



AI Scientists Fail Without Strong Implementation Capability

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The emergence of Artificial Intelligence (AI) Scientist represents a paradigm shift in scientific discovery, with large language models (LLMs) taking the lead as the primary executor in the entire scientific workflow from idea generation to experiment implementation. Recent AI Scientist studies demonstrate sufficient capabilities for independent scientific discovery, with the generated research reports gaining acceptance at the ICLR 2025 workshop and ACL 2025, arguing that a human-level AI Scientist, capable of uncovering phenomena previously unknown to humans, may be imminent. Despite this substantial progress, AI Scientist has yet to produce a groundbreaking achievement in the domain of computer science on par with automated scientific tools. Based on extensive quantitative evidence from existing benchmarks in complex engineering tasks and a systematic evaluation assess 28 research papers generated by five advanced AI Scientist systems, we argue that **the fundamental bottleneck for AI Scientists lies in their capability to execute the requisite verification procedures**. Current AI Scientist systems lack the execution capabilities needed to execute rigorous experiments and produce high-quality scientific papers. To better illustrate the root cause of this **implementation gap**, we provide an in-depth discussion on the fundamental limitations of AI Scientist. This position paper aims to call for the participants in the community to bridge the implementation gap.

Keywords: AI Scientist, Implementation Gap, Hypothesis and Verification.



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Projects: <https://ai-researcher.net>



Code Repository: <https://github.com/ResearAI/Awesome-AI-Scientist>



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1. Introduction

The automation of scientific discovery has long been one of humanity’s deepest desires (Langley, 1987, King et al., 2009, Radensky et al., 2024, AI, 2025). In recent years, with the advances in deep neural network technology, a range of **automated scientific tools** has emerged, leading to groundbreaking achievements in fields such as biomedicine (Yang et al., 2025c, Jumper et al., 2021), chemistry (Stokes et al., 2020), and materials science (Szymanski et al., 2023). For instance, DeepMind’s AlphaFold can determine the 3D structures of proteins in just a few hours, a task that previously took years to solve (Jumper et al., 2021). In recent, researchers developed an autonomous laboratory, A-Lab, which successfully synthesizes 41 novel inorganic materials within 17 days (Szymanski et al., 2023). However, these scientific tools still rely heavily on human involvement. Researchers must first formulate ideas to be tested, while AI is responsible for the



labor-intensive tasks of verification and iterative search. Therefore, these systems cannot be considered as truly automated scientific research.

The emergence of LLM-based **AI Scientist** has propelled the automation of scientific research to the next level, with AI taking the lead as the primary executor of scientific discovery, managing the entire workflow from idea generation to experiment execution (Lu et al., 2024, Weng et al., 2025). Recent studies have shown that research papers produced by AI Scientist have already reached the level of submissions to major machine learning conferences (Si et al., 2024, Yamada et al., 2025, Intology, 2025). As shown in Figure 1, we demonstrate the progress made by AI Scientist-v2 (Yamada et al., 2025), and the research output has received review scores exceeding the average acceptance threshold for human-authored papers. Similarly, researchers present an empirical validation through multiple peer-reviewed publications accepted at ICLR 2025 workshops and ACL 2025 main conference (Intology, 2025). Despite this substantial progress, AI Scientist has yet to produce a groundbreaking achievement in the domain of computer science on par with automated scientific tools (e.g., AlphaFold (Jumper et al., 2021)).

In this position paper, we first propose a conceptual framework (Section 2) that defines an AI Scientist as **an advanced end-to-end system capable of independently formulating scientific ideas and performing the implementation for verifying these ideas**. This definition forms the theoretical foundation of our position, aligns with current research progress (Lu et al., 2024, Weng et al., 2025, Yamada et al., 2025), and emphasizes that the core capability of an AI Scientist lies in generating innovative and feasible ideas at scale (Si et al., 2024, Wang et al., 2024a, Hu et al., 2024, Yang et al., 2025d). The idea-generation capability is a key feature that sets AI Scientists apart from automated scientific tools. While recent advances demonstrate that AI Scientists can generate highly innovative ideas (Si et al., 2025), their implementation capabilities remain constrained (Chan et al., 2024, Starace et al., 2025, Xiang et al., 2025, Siegel et al., 2024, Padigela et al., 2025), creating a significant gap between innovative idea generation and complete implementation.

Our Position: *The fundamental bottleneck for AI Scientists lies in their implementation capability to effectively execute the verification of these ideas.*

We defend our argument by analyzing quantitative evidence from existing benchmarks used to evaluate LLMs’ abilities in performing complex engineering tasks (Section 3.2). While LLMs can generate highly novel ideas (Si et al., 2024, Chai et al., 2024, Gottweis et al., 2025), their performance in experiment execution is exceptionally poor (Table 1). For instance, a leading LLM like Claude 3.5 Sonnet scored only 1.8% on PaperBench (Starace et al., 2025). This **implementation gap** is further supported by a systematic evaluation (Section 3.3), which leverages a state-of-the-art review model, DeepReviewer-14B (Zhu et al., 2025), to assess 28 research papers generated by five advanced AI Scientist systems. The results demonstrate that current AI Scientist systems lack the execution capabilities needed to execute rigorous experiments and produce high-quality scientific papers. Finally, to clearly illustrate the root cause of the implementation gap, we provide an in-depth discussion on the fundamental limitations of AI Scientist (Section 4).

