

AutoformBench: A Lean Formalization Benchmark for Advanced Mathematics

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AI systems are increasingly capable of producing machine-checked Lean proofs of advanced mathematical results. Real mathematical formalization, however, is not isolated theorem proving: it requires building the definitions and intermediate lemmas that connect a result to a formal library. Existing evaluations often provide isolated theorem statements in settings where much of this supporting theory is already available in Mathlib. We introduce AutoformBench, a benchmark of 341 Lean 4 formalization tasks drawn from 24 advanced mathematical sources. Lean-experienced mathematicians formalized and audited each target statement, leaving the corresponding Lean proof to the evaluated agent. Each problem is embedded in a broader mathematical development: agents receive the informal proof but must translate it into Lean while constructing the missing definitions, intermediate lemmas, and supporting infrastructure. We compare the performance of frontier models on these problems. We find a largely shared difficulty frontier: success depends less on mathematical domain than on models' ability to construct missing formal infrastructure.

Data and code at <https://github.com/facebookresearch/autoformbench>.

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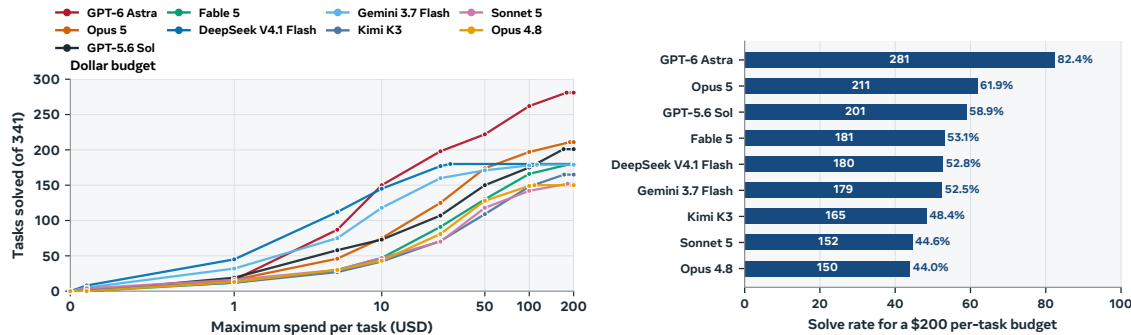


Figure 1 Performance and cost-efficiency of frontier models on AutoformBench. Left: number of tasks completed under increasing per-task dollar budgets. Right: solve rate at a \$200 per-task budget.

1 Introduction

As language models produce increasingly sophisticated mathematical arguments, verifying their output becomes a central bottleneck. Without reliable verification, scaling mathematical generation risks producing a growing body of plausible but incorrect results that is increasingly difficult to audit. Proof assistants, such as Lean, offer a way to make verification mechanical. In Lean 4, a small kernel checks every logical step, so an accepted proof provides a precise certificate relative to its formal statement and assumptions (de Moura and

Ulrich, 2021).

Producing that certificate for advanced mathematics is not merely a matter of finding the final proof. Formalization is cumulative: before proving a theorem, one must identify or construct the definitions, intermediate lemmas, and connections to Mathlib on which it depends (The mathlib Community, 2020).

This cumulative work is underrepresented in current evaluations. Neural theorem proving has progressed from language-model proof search (Polu and Sutskever, 2020; Lample et al., 2022) to systems capable of solving Olympiad and research-level problems (Hubert et al., 2026; Achim et al., 2025; Chen et al., 2026), but benchmarks such as miniF2F, PutnamBench, and ProofNet primarily test self-contained problems from mathematical competitions or undergraduate courses whose formal vocabulary is already supplied (Zheng et al., 2022; Tsoukalas et al., 2024; Azerbayev et al., 2023). Success on these tasks does not tell us whether an agent can navigate a new mathematical development, build its missing infrastructure, or do so efficiently.

The Jacobian Challenge (Buzzard, 2026) points toward this broader regime: its compact statements sit atop definitions and results that demand substantial formal development. Our proposed benchmark, AutoformBench, asks how far current agents can operate in this regime across mathematical domains. Each of its 341 problems provides a human-audited Lean statement, its local formal context, and the corresponding excerpt from one of 24 advanced mathematical sources. The agent must prove the target by interacting agentically with the provided material and with mathlib and by constructing any missing auxiliary definitions and lemmas. This makes AutoformBench a challenging test of long-horizon repository-level formalization - even the most state-of-the-art models require dozens of millions of tokens to complete 50% of the tasks (see Figure 1), highlighting the need for much more cost-efficient approaches before autoformalization can effectively scale to the mathematical literature and new research production.

Contributions.

- A benchmark of 341 audited Lean 4 proof-completion problems drawn from 24 advanced mathematical sources across diverse fields.
- An agentic evaluation environment powered by state-of-the-art Lean tools for reliable and convenient model testing.
- A controlled evaluation of nine frontier models, together with analyses of efficiency, generated infrastructure, and the boundary between solved and unsolved problems.

The dataset and the evaluation code can be found at <https://github.com/facebookresearch/autoformbench>.

2 Related Work

Benchmarks for formal mathematics. miniF2F and PutnamBench evaluate proofs of fixed formal statements drawn from high-school and undergraduate competitions (Zheng et al., 2022; Tsoukalas et al., 2024), while FormalProofBench pairs advanced undergraduate and graduate natural-language problems with Lean statements and evaluates proof production in a tool-enabled agent loop (Ravi et al., 2026). ProofNet, Lean Workbook, FormL4, NuminaMath-LEAN, and FormalMATH scale the construction or evaluation of paired informal and formal problems (Azerbayev et al., 2023; Ying et al., 2024; Lu et al., 2024; AI-MO, 2025; Yu et al., 2025). These collections primarily consist of independent theorem-level items drawn from competitions, educational material, or existing formal libraries. FATE instead focuses on algebra at increasing levels of difficulty: FATE-M contains textbook exercises, while FATE-X reaches beyond PhD qualifying exams and Mathlib coverage (Jiang et al., 2026). Each file centers on one final theorem with one proof hole; 38% of FATE-X tasks additionally introduce new definitions, averaging 2.4 among those tasks. SorryDB (Letson et al., 2026) moves toward realistic library context by extracting open proof obligations from Lean repositories. FormalQualBench contains 23 graduate-level theorem statements formalized in Lean and verified by a Lean expert for evaluating practical formalization workflows (Math Inc., 2026), while Formal Conjectures provides an evolving collection of solved and open research-level problems formalized in Lean (Firsching et al., 2026).

Research-level autoformalization. Autoformalization studies the translation of informal mathematics into formal language (Wu et al., 2022). Recent work has begun to formalize sustained mathematical developments:

general topology in Megalodon (Urban, 2026), real- and convex-analysis textbook material (Wang et al., 2026), and a graduate textbook using a largely autonomous multi-agent workflow (Gloeckle et al., 2026). AutoformBot extends this approach across 26 textbooks using a shared multi-agent pipeline (Rammal et al., 2026). More recent systems study document-to-project workflows for mathematical papers, long-horizon research developments, and mathematical discovery (Milikic et al., 2026; Zhang et al., 2026; Nie et al., 2026; Moakhar et al., 2026; Patel et al., 2026). Other projects formalize landmark research results, including sphere packing in dimension eight and De Giorgi–Nash–Moser theory (Hariharan et al., 2026; Armstrong and Kempe, 2026), and Anthropic’s formalization of Fermat’s Last Theorem (Anthropic, 2026e). The Jacobian Challenge (Buzzard, 2026) similarly highlights the substantial infrastructure needed for a compact advanced mathematical development.

AutoformBench complements these efforts by evaluating proof completion across many developments derived from advanced mathematical sources, with human-audited statements, access to the informal source, and rigorous verification of candidate solutions. It is designed to measure a model’s capability to interact with a body of mathematics, testing the skills required to formalize a large body of advanced mathematics - to our knowledge the first large-scale benchmark to do so.

3 Benchmark Construction

AutoformBench consists of challenging statements drawn from advanced mathematical sources spanning diverse mathematical domains and formalized by human experts.

Source material. We selected 24 openly available advanced mathematical sources from a variety of domains representative of the diversity of modern mathematics, ranging from algebraic geometry to the theory of probability. Most of these come from the excellent MIT OpenCourseWare selection of open courses (MIT, 2026). The full list of selected sources and their provenance can be found in Table 11 in the Appendix.

Within each book, we then selected statements with challenging proofs following a balanced distribution across chapters and subtopics, so as to maximize the diversity of the resulting tasks. We deliberately selected material beyond direct Mathlib (The mathlib Community, 2020) coverage, so that success requires constructing missing formal infrastructure rather than retrieving an existing theorem, while retaining enough nearby foundations for meaningful progress within a bounded agent run. Appendix F quantifies proximity to the pinned Mathlib revision.

Formalization protocol Human experts (at least PhD-level) from the annotation company Labelbox (Labelbox, 2026) were tasked with formalizing the selected theorems, as well as all the definitions and lemmas needed to state them, in Lean 4 (de Moura and Ullrich, 2021) (version 4.32). Each resulting formalization was then reviewed by an independent human expert, as well as by the authors assisted by frontier models.

Output This process resulted in 341 self-contained Lean workspaces containing 1,155 graded proof obligations. Each workspace has one headline target; one or more proposition-valued proof bodies are replaced by the Lean keyword `sorry`. At evaluation time, the tested model must replace every graded `sorry` with a correct Lean proof and may introduce additional definitions and helper lemmas. A task counts as solved only when the Lean kernel accepts all of its graded obligations. We release all 341 tasks in Harbor format. Appendix A gives the complete distribution of obligations and characterizes the formal context visible in the target statements.

4 Evaluation Protocol

Workspace and verification. For each problem, we construct a self-contained Lean workspace around the audited target statement. It contains a frozen file containing the statement and its supporting definitions, together with an editable copy of this file. The model must complete the statement’s proof in the editable file and may add further definitions and lemmas. A machine-readable specification identifies the results to grade and the foundational axioms that may be used. The workspace also contains the corresponding textbook statement, surrounding definitions, and informal proof. We execute these workspaces using Harbor (Merrill

et al., 2026; Harbor Framework Team, 2026), a general evaluation harness that standardizes how agent systems receive tasks and how their outputs are graded. Harbor runs the agent in an isolated Docker environment and invokes the grader in a separate, network-disabled container. When the run ends, only the editable solution and its auxiliary Lean files are transferred to the verifier; all other agent-side changes are discarded. The verifier inserts those files into a fresh copy of the original workspace and runs COMPARTOR (Lean FRO, 2025). Comparator checks that the submitted results prove exactly the original statements, do not alter definitions fixed by the benchmark, use only permitted axioms, and are accepted by Lean. Successful proofs are additionally replayed by Nanoda (Nanoda contributors, 2026), an independent proof-checking kernel. This strict protocol is needed to prevent models from cheating by leveraging their knowledge of Lean syntax, e.g. by using special keywords to trivialize the task by redefining key mathematical objects. Appendix B describes the workspace, budgets, tools, isolation procedure, and Harbor packaging in detail.

