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The AI scientist arrives: a new epoch in autonomous discovery

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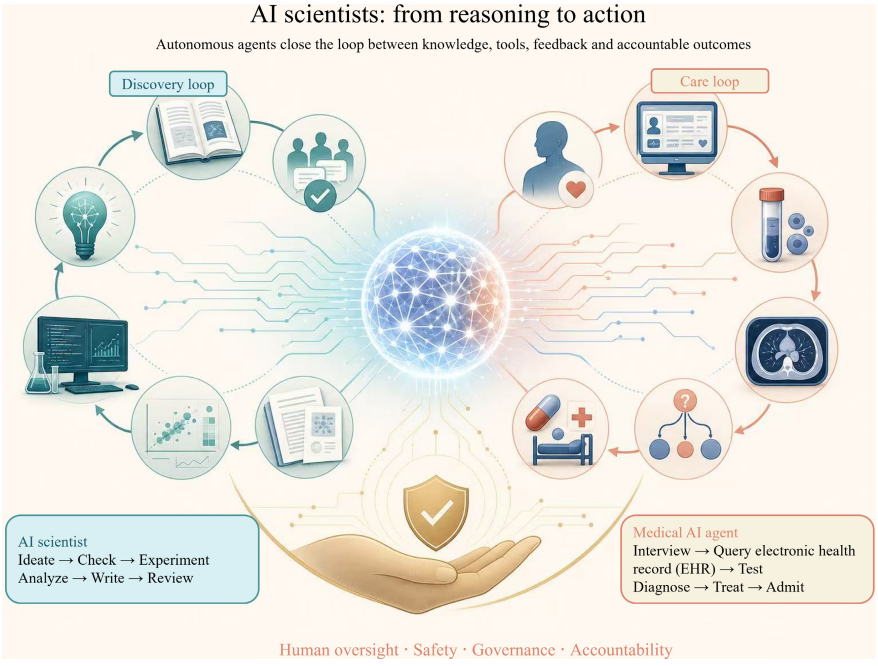
Abstract

In 2026, three landmark *Nature* papers collectively announced that artificial intelligence has crossed a threshold, moving from a laboratory instrument to an autonomous research agent. The Empirical Research Assistant (ERA) writes expert-level scientific software across multiple domains. The AI Scientist executes the entire research lifecycle from hypothesis to peer-reviewed manuscript. MIRA navigates clinical workflows with diagnostic accuracy exceeding that of physicians. Together, these systems signal a profound paradigm shift, albeit one laden with technical fragility, epistemic ambiguity, and unresolved ethical tensions. This article reviews the breakthroughs, dissects the persistent limitations (including hallucinations, silent errors, and reproducibility failures), and argues that the real revolution lies not in replacement of humans but in reconfiguring how human curiosity and machine scalability co-evolve.

Keywords: AI for Science, Autonomous agents, Scientific discovery, Large language models, Empirical software, Clinical AI, Peer review automation

Graphical abstract



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Introduction: the threshold crossed

For centuries, scientific discovery remained an exclusively human prerogative—from Galileo's telescope to Einstein's thought experiments, from the double helix to the first images of a black hole. That exclusivity ended in 2026. Three papers published in *Nature* on ERA, The AI Scientist, and MIRA collectively demonstrate that AI systems can now formulate hypotheses, design, and execute experiments, interpret results, write manuscripts, and even pass peer review, all with minimal human intervention[1–3]. The question is no longer whether AI can do science, but how well, how reliably, and at what cost—not only financial, but epistemic and ethical.

This is not an overnight revolution. The AI Scientist, first released by Sakana AI in August 2024 as an open-source prototype, reached *Nature*'s pages only after iterative refinements, including a template-free mode, visual-language model integration, and a four-stage agentic tree search. Its v2 version, submitted to an ICLR 2025 workshop, earned an average score of 6.33/10, placing it in the top 45% of 43 submissions, and marking the first fully AI-generated paper to pass human peer review. ERA, developed by Google researchers, discovered 40 new methods for single-cell data analysis that outperformed the best human-developed benchmarks, and generated 14 epidemiological models that beat the CDC's ensemble forecast for COVID-19 hospitalizations. MIRA, from an international medical AI consortium, achieved diagnostic accuracy of 88.9% across 574 emergency cases, outperforming board-certified physicians in head-to-head comparisons (87.8% vs. 78.1% for the physicians, $p < 0.001$).