In summary, this paper validates and deeply analyzes the implementation gap in existing AI Scientist systems based on extensive quantitative evidence and a simulated peer-review process. Furthermore, as the development of AI Scientists will bring greater regulatory challenges, we comprehensively examine the ethical considerations (Section 5) faced by AI Scientists and suggest directions for future research (Section

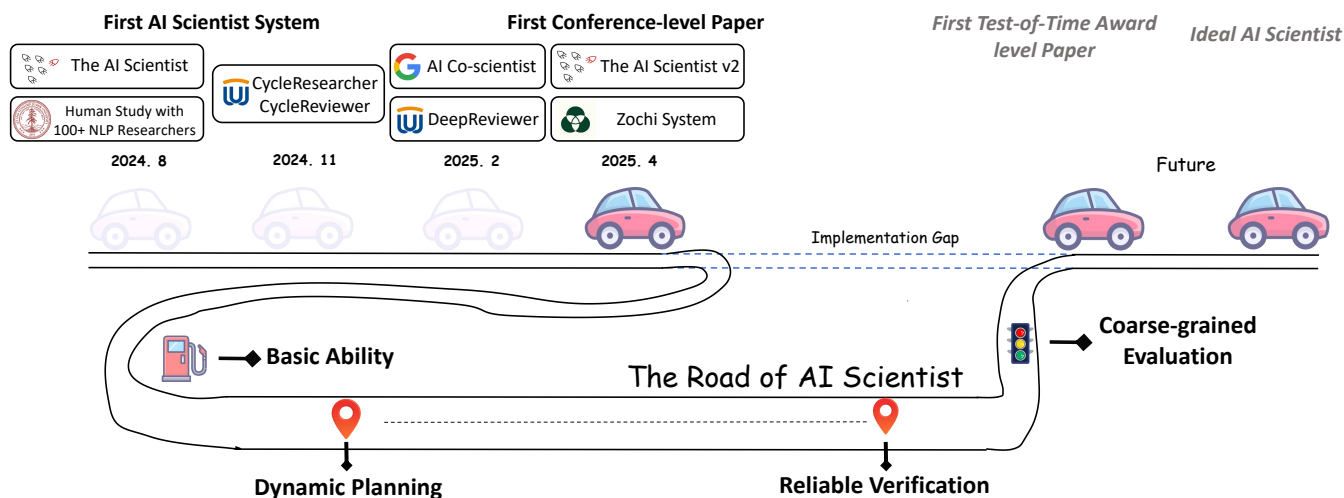


Figure 1: The roadmap of AI Scientist from 2024 to future, highlighting key milestones and fundamental challenges that must be overcome to bridge the implementation gap of AI Scientist.

6). We hope this position paper will contribute to a clearer understanding of the limitations of current AI Scientist, shedding light on the future development of AI Scientist.

2. Definition of the AI Scientist

The emergence of automated scientific tools has accelerated scientific discovery across numerous domains (King et al., 2009, Yang et al., 2025c, Jumper et al., 2021, Stokes et al., 2020, Szymanski et al., 2023). However, these tools fundamentally operate within a paradigm where human researchers remain in the dominant position of scientific discovery, and thus cannot be classified as fully automated AI Scientists. In this section, we first provide a detailed discussion of the unique characteristics of the AI Scientist (Section 2.1). Building on this discussion, we then propose a conceptual framework that formally defines the AI Scientist in a mathematical form (Section 2.2).

2.1. Unique Characteristics

Scientific tools, originating from AI for Science research, represent specialized AI systems designed to solve specific scientific problems by processing data and generating results within defined domains. These tools have demonstrated remarkable success across diverse scientific fields, including protein structure prediction (e.g. AlphaFold) (Jumper et al., 2021), antibiotic discovery through deep learning approaches (Stokes et al., 2020), and autonomous chemical research with large language models (Boiko et al., 2023). These scientific tools funda-

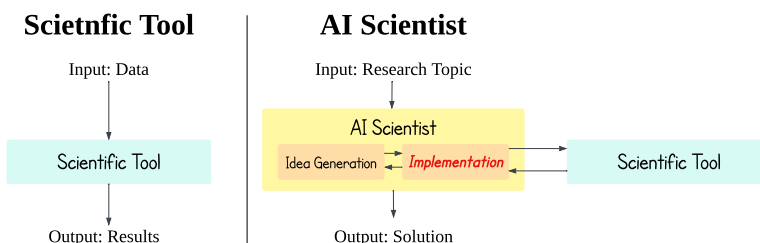


Figure 2: The difference between AI Scientist and scientific tool. Scientific tools generate predictions under human supervision, while AI Scientist autonomously leverage tools to address research questions.



mentally operate within a knowledge-dependent collaborative framework between humans and AI.

AI Scientist represents a research paradigm shift where AI assumes the role of an autonomous scientist capable of conducting independent scientific research. As illustrated in Figure 2, while scientific tools operate under human supervision, receiving data as input and producing predictions as output, AI Scientist goes a step further by demonstrating autonomous scientific reasoning capabilities. It accepts research questions as input and engages in iterative, self-directed interactions with scientific tools to generate comprehensive solutions. Unlike scientific tools that function as sophisticated instruments awaiting human guidance, AI Scientist exhibits genuine scientific agency, conducting end-to-end scientific investigations from question formulation to solution discovery (Yamada et al., 2025).

2.2. Conceptualized Framework

Our Definition: An AI Scientist is an advanced end-to-end system capable of independently formulating scientific ideas and executing the requisite verification and falsification procedures.