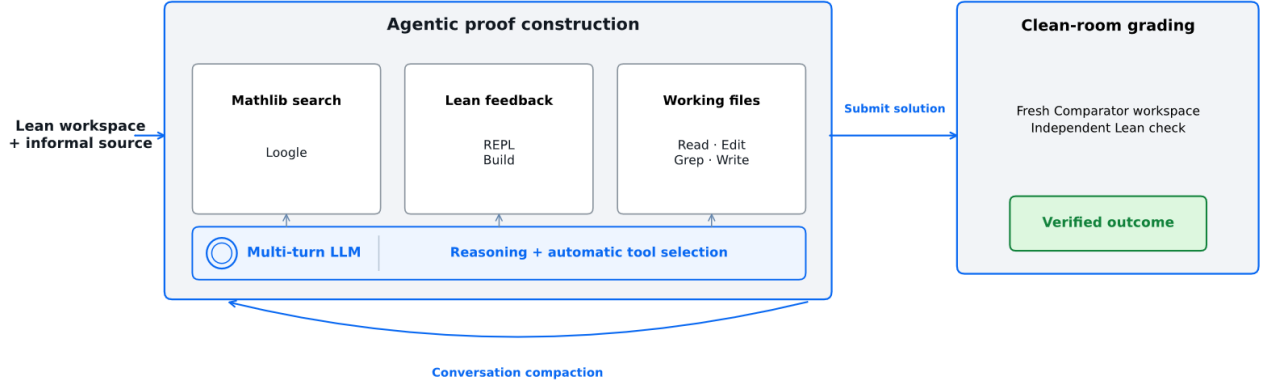


Figure 2 AutoformBench evaluation protocol. A multi-turn model edits an isolated Lean workspace using library search, executable Lean feedback, and file tools. Submitted solutions are independently checked in a fresh Comparator workspace; long runs continue through conversation compaction.

Agentic harness. Advanced formalization naturally requires an agentic workflow: the solver must navigate an unfamiliar development, search for existing library results, experiment with candidate proof fragments, interpret compiler feedback, and iteratively extend its solution. We therefore use a lightweight multi-turn harness. As shown in Figure 2, we provide three types of tools:

- **Filesystem tools** for navigating the workspace and editing submission files.
- **Lean-execution tools** that allow the model to test partial or complete candidate solutions against the Lean kernel and check their correctness.
- **Mathlib search** through Loogle (Breitner, 2023), for finding declarations in the pinned Mathlib library.

Tool execution is network-disabled, so the model cannot retrieve external solutions or documentation during a run.

The workspace serves as durable state throughout the trajectory. When the conversation approaches the model’s context limit, the harness compacts the interaction history into a summary while preserving the files and running tool environment. This allows the model to continue working across multiple context windows and enables test-time scaling through longer trajectories. Each run has a flat provider-cost cap of \$200 per problem. We derive reported dollar costs from provider-reported token counts using the public API prices for each model at the time of evaluation. A run terminates when the model calls `submit_report` or exhausts its budget.

5 Main Results

We evaluate OpenAI’s GPT-6 Astra and GPT-5.6 Sol (OpenAI, 2026b,a); Anthropic’s Claude Opus 5, Claude Opus 4.8, Claude Sonnet 5, and Claude Fable 5 (Fable 5 below) (Anthropic, 2026c,b,d,a); Google DeepMind’s Gemini 3.7 Flash (Google DeepMind, 2026); and DeepSeek V4.1 Flash and Kimi K3 (DeepSeek-AI, 2026; Kimi Team et al., 2026). The headline evaluation uses `xhigh` reasoning effort for GPT-5.6 Sol; `high` for

Gemini 3.7 Flash, Claude Sonnet 5, and Claude Opus 4.8; and **max** for Claude Opus 5, Fable 5, DeepSeek V4.1 Flash, Kimi K3, and GPT-6 Astra. A turn is one model response plus its tool-call batch. Figure 1 summarizes their verified performance with the \$200 budget cap. Appendix J.2 examines sensitivity to lower effort settings, while Appendix C gives the full cost breakdown. Note that the \$200 per-task budget used for the headline scores is a ceiling rather than a requirement for evaluating AutoformBench. Evaluators can choose a smaller fixed budget and still obtain a directly comparable leaderboard. We believe that this is an important point: cost efficiency is essential for the long-term impact of autoformalization, and formalizing the mathematical literature at well as the production of new research at scale will require models and inference harnesses that achieve strong performance at low computational cost. As such, AutoformBench can provide a natural benchmark for measuring progress under explicit cost constraints.

Budget-conditioned leaderboard. The tasks evaluated are extremely challenging, and most models require a very long context to solve them. Moreover, models can test their candidate solutions using Lean tools, which allows them to keep iterating until a correct solution is found. As such, the most informative metric is not the absolute success rate of a given model, but rather the number of problems solved given a certain budget (of tokens, turns, etc.).

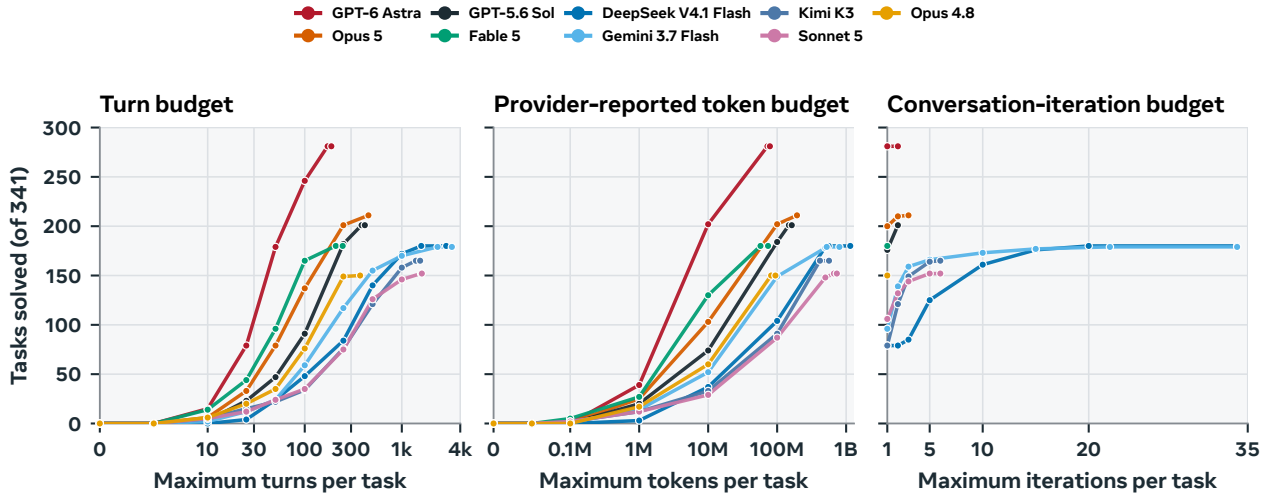


Figure 3 Budget-conditioned leaderboard on the 341 tasks by agent turns, provider-reported input plus output tokens, and conversation iterations (each context compaction starts a new iteration). Astra is highest from 10 turns, approximately 0.41 million total tokens, and the first conversation iteration onward. The corresponding dollar-budget view appears in Figure 1.

A verified task enters the curve once its recorded run reaches that resource level; failed tasks never enter. Figure 3 reports this score for three non-dollar per-task resource limits. At any fixed cutoff, the highest curve identifies the model with the greatest observed verified coverage under that constraint. We observe that our set of tasks is particularly challenging, with most frontier models requiring hundred of millions of read and written tokens to reach a 50% completion rate. A striking finding is that the efficiency frontier is dominated by two models embodying radically opposed design philosophies: Astra, a superlative frontier model which trades a high cost per token for a very high token-efficiency, and DeepSeek V4.1 Flash, an inference-optimized model with a very low cost per token.

Efficiency comparisons. Because models solve different task sets, we also compare them on the 129 tasks solved by all nine models. For each task and resource, we divide each model’s value by the median across models before summarizing the resulting ratios in Figure 4. DeepSeek has the lowest median recorded cost ($0.19\times$ the same-task median), whereas Astra uses the fewest turns ($0.28\times$) and produces the most concise answers ($0.59\times$). The separation between these dimensions shows that monetary cost, interaction length, and implementation size capture distinct aspects of agent efficiency. Appendix D gives the task-level distributions and taskwise-best comparison for this shared 129-task cohort.

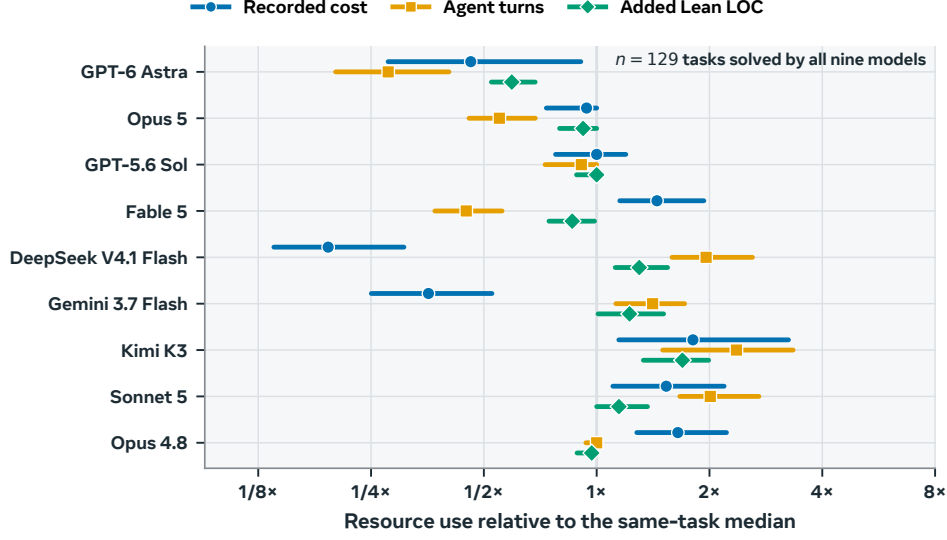


Figure 4 Compared efficiency on the 129 tasks solved by all nine models. For each task, cost, turns, and added Lean LOC are normalized by the median across models. Points show each model’s median ratio and horizontal bars show the interquartile range.

What makes a problem difficult? The nine models evaluated exhibit a strongly stratified difficulty frontier. Across all nine models, 129 tasks are solved by every model and 59 by none; 153 produce disagreement (Figure 13). Across all 36 possible model pairs, the higher-scoring model solves at least 95% of the lower-scoring model’s successes in 30 pairs. For the median pair, only two tasks are solved by the lower-scoring model but not by the higher-scoring model. Astra alone solves 281 tasks and uniquely solves 66 that every other model misses; conversely, only one task is solved by another model and missed by Astra. This strong nesting indicates a largely shared difficulty frontier.

Two related measures track this difficulty. Across the nine models, mean success falls from 66.4% on single-hole tasks to 32.5% on multi-hole tasks. Figure 5 compares GPT-6 Astra’s solution LOC with the number of models that solve the same task. Across Astra’s 281 verified solutions, the correlation is $\rho = -0.84$: longer solutions tend to correspond to tasks solved by fewer models. By contrast, we find little evidence of specialization by mathematical field; Appendix E reports the per-textbook results.

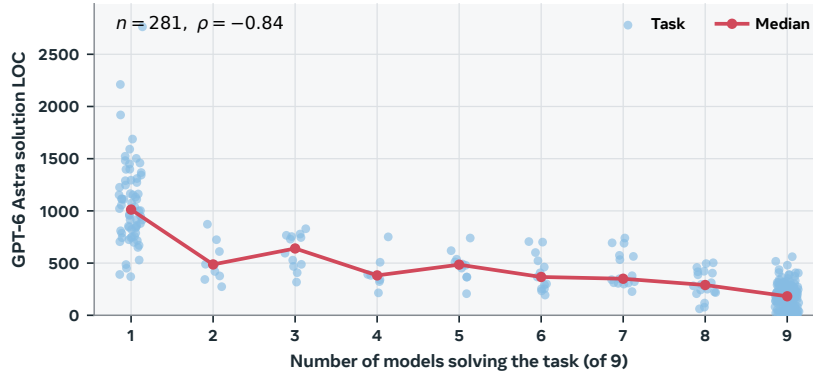


Figure 5 GPT-6 Astra solution LOC versus the number of models solving each task, restricted to Astra’s 281 verified successes. Each blue point is one task; the red line connects the median solution LOC at each solver count.

