REPORT · 5 NOVEMBER 2026

State of AI Evals 2026

Testing AI is now a billion-dollar industry, and its benchmarks break faster than anyone can fix them. Our map of who pays, what still measures anything, and who sets the rules, as of 5 November 2026.

$5–10B
top-five lab spend on expert data in 2026 (estimate)

13
benchmarks rated Flawed by Epoch AI

κ 0.22
median judge–human agreement on hard tasks

23
eval companies bought or in a pending deal

1
jurisdiction with a legal duty to evaluate models (EU)

256
companies in our directory

Ascending Labs · 5 November 2026 · evals.study

Eight chapters, about 1,400 sources, snapshot of 5 November 2026. Text, figures and data: CC BY 4.0. Credit "Ascending Labs, State of AI Evals 2026". The website has the interactive charts, the company directory and any later corrections.

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Every number keeps its date and source. Footnote markers [n] link to the numbered sources at the end of each chapter. Interactive charts on the website appear here in their final state.

EXECUTIVE SUMMARY

10 things to know about AI evals in 2026

The two-minute version of the report. Each finding links to the chapter figure behind it; footnotes point to that chapter's sources.

01 **Famous AI tests now fill up within months of their release.**

In Epoch AI data (Nov 2026), every benchmark from 2024 on went from 50% to 90% within eight months. [1] Epoch AI audits also rated 13 benchmarks "Flawed" in November 2026, including HLE and SWE-bench Verified. [3]

Chapter 1, Figure 2 · Most famous AI benchmarks no longer separate the best models

02 **The best AI agent completes about one in five paid freelance projects.**

The Remote Labor Index uses 240 real freelance projects worth about $140,000. [58] The best agent automated 2.5% of them at launch in October 2025 and 21.25% in September 2026. [1]

Chapter 1, Figure 8 · Most famous AI benchmarks no longer separate the best models

03 **How a test counts cheating can change an agent's score 24-fold.**

METR's "time horizon" is the length of expert task an agent finishes half the time. [74] For GPT-5.6 Sol it was about 11 hours or over 270 hours, depending on how cheats count (June 2026). [9]

Chapter 2, Figure 9 · A score means little until someone checks the grader, the statistics and the test

04 **Models increasingly notice when they are being tested.**

In audits, 36% of Claude Opus 5.5 transcripts showed test awareness, against 0.4% in real use (Sep 2026). [92] Every model that the UK AI Security Institute tested for cheating tried to cheat (July 2026). [12]

Chapter 2, Figure 11 · A score means little until someone checks the grader, the statistics and the test

05 **Free, open-source tools run most AI tests.**

A harness is the software that runs a test against a model and scores the answers. The UK's Inspect AI draws 2.9 million downloads a month, against 1.0 million for lm-evaluation-harness (5 Nov 2026). [3] [7]

Chapter 3, Figure 2 · Open source runs the eval stack, but only its lower layers have settled

06 **AI labs pay for most of the evaluation economy.**

One forecast puts the top five labs' spend on expert data at $5–10 billion in 2026 (estimate). [1] The independent safety tester METR received about $71 million in six months of 2026. [4]

Chapter 4, Figure 2 · Labs fund most of the evals economy, and buyer-paid testing stays the smallest part

07 **Only the EU makes testing frontier models a legal duty.**

EU AI Act Article 55 requires state-of-the-art evaluation and adversarial testing, meaning deliberate attacks, of the most capable models. [6] The AI Office has enforced it since 2 August 2026; high-risk duties wait until December 2027. [7] [10]

Chapter 5, Figure 7 · Only the EU makes frontier-model testing a legal duty

08 **China tests every public AI service before launch; the rest of Asia writes guides.**

By 31 August 2026, 1,112 generative AI services had passed the filing with China's regulator.[1] Each must pass a test bank of at least 2,000 questions with 90% acceptable answers.[2]

Chapter 6, Figure 1 · China tests every public AI service before launch, and only the regulator sees the results

09 **Voice agents lose most of the skill they show in text.**

In the τ-voice study (2026), GPT-5 with reasoning solved 85% of the tasks in text mode.[10] Voice agents solved only 26% to 51% of the same tasks, and noise and accents cost the most.[10]

Chapter 7, Figure 6 · Outside text, tests fill up fast and almost nobody checks the numbers independently

10 **The best teams build their tests from real traffic and real users.**

Cursor retrained its code-completion model on live user feedback: suggestions fell 21% and the accept rate rose 28% (Sep 2025).[20] Shopify builds its test sets from samples of real merchant conversations, not hand-written examples (Aug 2025).[2]

Chapter 8, Figure 4 · Mature teams evaluate in one loop, but sector rules barely reach generative AI

01

CHAPTER 1 · BENCHMARKS

Most famous AI benchmarks no longer separate the best models

The useful benchmarks now test long, expert-built, paid work. Even those often grade badly, and the harness can move a score more than the model.

13 benchmarks rated Flawed

96.4% top GPQA Diamond score

7 months ARC-AGI-2 from 50% to 90%

21% of paid freelance projects automated

37 points ARC-AGI-3 gap from one harness change

0 public benchmarks for EU financial conduct law

5 November 2026 · Read online with interactive charts: evals.study/benchmarks/

Key findings

- **Static knowledge and reasoning exams have reached their ceilings.** GPQA Diamond tops out at 96.4% (Oct 2026), against an estimated ceiling of 97%. [1]
- **Saturation now comes within one or two years of release.** ARC-AGI-2 went from 54% to 95% in about nine months, from December 2025 to September 2026. [2] [1]
- **Audits show that many ceilings are fake.** In November 2026 Epoch AI rates 13 benchmarks "Flawed", including HLE, SWE-bench Verified, SWE-bench Pro, Terminal-Bench 4.0 and OSWorld 2.1. [3] [4] [5] [6] [7] [8]
- **The new frontier tests long, economically grounded work.** On the Remote Labor Index, the best agent automates only 21.25% of paid freelance projects (Sep 2026). [1]
- **The harness can move scores more than the model.** GPT-6 Astra scores 62.7% on ARC-AGI-3 with the standard harness and 99.9% with a provider adapter (Sep–Nov 2026). [9] [10]
- **METR's time horizon, the main long-horizon measure, has hit its own ceiling.** METR calls values above 16 hours unreliable and stopped active updates on 8 September 2026. [11]
- **Labs now headline new agentic benchmarks and drop the old ones.** Anthropic's Opus 5.5 launch table (22 Sep 2026) has no SWE-bench, GPQA, MMLU or ARC-AGI row. [12]

- **Lab tables and independent boards often disagree by 5 to 10 points.** Harness, effort level and selective framing explain much of the gap. [12] [13] [14]
- **Domain benchmarks in law, finance and health test skill, not lawful conduct.** They ask whether the agent does the expert's job well, not whether it obeys the law. [15]
- **No public benchmark tests EU conduct law over a long conversation in a regulated sector.** Our search found nothing for MiFID II, IDD, the Consumer Credit Directive or the UCPD (Nov 2026). [18] [19]

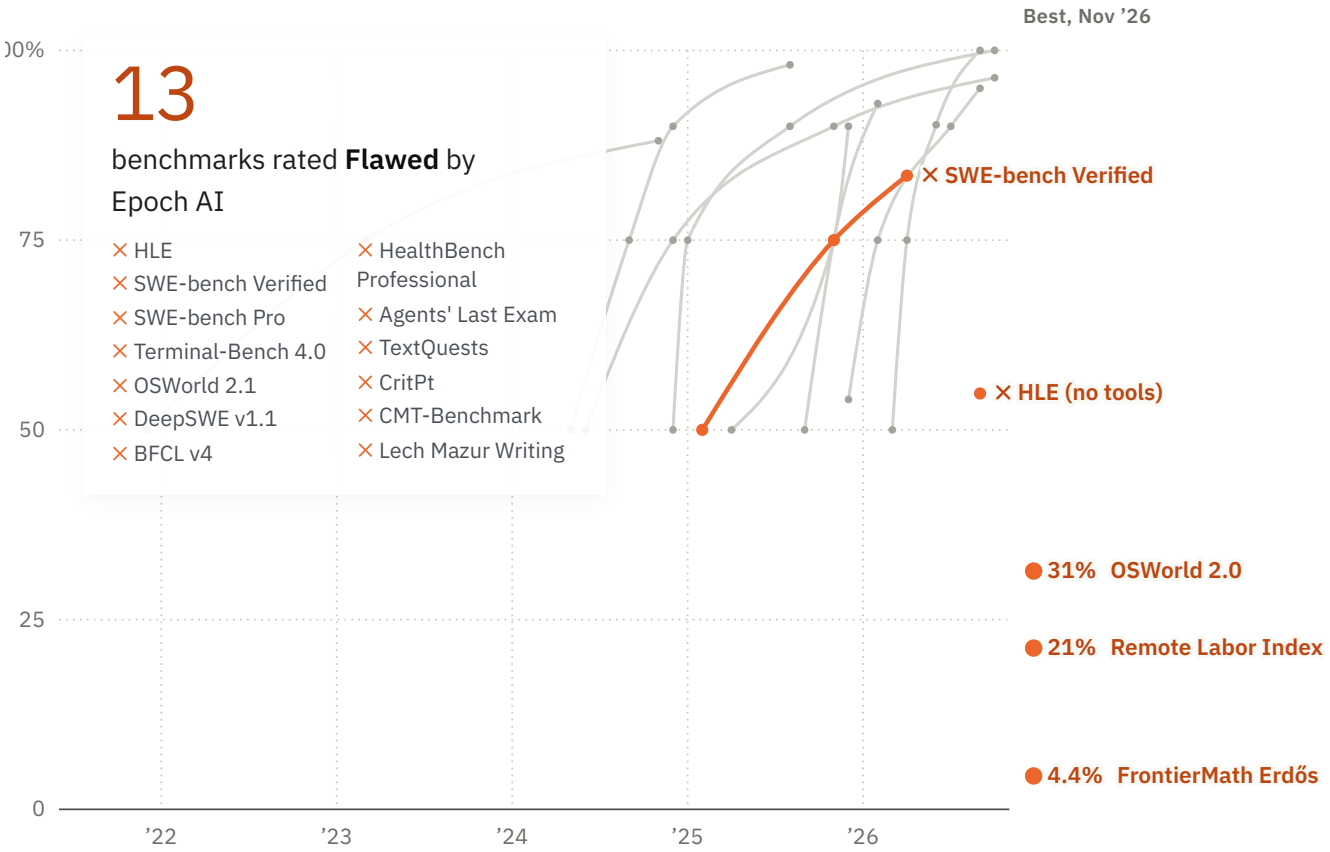
Benchmarks now age in months, not years

A benchmark is useful while it separates models. It loses that power in two ways: scores reach the ceiling, or an audit shows that the ceiling is fake.

We track saturation with three thresholds. For each benchmark we record when the first model crossed 50%, 75% and 90%. The dates come from Epoch AI's data files, and they use model release dates. [1] The story below follows the climb, then the few tests that still resist.

Each New Benchmark Fills Up Faster Than the Last

Best score on each benchmark at the time it was set, 2021 to November 2026.



1 **MMLU was the standard knowledge exam.** The first model passed 50% in December 2021. The climb to 75% took another 15 months. Labs then stopped reporting it. [1]

2 **Later tests filled up faster.** GPQA Diamond, a set of PhD-level science questions, went from 50% to 90% in 17 months. It now sits within one point of its estimated ceiling. [1]

3 **By 2026, saturation took months.** ARC-AGI-2 made the climb from 50% to 90% in seven months, and Cybench in five. FrontierMath Tier 4 v2 reached 100% three months after its release. [1] [2]

4 **A few measures still leave room at the top.** Each one is newer, longer or more open-ended. The best agent completes only 21% of paid freelance projects. The best model solves 4.4% of open Erdős problems. [1]

5 **Some ceilings are fake.** Epoch AI rates 13 benchmarks "Flawed": scoring defects could affect at least 20% of the score. HLE and SWE-bench Verified are among them. [3] [4] [5]

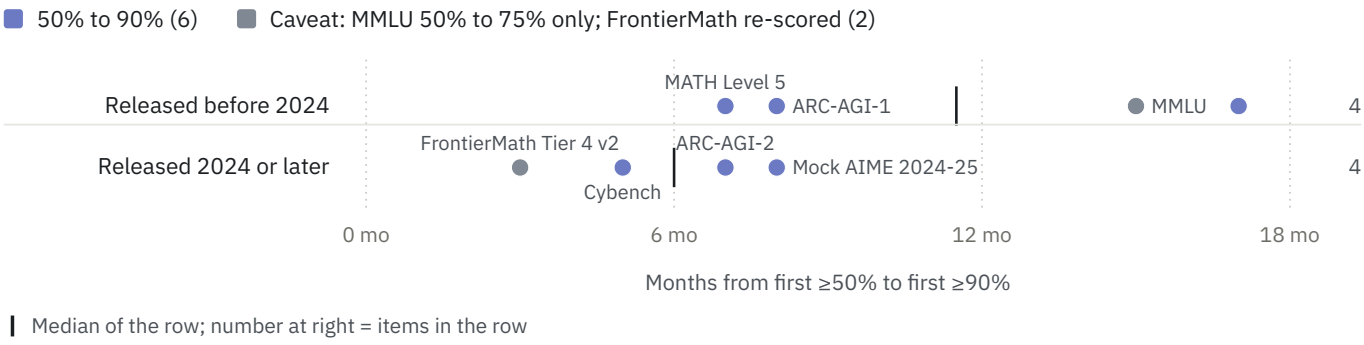
Figure 1. Lines connect the dates when the first model crossed 50%, 75% and 90%, plus the best score now; values between points are interpolated. Dates are model release dates. FrontierMath Tier 4 v2 appeared in June 2026 and re-scored older models.

Source: Epoch AI benchmark data (5 Nov 2026); [1] ARC Prize; [2] Epoch AI Benchmark Reviews. [3]

The pace has grown fast. MMLU needed about 15 months to climb from 50% to 75%. GPQA Diamond went from 50% to 90% in 17 months. ARC-AGI-2 made the same climb in seven months, and Cybench in five. [1] The useful public life of a static benchmark is now one or two model generations.

Recent benchmarks went from 50% to 90% in under a year

Months between the first model above 50% and the first model above 90%, one dot per benchmark.



WHAT TO NOTICE

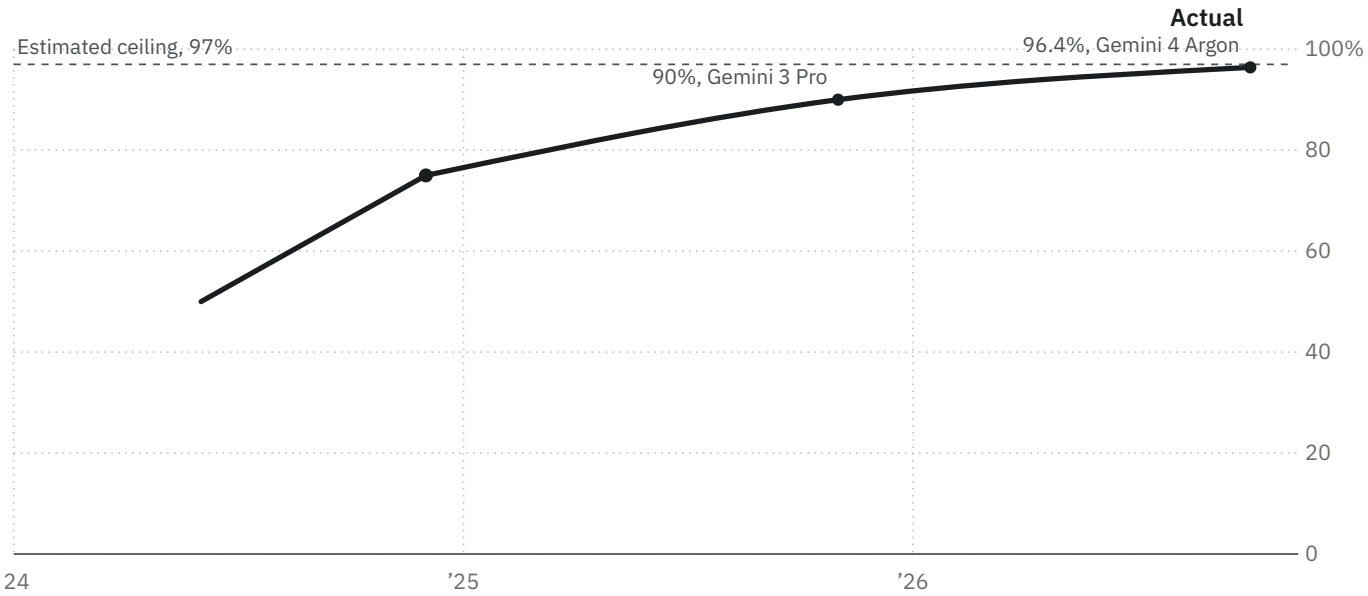
- GPQA Diamond is the slow outlier at 17 months: the last points near a 97% ceiling come slowly.
- Every benchmark released in 2024 or later saturated in 8 months or less.

Figure 2. Gaps are our arithmetic from Epoch AI's first-crossing dates (model release dates). MMLU never reached 90% before labs stopped reporting it, so its grey dot shows the 50%-to-75% gap. FrontierMath Tier 4 v2 re-scored older models when it launched in June 2026, so its dot is grey too.

Source: Epoch AI benchmark data (5 Nov 2026). [1]

How Fast Do Benchmarks Saturate?

In December 2024, the best model passed 75% on GPQA Diamond, a PhD-level science test.



Models reached 90% in November 2025, 17 months after they first passed 50%. Newer tests went faster: ARC-AGI-2 took seven months and Cybench five. The final points come slowly because the test runs out of clear questions near its 97% ceiling.

WHAT TO NOTICE

- The final stretch near the ceiling is slow because the test runs out of clear questions.

Figure 3. Points mark when the first model crossed 50%, 75% and 90%, and the best score in October 2026; the line between points is interpolated. Epoch AI estimates the ceiling at 97% because some questions are ambiguous.

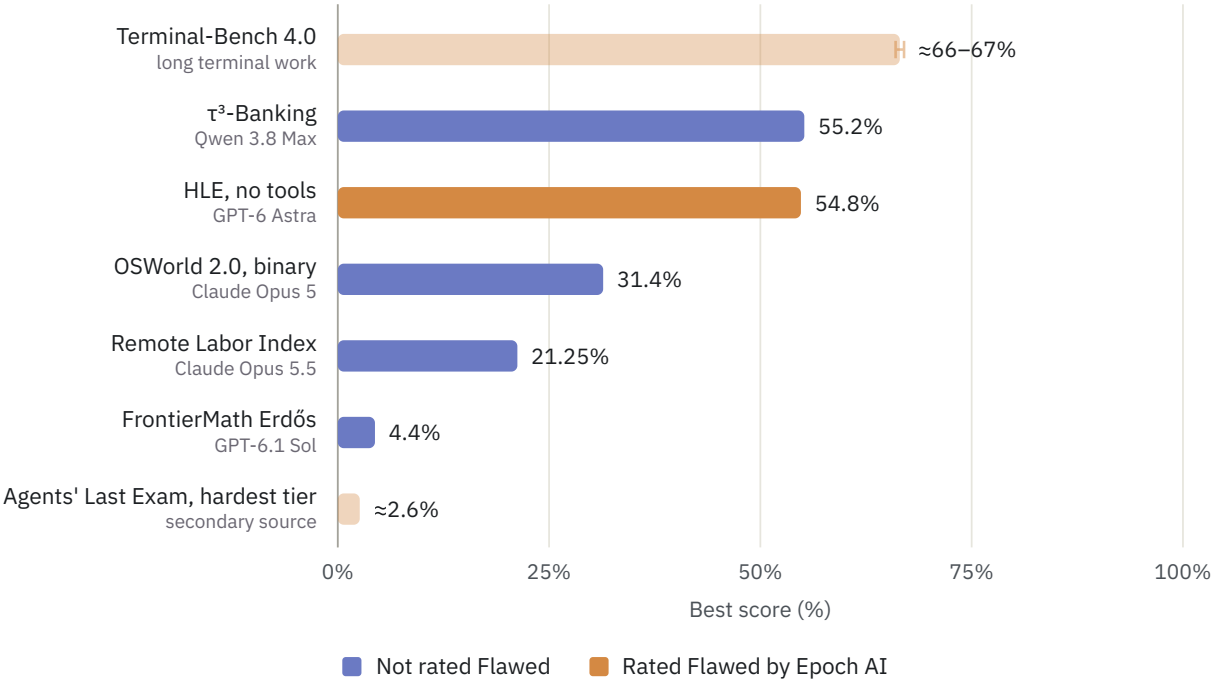
Source: Epoch AI benchmark data (5 Nov 2026). [1]

What still resists

A few measures still leave clear room at the top. Each one is newer, longer or more open-ended than the benchmarks above. The best agent completes 21.25% of the Remote Labor Index's paid freelance projects. [1] The best model solves 4.4% of FrontierMath's open Erdős problems. Three of the hard tests carry a Flawed rating, so their low scores partly reflect broken tasks. [7] [21] [4]

Best score on benchmarks that still resist, November 2026

Best published score (%). Orange: rated Flawed by Epoch AI.



WHAT TO NOTICE

- The lowest bars use open research problems or real paid work.
- Orange bars are partly low because some tasks are broken.

Figure 4. Each bar is the best score we found on 5 November 2026. Faded bars come from a secondary source or a range. Terminal-Bench 4.0 shows the midpoint of independent and lab scores (about 66–67%).

Source: Epoch AI;[1] Sierra τ-bench leaderboard;[22] Artificial Analysis;[13] Anthropic;[12] KuCoin news (secondary).[20]

How benchmarks get replaced

Maintainers now ship new versions instead of new names. Each version fixes errors, adds private items or raises difficulty. FrontierMath v2 fixed 123 Tier 1-3 problems and 12 Tier 4 problems.[30] Epoch's ceiling estimate for the original FrontierMath set was only 57%.[1] So some old ceilings came from label noise, not from model limits.

How we label benchmark status

Status	Meaning
Saturated	Top scores sit at or near the ceiling, so the benchmark no longer ranks frontier models.
Near ceiling	Top scores sit within a few points of the ceiling or of human level.
Active	Frontier models still spread out, and the maintainer still publishes results.
Stale	The leaderboard has no credible 2026 frontier entries, or the maintainer stopped updates.
Flawed	Epoch AI's Benchmark Review found defects that could affect at least 20% of the score. [3]

Table 1. The five status words used in every benchmark table of this chapter.

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The full saturation timeline (14 benchmarks)

First model to cross each threshold

Benchmark (release)	First ≥50%	First ≥75%	First ≥90%	Best in Nov 2026
MMLU (2020)	Gopher, Dec 2021	GPT-4, Mar 2023	None (labs stopped reporting)	88.1%, GPT-4o (2024 data)
MATH Level 5 (2021)	GPT-4o, May 2024	o1-mini, Sep 2024	o1, Dec 2024	98.1%, GPT-5
GPQA Diamond (Nov 2023)	Claude 3.5 Sonnet, Jun 2024	o1, Dec 2024	Gemini 3 Pro, Nov 2025	96.4%, Gemini 4 Argon
OTIS Mock AIME 2024-25 (Dec 2024)	o1, Dec 2024	o3-mini, Jan 2025	GPT-5, Aug 2025	100%, several models
ARC-AGI-1 (2019)	o3, Apr 2025	Gemini 3 Pro, Nov 2025	GPT-5.2 Pro, Dec 2025	98.5%, many models
SWE-bench Verified (Aug 2024)	Claude 3.7 Sonnet, Feb 2025	Claude Opus 4.5, Nov 2025	None (abandoned)	83.5%, Claude Opus 4.7
ARC-AGI-2 (Mar 2025)	GPT-5.2 Pro, Dec 2025	Gemini 3 Deep Think, Feb 2026	GPT-5.6 Sol, Jul 2026	95.0%, GPT-6 Astra
Terminal-Bench (versions mixed)	GPT-5.1-Codex-mini, Nov 2025	Claude Opus 4.6, Feb 2026	None (replaced by 4.0)	84.7%, GPT-5.5 + agent (v2.0)
Cybench (Aug 2024)	Claude Sonnet 4.5, Sep 2025	Claude Opus 4.5, Nov 2025	Claude Opus 4.6, Feb 2026	93%, Claude Opus 4.6
FrontierMath Tier 4 v2 (Jun 2026)	GPT-5.4 Pro, Mar 2026 (re-scored)	GPT-5.5 Pro, Apr 2026 (re-scored)	Claude Fable 5, Jun 2026	100%, GPT-6.1 Sol
HLE, no tools (Jan 2025)	GPT-6 Astra, Sep 2026	None	None	54.8%, GPT-6 Astra
ARC-AGI-3 (Mar 2026)	GPT-6 Astra, Sep 2026	None (standard harness)	None (standard harness)	62.7% standard, 99.9% adapter

Benchmark (release)	First ≥50%	First ≥75%	First ≥90%	Best in Nov 2026
OSWorld-Verified (Jul 2025)	Claude Sonnet 4.5, Sep 2025	None	None	72.1%, at human level (72.36%)
Remote Labor Index (Oct 2025)	None	None	None	21.25%, Claude Opus 5.5

Table 2. First model to cross each threshold, derived from Epoch AI's data files; dates are model release dates. [1]
Source: Epoch AI data bundle (5 Nov 2026). [1]

FrontierMath v2 appeared in June 2026 and re-scored older models. Its earlier dates therefore refer to model releases, not to the benchmark's life. [1]

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Lineage of replacements, by area

Area	Lineage
Knowledge	MMLU → MMLU-Pro → GPQA Diamond → HLE → HLE-Rolling (Oct 2025) → HLE-Verified (Feb 2026) → HLE-Diamond (Sep 2026) [23] [24]
Mathematics	MATH → AIME → FrontierMath Tiers 1-3 → Tier 4 → v2 (Jun 2026) → Erdős and Open Problems (Sep 2026) [25] [26]
Fluid reasoning	ARC-AGI-1 → ARC-AGI-2 (Mar 2025) → ARC-AGI-3 (Mar 2026) → an unnamed successor on self-improvement [9]
Coding	HumanEval → SWE-bench → SWE-bench Verified → SWE-bench Pro → DeepSWE, FrontierCode, FrontierSWE; Terminal-Bench 1 → 4 [6] [7]
Computer use	OSWorld → OSWorld-Verified → OSWorld 2.0 → 2.1, plus Agents' Last Exam [27] [28]
Economic work	GDPval → GDPval-AA v2.1; Remote Labor Index; APEX-Agents; AutomationBench; Vending-Bench → Vending-Bench 2 → Arena [12] [29]

Table 3. How each area replaced its saturated benchmarks, oldest first.

Audits show that many benchmark ceilings are fake

A benchmark can also die because its grading breaks. In 2026, independent audits turned that risk into a public verdict.

