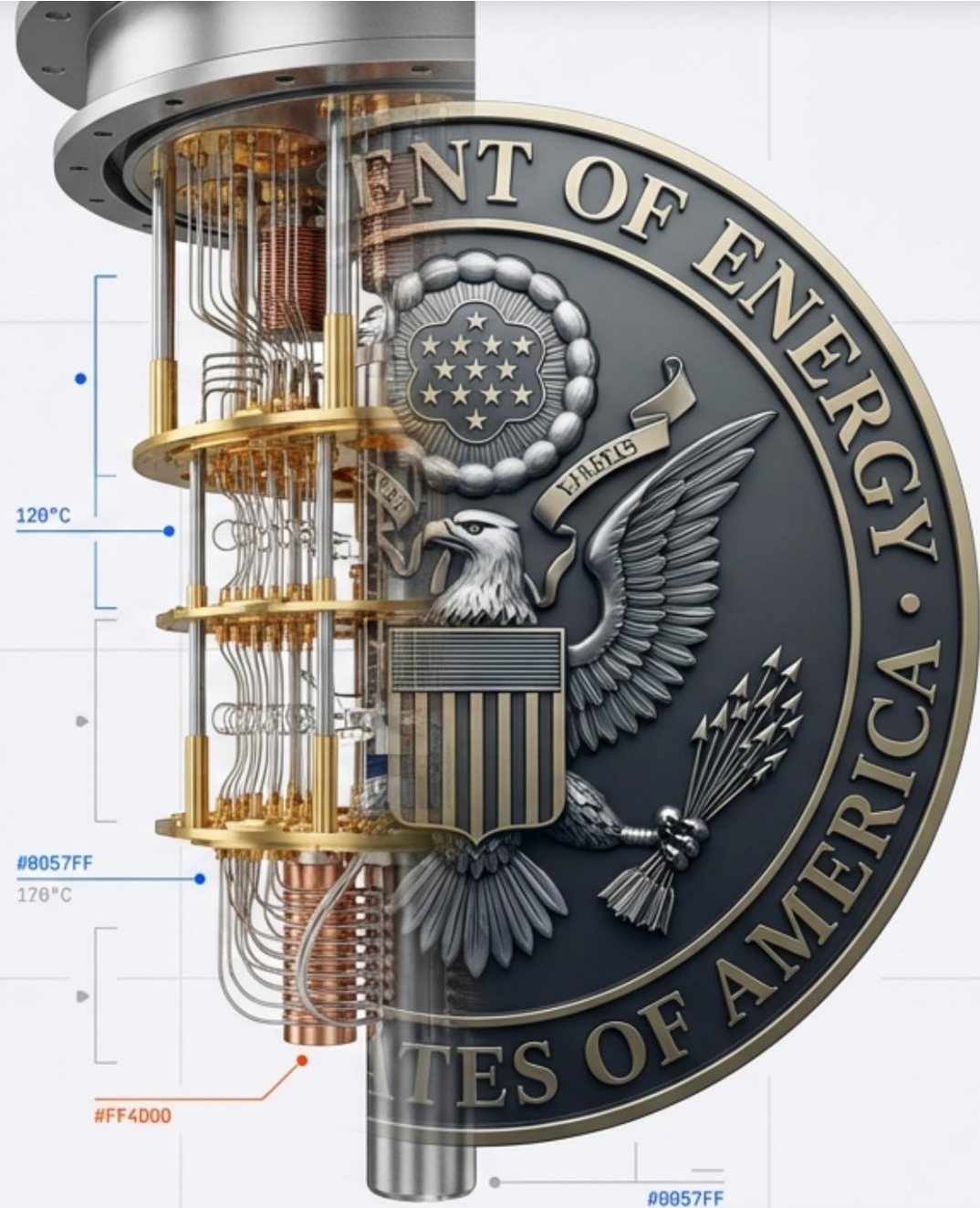


The Genesis Mission


A National Strategy to Accelerate Science Through Artificial Intelligence.

AUTHORITY: Executive Order | November 24, 2025
LEAD AGENCY: Department of Energy (DOE) + White House OSTP
LEADERSHIP: Dr. Darío Gil, Under Secretary for Science

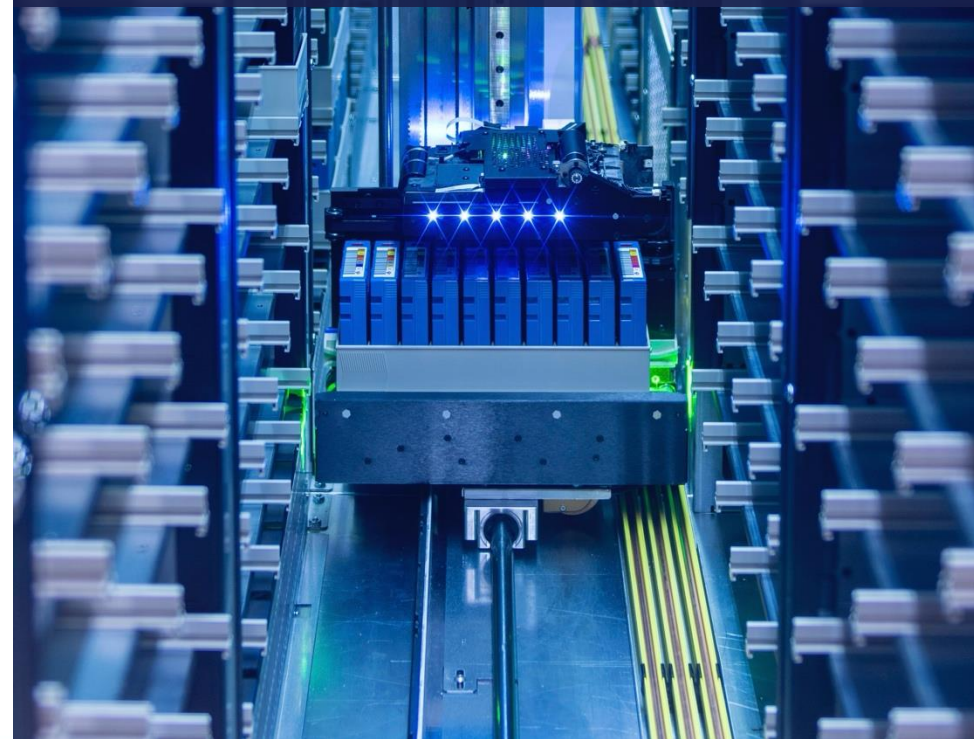


National Initiative for Science, National Security, and Innovation

Mission Goal: Use artificial intelligence to dramatically accelerate American scientific discovery and **strengthen** U.S. economic and national security leadership.



Genesis is not a tool or program it is a national capability that compounds scientific advantage over time



WHAT IS HAPPENING RIGHT NOW

The Largest Marshaling of Federal Scientific Resources Since Apollo

"We are going to act with an urgency that will feel deeply uncomfortable... Let's act like our lives depend on our execution (because they do)."

— Darío Gil, Under Secretary for Science & Genesis Mission Director



Executive Order

Signed Nov 24, 2025
Presidential mandate



National Scale

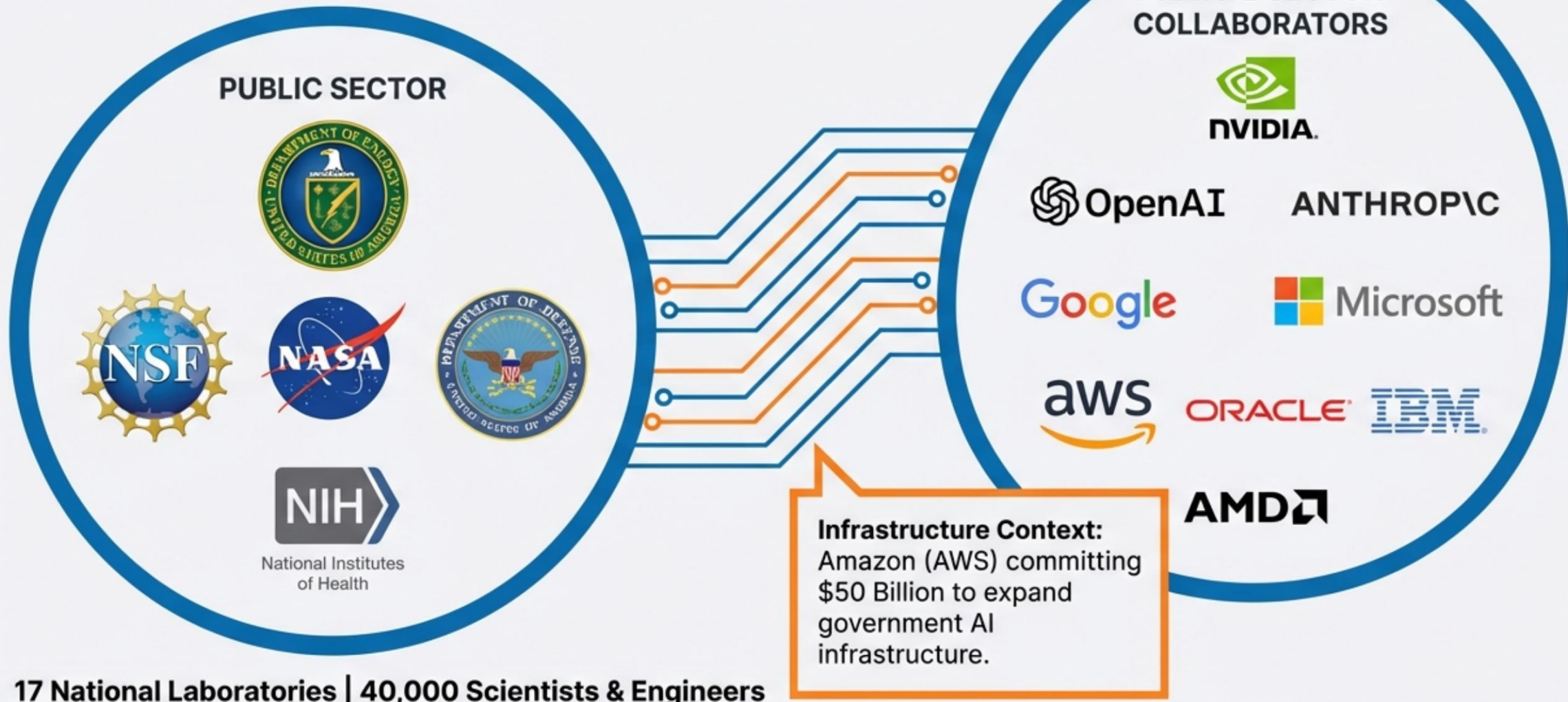
17 National Labs + industry
+ academia unified