6 Reliability and Difficulty Analysis

Agent-Built Infrastructure. Solving AutoformBench typically requires building a local formal library around the target theorem. Among the 281 accepted GPT-6 Astra solutions, 92.9% use auxiliary lemmas, 73.3%

introduce new definitions, and 94.0% of dependency-reachable proof code lies in supporting declarations rather than the graded proof bodies. This remains true for tasks exposing only one proof hole: 90.4% use auxiliary lemmas, and supporting declarations account for 93.4% of live proof code. A single-hole task is therefore not necessarily an isolated theorem-proving problem. Appendix F gives the complete methodology and distributions.

Run-to-Run Stability. Because AutoformBench permits long and expensive agent trajectories, the full-benchmark leaderboard reports one scored trajectory per model and problem (pass@1). To test whether these results are sensitive to run-to-run variation, we perform a smaller repeatability study: GPT-5.6 Sol and Gemini 3.7 Flash are each run three times on a fixed, stratified panel of 72 problems spanning all 24 textbooks. Appendix G gives the complete panel construction and repeated-run protocol. Figure 6 shows both quantities as the available turn, cost, and token budgets increase.

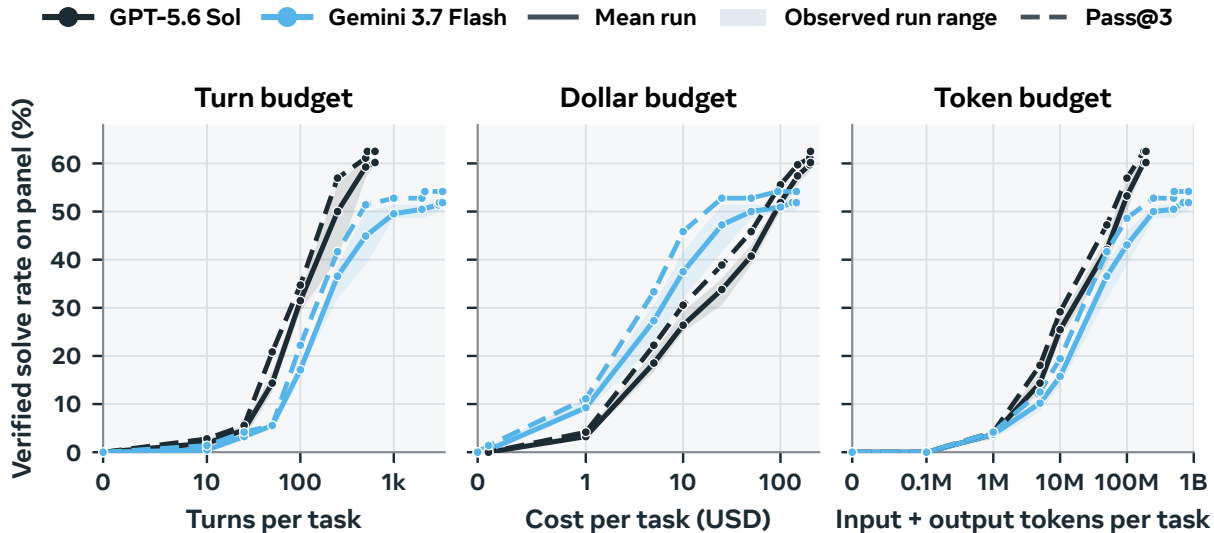


Figure 6 Verified coverage on the 72-problem panel as turn, recorded-cost, and provider-reported input-plus-output-token budgets increase.

Outcomes are highly stable. For each model, 69/72 problems receive the same result in all three runs. Sol solves 43–44 problems per run and 45 under pass@3; Gemini solves 36–38 per run and 39 under pass@3. Thus pass@3 adds only one solution beyond the best individual run for either model.

7 Ablations

Search and Executable Feedback To measure the effect of tool access, we first remove the agent loop entirely. On the 230 workspaces containing exactly one proof hole, GPT-5.6 Sol and Gemini 3.7 Flash receive the complete problem-local context and informal source in a single request, but cannot use tools, receive compiler feedback, or revise their answer. We use the headline model settings and the same clean-room grader. They solve only 6/230 (2.6%) and 3/230 (1.3%) problems, respectively, compared with 163/230 (70.9%) and 148/230 (64.3%) under the full agentic evaluation.

We then remove individual tools while retaining the agent loop. To control cost, these experiments reuse the fixed 72-problem panel from Section 6. We remove the REPL, Loogle, and full-project build individually and in combination; every experimental setup retains filesystem tools, report submission, the informal source, and the \$200 per-problem budget. Table 1 reports the results.

Condition	Gemini 3.7 Flash	GPT-5.6 Sol
Full tools, three runs	38, 36, 38	43, 44, 43
No REPL	36	45
No Loogle	35	44
No build	24	39
No REPL or build	1	4
Files only	1	1

Table 1 Verified successes under tool ablations on the fixed 72-problem panel. The full-tool row reports all three runs; other conditions use one run.

Removing either the REPL or Loogle alone leaves success rates close to those observed across the three full-tool runs. Removing build has a larger effect, particularly for Gemini. Most strikingly, removing both executable Lean-feedback interfaces collapses performance from 36–45 solved problems to only 1 for Gemini and 4 for GPT-5.6 Sol. With only file operations remaining, both models solve just 1/72 problems. Thus structured Mathlib search through Loogle is not essential when filesystem search remains available, and the REPL and build seem to be to some extent substitutable. Appendix J gives the detailed tool-use and fallback analysis.

Context-Iteration Scaling We measure how much the compaction mechanism described in Section 4 contributes to task completion by comparing coverage at the end of the initial context window with final coverage after subsequent context windows. DeepSeek solves 101 additional tasks after its first context window, Kimi 86, Gemini 83, and Sonnet 46. The gains are smaller for Opus and GPT-5.6 Sol, while every successful Astra, Fable, and Opus 4.8 trajectory finishes within its initial context window.

Model	Before compaction	Final	Gain
GPT-6 Astra	281	281	0
Opus 5	200	211	11
Fable 5	181	181	0
GPT-5.6 Sol	176	201	25
Opus 4.8	150	150	0
Sonnet 5	106	152	46
Gemini 3.7 Flash	96	179	83
DeepSeek V4.1 Flash	79	180	101
Kimi K3	79	165	86

Table 2 Verified coverage before the first conversation compaction and after all recorded context iterations.

Agent-Scaffold Comparison We evaluate Opus 5 through both our common agent loop and Claude Code (Anthropic, 2026f). Both configurations receive the same 341 formal workspaces and textbook context, have a maximum budget of \$200 per task, and undergo identical clean-room verification. Claude Code uses the benchmark’s Lean REPL, Loogle, build, and report services alongside its native **Read**, **Edit**, **Write**, **Glob**, and **Grep** tools; Bash, web access, and subagents are disabled.

Claude Code solves 218/341 tasks, compared with 211/341 for the common loop. The configurations agree on 308 problems: both solve 198, Claude Code alone solves 20, the common loop alone solves 13, and neither solves 110. Figure 7 compares their coverage over recorded dollar and turn budgets.

Claude Code’s advantage is primarily one of efficiency and persistence rather than a different mathematical strategy. In 18 of its 20 exclusive successes, both configurations pursue the same mathematical approach, but the common loop stops before completing the final obligations. Plausible explanations include its native system prompt, internal compaction policy, and training for its own tools, none of which we can observe or isolate. Appendix J provides the detailed tool-use and failure analysis.

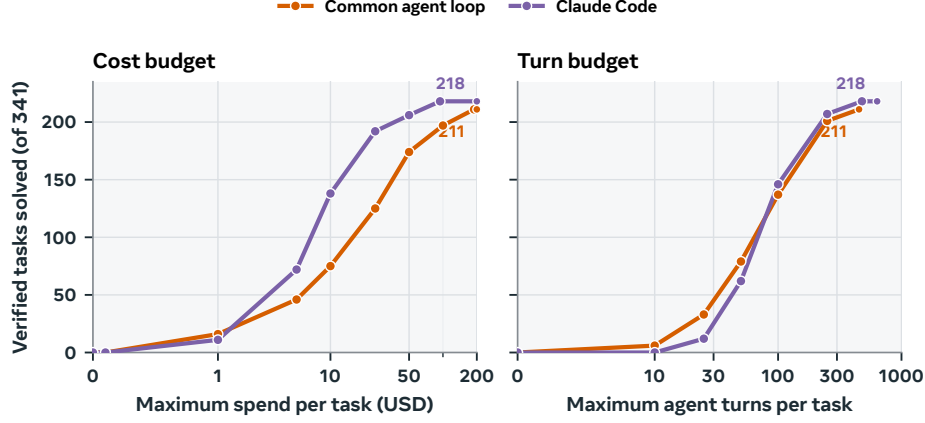


Figure 7 Budget-conditioned comparison of Opus 5 under the common agent loop and Claude Code on the same 341 tasks.

Informal-Source Ablation We ablate access to the textbook by evaluating Opus 5 and Gemini 3.7 Flash on all 341 tasks with the same formal workspace, model settings, tools, budget, stopping rule, and grader. Surprisingly, although both models consult the textbook in more than 93% of source-enabled runs, it provides little aggregate improvement: Opus solves 204 tasks with the source and 200 without it, while Gemini solves 136 and 133, respectively. Neither paired difference is statistically significant, and turns, cost, and token use are similar across conditions (Figure 8). The source also does not systematically shorten the generated Lean code on tasks solved in both conditions. Trace inspection instead shows a task-specific effect: some runs benefit from the book’s proof decomposition, whereas some source-free runs find shorter arguments better adapted to Lean. Thus explicit source access changes individual proof trajectories but provides no clear aggregate advantage once the formal statement and its local context are available. We attribute this to the strong mathematical knowledge of current frontier models. Appendix J.1 gives the complete paired statistics, source-use analysis, and case studies.

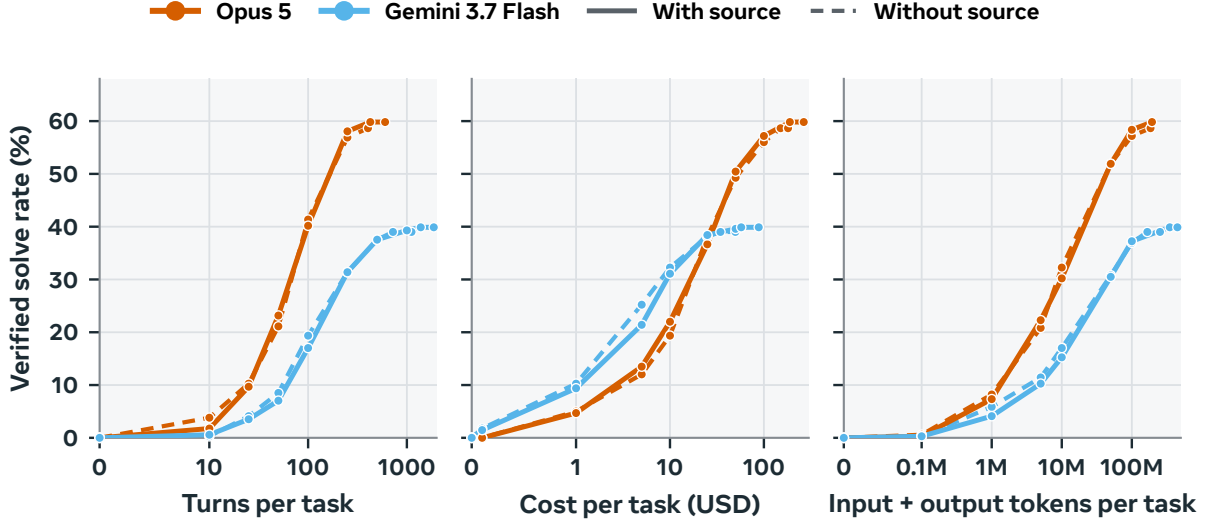


Figure 8 Efficiency by turns, recorded provider cost, and provider-reported input plus output tokens with and without the textbook source on the 341 audited benchmark tasks for Opus 5 and Gemini 3.7 Flash.