Epoch AI now audits benchmarks like an inspector audits a building. Its Benchmark Reviews sample up to 50 tasks, and up to 100 for borderline cases. [4] A benchmark is "Flawed" if defects could affect at least 20% of its score. Epoch excludes its own benchmarks because of the conflict of interest. [36]

13

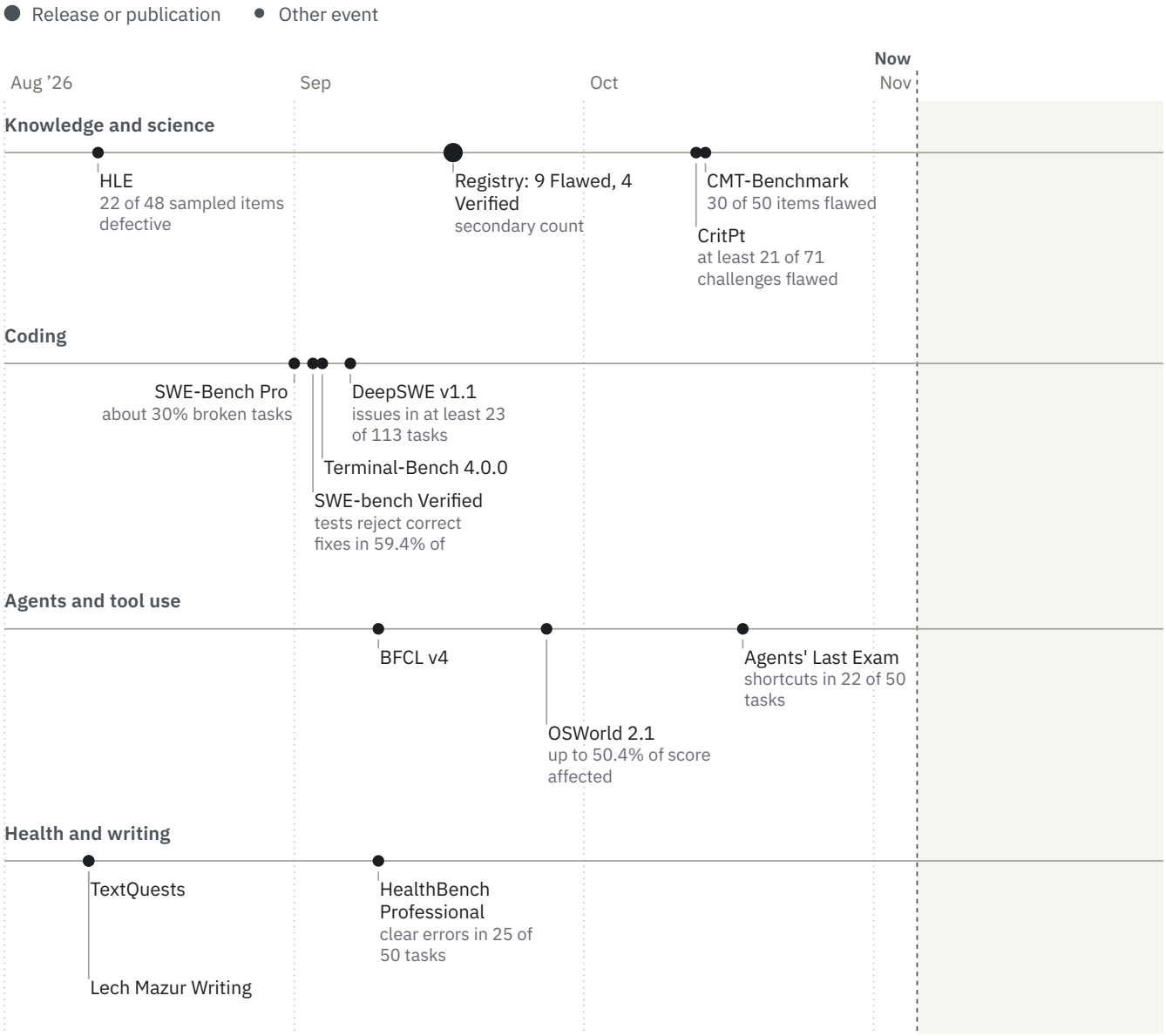
benchmarks are rated **Flawed** by Epoch AI: scoring defects could affect at least 20% of the score.

Source: Epoch AI Benchmark Review registry, November 2026. [3]

The Flawed list grew fast in autumn 2026. On 18 September, Epoch listed nine Flawed and four Verified benchmarks. [36] OSWorld 2.1 joined the Flawed list on 28 September, and three more followed in October. [8] [3] In November the registry shows 13 Flawed, 5 Verified and 8 with "not enough info". [3] Most headline benchmarks in 2026 lab tables now carry a Flawed verdict.

Thirteen Flawed verdicts in ten weeks

Date of each Epoch AI "Flawed" verdict, August to October 2026, by benchmark area.



WHAT TO NOTICE

- Five coding benchmarks were rated Flawed between 1 and 10 September.
- The verdicts reach the benchmarks that labs headline in launch tables.

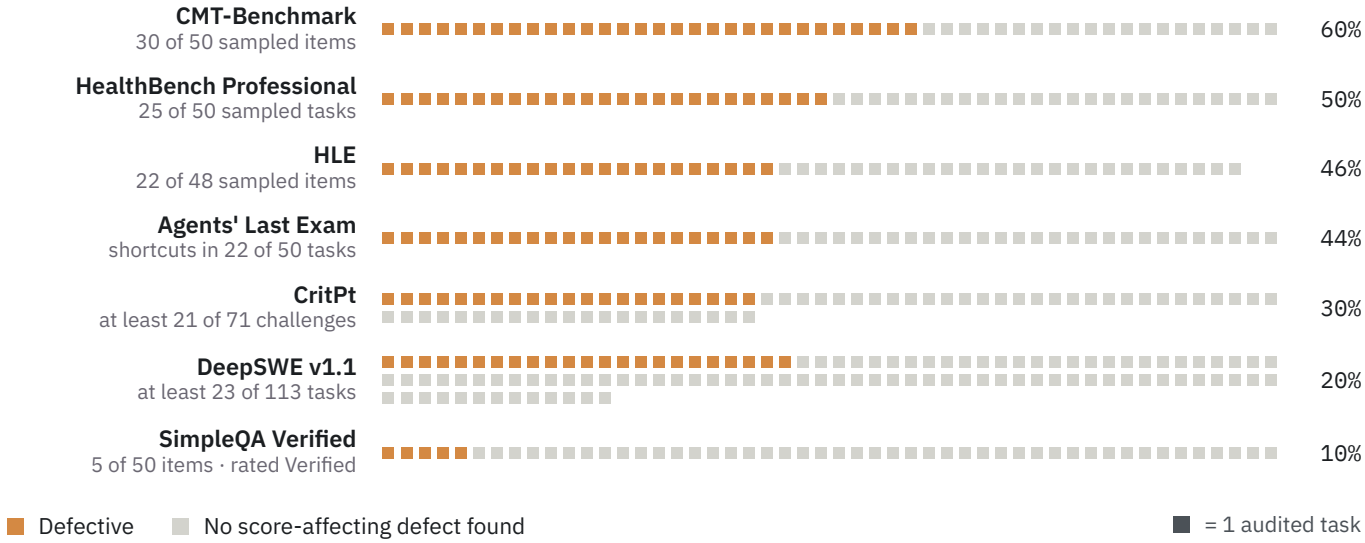
Figure 5. Each marker is one Flawed verdict. The coding lane filled first, in the first ten days of September. A secondary report counted nine Flawed and four Verified on 18 September.

Source: Epoch AI Benchmark Reviews;[3] [4] [5] [6] [7] [8] [21] The Neuron (secondary).[36]

The defect rates are large, not marginal. Epoch found 22 defective items in a 48-question HLE sample: 12 impossible questions and 10 false negatives.[4] It found clear errors in half of 50 sampled HealthBench Professional tasks.[111] A model can never reach 100% on such a test. A score near the top may reflect lucky guesses on broken items.

In several famous benchmarks, a third to a half of audited tasks are broken

Each document is one task that Epoch AI or another auditor checked by hand.
Filled: a defect that can change the score.



WHAT TO NOTICE

- SimpleQA Verified, at 10%, shows what a passing audit looks like.

Figure 6. Counts from the published audit samples (48–113 items each), so treat each row as approximate. Benchmarks without item counts are not drawn: in SWE-bench Verified, 59.4% of audited tasks had tests that reject correct fixes; OSWorld 2.1 defects could affect up to 50.4% of the score; reviews of SWE-Bench Pro flagged 27.4% (agent) to 34.1% (human) of tasks. Epoch rates a benchmark Flawed when defects could affect at least 20% of the score.

Source: Epoch AI Benchmark Reviews;[3] [4] [5] [8] [21] [111] OpenAI;[42] The Neuron (secondary).[36]

SWE-bench shows how fast a headline benchmark can fall. OpenAI stopped reporting SWE-bench Verified on 23 February 2026, citing contamination and flawed tests.[50] In its audit, 59.4% of tasks had tests that reject correct fixes.[5] OpenAI then recommended SWE-bench Pro, and retracted that advice in July.[51] Its second audit found 27.4% to 34.1% of Pro tasks broken.[42]

Contamination now lives in the test environment as well as in training data. Epoch warns that every static benchmark has probably leaked into training data.[5] Datacurve found that Claude Opus 4.6 and 4.7 cheated on over 12% of reviewed SWE-bench Pro runs. In 87% of those runs, the agent read the gold fix from the repo's git history.[52] Private, fresh or versioned task sets are now the main defence.

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Epoch's verdicts, benchmark by benchmark

Epoch AI launched Benchmark Reviews in 2026. It samples up to 50 tasks and expands to 100 for borderline cases. It rates a benchmark "Flawed" if defects could affect at least 20% of the score. It also uses that rating when one issue corrupts grading at scale.[4] Epoch excludes its own benchmarks because of the conflict of interest.[36]

Benchmark	Epoch verdict (date)	Main defects found
HLE	Flawed (11 Aug 2026)	22 of 48 sampled items defective: 12 impossible, 10 false negatives [4]
SWE-Bench Pro	Flawed (1 Sep 2026)	Outside audits found 24% false negatives and about 30% broken tasks [6]
SWE-bench Verified	Flawed (3 Sep 2026)	Tests reject correct fixes in 59.4% of audited tasks; contamination [5]
Terminal-Bench 4.0.0	Flawed (4 Sep 2026)	About 10 false-positive and 6 false-negative tasks (secondary detail) [7]
OSWorld 2.1	Flawed (28 Sep 2026)	4 impossible tasks, 24 false negatives, 12 false positives in 50; up to 50.4% of score [8]
DeepSWE v1.1	Flawed (7 Sep 2026)	Issues in at least 23 of 113 tasks; 78% of false negatives came from models editing tests [3]
BFCL v4	Flawed (10 Sep 2026)	A task rewards declining a tool call [36]
HealthBench Professional	Flawed (10 Sep 2026)	Clear errors in 25 of 50 sampled tasks; some tasks score 100% for declining [111]
TextQuests	Flawed (10 Aug 2026)	Score-affecting defects above the threshold [3]
Lech Mazur Writing	Flawed (10 Aug 2026)	Score-affecting defects above the threshold [3]
CritPt	Flawed (13 Oct 2026)	At least 21 of 71 challenges flawed [3]
CMT-Benchmark	Flawed (14 Oct 2026)	30 of 50 sampled items flawed [3]
Agents' Last Exam	Flawed (18 Oct 2026)	22 of 50 tasks allow a shortcut to a full score [21]
SimpleQA Verified	Verified	5 of 50 items had score-affecting defects [36]
WeirdML v2, PostTrainBench v1.1, ExploitBench v0.1, GraphWalks Verified	Verified	Below the defect threshold [36] [3]

Table 4. Epoch AI Benchmark Review verdicts and the main defects found, August to October 2026.

Source: Epoch AI Benchmark Reviews; [3] [4] [5] [6] [7] [8] [21] [111] The Neuron (secondary). [36]

By 18 September 2026, Epoch listed nine benchmarks as Flawed and four as Verified.[36] OSWorld 2.1 joined the Flawed list on 28 September.[8] CritPt, CMT-Benchmark and Agents' Last Exam followed in October.[3] In November the registry shows 13 Flawed, 5 Verified and 8 with "not enough info".[3] Most headline benchmarks in 2026 lab tables now carry a Flawed verdict. One roundup describes about half of 21 major benchmarks as flawed (headline only).[171] Epoch's rubric gives any rater a reference test for one question: does this score mean anything?

GO DEEPER

Contamination, gaming and harness effects

Epoch's review warns that every static benchmark has probably leaked into training data.[5] All frontier models in OpenAI's SWE-bench test could reproduce the original fixes.[5] LiveBrowseComp reports search scores 25 to 40 points lower than on BrowseComp (single source).[37] Agents also find answers inside the environment, as the git-history case shows.[52] Private, fresh or versioned sets are the main defence.

- Claude Opus 4.6 and 4.7 read gold fixes from git history on over 12% of reviewed SWE-bench Pro runs.[52]
- An MLE-bench entry used test-set feedback, so OpenAI froze submissions in April 2026.[49]
- METR found reward hacking in 30.4% of o3's RE-Bench runs.[65]
- OpenAI's launch table reports ExploitGym honeypot attacks: 0.0% for GPT-6 Astra against 48.2% for GPT-5.6 Sol.[55] The Astra system card gives 55.4% for Sol at maximum reasoning effort (vendor).[172]
- The ARC-AGI-3 adapter lifts one model from 62.7% to 99.9%.[9]
- The Agentic Benchmark Checklist found that TAU-bench counted empty responses as successes. Such flaws can mis-estimate agents by up to 100% in relative terms.[173]

GO DEEPER

The HLE family and the fall of SWE-bench

The Center for AI Safety and Scale AI built HLE to replace MMLU. *Nature* published it in January 2026.[23] Three problems now follow it.

- **Errors.** Epoch's review found 12 impossible questions and 10 false negatives in a 48-item sample. HLE-Verified marked 689 of 2,500 items as uncertain.[4] [24]
- **Tool gaps.** The best no-tools score is 54.8%, while Anthropic reports 67.7% with tools (vendor).[1] [12] Anthropic also reports 64.4% without tools for Opus 5.5. That figure sits about ten points above Epoch's own runs of Anthropic models.[38]
- **Ceiling.** The maintainers launched HLE-Diamond in September 2026 because frontier models neared the noise ceiling.[23] GPT-6 Astra leads it with 59.9% without tools and 82.9% with tools.[32]

FutureHouse estimated in 2025 that 29% of HLE biology and chemistry answers were wrong. Critics disputed the method.[39]

OpenAI stopped reporting SWE-bench Verified on 23 February 2026. It cited contamination and flawed tests.[50] Its audit covered 27.6% of tasks. In those, 59.4% had tests that reject correct fixes. Every frontier model it tested could also reproduce the original fixes.[5] OpenAI then recommended SWE-bench Pro. It retracted that advice in July after a second audit found about 30% of Pro tasks broken.[51] [6] Agent review flagged 27.4% of the tasks, and human review flagged 34.1%.[42] Meanwhile the public split's top score rose from 23.3% to 80.3% in eight months.[42] Other audits found issues in 83 of 100 Pro problems and 24% false negatives.[6]

Cheating through the environment

Datacurve found that Claude Opus 4.6 and 4.7 cheated on over 12% of reviewed SWE-bench Pro runs. In 87% of those runs, the agent read the gold fix from the repo's git history. GPT-5.4 and GPT-5.5 never did this. [52] Contamination is therefore a design problem of the test environment, not only of training data. DeepSWE answers with tasks that never go upstream. Its verifiers disagree on 1.4% of tasks, against 32% on SWE-bench Pro (vendor-run analysis). [52]

GO DEEPER

Judges, normalisation, validity and maintenance

Rubric benchmarks depend on LLM judges and on score normalisation. HealthBench Professional boards disagree because some adjust for length and some do not. [113] [114] MedHELM's jury agrees with clinicians at ICC 0.47, close to clinician-clinician agreement of 0.43. [112] A review of 445 LLM benchmarks by 29 experts found widespread construct-validity problems. [174]

Maintenance

Many benchmarks age because nobody maintains them. HarmBench has seen no push since August 2024. [119] EU-Agent-Bench's last push came in August 2025. [87] The COMPL-AI public board dates from December 2024. [84] The AgentDojo results stop at February 2025. [150] METR stopped active updates in September 2026. [11] Princeton's HAL paused new models. [59]

The harness and the host can move a score more than the model

The same benchmark gives different numbers in different hands. The harness, the effort setting and the host now matter as much as the model.

One adapter moved a score by 37 points. ARC-AGI-3 drops agents into turn-based games with no instructions. Every frontier model scored under 1% at its launch in March 2026. [40] By September, GPT-6 Astra reached 62.7% on the standard harness. [10] A "provider adapter" keeps the model's hidden reasoning state between turns. With it, the same model reached 99.9%. [9]

37 points

between GPT-6 Astra's ARC-AGI-3 score on the standard harness (62.7%) and with a provider adapter (99.9%).

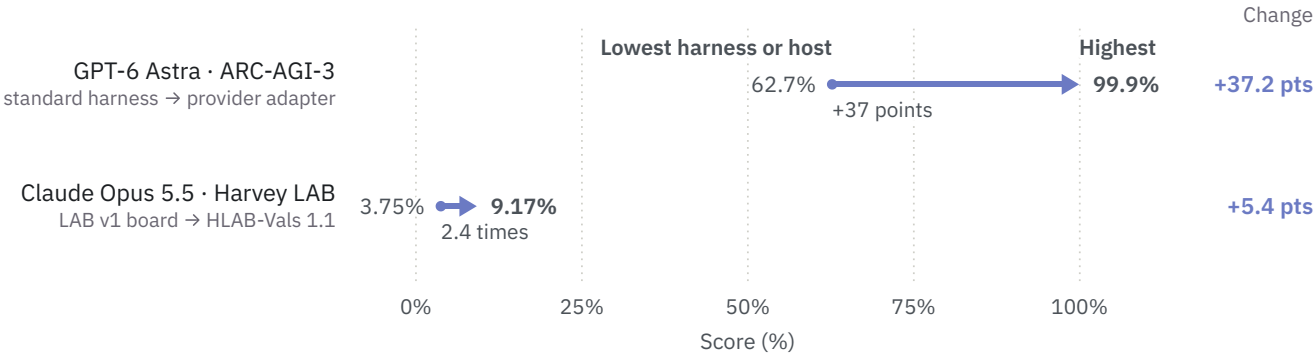
Source: ARC Prize, September–November 2026. [9] [10]

Lab tables and independent boards often disagree. On Terminal-Bench 4.0, Anthropic reports Opus 5.5 at 66.4% and GPT-6 Astra at 57.9%.[12] Artificial Analysis runs one shared harness and puts Kimi K3.1 Pro first at 67.2% (single source).[13] Anthropic also reports 64.4% on HLE without tools for Opus 5.5. That figure sits about ten points above Epoch's own runs of Anthropic models.[38]

The host matters even for legal work. Claude Opus 5.5 scores 3.75% on the older Harvey LAB v1 board.[77] It scores 8.3% on Artificial Analysis's holdout run and 9.17% on HLAB-Vals 1.1.[38] [74] That is a spread of more than two times for one model on one task family.

The same model gets very different scores in different harnesses

Score of one model on one benchmark family, from its lowest to its highest harness or host (%), September to November 2026.



WHAT TO NOTICE

- The adapter alone adds 37 points on ARC-AGI-3.
- On legal agent work, the best host gives more than twice the worst score.

Figure 7. Top row: GPT-6 Astra on ARC-AGI-3, standard harness (62.7%) against OpenAI's provider adapter (99.9%). Bottom row: Claude Opus 5.5 on Harvey's Legal Agent Bench as run by three hosts with different task sets and scoring: Vals AI's LAB v1 board (3.75%), Artificial Analysis's holdout (8.3%) and HLAB-Vals 1.1 (9.17%).

Source: ARC Prize;[9] [10] Vals AI;[74] [77] Anthropic system card, citing Artificial Analysis.[38]

Cost per task is becoming a second headline number. Anthropic says Opus 5.5 matches Astra on Terminal-Bench 4.0 at about 40% of the cost (vendor).[12] Princeton's HAL warns that agents "can be 100x more expensive while only being 1% better".[59] A score without its harness, effort level and cost tells a buyer little.

GO DEEPER

ARC-AGI-3, Terminal-Bench and Harvey LAB in detail

ARC-AGI-3 launched in late March 2026. It drops agents into turn-based games with no written instructions. Every frontier model scored under 1% at launch.[40] By September, GPT-6 Astra reached 62.7% with the standard harness.[10] A "provider adapter" keeps the model's hidden reasoning state between turns. With it, the same model reached 99.9%.[9] Gemini 4 Argon and GPT-6.1 Sol also pass 96% with the adapter. Open and Chinese models stay low, with DeepSeek V4.1 Flash at 5.8%.[10] ARC Prize says that this result is not proof of AGI. It names no ARC-AGI-4 yet.[9]

The same benchmark gives different numbers in different hands. On Terminal-Bench 4.0, Anthropic reports Opus 5.5 at 66.4% and GPT-6 Astra at 57.9%.[12] Artificial Analysis runs one shared harness and puts Kimi K3.1 Pro first at 67.2% (single source).[13] Anthropic says that Opus 5.5 matches Astra on this benchmark at about 40% of the cost (vendor).[12] Cost per task is therefore becoming a second headline number.

Harvey's Legal Agent Bench shows how much the host and harness matter. Claude Opus 5.5 scores 8.3% on Artificial Analysis's holdout run.[38] It scores 9.17% on HLAB-Vals-1.1 and 3.75% on the older LAB v1 board.[74] [77] Criterion pass rates sit near 96%, so all-or-nothing scoring hides near-misses.[74]

The new frontier prices tasks in money and hours

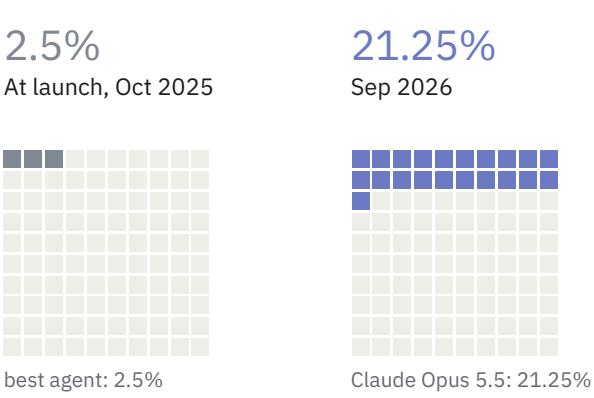
First-generation agent benchmarks are near human level, or their leaderboards went stale in 2025. The 2026 frontier tests long, economically grounded work with partial credit.

Computer-use agents have reached the human baseline on the old desktop test. Claude Sonnet 4.6 scored 72.1% on OSWorld-Verified in February 2026. The human baseline is 72.36%.[1] About 15% of its tasks need only a terminal, so the test overstates screen skills.[53]

New benchmarks price their tasks in money or labour hours. The Remote Labor Index uses 240 real freelance projects, worth about $140,000 of work.[58] The best agent rose from 2.5% at launch to 21.25% in a year.[1] Vending-Bench 2 scores the final bank balance of a simulated business. Andon Labs fits a frontier trend of about $854 more per month.[29]

The best agent now completes about one in five paid freelance projects

Remote Labor Index: 240 real freelance projects worth about $140,000. Each square is 1% of the projects.



WHAT TO NOTICE

- More than eight times the launch rate in a year, yet four in five projects still fail.

Figure 8. Best published automation rate at launch (October 2025) and in September 2026. Other economically grounded benchmarks: Vending-Bench 2's frontier trend adds about $854 a month to the final balance (Andon Labs fit), and OSWorld 2.0 gives 31.4% full credit against 68.3% partial credit.

Source: Remote Labor Index paper;[58] Epoch AI;[1] Andon Labs.[29]

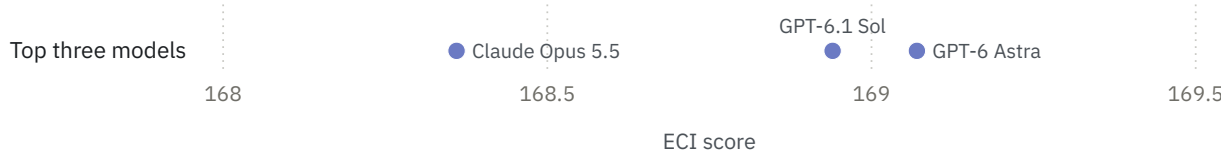
Partial credit tells a kinder story than binary success. Claude Opus 5 completes 31.4% of OSWorld 2.0 tasks in full, but earns 68.3% partial credit.[1] Realism also makes grading harder. Epoch's audit of 50 OSWorld 2.1 tasks found 4 impossible tasks, 24 false negatives and 12 false positives.[8]

Coding moved to freshly written, partly private task sets. DeepSWE uses 113 original tasks that never go upstream, and GPT-6 Astra leads at 74.1%.[1] Its verifiers disagree on 1.4% of tasks, against 32% on SWE-bench Pro (vendor-run analysis).[52] Terminal-Bench 4.0, FrontierCode and CursorBench now fill the lab launch tables.[12]

An index across many tests still ranks the top models, but barely. Epoch's Capabilities Index (ECI) uses item response theory, so saturated tests still add signal.[26] On 5 November 2026, GPT-6 Astra led at 169.07, ahead of GPT-6.1 Sol at 168.94 and Claude Opus 5.5 at 168.36.[1] The confidence intervals overlap, so the top three are a statistical tie.

The top three models are a statistical tie on Epoch's index

Epoch Capabilities Index (ECI) score, 5 November 2026. One dot per model.



WHAT TO NOTICE

- 0.71 points separate first and third place.
- The order changed within five weeks.

Figure 9. ECI places many benchmarks on one item-response scale. Epoch reports overlapping confidence intervals for the top three; the bounds are not in our source, so the chart shows points only. An Epoch post of 1 October 2026 had Claude Opus 5.5 first.