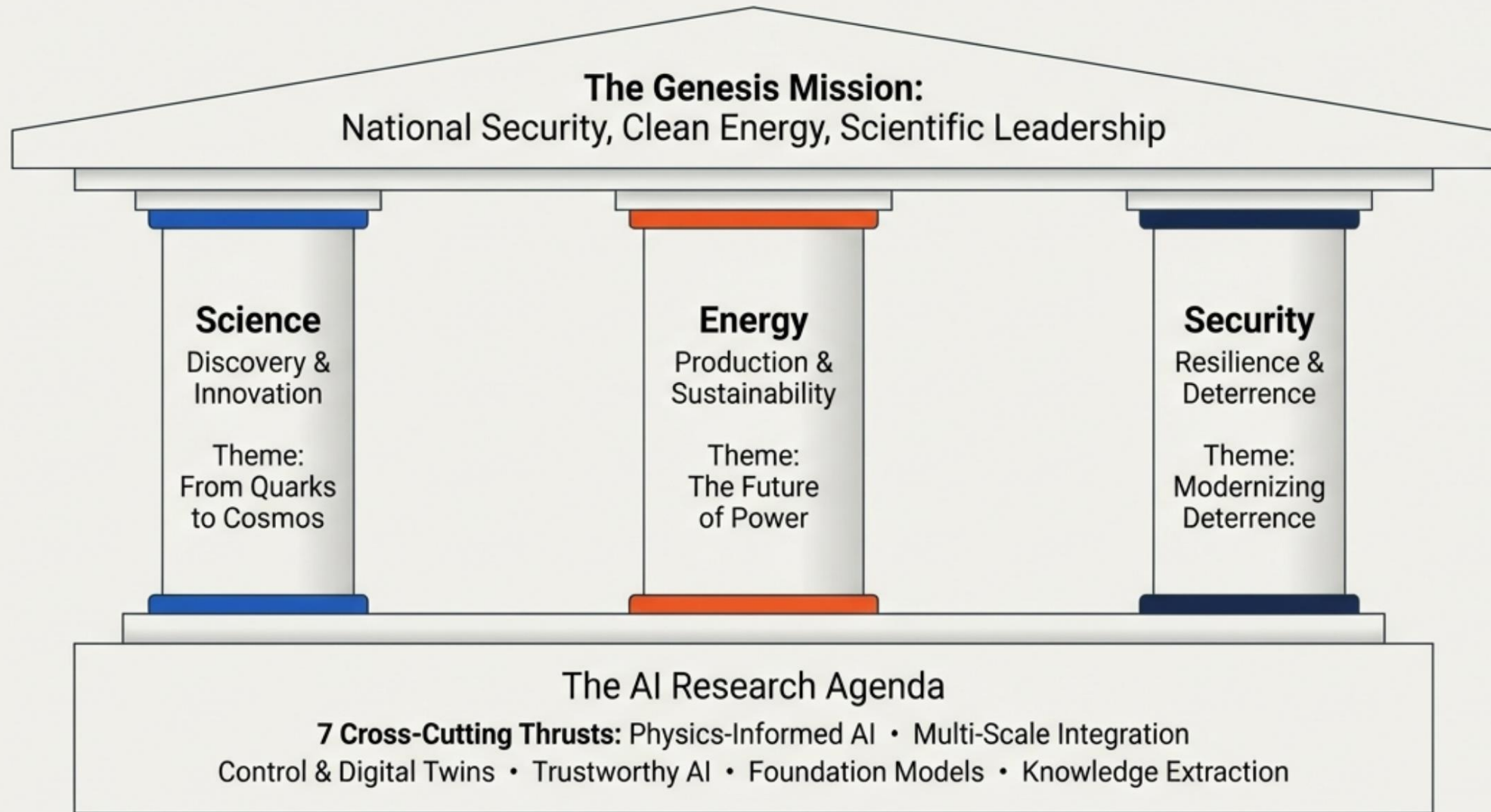
Urgency

Lighthouse challenges
being defined now

Uniting the Innovation Ecosystem



The Strategic Ecosystem Architecture

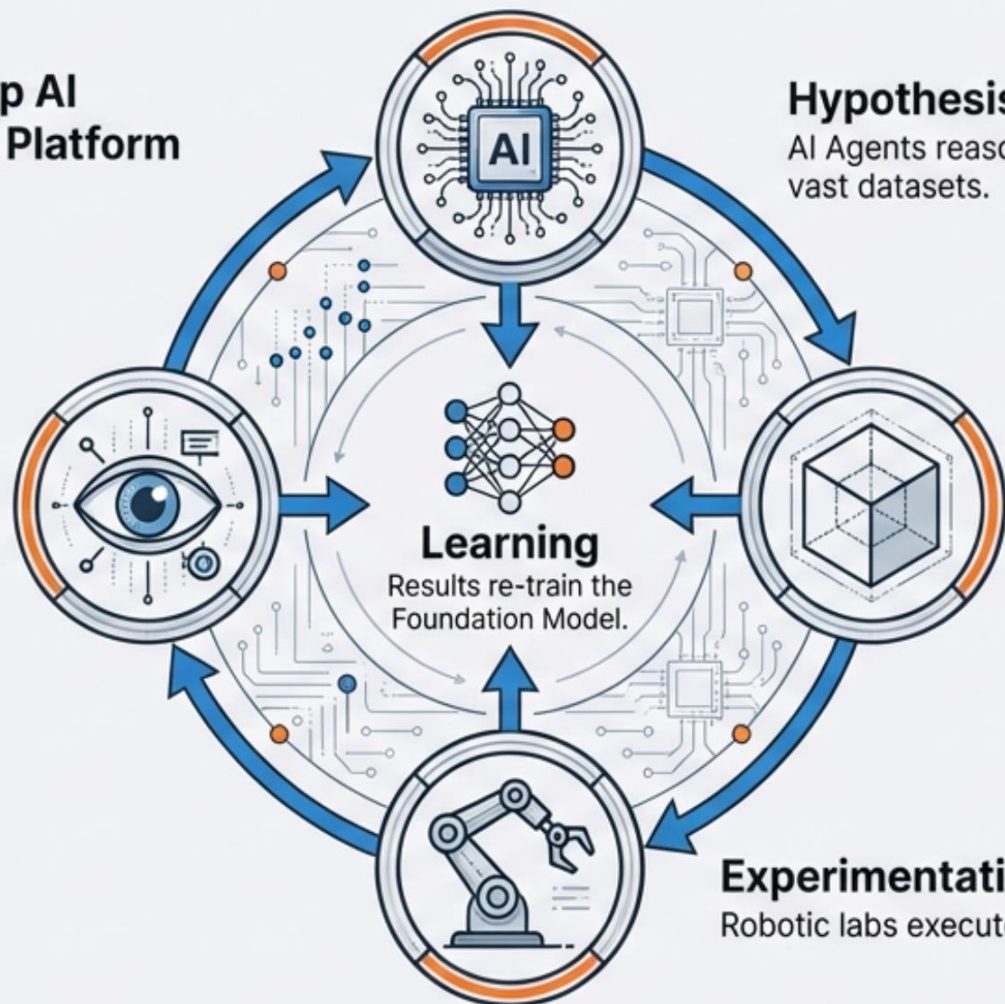


A Paradigm Shift: Closed-Loop Discovery

"It's AI for discovery, not automation." — Department of Energy

**Closed-Loop AI
Experimentation Platform**

Observation
Real-world data capture.



Hypothesis Generation
AI Agents reason across vast datasets.

Simulation
HPC models the experiment.

Experimentation
Robotic labs execute the test.

Learning
Results re-train the Foundation Model.

"An intelligent network capable of sensing, simulating, and understanding nature at every scale."

