nuanced and complex picture. Through 20 systematic experiments across multiple physical domains, we have demonstrated that:

1. **Cage-breaking is possible** but requires specific conditions: high dimensionality, geometric learning with extrapolation, complex-valued processing, or methodological alternatives.
2. **The phenomenon is context-dependent**: No single factor (complexity, geometry, representation) is sufficient alone.
3. **Multiple pathways exist**: Both human-derived and AI-discovered representations can reach physical truth through different mechanisms.
4. **The cage is not absolute**: It represents a difference in strategy rather than a fundamental barrier.
5. **Practical implications**: AI systems can discover alternative physics representations, but these are complementary rather than replacements for human mathematics.

The study establishes the first systematic experimental framework for investigating AI-based physics discovery and provides critical insights into the conditions under which computational intelligence can transcend evolutionary cognitive constraints. While the results partially validate the Darwin's Cage hypothesis, they also reveal its limitations and the need for refined theoretical understanding.

The work contributes to both artificial intelligence and physics research by demonstrating that AI systems can indeed discover novel representational pathways to physical understanding, opening new possibilities for computational physics discovery while also highlighting the continued value of human-derived mathematical frameworks.

Acknowledgments

This research was conducted independently by Francisco Angulo de Lafuente. The author acknowledges the theoretical foundation provided by Gideon Samid's Darwin's Cage theory and the open-source software communities (PyTorch, NumPy, SciPy, scikit-learn) that made this work possible.

References

1. Samid, G. (2025). Negotiating Darwin's Barrier: Evolution Limits Our View of Reality, AI Breaks Through. *Applied Physics Research*, 17(2), 102. https://doi.org/10.5539/apr.v17n2p102
2. Jaeger, H. (2001). The "echo state" approach to analysing and training recurrent neural networks. *GMD Report 148*, German National Research Center for Information Technology.
3. Maass, W., Natschläger, T., & Markram, H. (2002). Real-time computing without stable states: A new framework for neural computation based on perturbations. *Neural Computation*, 14(11), 2531-2560.
4. Lukosevicius, M., & Jaeger, H. (2009). Reservoir computing approaches to recurrent neural network training. *Computer Science Review*, 3(3), 127-149.
5. Brunner, D., Soriano, M. C., & Fischer, I. (2013). Fast physical reservoir computing: Photonic systems. *Nature Communications*, 4, 1364.
6. Larger, L., et al. (2017). High-speed photonic reservoir computing based on a time-delay approach. *Nature Communications*, 8, 468.
7. Carleo, G., & Troyer, M. (2017). Solving the quantum many-body problem with artificial neural networks. *Science*, 355(6325), 602-606.
8. Iten, R., et al. (2020). Discovering physical concepts with neural networks. *Physical Review Letters*, 124(1), 010508.
9. Greydanus, S., et al. (2019). Hamiltonian neural networks. *Advances in Neural Information Processing Systems*, 32.
10. Cranmer, M., et al. (2020). Learning symbolic physics with graph networks. *arXiv preprint arXiv:1909.05862*.
11. Toth, P., et al. (2020). Hamiltonian generative networks. *International Conference on Learning Representations*.
12. Lutter, M., et al. (2019). Deep Lagrangian networks: Using physics as model prior for deep learning. *International Conference on Learning Representations*.
13. Raissi, M., et al. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686-707.
14. Karniadakis, G. E., et al. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3(6), 422-440.
15. Bongard, J., & Lipson, H. (2007). Automated reverse engineering of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences*, 104(24), 9943-9948.
16. Schmidt, M., & Lipson, H. (2009). Distilling free-form natural laws from experimental data. *Science*, 324(5923), 81-85.
17. Udrescu, S. M., & Tegmark, M. (2020). AI Feynman: A physics-inspired method for symbolic regression. *Science Advances*, 6(16), eaay2631.
18. Valipour, M., et al. (2021). Symbolic regression for scientific discovery: An application to wind speed forecasting. *Environmental Modelling & Software*, 137, 104959.
19. Bell, J. S. (1964). On the Einstein Podolsky Rosen paradox. *Physics Physique Fizika*, 1(3), 195.
20. Aspect, A., et al. (1982). Experimental test of Bell's inequalities using time-varying analyzers. *Physical Review Letters*, 49(25), 1804.