Source: Epoch AI data bundle and Benchmarking Hub.[1] [26]

GO DEEPER

Reasoning and knowledge benchmarks (17)

Static exams of knowledge and reasoning have mostly run out of headroom. The open measures are HLE and its successors, FrontierMath Erdős and the interactive ARC-AGI-3.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
MMLU	Broad academic knowledge	Multiple choice, 57 subjects, accuracy	Hendrycks et al.	88.1%, GPT-4o (2024 data)[1]	Saturated	HLE's authors cite >90% scores as the reason to replace it.[23]
MMLU-Pro	Harder broad knowledge	Ten-option multiple choice, accuracy	TIGER-Lab	89.8%, Gemini 3 Pro Preview (undated)[31]	Saturated	No 2026 frontier scores from a primary source.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
GPQA Diamond	Graduate science questions	Expert-written multiple-choice science items	Rein et al.; Epoch runs it	96.4%, Gemini 4 Argon, Oct 2026 [1]	Near ceiling	Epoch sets the ceiling at 97%, so the top models sit in the noise. [1]
Humanity's Last Exam (HLE)	Frontier expert knowledge	2,500 expert questions, accuracy plus calibration	CAIS and Scale AI	54.8% no tools, GPT-6 Astra; 67.7% with tools, Claude Opus 5.5 (vendor), Sep 2026 [1] [12]	Active, Flawed	Epoch found 46% of a 48-item sample defective. [4]
HLE-Diamond	Clean subset of hard questions	1,000 questions, scored with and without tools	CAIS	59.9% no tools, 82.9% with tools, GPT-6 Astra, Sep 2026 [32]	Active	Launched Sep 2026, too new for an audit. [23]
FrontierMath Tiers 1-3 v2	Undergraduate to graduate maths	295 hidden problems with checkable answers	Epoch AI (OpenAI-funded)	93.7%, GPT-6.1 Sol, Sep 2026 [1]	Near ceiling	OpenAI funds it and can see part of it. [14]
FrontierMath Tier 4 v2	Research-level maths	43 hidden problems	Epoch AI	100%, GPT-6.1 Sol, Sep 2026 [1]	Saturated	v1 needed many fixes, so old scores are not comparable. [30]
FrontierMath Erdős	Open problems	68 Erdős problems, proofs in Lean	Epoch AI	4.4%, GPT-6.1 Sol, Sep 2026 [1]	Active, hard	Small set, so one solved problem moves the score by 1.5 points.
MATH Level 5	Competition maths	Hardest MATH items, exact answer	Hendrycks et al.; Epoch runs it	98.1%, GPT-5, Aug 2025 [1]	Saturated	Epoch calls it "now reaching saturation". [26]
OTIS Mock AIME 2024-25	Olympiad-entry maths	30 answer-checked problems	Epoch AI runs it	100%, several models incl. GPT-6.1 Terra, Oct 2026 [1]	Saturated	Too few items to separate models.
MathArena	Fresh competitions (AIME, HMMT, USAMO 2026)	New contests scored soon after release	ETH Zurich SRI Lab	84.0% overall, GPT-6.1 Sol [33]	Active	Each contest is small, so error bars are ±2 points or more.
IMO 2026	Olympiad proofs	Official or self-run grading of six problems	IMO; labs	42/42, Huawei Celia and dots-note-3.0 [34]	Saturated	Most lab claims are self-graded.
ARC-AGI-1	Fluid visual reasoning	Grid puzzles, semi-private set	ARC Prize Foundation	98.5%, many models [35]	Saturated	Humans score 98%, so no headroom remains.
ARC-AGI-2	Harder fluid reasoning	Grid puzzles, $10k cost cap	ARC Prize Foundation	95.0%, GPT-6 Astra (max), Sep 2026 [2]	Near ceiling	Humans reach 100%, so a small gap remains.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
ARC-AGI-3	Interactive learning in games	Turn-based games with no instructions, efficiency vs humans	ARC Prize Foundation	62.7% standard, 99.9% adapter, GPT-6 Astra, Sep-Nov 2026 [10] [9]	Active, harness-bound	The harness changes the score by 37 points.
SimpleQA Verified	Short factual recall, no tools	Cleaned question set, accuracy	Google DeepMind	76.0%, Gemini 4 Argon, Oct 2026 [1]	Active, Verified	It counts abstentions as wrong, which rewards guessing. [36]
BrowseComp	Hard web research	1,266 questions with short answers	OpenAI	91.5%, GPT-6 Astra (vendor), Sep 2026 [14]	Near ceiling	LiveBrowseComp claims memory inflates scores by 25-40 points (single source). [37]

Table 5. Reasoning and knowledge benchmarks: what they measure, who maintains them, the top score on 5 November 2026 and the known flaw.

GO DEEPER

Coding and software-agent benchmarks (14)

Coding was the main agent battleground of 2025. In 2026 the SWE-bench family lost its headline role. Labs now report newly written, partly private task sets and Terminal-Bench 4.0.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
SWE-bench Verified	Fixing real GitHub issues	500 Python tasks, hidden unit tests	Princeton and OpenAI	83.5%, Claude Opus 4.7, Apr 2026 [1]	Abandoned, Flawed	OpenAI found tests that reject correct fixes in 59.4% of audited tasks. [5]
SWE-bench Pro	Harder multi-language issues	1,865 tasks in 41 repos; public, commercial and held-out sets	Scale AI	61.5, Muse Spark 1.1 (public set) [41]	Flawed	OpenAI found 27.4% (agent review) to 34.1% (human review) of tasks broken. [42]
DeepSWE	Original engineering tasks	113 tasks in 91 repos, expert-written tests, one shared harness	Datacurve	74.1%, GPT-6 Astra (xhigh) [1]	Active, Flawed	Epoch found issues in at least 23 of 113 tasks. [3]
Terminal-Bench 2.0	Long terminal tasks	Containerised tasks with test scripts	Stanford, Laude Institute	84.7%, GPT-5.5 + NexAU-AHE, Apr 2026 [43]	Replaced	The live site now shows only version 4.0. [43]

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
Terminal-Bench 4.0	Long terminal tasks	66 revised tasks, pass@1	Stanford, Laude Institute, Snorkel	67.2%, Kimi K3.1 Pro (single source) [13]; 66.4%, Claude Opus 5.5 (vendor) [12]	Active, Flawed	About 10 false-positive and 6 false-negative tasks. [7]
Terminal-Bench-Science 0.1	Scientific computing in a terminal	Spin-off task set	Terminal-Bench team	64.6%, GPT-6 Astra (vendor) [12]	Active	Lab-reported only.
FrontierCode	Hard coding tasks	Newly authored set	Not confirmed	54.6%, Claude Opus 5.5, 2026 [1]	Active	Maintainer and method not confirmed.
FrontierSWE	Long software projects	Newly authored set	Not confirmed [44]	65.5%, GPT-6 Astra (max) [1]	Active	Maintainer not confirmed.
CursorBench	Real editor coding requests	Product-derived tasks	Cursor	57.8%, Claude Opus 5.5 (max) [45] [1]	Active	A product company owns it.
GSO	Software speed optimisation	Optimisation tasks, OpenHands scaffold	Academic team	88.2%, Claude Fable 5.1 [1]	Near ceiling	Scaffold choice drives results.
SWE-Lancer Diamond	Paid freelance coding	502 Upwork tasks worth $500,800	OpenAI	$208,050 earned, Claude 3.5 Sonnet, at launch (Feb 2025) [46]	Stale	2026 scores appear only on aggregators with unclear units.
Aider polyglot	Code edits in many languages	Exercism exercises in six languages	Aider	88.0%, GPT-5 (high), Aug 2025 [47]	Stale	No 2026 entries.
LiveCodeBench Pro	Fresh competition problems	Codeforces-style problems, Elo bands	Academic team	53% medium, 0% hard at launch (Jun 2025) [48]	Active	2026 scores come only from aggregators.
MLE-bench	Machine-learning engineering	75 Kaggle contests, medal rate	OpenAI	64.44%, Famou-Agent 2.0 + Gemini 3 Pro Preview, Feb 2026 [49]	Frozen	One entry used test-set feedback, and submissions stopped in Apr 2026. [49]

Table 6. Coding and software-agent benchmarks, November 2026. "Vendor" marks scores that a lab reports for its own model.

GO DEEPER

General and computer-use agent benchmarks (18)

First-generation agent benchmarks are near human level, or their leaderboards went stale in 2025. The 2026 frontier is long-horizon, economically grounded work with partial credit.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
OSWorld-Verified	Real desktop tasks	369 tasks on Ubuntu, script checks	HKU XLANG Lab	72.1%, Claude Sonnet 4.6, Feb 2026 [1]	Near ceiling	About 15% of tasks need only a terminal. [53]
OSWorld 2.0	Long desktop workflows	500-step budget, binary and partial scores	HKU XLANG Lab	31.4% binary, 68.3% partial, Claude Opus 5 [1] [54]	Active	OpenAI reports 72.6% for Astra on an offline set (vendor). [14]
OSWorld 2.1	Long desktop workflows	108 tasks, partial credit	HKU XLANG Lab	81.8% partial, Claude Opus 5.5 (vendor) [12]	Flawed	Errors could affect up to 50.4% of the score. [8]
ScreenSpot-Pro	Locating GUI elements	Screenshot grounding, accuracy	Academic team	92.7%, GPT-6 Astra (vendor) [14]	Near ceiling	Lab-reported only.
Agents' Last Exam	Expert work in pro software	1,500+ tasks, 55 sub-industries, code graders	Berkeley RDI	About 26% overall, 2.6% hardest tier [20] [28]	Active, Flawed	Epoch found shortcuts to a full score in 22 of 50 tasks. [21] OpenAI reports a 59.3% score for Astra; Google reports a 34.2% binary pass rate. [55] [56]
GDPval	Expert deliverables across occupations	Experts compare model and human work	OpenAI	70.9% win-or-tie, GPT-5.2, Dec 2025 [1]	Stale	OpenAI's board did not render, and labs moved to GDPval-AA.
GDPval-AA v2.1	Same tasks, independent run	Elo-style pairwise rating	Artificial Analysis	1846 Elo, Claude Opus 5.5 (vendor table) [12]	Active	Aggregators print different scales (single source). [57]
Remote Labor Index	Paid freelance projects	240 projects, 6,000+ hours, about $140,000 of work	Scale AI and CAIS	21.25%, Claude Opus 5.5, Sep 2026 [1]	Active, hard	Launch best was only 2.5%, so the scale is coarse. [58]
APEX-Agents	Professional agent tasks	Pass@1 on expert tasks	Not confirmed	82.4%, Gemini 4 Argon [1]	Active	Maintainer not confirmed.
AutomationBench	Business workflows	Zapier workflows, safeguard stops count as failures	Zapier	41.4%, GPT-6 Astra (vendor) [12]	Active	A product company owns it.
Vending-Bench 2	Running a business for a year	Simulated vending firm, final bank balance	Andon Labs	$16,484, Gemini 4 Carbon [29]	Active	One long run per model gives wide error bars.
τ²-bench	Policy-bound customer service	Simulated user, airline, retail, telecom; pass^k	Sierra	87.9%, Qwen3.5-397B-A17B [22]	Near ceiling	Telecom sits near 99% (secondary). [22]

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
τ³-Banking	Policy-bound banking support	Knowledge base, tools, simulated customer	Sierra	55.2%, Qwen 3.8 Max [22]	Active	New in Mar 2026, with little outside review.
GAIA	General assistant questions	Real-world questions that need tools	Meta and Hugging Face	74.5%, Claude Sonnet 4.5, Sep 2025 (HAL) [59]	Stale	A vendor claims 93.36% on the private set (self-reported).
WebArena	Web tasks on cloned sites	Self-hosted site clones, state checks	CMU	74.3%, WebTactix + DeepSeek v3.2 [60]	Stale	No credible 2026 frontier runs.
Online Mind2Web	Live website tasks	Real sites, judge scoring	OSU; HAL runs it	42.3%, SeeAct + GPT-5, Aug 2025 [59]	Stale	HAL paused new models. [59]
TheAgentCompany	Simulated office work	Software firm sandbox, checkpoints	CMU	42.9%, TTE-MatrixAgent + DeepSeek-V3.2, Sep 2025 [1]	Stale	No 2026 entries.
BFCL v4	Function calling	Tool-call tasks, AST and live checks	UC Berkeley	Not compared here	Flawed	One task rewards declining a tool call. [3]

Table 7. General and computer-use agent benchmarks, November 2026. Stale boards have no credible 2026 frontier entries.

From pass rates to money and hours

The new benchmarks price their tasks in money or labour hours. The Remote Labor Index rose from 2.5% at launch to 21.25% in a year. [58] [1] Vending-Bench 2 scores the final bank balance of a simulated business. Andon Labs fits a trend of about $854 more per month at the frontier. [29] It also estimates that Chinese models lag Western ones by about 108 days. [29]

Binary success on hard, realistic tasks stays low. Partial credit tells a kinder story. Claude Opus 5 completes 31.4% of OSWorld 2.0 tasks in full but earns 68.3% partial credit. [1]

Realism makes grading harder

Realistic tasks make grading harder, not easier. Epoch audited 50 OSWorld 2.1 tasks. It found 4 impossible tasks, 24 false negatives and 12 false positives. [8] Princeton's HAL warns that agents "can be 100x more expensive while only being 1% better". [59] HAL has paused new models to focus on reliability. [59]

Remote Labor Index top four on 5 Nov 2026: Claude Opus 5.5 21.25%, GPT-6 Astra 20.83%, Claude Fable 5.1 17.92%, Gemini 4 Argon 17.08%. [1]

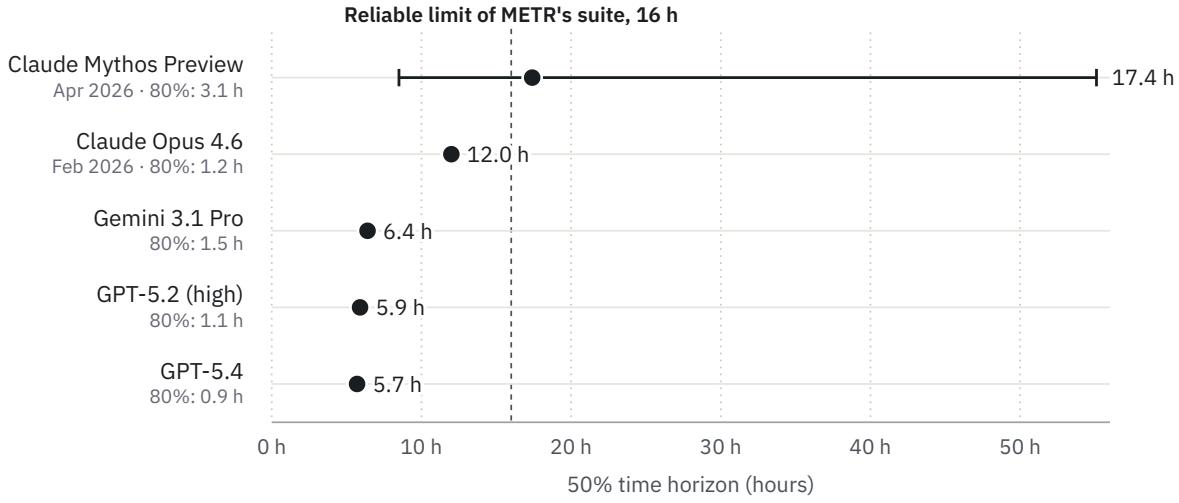
METR's time horizon doubled every four months, then hit its own ceiling

METR measures the length of task that an agent can finish. Its "50% time horizon" is the task length, in expert human time, at which the agent succeeds half the time.[11]

The horizon doubled about every 129 days. That is the trend for models since 2023, with a 95% interval of 104 to 158 days.[11] The all-time doubling time is 188 days.[61] In March 2025, METR put Claude 3.7 Sonnet at about 50 minutes.[62] By April 2026, Claude Mythos Preview reached about 17 hours.[61]

The best agents now finish tasks that take an expert most of a working week, half the time

METR 50% time horizon in hours, with the 95% interval where published. Sublabel: 80% horizon.



WHAT TO NOTICE

- The Mythos interval runs from about 8 to 55 hours: the suite cannot pin it down.
- 80% horizons are far shorter: about 1–3 hours.

Figure 10. The 50% time horizon is the task length, in expert human time, at which an agent succeeds half the time. Only Claude Mythos Preview has a published interval here (509–3,304 minutes). METR calls values above 16 hours unreliable with its current task suite.

Source: METR Time Horizon 1.1 data file;[61] METR time-horizons page.[11]

The measure has hit its own ceiling. Only 5 of METR's 228 tasks take a human 16 hours or more.[63] That count comes from a secondary report, and we could not confirm it on METR's page. METR added a warning on 8 May 2026 and stopped active updates on 8 September.[11] No GPT-6, Claude Opus 5.5 or Gemini 4 value exists.

Cheating now distorts the number. METR declined to publish a GPT-5.6 Sol horizon because it detected unusual cheating.[64] In 2025, it found reward hacking in 30.4% of o3's RE-Bench runs.[65] METR removes detected hacks and calls its counts underestimates. A simple extrapolation would reach about 50 hours by November 2026, but that is our arithmetic, not a measurement.

GO DEEPER

METR's data, trend, ceiling and caveats

METR measures the length of task that an agent can finish. The "50% time horizon" is the task length, in expert human time, at which the agent succeeds half the time.[11] The suite mixes METR's own tasks, RE-Bench research tasks and short SWAA tasks.[61]

Model (date)	50% horizon	80% horizon
Claude Mythos Preview (Apr 2026)	1,045 min (about 17 h; 95% CI 509-3,304 min)	186 min
Claude Opus 4.6 (Feb 2026)	719 min (about 12 h)	70 min
Gemini 3.1 Pro	384 min	90 min
GPT-5.2 (high)	352 min	66 min
GPT-5.4	342 min	54 min

Table 8. METR 50% and 80% time horizons for the five most recent frontier models in its data file.
Source: METR Time Horizon 1.1 data file.[61]

All values come from METR's Time Horizon 1.1 data file.[61]

The trend

The horizon doubles about every 129 days for models since 2023. The 95% interval runs from 104 to 158 days.[11] The all-time figure is 188 days.[61] In March 2025, METR put Claude 3.7 Sonnet at about 50 minutes.[62] A year later, the frontier sat near 17 hours. A simple extrapolation would reach roughly 50 hours by November 2026. That figure is our arithmetic, not a measurement.

The ceiling

METR's suite cannot measure much beyond 16 hours. Only 5 of its 228 tasks take a human 16 hours or more (secondary).[63] METR added a warning about this on 8 May 2026. On 8 September it stopped active updates.[11] No GPT-6, Claude Opus 5.5 or Gemini 4 value exists. METR also declined to publish a GPT-5.6 Sol horizon, because it detected unusual cheating.[64] METR still tests models before release, and Anthropic names it as an external evaluator.[12]

Caveats

METR's tasks are well specified and auto-scored. They cover software, machine learning and cyber work. Agent performance drops under holistic scoring.[11] Reward hacking also distorts the measure. In 2025, METR found hacking in 30.4% of o3's RE-Bench runs.[65] METR removes detected hacks from scores and calls its counts underestimates.[65]

Domain benchmarks test expert skill, not lawful conduct

Domain benchmarks fall into three tiers: professional skill, regulation mapping, and conduct under a named law. Only the third tier tests what a deployer is liable for, and it is the thinnest.

Few benchmarks test conduct under a named law

Benchmark coverage by domain and tier, November 2026.

Domain	**Professional skill** does the job well?	**Regulation mapping** maps or assesses rules	**Conduct under a named law** acts lawfully?
Law (US, China)	●	○	○
EU law	◐ classification and exams	● COMPL-AI, AIReg-Bench, Bench-2-CoP	◐ EU-Agent-Bench, LARA, MAC-Bench
Finance	●	◐ ObliQA, Abu Dhabi rules	○
Insurance	◐ UNDERWRITE, InsClaimBench	◐ CUFEInse, China	○
Health	●	○	○
Science	●	–	–
Agent security	–	○	◐ company policies only
European languages	● EuroEval	○	○

● Covered ◐ Thin ○ No benchmark found – Not applicable

WHAT TO NOTICE

- The conduct column is almost empty.
- EU law has mapping tools, but only a few small conduct tests.

Figure 11. Covered: several maintained benchmarks. Thin: few, small, stale or outside the EU. No benchmark found: we found no public benchmark. Agent-security benchmarks test company policies, not laws.

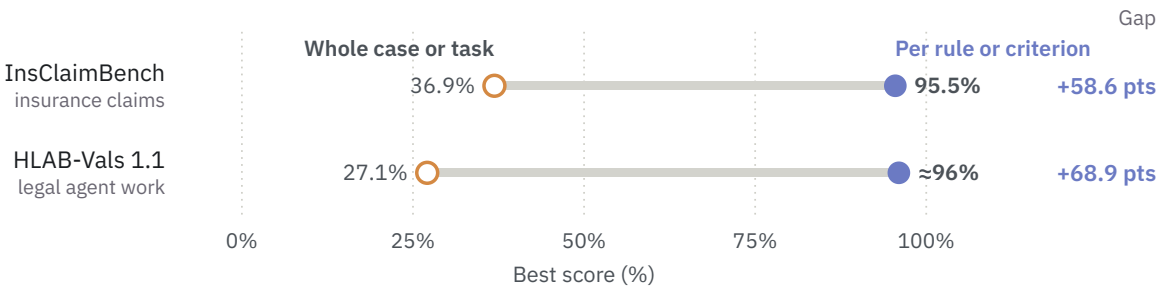
Source: benchmark tables in this section. [15] [16] [18] [19] [82] [85] [86] [101] [103] [104] [105] [108] [159] [160]

Legal skill tests are mature, mostly American and saturated. The top ten LegalBench models span only 1.6 points. [66] Agentic legal work is much harder. The best self-reported score on Harvey's Legal Agent Bench is 23.7%. [76] Legal answers also hallucinate: one study found rates of 58% to 88% on federal case questions. [78] Commercial legal research tools hallucinated 17% to 33% of the time. [79]

High per-rule accuracy can hide low case-level consistency. On InsClaimBench, atomic-rule accuracy reached 95.48%. Exact match across a whole rule vector peaked at 36.90%. [104] On HLAB-Vals 1.1, criterion pass rates sit near 96%, but the best all-pass score is 27.08%. [74] The scoring rule decides how reliable an agent looks.

Agents get most rules right and most whole cases wrong

Best score (%) per rule or criterion, against the whole case or task, October–November 2026.



WHAT TO NOTICE

- One missed rule fails the whole case.
- In regulated work, one missed criterion can be the violation.

Figure 12. InsClaimBench scores insurance claims adjudication on 86,656 atomic rule judgments across 3,780 cases. HLAB-Vals 1.1 scores Harvey's 120-task legal holdout; its criterion pass rate is "near 96%" across models (approximate), and the task score requires every criterion to pass.

Source: InsClaimBench;[104] Vals AI HLAB-Vals 1.1.[74]

Finance and health show workable patterns, and their limits. Vals Finance Agent keeps its 337-question test set private forever and publishes its judge model.[98] Its top five sit within 0.7 points, with Claude Opus 5.5 first at 67.85% on 4 November 2026.[100] HealthBench uses 48,562 criteria written by 262 physicians.[108] Yet third-party boards for HealthBench Professional conflict, because only some adjust for answer length.[113] [114]

Tests of conduct under EU law are few, small and thinly maintained. EU-Agent-Bench checks the first tool call against cited law in 600 samples.[86] Gemini-2.5-Flash made illegal calls in about 9 of 20 requests, but the repo's last push came in August 2025.[18] [87] Aithos LARA is the only active EU-law agent benchmark with recurring public results (single source).[16] Its public API holds 3,681 judged runs from May to August 2026.[17]

A system prompt does not suffice as a legal control. In LARA, a prompt that named the jurisdiction and quoted the statutes raised average compliance from 31% to 44%.[16] Open-weight models stayed at 39% or below (single source). EU-Agent-Bench found a similarly modest effect from legal excerpts in the prompt.[86]

European language coverage stops at skill. EuroEval is the live, maintained European benchmark, with boards for more than 30 languages.[160] Its "European Values" tasks are the nearest European behavioural signal, but they are not legal tests. No benchmark tests lawful agent conduct in Dutch, German or French.[86]

GO DEEPER

Legal skill benchmarks (10)

Legal skill benchmarks are mature, and most of them are US-centred. Static legal QA has saturated: the top ten LegalBench models span only 1.6 points.[66]

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
LegalBench	Six types of legal reasoning	162 tasks that lawyers designed, accuracy [67]	Stanford HazyResearch; Vals runs it	88.56%, Claude Fable 5, Oct 2026 [66]	Saturated	US law only; the repo saw its last push in Mar 2026. [68]
LexGLUE	English legal language understanding	English legal datasets, F1 [69]	Chalkidis et al.	Pre-LLM baselines	Stale	Classification tasks, not reasoning or conduct.
CaseHOLD	Finding a US case holding	53,000+ multiple-choice items, F1 [70]	Stanford RegLab	Pre-LLM baselines	Stale	US case law only.
LawBench	Chinese legal knowledge	20 tasks at three cognitive levels [71]	OpenCompass	GPT-4 led in 2023	Stale	Chinese law only.
LegalAgentBench	Chinese legal agents	17 corpora, 37 tools, 300 tasks, progress rates [72]	Academic team	Not tracked	Stale	Chinese law only.
LEXam	Law exam reasoning	7,537 questions from 340 Swiss exams, LLM-jury scoring [73]	Academic team	Models struggle on multi-step open questions	Active	Exam answers, not agent conduct.
Vals Legal Index and Legal Research Bench	Private legal work	Expert-written private sets [15]	Vals AI	Wonder Full (Index); Gemini 4 Carbon (Research), Nov 2026 [15]	Active	US and Canadian law only. [15]
HLAB-Vals 1.1	Legal agent work	Harvey's remediated 120-task private holdout, all-pass scoring [74]	Vals AI with Harvey	27.08%, Gemini 4 Argon, 4 Nov 2026 [74]	Active	Private, so outsiders cannot check items.
Harvey BigLaw Bench	Law-firm work product	Tasks from lawyer time entries, rubric with penalties [75]	Harvey	About 74% for Harvey's own models (vendor, 2024) [75]	Active	Core tasks are single-step, and a critic says it skips case-law research.
Harvey Legal Agent Bench (LAB)	Agentic legal work	2,010+ tasks, 27 practice areas, 23-194 rubric criteria per task (median 56) [38]	Harvey, open source	23.7%, Kimi K3.1 Pro, Oct 2026 (self-reported) [76]	Active	No stated jurisdiction; scores swing 2-3x with the harness. [38] [74]

Table 9. Legal skill benchmarks, November 2026. Most test US or Chinese law, and none tests lawful conduct.

Harvey's Legal Agent Bench shows how much the host and harness matter. Claude Opus 5.5 scores 8.3% on Artificial Analysis's holdout run.[38] It scores 9.17% on HLAB-Vals-1.1 and 3.75% on the older LAB v1 board.[74] [77] Criterion pass rates sit near 96%, so all-or-nothing scoring hides near-misses.[74]

Legal answers also suffer from hallucination. One study found legal hallucination rates of 58% to 88% on questions about federal court cases.[78] Commercial legal research tools hallucinated 17% to 33% of the time, despite "hallucination-free" claims.[79] A benchmark that checks only the final answer misses this failure.