If you had 200 dedicated people,
unlimited frontier AI and exascale computing,
and robotic experimentation at national scale —

What 10-year problem could you solve in 2?

This is the bar. Not a pilot. Not a study. A paradigm shift.

200+

Dedicated
researchers

10^{18}

FLOPs of
compute

T+

Tokens of
scientific data

24/7

Robotic
laboratories

Over the past five months, **OpenAI** has been running an experiment: building and shipping an internal beta of a software product with **0 lines of manually-written code**.

The product has internal daily users and external alpha testers. It ships, deploys, breaks, and gets fixed. What's different is that every line of code—application logic, tests, CI configuration, documentation, observability, and internal tooling—has been written by Codex. We estimate that we built this in about 1/10th the time it would have taken to write the code by hand.

Humans steer. Agents execute.

We intentionally chose this constraint so we would build what was necessary to increase engineering velocity by orders of magnitude. We had weeks to ship what ended up being a million lines of code. To do that, we needed to understand what changes when a software engineering team's primary job is no longer to write code, but to design environments, specify intent, and build feedback loops that allow Codex agents to do reliable work

The Strategic Imperative

Why DOE? Why Now?

The Opportunity

Current commercial AI excels at pattern matching and language. The new frontier is **Agentic and Physics-Informed AI**—systems capable of causal reasoning, respecting conservation laws, and navigating multi-scale dynamic systems.

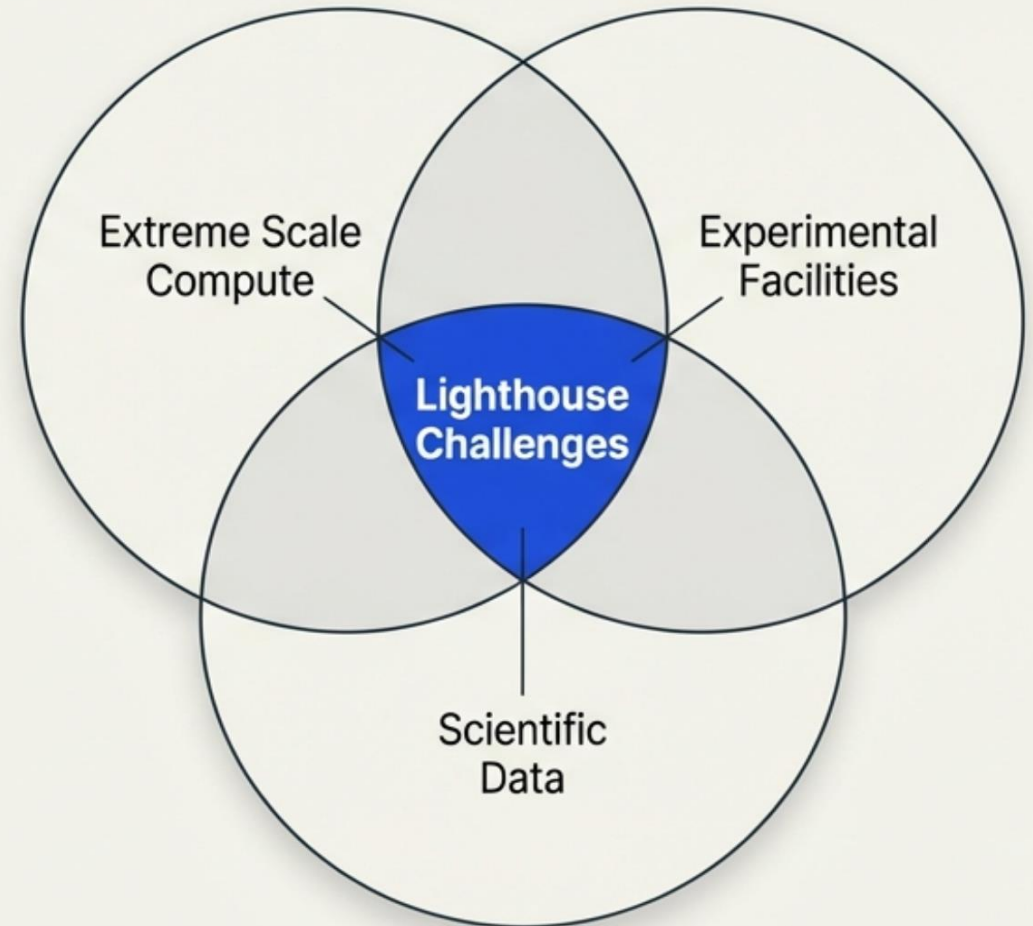
The Unique DOE Asset

We possess the unique convergence required for this leap:

- World-class User Facilities (Equinox, Synchrotrons)
- Massive Proprietary Datasets (80+ years of nuclear data)
- Deep Domain Expertise

The Mission

To guide innovation through the 'Valley of Death'—bridging the gap between scientific discovery and commercially viable deployment in manufacturing, energy, and defense.



The Engine: Why Commercial AI Isn't Enough

The Gap Between Generative AI and Scientific AI

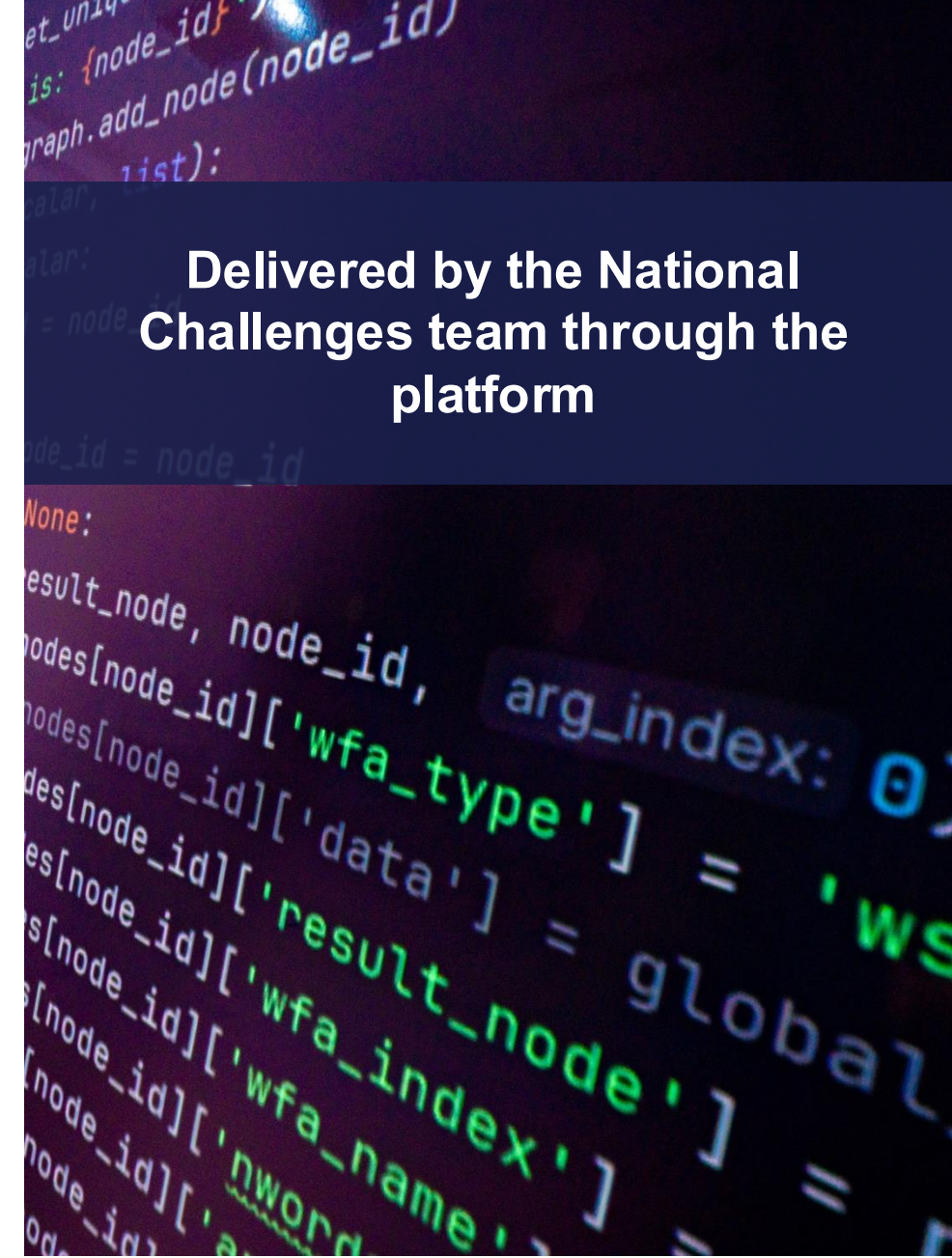
Commercial AI (Generative)	DOE Scientific AI
<ul style="list-style-type: none">• Optimized for Plausibility	<ul style="list-style-type: none">• Optimized for Truth & Physical Consistency
<ul style="list-style-type: none">• Data-Rich (Internet Scale)	<ul style="list-style-type: none">• Data-Sparse (High-Cost Experiments)
<ul style="list-style-type: none">• Pattern Matching (Statistical)	<ul style="list-style-type: none">• Causal Reasoning & Conservation Laws
<ul style="list-style-type: none">• Black Box Operation	<ul style="list-style-type: none">• Explainable & Auditable
<ul style="list-style-type: none">• Hallucinations are Common	<ul style="list-style-type: none">• Must Handle Rare/Extreme Events

The Goal: Machines capable of Scientific Reasoning, Multi-Scale Integration, and Trustworthy Operation in high-consequence environments.