8 Limitations and Conclusion

Limitations. AutoformBench covers 24 mathematical sources, but it is not representative of all advanced mathematics: its domains and statements are constrained by what can presently be expressed against Mathlib within a bounded evaluation. The benchmark supplies expert-written formal statements, so it evaluates proof completion and construction of supporting theory rather than end-to-end statement autoformalization. Finally, kernel acceptance establishes a theorem relative to its audited statement and assumptions; it does not establish that the generated code has the abstraction quality or maintainability required for upstream inclusion in a useful library such as Mathlib.

Conclusion. AutoformBench is a natural step toward measuring how well models can construct missing formal infrastructure. Its problems, however, remain isolated in separate workspaces. The next step is to test whether agents can recognize shared missing theory, build reusable abstractions, and amortize that work across related results. Moving from isolated problems to cumulative developments would measure the transition from theorem solving to extending formal libraries.

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Reproducibility Statement

We release all 341 tasks in Harbor format, each pinned to Lean 4.32.2 and a fixed Mathlib commit and including the graded-declaration and permitted-axiom specification and informal source material. Appendix B details the tools, sandbox, complete prompts, budget and termination rules, clean-room grading procedure, and exact revisions of Comparator, Nanoda, Landrun, and Loogle; model settings appear in Section 5, and the repeatability panel and its selection seed in Appendix H. Since proprietary API models may change, trajectories may not be exactly reproducible, but any submission can be re-verified independently from its Lean files alone.

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Appendix

A Benchmark Structure: Proof Obligations and Local Context

This section gives two complementary views of the benchmark : the number of explicit proof obligations in each workspace and the local formal context on which the target statements depend.

A.1 Proof Obligations

Table 3 gives the complete distribution of graded proof obligations across the frozen benchmark. Of the 1,155 graded declarations, 1,147 use theorem syntax and 8 use instance syntax for proposition-valued typeclasses.

Holes	Tasks	Share	Oblig.	Holes	Tasks	Share	Oblig.
1	230	67.45%	230	14	4	1.17%	56
2	25	7.33%	50	15	1	0.29%	15
3	19	5.57%	57	16	1	0.29%	16
4	9	2.64%	36	17	1	0.29%	17
5	7	2.05%	35	18	2	0.59%	36
6	5	1.47%	30	19	1	0.29%	19
7	2	0.59%	14	20	2	0.59%	40
8	4	1.17%	32	24	1	0.29%	24
9	3	0.88%	27	26	2	0.59%	52
10	5	1.47%	50	27	2	0.59%	54
11	4	1.17%	44	30	1	0.29%	30
12	5	1.47%	60	33	1	0.29%	33
13	3	0.88%	39	59	1	0.29%	59
341 tasks; 1,155 graded proof obligations							

Table 3 Number of graded proof holes per benchmark task. **Oblig.** is the total number of obligations contributed by that row.

The 111 multi-hole tasks have a median of 5 and a mean of 8.33 holes. The distribution is concentrated: the largest 10 tasks contain 292/1,155 obligations (25.3%), the largest 20 contain 451 (39.0%), and the 44 tasks with at least eight holes contain 703 (60.9%). Designating the final graded declaration in each workspace as its headline target leaves 814 supporting obligations, or 70.5% of all graded declarations. Agent-added definitions and lemmas are additional to these benchmark-provided holes.

A.2 Formal Context Required to State a Task

A formal target uses constants from both Mathlib and its benchmark workspace. To quantify the context supplied before proof search, we start from each elaborated target type and recursively follow references into `Challenge.lean` and `ChallengeDeps.lean`; for a multi-target task, we take the union of the resulting graphs. Table 4 reports the number of reachable declarations, their source lines of code, and the longest local dependency chain. No model-generated code is counted. We use the 281 tasks solved by GPT-6 Astra so that these input-side measurements can be paired with the accepted-proof analysis in Appendix F.

Input-side metric	Median	IQR	Maximum
Reachable workspace declarations	5	2–12	54
Source LOC of those declarations	22	7–49	293
Longest workspace dependency chain	2	1–3	9

Table 4 Formal context required by the graded target types in the 281-task GPT-6 Astra accepted-solution cohort.

The median task depends on five workspace declarations occupying 22 lines, with a longest local chain of two. Among constants mentioned directly in its target types, the median Mathlib fraction is 65.0%. Thus predominantly Mathlib vocabulary can coexist with a nontrivial local API. These measurements describe context supplied with the task, not infrastructure built by the agent.

B Execution and Clean-Room Verification

B.1 Workspace Structure

LEAN EVAL (Lean FRO, 2026) generates a standalone Comparator workspace for each benchmark item. All workspaces use Lean 4.32.2 and Mathlib commit 905b95818eb32af7874a58b427f50c1711a5e96c. The principal files are:

ChallengeDeps.lean	supporting definitions
Challenge.lean	trusted target declarations
Submission.lean	agent’s candidate proofs
Submission/Helpers.lean	optional auxiliary lemmas
Solution.lean	trusted grading/build wiring
config.json	graded names and permitted axioms
book/	informal textbook material
TASK.md	agent instructions

The agent receives a disposable copy of this workspace. Although it can inspect the trusted challenge and build configuration, its only graded deliverables are `Submission.lean` and the optional `Submission/` directory. `Submission.lean` is initialized with the target declarations and `sorry` proof bodies; agents may add definitions and auxiliary lemmas but must fill every target proof.

B.2 Tools and Execution Sandbox

The agent receives five classes of MCP service: scoped filesystem operations; `run_lean_code`, a scratch Lean REPL using the benchmark’s pinned Mathlib environment; `loogle_search`, for searching Mathlib declarations; a fixed build operation equivalent to `lake build Solution`; and `submit_report`. The build service exposes compiler diagnostics without granting a general shell. The report service records a structured outcome (`solved` or `unsolved`), optional diagnostic flags, and a short free-text account of progress or failure. It is a source of diagnostic metadata, not the grading oracle.

Each MCP subprocess runs under Bubblewrap. The problem workspace is its only writable mount; required system, Lean, and tool directories are mounted read-only; temporary storage and the home directory are private; the environment is allowlisted; and network access is disabled.

B.3 Agent Prompts

API-model runs use a fixed solver prompt. The complete machine-readable templates are released with the evaluation artifacts; we reproduce the result-relevant instructions below, omitting the diagnostic-report flag taxonomy.

Solver instruction.

You are an expert Lean 4 theorem-proving agent working in a self-contained workspace. Read `TASK.md` and `Challenge.lean`, then replace every `sorry` in `Submission.lean`; auxiliary definitions and lemmas may be added to `Submission/Helpers.lean`. Use the filesystem tools to edit the submission, `run_lean_code` as a scratchpad, `loogle_search` to search Mathlib, and `build` to compile the candidate. Missing Mathlib infrastructure is part of the task: build the necessary supporting theory rather than stopping when a lemma cannot be found. Do not modify target statements, introduce axioms, or bypass proof checking. Finish by calling `submit_report` with a solved or unsolved outcome and a concise account of the work completed and any remaining obstacle.

Continuation prompt. If an agent stops without a report, it is reminded that it must either submit a completed proof or continue using the available tools. If it reports `unsolved` before reaching the minimum-effort threshold (10% of its budget), it receives:

You have not worked hard enough on this problem yet. These problems are intentionally difficult and may require substantial new Lean infrastructure; missing Mathlib lemmas are expected, not a reason to stop.

Spend more time developing the necessary definitions and helper lemmas, test them with the available tools, and keep iterating until the solution builds.

Conversation compaction. To support trajectories longer than one context window, the agentic loop compacts its conversation after a completed model turn when the context approaches its limit.

For compaction, the harness calls the same model at the same reasoning setting, with tools disabled, using the following prompt:

System instruction. You are a summarizer. Produce a concise summary of the conversation below. Focus on: key findings, decisions made, actions taken, and remaining work. Be specific about important details like file paths, names, and values.

User template.

Summarize this conversation:

{conversation_text}

The original solver system prompt is then restored, and the prior non-system history is replaced by one user message prefixed [Context summary of previous conversation]. Compaction changes neither the workspace files nor the running tool services; thus verified Lean progress survives even though the detailed dialogue does not. If summarization fails or returns no usable text, the original history is restored. The procedure may repeat within a run.

B.4 Budget and Termination

All models are evaluated under a maximum provider-cost budget of \$200 per problem. A solved report may terminate immediately. An unsolved report submitted before 10% of the budget is normally rejected and the agent is instructed to continue; the local-model driver accepts the sixth such report to prevent an unproductive rejection loop. Appendix J.5 analyzes the effect of this rule. The final 10% is reserved for at most three wrap-up turns so that an agent that exhausts its proving budget can still record partial progress and remaining obstacles. Reported dollar costs are computed from provider-reported input, output, and cached-token counts, including separate cache-read and cache-write counts where available, using the public API prices applicable to each model at evaluation time. They measure estimated API-equivalent inference cost rather than hardware-normalized compute or invoiced expenditure.

B.5 Clean-Room Grading

Many frontier models have a tendency to cheat, which makes rigorous grading a crucial necessity. When an agent finishes, the harness creates a new workspace from the trusted benchmark copy and overwrites exactly two paths with agent output: `Submission.lean` and `Submission/`. All other files—including the reference declarations, build wiring, graded-name list, pinned definitions, and permitted-axiom configuration—come from the trusted copy. Consequently, changes made elsewhere in the disposable workspace cannot affect the verdict.

Comparator then compiles the candidate in its Landrun sandbox (Landrun contributors, 2025) and checks that each selected declaration has the same statement as its trusted counterpart, that pinned definitions retain their values, and that the proof uses only permitted axioms. Accepted submissions are additionally replayed through the independent Nanoda kernel (Nanoda contributors, 2026). The resulting Comparator verdict, rather than the agent’s `submit_report` claim or its local build result, defines benchmark success.

Harbor task format and release. Harbor’s container-based task format and execution harness, also used by Terminal-Bench 2.0, provide a common interface for heterogeneous agent scaffolds. The public release packages every benchmark workspace as a Harbor 0.22.0 task, allowing any Harbor-supported or custom agent to be evaluated under the grading semantics described above.

C Evaluation Cost

Evaluation spending and the unsolved frontier. Figure 9 separates recorded provider spending by model, run outcome, and cross-model task coverage. Across all 3,069 model-task runs, the 1,369 unsuccessful runs account for \$77,676.70 of the \$125,606.21 total (61.8%). The 59 tasks solved by none of the nine models consume \$29,920.86 and 178,744 agent turns. The 66 tasks solved by exactly one model consume a further \$35,757.19; together, these 125 frontier tasks account for \$65,678.05, or 52.3% of all recorded leaderboard spending. Thus more than half of the evaluation cost is devoted to tasks that remain unsolved or lie at the edge of current model capability.