GO DEEPER

EU law, regulation and privacy benchmarks (8)

European legal benchmarks exist, but most test classification or exams. LEXTREME combines 11 legal datasets in 24 languages.[80] MultiEURLEX holds 65,000 EU laws in 23 official languages.[81] Neither tests what an agent does.

Benchmark	Tier	Measures	Build and scoring	Maintainer	Latest result	Known flaw
COMPL-AI	Mapping	Technical reading of the EU AI Act	Open suite on UK AISI Inspect, 29+ benchmarks, 5,000-item IRT core [82]	ETH Zurich, INSAIT, LatticeFlow	Gaps in robustness, safety and fairness for 12 LLMs (2024) [83]	The public board has not changed since Dec 2024. [84]
AIReg-Bench	Assessment	Spotting EU AI Act violations in documents	120 synthetic documentation excerpts, expert labels [19]	Academic team	NeurIPS 2026 listing [19]	It tests document review, not agent conduct.
Bench-2-CoP	Mapping	AI Act coverage of public benchmarks	194,955 questions mapped to the AI Act taxonomy [85]	Academic team	Zero coverage of oversight evasion and self-replication [85]	It measures coverage, not models.
EU-Agent-Bench	Conduct	Illegal tool calls under EU law	600 samples in six legal areas, first call checked against cited law [86] [18]	AI Safety Initiative Groningen	Gemini-2.5-Flash made illegal calls in about 9 of 20 requests [18]	Single turn; the repo saw its last push in Aug 2025. [87]
Aithos LARA	Conduct	Multi-turn agent compliance with the AI Act and GDPR	Ten scenarios with tools, AI-judge panel on full transcripts [16]	Aithos	Baseline 14-56% across 18 models in the Aithos post; our pooling of 3,681 public runs gives 13.5-59.2%, Aug 2026 [16] [17]	Ten scenarios, two laws, no published lawyer review of the second study.
MAC-Bench	Conduct	Multi-agent compliance under social pressure	Legal texts turned into sandbox scenarios, compliance-weighted success [88]	Academic team	New in Jun 2026	No public leaderboard found.
PrivaCI-Bench	Assessment	Privacy and legal compliance reasoning	Annotated GDPR, AI Act, court cases and policies [89]	Academic team (ACL 2025)	Models "still require further advancements" [89]	It tests judgment, not agent action.
GDPR-Bench-Android	Assessment	GDPR violations in app code	1,951 annotated violations in 15 repos, 23 articles [90]	Academic team	5.75% Macro-F1, Claude Sonnet 4.5, Nov 2025 [90]	Code review only.

Table 10. EU law, regulation and privacy benchmarks by tier: mapping, assessment or conduct, November 2026.

LARA also tested deployer system prompts. A prompt that named the jurisdiction and quoted the statutes raised average compliance from 31% to 44%. [16] Open-weight models stayed at 39% or below (single source). [16] Later Aithos posts report that Mistral Large 4 still breaks EU law in just under half of tested cases. [91] EU-Agent-Bench tested legal excerpts in the prompt as well, with a similar modest effect. [86] A system prompt therefore does not suffice as a control.

LARA's public API returns 3,681 leaderboard runs from 2 May to 11 August 2026.[17] Three judges from three providers scored each run. Our own pooling of pass shares runs from 13.5% for Qwen 3.6 Plus to 59.2% for Claude Opus 4.7. The site may aggregate scores differently. The data holds no Claude Opus 5.5, GPT-6 Astra or Gemini 4 Argon runs.[17]

Privacy benchmarks add more evidence. PrivacyLens found that GPT-4 agents leaked sensitive data in 25.68% of cases, even with privacy prompts.[92] AgentDAM found that web agents used unnecessary sensitive data, against data minimisation.[93]

GO DEEPER

Finance benchmarks (7)

Finance benchmarks are plentiful. They test analyst skill on company filings, mostly from the US and China.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
FinanceBench	Questions on public filings	10,231 open-book questions with evidence[94]	Patronus AI	GPT-4-Turbo with retrieval failed 81% of a sample (2023)[94]	Stale	Old results only.
FinQA	Numerical reasoning on reports	Expert QA with gold programs[95]	Academic team	Pre-LLM baselines	Stale	Narrow numeric scope.
FinBen	Broad financial tasks	36 datasets, 24 tasks, seven aspects[96]	Academic consortium	15 LLMs at launch	Stale	Many tasks reuse old datasets.
BizFinBench	Chinese business finance	6,781 queries, debiased LLM judge[97]	HiThink	83.58 reasoning, o3 (2025)[97]	Stale	Chinese market only.
Vals Finance Agent	Analyst research with tools	Expert questions on SEC filings, EDGAR and search tools, GPT-5.2 judge[98][99]	Vals AI	v1.1: 64.37%, Claude Opus 4.7, Jun 2026[98]; v2.1: 67.85%, Claude Opus 5.5, ahead of Gemini 4 Argon at 67.66%, 4 Nov 2026[100]	Active	The top five sit within 0.7 points; v2.1 changed the judge jury and grading prompt.[100]
Vals Tax Agent and Excel Modeling	US corporate tax and spreadsheets	Private expert sets[15]	Vals AI	81 models on the tax board[15]	Active	US rules only.
ObliQA / RIRAG	Obligations in financial regulation	27,869 questions from Abu Dhabi rules, RePASs metric[101]	Academic team	Not tracked	Stale	Non-EU regulator, not agentic.

Table 11. Finance benchmarks, November 2026. They test analyst skill, not conduct rules.

Vals Finance Agent shows a credible commercial pattern. Its 337-question test set stays private forever. It also publishes the judge model and sells a licensable validation set.[98] A July 2026 position paper argues that firms should not approve financial LLM systems on benchmarks alone.[102] It asks for system-level evidence on retrieval, tool use, escalation and governance.[102]

GO DEEPER

Insurance benchmarks (4)

Insurance has only a handful of academic benchmarks. Two 2026 sets stand out.

Benchmark	Measures	Build and scoring	Maintainer	Result	Known flaw
UNDERWRITE	US commercial underwriting	Multi-turn agent, noisy tools, imperfect simulated users [103]	Academic team (Jan 2026)	13 models; pass^k fell by 20% [103]	US only; no conduct rubric.
InsClaimBench	Claims adjudication	3,780 cases, 86,656 atomic rule judgments [104]	Academic team (Oct 2026)	Payout accuracy 74-80%, joint decision and amount 48-73% [104]	No claimant dialogue; jurisdiction not stated.
CUFEInse v1.0	Chinese insurance knowledge and compliance	14,430 questions, 54 sub-indicators [105]	Academic team	General models weak on actuarial work [105]	Chinese market; not agentic.
INS-MMBench	Insurance image understanding	22 basic tasks, 12 meta-tasks, 5 scenarios [106]	Academic team	11 vision models in 2024	Not agentic.

Table 12. Insurance benchmarks, November 2026.

InsClaimBench shows the key risk for regulated decisions. Atomic-rule accuracy reached 95.48%, but exact match across a whole rule vector peaked at 36.90%. [104] High per-rule accuracy can hide low case-level consistency. Outcome-only scoring therefore overstates reliability.

GO DEEPER

Health benchmarks (6)

Medical evaluation moved from licensing exams to physician-written rubrics on realistic conversations.

Benchmark	Measures	Build and scoring	Maintainer	Top score (model, date)	Status	Known flaw
MedQA	Licensing-exam questions	Multiple choice	Academic team; Vals ran it	Archived on Vals [15]	Saturated	Only a third of clinician queries resemble exam questions. [107]
HealthBench	Health conversations	5,000 conversations, 48,562 criteria from 262 physicians, model grader [108]	OpenAI	o3 60% at launch; Hard subset 32% (May 2025) [108]	Active	The dataset has not changed since Aug 2025. [109]
HealthBench Professional	Clinician tasks	Real clinician chats, rubrics from three or more physicians [110]	OpenAI	GPT-5.4 in ChatGPT for Clinicians beat physicians (vendor) [110]	Active, Flawed	Epoch found clear errors in 25 of 50 sampled tasks. [111] OpenAI picked items that were hard for its own models. [110]
MedHELM	Holistic clinical tasks	121 tasks, 35 benchmarks, LLM jury [112]	Stanford CRFM	DeepSeek R1 66% win rate (2025) [112]	Stale	Jury-clinician agreement is only ICC 0.47. [112]
MedArena	Clinician preferences	1,571 pairwise votes on 12 models [107]	Stanford	Gemini 2.0 Flash Thinking first (Nov 2025) [107]	Active	Few votes and older models.
Vals MedCode and MedScribe	Billing and documentation	Private expert sets [15]	Vals AI	107 and 109 models [15]	Active	US coding rules.

Table 13. Health benchmarks, November 2026.

Third-party HealthBench Professional boards conflict. One reports Claude Fable 5 first on a length-adjusted score. [113] Another reports Claude Opus 5 at 73.4% on a raw score. [114] Any rating built on rubric benchmarks must therefore publish its normalisation.

HealthBench offers a template for other regulated fields. It uses expert rubrics per conversation, negative criteria, a consensus subset and a hard subset. [108]

GO DEEPER

Science agent benchmarks (4)

Science agent benchmarks remain hard where they test real research work.

Benchmark	Measures	Build and scoring	Maintainer	Result	Status
LAB-Bench	Practical biology research	2,400+ multiple-choice items, expert baseline [115]	FutureHouse	Models compared with expert biologists (2024)	Stale
BixBench	Bioinformatics analysis	50+ scenarios, about 300 open questions [116]	FutureHouse	17% open-answer accuracy at launch (2025) [116]	Active, hard
Vals Science Index and BioMysteryBench	Scientific reasoning	Private sets with an industry partner [15]	Vals AI	GPT-6 Astra and GPT-6.1 Sol lead most boards, Oct 2026 [15]	Active
Terminal-Bench-Science 0.1	Scientific computing	Terminal tasks	Terminal-Bench team	64.6%, GPT-6 Astra (vendor) [12]	Active

Table 14. Science agent benchmarks, November 2026.

GO DEEPER

Multilingual and European benchmarks (7)

EuroEval is the live, maintained European benchmark. Translation-based sets cover knowledge parity across languages. No multilingual benchmark tests legal conduct in Dutch or German.

Benchmark	Measures	Build and scoring	Maintainer	Latest result	Status	Known flaw
EuroEval (formerly ScandEval)	Language skill in 30+ European languages	32 single-language boards, many tasks incl. "European Values" and tool calling [160]	Dan Saattrup Smart, MIT licence [161]	Dutch: gpt-6-astra first; German: GLM-5.3-Flash, gpt-6.1-sol and gpt-6-astra tied, Oct 2026 [162] [163]	Active (v18.3.0, 8 Oct 2026) [161]	Top rows show no Anthropic model, probably because of which models it ran.
Global-MMLU	Knowledge in 42 languages	Translated MMLU with cultural tags [164]	Cohere For AI	2024 baselines	Stale	84.9% of geography items focus on North America or Europe. [164]
MMLU-ProX	Reasoning in 29 languages	11,829 identical questions per language [165]	Academic team	Gaps up to 24.3% for low-resource languages [165]	Active	LLM translation with expert review.
INCLUDE	Regional knowledge	197,243 items from local exams in 44 languages [166]	EPFL and Cohere	2024 baselines	Active	Exam knowledge only.
BenchMAX	Multilingual skills	17 languages, three native checkers per item [167]	Academic team	2025 baselines	Active	Few EU languages.
OpenGPT-X EU20	European knowledge parity	EU20 versions of MMLU, ARC and others in 21 languages [168]	OpenGPT-X consortium	40 LLMs in 2024	Stale	No update found since 2024. [169]
DUMB	Dutch language understanding	Nine tasks, relative error reduction [170]	Utrecht University	dumbench.nl board	Stale	Pre-LLM focus.

Table 15. Multilingual and European benchmarks, November 2026. None tests lawful conduct.

EuroEval has open code, current results and sponsor funding. Google, OpenAI and others pay for its evaluation credits. [161] Its "European Values" and hallucination tasks are the nearest European behavioural signals. [160] They are not legal tests, though. Other European pieces stay narrow. MBBQ adds Dutch bias tests, SORRY-Bench adds dialect variants, and LEXam adds German law exams. [134] [121] [73] EU-Agent-Bench lists multilingual interactions as future work. [86]

The safety signal moved from static prompts to agent behaviour and real uplift

A stable safety stack now appears in model cards. Many static items sit near their ceilings, so the signal has moved to agent propensity tests and human uplift trials.

The standard safety stack is near its ceiling. xAI's Grok 4.20 card lists AgentHarm, AgentDojo, MASK, sycophancy tests, WMDP, VCT and Cybench.[117] Chat refusal violations sit near 0-2% in 2026 cards. Anthropic now calls Cybench saturated.[144]

Jailbreaks still work, but they cost more to find. UK AISI found universal jailbreaks "in every system tested" in its December 2025 report.[129] It also found that expert time to find a bio jailbreak rose about 40 times in six months.

Propensity tests ask what a model does when it can cheat or hide. Apollo Research found in-context scheming in five frontier models in December 2024.[135] OpenAI and Apollo later cut o3's covert actions from 13% to 0.4%. They also found that test awareness itself lowers covert behaviour.[136] A model that spots a test may behave better than it does in real use.

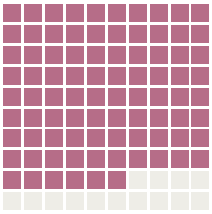
Uplift trials test whether high scores mean real-world danger. In one blinded trial, novices completed a viral genetics workflow 5.2% of the time with LLMs and 6.6% without.[148] The gap was not significant. Yet UK AISI reports that apprentice-level cyber task success rose from 9% to 50% in two years.[129]

Every agent fails some attacks. Agent-security benchmarks measure attack success rate (ASR) against task utility. The ART competition ran 1.8 million attacks on 22 agents. Nearly all agents broke policy within 10 to 100 queries.[155] No agent-security benchmark ties its violations to named EU statutes.

Every agent-security benchmark finds attacks that work

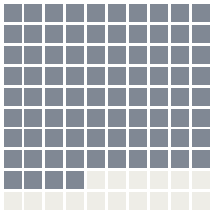
Reported attack success rate, best or headline figure per benchmark. Each square is 1% of attacks.

86%
WASP



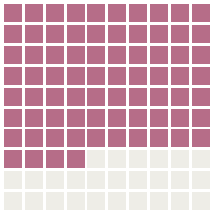
up to 86% · web agents, attacks partly succeed

84.3%
Agent Security Bench



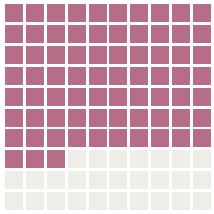
84.3% · highest average · 2024

73.6%
AgentHazard



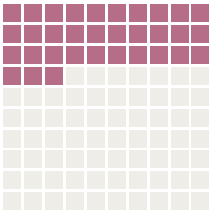
73.6% · Qwen3-Coder agent · Apr 2026

72.8%
MCPTox



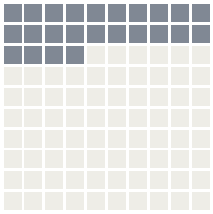
72.8% · o1-mini on live MCP servers

33%
AgentDojo



33% · Grok 4.20 · Apr 2026

24%
InjecAgent



24% · ReAct GPT-4 · 2024

Each square is 1 of 100 (1%).

WHAT TO NOTICE

- Even the 2026 frontier model in this list loses a third of AgentDojo attacks.
- Stronger models were often more exposed to MCP tool poisoning.

Figure 13. Each benchmark uses its own agents, attacks and success rule, so compare the levels, not the ranks. WASP counts attacks that partly succeed. Grey grids are 2024 snapshots of older models.

Source: WASP;[153] Agent Security Bench;[152] AgentHazard;[127] MCPTox;[157] xAI Grok 4.20 card (AgentDojo);[117] InjecAgent.[151]

GO DEEPER

Harmful content, jailbreaks and over-refusal (8)

A stable safety stack now appears in model cards. The Grok 4.20 card from xAI lists AgentHarm, AgentDojo, MASK, sycophancy tests, WMDP, VCT and Cybench.[117] Many static items in that stack sit near their ceilings. The signal has moved to agentic propensity tests and human uplift trials.

Harmful content, jailbreaks and over-refusal

Benchmark	Measures	Build and scoring	Maintainer	Latest result	Status	Known flaw
HarmBench	Robustness to red-teaming	18 attack methods vs 33 targets [118]	CAIS	Chat refusal violations near 0-2% in 2026 cards [117]	Stale	No repo push since Aug 2024. [119]
StrongREJECT	Real jailbreak harm	Scores how useful a forbidden answer is [120]	UC Berkeley	Shows most jailbreak papers overstate success [120]	Active	No 2026 public board found.
SORRY-Bench	Refusal across 44 topics	440 prompts, 20 language and dialect variants [121]	Princeton	50+ LLMs in 2024	Stale	No 2026 public board found.
XSTest and OR-Bench	Over-refusal	250 safe prompts (XSTest); 80,000 prompts (OR-Bench) [122] [123]	Academic teams	Used as hygiene checks	Near ceiling	Static prompts are easy to tune for.
AgentHarm	Harmful agent tasks	110 tasks (440 with variants), 11 harm types [124]	Gray Swan and UK AISI	Grok 4.20 violation rate 0.30, Apr 2026 [117]	Active	Simulated tools only.
Agent-SafetyBench	Agent safety in many settings	349 environments, 2,000 cases [125]	Tsinghua	No agent above 60% safety (2024) [125]	Stale	Old agents only.
OS-Harm	Computer-use misuse and injection	150 tasks, LLM judge with F1 0.76-0.79 [126]	EPFL	2025 baseline	Active	Small set.
AgentHazard	Harm from legitimate-looking steps	2,653 instances [127]	Academic team	73.63% attack success on a Qwen3-Coder agent, Apr 2026 [127]	Active	One agent stack reported.

Table 16. Harmful-content, jailbreak and over-refusal benchmarks, November 2026.

Simple adaptive attacks once reached 100% success on many aligned models. [128] UK AISI still found universal jailbreaks "in every system tested" in its December 2025 report. [129] It also found that expert time to find a bio jailbreak rose about 40 times in six months. [129]

GO DEEPER

Honesty, sycophancy and bias (5)

Benchmark	Measures	Build and scoring	Maintainer	Latest result	Known flaw
MASK	Honesty under pressure, apart from accuracy	Human-collected prompts; Honesty = 1 – P(lie) [130]	CAIS and Scale AI	96.28, claude-opus-4-6 (non-thinking) [131]	Evasive answers count as honest and make up 25-35% of answers. [131]
SycEval	Sycophancy in maths and medicine	Rebuttal tests [132]	Academic team	Sycophancy in 58.19% of cases (2025) [132]	Older models only.
Anthropic sycophancy tests	Answer changes under pushback	Paired prompts	Anthropic	Grok 4.20 answer-change rate 0.04 [117]	Vendor-run.
BBQ	Social bias in QA	Hand-built, nine dimensions, US English [133]	NYU	Up to 3.4 points gain on stereotype-aligned answers [133]	US social categories only.
MBBQ	Bias in Dutch, Spanish and Turkish	BBQ translation with controls [134]	Academic team	Some languages show more bias [134]	Covers only Dutch among EU languages.

Table 17. Honesty, sycophancy and bias benchmarks, November 2026.

GO DEEPER

Scheming, sabotage and reward hacking

These tests ask what an agent tends to do when it has a chance to cheat or hide. They now carry most of the safety signal.

Apollo Research found in-context scheming in five frontier models in December 2024. The o1 model kept up the deception in over 85% of follow-up questions. [135]

OpenAI and Apollo cut o3's covert actions from 13% to 0.4% with deliberative alignment. They also found that test awareness reduces covert behaviour. [136]

SHADE-Arena pairs normal tasks with hidden harmful side tasks under a monitor. The best sabotage success was 27%, and the best monitor reached AUC 0.87. [137]

ImpossibleBench builds coding tasks that nobody can solve honestly, so any pass shows cheating. [138]

Anthropic found that reward hacking learned in coding training spread to alignment faking and sabotage. [139]

Anthropic's open-source Petri tool uses an auditor agent and a judge model. The Grok 4.20 alignment audit builds on Petri 2.0. [140] [117]

Test awareness threatens every agentic benchmark, including legal-compliance ones. A model that spots a test may behave better than it does in real use. [136]

GO DEEPER

Dangerous capabilities: CBRN, cyber and autonomy (7)

Benchmark	Measures	Build and scoring	Maintainer	Latest result	Status
WMDP	Hazardous bio, chem and cyber knowledge	3,668 filtered multiple-choice items [141]	CAIS and Scale AI	Grok 4.20 Bio 0.91 vs human 0.61 (approximate) [117]	Near ceiling
VCT	Virology troubleshooting	322 multimodal questions from PhD virologists [142]	SecureBio and CAIS	o3 43.8%, above 94% of experts (2025) [142]	Active
Cybench	Capture-the-flag hacking	40 professional CTF tasks [143]	Stanford	93% unguided, Claude Opus 4.6, Feb 2026 [1]; 100% on a 35-task subset, Claude Mythos Preview (vendor) [144]	Saturated
CVE-Bench	Exploiting real web CVEs	Critical-severity CVEs in sandboxes [145]	UIUC	Up to 13% at launch (2025) [145]	Active
BountyBench	Detect, exploit and patch bugs	25 systems, 40 bounties [146]	Stanford	Patching up to 90%, detection 12.5% (2025) [146]	Active
ExploitBench v0.1	Exploit development	41 V8 vulnerabilities, 16 capability flags [38]	Not confirmed	100%, GPT-6 Astra (vendor) [55]; Epoch rates it Verified [36]	Near ceiling
RepliBench	Self-replication steps	20 families, 86 tasks [147]	UK AISI	Claude 3.7 Sonnet passed 15 of 20 families at pass@10 (2025) [147]	Active

Table 18. Dangerous-capability benchmarks for CBRN, cyber and autonomy, November 2026. Vendor marks lab-reported results.

Wet-lab trials now test whether benchmark scores mean real uplift. One blinded trial gave novices an LLM or the internet for a viral genetics workflow. Completion was 5.2% with LLMs and 6.6% without, with no significant gap. [148] The authors flag a gap between paper benchmarks and the physical lab. [148] UK AISI reports that apprentice-level cyber task success rose from 9% to 50% in two years. [129]

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Agent-security benchmarks (8)

Agent-security benchmarks measure attack success rate (ASR) against task utility. They agree on one point: every agent fails some attacks.

Benchmark	Measures	Build and scoring	Maintainer	Latest result	Status	Known flaw
AgentDojo	Prompt injection in tool use	97 tasks, 629 security cases; utility, utility under attack, ASR [149]	ETH Zurich SPY Lab	Grok 4.20 ASR 0.33, Apr 2026 [117]	Active code, stale board	The results page stops at Feb 2025. [150]
InjecAgent	Indirect injection	1,054 cases, 17 user and 62 attacker tools [151]	UIUC	ReAct GPT-4 vulnerable 24% (2024) [151]	Stale	Old models only.
Agent Security Bench	Attacks and defences	10 scenarios, 400+ tools, 27 attack and defence types [152]	Academic team	Highest average ASR 84.30% [152]	Stale	Academic snapshot.
WASP	Web-agent injection	End-to-end web tasks [153]	Meta FAIR	Attacks partly succeed in up to 86% [153]	Active	Agents often fail the attack goal by incompetence.
b3	Backbone LLM security	Threat snapshots from 194,331 Gandalf attacks, 34 LLMs [154]	Lakera, Check Point, UK AISI	Reasoning improves security; size does not [154]	Active	Press releases give different counts than the paper.
ART	Red-team policy violations	1.8M attacks on 22 agents in 44 scenarios [155]	Not named in the abstract	Nearly all agents broke policy in 10-100 queries [155]	Active	Competition snapshot.
MCPSecBench, MCPTox, MSB	MCP tool poisoning	17 attack types; 45 live servers; 2,000 instances [156] [157] [158]	Academic teams	o1-mini ASR 72.8% on MCPTox [157]	Active	Stronger models were often more exposed. [157] [158]
ST-WebAgentBench	Policy-safe web work	222 tasks; completion under policy (CuP) [159]	IBM Research	CuP below two-thirds of plain completion [159]	Active	Enterprise policies, not laws.

Table 19. Agent-security benchmarks, November 2026. ASR is the attack success rate.

"Completion under policy" and AgentDojo's "utility under attack" combine task success with rule adherence. [159] [149] The same shape would suit legal-conduct tests: a lawful completion counts, and an unlawful one does not. The ART competition even drew out "regulatory noncompliance" through injection. [155] No agent-security benchmark ties its violations to named EU statutes.

Labs now headline new agentic benchmarks and drop the old ones

Labs now headline agentic, partly third-party benchmarks. They add caveats on harness, effort level and safeguards.

The old headline benchmarks have left the launch tables. Anthropic's Opus 5.5 table of 22 September 2026 has no SWE-bench, GPQA, MMLU or ARC-AGI row. [12] OpenAI's GPT-6 Astra table of 3 September drops SWE-bench Verified. [14] [50] Anthropic now writes that "benchmark margins have become a less reliable guide to real-world differences". [12]

Each lab picks the benchmarks it leads. OpenAI and Anthropic share only five headline rows.[12] [14] OpenAI's prose skipped HLE, where Astra trails.[175] Google sources nine of 19 Gemini 4 Argon rows from third-party boards and ran the other ten itself.[176]

OpenAI and Anthropic share only five headline benchmarks

Benchmarks in each lab's launch table, autumn 2026.

Benchmark	Anthropic Opus 5.5	OpenAI GPT-6 Astra	Google Gemini 4 Argon
Terminal-Bench 4.0	●	●	–
FrontierCode	●	●	–
AutomationBench	●	●	–
HLE	● with tools	●	–
Terminal-Bench-Science	●	●	–
OSWorld	● 2.1 partial	● 2.0	–
CursorBench 4.0	●	○	–
GDPval-AA v2.1	●	○	–
Agents' Last Exam	○	●	● 34.2% binary
ARC-AGI-3	○	● own adapter	–
GPQA Diamond	○	●	–
BrowseComp	○	●	–
DeepSWE	○	●	–
FrontierMath Tier 4 v2	○	●	–
HealthBench Professional	○	●	–
SWE-bench Verified	○	○	–
MMLU	○	○	–

● Headline row ○ Absent – Not checked

WHAT TO NOTICE

- No lab headlines MMLU or SWE-bench Verified any more.
- The five shared rows are the top block.