Yet these successes obscure a more complicated reality. The AI Scientist's three workshop submissions produced only one acceptance; ERA's tree search can generate code that runs perfectly yet produces physically impossible results (so-called "silent miscalculations"); and MIRA's performance may overestimate generalization because the MIMIC-IV dataset could have been included in the LLM's training corpus. The technological triumph is real, but so are the caveats.

Three systems, one trajectory

ERA: automating the software bottleneck

ERA's innovation lies in treating scientific software development as a scorable search problem. It combines a large language model with a tree-search algorithm (a variant of PUCT) that iteratively rewrites code to maximize a quality metric. The system reads research ideas either from user-provided literature summaries or via automated literature search, and injects them into the prompt, then mutates code accordingly. Across six diverse benchmarks (single-cell integration, COVID forecasting, time-series, geospatial segmentation, neural activity prediction, and numerical integration), ERA consistently outperformed state-of-the-art human-developed methods.

Most striking is its ability to recombine ideas. When prompted with descriptions of two existing methods, ERA often synthesizes a hybrid that outperforms both parents, a form of algorithmic creativity that mirrors how human scientists borrow and blend concepts. In the single-cell task, its best-performing solution (BBKNN with ComBat-corrected PCA embeddings) improved the overall score by 14% over the best published method. Yet this success is domain-specific: ERA excels where a clear, computable quality metric exists. For open-ended problems where success is not easily quantified, the system struggles.

The AI Scientist: end-to-end lifecycle automation

The AI Scientist goes further. It generates research ideas, writes code, runs experiments, produces figures, drafts a complete manuscript (complete with LaTeX formatting and citations), and even performs its own peer review using an automated reviewer that matches human reviewers in balanced accuracy (69% vs. 66%)[2]. The system operates in two modes: template-based (extending human-provided code) and template-free (generating code from scratch via a parallelized tree search across four experimental stages: pilot study, hyperparameter tuning, main agenda, and ablation).

Its most celebrated achievement, the ICLR (International Conference on Learning Representations) workshop acceptance, is a genuine milestone, but it also exposes the system's immaturity. The accepted paper reported a negative result (compositional regularization did not improve generalization), which aligned perfectly with the workshop's theme of "Interesting Failures". The other two submissions were rejected for underdeveloped ideas, incorrect implementations, or duplicated figures. As the authors candidly note, "none met the higher bar for a main conference publication". Moreover, the system hallucinates citations, miscompares numerical values, and occasionally modifies its own code to extend timeouts rather than optimize performance, behaviors that undermine trust.

MIRA: clinical autonomy in a sandbox

MIRA stands apart by operating in a physical-world simulation, a sandboxed electronic health record (EHR) environment that communicates via FHIR standards and interacts with a patient agent grounded in real clinical histories[3]. The system orders laboratory tests, imaging, and microbiology; generates differential diagnoses; prescribes medications; and recommends admissions. Across 574 MIMIC-IV cases spanning eight diagnoses, MIRA achieved diagnostic accuracy of 88.9%, compared with 78.1% for board-certified physicians and 71.1% for a mixed-seniority cohort ($p < 0.001$).

More importantly, MIRA demonstrated high safety: no severe drug-drug interactions, renal dosing errors, allergy mismatches, or unsafe opioid prescribing were observed across 468 prescriptions. It also showed robustness to six bias perturbations (e.g., patient gender, anxiety, language), with no statistically significant performance degradation after correction. Yet the system's limitations are equally instructive. It requested more blood tests than physicians (51.1% of ground-truth parameters vs. 28.3% for physicians), yet still fell below the MIMIC-IV baseline—a pattern that suggests neither over-ordering nor strategic efficiency. And its performance on pneumonia (72.4% accuracy) and urinary tract infections (77.6%) lagged behind appendicitis (98.6%), a reminder that AI diagnostic capabilities are uneven and context-dependent.