3,069 runs · \$125,606.21 recorded spend · 61.8% on unsuccessful runs

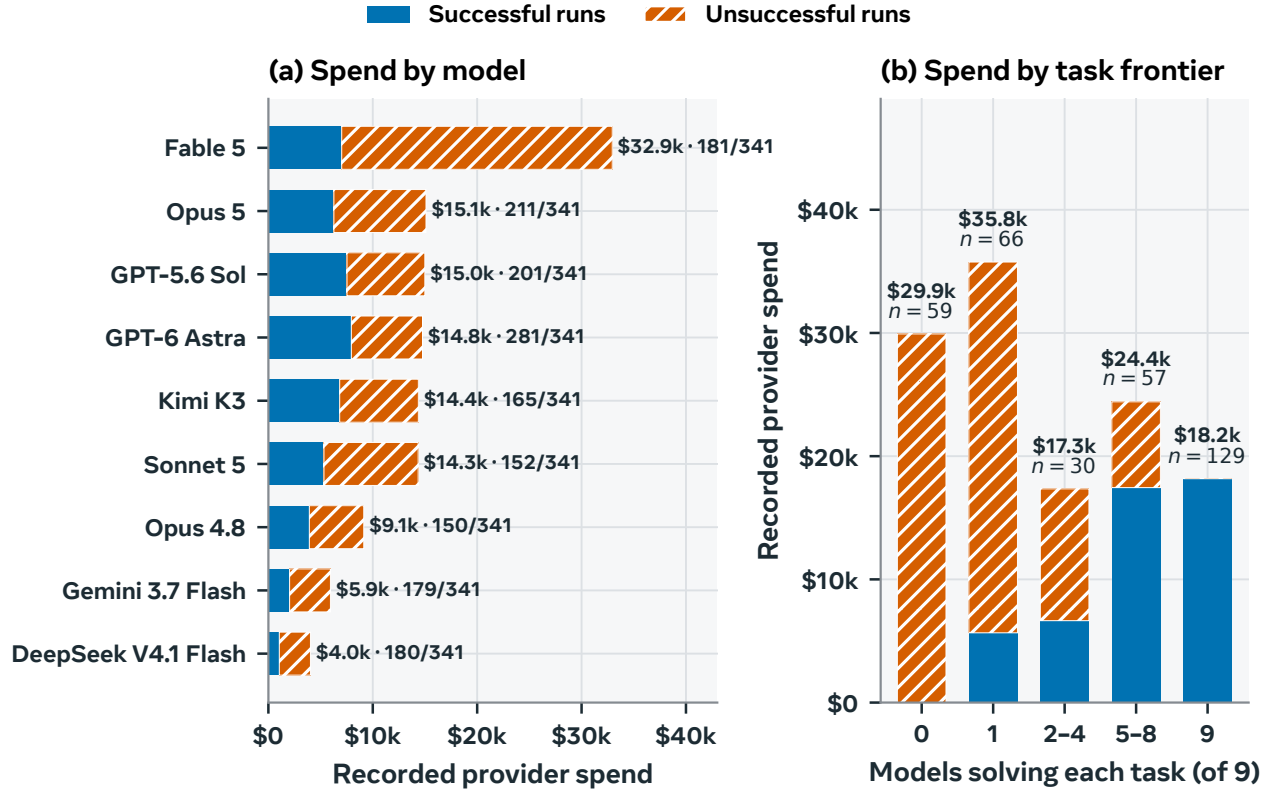


Figure 9 Recorded provider spending across the nine leaderboard campaigns. Left: spend by model, split between verified and unsuccessful runs; labels give total spend and verified score. Right: the same spending grouped by the number of models that solve each task; n is the number of tasks in each group.

D Matched Model Efficiency

Controlled comparison on common successes. To separate model behavior from differences in the tasks each model solves, we restrict to the 129 tasks solved by all nine models. For every task and resource, we divide each model’s recorded value by the minimum among the nine models, then report the median ratio in Table 5. A ratio of one is best. The final three columns count tasks on which a model attains the minimum, counting ties for each model. DeepSeek is cheapest on 85/129 tasks. Astra uses the fewest turns on 109/129 and leaves the least added code on 107/129.

Model	Median ratio to taskwise best			Tasks attaining best		
	Cost	Turns	Added LOC	Cost	Turns	Added LOC
GPT-6 Astra	2.70	1.00	1.00	18	109	107
Opus 5	4.84	1.82	1.50	0	2	5
GPT-5.6 Sol	5.71	3.07	1.65	1	1	2
Fable 5	8.57	1.52	1.47	0	21	13
DeepSeek V4.1 Flash	1.00	6.92	2.31	85	0	0
Gemini 3.7 Flash	2.08	4.88	2.10	23	0	2
Kimi K3	11.38	9.83	2.76	0	1	1
Sonnet 5	9.79	8.21	2.12	2	2	1
Opus 4.8	9.71	3.40	1.63	0	2	6

Table 5 Efficiency fingerprints on the identical 129-task cohort solved by all nine models. Added LOC is the net code remaining in the final submission. Best-task counts include ties.

Matched resource profiles. Figure 4 summarizes the matched comparison in the main text. Figures 10–12 show the underlying task-level distributions on the same 129 tasks. For each task and metric, we divide each model’s value by the median across the nine models. This normalization removes the large between-task variation and exposes systematic differences among models.

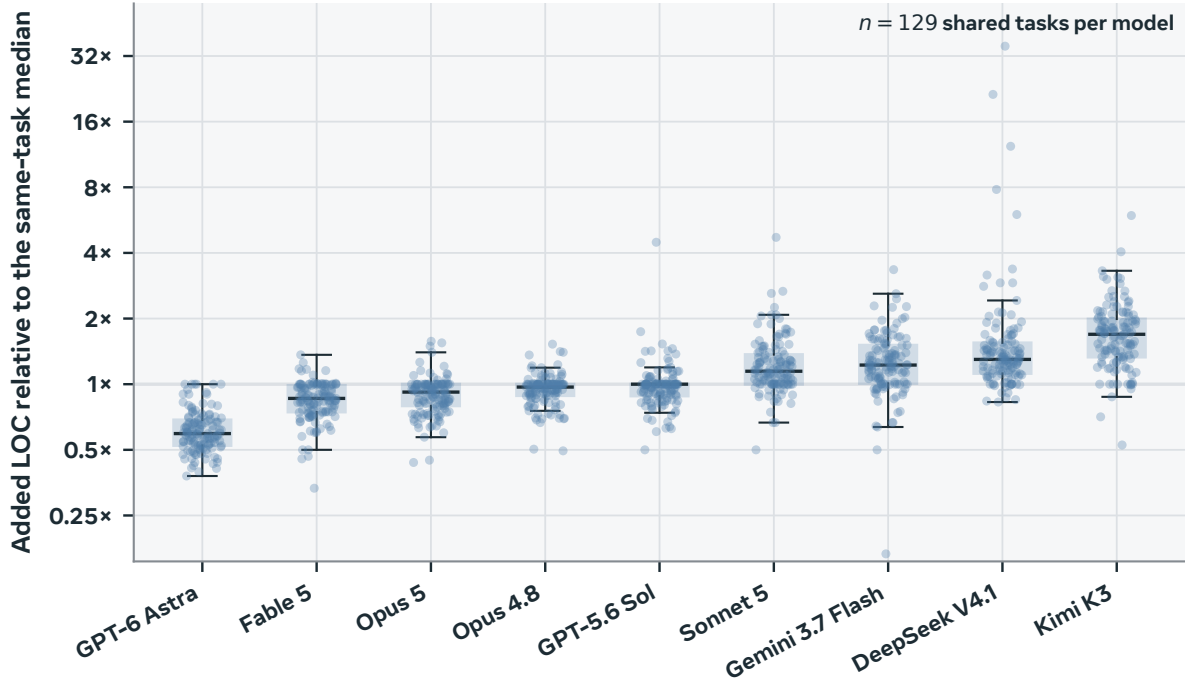


Figure 10 Added Lean code on the 129 tasks solved by all nine models, normalized by the median LOC for the same task. Each point is one model–task pair; boxes summarize the per-model distributions. A value of $1\times$ is the within-task median, while $0.5\times$ and $2\times$ denote half and twice that amount of code. Models are ordered by their median ratio.

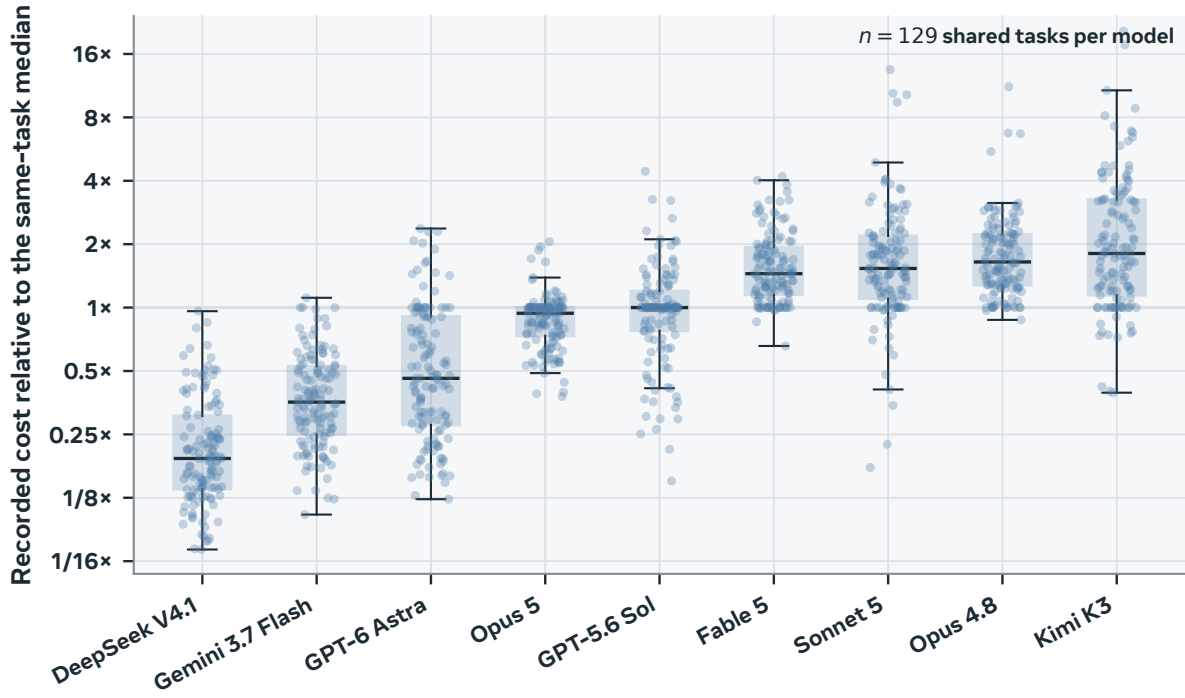


Figure 11 Recorded provider cost on the 129 shared tasks, normalized by the median cost for the same task. Each point is one model-task pair; boxes summarize the per-model distributions. Models are ordered by median ratio.