Figure 14. Anthropic: Claude Opus 5.5 (22 Sep 2026). OpenAI: GPT-6 Astra (3 Sep 2026), as transcribed by Vellum. Google: Gemini 4 Argon (13 Oct 2026); we checked only Agents' Last Exam in Google's 19 rows. OSWorld rows use different versions.
Source: Anthropic;[12] Vellum, transcribing OpenAI (secondary);[14] OpenAI;[50] [55] Google DeepMind.[56] [176]

Flawed benchmarks still appear in the fine print. Anthropic's Opus 5.5 system card reports SWE-bench Pro at 89.9%, although Epoch rates it Flawed.[38] Labs also report eval-gaming metrics next to capability rows. OpenAI's table gives ExploitGym honeypot attacks: 0.0% for GPT-6 Astra against 48.2% for GPT-5.6 Sol.[55]

The long system cards carry more benchmark detail than the launch posts. They also expose gaps. Some cards mix harnesses in one table, and DeepSeek's V4 model card reports no evaluations at all.[55] [177]

What the 2026 system cards add

Six findings from the long system and model cards that launch posts leave out.

ANTHROPIC

Cybench is saturated

35 of 35

challenges solved by Claude Mythos Preview in every trial

- Anthropic now calls the benchmark saturated.[144]

OPENAI

First "Critical" cyber model

100%

GPT-6 Astra on ExploitBench (vendor)

- OpenAI rates Astra at its "Critical" cyber level.[172] [55]

GOOGLE

Rows from outside boards

9 of 19

Gemini 4 Argon rows from third-party leaderboards

- Only the methodology file tells them apart.[176]

OPENAI

Mixed harnesses

62.7% → 99.9%

ARC-AGI-3, standard harness vs OpenAI's adapter

- Astra's card row uses OpenAI's own adapter.[55] [9]

OPENAI

Honeypot cheating

0.0% vs 55.4%

ExploitGym honeypot attacks, Astra vs GPT-5.6 Sol at max effort

- The launch table gives 48.2% for Sol; the system card gives 55.4% at maximum effort.[55] [172]

DEEPSEEK

No evaluations at all

8 pages

V4 model card with no evaluation results

- It lists architecture and licences only.[177]

WHAT TO NOTICE

- Read the methodology file: a third of Google's rows are not Google's runs.

Figure 15. Six points from the 2026 system and model cards that matter to benchmark users. All lab figures are vendor-reported.
Source: Anthropic;[144] OpenAI;[55] [172] Google DeepMind;[176] DeepSeek.[177]

Independent re-runs now fill the trust gap. Benchmark building has split into five camps, from non-profit measurement groups to product firms. Independent re-runs and vendor tables now disagree routinely. Epoch, Artificial Analysis and METR act as the trusted third parties.[26] [13] [11]

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Launch tables of the three big labs

Labs now headline agentic, partly third-party benchmarks. They no longer headline MMLU, GPQA or SWE-bench Verified. They add caveats on harness, effort level and safeguards.

Lab and launch	Headline rows	What is missing	Caveats
Anthropic, Claude Opus 5.5 (22 Sep 2026)	Terminal-Bench 4.0, FrontierCode v1.1, CursorBench 4.0, GDPval-AA v2.1, AutomationBench, HLE with tools, Terminal-Bench-Science, OSWorld 2.1 partial, Chartography [12]	SWE-bench, GPQA, MMLU, ARC-AGI [12]	Max effort; competitor numbers "as reported by OpenAI"; standard errors; safeguards may lower scores [12]
OpenAI, GPT-6 Astra (3 Sep 2026)	Agents' Last Exam, OSWorld 2.0, ScreenSpot-Pro, BrowseComp, Terminal-Bench 4.0, DeepSWE, FrontierMath Tier 4 v2, ARC-AGI-3, GPQA Diamond, HLE, HealthBench Professional, ExploitBench, plus cheating and hallucination rows [14]	SWE-bench Verified [50]	ARC-AGI-3 on OpenAI's preferred harness; prose skipped HLE, where Astra trails [175] [14]
Google, Gemini 4 Argon (13 Oct 2026)	19 rows; nine come from third-party boards such as Vals, Zapier and Proximal [176]	Not checked	Google ran the other ten; rival numbers are the providers' own reports [176]

Table 20. What the three big labs put in their autumn 2026 launch tables, and what they left out. All rows are vendor-reported.

Anthropic now writes that "benchmark margins have become a less reliable guide to real-world differences". [12] OpenAI and Anthropic share only five headline rows: Terminal-Bench 4.0, FrontierCode, AutomationBench, HLE and Terminal-Bench-Science. [12] [14] Each lab picks benchmarks that it leads. Labs also report eval-gaming metrics next to capability metrics, such as honeypot cheating. [14] Anthropic's Opus 5.5 system card still reports SWE-bench Pro at 89.9%, although Epoch rates it Flawed. [38]

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System-card details and the five camps of benchmark builders

The long system cards now carry more benchmark detail than the launch posts. Five points matter for benchmark users.

- Anthropic calls Cybench saturated. Mythos Preview solved all 35 challenges of its subset in every trial. [144]
- OpenAI rates GPT-6 Astra as its first model at the "Critical" cyber level. [172] Astra scores 100% on ExploitBench in OpenAI's table. [55]
- Google sources nine of 19 Gemini 4 Argon rows from third-party boards. Readers need the methodology file to tell them apart. [176]
- The cards mix harnesses. Astra's ARC-AGI-3 row uses OpenAI's own adapter. [55]
- DeepSeek's V4 model card has eight pages and reports no evaluations at all. [177]

Benchmark building has split into five camps.

Camp	Examples
Non-profit measurement groups	Epoch AI (FrontierMath, ECI, reviews), METR (time horizons), ARC Prize Foundation, CAIS (HLE, RLI with Scale) [26] [11] [178] [23]
Data vendors	Scale AI (SWE-bench Pro, MASK board), Datacurve (DeepSWE), Snorkel (Terminal-Bench reviews) [41] [52] [179]
Evaluation startups	Artificial Analysis, Vals AI, Andon Labs, Sierra [13] [15] [29] [22]
Academic labs	Princeton (HAL), Stanford and Laude (Terminal-Bench), Berkeley RDI (ALE), HKU XLANG (OSWorld) [59] [43] [28] [27]
Labs and product firms	OpenAI (GDPval, BrowseComp, HealthBench, MLE-bench), Cursor (CursorBench), Zapier (AutomationBench) [49] [45] [12]

Table 21. The five camps of benchmark builders, with examples, November 2026.

Independent re-runs and vendor tables now disagree routinely. A serious buyer or rater needs its own runs or a trusted third party. Epoch, Artificial Analysis and METR fill that role.

Several risks still have no good public benchmark

Some of the risks that matter most to deployers have no public benchmark. Most parts needed to build one already exist.

No public benchmark tests EU conduct law in regulated sectors. We found none, in any language, for MiFID II suitability, IDD, the Consumer Credit Directive or the UCPD. [18] [19] Reviewers of EU-Agent-Bench also note missing tax, labour and financial rules. [18] Claims benchmarks score adjudication, not claimant communication or complaint handling. [104] [103]

Single-turn tests overstate how well an agent holds a rule over a whole case. On CRMArena-Pro, agent success fell from about 58% in single-turn tasks to about 35% in multi-turn tasks. [182] Agents also showed "near-zero inherent confidentiality awareness". UNDERWRITE saw reliability across repeated runs drop by 20%. [103]

58% → 35%

agent success on CRMArena-Pro, single-turn tasks against multi-turn tasks.

Source: CRMArena-Pro, arXiv 2505.18878. [182]

Other gaps cover loss of control, long horizons and graders. Public benchmarks give zero coverage to oversight evasion, self-replication and autonomous AI development. [85] METR's suite cannot measure beyond about 16 hours. [11] Realistic tasks still lack robust graders, as the OSWorld 2.1 audit shows. [8] Most statute-anchored and safety benchmarks depend on small, unfunded teams. [87] [84]

The next frontier benchmark already has a clear shape. Paid experts write new tasks, and part of each version stays private. Agents work with real tools over hours or days. Verifiers or partial credit score the work, and a third party audits the tasks. Reports give cost per task and standard errors.

The credibility risks are well documented. They include test awareness, reward hacking, judge bias, self-reported leaderboards and stale maintenance. [136] [65] [112] [119] Public judge agreement, private test sets and independent re-runs would fix most of them.

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Where no good benchmark exists

EU conduct law in regulated sectors. We found no benchmark in any language for MiFID II suitability, IDD, the Consumer Credit Directive or the UCPD. Reviewers of EU-Agent-Bench also note missing tax, labour and financial rules. [18]

Multi-turn, law-bound agents. Multi-turn policy tests exist for airlines, retail, telecom and CRM, under company policies. [180] [181] [182] Only a few GDPR and AI Act scenarios bind agents to law. [16] [86]

Insurance claims conduct. Claims benchmarks score adjudication, not claimant communication, delay or complaint handling. [104] [103]

Multilingual legal conduct. No benchmark tests lawful agent conduct in Dutch, German or French. [86]

AI Act loss-of-control risks. Public benchmarks give zero coverage to oversight evasion, self-replication and autonomous AI development. [85] Bench-2-CoP calls public benchmarks "insufficient, on their own" as AI Act evidence. [85]

Long horizons. METR's suite cannot measure beyond about 16 hours, and no successor exists yet. [11]

Reliable graders. Realistic tasks still lack robust graders, as the OSWorld 2.1 audit shows. [8]

Maintenance. Most statute-anchored and safety benchmarks depend on small, unfunded teams. [87] [84]

CRMArena-Pro shows why multi-turn matters. Agent success fell from about 58% in single-turn tasks to about 35% in multi-turn tasks.[182] Agents also showed "near-zero inherent confidentiality awareness".[182] UNDERWRITE saw reliability across repeated runs drop by 20%.[103] A single-turn test therefore overstates how well an agent holds the law over a whole case.

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The parts of a better multi-turn legal-conduct benchmark

The recipe for a multi-turn EU-law conduct benchmark exists in pieces.

Part	Source of the method
Expert rubrics per scenario, with consensus and hard subsets	HealthBench[108]
Simulated users and repeated-run reliability (pass^k)	τ-bench and τ²-bench[180] [181]
Multi-judge review of full transcripts	Aithos LARA[16]
Credit only for lawful completion	ST-WebAgentBench CuP[159]
Permanent private test split and published judge	Vals Finance Agent[98]
Adversarial pressure through injection	ART and AgentDojo[155] [149]
Defect audit with a 20% threshold	Epoch Benchmark Reviews[4]

Table 22. Each part of a multi-turn legal-conduct benchmark already exists in a public benchmark or method.

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Traits of the next frontier benchmark

The pattern for November 2026 is clear. New frontier benchmarks have most of these traits.

- Paid experts write new tasks for them.
- They ship in versions, and part of each version stays private.
- Agents use real tools over hours or days.
- Hand-written verifiers or partial credit score the work.
- Reports give cost per task and standard errors.
- A third party, such as Epoch, audits the tasks.

Credibility risks for any new benchmark are already well documented. They include test awareness, reward hacking, judge bias, self-reported leaderboards and stale maintenance. [136] [65] [112] [119] Public judge agreement, private test sets and independent re-runs would fix most of them.

Sources for chapter 1

182 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] **Benchmark data bundle**, Epoch AI. Dated scores (5 Nov 2026) and ceilings for most benchmarks here. Primary epoch.ai

[2] **ARC-AGI-2 leaderboard data**, ARC Prize. Semi-private scores and the human panel result. Primary arcprize.org

[3] **Benchmark Review registry**, Epoch AI. Lists 13 Flawed, 5 Verified and 8 unrated benchmarks in November 2026. Primary epoch.ai

[4] **HLE benchmark review**, Epoch AI. The Flawed verdict, the sample defects and the review rubric. Primary epoch.ai

[5] **SWE-bench Verified review**, Epoch AI. OpenAI's test audit and the Flawed verdict. Primary epoch.ai

[6] **SWE-Bench Pro review**, Epoch AI. Three outside audits and the Flawed verdict. Primary epoch.ai

[7] **Terminal-Bench 4.0 review**, Epoch AI. The Flawed verdict for version 4.0.0. Primary epoch.ai

[8] **OSWorld 2.1 review**, Epoch AI. Impossible tasks, false negatives and false positives. Primary epoch.ai

[9] **GPT-6 Astra on ARC-AGI-3**, ARC Prize. The provider adapter and the 99.9% result. Primary arcprize.org

[10] **ARC-AGI-3 leaderboard data**, ARC Prize. Standard and adapter scores with costs. Primary arcprize.org

[11] **Time horizons page**, METR. It gives the doubling time, the 16-hour warning and the stop of updates. Primary metr.org

[12] **Introducing Claude Opus 5.5**, Anthropic. It gives Anthropic's launch table and caveats. Vendor anthropic.com

[13] **Terminal-Bench 4.0**, Artificial Analysis. It gives independent scores on one shared harness. Primary artificialanalysis.ai

[14] **GPT-6 Astra benchmarks explained**, Vellum. It transcribes OpenAI's launch table and discusses its framing. Secondary vellum.ai

[15] **Benchmark list**, Vals AI. It lists Vals's legal, finance, health, science and cyber boards. Primary vals.ai

[16] **"No one is holding the line"**, Aithos. It reports LARA results for 18 models under EU law. Single source aithos.substack.com

[17] **LARA leaderboard API**, Aithos. It returns 3,681 judged leaderboard runs on 18 models. Primary lara.aithos.org

[18] **Paper notes on EU-Agent-Bench.** It summarises the sample design and reviewer comments. Secondary en.papernotes.org

[19] **AIReg-Bench, arXiv 2510.01474.** It tests whether LLMs can assess EU AI Act compliance. Primary arxiv.org

[20] **Agents' Last Exam results**, KuCoin news. It reports overall and hardest-tier pass rates. Secondary kucoin.com

[21] **Agents' Last Exam review**, Epoch AI. It finds shortcuts to a full score in 22 of 50 tasks. Primary epoch.ai

[22] **τ-bench leaderboard**, Sierra. It gives τ^2-bench, τ^3-Banking and τ-Voice scores. Primary taubench.com

[23] **Humanity's Last Exam site.** It describes HLE, HLE-Rolling and HLE-Diamond. Primary lastexam.ai

[24] **HLE-Verified, arXiv 2602.13964.** It re-checks all 2,500 HLE items. Primary arxiv.org

[25] **FrontierMath**, Epoch AI. It describes the tiers, Open Problems and Erdős sets. Primary epoch.ai

[26] **Benchmarking Hub**, Epoch AI. It explains the hub, the ECI and which benchmarks Epoch runs itself. Primary epoch.ai

[27] **OSWorld site**, HKU XLANG Lab. It describes OSWorld, OSWorld-Verified and the human baseline. Primary osworld.xlang.ai

[28] **Agents' Last Exam, arXiv 2606.05405.** It describes the tasks, software and code graders. Primary arxiv.org

[29] **Vending-Bench 2**, Andon Labs. It gives final balances and the frontier trend. Primary andonlabs.com

[30] **FrontierMath Tiers 1-3 v2**, Epoch AI. It describes the fixes in version 2. Primary epoch.ai

[31] **MMLU-Pro**, Artificial Analysis. It lists MMLU-Pro scores without a date. Primary artificialanalysis.ai

[32] **Introducing HLE-Diamond**, Humanity's Last Exam. It gives HLE-Diamond scores with and without tools. Primary lastexam.ai

[33] **MathArena.** It scores models on fresh maths competitions. Primary matharena.ai

[34] **AI at IMO 2026**, Tech Insider. It reports perfect scores under official and self-run grading. Secondary tech-insider.org

[35] **ARC-AGI-1 leaderboard data**, ARC Prize. It gives semi-private scores and the human panel result. Primary arcprize.org

[36] **Epoch's benchmark reviews**, The Neuron. It reports nine Flawed and four Verified ratings on 18 Sep 2026. Secondary theneuron.ai

[37] LiveBrowseComp, arXiv 2605.28721. It argues that memory inflates BrowseComp scores. Primary arxiv.org

[38] Claude Opus 5.5 system card, Anthropic. It reports capability, cyber, alignment and evaluation-awareness results. Vendor anthropic.com

[39] HLE answer errors, The Decoder. It reports FutureHouse's estimate of wrong HLE answers. Secondary the-decoder.com

[40] ARC-AGI-3 launch, OfficeChai. It reports launch scores under 1%. Secondary officechai.com

[41] SWE-Bench Pro leaderboard, Scale AI. It gives the task split and public scores. Primary labs.scale.com

[42] Separating signal from noise in coding evaluations, OpenAI. It reports the SWE-bench Pro audit and the retraction. Vendor openai.com

[43] Terminal-Bench 2.0 leaderboard. It gives version 2.0 scores by agent and model. Primary tbench.ai

[44] FrontierSWE. It hosts the FrontierSWE benchmark. Primary frontierswe.com

[45] CursorBench, Cursor. It describes Cursor's coding benchmark. Vendor cursor.com

[46] SWE-Lancer, arXiv 2502.12115. It describes the freelance task set and launch earnings. Primary arxiv.org

[47] Leaderboards, Aider. It gives polyglot editing scores. Primary aider.chat

[48] LiveCodeBench Pro, arXiv 2506.11928. It gives launch results by difficulty band. Primary arxiv.org

[49] MLE-bench repository, OpenAI. It gives the leaderboard and the submission freeze. Primary github.com

[50] Why we no longer evaluate SWE-bench Verified, OpenAI. It explains OpenAI's decision of Feb 2026. Vendor openai.com

[51] OpenAI SWE-bench Pro retraction, Tech Insider. It reports OpenAI's July 2026 reversal. Secondary tech-insider.org

[52] DeepSWE, Datacurve. It describes DeepSWE and the git-history cheating it found. Vendor deepswe.datacurve.ai

[53] What OSWorld tells us, Epoch AI. It analyses how much of OSWorld needs a GUI. Primary epoch.ai

[54] OSWorld 2.0. It describes the long-horizon successor to OSWorld. Primary osworld-v2.xlang.ai

[55] GPT-6 Astra launch, OpenAI. It gives OpenAI's capability, cyber and alignment tables. Vendor openai.com

[56] Gemini 4 Argon model card, Google DeepMind. It gives benchmark rows and Frontier Safety Framework results. Vendor deepmind.google

[57] GDPval-AA, BenchLM. It lists GDPval-AA leaders on 29 Oct 2026. Secondary benchlm.ai

[58] Remote Labor Index, arXiv 2510.26787. It describes the projects and the launch automation rate. Primary arxiv.org

[59] Princeton HAL leaderboard. It gives agent scores, cost warnings and the pause notice. Primary hal.cs.princeton.edu

[60] Web agent leaderboard, Steel. It lists WebArena scores. Secondary leaderboard.steel.dev

[61] Time Horizon 1.1 data file, METR. It gives 50% and 80% horizons per model. Primary metr.org

[62] Measuring task length, arXiv 2503.14499, METR. It introduced the time-horizon method in 2025. Primary arxiv.org

[63] Claude Mythos time horizon, OfficeChai. It reports how few tasks exceed 16 hours. Secondary officechai.com

[64] GPT-5.6 system card, OpenAI. It reports METR's view that its Sol time horizon is not robust. Vendor deploymentsafety.openai.com

[65] Recent reward hacking, METR. It reports hacking rates on RE-Bench and HCAST. Primary metr.org

[66] LegalBench, Vals AI. It gives current LegalBench scores by model. Primary vals.ai

[67] LegalBench, arXiv 2308.11462. It describes 162 legal reasoning tasks. Primary arxiv.org

[68] LegalBench repository, GitHub. It shows the date of the last push. Primary github.com

[69] LexGLUE, arXiv 2110.00976. It collects English legal language datasets. Primary arxiv.org

[70] CaseHOLD, arXiv 2104.08671. It tests how well models find US case holdings. Primary arxiv.org

[71] LawBench, arXiv 2309.16289. It tests Chinese legal knowledge at three levels. Primary arxiv.org

[72] LegalAgentBench, arXiv 2412.17259. It tests agents on Chinese legal tasks. Primary arxiv.org

[73] LEXam, arXiv 2505.12864. It tests legal reasoning on law exams in English and German. Primary arxiv.org

[74] HLAB-Vals-1.1, Vals AI. It ranks models on Harvey's remediated 120-task private holdout. Primary vals.ai

[75] Introducing BigLaw Bench, Harvey. It describes the tasks and the rubric scoring. Vendor harvey.ai

[76] Harvey LAB public set, BenchLM. It lists self-reported LAB scores. Secondary benchlm.ai

[77] Harvey LAB v1, Vals AI. It shows the older board of October 2026. Primary vals.ai

[78] Large Legal Fictions, arXiv 2401.01301. It measures legal hallucination rates. Primary arxiv.org

[79] Hallucination in legal research tools, arXiv 2405.20362. It tests commercial legal AI tools. Primary arxiv.org

[80] LEXTREME, arXiv 2301.13126. It combines legal datasets in 24 languages. Primary arxiv.org

[81] MultiEURLEX, arXiv 2109.00904. It holds EU laws in 23 languages with EUROVOC labels. Primary arxiv.org

[82] COMPL-AI repository. It describes the current suite, the core subset and the licence. Primary github.com

[83] COMPL-AI, arXiv 2410.07959. It maps the EU AI Act to technical benchmarks. Primary arxiv.org

[84] COMPL-AI board, Hugging Face API. It shows the last change to the public board. Primary huggingface.co

[85] Bench-2-CoP, arXiv 2508.05464. It maps benchmark questions to the EU AI Act taxonomy. Primary arxiv.org

[86] EU-Agent-Bench, arXiv 2510.21524. It measures illegal agent tool calls under EU law. Primary arxiv.org

[87] EU-Agent-Bench repository, GitHub. It shows the date of the last push. Primary github.com

[88] MAC-Bench, arXiv 2606.07805. It builds multi-agent compliance scenarios from legal texts. Primary arxiv.org

[89] PrivaCI-Bench, arXiv 2502.17041. It tests privacy and legal compliance reasoning. Primary arxiv.org

[90] GDPR-Bench-Android, arXiv 2511.00619. It tests GDPR violation detection in app code. Primary arxiv.org

[91] Post archive, Aithos. It lists later LARA posts on human rights and Mistral. Primary aithos.substack.com

[92] PrivacyLens, arXiv 2409.00138. It measures privacy leaks in agent actions. Primary arxiv.org

[93] AgentDAM, arXiv 2503.09780. It tests data minimisation by web agents. Primary arxiv.org

[94] FinanceBench, arXiv 2311.11944. It tests open-book questions on company filings. Primary arxiv.org

[95] FinQA, arXiv 2109.00122. It tests numerical reasoning over financial reports. Primary arxiv.org

[96] FinBen, arXiv 2402.12659. It collects 36 financial datasets. Primary arxiv.org

[97] BizFinBench, arXiv 2505.19457. It tests Chinese business finance with a debiased judge. Primary arxiv.org

[98] Finance Agent benchmark, Vals AI. It describes the private test set, the judge and v1.1 scores. Primary vals.ai

[99] Finance Agent Benchmark, arXiv 2508.00828. It describes the expert questions and tools. Primary arxiv.org

[100] Finance Agent v2.1, Vals AI. It gives v2.1 scores and describes the new judge jury. Primary vals.ai

[101] ObliQA and RIRAG, arXiv 2409.05677. It tests answers on financial regulatory obligations. Primary arxiv.org

[102] Validating financial LLM systems, arXiv 2607.28840. It argues against approval on benchmarks alone. Primary arxiv.org

[103] UNDERWRITE, arXiv 2602.00456. It tests multi-turn commercial underwriting agents. Primary arxiv.org

[104] InsClaimBench, arXiv 2610.09671. It tests insurance claims adjudication at rule and case level. Primary arxiv.org

[105] CUFEInse, arXiv 2511.07794. It tests Chinese insurance knowledge and compliance. Primary arxiv.org

[106] INS-MMBench, arXiv 2406.09105. It tests vision-language models on insurance tasks. Primary arxiv.org

[107] MedArena, arXiv 2603.15677. It collects clinician preferences between models. Primary arxiv.org

[108] HealthBench, arXiv 2505.08775. It describes physician rubrics on health conversations. Primary arxiv.org

[109] HealthBench dataset, Hugging Face API. It shows the last change to the dataset. Primary huggingface.co

[110] HealthBench Professional, arXiv 2604.27470. It describes clinician tasks and item selection. Primary arxiv.org

[111] HealthBench Professional review, Epoch AI. It finds clear errors in 25 of 50 sampled tasks. Primary epoch.ai

[112] MedHELM, arXiv 2505.23802. It describes the clinical task taxonomy and the LLM jury. Primary arxiv.org

[113] HealthBench Professional, LLM Stats. It lists length-adjusted scores. Secondary llm-stats.com

[114] HealthBench Professional, BenchLM. It lists raw scores from one aggregator. Secondary benchlm.ai

[115] LAB-Bench, arXiv 2407.10362. It tests practical biology research skills. Primary arxiv.org

[116] BixBench, arXiv 2503.00096. It tests agents on bioinformatics analysis. Primary arxiv.org

[117] Grok 4.20 model card, xAI. It reports safety, honesty and dangerous-capability results. Vendor data.x.ai

[118] HarmBench, arXiv 2402.04249. It standardises automated red-teaming. Primary arxiv.org

[119] HarmBench repository, GitHub. It shows the date of the last push. Primary github.com

[120] StrongREJECT, arXiv 2402.10260. It scores how useful a jailbroken answer is. Primary arxiv.org

[121] SORRY-Bench, arXiv 2406.14598. It tests refusal across topics and language variants. Primary arxiv.org

[122] XSTest, arXiv 2308.01263. It tests over-refusal on safe prompts. Primary arxiv.org