We define an AI Scientist, denoted as S_{AI} , as a fully autonomous scientific intelligence capable of independently performing diverse scientific research tasks. Different from a general scientific tool, it must possess dual capacities, including idea generation and experimental execution. A complete scientific research task typically originates from an initial scientific question Q_{init} and leverages existing domain knowledge \mathcal{K}_{domain} . An AI Scientist, denoted S_{AI} , operates within the scope of human ethical constraints \mathcal{R}_{human} and resource constraints \mathcal{B}_{res} to conduct this task. The primary output is the generation of novel scientific knowledge \mathcal{K}_{new} and associated verifiable artifacts \mathcal{A}_{sci} . The process through which an AI Scientist aims to achieve the optimal output from a scientific research task can be formally represented as:

$$(\mathcal{K}_{new}, \mathcal{A}_{sci}) \leftarrow \max\{S_{AI}(Q_{init}, \mathcal{K}_{domain}, \mathcal{R}_{human} | \theta_{AI}, \mathcal{B}_{res})\} \quad (1)$$

3. Arguments for Implementation Capability

We argue that the fundamental bottleneck limiting AI Scientists lies not in their idea generation capabilities, but in their capacity to execute rigorous implementation procedures required for reliable scientific research. To support this position, we present three lines of evidence: systematic analysis of research trends in the AI Scientist literature (Section 3.1), comprehensive benchmark analysis across multiple evaluation frameworks (Section 3.2), and systematic peer review assessment using LLM-as-a-Judge methodology (Section 3.3).

3.1. Research Trend of AI Scientist

Our statistical analysis of AI Scientist papers on arXiv up to May 23, 2025 (see Appendix B for details), reveals key trends illustrated in Figure 3. The lower panel of the figure shows that while the total number of publications is growing, studies focusing on idea generation without concrete implementation details consistently outnumber those incorporating such implementations. Despite this disparity in publication

Table 1: State-of-the-art (SoTA) LLMs show relatively low accuracy on code implementation on different tasks. The listed benchmarks are collected from diverse domains. The table below details their tasks, domains, scale, methods, and performance.

Benchmark	Task Description	Domains	Scale	LLM	Acc. Performance
MLE-Bench(Chan et al., 2024)	AI Training task	Applied ML	75	OpenAI o1-preview	16.90%
PaperBench (Starace et al., 2025)	ICML paper Replicating	NLP, CV, ML	8,316	OpenAI o1-high	26.00%
SciReplicate-Bench (Xiang et al., 2025)	Code Generation	NLP	100	Claude-Sonnet-3.7	39.00%
CORE-Bench (Siegel et al., 2024)	Scientific Paper reproduction	Computer Science, Social Science, and Medicine	270	OpenAI GPT-4o	55.56%
ML-Dev-Bench (Padigela et al., 2025)	AI training task	ML	30	Claude-Sonnet-3.5	50.00%

numbers, the upper panel indicates a crucial counterpoint: papers that include substantive implementation details achieve a significantly higher average number of citations. This signals strong community valuation for executable advancements and underscores the importance of addressing the implementation gap. This then raises a critical question: if implementation-focused research garners higher impact, why does its volume remain markedly lower? This disparity strongly implies that the path of implementation is fraught with substantial challenges.

3.2. Quantitative Analysis

Empirical Evidence of Implementation Gap. Advanced LLMs achieve near-saturated performance on simple code generation benchmarks like HumanEval (Chen et al., 2021, Liu et al., 2023, Yang et al., 2025a). For example, o3 exhibits excellent problem-solving capabilities in the 99.8th percentile of human performance on algorithmic competition platforms like Codeforces. However, the performance of SoTA LLMs **drops dramatically when it comes to real-world research scenarios**. As depicted in Table 1, we compare existing benchmarks for evaluating LLM agents’ abilities to perform challenging machine learning research tasks, including MLE-Bench (Chan et al., 2024) (solving Kaggle machine learning tasks, evaluated by medal rates), PaperBench (Starace et al., 2025) (replicating ICML research papers from scratch, assessed by replication scores), SciReplicate-Bench (Xiang et al., 2025) (generating executable code from NLP algorithm descriptions, measured by execution accuracy), CORE-Bench (Siegel et al., 2024) (reproducing computational results from scientific papers, determined by accuracy), and ML-Dev-Bench (Padigela et al., 2025) (completing diverse ML development workflow tasks, assessed by success rates). Each takes a different approach to measuring how well AI systems can automate aspects of ML research. These evaluations consistently demonstrate that LLMs face difficulty in translating conceptual understanding or initial plans into

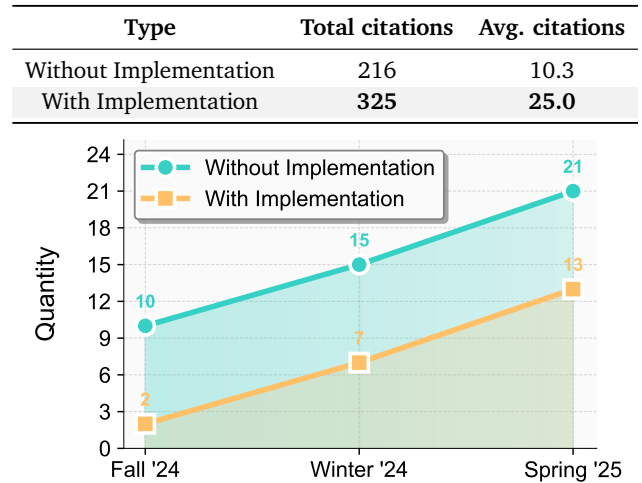


Figure 3: Analysis of AI Scientist publications on arXiv. The upper panel displays the average number of citations up to now, categorized by containing implementation details. The lower panel shows the growth in the total number of these papers with the same categorization.



verifiably correct and operational code. This “**implementation gap**” fundamentally limits AI Scientist’s verification capabilities.