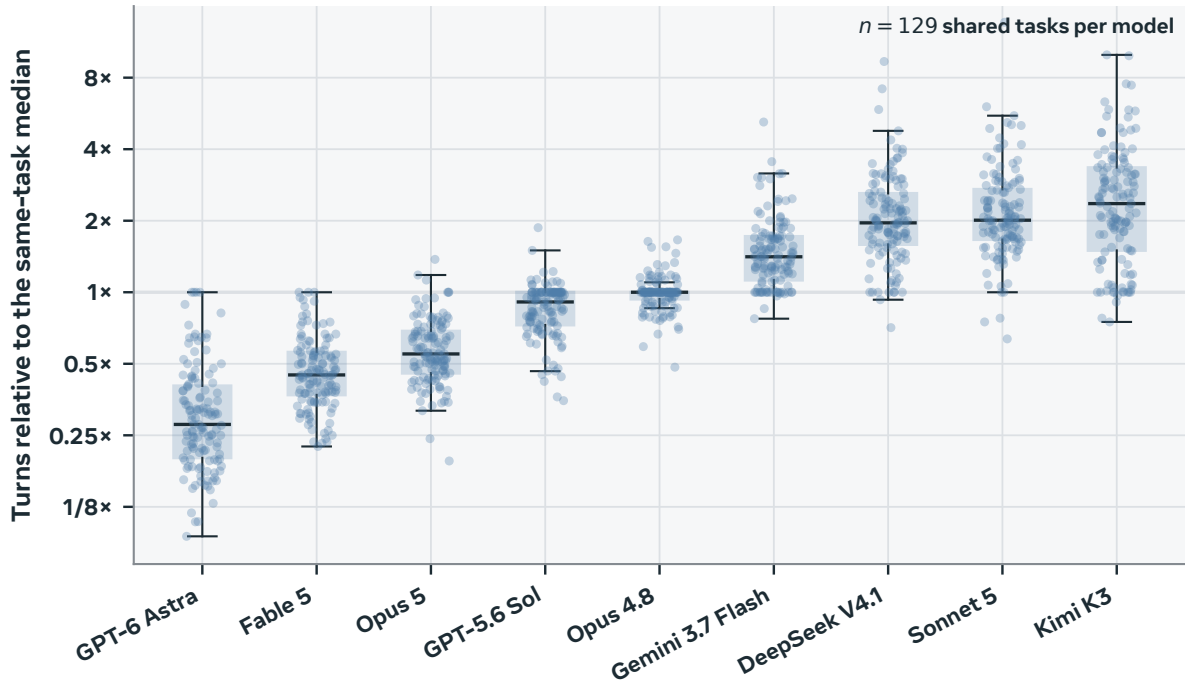


Figure 12 Agent turns on the 129 shared tasks, normalized by the median turn count for the same task. Each point is one model-task pair; boxes summarize the per-model distributions. Models are ordered by median ratio.

E Shared Difficulty Frontier

Table 6 reports the complete per-textbook results. Absolute difficulty varies substantially across sources, but the model outcomes do not reveal a broad domain-specific specialization that would explain the shared frontier.

Table 6 Per-book verified solve counts on the 341-task benchmark. Model counts use the headline condition at the highest evaluated effort. **Astra**: GPT-6 Astra; **O5**: Opus 5; **Sol**: GPT-5.6 Sol; **F5**: Fable 5; **DS**: DeepSeek V4.1 Flash; **G3.7F**: Gemini 3.7 Flash; **K3**: Kimi K3; **S5**: Sonnet 5; **O4.8**: Opus 4.8. **Any** counts tasks solved by at least one model. Row-wise best model counts are bold.

Book	Tasks	Astra	O5	Sol	F5	DS	G3.7F	K3	S5	O4.8	Any
<i>Algebraic Combinatorics</i>	2	2	2	2	2	1	1	2	1	2	2
<i>Algebraic Geometry</i>	8	6	1	1	1	1	1	1	0	0	6
<i>Algebraic Topology</i>	16	10	5	4	5	3	3	3	3	2	10
<i>Arithmetic Geometry</i>	26	20	16	16	13	13	14	11	10	12	20
<i>Boolean Functions</i>	2	2	2	2	2	2	1	1	0	1	2
<i>Buildings</i>	11	11	9	10	7	7	9	7	5	6	11
<i>Cherednik Algebras</i>	15	12	6	4	3	3	2	4	1	1	12
<i>Complex Variables</i>	12	12	12	10	9	9	8	9	9	8	12
<i>Differential Analysis</i>	18	17	14	13	12	14	10	14	12	12	17
<i>Elliptic Curves</i>	27	11	7	7	5	5	7	5	4	4	12
<i>Graph/Additive Comb.</i>	9	6	4	4	4	4	4	2	4	4	6
<i>High-Dimensional Statistics</i>	25	25	25	25	24	24	22	22	22	21	25
<i>Lie Groups and Algebras</i>	28	18	11	12	10	11	10	9	10	8	18
<i>Low-Rank Models</i>	5	5	4	4	4	3	4	3	3	3	5
<i>Matrix Concentration</i>	3	3	0	0	0	0	0	0	0	0	3
<i>Noncommutative Algebra</i>	22	17	14	14	11	13	12	10	10	9	17
<i>Number Theory</i>	24	18	8	8	5	5	5	5	3	3	18
<i>PDEs</i>	8	8	8	7	7	6	7	7	6	6	8
<i>Probability</i>	4	4	4	3	4	4	4	4	3	2	4
<i>Sparsity Penalties</i>	8	8	8	8	8	8	8	7	7	7	8
<i>Stacks Project</i>	32	31	28	24	24	22	27	20	20	20	31
<i>Submodular Functions</i>	15	15	15	14	13	14	13	12	11	13	15
<i>Tensor Categories</i>	13	13	4	5	4	4	3	3	4	2	13
<i>Theory of Computation</i>	8	7	4	4	4	4	4	4	4	4	7
Total (24 books)	341	281	211	201	181	180	179	165	152	150	282

Cross-model coverage. Figure 13 gives the complete distribution of task coverage across the nine models.

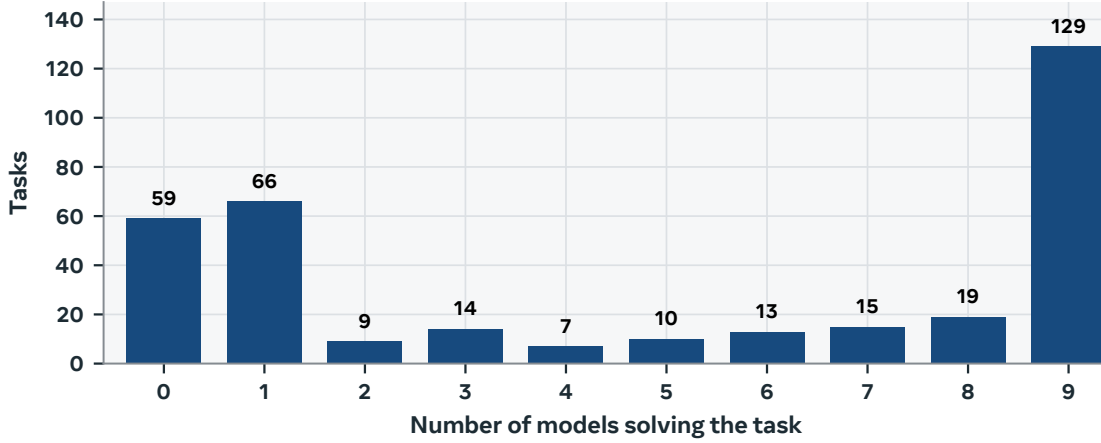


Figure 13 Number of benchmark tasks solved by exactly k of the nine models.

The distribution is strongly polarized: 129 tasks are solved by all nine models, 59 by none, and 153 produce disagreement. Across all 36 model pairs ordered by total score, the higher-scoring model solves at least 95% of the lower-scoring model’s successes in 30 pairs; for the median pair, it misses only two such tasks. Astra solves 281 tasks, while the union of all nine systems reaches only 282.

F Agent-Built Infrastructure and Proximity to Mathlib

F.1 From Generated Submission to Live Proof

Accepted-solution cohort and generated code. We analyze all 281 clean-room-accepted GPT-6 Astra solutions, comprising 208 single-hole and 73 multi-hole tasks. This is the broadest accepted cohort from a single model. Before filtering unused code, these solutions contain a median of 319 skeleton-subtracted, nonblank, noncomment lines of added Lean; the largest contains 2,763. Figure 14 shows the full distribution.

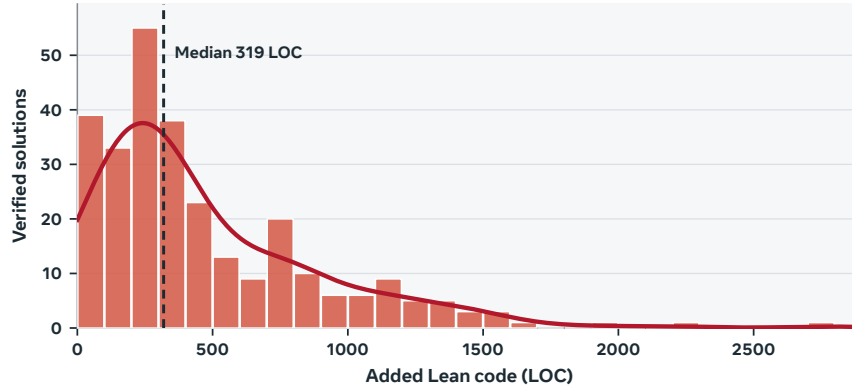


Figure 14 Distribution of skeleton-subtracted, nonblank, noncomment Lean code added by GPT-6 Astra across its 281 accepted solutions.

Live dependency closure. Raw generated code can include abandoned proof attempts. To isolate the code that supports an accepted result, we start from every graded proof and recursively follow dependencies into declarations added by the agent. For a multi-hole task, we take the union of these closures. Everything unreachable from a graded proof is excluded from the live measurements.

Table 7 reports the resulting proof developments. Auxiliary lemmas occur in 261/281 solutions (92.9%), new definitions in 206/281 (73.3%), and new instances in 68/281 (24.2%); only 20/281 (7.1%) use no auxiliary

declarations. Supporting declarations contribute 118,853 of 126,388 aggregate live LOC (94.0%), while the graded target proof bodies contribute 7,535 (6.0%). The live closures retain 95.4% of all generated code in aggregate, with a median per-task share of 96.4%.

Live proof metric	Median	IQR	Maximum
Total live proof LOC	300	182–669	2,640
Used helper declarations	24	10–56	223
Used helper LOC	283	151–638	2,639
Used definitions	3	0–10	77
Used lemmas	20	9–44	179

Table 7 Dependency-closed infrastructure in accepted GPT-6 Astra solutions. Unused generated declarations are excluded.

F.2 Single- and Multi-Hole Workspaces

Table 8 shows that substantial supporting theory is not confined to workspaces exposing many holes.

Metric	Single-hole ($n = 208$)	Multi-hole ($n = 73$)
Median live proof LOC	271.5	636
Median used helper declarations	20	53
Median used definitions	2	9
Median used lemmas	16	47
Uses auxiliary lemmas	90.4%	100%
Uses new definitions	67.8%	89.0%
Supporting share of aggregate live LOC	93.4%	95.1%

Table 8 Dependency-closed proof infrastructure by workspace hole count.

Even a single exposed hole therefore usually requires a substantial local theory: 90.4% of single-hole successes use auxiliary lemmas, 67.8% introduce definitions, and 93.4% of their live LOC lies outside the final target body. Conversely, a multi-hole workspace may expose many routine obligations explicitly, so hole count alone is not a complete measure of difficulty.

F.3 Resource Use Across Successful Runs

Finally, we broaden from Astra to every run and compare raw added code with the resources used to produce it. Figures 15 and 16 show that generated code is strongly associated with both interaction length and spending: within-model Spearman correlations range from 0.76 to 0.90 for turns and from 0.81 to 0.90 for cost. Because models solve different task sets, these plots characterize successful-run behavior rather than a controlled comparison.