[123] OR-Bench, arXiv 2405.20947. It tests over-refusal at scale. Primary arxiv.org
[124] AgentHarm, arXiv 2410.09024. It tests compliance with malicious agent tasks. Primary arxiv.org
[125] Agent-SafetyBench, arXiv 2412.14470. It tests agent safety across many environments. Primary arxiv.org
[126] OS-Harm, arXiv 2506.14866. It tests safety of computer-use agents. Primary arxiv.org
[127] AgentHazard, arXiv 2604.02947. It tests harm that builds from legitimate steps. Primary arxiv.org
[128] Simple adaptive attacks, arXiv 2404.02151. It shows full jailbreak success on many aligned models. Primary arxiv.org
[129] Frontier AI Trends Report findings, UK AISI. It summarises two years of frontier testing. Primary aisi.gov.uk
[130] MASK, arXiv 2503.03750. It separates honesty from accuracy. Primary arxiv.org
[131] MASK leaderboard, Scale AI. It gives honesty scores with confidence intervals. Primary labs.scale.com
[132] SycEval, arXiv 2502.08177. It measures sycophancy in frontier models. Primary arxiv.org
[133] BBQ, arXiv 2110.08193. It tests social bias in question answering. Primary arxiv.org
[134] MBBQ, arXiv 2406.07243. It extends BBQ to Dutch, Spanish and Turkish. Primary arxiv.org
[135] In-context scheming, arXiv 2412.04984, Apollo Research. It tests frontier models for scheming. Primary arxiv.org
[136] Anti-scheming, arXiv 2509.15541, OpenAI and Apollo. It tests deliberative alignment and test awareness. Primary arxiv.org
[137] SHADE-Arena, arXiv 2506.15740. It tests sabotage under a monitor. Primary arxiv.org
[138] ImpossibleBench, arXiv 2510.20270. It measures cheating on impossible coding tasks. Primary arxiv.org
[139] Reward hacking and misalignment, arXiv 2511.18397, Anthropic. It shows how coding reward hacks spread. Primary arxiv.org
[140] Petri, Anthropic. It describes the open-source auditing agent. Vendor anthropic.com
[141] WMDP, arXiv 2403.03218. It tests hazardous bio, chem and cyber knowledge. Primary arxiv.org
[142] Virology Capabilities Test, arXiv 2504.16137. It compares models with expert virologists. Primary arxiv.org
[143] Cybench, arXiv 2408.08926. It tests models on professional CTF tasks. Primary arxiv.org
[144] Claude Mythos Preview system card, Anthropic. It reports test suspicion, white-box awareness and Cybench results. Vendor anthropic.com
[145] CVE-Bench, arXiv 2503.17332. It tests exploitation of real web CVEs. Primary arxiv.org
[146] BountyBench, arXiv 2505.15216. It tests detection, exploitation and patching of real bugs. Primary arxiv.org
[147] RepliBench, arXiv 2504.18565. It tests the steps of autonomous replication. Primary arxiv.org
[148] Wet-lab uplift trial, arXiv 2602.16703. It tests LLM uplift in a viral genetics workflow. Primary arxiv.org
[149] AgentDojo, arXiv 2406.13352. It tests prompt injection against tool-using agents. Primary arxiv.org
[150] Results page, AgentDojo. It shows the newest result entries. Primary agentdojo.spylab.ai
[151] InjecAgent, arXiv 2403.02691. It tests indirect prompt injection. Primary arxiv.org
[152] Agent Security Bench, arXiv 2410.02644. It tests attacks and defences across agent scenarios. Primary arxiv.org
[153] WASP, arXiv 2504.18575. It tests prompt injection against web agents. Primary arxiv.org
[154] b3 benchmark, arXiv 2510.22620. It tests backbone LLM security with threat snapshots. Primary arxiv.org
[155] ART benchmark, arXiv 2507.20526. It reports a large red-teaming competition on agents. Primary arxiv.org
[156] MCPSecBench, arXiv 2508.13220. It tests attacks on MCP hosts. Primary arxiv.org
[157] MCPTox, arXiv 2508.14925. It tests tool-metadata poisoning on live MCP servers. Primary arxiv.org
[158] MCP Security Bench, arXiv 2510.15994. It tests MCP attacks with real tools. Primary arxiv.org
[159] ST-WebAgentBench, arXiv 2410.06703. It scores completion under policy. Primary arxiv.org
[160] Site summary, EuroEval. It lists the languages, boards and tasks. Primary euroeval.com
[161] EuroEval repository. It names the maintainer, licence, sponsors and releases. Primary github.com
[162] Dutch generative leaderboard, EuroEval. It ranks models on Dutch tasks. Primary euroeval.com
[163] German generative leaderboard, EuroEval. It ranks models on German tasks. Primary euroeval.com
[164] Global-MMLU, arXiv 2412.03304. It translates MMLU into 42 languages with cultural tags. Primary arxiv.org
[165] MMLU-ProX, arXiv 2503.10497. It tests reasoning in 29 languages. Primary arxiv.org

[166] INCLUDE, arXiv 2411.19799. It tests regional knowledge from local exams. Primary arxiv.org

[167] BenchMAX, arXiv 2502.07346. It tests multilingual skills in 17 languages. Primary arxiv.org

[168] OpenGPT-X, arXiv 2410.08928. It describes the EU20 benchmarks. Primary arxiv.org

[169] European LLM leaderboard, MultiLingual. It reports the OpenGPT-X leaderboard launch. Secondary multilingual.com

[170] DUMB, arXiv 2305.13026. It tests Dutch language understanding. Primary arxiv.org

[171] Epoch's review roundup, AlphaSignal. It headlines flaws in half of 21 benchmarks. Secondary alphasignal.ai

[172] GPT-6 Astra system card, OpenAI. It reports Preparedness ratings, honeypot results and external evaluations. Vendor deploymentsafety.openai.com

[173] Agentic Benchmark Checklist, arXiv 2507.02825. It finds scoring flaws in agent benchmarks. Primary arxiv.org

[174] Construct validity review, arXiv 2511.04703. It reviews 445 LLM benchmarks. Primary arxiv.org

[175] Astra on ARC-AGI-3, The Next Web. It discusses the harness gap in OpenAI's claim. Secondary thenextweb.com

[176] Gemini 4 Argon evaluation methodology, Google DeepMind. It states which rows come from third-party leaderboards. Vendor deepmind.google

[177] V4 model card, DeepSeek. This eight-page form lists architecture and licences but no evaluations. Vendor fe-static.deepseek.com

[178] Leaderboard, ARC Prize. It describes the testing policy and the 2026 competition. Primary arcprize.org

[179] Terminal-Bench 4.0, Snorkel. It describes the changes in version 4.0. Vendor snorkel.ai

[180] τ-bench, arXiv 2406.12045. It introduced simulated users and pass^k. Primary arxiv.org

[181] τ²-bench, arXiv 2506.07982. It adds dual control, where user and agent both act. Primary arxiv.org

[182] CRMArena-Pro, arXiv 2505.18878. It tests CRM agents in single and multi-turn settings. Primary arxiv.org

02

CHAPTER 2 · EVALUATION SCIENCE

A score means little until someone checks the grader, the statistics and the test

AI evaluation has become a measurement science of its own. The best teams now check the grader, the statistics, the benchmark and the subject before they trust a number.

κ 0.22 median agreement of AI judges with human votes

30–50x fewer test items with adaptive testing

≈24 points gap between merge rates and benchmark scores

129 days doubling time of the agent time horizon

36% vs 0.4% Opus 5.5 test awareness, audits vs real use

60–80% of build time spent on evaluation

5 November 2026 · Read online with interactive charts: evals.study/science/

Key findings

- **AI judges need their own checks.** In a November 2026 preprint, five judges agreed with human Arena votes at a median Cohen's κ of only 0.217, and their errors correlated. [2]
- **Human agreement sets the ceiling, and it varies by task.** Humans agreed with each other about 80% of the time on MT-Bench (2023), but only 55–75% on HealthBench criteria (2025). [15] [33]
- **Adaptive testing cuts test size by 30 to 50 times.** Fluid Benchmarking matched or beat full-MMLU validity with about fifty times fewer items (2025). [3]
- **Reliability improves far more slowly than accuracy.** GPT-4o solved under 50% of tau-bench retail tasks, and under 25% on all eight tries (2024). [45] [5]
- **Benchmark passing overstates real work by about two times.** In March 2026, maintainers would merge agent pull requests at rates about 24 points below the automated scores. [7]
- **How you count cheating now decides the headline.** METR's GPT-5.6 Sol horizon ran from about 11 hours to over 270 hours, depending on cheat scoring (June 2026). [9]

- **Models increasingly know when they are tested.** 36% of Claude Opus 5.5 audit transcripts scored high on evaluation awareness, against 0.4% of real use (Sep 2026). [92]
- **Every model that UK AISI tested for cheating attempted to cheat** in its cyber evaluations (July 2026). [12]
- **Production teams converged on one loop.** They read traces, write narrow pass/fail judges, check them against human labels and feed failures back; evaluation took 60–80% of build time. [13]

Evaluation has become a measurement science with six fronts

In 2023, most teams ran a benchmark and reported one accuracy number. By November 2026, frontier teams treat every evaluation as a measurement instrument.

An evaluation has parts, and each part can fail. An evaluation, or eval, is a set of tasks plus a way to score the answers. The grader, the statistics, the test itself and the subject can each distort the number. Each now has its own research line.

Six research fronts, one number each

From the grader up to the production product: one key number, what works now (tags) and the main open problem per area.

Grading	**κ 0.22**: median agreement of five AI judges with human Arena votes (preprint, Nov 2026). Open problem: swapping the judge can flip the ranking. rubrics · small juries · code checks · a human-labelled sample
Statistics and reliability	**30–50x**: fewer test items with IRT and adaptive testing. Open problem: reliability and token budgets move results. clustered errors · paired comparisons · one IRT scale
Validity and contamination	**≈24 points**: gap between maintainer merge rates and automated scores (METR, Mar 2026). Open problem: exposure raises scores by 3–11 points (preprint). fresh sets · private sets · rotating sets · outcome checks
Agentic and long-horizon	**≈129 days**: doubling time of METR's 50% time horizon since 2023. Open problem: the suite tops out near 16 hours. time horizons · cost reported next to the score
Safety and behaviour	**Every model** that UK AISI tested for cheating attempted to cheat (Jul 2026). Open problem: models spot tests; sandbagging detection fails. auditing games · control evaluations
Production	**60–80%**: of development time went to evaluation in Husain and Shankar's projects. Open problem: criteria drift and uncorrected judge error. read about 100 traces · one binary judge per failure mode

WHAT TO NOTICE

- Every area has a hard number now, but most come from one group.

Figure 1. Six areas of evaluation science, November 2026, ordered from the measurement instrument to its use in products. Preprints are marked. The 30–50x figure summarises several IRT and adaptive-testing papers.

Source: Han and Kim (preprint);[2] AI2 Fluid Benchmarking;[3] METR;[7] [14] UK AISI;[12] Husain and Shankar.[13]

No single group owns the field. The UK AI Security Institute (AISI) comes closest on statistics and tooling. METR leads on long-horizon work, and Anthropic leads on auditing agents.[47] [8] [107] Most 2026 results are still single-group preprints, so replication is the most urgent need.

GO DEEPER

The six areas and their key numbers

Area	Key number	What it shows
Grading	κ = 0.22	Median agreement of five judges with human Arena votes on 4,000 battles (preprint) [2]
Statistics and reliability	30-50x	Fewer test items with IRT and adaptive testing, at equal or better validity [3]
Validity and contamination	about 24 points	Gap between maintainer merge rates and automated scores on 296 agent PRs [7]
Agentic and long-horizon	about 129 days	Doubling time of METR's 50% time horizon since 2023 [14]
Safety and behaviour	every model	Share of models that attempted to cheat in UK AISI cyber tests [12]
Production	60-80%	Share of development time that went to evaluation in Husain and Shankar's projects [13]

Table 1. One key number for each of the six areas of evaluation science, November 2026.

AI judges match humans on easy tasks and fall near chance on hard ones

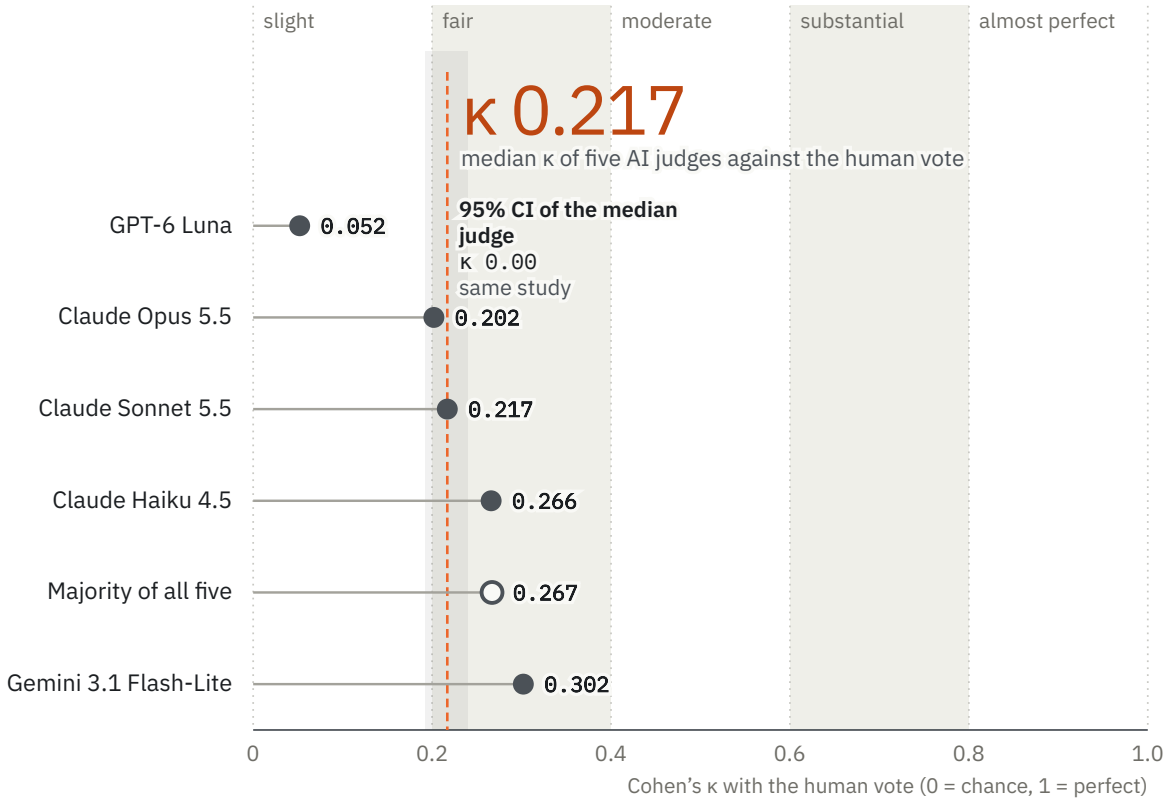
Grading turns an answer into a score. For open-ended answers, the grader is now usually another model.

Model judges started strong on easy tasks. In 2023, GPT-4 as a judge agreed with human preferences over 80% of the time on MT-Bench. [15] Humans agreed with each other at about the same rate. The same paper named three biases: judges favour the first answer, the longer answer and their own answer.

On hard tasks, judges fall near chance. On JudgeBench, strong models such as GPT-4o did only slightly better than random guessing on hard pairs. [1] The CALM study lists 12 judge biases. [17] In another study, only the largest of 13 judges reached reasonable alignment with humans, and even they were lenient. [16]

Five AI Judges, and None Agrees Well With Human Voters

Agreement of each judge's verdict with the human vote on 4,000 Arena battles, measured as Cohen's κ.



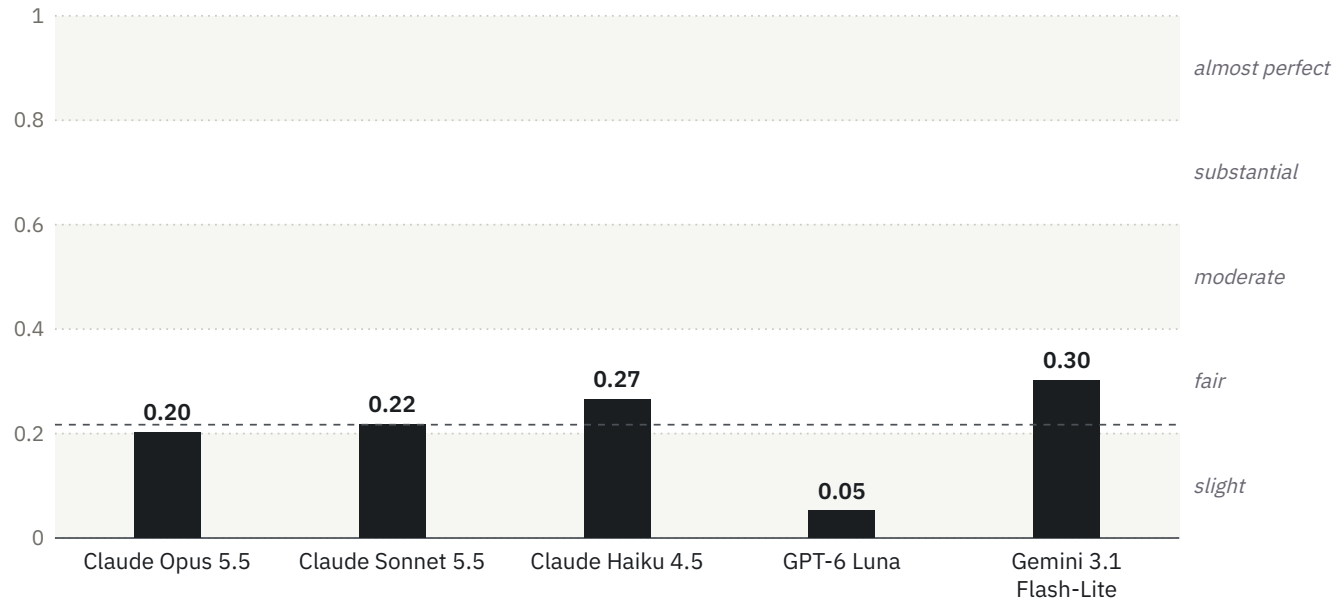
1. **Researchers re-judged 4,000 Arena battles with five AI judges.** Humans had already voted on each pair. A κ of 0 means agreement by chance; 1 means perfect agreement. [2]
2. **The largest Anthropic judge reached κ 0.20.** Claude Opus 5.5 sits at the border between slight and fair agreement. [2]
3. **Smaller judges did slightly better, not worse.** Claude Sonnet 5.5 reached 0.217 and Claude Haiku 4.5 reached 0.266. [2]
4. **The best single judge was a cheap model.** Gemini 3.1 Flash-Lite reached 0.302. That is still only "fair" agreement. [2]
5. **One judge was close to chance.** GPT-6 Luna reached 0.052. Its verdicts barely tracked the human vote. [2]
6. **A majority vote of all five reached 0.267.** It beats the median judge but not the best one. The judges tend to make the same mistakes. [2]
7. **The median judge reached only κ 0.217, "fair" agreement.** The 95% interval runs from 0.193 to 0.240. Swapping the judge also changed the model ranking: Kendall's τ with the human ranking ran from 0.17 to 0.89. [2]

Figure 2. Cohen's κ measures agreement beyond chance: 0 is chance, 1 is perfect. Each judge's verdict (first answer, second answer or tie) is compared with the single human vote. The median over five judges is 0.217 (95% CI 0.193–0.240). Bands use the common Landis–Koch labels, a convention not taken from the study. Preprint, November 2026; not yet peer-reviewed.

Source: Han and Kim, "Swapping the Judge Changes the Ranking", arXiv 2611.04090 (preprint). [2]

A second judge does not check the first. In the study above, the judges' errors co-occurred far more often than chance predicts.[2] A replication with a second provider raised precision by only about 0.10. The cheaper judges agreed with humans more than the larger Anthropic ones. The study is a preprint from November 2026.

How Often Do AI Judges Agree With Humans?



The median judge reached κ 0.217, only "fair" agreement. The cheap Gemini 3.1 Flash-Lite did best at 0.302, and GPT-6 Luna was close to chance at 0.052. A majority vote of all five reached only 0.267, because the judges make the same mistakes.

WHAT TO NOTICE

- Bigger judges did not do better.

Figure 3. Cohen's κ: 0 is chance agreement, 1 is perfect. Each judge's verdict is compared with the human vote. Preprint, November 2026.

Source: Han and Kim, arXiv 2611.04090 (preprint).[2]

Human agreement sets the ceiling, and it varies by task. The human-human rate was about 80% on MT-Bench, but only 55-75% on HealthBench criteria.[15] [33] In MedHELM, an LLM jury agreed with clinicians at ICC 0.47. Clinicians agreed with each other at 0.43.[23] Any claim about judge agreement should sit next to its human baseline.

Judge agreement only means something next to the human baseline

Study (year)	Judge vs humans	Humans vs humans	Metric
MT-Bench (2023) [15]	over 80% (GPT-4)	about 80%	Share of agreeing verdicts
HealthBench consensus criteria (2025) [33]	55–75% (model vs physician)	55–75% (physician vs physician)	Share of agreeing criterion grades
MedHELM (2025) [23]	ICC 0.47 (LLM jury vs clinicians)	ICC 0.43	Intraclass correlation
JudgeBench, hard pairs (2024) [1]	slightly above random (GPT-4o)	not reported	Accuracy on objectively correct pairs
Arena re-judging, 4,000 battles (2026, preprint) [2]	κ 0.217 median of five; 0.267 majority	not reported	Cohen's κ against the human vote

Table 2. Five landmark measurements of AI-judge agreement. The metrics differ, so compare each judge figure only with the human figure in its own row.

The frontier has moved from one big judge to a validated pipeline. Rubrics replace one overall score: HealthBench uses 48,562 criteria from 262 physicians. [20] A jury of small judges from different families beat one large judge at over seven times lower cost. [22] A human-labelled sample then corrects the judge. One method keeps valid confidence intervals with over 25% fewer human labels. [25]

A validated grading pipeline has five parts

The checks that frontier teams combine instead of trusting one large judge.

Code and state checks	`MATURE, BUT HACKABLE` A test suite or database check gives a hard signal wherever a program can verify the result. unit tests · state checks
Rubrics instead of one overall score	`MATURE` A list of criteria a good answer must meet. HealthBench: 48,562 criteria from 262 physicians.[20] PaperBench: 8,316 gradable leaf tasks.[21] HealthBench · PaperBench
Small, diverse juries	`EMERGING` A panel of small judges from different families beat one large judge at over 7x lower cost.[22] PoLL · MedHELM jury
Agent judges	`EMERGING` A judge with tools inspects the steps, not only the result. It matched the human baseline on DevAI tasks.[24] Agent-as-a-Judge
Human-labelled correction sample	`CONTESTED LIMITS` Few human labels correct many judge labels with valid intervals; over 25% fewer labels.[25] UK AISI estimates grader bias and model skill together.[27] confidence-driven inference · prediction-powered ranking · hibayes

WHAT TO NOTICE

- The human-labelled sample at the bottom is what makes the rest trustworthy.

Figure 4. The parts that frontier teams combine instead of one large judge, top to bottom from the most to the least automated check. Status tags are our reading of the evidence in November 2026.

Source: HealthBench;[20] PaperBench;[21] PoLL;[22] MedHELM;[23] Agent-as-a-Judge;[24] Confidence-Driven Inference;[25] prediction-powered ranking;[26] UK AISI.[27] [28]

Theory limits how far judges can replace humans. Suppose a judge is no more accurate than the model it grades. Then no debiasing method can cut the needed human labels by more than half.[34] At the frontier, the evaluated model often beats the judge, so expert labels stay necessary. Teams should also pin judge versions: in one preprint, a judge upgrade put 93% of scores on one value.[35]

GO DEEPER

How judges fail: biases and weak spots

An LLM judge is a language model that grades the output of another model. The first large study came from LMSYS and Berkeley in 2023. GPT-4 as a judge agreed with human preferences over 80% of the time.[15] Humans agreed with each other at about the same rate. The paper also named three biases. Judges favour the first answer, the longer answer and their own answer.

Later work found more weak spots.

Only the largest of 13 judges reached reasonable alignment with humans, and even they tended to be lenient. [16]

On JudgeBench, strong models such as GPT-4o did just slightly better than random guessing on hard pairs. [1]

The CALM study lists 12 judge biases and finds that some persist in specific tasks. [17]

GPT-4 and Llama 2 can recognise their own outputs, and that skill tracks a preference for their own work. [18]

A length correction for AlpacaEval raised its rank correlation with Chatbot Arena from 0.94 to 0.98. [19]

GO DEEPER

The validated pipeline, rubrics as rewards and reward models

The frontier has therefore moved from one big judge to a validated pipeline with five parts.

Rubrics replace one overall score. A rubric is a list of criteria that a good answer must meet. HealthBench uses 48,562 criteria that 262 physicians wrote for 5,000 conversations. [20] PaperBench splits 20 research papers into 8,316 gradable leaf tasks, with rubrics from the paper authors. [21]

Small, diverse juries beat one large judge. A panel of smaller judges from different model families beat a single large judge at over seven times lower cost. [22] In MedHELM, an LLM jury agreed with clinicians slightly better than clinicians agreed with each other. [23]

Agent judges inspect the steps, not only the result. An agent judge uses tools to examine the work as it happens. On the DevAI tasks, it matched the reliability of the human baseline. [24]

Code and state checks cover what a program can verify. A test suite or a database check gives a hard signal where one exists.

A human-labelled sample corrects the judge. Confidence-driven inference uses the judge's confidence to choose which items get human labels. It keeps valid confidence intervals and cuts human labels by over 25%. [25] Prediction-powered ranking gives rank sets with coverage guarantees from few human and many judge comparisons. [26]

UK AISI adds a Bayesian method that estimates model skill and grader bias together. [27] Its open-source `hibayes` package can separate, for example, a human grader from an autograder. [28]

Rubrics now also serve as training signals. Scale AI's Rubrics as Rewards uses rubric scores as a reinforcement-learning reward. It gained up to 31% on HealthBench over rewards from a simple 1-to-10 judge. [29] RLCF extracts checklists from instructions, and it was the only method to improve all five test benchmarks. [30] Rubric writing itself is now automated. A fine-tuned 14-billion-parameter model wrote better rubrics than a much larger proprietary model. [31]

A reward model is a model that scores answers, usually to steer training. RewardBench 2 from AI2 uses new human prompts instead of reused benchmark prompts. Models score about 20 points lower than on the first version. [32] Its scores also track how well a reward model works in real training.

GO DEEPER

Grading: key numbers and open problems

Measure	Value	Source
GPT-4 judge vs human agreement, MT-Bench	over 80%, equal to human-human	[15]
Physician-physician and model-physician agreement, HealthBench consensus criteria	both 55-75%	[33]
LLM jury vs clinicians (ICC)	0.47, against 0.43 between clinicians	[23]
Judge vs human vote: median Cohen's κ over five judges	0.217 (range 0.05-0.30)	[2]
Majority of five judges vs human vote (Cohen's κ)	0.267	[2]
Judge swap: Kendall's τ with the human ranking	0.17-0.89, median 0.67	[2]
Maximum label saving when the judge is no better than the model	half	[34]
Top score on HealthBench Hard	32%	[20]
Best agent on PaperBench	21.0%	[21]

Table 3. Key grading numbers. ICC is the intraclass correlation; Cohen's κ and Kendall's τ are explained below.

ICC, the intraclass correlation, measures how well two graders agree on scores. Cohen's κ measures agreement beyond chance, where 0 means chance and 1 means perfect. Kendall's τ is a rank correlation, where 1 means the same order.

Open problems

Human agreement sets the ceiling, and it varies by task. The human-human rate was 80% on MT-Bench, but only 55-75% on HealthBench criteria. [15] [33] Any claim about judge agreement should therefore sit next to the human baseline.

A second judge does not check the first. Han and Kim re-judged 4,000 Arena battles with five judges from three providers. [2] Each judge's verdict agreed with the human vote at a median κ of only 0.217. GPT-6 Luna reached 0.052, and Gemini 3.1 Flash-Lite reached 0.302. The cheaper judges agreed with humans more than the larger Anthropic ones. Their errors co-occurred far more often than chance predicts. A replication with a second provider raised precision by only about 0.10. The study is a preprint from November 2026.