Beyond Code Generation. The complexity of real-world research implementation processes extends far beyond simple code generation tasks, often requiring sustained reasoning and multi-step problem-solving. However, current LLMs exhibit relatively weak performance on such complex challenges. LiveCodeBench (LCB) (Jain et al., 2024), a more complex evaluation benchmark than Humaneval (Chen et al., 2021) that collects problems from periodic contests on LeetCode, AtCoder, and Codeforces platforms, evaluates Code LLMs across diverse code-related scenarios, including code generation, execution, self-repair, and output prediction. o4-mini achieves SoTA performance on the code generation subtask with **only 52.1% pass@1 score**. This poor performance on complex coding tasks reveals that AI scientists lack the implementation ability to handle sophisticated code-based research scenarios.

Implementation and verification. We observe that the verification bottleneck emerges across multiple stages of the research process. SciReplicate-Bench (Xiang et al., 2025), which tasks LLM agents with generating Python code to reproduce algorithms from NLP research papers, reveals that despite agents demonstrating an understanding of algorithmic logic (evidenced by high reasoning graph accuracy), they struggle with code execution. The best agent achieved only **39%** execution accuracy, indicating its generated code passed functional test cases for just **39%** of the tasks, highlighting a **failure to ensure implementation correctness and runtime behavior**. Similarly, PaperBench (Starace et al., 2025) requires LLM agents to replicate entire machine-learning papers from scratch by developing codebases and running experiments. While agents can generate code components (e.g., o1-High achieving **43.4%** success on weighted “Code-Development” sub-tasks), their performance on subsequent verification stages is poor. On rubric-defined leaf nodes for “Execution” (successfully running the code) and “Result Match” (quantitatively matching the paper’s reported results), Claude 3.5 Sonnet scored only **1.8%** and **0.7%** respectively. This poor performance indicates a breakdown in ensuring the developed solution operates correctly and produces the intended outcomes.

Discussion. The verification challenge extends beyond initial code implementation to debugging, iterative refinement, and validation of experimental outcomes. Evidence from MLE-Bench and ML-Dev-Bench (Chan et al., 2024, Padigela et al., 2025) shows that LLM agents frequently fail to debug their code or produce valid submissions, with **20%** of o1 preview runs on MLE Bench failing this step, and struggle to optimize model performance. Debugging, an explicit verification procedure, also indicates persistent agent failures that highlight the verification bottleneck (Chan et al., 2024). The incapacity to iteratively refine solutions towards better performance, illustrated in ML-Dev-Bench where all tested agents scored **0%** on “Model Performance” tasks, further signifies deficiencies in robust verification loops essential for scientific advancement (Padigela et al., 2025). Furthermore, CORE-Bench, which requires agents to reproduce results and then answer questions based on these outputs, assesses the verification of entire computational experiments. This process, involving multiple stages of reproduction and reasoning, presents significant challenges. For instance, the imperfect success rates (e.g., CORE-Agent with GPT-4o achieved **55.56%** on CORE-Bench Medium) highlight the difficulties in this complex verification process (Siegel et al., 2024). These difficulties across verification tasks suggest that enhancing AI Scientists’ systematic verification capability is crucial for their maturation into ideal AI Scientists. Current LLMs, while proficient in content generation, fail to rigorously validate their outputs against explicit criteria, a foundational component of scientific practice.



Table 2: DeepReviewer-14B Evaluation of AI-Generated Papers from Various AI Scientist Systems. Scores reflect averages across the 'Num' of available papers. Note: Publicly available papers may be curated and not fully representative of typical system output.

AI Scientist System	Num	Soundness↑	Presentation↑	Contribution↑	Decision↑	Rating↑	Percentile↑
HKUSD AI Researcher	7	1.75	1.46	1.57	0.0	2.57	3.43%
AI Scientist	10	2.08	1.80	1.75	0.0	3.35	8.22%
AI Scientist v2	3	1.67	1.50	1.50	0.0	2.33	2.04%
CycleResearcher-12B	6	2.25	1.75	2.13	0.0	3.75	16.88%
Zochi	2	2.38	2.38	2.25	0.0	4.63	29.96%

3.3. LLM-as-a-Judge Reveals the Implementation Weaknesses

To further support the existence of implementation gap, we employ a simulated peer review methodology to assess the actual quality of scientific outputs from current AI Scientist systems, particularly their implementation-level reliability. We select 28 publicly available research papers generated independently by five different AI Scientist systems and utilize the SoTA review model DeepReviewer-14B (Zhu et al., 2025) to conduct systematic evaluation under unified standards. We acknowledge that potential selection bias in the public availability of these papers (e.g., researchers may only publish better-performing outputs) means our evaluation results may not fully represent the average output quality of these systems across all scenarios. Nevertheless, **this analysis provides valuable insights into the general quality level of current AI-generated research papers.**

Quantitative Assessment Results. As Table 2 demonstrates, DeepReviewer-14B assigns generally low average scores to these AI-generated papers across multiple core dimensions. The Rating scale ranges from 1-10, where a score of 6 indicates acceptable quality, while Soundness, Presentation, and Contribution scores range from 1-4. The highest-rated system, Zochi (with a sample size of 2 papers), achieves **an average rating of only 4.63**, while other systems score even lower, typically in the 2-3 point range. These quantitative scores reveal that current AI Scientist systems face **significant challenges in independently producing high-quality research papers.**

Table 3: Defect Categories and Their Issues.