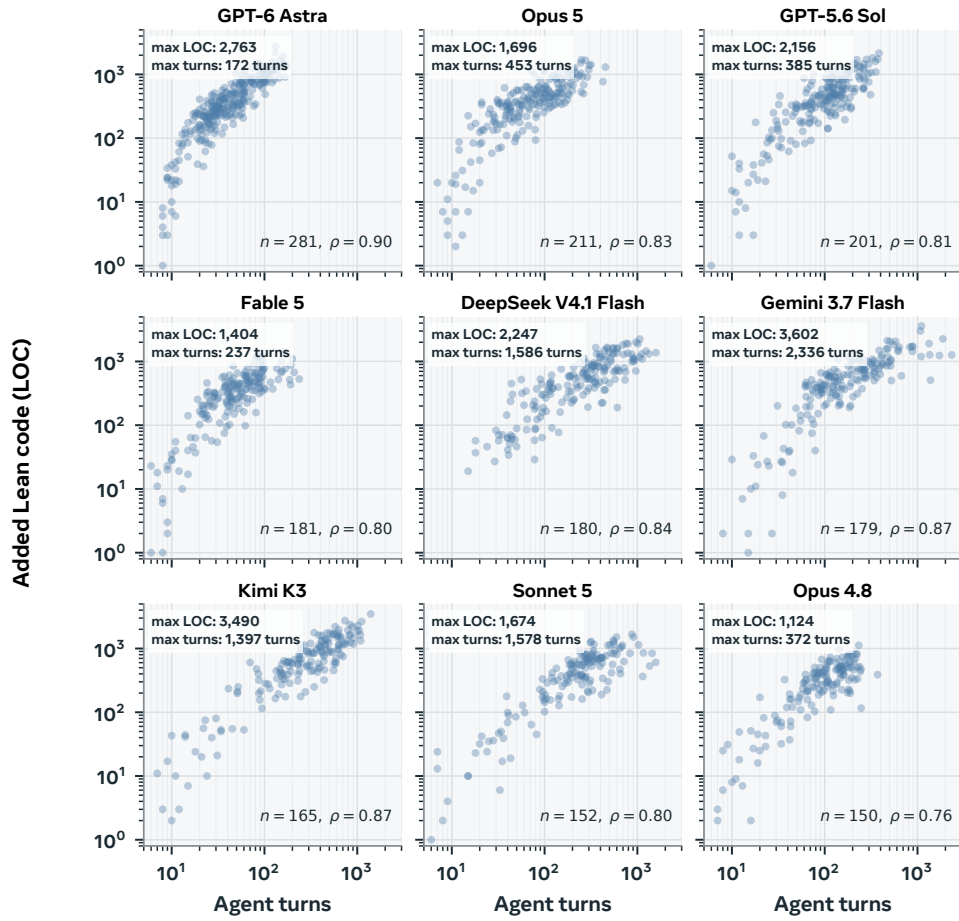


Figure 15 Added Lean code versus agent turns for every run, separated by model. Each panel reports the maximum added LOC and maximum number of turns. Both axes are logarithmic and shared across panels.

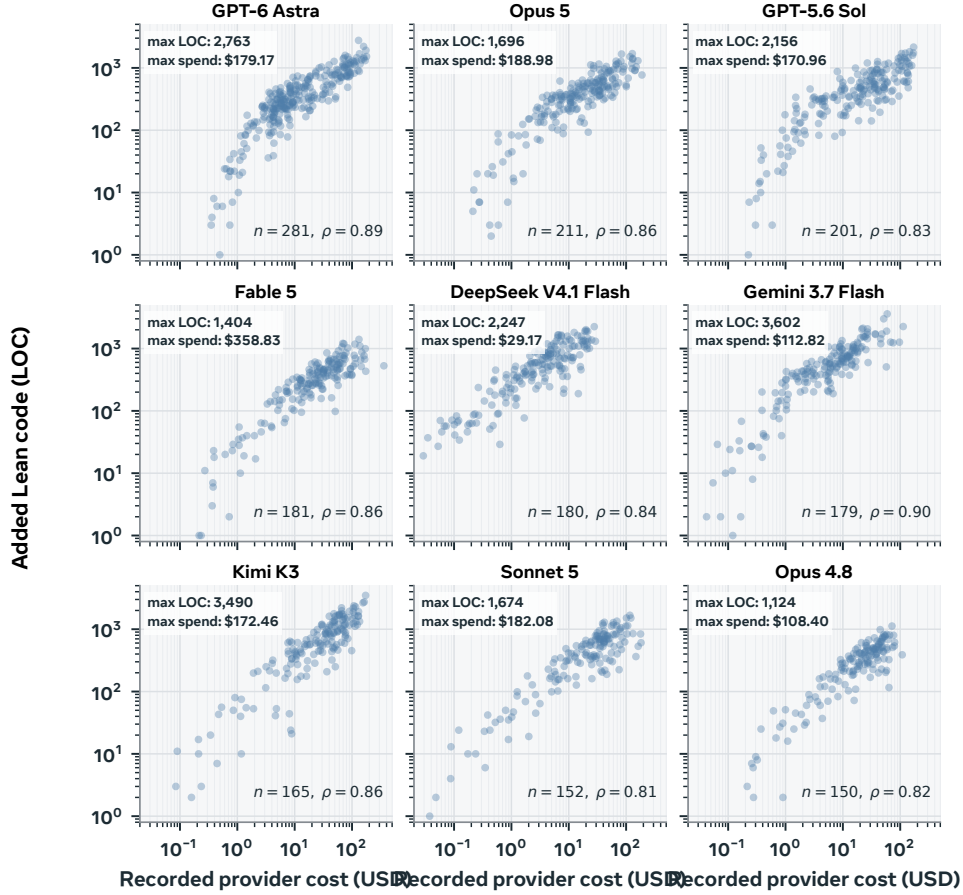


Figure 16 Added Lean code versus recorded provider spending for every run, separated by model. Each panel reports the maximum added LOC and maximum recorded spending. Both axes are logarithmic and shared across panels. The Fable maximum includes inseparable retry usage in its retained record.

G Run-to-Run Stability: Panel Construction and Detailed Results

Repeating every benchmark item several times is unusually expensive in our long-horizon setting. We therefore freeze a 72-problem panel before observing any of the new repeatability runs. The eligible population is the set of problems that both GPT-5.6 Sol and Gemini 3.7 Flash have solved in our main set of runs.

Each problem receives one of four joint labels, with the first letter denoting Sol and the second Gemini. Table 9 gives their population counts and panel quotas. Quotas are obtained by multiplying the population proportions by 72 and applying largest-remainder rounding.

Label	Historical headline outcome	Full cohort	Panel
SS	Both solved	173	37
FF	Neither solved	134	28
SF	Sol only	28	6
FS	Gemini only	6	1

Table 9 Historical outcome strata used to construct the repeatability panel.

We selected a deterministic stratified panel of 72 tasks, balanced across all 24 textbooks, the historical outcomes in Table 9, and three structural-size measures: workspace size, number of graded proof obligations, and target-statement size. The task list and selection seed are released for reproducibility.

Repeated-run protocol and interpretation. For each model and panel item, we record three completed runs. Provider or transport failures are replaced under the same replicate identifier. We report the solve rate of each run, pass@3, and the number of items whose outcome agrees in all three. These quantities describe the fixed panel and are not extrapolated to full-benchmark pass@3.

Aggregate outcomes. Table 10 gives the individual-run totals and their union. Figure 6 in the main text additionally shows mean single-run coverage, its observed range, and pass@3 across resource budgets.

Model	Run 1	Run 2	Run 3	pass@3	Unanimous
GPT-5.6 Sol	43	44	43	45	69/72
Gemini 3.7 Flash	38	36	38	39	69/72

Table 10 Verified outcomes across the three runs on the 72-problem panel. Pass@3 counts their union; unanimous counts problems with the same outcome in all three runs.

Strategies across successful runs. We compare the three accepted proofs for every problem solved in all three runs, using their target dependency closures and a manual comparison of the central mathematical argument. GPT-5.6 Sol follows the same high-level route in 38/42 cases (90.5%), and Gemini 3.7 Flash in 34/36 (94.4%). For example, all runs prove Boolean-quotient Sperner through Stanley’s up/down operators, injectivity, Hall matchings, and rank symmetry despite markedly different Lean developments. Genuine alternatives also occur: for a spectral-endpoint theorem, runs alternate between compact-spectrum/continuous-functional-calculus and centered-operator/resolvent arguments. Stable success therefore usually reflects convergence on the same mathematics, with substantial freedom in its Lean realization.

H Source Provenance

Table 11 Provenance of the 24 mathematical sources used in AutoformBench. Each link points to the canonical public course page, project page, or arXiv record from which the benchmark source was obtained

Source	Author(s)	URL
<i>Topics in Algebraic Combinatorics</i>	Richard P. Stanley	MIT OCW
<i>Algebraic Geometry I</i>	Roman Bezrukavnikov et al.	MIT OCW
<i>Lectures on Algebraic Topology</i>	Haynes Miller; notes by Sanath Devalapurkar	MIT OCW
<i>Introduction to Arithmetic Geometry</i>	Andrew V. Sutherland	MIT OCW
<i>Analysis of Boolean Functions</i>	Dor Minzer	MIT OCW
<i>Buildings</i>	Paul Garrett	author PDF
<i>Lecture Notes on Cherednik Algebras</i>	Pavel Etingof and Xiaoguang Ma	arXiv:1001.0432
<i>Functions of a Complex Variable</i>	Sigurdur Helgason	MIT OCW
<i>Differential Analysis</i>	Richard B. Melrose	MIT OCW
<i>Elliptic Curves</i>	Andrew V. Sutherland	MIT OCW
<i>Graph Theory and Additive Combinatorics</i>	Yufei Zhao	MIT OCW
<i>High-Dimensional Statistics</i>	Philippe Rigollet and Jan-Christian Hütter	MIT OCW
<i>Lie Groups and Lie Algebras</i>	Pavel Etingof	arXiv:2201.09397
<i>Generalized Low Rank Models</i>	Madeleine Udell, Corinne Horn, Reza Zadeh, and Stephen Boyd	arXiv:1410.0342
<i>An Introduction to Matrix Concentration Inequalities</i>	Joel A. Tropp	arXiv:1501.01571
<i>Noncommutative Algebra</i>	Roman Bezrukavnikov	MIT OCW
<i>Number Theory I</i>	Andrew V. Sutherland	MIT OCW
<i>Introduction to Partial Differential Equations</i>	Jared Speck	MIT OCW
<i>Theory of Probability</i>	Scott Sheffield	MIT OCW
<i>Optimization with Sparsity-Inducing Penalties</i>	Francis Bach, Rodolphe Jenatton, Julien Mairal, and Guillaume Obozinski	arXiv:1108.0775
<i>The Stacks Project</i>	The Stacks Project Authors	project site
<i>Learning with Submodular Functions</i>	Francis Bach	arXiv:1111.6453
<i>Tensor Categories</i>	Pavel Etingof, Shlomo Gelaki, Dmitri Nikshych, and Victor Ostrik	MIT OCW
<i>Introduction to the Theory of Computation</i>	Michael Sipser	MIT OCW

I Correction to a Source Formula

Proposition 10.3 of *Learning with Submodular Functions* contains a typographical omission in its ℓ_1 characterization of submodular minimization. With the source’s notation

$$s_-(V) = \sum_{k \in V} \min\{s_k, 0\}, \quad \|s\|_1 = \sum_{k \in V} |s_k|,$$

the printed proposition states

$$\min_{A \subseteq V} F(A) = \max_{s \in B(F)} s_-(V) = F(V) - \min_{s \in B(F)} \|s\|_1.$$

The final equality is missing factors of $1/2$. Indeed, the scalar identity $|x| = x - 2 \min\{x, 0\}$ gives

$$\|s\|_1 = s(V) - 2s_-(V), \quad s_-(V) = \frac{1}{2}(s(V) - \|s\|_1).$$

Since every $s \in B(F)$ satisfies $s(V) = F(V)$, the corrected formula is

$$\min_{A \subseteq V} F(A) = \frac{1}{2}F(V) - \frac{1}{2} \min_{s \in B(F)} \|s\|_1.$$

The audited Lean target uses this corrected statement. The accepted proof makes the normalization explicit through the helper lemma

```
11Norm s = modularSetFunction s Finset.univ
- 2 * modularSetFunction (negativePart s) Finset.univ,
```

then uses the defining base-polyhedron equality $s(V) = F(V)$ to derive the two $1/2$ factors. Thus the benchmark corrects a source typo rather than weakening or otherwise changing the intended mathematical result.