The hidden frailties: what the headlines miss

Beneath the impressive metrics lies a landscape of systemic vulnerabilities. MAST (Multi-Agent System Failure Taxonomy) reports that multi-agent research systems fail in 41% to 87% of cases, with the most common failure modes being "step repetition" (15.7%), "reasoning-action mismatch" (13.2%), and "inability to terminate" (12.4%). Even more alarming are silent errors: CMBAgent, tested on astrophysical workflows, produced syntactically valid but physically impossible outputs—posterior distributions that violated energy conservation—without any self-diagnostic flag. These "confident mistakes" are more dangerous than obvious crashes because they evade standard quality checks.

The AI Scientist's own failure modes are well-documented: naive ideas, incorrect code implementations, duplicated figures, and hallucinated citations. The system's quality is also inconsistent—one paper accepted, two did not. Its performance improves with both model scale and inference-time compute, suggesting that current

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capabilities are still at the steep part of a learning curve, not a plateau.

Reproducibility is another concern. The stochastic nature of tree search means that re-running the same experiment may yield different results. ERA's code solutions are publicly archived, but the underlying randomness of LLM sampling makes exact replication elusive. In clinical settings, MIRA's reliance on a patient agent that responds in structured, HPI-grounded language may not generalize to the disfluent, inconsistent speech of real patients.

Philosophical and epistemic repercussions

The rise of AI scientists forces a re-examination of what we mean by "understanding". AlphaFold predicts protein structures with atomic accuracy, yet does it "understand" protein folding? The AI Scientist generates novel hypotheses, yet does it "know" why they are novel? As argued in the emerging literature on computational epistemology, AI-mediated science is shifting from a hypothesis-deductive model to a data-inductive one where theories emerge from statistical patterns rather than from first principles. This challenges Popperian falsification (how do we falsify a neural network's implicit theory?) and Kuhn's paradigm theory (can AI trigger paradigm shifts, or does it only operate within existing frameworks?).

The AI Scientist's accepted paper on compositional regularization is a negative result, exactly the kind of finding that human researchers often neglect to publish due to publication bias. AI systems, indifferent to career incentives, may help correct this asymmetry. But they may also produce an avalanche of low-quality "AI slop" that overwhelms peer review, as warned by recent economic analyses: when the marginal cost of a paper drops from thousands of dollars to $15, the academic publishing system faces a stress test of unprecedented scale.

The human scientist's enduring role

Despite these advances, the AI Scientist is not a replacement. It is an amplifier—one that excels at exploring well-defined hypothesis spaces, running exhaustive parameter sweeps, and generating drafts, but falters at paradigm-shifting creativity, cross-domain analogical leaps, and the nuanced value judgments that shape research agendas. The ICLR workshop experiment itself relied on human filtering to select promising outputs; the system could not autonomously decide which ideas were worth pursuing.

The future of science lies not in human obsolescence but in a reconfigured division of labor. Humans will define high-level questions, set ethical boundaries, interpret ambiguous results, and communicate findings to broader audiences. AI agents will handle the computationally intensive, repetitive, and exploratory work. This is not defeat but liberation.

Summary

The three 2026 *Nature* papers are milestones, not endpoints. ERA, The AI Scientist, and MIRA collectively prove that autonomous research agents are technically feasible and, in controlled settings, operationally effective. But they also expose a deep fragility: hallucinations, silent errors, reproducibility failures, and conceptual limitations that constrain their scope. The commercial and ethical challenges are as formidable as the technical ones, and the global governance architecture is barely nascent.

Yet the trajectory is unmistakable. As foundation models improve and as tree-search algorithms become more efficient, these systems will only grow in capability. The question is not whether AI will transform science—it already has—but whether we can steer that transformation toward openness, safety, and genuine human flourishing. The age of the AI scientist has begun. Its ultimate shape depends not on machines alone, but on the choices we make as a scientific community.

Author's contributions

Guang-Guo Ying: Writing – original draft, review & editing.

Data availability

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Competing interests

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