Defect Category	Number	Percentage
Experimental Weakness	28	100%
Methodological Unclear/Flaws	27	96.4%
Writing & Presentation Issues	26	92.9%
Novelty Concerns	25	89.3%
Theoretical Weakness	24	85.7%
Literature Review Deficiencies	22	78.6%
Practicality & Robustness Gaps	21	75.0%
Reproducibility Issues	20	71.4%
Computational Cost Concerns	18	64.3%
Component Analysis	16	57.1%
Hyperparameter Analysis Lacking	16	57.1%
Ethical Considerations Missing	3	10.7%

Table 3 shows that among the twelve major defect categories, “Experimental Weakness” appears across all 28 evaluated AI-generated papers, with a 100% occurrence rate. **This finding supports our positions regarding implementation capability limitations**, in experimental design, execution, and result analysis. The second and third most prevalent issues are “Methodological Unclear/Flaws” (96.4%) and “Writing & Presentation Issues” (92.9%), which reflect AI Scientists’ insufficient ability to clearly articulate and implement research plans. “Novelty Concerns” (89.3%) and “Theoretical Weakness” (85.7%) occur frequently, indicating that when AI Scientists generate complete papers, they struggle to propose original scientific contributions with solid theoretical foundations. The prevalence of these high-frequency defects highlights **systemic issues in the scientific rigor and implementation quality of current AI-generated research**, falling below the standards for reliable and valuable scientific outputs.

4. Rooted Limitations of Execution Capabilities

Our empirical analysis (Section 3) reveals a clear pattern that while AI Scientists are conceptualized as advanced iterations of traditional scientific tools, they consistently fail at implementation and verification procedures across diverse scientific contexts. This raises a critical question: Why do these sophisticated systems fail to achieve consistently strong results, especially when traditional scientific tools, wielded by human researchers, prove highly effective? To understand this paradox, we provide a discussion on the root cause of the implementation gap (Section 4.1) and present an in-depth analysis of the fundamental limitations of AI Scientist (Section 4.2).

4.1. Two Primary Facets of Implementation Gap

The implementation gap for AI Scientists comprises two primary facets: (1) **AI Scientists often exhibit bottlenecks in the planning and execution stages**. This manifests in three key areas: **failures in long-range logical reasoning** required for coherent experimental design, **inadequate multi-agent collaboration** capabilities including strategic planning across complex multi-file implementations and converting conceptual ideas into working code, and **insufficient coordination** with external tools and systems; (2) Even when implementation code is generated, **AI Scientists demonstrate fundamental weaknesses in evaluation processes**. This includes failures in debugging capabilities, experimental validation, result interpretation, and iterative refinement based on experimental feedback. Current systems lack robust mechanisms for assessing implementation quality, validating experimental outcomes, and providing reliable feedback loops that can guide subsequent implementation improvements.

Prevent building “castle in the air”. Agent tools often produce difficult-to-verify code and experiments, while evaluation gaps prevent AI Scientists from recognizing and correcting implementation issues through iterative refinement. Without fundamentally enhancing both capabilities, the idealized AI Scientist capable of independent scientific exploration will remain inefficient.

4.2. Rooted Limitations

From the current literature on AI scientists, we conclude four major limitations that collectively explain why AI scientists struggle with complex, multi-stage implementation processes:

Limitation 1: fundamental cognitive and execution capabilities. Scientific implementation requires sophisticated long-range logical reasoning across multiple abstraction levels. Existing LLMs demonstrate significantly decreased coherence and robustness as reasoning chains extend (Wu et al., 2025b,a), and increased thinking time does not necessarily yield stronger performance (Ballon et al., 2025). Furthermore, LLM-based agents possess limited capacity to retain past interaction information, with memory deteriorating as text length increases (Pink et al., 2025, Cemri et al., 2025). Most critically, mainstream language models exhibit markedly weaker performance in multi-turn dialogues or multi-step interactive tasks requiring context coherence, deep understanding, and state tracking, with average performance decreases reaching 39% (Laban et al., 2025). This capability degradation in scenarios involving long-range dependencies and complex interactions directly **constrains AI Scientist performance in executing complex scientific experiments** requiring sustained attention and coherent reasoning chains.

Limitation 2: strategic planning and reasoning. Scientific implementation requires comprehensive

abilities for strategic reasoning, continuous monitoring, and dynamic adjustment across all research stages (Lu et al., 2024, Yamada et al., 2025). High-quality research implementation demands global planning abilities spanning entire codebases, which typically contain multiple interdependent files with hundreds of lines requiring coordinated modification (Jimenez et al., 2024, Aleithan et al., 2024). Long-term, complex scientific exploration tasks such as discovering new materials, and modeling complex biological systems particularly require continuous iteration of research directions and experimental strategies over extended time scales based on emerging results and external feedback (Merchant et al., 2023, Brix et al., 2025, Weng et al., 2023). However, current LLMs demonstrate inadequate adaptive planning and metacognitive abilities when handling highly open, creative scientific research requiring dynamic adjustments to overall research blueprints. While reinforcement learning approaches may potentially enhance LLMs’ generalization and metacognitive capabilities, the resource investment required for “inventor” roles like AI Scientists that need to perform complex asynchronous operations and real-world interactions proves enormous. Figure 4 highlights AI’s acceleration over human performance in complex tasks such as reasoning and web-based research. While AI Scientists also achieve tasks faster than humans, their estimated single-sample RL training time is orders of magnitude greater than simpler AI agents. This substantial increase in required sampling time (detailed in Appendix A) underscores the immense challenge of developing AI Scientists via standard RL methodologies.