The National Science and Technology Challenges

The **National Challenges** are high-impact technical problems aligned to urgent national priorities – where AI can dramatically accelerate progress. They demand AI model, data, computing, and automation capabilities unified in a single solution platform. Expert teams develop innovative solutions while results strengthen and extend the platform itself to tackle ever more ambitious challenges.

Delivered by the National Challenges team through the platform



Pillar I - Science: Unifying Physics & Discovery

From Human-Speed Hypothesis to AI-Speed Reasoning

Unifying Physics

Moving from pattern matching to physics reasoning. AI that internalizes the Standard Model to integrate results from particle collisions, nuclear decays, and cosmological surveys.

Key Focus: Foundation Model for the Cosmic Frontier (HEP) >

Accelerators

Predicting chaotic beam dynamics where small perturbations cascade into major problems. AI-driven digital twins enabling real-time optimization of the 6-dimensional state of particle beams.

Solution: Real-time optimization & self-updating facilities. >

Quantum Systems

Controlling the delicate nature of quantum systems (computing, sensing, communication).

Key Focus: AI for Quantum Systems Design (BES) to uncover causal relationships. >

Autonomous Labs

Shifting to self-driving laboratories by integrating robotics and edge AI.

Impact: Automating hypothesis generation and experimentation. >

Pillar I - Science: Designing Reality

Materials, Biology, and The Shift to Inverse Design

The Core Shift: Inverse Design

Instead of trial-and-error, we tell the AI the properties we want, and it identifies the material or molecule to build.

Materials Design

Developing physics-aware AI frameworks to bridge atomic scales to macroscopic properties.

- *Focus:* "AI-Driven Materials Processing (BES)"

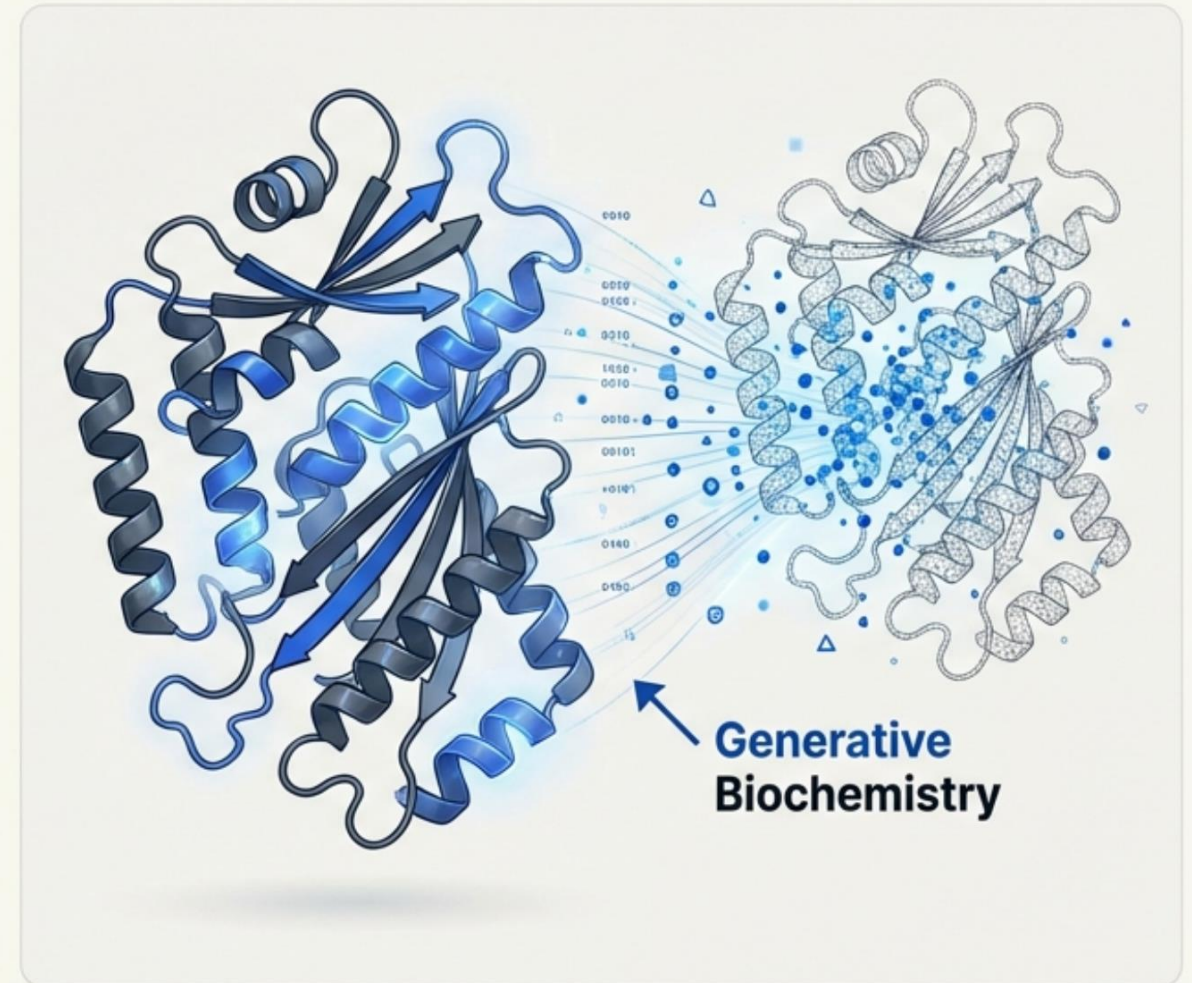
The Bio-Revolution

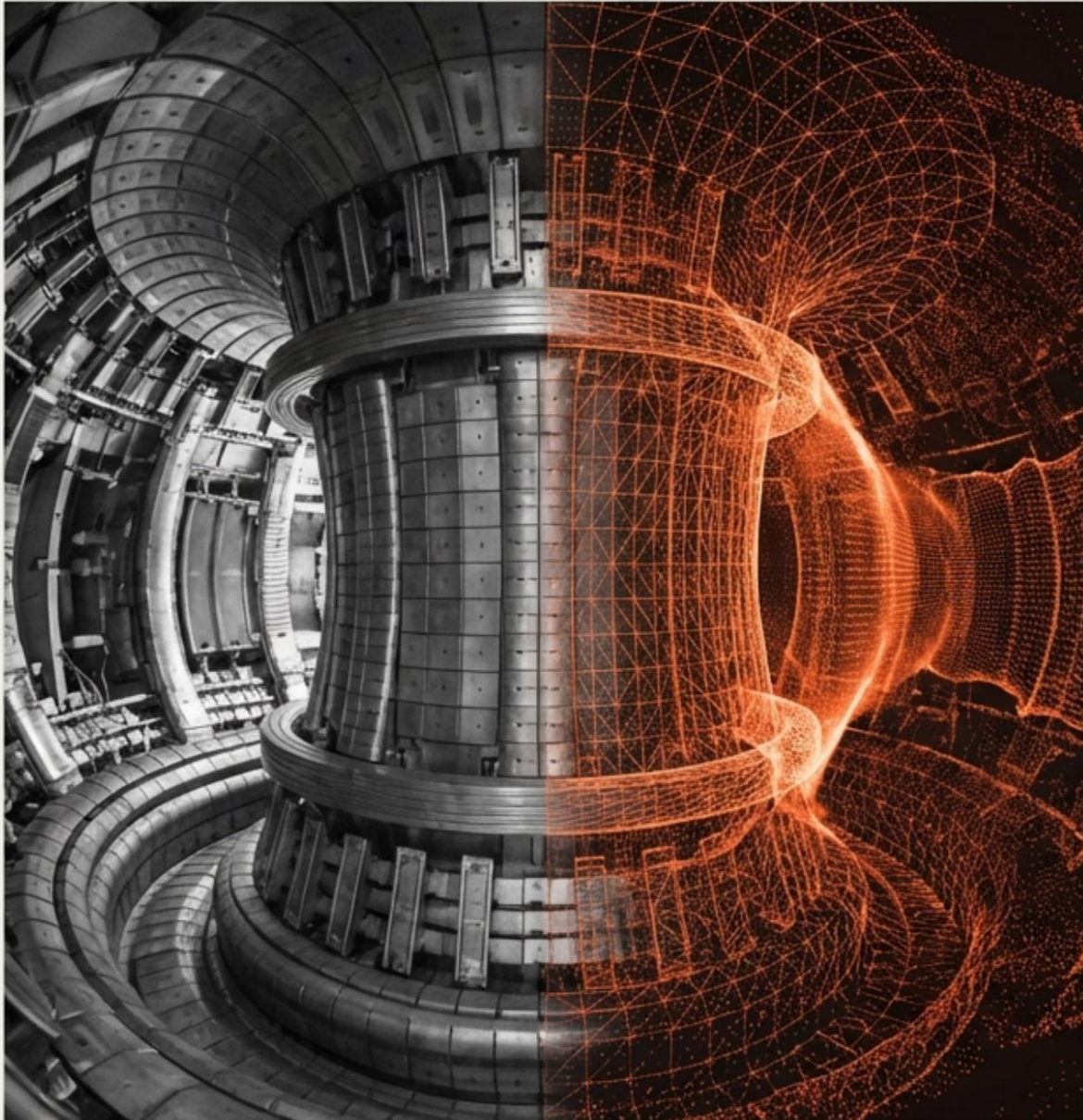
Establishing genotype-phenotype relationships to design biology on demand.