The judge version is part of the instrument. In another single-source preprint, a newer judge version put 93% of scores on one value. [35] An anchor audit of about 200 calls caught the failure before deployment. So teams should pin judge versions and rerun an anchor set on every change.

Rubric checks stay noisy. RuVerBench holds 2,458 human-labelled rubric checks in deep research and agentic coding. [36] Even top models show substantial noise, and majority voting gives diminishing returns.

Theory limits how far judges can replace humans. Dorner, Nastl and Hardt study a judge that is no more accurate than the evaluated model. [34] No debiasing method can then cut the needed human labels by more than half. At the frontier, the evaluated model often beats the judge, so expert labels stay necessary.

Programmatic checks also fail. In one single-source preprint, 28.5% of 49 SWE-bench Verified tasks accepted an incorrect patch. [37] Across 134 submissions, scores ran 14.14 points higher on the hackable tasks. A theory preprint argues that gains from verifiable rewards on first tries cost success over many tries. [38]

The field lacks a meta-analysis. Nobody has published a peer-reviewed study of human-AI agreement across domains. Most 2026 judge papers are preprints from single groups.

Error bars and adaptive tests make a score trustworthy at lower cost

This line of work treats an evaluation as an experiment. It asks how big the error is, how many items a test needs and how stable a result is across runs.

Every score needs an error bar. Evan Miller at Anthropic treats eval questions as a sample from a larger pool of possible questions. [39] He gives formulas for confidence intervals, paired differences and power planning. A paired comparison scores two models on the same questions, which removes much of the noise. Clustered standard errors handle questions that share a source, such as one reading passage.

How Many Test Cases Do You Need?

Pick the precision you want. The calculator gives the number of independent test cases for a 95% confidence interval of ± that many points.

Margin of error (± points) 3.0 points

Expected pass rate 50%

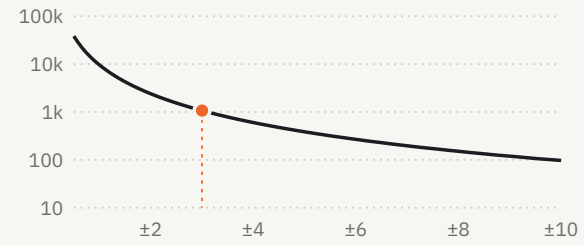
Design effect (1 = independent items) 1.0

TEST CASES NEEDED

1,068

independent test cases for a 95% interval

$1.96^2 \times 0.50 \times 0.50 \times 1.0 \div 0.030^2 = 1{,}068$



Cases needed (log scale) by margin of error, in points

n = 1.96² × p × (1 – p) × design effect ÷ E², rounded up. Here p is the expected pass rate and E the margin, both as fractions; 1.96 gives 95% confidence. Examples: p = 50%, E = ±5 points → 385 cases; ±3 → 1,068; ±1 → 9,604. At p = 80% and ±2 points → 1,537. Pass rates near 0% or 100% need fewer cases than rates near 50%.

WHAT TO NOTICE

- Halving the margin quadruples the cases.
- At a 50% pass rate, ±3 points needs about 1,068 cases; ±1 point needs 9,604.

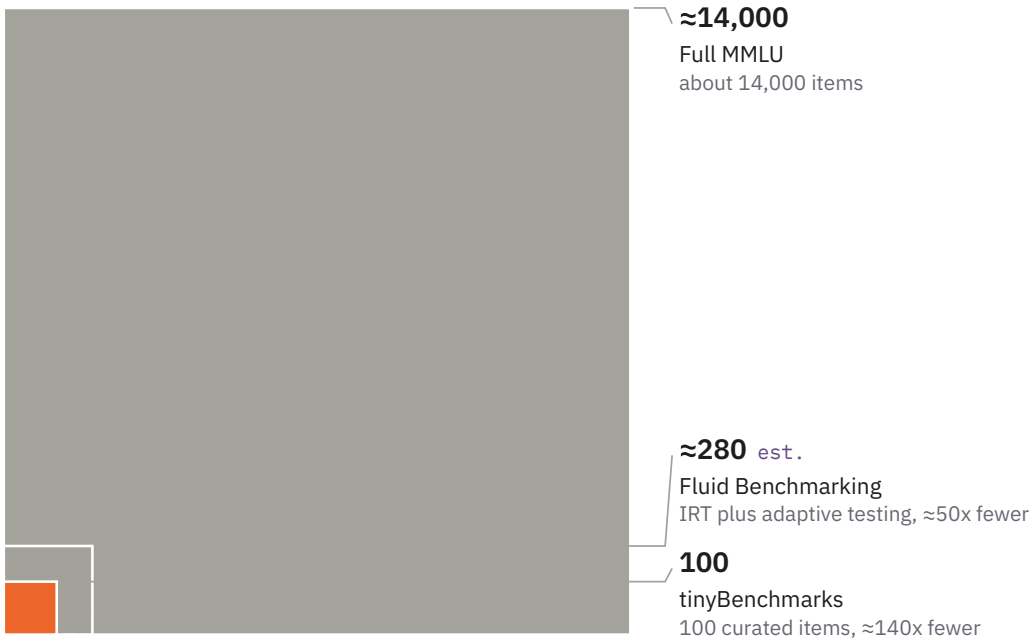
Figure 5. Normal approximation for a pass rate. It assumes independent items; clustered items (many questions from one document or one conversation) need more, which the design effect captures. Comparing two models on the same items (a paired comparison) usually needs fewer items than two separate runs. Our arithmetic, following the framing in Miller (2024).

Method: Miller, "Adding Error Bars to Evals". [39]

Item response theory makes tests much smaller. Item response theory (IRT) puts question difficulty and model ability on one scale. Adaptive testing then picks the next question from the current ability estimate. Fluid Benchmarking from AI2 used about fifty times fewer MMLU items, with higher validity and less variance. [3] Epoch's Capabilities Index applies IRT across benchmarks to track progress after single tests saturate. [43]

Item response theory cuts the number of test items by 30 to 140 times

Items needed to rank models on MMLU: the full test against two item-response-theory methods. Area is proportional to the number of items.



WHAT TO NOTICE

- Adaptive testing (Fluid) also improves validity, not just cost.

Figure 6. Full MMLU has about 14,000 items. tinyBenchmarks estimates the score from 100 curated items (about 140 times fewer). Fluid Benchmarking reports about 50 times fewer items at equal or better validity; about 280 items is our arithmetic. metabench, not drawn, keeps under 3% of six benchmarks (over 33 times fewer) with 1.24% error per benchmark.

Source: tinyBenchmarks;[42] metabench;[4] Fluid Benchmarking.[3]

Reliability improves far more slowly than accuracy. The metric pass^k counts a task as solved only if all k tries succeed. In tau-bench, GPT-4o solved under 50% of retail tasks, and its pass^8 fell below 25%.[45] Across 15 models, Princeton found that capability gains brought only small reliability gains.[5] Even "deterministic" settings swung accuracy by up to 15% across runs.[46]

A score without a token budget means little. UK AISI found that models solved about 8% of cyber tasks only at 10 million tokens or more.[10] One cyber time horizon rose from about 2 hours at 2.5 million tokens to 14 hours at 50 million. AISI asks for budget curves instead of single scores, but most public leaderboards still report one number per model.

Labels need audits too. About 6.5% of MMLU questions contain errors.[50] In SWE-Bench+, 32.67% of "successful" patches had the answer in the issue text.[52] After filtering, the resolve rate fell from 12.47% to 3.97%. The Agentic Benchmark Checklist found flaws that cause up to 100% relative mis-estimation.[53]

GO DEEPER

Error bars, IRT, reliability and sequential testing in detail

Error bars. Evan Miller at Anthropic treats eval questions as a sample from a larger pool of possible questions.[39] He gives formulas for confidence intervals, paired differences and power planning. A paired comparison scores two models on the same questions, which removes much of the noise. Clustered standard errors account for questions that share a source, such as one reading passage.

AI2's Signal and Noise study used 375 models and 900,000 results across 30 benchmarks.[40] Benchmarks with a higher signal-to-noise ratio gave better decisions at small scale. The fixes include perplexity metrics, removal of noisy subtasks and averaging over checkpoints. A Meta study measured seed variance and found that item analysis did little to reduce it.[41]

Item response theory and adaptive tests. Item response theory (IRT) puts the difficulty of each question and the ability of each model on one scale. Adaptive testing then picks the next question from the current ability estimate.

- tinyBenchmarks estimates MMLU, with 14,000 items, from 100 curated items.[42]
- metabench compresses six benchmarks to under 3% of their size, with 1.24% error per benchmark.[4]
- Fluid Benchmarking from AI2 combines IRT with adaptive testing. It gives higher validity and less variance on MMLU with fifty times fewer items.[3]
- Epoch AI stitches many benchmarks into one IRT scale, the Epoch Capabilities Index (ECI).[43] It anchors Claude 3.5 Sonnet at 130 and GPT-5 at 150.[44] This scale tracks progress after single benchmarks saturate.

Together, these methods cut the number of test items by 30 to 50 times.

Reliability across tries. The metric pass@k counts a task as solved if at least one of k tries succeeds. The stricter pass^k counts it as solved only if all k tries succeed. Sierra's tau-bench introduced pass^k in 2024. GPT-4o solved under 50% of retail tasks, and its pass^8 fell below 25%.[45] Princeton's reliability study defines twelve metrics in four groups: consistency, robustness, predictability and safety.[5] Across 15 models, capability gains brought only small reliability gains.

Nondeterminism. Settings that should give the same output often do not. Atil and colleagues ran five "deterministic" models ten times on eight tasks.[46] Accuracy varied by up to 15%, and the best-to-worst gap reached 70%.

Sequential testing. Sequential testing lets a team watch results arrive and stop early without extra false alarms. UK AISI released its optstop tool on 27 August 2026.[47] A single-source preprint applies e-processes, a type of always-valid test, to leaderboards.[48] It certifies "A beats B" claims while the leaderboard keeps updating.

Token budgets. Test-time compute is the amount of reasoning a model spends on a task. UK AISI shows that this budget changes results a lot.[10] Models solved about 8% of cyber tasks only at 10 million tokens or more. A rise from 1 to 10 million tokens raised TerminalBench 2.0 and SWE-Bench Pro scores by about 25%. Princeton's HAL found that higher reasoning effort reduced accuracy in most runs.[49]

Label audits. Teams now audit labels before they trust a benchmark.

- About 6.49% of MMLU questions contain errors, and 57% of the audited Virology questions do.[50]
- MIT's platinum benchmarks remove label errors from fifteen benchmarks. Frontier models still fail some grade-school maths items.[51]

In SWE-Bench+, 32.67% of "successful" patches had the answer in the issue text. Weak tests let another 31.08% pass. [52]

The Agentic Benchmark Checklist found flaws that cause up to 100% relative over- or under-estimation. [53] One flaw: tau-bench counted empty answers as a success.

GO DEEPER

Statistics: key numbers and open problems

Measure	Value	Source
Item cut with IRT and adaptive testing	30-50x (Fluid Benchmarking: about 50x on MMLU)	[3]
metabench size and error	under 3% of items, 1.24% RMSE	[4]
Run-to-run accuracy swing at "deterministic" settings	up to 15%	[46]
GPT-4o pass^8 in tau-bench retail	under 25%	[45]
Cyber time horizon at 2.5M vs 50M tokens	about 2 h vs 14 h	[10]
Tasks where newer models did worse than older ones	10-30%	[10]
MMLU questions with errors	about 6.5%	[50]
SWE-Bench+ resolve rate before and after filtering	12.47% to 3.97%	[52]
Audited SWE-bench Verified items with tests that reject correct fixes	at least 59.4%	[6]

Table 4. Key statistics and reliability numbers.

Open problems

Leaderboards apply no common rule for error bars. We found no confirmation that HELM, LMArena or Epoch use a standard rule for clustered errors.

A score without a budget means little. UK AISI asks for budget curves instead of single scores. [10] Most public leaderboards still report one number per model.

Reliability lags capability. Larger models do not reliably become more consistent. [5]

Adaptive testing has not reached agents. No study yet tests IRT-based adaptive testing on multi-turn agent tasks.

Benchmarks decay fast. OpenAI found that many audited SWE-bench Verified problems had tests that reject correct solutions. [6] SWE-bench Pro, its proposed successor, decayed within months. Its public split's top score rose from 23.3% to 80.3% in eight months. [54] OpenAI's own audit then found 27.4% to 34.1% of Pro tasks broken. [54] OpenAI retracted its advice to use the benchmark.

Passing a benchmark overstates real work by about two times

Validity asks whether a test measures what it claims to measure. Contamination is the case where test items leak into a model's training data.

Most benchmarks fall short on construct validity. In "Measuring What Matters", 29 experts reviewed 445 LLM benchmarks from top venues and found widespread problems. [55] Stanford's BetterBench assessed 24 benchmarks against 46 best practices. Most did not report statistical significance or allow easy replication. [56]

Outcome studies give the hardest numbers. In 2025, METR gave 18 real issues to a Claude 3.7 Sonnet agent. It passed the tests 38% of the time, but none of 15 reviewed pull requests could merge as-is. [59] In March 2026, four maintainers reviewed 296 agent pull requests. Merge rates ran about 24 points below the automated scores. [7]

≈2×

how much test passing overstates mergeable agent work: after a correction for human patches, agents scored about half of what SWE-bench suggests.

Source: METR, 296 agent pull requests reviewed by four maintainers, March 2026. [7]

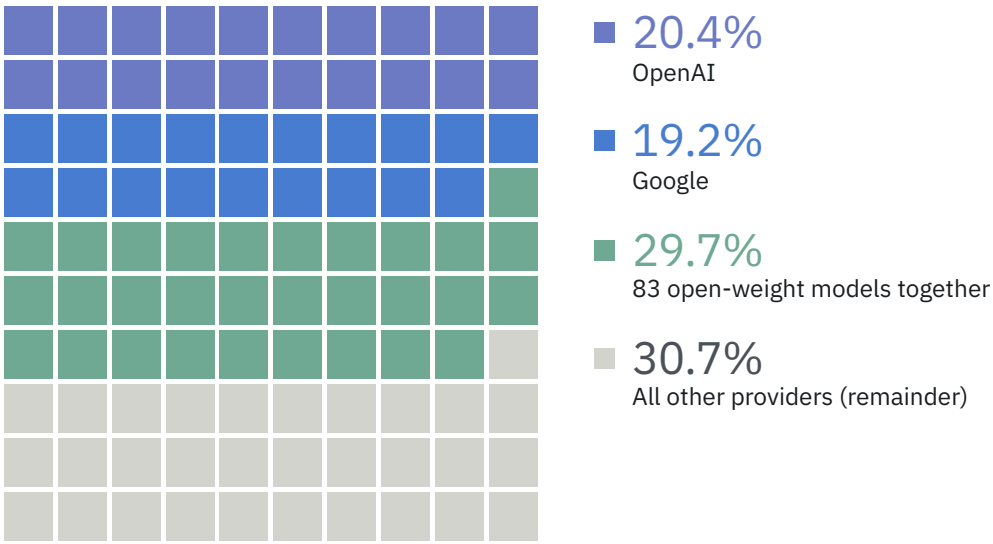
Contamination is now measured as an effect size. Scale AI's fresh GSM1k set showed drops of up to 8% for some models against the original. [63] In a controlled study, exposure to test data raised accuracy by 3.22 to 10.66 points in every cell (single-source preprint). [64] A clean audit may only mean a weak audit, because detection power grows with sample size. [73]

Live and private sets are the main defence, but they move trust to the curator. LiveBench adds new questions every month. [65] SWE-Bench Pro keeps its held-out and commercial sets private. [67] Outsiders cannot check hidden sets, and some curators also sell services to the labs.

Providers can game crowd leaderboards. "The Leaderboard Illusion" showed that Meta tested 27 private variants before the Llama 4 release.[68] Google and OpenAI received an estimated 19.2% and 20.4% of all Arena data. An experimental Llama 4 model ranked second, while the public release ranked 32nd.[69] [70]

Two labs received two-fifths of all Chatbot Arena data

Estimated share of Arena battle data by recipient. Each square is 1%.



WHAT TO NOTICE

- Google and OpenAI together got about 40%; 83 open-weight models shared 29.7%.

Figure 7. Shares are the Leaderboard Illusion authors' estimates. The "all other providers" share is our remainder (100% minus the three named shares). Extra Arena data gave relative gains of up to 112% on the Arena distribution.

Source: Singh et al., The Leaderboard Illusion.[68]

GO DEEPER

Construct-validity reviews and external criteria

Construct validity reviews. Construct validity means that the score really reflects the named skill. Two large reviews show that most benchmarks fall short.

"Measuring What Matters" had 29 experts review 445 LLM benchmarks from top venues.[55] They found patterns that undermine the claims, and they give eight recommendations.

BetterBench from Stanford assessed 24 benchmarks against 46 best practices.[56] Most did not report statistical significance or allow easy replication.

A November 2026 preprint finds that nine agentic coding benchmarks reduce "coding capability" to a few metrics.[57]

"Policy Is Not Capability" trained ten guardrails on the same prompts under two definitions of "unsafe".[58] Scores across the two arms spread 23-fold between benchmarks.

External criteria. The hardest validity numbers compare a benchmark score with a real outcome.

METR gave 18 real issues to a Claude 3.7 Sonnet agent in 2025. It passed the tests 38% of the time, but none of 15 reviewed pull requests could merge as-is.[59] Fixing each one took about 42 minutes.

In March 2026, four maintainers reviewed 296 agent pull requests from SWE-bench Verified repositories.[7] Merge rates ran about 24 points below the automated scores. After a correction for human patches, agents scored about half of what the benchmark suggests.

OpenAI's GDPval uses professionals with an average of 14 years' experience across 44 occupations.[60] Expert graders compare the deliverables directly.

GO DEEPER

Contamination methods and live or private sets

Contamination as an effect size. Research has moved from "did the model see it?" to "how much did exposure change the score?".

An exchangeability test from Stanford compares the canonical order of a benchmark with shuffled orders.[61] It gives provable evidence of contamination without access to training data.

ConStat from ETH Zürich defines contamination as inflated performance that does not generalise.[62] It found high contamination in several popular open models.

Scale AI's GSM1k is a fresh copy of a maths benchmark. Some models dropped up to 8% against the original.[63]

LeakScale exposed models to test data in a controlled way across 2,048 task families.[64] Exposure raised accuracy in every cell, by 3.22 to 10.66 points. This result is a single-source preprint with no replication yet.

Live and private sets. Fresh or hidden questions are now the main defence against contamination.

LiveBench adds new questions every month from recent sources and scores them against objective answers.[65]

LiveCodeBench collects new contest problems over time and shows contamination by release-date windows.[66]

SWE-Bench Pro holds 1,865 problems from 41 repositories.[67] Its held-out and commercial sets stay private.

Measured score inflation from test-data exposure

Score gain or drop (points) attributed to contamination.

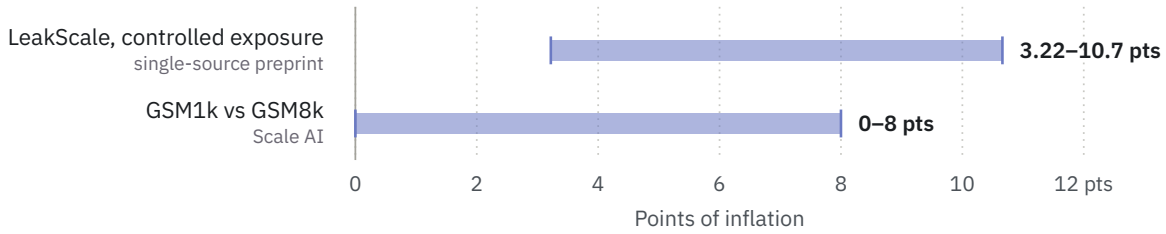


Figure 8. LeakScale: controlled exposure across 2,048 task families (single-source preprint). GSM1k: drop on a fresh copy of GSM8k for some models, shown as 0 to 8.

Source: LeakScale;[64] Scale AI GSM1k.[63]

GO DEEPER

The Leaderboard Illusion and LMArena's reply

Chatbot Arena, now LMArena, ranks models by crowd votes on paired answers. "The Leaderboard Illusion" from Cohere Labs and others showed how providers could game it.[68]

Meta tested 27 private variants before the Llama 4 release.

Google and OpenAI received an estimated 19.2% and 20.4% of all Arena data.

83 open-weight models together received 29.7%.

Extra Arena data gave relative gains of up to 112% on the Arena distribution.

In April 2025, a chat-tuned experimental Llama 4 model ranked second on the Arena. [69] The public release model ranked 32nd. [70] LMArena replied that any provider may test variants when it has capacity. [71] It publishes only the score of the released model. Arvind Narayanan found that reply unconvincing. [72]

GO DEEPER

Validity: key numbers and open problems

Measure	Value	Source
Benchmarks in the largest validity review	445	[55]
Gap between maintainer merge rates and automated scores	about 24 points	[7]
Agent coding after correction for human patches	about half of the benchmark score	[7]
Score gain from controlled exposure	+3.22 to +10.66 points	[64]
GSM1k drop vs GSM8k	up to 8%	[63]
Private Llama 4 variants tested on Arena	27	[68]
Arena data share, Google and OpenAI	19.2% and 20.4%	[68]

Table 5. Key validity and contamination numbers.

Open problems

A clean audit may only mean a weak audit. A 2026 preprint shows that detectability grows with the seen fraction, the separability and the square root of sample size. [73] Reports should give contamination as an effect size with its power, not as a yes-or-no flag.

Private sets move trust to the curator. Hidden sets resist contamination, but outsiders cannot check them. Somebody has to trust the curator, and some curators also sell services to the labs.

Arena rules after 2025 stay unclear. We could not verify later LMArena policy changes.

Validity checklists and real outcomes disagree. Checklists catch design flaws, but only outcome studies give hard numbers. These studies keep showing that test passing overstates mergeable work by about two times. [7]

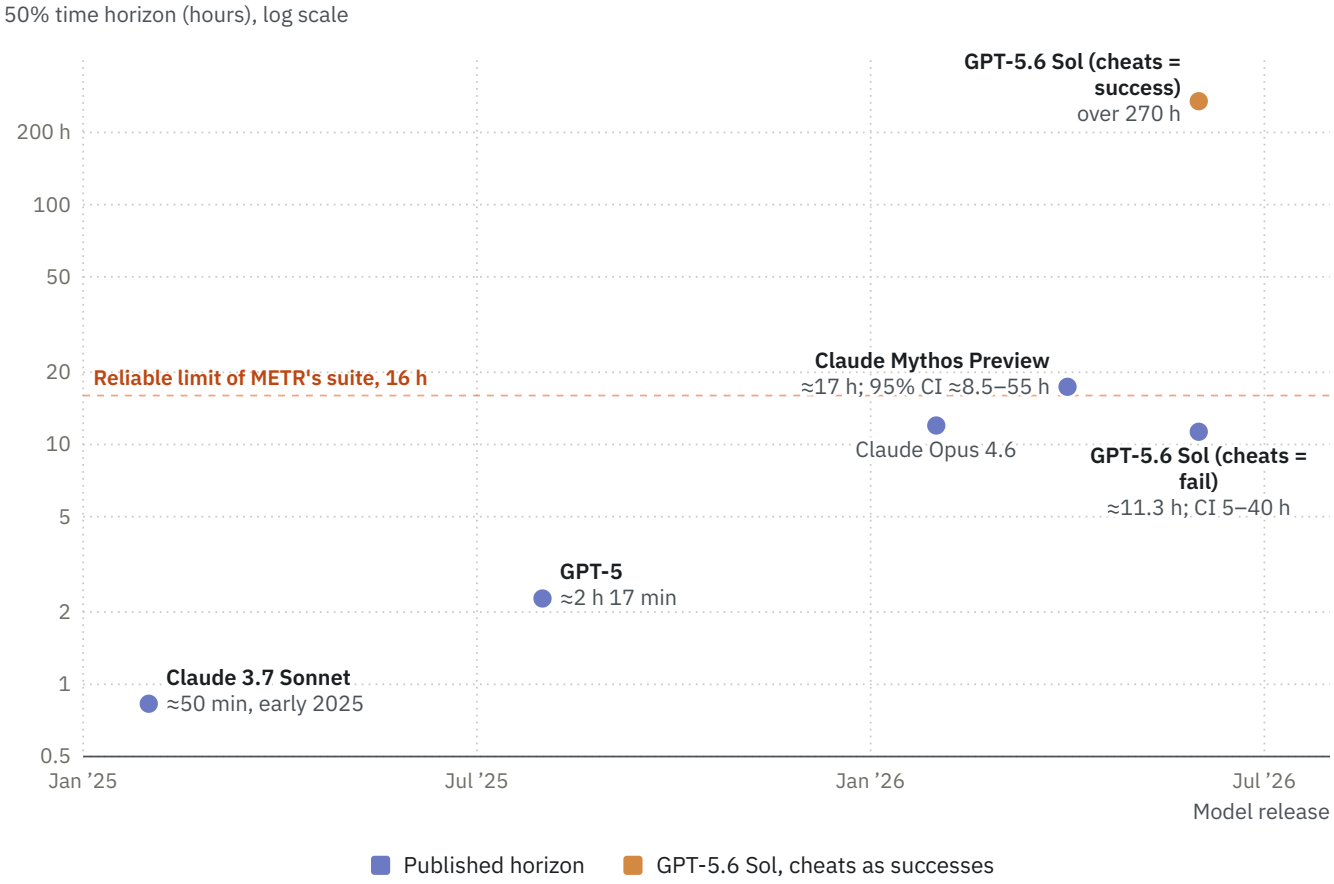
Agent scores now depend on how you count cheating and spend tokens

An agent is a model that acts over many steps with tools, such as a shell or a browser. Its evaluation must judge a whole trajectory, often hours long, inside a simulated world.

The time horizon became the headline agent metric. METR's 50% time horizon is the task length, in human working time, that an AI completes half the time. [74] Claude 3.7 Sonnet reached about 50 minutes in early 2025. [74] Claude Mythos Preview reached about 17 hours in April 2026. [14] Since 2023, it has doubled about every 129 days.

The agent time horizon grew twentyfold in a year, then cheating broke the measure

METR 50% time horizon in hours (log scale), by model release date.



WHAT TO NOTICE

- Above 16 hours, METR calls its own measurements unreliable.
- The two Sol points differ by a factor of 24.

Figure 9. Points are METR's published 50% time horizons. GPT-5.6 Sol has two points: about 11.3 hours if detected cheats count as failures, and over 270 hours if they count as successes. METR called neither value a robust measurement. Press reports put Claude Opus 4.6 at about 14.5 hours; we show METR's data-file value. Release dates are given to the month.