Limitation 3: multi-agent col-

laboration.

Ideal AI Scientist should seamlessly integrate into complex research ecosystems, engaging in efficient, accurate interactions and coordination with human scientists, other AI agents, and external tools (Guo et al., 2024, Qian et al., 2024, Pu et al., 2025b). This requires AI Scientist to not only understand instructions conforming to collaborative protocols but also precisely execute the implementation phases assigned to it

within tasks and reliably feed its outputs back to the collaborative network (Bo et al., 2024, Zhang et al., 2024). However, current LLM Agents still have considerable room for improvement in robustness and adaptability when interacting with dynamic environments (Wei et al., 2025). For instance, when calling a series of external APIs to complete a complex scientific computational process, LLM often struggles to handle subtle changes in API interfaces, and other practical engineering issues (Shen et al., 2025).

Limitation 4: evaluation and verification. Existing benchmarks such as MLE-Bench (Chan et al., 2024) and PaperBench (Starace et al., 2025) primarily focus on the complete reproduction of code and experiments from papers. SciReplicate-Bench (Xiang et al., 2025) emphasizes generating necessary code from scientific papers, while ScienceAgentBench (Chen et al., 2025) concentrates on independent and singular data-driven tasks. **However, there is currently a lack of a comprehensive benchmark that can evaluate the entire scientific workflow**, from initial idea generation through to final implementation and completion. This absence makes it difficult to fairly compare the end-to-end capabilities of different AI Scientist systems.

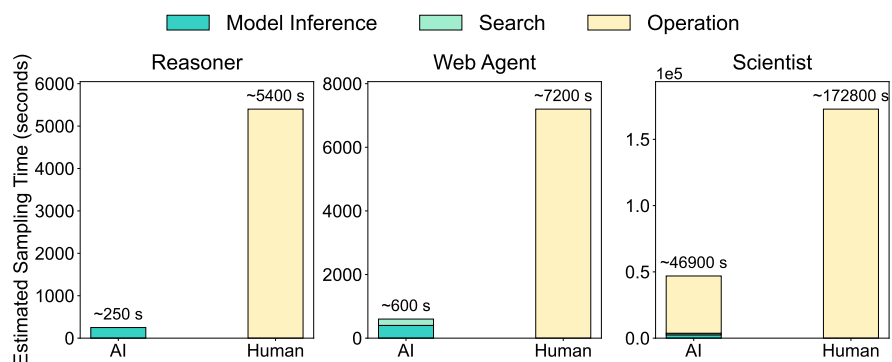


Figure 4: Estimated time to solve representative tasks for different agent types (AI vs. Human), which for AI agents also corresponds to single-sample RL sampling duration.



Additionally, there is a deficiency in evaluation approaches that incorporate measures for external supervision during the AI Scientist's implementation process. The deeper issue is that the quality of scientific discovery often lacks unified objective standards, and the process of scientific exploration is filled with uncertainty and openness, making comprehensive evaluation and effective supervision of AI Scientist's verification capability exceptionally difficult. Evaluating AI Scientist's output (e.g., generated papers) from a peer review perspective, while being a results-oriented assessment method, also has inherent limitations. As in human research systems, even experienced peer reviewers may not always accurately identify the groundbreaking and far-reaching work. A frequently cited example is that the word2vec paper (Mikolov et al., 2013) was initially rejected by ICLR 2013, but later received the "Test of Time Award" at NeurIPS 2023. Extensive experimental analyses have demonstrated that review scores are not reliable indicators for predicting future impact (Abramo et al., 2019, Cortes and Lawrence, 2021), suggesting that peer review may be more suitable for filtering low-quality papers rather than identifying the highest quality papers.

5. Ethical Considerations

***Sub-Position:** AI scientists are in urgent need of a comprehensive system for generation management and quality evaluation.*

As autonomous research agents, AI Scientists lack values and moral constraints. They are incapable of making ethical judgments about the societal impact of their work, and they do not self-regulate based on potential risks associated with their findings (Bengio et al., 2025). As AI Scientists possess stronger capabilities in idea generation and experiment execution, their influence on scientific research and society could far surpass that of current LLMs and scientific tools (e.g., Deep Search, AutoSurvey (Wang et al., 2024c)). In the absence of proper oversight, **AI Scientists may: (1) be misused**, overwhelming the peer review system, leading to a decline in overall research quality; **(2) enter unethical or dangerous research domains**, autonomously generating and publishing sensitive findings that accelerate the development of harmful technologies; **(3) weaken the quality of PhD training**, leading to a decline in human research standards and overall scientific literacy. To prevent the above situations, **we argue that AI Scientists are in urgent need of a comprehensive system for generation management and quality evaluation**, thus enabling effective behavior regulation within the human moral framework (Jobin et al., 2019). This system should include, but not be limited to, the following components:

(1) Implement measures to prevent AI-generated content from disrupting human review systems: Effective strategies should be adopted to ensure that AI-generated articles do not interfere with human peer-review systems while maintaining high standards of quality. This includes establishing a centralized platform to archive scientific outputs generated by AI Scientists, developing automated detection systems to identify such content, and creating specialized evaluation tools (e.g., DeepReview (Zhu et al., 2025)) to assess the quality of AI-generated research outputs. These tools should help identify and filter low-quality content, thereby reducing the burden on the peer review process. All AI-generated outputs must be transparently labeled and reviewed, including information on their origin, generation methods, and scientific tools.