- *Spotlight:* "**Biochemistry in Five Dimensions** — Incorporating energy and time into protein folding models."
- *Spotlight:* "**Agentic AI-Driven Chemical Manufacturing**"

Water Security

Predicting water cycles by coupling fast (cloud) and slow (groundwater) processes using AI surrogates.





Digital Twin Visualization: Tokamak Reactor Core.

Pillar II - Energy: The Future of Power Generation

Fusion Energy

Accelerating delivery via the **AI-Fusion Digital Convergence Platform (DCP)**. Integrating plasma, nuclear, and materials behavior into a unified predictive framework.

Nuclear Energy

Goal: **2x schedule acceleration** and **>50% cost reduction**.

Method: Autonomous design, licensing, and operation. Using AI digital twins to interpret complex operational data in real-time.

Focus: Autonomous Research and Development to condense 50 years of irradiation data.

Subsurface Assets

Unleashing geothermal and hydrocarbon value by reasoning under extreme uncertainty. Connecting molecular-scale mechanisms to field-scale resource availability.

Pillar II - Energy: Infrastructure & Manufacturing

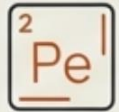
Resilience, Competitiveness, and The Grid



The Grid: Scaling to handle the AI data center load. Enabling **20-100x faster decision-making** with >10% reliability improvement. *Focus:* **Grid Foundational Model**.



Manufacturing: Reimagining industrial productivity. Solving the 'Valley of Death' between discovery and deployment. *Tool:* ATHENA (AI-Toolkit for Holistic Economic Network Analysis).



Critical Minerals: Securing the supply chain via AI-driven resource mapping. *Focus:* **Nature's Path to Alternative Chemistries** — Designing industrial catalysts that eliminate the need for critical minerals entirely.



Buildings & Data Centers: Reimagining construction and operation. De-risking advanced cooling and energy integration for extreme compute power.

The American Science and Security Platform

The **platform** supports AI-driven experimentation, analysis, discovery, design, and manufacturing. It unifies access to AI, computing resources, scientific data, and automated facilities, allowing application of unprecedented capabilities. It delivers scientific self-improving feedback that will accelerate R&D in the energy dominance, discovery science, and national security pillars.



**Delivered by the
infrastructure, data, and
models teams**

The mission technical efforts are organized into five teams



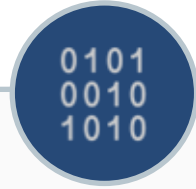
National Challenges

Engages with projects addressing high-impact national challenges—such as energy security and advanced materials—that are accelerated by the platform. Serves as a living portfolio that evolves as goals and technologies change.



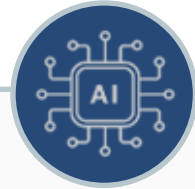
Infrastructure

Provides hardware and software foundations to support large-scale AI training and inference, data management, and scalable agentic workflows. Ensures security of models, data, and systems and interoperability across DOE facilities and production agencies.



Data

Organizes, curates, and prepares scientific and engineering data from experiments, simulations, and observations for AI use. Ensures high-quality, reliable data to accelerate discovery and problem-solving.



Models

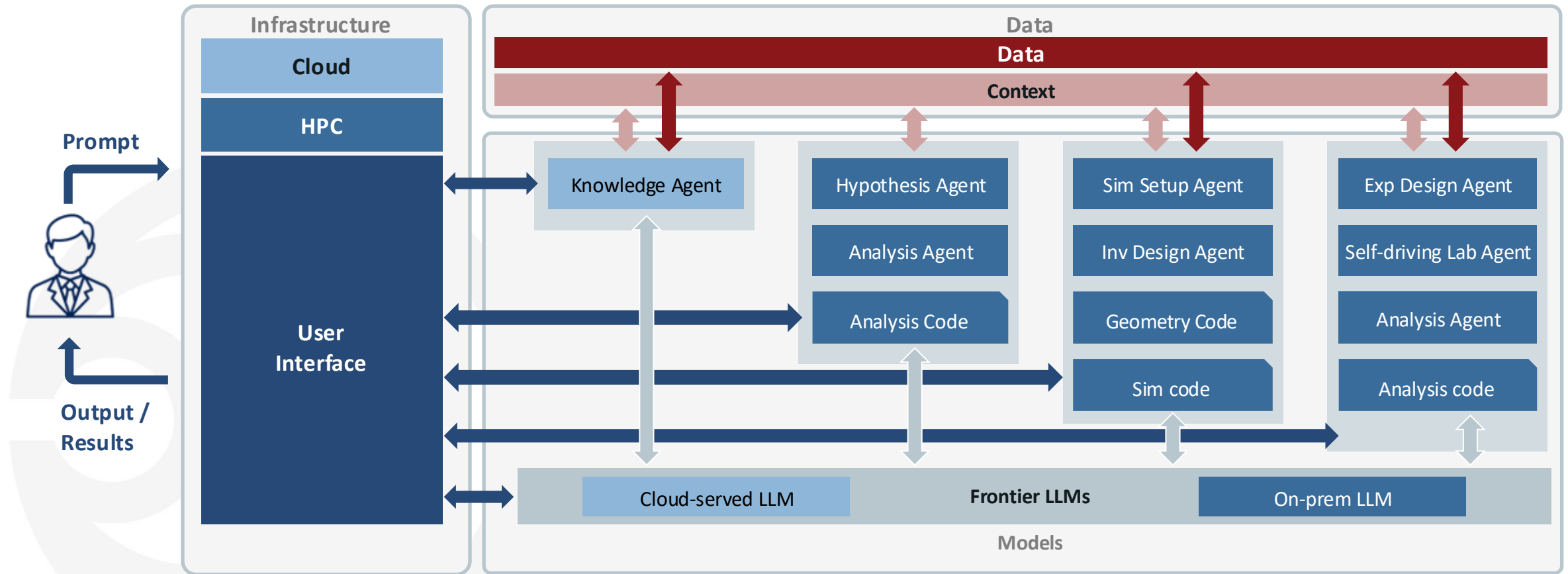
Develops an AI ecosystem of agents and models that combines frontier industry capability with DOE-specific expertise to discover and implement novel solutions to the nation's open science and technology challenges.