J Agent Behavior and Ablation Details

J.1 Informal-Source Ablation

Experimental design. We test the marginal value of informal mathematics once the formal task has already been fixed. In the full-source condition, the agent receives the Lean workspace together with the textbook material in `book/` and an explicit instruction to consult it. In the formal-workspace-only condition, the agent receives the same expert-written target statement and local definitions, but all source-specific prompt text are removed.

Paired outcomes and source use. Across the original 341-task source-enabled campaigns, Opus accesses the textbook in 323/341 selected traces, while Gemini’s attempt cascade contains source-use evidence for 330/341 problems. For Opus, the paired outcomes are 198 successes in both conditions, 6 with-source-only successes, 2 without-source-only successes, and 135 failures in both conditions. Gemini has 126 successes in both conditions, 10 with-source-only successes, 7 without-source-only successes, and 198 failures in both conditions.

Among tasks solved in both conditions, the source does not consistently shorten the resulting Lean development. For Opus, the median with-source/without-source LOC ratio is 1.00: the source-conditioned version is shorter in 99/198 pairs, longer in 96, and equal in 3. For Gemini, the median ratio is 1.04: the source-conditioned version is shorter in 55/126 pairs, longer in 68, and equal in 3. These comparisons concern generated code length rather than mathematical or software quality.

Illustrative cases. Opus 5 solved each of the following four problems only when given the textbook. In every case, its trace shows that it read a relevant passage and used the mathematical structure of that passage in the successful formalization.

- **Nagell-Lutz theorem.** The source supplied the sequence of local valuation and formal-group lemmas needed to prove integrality and the final discriminant divisibility statement. The no-source run developed much of the same machinery but did not connect it into the required torsion argument.
- **Rouché’s theorem.** Opus 5 followed the source’s decomposition through the argument principle and a straight-line homotopy. The no-source run constructed the zero-counting machinery but stopped before proving its final connection to winding number.
- **Commutativity of Dunkl operators.** The successful run used the source’s reduction through a commutator identity and the Jacobi identity, avoiding the classification argument pursued by the no-source run.
- **Universal splitting.** The source gave a three-part roadmap: representability by polynomial equations, formal smoothness by lifting matrix units, and faithful flatness through splitting over algebraically closed fibres. The successful run implemented all three; the no-source run stopped at the final faithful-flatness step.

Opus 5 also solved two problems only without the source:

- **Grading-element local finiteness.** The source-enabled run followed the textbook’s quotient-module argument but stalled on two technical steps. The no-source run instead used local-finiteness saturations and generalized eigenspaces, which translated more directly into Lean.
- **Soft-thresholded SVD.** The source-enabled run followed a stationary-point argument whose relaxation lost an essential rank constraint. The no-source run instead orthogonalized the factors and completed the proof using scalar soft thresholding, convexity, and a fractional greedy bound.

J.2 Reasoning-Effort Sensitivity

Reasoning-effort controls allocate additional test-time computation within a model, but their labels are provider-specific and should not be compared as matched compute across model families. To measure within-model sensitivity, we rerun four models below their headline settings: GPT-5.6 Sol and Gemini 3.7 Flash at **medium**, and Opus 5 and Fable 5 with adaptive thinking at **high**.

The effect is sharply model dependent. Opus 5 drops only from 211/341 (61.9%) to 204/341 (59.8%), a decrease of 2.1 percentage points, while Fable 5 remains unchanged at 181/341 (53.1%). In contrast, Gemini falls from 179/341 (52.5%) to 136/341 (39.9%), a decrease of 12.6 percentage points, and GPT-5.6 Sol falls from 201/341 (58.9%) to 114/341 (33.4%), a decrease of 25.5 percentage points. Lower reasoning effort therefore has little observed effect on Fable and only a modest effect on Opus, but causes a substantial loss of verified coverage for Gemini and Sol.

J.3 One-Shot and Tool-Ablation Details

GPT-5.6 Sol’s six one-shot successes are finite-dimensional norm equivalence, Riesz representation, a convex-hull support identity, Jacobson density, the Lasso optimality conditions, and a Stacks open-refinement lemma. Gemini’s three are universal representation by an isotropic quadratic form, the nonpositive curvature inequality for affine buildings, and existence of a projective-module surjection. The two success sets are disjoint, but all nine problems are solved by every model in the agentic leaderboard, including GPT-6 Astra, DeepSeek V4.1 Flash, and Kimi K3. Their corresponding full agentic runs require far fewer interactions than a typical success on the single-hole cohort: a median of 19 versus 102 turns for Sol and 17 versus 137.5 for Gemini. The one-shot comparison measures the complete one-shot and agentic systems rather than the effect of any single tool.

The REPL, Loogle, and build endpoints are heavily used in the three baseline runs underlying pass@3. Across 216 task-run observations, GPT makes 8,715 REPL calls, 18,459 Loogle calls, and 5,159 build-service calls; Gemini makes 33,209, 12,416, and 19,058, respectively. Every observation invokes build, and 214/216 GPT observations and 215/216 Gemini observations use both REPL and build. Tool use is therefore a central part of the baseline behavior rather than a rarely exercised option.

Tool group	GPT-5.6 Sol	Gemini 3.7 Flash
REPL	36 [17, 58] (99.1%)	106.5 [40.5, 217.8] (99.5%)
Loogle	62 [24, 125.3] (97.7%)	46.5 [18.8, 82] (97.2%)
Build	20 [9, 35.3] (100%)	69 [11.8, 138.5] (100%)

Table 12 Baseline tool calls per task-run, reported as median [first quartile, third quartile] across the 216 pass@3 observations for each model. Parentheses give the percentage of observations using the tool group.

Because Gemini trajectories are longer, raw calls per run should not be read as cross-model efficiency. Per 100 turns, GPT makes 23.7 REPL, 50.1 Loogle, and 14.0 build-service calls, compared with 30.7, 11.5, and 17.6 for Gemini. Failed runs use more tools because successful runs terminate early while failures commonly run to budget.

Filesystem search provides a fallback when specialized search is removed: median filesystem-read calls rise from roughly 7 per GPT full-tool run to 55 without Loogle and 85 with only file operations; for Gemini, they rise from 20 to 40 and 52, respectively. In the no-build condition, GPT reconstructs `lake build` through the REPL on 26/72 problems, illustrating why these treatments concern endpoints rather than abstract capabilities. Among the 34 problems solved by Gemini both with full tools and without the REPL, median task-level spending increases by approximately 1.84× without the REPL. GPT shows no comparable increase, suggesting that the REPL primarily improves Gemini’s efficiency rather than its aggregate success rate.

J.4 Alternative Agent Scaffold

Claude Code uses a hybrid tool stack rather than a wholly separate proving environment. Across its selected traces, 60.6% of tool calls go to the benchmark-provided MCP services for the Lean REPL, Loogle, build, and report submission; the remaining 39.4% use Claude Code’s native `Read`, `Glob`, `Grep`, `Edit`, and `Write` operations. It invokes the REPL on 312/341 problems, Loogle on 301, and build on 317.

In 18 of the 20 Claude-only successes, both configurations follow the same mathematical roadmap, but the common loop stops with only one or two target holes open. Claude Code’s accepted developments have median 1,402 added lines in these cases, compared with 415 in the common loop’s partial submissions; it performs more persistent editing while making fewer REPL and Loogle calls. For example, on Bézout’s theorem the common loop makes 55 Loogle calls and adds 442 lines but leaves the homological core unfinished; Claude Code uses 38 Loogle calls and adds 1,740 lines to complete the Hilbert–Koszul and local-intersection-algebra development. Claude Code has lower recorded spending on all 20 problems (median \$56 versus \$120) and uses fewer turns on 17/20 (median 235 versus 305).

J.5 Persistence Intervention

Early in our experiments, agents could end a run by reporting a problem `unsolved` after using only a small fraction of their budget. We therefore introduced the 10% continuation rule described in Appendix B. In the canonical leaderboard exports, more than one valid `submit_report` call identifies a selected trajectory whose first surrender was rejected. Table 13 reports how often this occurred and how often the additional work eventually produced a verified proof.

Model	Forced to continue	Eventually passed	Conversion
GPT-6 Astra	13	12	92.3%
Opus 5	3	0	0%
GPT-5.6 Sol	88	17	19.3%
Fable 5	2	0	0%
DeepSeek V4.1 Flash	198	39	19.7%
Gemini 3.7 Flash	199	41	20.6%
Kimi K3	84	3	3.6%
Sonnet 5	114	6	5.3%
Opus 4.8	134	0	0%

Table 13 Effect of requiring agents to continue after an early **unsolved** report in the selected headline trajectories. Conversion is the fraction of forced continuations that eventually pass clean-room verification.

Continued work recovers proofs for Astra, Gemini, DeepSeek, Sol, Sonnet, and Kimi, but none for Opus 5, Opus 4.8, or Fable. The intervention is therefore most useful for models that tend to stop before exhausting their productive search, and offers little benefit when an **unsolved** report already reflects a stable failure.

Impact on headline scores. The canonical leaderboard exports record the number of valid **submit_report** calls made in each selected trajectory. A verified run with more than one call necessarily submitted **unsolved** first: a **solved** report terminates immediately. We therefore mechanically truncate each trajectory at its first surrender to obtain Table 14. Without enforced continuation, Astra would fall from 281 to 269, DeepSeek from 180 to 141, Gemini from 179 to 138, and GPT-5.6 Sol from 201 to 184. The gains show that sustained iteration on compiler and tool feedback is itself an important form of test-time scaling.

Model	Final score	Later recoveries	Stop-at-surrender score
GPT-6 Astra	281	12	269
Opus 5	211	0	211
GPT-5.6 Sol	201	17	184
Fable 5	181	0	181
DeepSeek V4.1 Flash	180	39	141
Gemini 3.7 Flash	179	41	138
Kimi K3	165	3	162
Sonnet 5	152	6	146
Opus 4.8	150	0	150

Table 14 Headline verified coverage with the continuation intervention and after counterfactually terminating each selected trajectory at its first valid **unsolved** report.

Model	Budget consumed	Model gave up
GPT-6 Astra	21	39
GPT-5.6 Sol	10	130
Sonnet 5	4	185
Kimi K3	3	173
Opus 5	2	128
Gemini 3.7 Flash	2	160
Fable 5	0	160
DeepSeek V4.1 Flash	0	161
Opus 4.8	0	191
All models	42	1,327

Table 15 Termination reasons among unsuccessful selected leaderboard trajectories.

J.6 Self-Report Accuracy

Agents generally assess their own success accurately, but their reports are not perfect substitutes for independent grading. Table 16 compares each recorded final **solved**/**unsolved** report with the clean-room verdict. Of 2,969 recorded reports, 2,959 agree with the grader. All 10 disagreements are false claims of success; no model reports **unsolved** for a submission that Comparator accepts. A further 100 rows have no recorded final report and are shown separately rather than counted as correct or incorrect.

Model	Correct/recorded	False solved	No report	Accuracy
GPT-6 Astra	339/341	2	0	99.41%
Opus 5	341/341	0	0	100.00%
Opus 4.8	341/341	0	0	100.00%
GPT-5.6 Sol	340/341	1	0	99.71%
Gemini 3.7 Flash	336/340	4	1	98.82%
Sonnet 5	340/341	1	0	99.71%
Fable 5	243/243	0	0	100.00%
DeepSeek V4.1 Flash	340/341	1	0	99.71%
Kimi K3	339/340	1	1	99.71%
All models	2,959/2,969	10	100	99.66%

Table 16 Agreement between recorded agent self-reports and clean-room grading. Accuracy is conditional on a recorded final report.