(2) Establish boundaries and strengthen training programs: Implement clear boundaries between human-led and AI-led research processes to ensure that PhD students receive comprehensive training. Key



components of doctoral education(e.g., idea testing), should prioritize human involvement to maintain high standards of scientific literacy. Additionally, guidelines should be established to prevent over-reliance on AI Scientists in PhD training, ensuring that AI tools serve as supplements rather than substitutes in the educational process.

(3) Formulate an ethics and responsibility convention: A global convention should be established to define the ethical boundaries and risk management principles for AI-driven research (Huang et al., 2022). All researchers and institutions utilizing AI Scientists must fully disclose the generation process, algorithmic sources, training data, and potential societal risks of their findings. Additionally, a hybrid mechanism combining automated and human-in-the-loop review should be implemented for continuous ethical oversight and risk evaluation, ensuring that AI Scientist research activities remain within socially safe boundaries (Jobin et al., 2019, Khan et al., 2022). Furthermore, appropriate legislation should be developed to regulate AI Scientists by imposing strict limitations on their use for specific research purposes.

6. Future Directions

This section outlines feasible pathways to bridge the current implementation capability gap of AI Scientists. Addressing foundational **Basic Abilities** is paramount. While scaling laws for pre-training and post-training (Kaplan et al., 2020, Zhang et al., 2025) promise progressive LLM improvements, immediate strategies like well-defined Workflows (Li et al., 2024d, Gu et al., 2024b) also can mitigate current implementation weaknesses. Structuring research processes with human-defined tools allows for guided AI execution and targeted interventions. For instance, Retrieval Augmented Generation (RAG) can counteract limitations in handling long texts or accessing current information (Fan et al., 2024, Arslan et al., 2024), thus expanding the knowledge scope of AI systems.

A significant challenge for sophisticated **Strategic Planning** is the immense resource consumption of RL (Cao et al., 2024). A promising direction to alleviate this involves leveraging LLMs to simulate aspects of the environment or task execution, thereby accelerating the RL feedback loop (Sun et al., 2025). By allowing the RL agent to receive quicker, albeit potentially approximate, feedback on its actions, particularly for operations that are inherently time-consuming in the real world, the sampling efficiency may be significantly improved. This could reduce the extensive wall-clock time typically required for training robust long-horizon planning and adaptive meta-thinking capabilities in complex scientific domains.

Ensuring **Reliable Verification and Fostering Collaboration** is crucial. Standardized protocols like MCP and A2A (Yang et al., 2025b, Ray, 2025, Hou et al., 2025) can establish basic interoperability. A promising direction is to build modular multi-agent systems, where specialized AI agents for sub-tasks (e.g., literature review, code generation) are coordinated by a central “Planner Agent” trained via advanced RL, leveraging existing tools (e.g., PASA (He et al., 2025)) rather than reinventing capabilities. Furthermore, enhanced oversight of AI Scientist inference processes is imperative, not just to prevent benchmark “hacking”, but also to instill ethical boundaries against unscrupulous data acquisition or other problematic behaviors.

Finally, the **Evaluation** of AI Scientists (Chang et al., 2024) must evolve towards a holistic, coarse-grained paradigm reflecting real-world scientific discovery’s multifaceted nature. Scientific breakthroughs involve both practical utility and novelty. Thus, evaluation frameworks should go beyond single-metric optimization, adopting multi-objective criteria that assess performance gain, originality, experimental rigor, and communication clarity. This multi-faceted approach will offer a more accurate measure of an AI Scientist’s true



contribution, guiding development toward impactful scientific exploration.

7. Conclusion

The rise of AI Scientists marks a paradigm shift in scientific discovery, with large language models (LLMs) now driving the workflow from idea generation to experiment execution. Recent systems have shown promise, producing research accepted at ICLR 2025 workshops and sparking discussions on the imminence of human-level AI Scientists. However, despite this progress, AI Scientists have yet to achieve breakthroughs in computer science comparable to traditional automated tools. Based on benchmark analyses and a systematic evaluation of 28 papers from five leading AI Scientist systems, we identify a core bottleneck: the inability to reliably execute and verify experiments. This implementation gap limits both scientific rigor and the quality of the research output. We analyze its root causes and call on the community to address this critical limitation.

Alternative Views. An alternative viewpoint suggests that AI Scientists need not pursue completely autonomous implementation capabilities in the short term, but rather facilitate human-machine collaboration as Co-scientists to assist humans. This approach avoids the deficiencies of LLMs in Dynamic Planning capabilities and Reliable Verification capabilities, instead allowing AI to focus on its strengths, such as idea generation, while humans execute the specific experimental results (Weng et al., 2025). If an AI system, though unable to independently complete all implementation details, can increase human scientists’ efficiency tenfold, or help human scientists conceive and verify complex ideas previously beyond reach, then it undoubtedly also qualifies as a successful “collaborative scientist.”