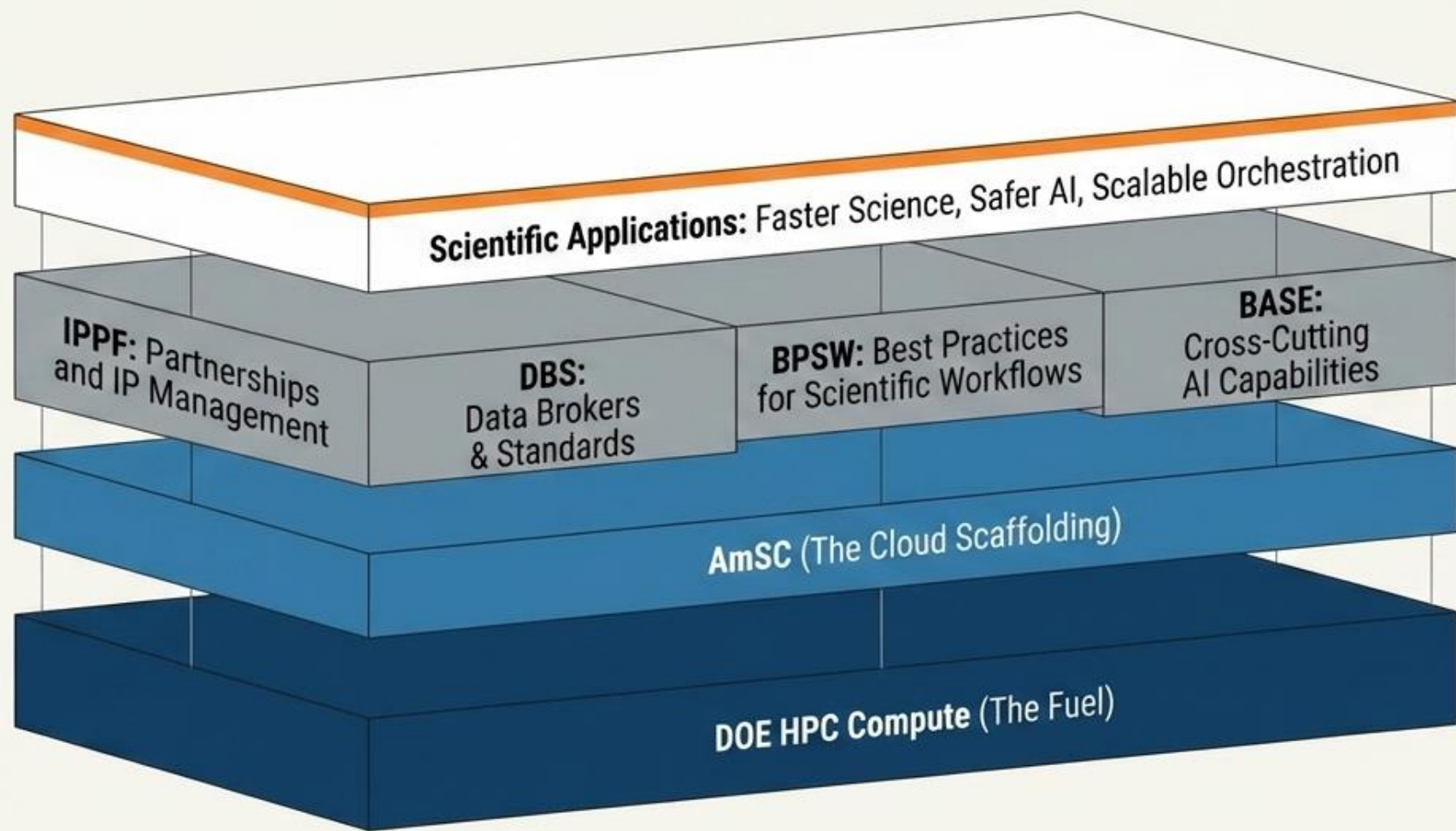
Partnerships

Builds collaborations across government, industry, and academia to advance AI innovation. Leverages shared expertise and resources to deliver real-world impact at national scale.

Each team provides a collection of subcomponents that interoperate to enable new workflows

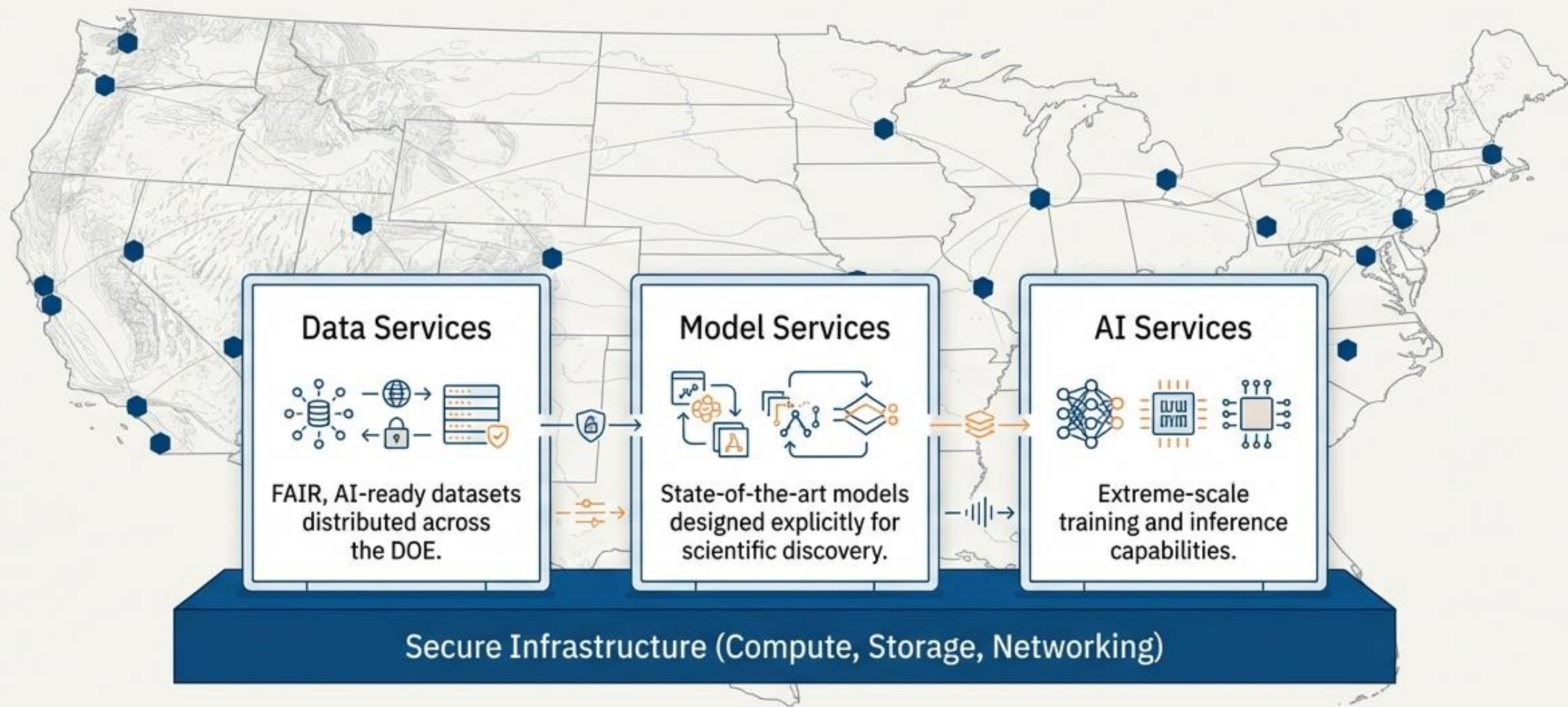


The Architecture of AI-Driven Discovery



The American Science Cloud (AmSC) Scaffolds the Genesis Mission

AmSC is a secure, federated, and science-optimized environment integrating DOE's world-leading computing, experimental facilities, and HPC networks.

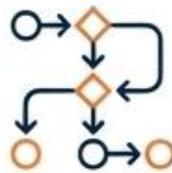


The Cross-Cutting Services Scaffolding



Data Brokers & Standards (DBS)

Managing the Genesis Central Catalog.
Ensuring petabytes of data are FAIR and AI-ready using standardized data cards and automated curation tools.



Best Practices for Scientific Workflows (BPSW)

Providing a catalog of AI integration patterns (e.g., RAG, surrogate optimization) and maintaining a Genesis AI Resource Hub of 330+ curated model and agent cards.



IP & Partnership Formation (IPPF)

Streamlining collaboration. Offering pre-approved agreement templates (SOWs, NDAs) and a Virtual Lab Teaming Framework to rapidly integrate industry and academic partners.

Baseline AI R&D Capabilities (BASE)

Diagnostic Dashboard for Model Teams



Core Agentic Framework (CAF)

Scalable orchestration supporting 1000s of concurrent agents and tool calls.



AI-Ready Data (DATA)

Autonomous pipelines transforming raw scientific data into training-ready form.



Model Evaluation (EVAL)

Comprehensive suites assessing robustness, generalizability, and scientific validity.



Multimodal Reasoning (MM)

PRISM architecture for cross-modal reasoning (text, images, graphs, geometry).



Self-Improving Models (SIM)

APEIRON framework for continuous learning as new experimental data emerges.

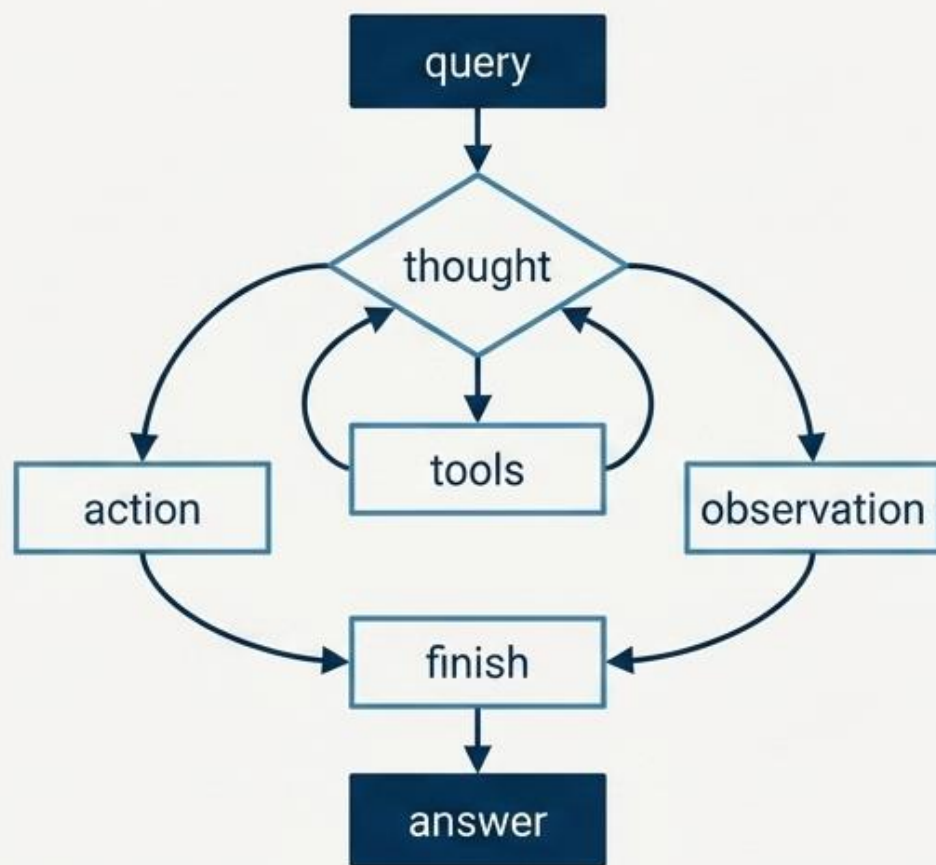


Safety & Security (SAFE)

Rigorous frameworks for red/blue teaming, uncertainty quantification, and CI pipeline safeguarding.