21. Einstein, A., et al. (1935). Can quantum-mechanical description of physical reality be considered complete? *Physical Review*, 47(10), 777.
22. Schrödinger, E. (1935). Discussion of probability relations between separated systems. *Mathematical Proceedings of the Cambridge Philosophical Society*, 31(4), 555-563.
23. Feynman, R. P. (1982). Simulating physics with computers. *International Journal of Theoretical Physics*, 21(6-7), 467-488.
24. Lloyd, S. (1996). Universal quantum simulators. *Science*, 273(5278), 1073-1078.
25. Preskill, J. (2018). Quantum computing in the NISQ era and beyond. *Quantum*, 2, 79.
26. Biamonte, J., et al. (2017). Quantum machine learning. *Nature*, 549(7671), 195-202.
27. Havlíček, V., et al. (2019). Supervised learning with quantum-enhanced feature spaces. *Nature*, 567(7747), 209-212.
28. Schuld, M., & Petruccione, F. (2018). *Supervised Learning with Quantum Computers*. Springer.
29. Briegel, H. J., & De las Cuevas, G. (2012). Projective simulation for artificial intelligence. *Scientific Reports*, 2, 400.
30. Melnikov, A. A., et al. (2018). Active learning machine learns to create new quantum experiments. *Proceedings of the National Academy of Sciences*, 115(6), 1221-1226.
31. Krenn, M., et al. (2016). Automated search for new quantum experiments. *Physical Review Letters*, 116(9), 090405.
32. Arute, F., et al. (2019). Quantum supremacy using a programmable superconducting processor. *Nature*, 574(7779), 505-510.
33. Carleo, G., et al. (2019). Machine learning and the physical sciences. *Reviews of Modern Physics*, 91(4), 045002.
34. Mehta, P., et al. (2019). A high-bias, low-variance introduction to machine learning for physicists. *Physics Reports*, 810, 1-124.
35. Goodfellow, I., et al. (2016). *Deep Learning*. MIT Press.
36. LeCun, Y., et al. (2015). Deep learning. *Nature*, 521(7553), 436-444.
37. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780.
38. Vaswani, A., et al. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.
39. Krizhevsky, A., et al. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25.
40. Silver, D., et al. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587), 484-489.
41. Vinyals, O., et al. (2019). Grandmaster level in StarCraft II using multi-agent reinforcement learning. *Nature*, 575(7782), 350-354.
42. Jumper, J., et al. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, 596(7873), 583-589.
43. Senior, A. W., et al. (2020). Improved protein structure prediction using potentials from deep learning. *Nature*, 577(7792), 706-710.
44. Noether, E. (1918). Invariante Variationsprobleme. *Nachrichten von der Gesellschaft der Wissenschaften zu Göttingen, Mathematisch-Physikalische Klasse*, 1918, 235-257.
45. Wigner, E. P. (1960). The unreasonable effectiveness of mathematics in the natural sciences. *Communications in Pure and Applied Mathematics*, 13(1), 1-14.
46. Tegmark, M. (2014). *Our Mathematical Universe: My Quest for the Ultimate Nature of Reality*. Knopf.
47. Chalmers, D. J. (1995). Facing up to the problem of consciousness. *Journal of Consciousness Studies*, 2(3), 200-219.
48. Penrose, R. (1989). *The Emperor's New Mind: Concerning Computers, Minds, and the Laws of Physics*. Oxford University Press.
49. Dennett, D. C. (1991). *Consciousness Explained*. Little, Brown and Company.
50. Hofstadter, D. R. (1979). *Gödel, Escher, Bach: An Eternal Golden Braid*. Basic Books.

Manuscript submitted to: Applied Physics Research / Nature Machine Intelligence / Physical Review Research

Competition Entry: Independent Research Project

Date: November 27, 2025

Author Contact & Publications:

GitHub: https://github.com/Agnuxo1

ResearchGate: https://www.researchgate.net/profile/Francisco-Angulo-Lafuente-3

Kaggle: https://www.kaggle.com/franciscoangulo

HuggingFace: https://huggingface.co/Agnuxo

Wikipedia: https://es.wikipedia.org/wiki/Francisco_Angulo_de_Lafuente