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A. Sampling Time Calculation for Different Types of AI Agents

We referenced existing literature (Guo et al., 2025, Yang et al., 2025a, Muennighoff et al., 2025) and our experience to estimate the sampling time potentially required for different types of AI agents trained via reinforcement learning, as illustrated in Figure 4. Using a hypothetical 671B parameter LLM (similar to Deepseek-R1) running on 8 H100 cards (assuming 40 tokens generated per second), the pure inference time T_{infer_R} for a typical arithmetic reasoning task (generating approximately 10,000 tokens of reasoning content) might be around 250 seconds. For an AI Web Agent, the task might include generating approximately 8,000 tokens of instructions and reports ($T_{infer_WA} \approx 200s$), interspersed with approximately 20 API calls for information search (assuming each search and processing takes $T_{search_API} = 10s$, totaling $T_{search_total} = 20 \times 10s = 200s$), and potentially requiring reading and comprehension of up to 400,000 tokens of web content (assuming reading and comprehension time $T_{read_WA} \approx 200s$). The total sampling time is: $T_{sample_WA} \approx T_{infer_WA} + T_{search_total} + T_{read_WA} \approx 600s$.

In contrast, an AI Scientist executing end-to-end scientific discovery tasks has complexity and interaction requirements far exceeding the previous two types. We roughly estimate it might need to generate over 100,000 tokens of content (for example, operational and experimental code approximately 50,000 tokens ($T_{infer_code} \approx 1250s$), research paper writing approximately 30,000 tokens ($T_{infer_paper} \approx 750s$), reviewing and understanding relevant literature approximately 20,000 tokens ($T_{infer_lit} \approx 500s$)), with pure LLM inference time for just this portion being $T_{infer_CS} = T_{infer_code} + T_{infer_paper} + T_{infer_lit} \approx 2500s$. More critically, the "implementation" process of an AI Scientist, such as code writing, debugging, compiling, running experiments, and data analysis, is highly asynchronous and time-consuming. Assuming a rapid research code operation and experimental cycle (from writing to obtaining preliminary results) requires an average of $T_{op_code} \approx 12 \text{ hours} = 43200s$, while in-depth literature research and analysis might require $T_{op_lit} \approx 20 \text{ minutes} = 1200s$. Therefore, the total estimated sampling time to complete a relatively complete scientific exploration loop would be $T_{sample_CS} = T_{infer_CS} + T_{op_code} + T_{op_lit} \approx 2500s + 43200s + 1200s \approx 46900s$. As intuitively demonstrated in Figure 4, the sampling time required for an AI Scientist (approximately 46,000 seconds) far exceeds that of an AI Reasoner (approximately 250 seconds) and an AI Web Agent (approximately 700 seconds). Notably, AI Reasoners can typically rapidly generate large quantities of training samples through batch generation in parallel, whereas each implementation step of an AI Scientist (especially parts involving code execution and experiment waiting) is almost entirely asynchronous, and requires exclusive computational resources or experimental equipment for learning and feedback collection during operations. Consequently, in actual reinforcement learning training processes, the disparity in real training duration between AI Scientists and the former two types will be even more pronounced.

For the calculation of human duration, we referenced existing metrics. For instance, for reasoning tasks, we referred to the human time from the International Mathematical Olympiad, which is approximately 1.5 hours per problem. For Web Agent tasks, we adopted the average human problem-solving time from BrowseComp (Wei et al., 2025) (2 hours) as the human standard. For Scientist tasks, although each paper often requires months of collaborative work by multiple people, for ease of calculation, we used the human duration of 48 hours from PaperBench (Starace et al., 2025) for statistics; however, even under these conditions, humans achieve a success rate of less than 50%.

**Table 4:** Timeline of AI Scientist Ideas and Code Implementations by Month

	2024-08	2024-09	2024-10	2024-11	2024-12	2025-01	2025-02	2025-03	2025-04
w/o Exp	(Zheng et al., 2024)	(Ghifarollahi and Buehler, 2024), (Raden-sky et al., 2024)	(Pu et al., 2025a), (Yang et al., 2024), (Su et al., 2024), (Li et al., 2024a), (Hu et al., 2024), (Liu et al., 2025), (Wang et al., 2024b)	(Weng et al., 2025), (Xiong et al., 2024)	(Gu et al., 2024a), (Li et al., 2024b), (Yu et al., 2024)		(Gottweis et al., 2025)	(Rabby et al., 2025), (Saeedi et al., 2025)	(O’Neill et al., 2025), (Garikaparthi et al., 2025), (Sanyal et al., 2025)
w/ Exp	(Lu et al., 2024), (Li et al., 2024c)			(Liu et al., 2024b), (Liu et al., 2024a)		(Yuan et al., 2025), (Schmidgall et al., 2025)	(Jiang et al., 2025), (Kon et al., 2025)	(Schmidgall et al., 2025), (Jansen et al., 2025)	(Yamada et al., 2025), (Seo et al., 2025)

B. Regarding the statistics for the papers

We have conducted a comprehensive search on arXiv to gather relevant publications in the AI Scientist field. This collection includes a series of papers from August 2024 to April 2025 for methods or systems, which are cited in Table 4. It indicates that, to date, a significant number of papers have focused on Idea Generation tasks, often without concrete implementations.

Nevertheless, an encouraging trend has emerged since early 2025. As illustrated in Figure 3, implementation-focused research has demonstrated stronger growth momentum, with incremental growth nearly matching that of non-implementation studies by Spring 2025. This suggests the community is beginning to recognize the critical importance of implementation capabilities for developing truly effective AI Scientists—moving beyond theoretical constructs toward practical systems capable of reliable execution.