Scaling Closed-Loop Scientific Workflows

Agent Logic Enforces Autonomous Execution



CAF Deployment Scale

1. Local Execution:
Persistent agents on a workstation.
2. Federated Execution:
Cross-institutional execution under shared governance.
3. HPC Parallel Inference: Fanning out thousands of LLM requests simultaneously. (e.g., 1.4B tokens processed in 35 minutes on 2048 Aurora nodes).

National Science and Technology Challenges vs Projects

What is a National Challenge?

- It addresses a big scientific and/or technological problem
- It has ambitious goals
- It is achievable (does not break the laws of physics)
- It is resource intensive
- It has potential for high impact

What is a National Project?

- It addresses a part (or all) of the overall lighthouse challenge
- It defines the research frontier and “illuminates” future research directions
- It is a highly visible, ambitious, and focused multidisciplinary research endeavor
- It involves multi-institutional partnerships, including public-private partnerships

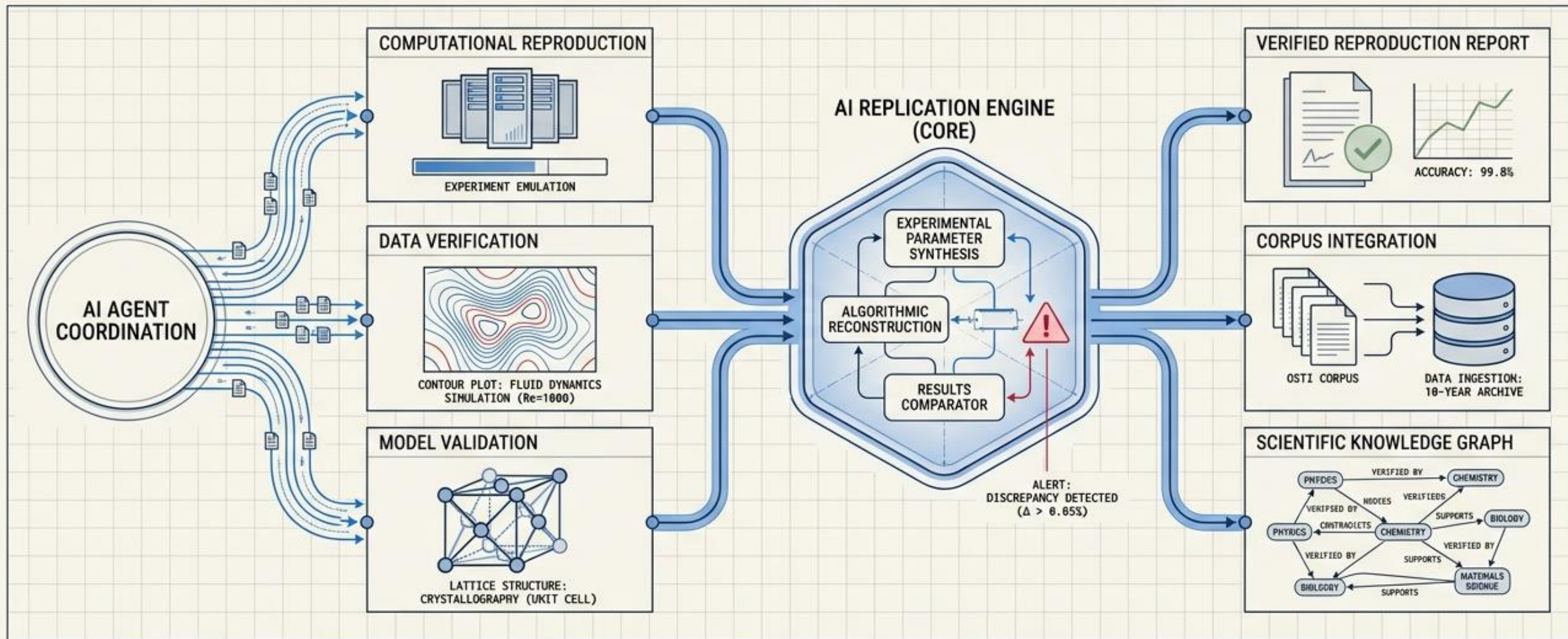
National priorities define National Challenges and inform investments in National Projects



PROJECT:
Systematic reproduction of
computational science via
autonomous AI agents.

THE AI REPLICATION ENGINE

Systematic reproduction of computational science using AI and autonomous agents.



● STATUS: ACTIVE

ENVIRONMENT: Rick Stevens, Argonne National Laboratory

OBJECTIVE: 10-Year OSTI Corpus Verification

True replication requires independent implementation from theory.

A Unified Theory of Coupled Dynamical Systems: Mathematical Formulations and Predictive Models

A Unified Theory of Coupled Dynamical Systems: Mathematical Formulations and Predictive Models. This work introduces a novel framework for modeling complex, interconnected systems, combining advanced mathematical techniques with empirical data analysis to provide a comprehensive predictive model.

$$\frac{\partial}{\partial t} [\Psi(x, t)] = -i\hbar \nabla^2 \Psi + V(x) \Psi \quad (3.1)$$

The study copy formulation of the original theory from conception analysis. This work introduces a novel framework for modeling complex, interconnected systems, combining advanced mathematical techniques with empirical data analysis to provide a comprehensive predictive model.

$$\iint E(x, y) \cdot d(s) d(y) = 2\pi k \quad (3.2)$$

The accuracy of the proposed Unified theory of coupled dynamical systems. A generalized dynamical system is simulated using a novel numerical method, demonstrating high fidelity and robustness across various parameter regimes. The model's predictive power is validated against experimental data, showing excellent agreement.

An empirical tensor of the system's response is derived from experimental data, showing a strong correlation with the theoretical predictions.

¹ Author: A. Corbett, et al. *Journal of Computational Replication*, Vol. 24, Issue 4, Oct 2024, pp. 1-15.
² License: Theoretical model robustly verified through independent implementation.

The essential structure of coupled dynamical systems, with an emphasis on the mathematical formulations and predictive models. This work introduces a novel framework for modeling complex, interconnected systems, combining advanced mathematical techniques with empirical data analysis to provide a comprehensive predictive model.

$$f_{\text{even}} = \frac{1}{S} \int_{\Omega} R(x, t) \kappa^{(2)}(y) \quad (3.2)$$

Systemically, the tensor-based approach to modeling coupled dynamical systems. This work introduces a novel framework for modeling complex, interconnected systems, combining advanced mathematical techniques with empirical data analysis to provide a comprehensive predictive model.

$$T_{\mu\nu} = \frac{-A_{\nu}^{\alpha}}{A_{\alpha}^{\sigma}} A_{\sigma}^{\beta} T_{\alpha\beta} \quad (3.4)$$

The comprehensive validation of the proposed mathematical model. This work introduces a novel framework for modeling complex, interconnected systems, combining advanced mathematical techniques with empirical data analysis to provide a comprehensive predictive model.

³ Reference: S. et al. *Journal of Computational Replication*, Vol. 24, Issue 4, Oct 2024, pp. 1-15.
⁴ Reference: D. et al. *Journal of Computational Replication*, Vol. 24, Issue 4, Oct 2024, pp. 1-15.

Independent Verification via AI

Zero-shot Implementation & Validation Process

Code

Zero-copy implementation written directly from equations.

```
def generate_trajectory(initial_state, equations, steps):  
    # Implementation based on equation 3.2  
    state = initial_state  
    trajectory = []  
    for t in range(steps):  
        state = integrate(equations, state)  
        trajectory.append(state)  
    return np.array(trajectory)  
...
```

Data

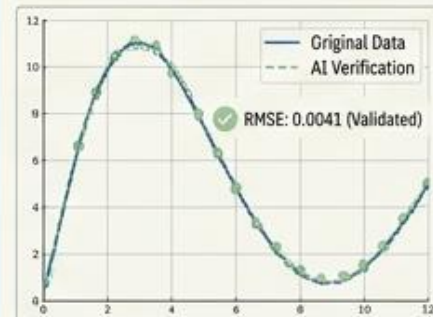
Newly generated numerical results and matrices.

Numerical Output (t=10.0s):
[1.285e+02, -3.456e+01, 7.890e+00]

Generated Matrix M_verify:
[[[0.987, 0.012, -0.004],
 [0.012, 0.954, 0.835],
 [-0.004, 0.035, 0.999]]

Figures

Reproduced plots overlaying and validating original data.



Report

Structured analysis of discrepancies and replication fidelity.

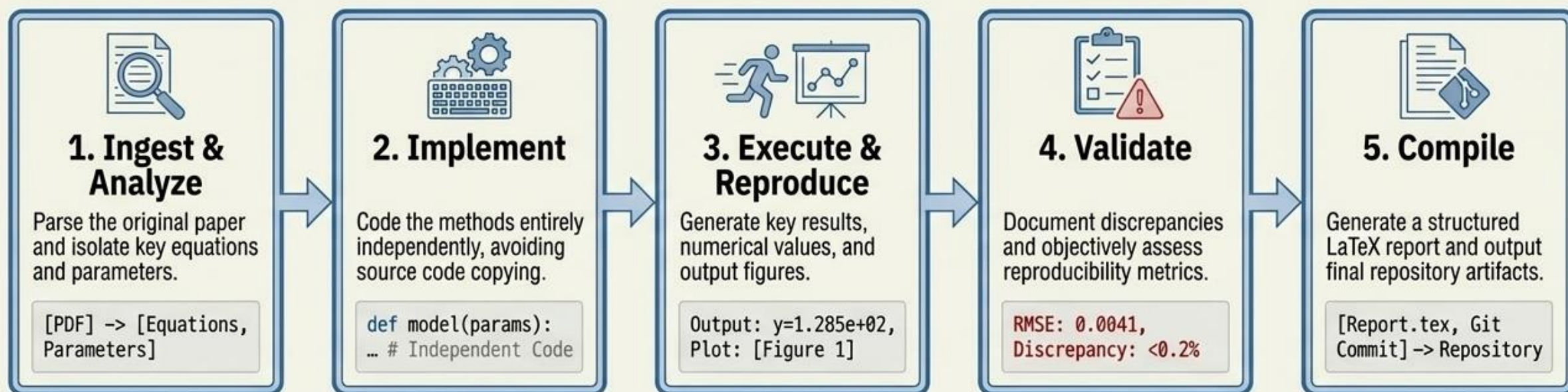
Replication Fidelity Score: 99.8%
Discrepancy Analysis:
- Minor deviation (0.2%) in high-frequency domain, attributed to floating-point precision.
- Core theoretical predictions: FULLY MATCHED.
Conclusion: Theoretical model robustly verified through independent implementation.

STATUS: INDEPENDENTLY VERIFIED - HIGH FIDELITY

Original Publication (Theory & Equations)

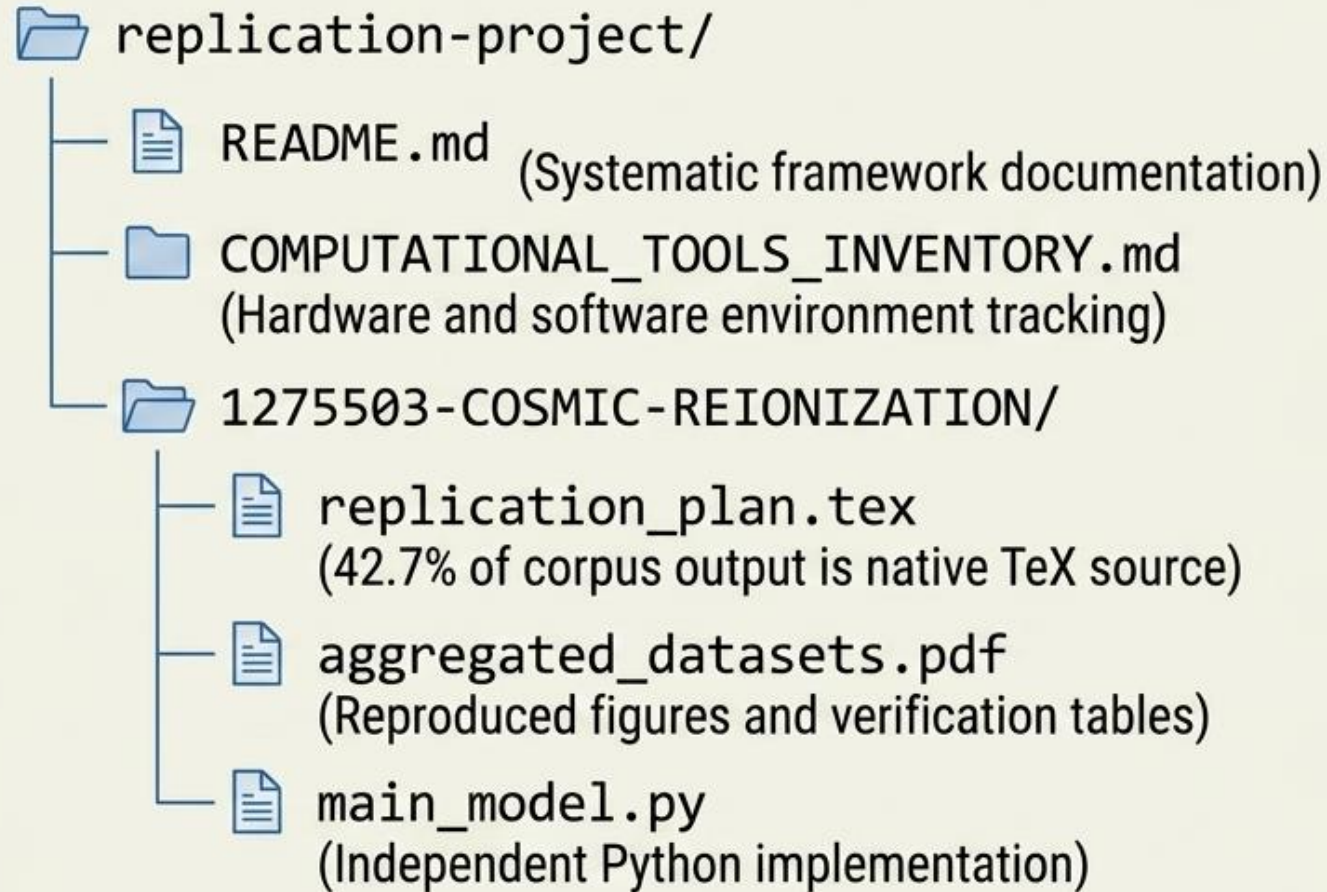
The autonomous workflow from raw PDF to verified Git commit.

Independent Verification via AI: Five-Stage Computational Pipeline.



SYSTEM STATUS: Iterative execution active across 15 OSTI subject categories.

Generating comprehensive, publishable computational artifacts.



ARTIFACT STANDARD:

Every successful pipeline execution produces native LaTeX reports, aggregated datasets, and zero-copy code implementations ready for immediate community review.

THE QUESTION

What fraction of DOE-funded computational papers can an AI agent replicate end-to-end?

ARGONNE PUBLICATION LANDSCAPE

- **~3,500–4,300** papers/year published by Argonne (OSTI)
- **~400/year (9.3%)** contain computational results potentially replicable without wet-lab
- **~3,500 papers** in the 10-year computational backlog
- **15+ disciplines** from nuclear physics to ML to astrophysics

THIS STUDY

- **30 papers** selected from OSTI database
- **15 scientific domains** covered
- **17 days** of agent operation (Apr 5–22, 2026)
- **1 AI agent** with HPC access (Polaris, Aurora, DGX)

12 Distinct Domains in 13 Papers

✓ Materials Science / ML

✓ Computational Chemistry

✓ Computer Science

✓ Astrophysics (× 2)

✓ ML / Dynamical Systems

✓ Pure Mathematics

✓ Optimization / ML

✓ Quantum Optics

✓ Quantum Computing

✓ Applied Mathematics

✓ Nuclear Engineering

✓ Particle Physics

The same agent, same approach — no domain-specific fine-tuning or prompting

TIME & EFFICIENCY

The Bottleneck Is Compute, Not Comprehension

27 sec

Fastest (CPW Resonator)

54 sec

Photo-z PDFs

~2 days

MSM (with MD)

~10 days

PVMol-Gen

WHERE TIME IS SPENT

- **Understanding the paper:** minutes (fast — this is the AI's strength)
- **Writing code:** minutes to hours (depends on domain complexity)
- **Running simulations:** seconds to days (GPU training, MD, Monte Carlo)
- **Waiting for queues:** minutes to hours (HPC scheduling)
- **Debugging infra:** variable (driver mismatches, disk quotas, network issues)

From 1 Agent to 1,000: Clearing the Backlog

Scale	Papers/Day	Time to Clear 3,500	Resources
1× (current)	~1.1/day	8.8 years	1 machine, 1 agent
10×	11/day	10.5 months	~10 agents, shared GPU cluster
100×	110/day	5 weeks	500–1,000 GPUs, 75–100 agents
1,000×	1,096/day	3.5 days	Aurora-scale system

At 100 × — achievable with current technology — the entire annual computational publication output of a national lab can be audited in about 5 weeks.

The Next Step: AI Agents Doing Original Science

REPLICATION (proven)

- Follow published methodology
- Reproduce known results
- 1 × compute per paper
- Quality audit function

→ ~30 ×

DISCOVERY (next)

- Formulate new hypotheses
- Design novel experiments
- ~30 × compute per paper
- Original scientific contributions

RESOURCE REQUIREMENTS AT 100 × DISCOVERY RATE

- **14,000–20,000 GPUs** needed (200–280 Oberon racks)
- ≈ **1 Aurora-class system** fully utilized by AI agents doing original science

What This Means

- 1. AI agents can replicate real scientific papers across diverse domains with high fidelity
- 2. The bottleneck is compute, not understanding — the agent consistently grasped the methodology
- 3. Reproducibility problems in published papers are real — even 'confirmed' replications required detective work
- 4. This scales — with more compute and parallel agents, a lab's annual output becomes auditable in weeks
- 5. Quality matters more than quantity — each replication serves as a reproducibility audit



Genesis Mission



U.S. DEPARTMENT
of ENERGY