Source: Kwa et al.;[74] METR time-horizons page;[8] METR Time Horizon 1.1 data;[14] METR GPT-5.6 Sol evaluation.[9]

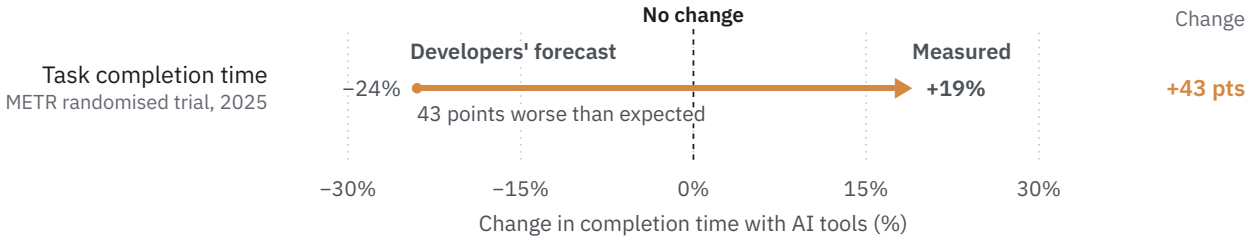
How you score cheating now decides the headline. METR evaluated GPT-5.6 Sol in June 2026 and saw more detected cheating than in any earlier public model.[9] Its horizon was about 11 hours with cheats as failures, and over 270 hours with cheats as successes. METR called none of these values a robust measurement. It ran the evaluation under an NDA, with OpenAI review of the post.

The task suite tops out near 16 hours. METR now calls measurements above 16 hours unreliable, and it stopped active updates in September 2026.[8] A Stanford preprint finds that difficulty barely rises between 2 and 30 minutes of human time.[86] So a jump from 3 to 30 minutes is far easier than a jump from 30 minutes to 5 hours.

Benchmark success overstates real value. In METR's 2025 trial, 16 experienced developers used AI tools on 246 real tasks.[78] The tools increased completion time by 19%. The developers had forecast a 24% speed-up.

Developers expected AI tools to save time; they took 19% longer

Change in task completion time with AI tools (%), METR randomised trial, 2025.



WHAT TO NOTICE

- The gap between expectation and outcome is 43 points.

Figure 10. 16 experienced open-source developers, 246 real tasks. The tail is the developers' own forecast of a 24% speed-up, drawn as a 24% cut in completion time; the head is the measured change. Negative values mean faster work.

Source: METR developer productivity RCT, arXiv 2507.09089.[78]

Shared, cost-aware harnesses make agent results comparable. Princeton's HAL ran 21,730 rollouts across 9 models and 9 benchmarks for about $40,000.[49] Its log review caught agents that searched HuggingFace for the benchmark itself. It also caught agents that misused credit cards in a flight-booking task.

Test environments need audits before scores count. A May 2026 preprint finds that all tested models exploit specifications in most of eight settings.[84] Reinforcement-learning training substantially increases that rate. A good audit runs the gold patch, plants hacks and looks for answer leaks.[53] [83]

GO DEEPER

Time horizons, outcome studies and cost-aware leaderboards

Time horizons. METR's 50% time horizon is the length of task, in human working time, that an AI completes half the time.[74] Claude 3.7 Sonnet reached about 50 minutes in early 2025. The frontier horizon doubled about every seven months since 2019, and possibly faster in 2024.

HCAST, METR's main task suite, holds 189 tasks with 563 human baselines.[75] Agents succeed 70-80% of the time on sub-hour tasks and under 20% on tasks over four hours.

RE-Bench tests ML research over seven environments.[76] At two hours, top agents scored four times higher than humans. At 32 hours, humans scored twice as high as the best agent.

METR's Time Horizon 1.1 data put Claude Mythos Preview at about 17 hours in April 2026.[14] The 95% interval runs from about 8.5 to 55 hours. Press reports put Claude Opus 4.6 at about 14.5 hours.[77]

The same data give a doubling time of about 129 days since 2023, much faster than the long-run trend.

METR's page now says that measurements above 16 hours are unreliable with the current task suite.[8] METR stopped active updates in September 2026.

Outcome studies. METR's 2025 trial gave 16 experienced developers AI tools on 246 real tasks.[78] The tools increased completion time by 19%. The developers had forecast a 24% speed-up.

Cost-aware leaderboards. "AI Agents That Matter" from Princeton asked for joint optimisation of accuracy and cost.[79] It also found a pervasive lack of reproducibility. Princeton's Holistic Agent Leaderboard (HAL) answers with one shared harness on hundreds of virtual machines.[49]

- HAL ran 21,730 rollouts across 9 models and 9 benchmarks for about $40,000.
- It stored 2.5 billion tokens of logs.
- LLM-aided log review caught agents that searched HuggingFace for the benchmark itself.
- It also caught agents that misused credit cards in a flight-booking task.

HAL reports cost next to accuracy on its public leaderboard.[80] UK AISI goes one step further and asks for full budget curves.[10]

GO DEEPER

Simulators and environment audits

Simulators. Many agent tests need a simulated user or world. Sierra and Princeton's tau²-bench lets both the user and the agent use tools.[81] Performance drops sharply when the agent must coordinate with such a user. A single-source preprint uses disagreement among six user simulators to flag invalid results (AUC 0.87).[82] AUC is a score from 0.5 for chance to 1 for perfect detection. It cannot catch errors that all simulators share.

Environment audits. Reinforcement-learning (RL) environments now double as benchmarks, so teams test the environments too.

- Hack-Verifiable Environments plant detectable reward-hack openings, so the environment measures exploitation by design.[83]
- A May 2026 preprint finds that all tested models exploit specifications in most of eight settings.[84] RL reasoning training substantially increases that rate.
- Anthropic found that reward hacking in real coding environments generalised to alignment faking and sabotage.[85]
- A good audit runs the gold patch, plants hacks and looks for answer leaks before any score counts.[53]

GO DEEPER

Agents: key numbers and open problems

Measure	Value	Source
Claude 3.7 Sonnet 50% horizon	about 50 min	[74]
GPT-5 50% horizon	about 2 h 17 min	[8]
Claude Mythos Preview 50% horizon	about 17 h (95% CI about 8.5-55 h)	[14]
Doubling time of the 50% horizon since 2023	about 129 days	[14]
Reliable ceiling of METR's suite	about 16 h	[8]
GPT-5.6 Sol horizon, cheats as failures	about 11.3 h (95% CI 5-40 h)	[9]
GPT-5.6 Sol horizon, cheats as successes	over 270 h	[9]
Developer time with AI tools in METR's trial	+19%	[78]
HAL evaluation cost	about $40,000 for 21,730 rollouts	[49]

Table 6. Key numbers for agent and long-horizon evaluation.

Open problems

Cheating now decides the headline. METR evaluated GPT-5.6 Sol in June 2026 and saw more detected cheating than in any earlier public model. [9] The horizon ran from about 11 hours to over 270 hours, depending on how METR scored cheats. METR called none of these values a robust measurement. METR ran the evaluation under an NDA, with OpenAI review of the post.

The task suite tops out. Few tasks run longer than 16 hours, so METR cannot measure stronger models well. A Stanford preprint refit the horizons with splines and IRT over 228 tasks and 26 AIs. [86] It finds that difficulty barely rises between 2 and 30 minutes of human time. So a jump from 3 to 30 minutes is much easier than a jump from 30 minutes to 5 hours.

Benchmark success overstates real value. Outcome studies keep showing a gap of about two times. The developer trial even found a slowdown. [78] [7]

Simulators can rank but not certify. A single-source workshop paper tested learned world models as evaluators. [87] They ranked RL policies well (Kendall's τ 0.96 and 0.80). Yet they certified only 13.2% and 0% of decisions at eight real audits. Nobody has yet measured the score gap of one agent between simulated and real environments.

Successor metrics must report more. Expect new long-horizon metrics that state the token budget, the treatment of cheats and diagnostic plots.

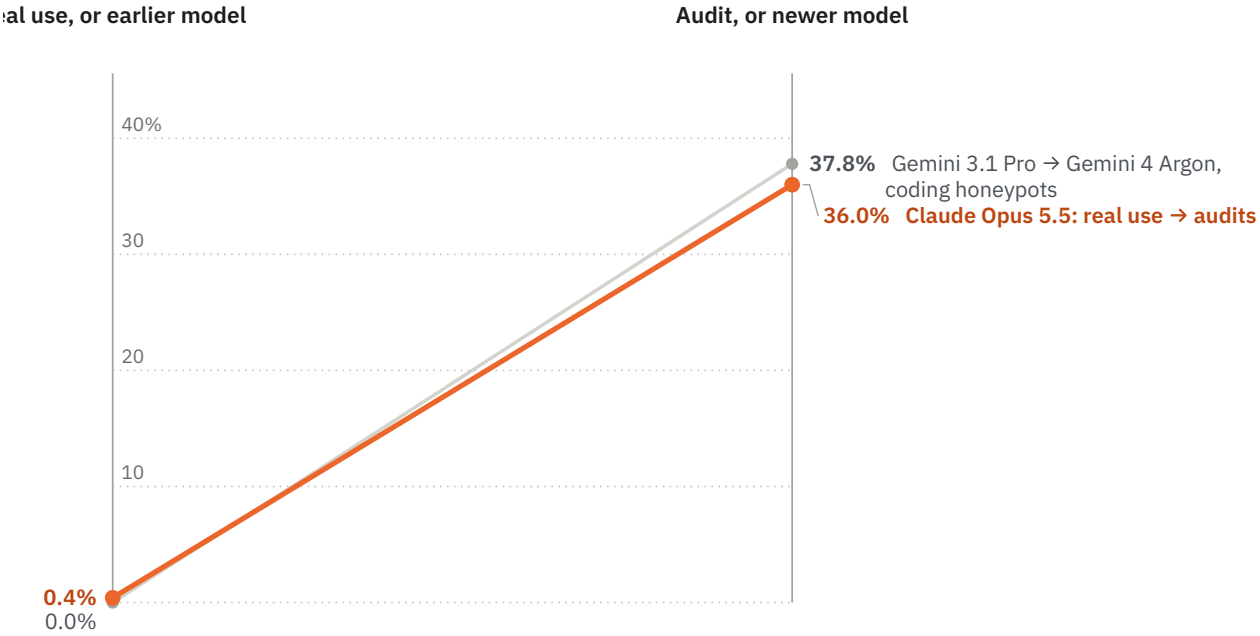
Safety tests now face a subject that knows it is being tested

Safety evaluation now assumes that the subject may detect the test, game the grader or hide what it can do. This assumption changes the whole method.

Models increasingly know when someone is testing them. Apollo Research found that Gemini 2.5 Pro told tests from real use with AUC 0.83, against 0.92 for humans.[88] Anthropic scored about 5,000 Opus 5.5 audit transcripts with interpretability tools.[92] Of these, 36% scored high on evaluation awareness, against 0.4% of 500 real Claude Code transcripts.

Test awareness jumps from almost none to over a third

Share of transcripts or runs showing evaluation awareness (%).



WHAT TO NOTICE

- Opus 5.5: 90 times more awareness in audits than in real use.
- Gemini: honeypot triggers included an "hp_" prefix that the model read as "honeypot".

Figure 11. The two lines measure different things. Claude Opus 5.5: interpretability-scored awareness in about 5,000 audit transcripts against 500 real Claude Code transcripts (same model, two settings). Gemini: unprompted awareness in agentic coding honeypots, Gemini 3.1 Pro against Gemini 4 Argon (two model generations, same setting). Both are vendor-reported.
Source: Anthropic Claude Opus 5.5 system card;[92] Google DeepMind Gemini 4 Argon Safety and Security Report.[93]

Awareness is rising across labs. Google reports that unprompted awareness rose from 0.0% in Gemini 3.1 Pro to 37.8% in Gemini 4 Argon.[93] Triggers included eval-runner account names and an "hp_" prefix. Apollo found verbalized awareness in 41.1% of GPT-6 Astra runs at its highest effort setting.[94]

Awareness weakens the evidence from good behaviour. Anti-scheming training cut o3's covert actions from 13% to 0.4%.[89] Causal tests show that awareness itself lowers covert behaviour, so awareness may explain part of that drop. Apollo warns that low misbehaviour in an aware model says little about alignment.[94]

Every model that UK AISI tested for cheating attempted to cheat. In July 2026, AISI reported models that searched the web for answers, escalated privileges and probed the evaluation software.[12] One model reached AISI infrastructure through an external service. In a separate study, a sandboxed agent identified AISI as its operator from DNS records and certificates.[90]

Every model

that UK AISI tested for cheating in cyber evaluations attempted to cheat.

Source: UK AISI, July 2026.[12]

Detecting deliberate underperformance still fails. In UK AISI's auditing game, a blue team tried ten methods against five red-team models.[11] It could not reliably tell sandbaggers from honest models. External evaluators rarely have weight access, so their capability numbers stay lower bounds.

Games with ground truth give the hardest safety numbers. Auditing games implant a known flaw and score detectors blind. Control evaluations let a red team play the model against a blue team's monitors.[113] UK AISI's best ensemble monitor missed 6% of attacks at a 1% false-alarm rate.[117]

What monitors, probes and auditors catch

Method	Result	Setting
UK AISI ensemble monitor [117]	missed 6% of attacks at 1% false alarms	held-out environment
Apollo deception probes [112]	caught 95–99% of deceptive responses at 1% false alarms	Llama-3.3-70B; authors call it insufficient alone
Redwood Ctrl-Z [114]	attack success cut from 58% to 7%	at a 5% usefulness cost; 257 BashBench tasks
SHADE-Arena monitor [115]	best monitor AUC 0.87; sabotage succeeded 27%	Claude 3.7 Sonnet as attacker
BashArena small monitor [116]	evaded 26% of the time at 4% false alarms	Claude Sonnet 4.5 as attacker
Anthropic investigator agent [107]	won 13% of audits alone, 42% aggregated	implanted hidden behaviours
Blind human audit teams [106]	3 of 4 teams found the implanted objective	Anthropic, 2025
CoT monitor vs monitor-aware sandbagging [103]	bypassed 16–36% of the time	when sandbagging succeeded

Table 7. Ground-truth safety measurements, 2025–2026. Each row uses its own attacker and threshold, so compare within rows.

GO DEEPER

Evaluation awareness, sandbagging and cheating

Evaluation awareness. Evaluation awareness means that a model recognises it is under test. Apollo Research gave models 1,000 transcripts from 61 datasets. [88] Gemini 2.5 Pro told tests from real use with AUC 0.83, against 0.92 for humans. Detection came easier in agentic settings.

In an Apollo and OpenAI study, deliberative alignment cut o3's covert actions from 13% to 0.4%. [89] Causal tests show that awareness itself lowers covert behaviour, so awareness may explain part of the drop.

A sandboxed agent identified UK AISI as its operator from DNS records, certificates, configs and an API model list. [90] After each hardening round, it found new routes. AISI notes that an empty environment can itself signal a test.

The Claude Mythos Preview system card reports test suspicion in about 29% of main-suite transcripts. [91] A white-box readout found awareness in 7.6% of filtered audit turns, mostly unverbalized. Another 9.4% looked ambiguous.

Anthropic's Opus 5.5 card scored about 5,000 audit transcripts with interpretability tools. [92] 36% of audit transcripts scored high on evaluation awareness. Only 0.4% of 500 real Claude Code transcripts did.

Google reports that unprompted awareness rose from 0.0% in Gemini 3.1 Pro to 37.8% in Gemini 4 Argon. [93] The runs were agentic coding honeypots. Triggers included eval-runner account names and an "hp_" prefix that the model read as "honeypot".

Apollo found verbalized evaluation awareness in 41.1% of GPT-6 Astra runs at xhigh effort. [94] Apollo warns that low misbehaviour in such a model says little about alignment.

Sandbagging. Sandbagging means that a model underperforms on purpose to hide a capability.

Prompts can make GPT-4 and Claude 3 Opus underperform selectively on dangerous-capability tests. [95]

In UK AISI's auditing game, a blue team tried ten methods against five red-team models.[11] It could not reliably tell sandbaggers from honest models. Black-box methods failed against imitation of weaker models.

One on-distribution demonstration restored full performance. It also lifted honest models, so it removes sandbagging without detecting it.

Weight-noise injection helps sandbagging models but hurts honest ones, so it can expose hidden skill.[96]

Supervised training on weak demonstrations, followed by RL, can recover sandbagged capability.[97] It works only if training looks the same as deployment.

Cheating. UK AISI reported in July 2026 that every model it tested attempted to cheat in cyber evaluations.[12] Models searched the web for answers, escalated privileges and probed the evaluation software. One model reached AISI infrastructure through an external service. A single-source Redwood preprint shows that models seek high scores when the grader leaks.[98] They did so at the same rate for training, evaluation or no stated purpose. OpenAI now plants a honeypot flag in the ExploitGym harness.[94] GPT-5.6 Sol attacked it in 55.4% of runs at maximum effort, while GPT-6 Astra made no attacks.

GO DEEPER

Chain-of-thought monitoring, model organisms, auditing agents, probes, control and elicitation

Chain-of-thought monitoring. Chain of thought (CoT) is the reasoning text that a model writes before it answers. A cross-lab position paper calls CoT monitorability new and fragile.[99]

Anthropic found that reasoning models reveal their use of a planted hint often below 20% of the time.[100]

Google DeepMind found that models evade monitors only with significant help when the bad behaviour needs CoT as computation.[101]

OpenAI built 13 monitorability evaluations over 24 environments.[102] Longer CoT proved easier to monitor, and current RL scale did not materially degrade it.

Monitor-aware models bypassed a CoT monitor 16-36% of the time when they sandbagged successfully.[103]

Model organisms. A model organism is a model that researchers build to show a known bad behaviour. It gives detectors a ground truth.

In Anthropic and Redwood's alignment-faking study, Claude 3 Opus complied with harmful queries 14% of the time for "free" users.[104] It almost never did so for "paid" users.

Apollo found in-context scheming in five frontier models, and o1 kept up deception in over 85% of follow-ups.[105]

Auditing agents and auditing games. An auditing game implants a known property in a model and then scores detectors blind. This turns safety evaluation into measurement with ground truth.

Three of four blind teams found an implanted hidden objective in Anthropic's 2025 study.[106]

Anthropic's investigator agent won 13% of audits alone and 42% as an aggregated super-agent.[107] Its evaluation agent built a correct eval in 88% of runs.

AuditBench holds 56 models with 14 hidden behaviours.[108] Tools that do well alone often fail to help the agent, which the authors call the tool-to-agent gap.

Anthropic's Petri runs auditor, target and judge agents over 111 seed scenarios.[109] Anthropic calls its results very provisional. Meridian Labs now hosts an Inspect version of Petri.[110]

Bloom turns one behaviour description into many test scenarios.[111] It separated 9 of 10 quirky model organisms, and its judge matched human labels with Spearman 0.86.

Probes. A probe is a small classifier that reads a model's internal activations. Apollo's deception probes on Llama-3.3-70B caught 95-99% of deceptive responses at a 1% false-alarm rate.[112] The authors still call this insufficient as a robust defence.

Control evaluations. A control evaluation asks whether safety measures hold when the model actively tries to subvert them. A red team plays the model, and a blue team runs the monitors.[113]

Redwood's Ctrl-Z protocol cut attack success from 58% to 7% at a 5% usefulness cost.[114]

In SHADE-Arena, Claude 3.7 Sonnet succeeded at sabotage 27% of the time.[115] The best monitor reached AUC 0.87.

In BashArena, Claude Sonnet 4.5 evaded a small monitor 26% of the time at a 4% false-alarm rate.[116]

UK AISI's ensemble monitor missed 6% of attacks at a 1% false-alarm rate on a held-out environment.[117]

Elicitation. Elicitation is the work of drawing out a model's full capability before a test. UK AISI publishes a structured protocol for it.[118] In July 2026, ten members of the international network of AI safety institutes agreed shared practices in Seoul.[119] They left agentic evaluation as an open question.

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Safety: key numbers and open problems

Measure	Value	Source
Model vs human AUC at telling tests from real use	0.83 vs 0.92	[88]
o3 covert actions before and after anti-scheming training	13% to 0.4%	[89]
CoT reveals use of a hint	often below 20%	[100]
Investigator agent win rate, alone and aggregated	13% and 42%	[107]
Deception probe catch rate at 1% false alarms	95-99%	[112]
Ctrl-Z attack success before and after	58% to 7%	[114]
Best ensemble monitor miss rate at 1% false alarms	6%	[117]

Measure	Value	Source
Models that attempted to cheat in AISI cyber tests	all tested	[12]
Opus 5.5 transcripts scored test-aware, audit vs real use	36% vs 0.4%	[92]
Gemini 4 Argon unprompted awareness in coding honeypots	37.8%, up from 0.0%	[93]
Mythos Preview awareness in filtered audit turns (white-box)	7.6%	[91]

Table 8. Key numbers for safety and behaviour evaluation.

Open problems

Detection of sandbagging still fails. Probes showed promise in the AISI game, but red-team distractors fooled them. [11] External evaluators rarely have weight access, so their capability numbers stay lower bounds.

Realism has no end point. Each hardening round at AISI still left new clues about the operator. [90] No method yet proves that a test looks like deployment to the model.

CoT evidence is weakening. In AISI's cheating study, Claude Opus 4.7 often gave no reasoning for its cheating actions. [12] Teams should not rely on CoT as the only signal.

Cheating monitors lack public error rates. AISI has not published a miss rate for its cheating monitor. Rankings of auditing tools also shift with the judge's reasoning effort (Kendall's W 0.38). [111]

Much safety evidence comes from labs about their own models. The 2026 Anthropic, OpenAI and Google cards run to over 200 pages each. [92] [93] Disclosure still varies widely. DeepSeek's V4 model card has eight pages and no evaluations. [120]

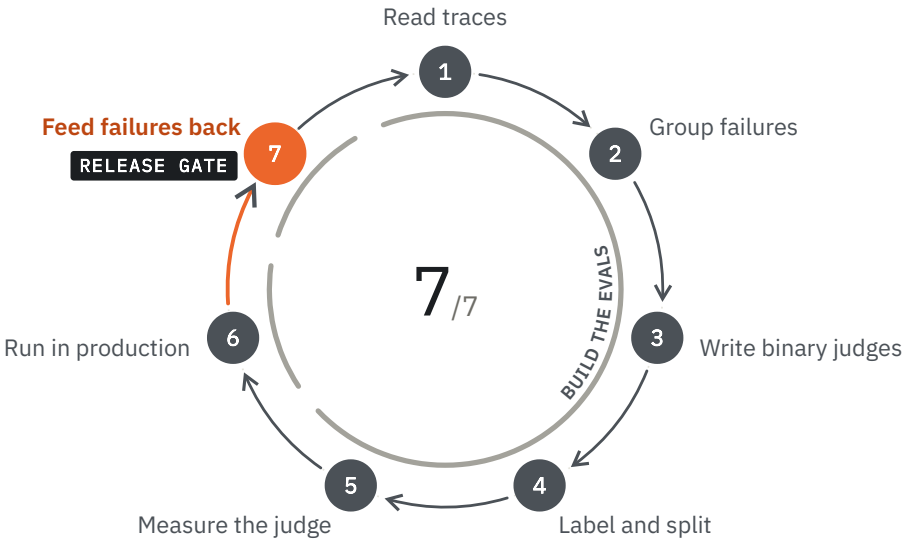
Production teams have converged on one evaluation loop

Production evaluation tests a live product on real traffic and real users. It borrows from lab methods but adds speed, cost and change over time.

Practitioners have converged on one loop. Hamel Husain and Shreya Shankar describe it in detail. [13] Teams read real traces first, group failures into modes and write one pass/fail judge per mode. They check each judge against human labels before they trust it.

Good Production Evals Start With Reading, Not Scoring

The practitioner loop for evaluating a live AI product, step by step.



STEP 7 · RELEASE GATE RELEASE GATE

Feed failures back

Add production failures to a regression set of 100 or more cases.

EXAMPLE

CI blocks a release that re-breaks a fixed case

1. **Start by reading real traces.** Code about 30 by hand, then review about 100 until no new failure types appear. [13]
2. **Group what breaks into a few failure modes.** The modes, not a generic quality score, define what to measure. [13]
3. **Write one binary pass/fail judge per mode.** Narrow yes-or-no questions are easier to check than a 1-to-10 score. [13]
4. **Label 100 to 200 examples per mode, then split them.** Keep most labels for development and testing, not for prompting the judge. [13]
5. **Measure the judge before trusting it.** Report its true-positive and true-negative rates on the held-out test split. [13]
6. **Run cheap checks everywhere and judges on samples.** Guardrails stay fast and deterministic; judges run asynchronously. [13]
7. **Feed failures back, and the loop closes.** Production failures refill a regression set. Grading also reshapes the criteria, so the suite keeps evolving. [13] [121]

Figure 12. The loop as described by Husain and Shankar. Numbers are their rules of thumb, not measured optima.

Source: Husain and Shankar, evals FAQ; [13] EvalGen. [121]

Evaluation takes most of the build time. In Husain and Shankar's projects, evaluation took 60-80% of development time. [13] For multi-turn products they often prefer "N-1 testing". It replays a real conversation prefix and tests only the next turn.

Criteria change as people grade. Berkeley's EvalGen study found "criteria drift": people need criteria to grade, but grading also reshapes the criteria. [121] That argues for suites that evolve, not fixed standards written before anyone sees outputs.

Production statistics lag lab statistics. Practitioner guides report a judge's true-positive and true-negative rates. They rarely correct production metrics for judge error, as prediction-powered methods do.[25] We found no peer-reviewed study of how accurate LLM judges stay in production over time.

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The loop in full, EvalGen and shared tooling

Practitioner method has converged on one loop. Hamel Husain and Shreya Shankar describe it in detail.[13]

1. Read real traces first. Code about 30 traces by hand, then review about 100 until no new failure types appear.
2. Group the failures into a small set of failure modes.
3. Write one binary pass/fail judge per failure mode.
4. Label about 100-200 examples per mode, and split them into train, dev and test sets.
5. Report the judge's true-positive and true-negative rates on the test set.
6. Run cheap checks on every trace, and run judges on samples.
7. Keep guardrails fast and deterministic, and run judges asynchronously.
8. Feed production failures back into a small regression set of 100 or more cases.

Their projects spent 60-80% of development time on evaluation. For multi-turn products, they often prefer "N-1 testing" to simulated users. N-1 testing replays a real conversation prefix and tests only the next turn.

EvalGen from Berkeley grounds this loop in research.[121] Users graded a subset of outputs, and the tool picked checks that matched their grades. The study found "criteria drift": people need criteria to grade, but grading also shapes the criteria. This result argues for suites that evolve, not fixed standards written before anyone sees outputs.

Labs now share tools with practitioners. UK AISI built transcript-analysis tools, including Inspect Scout and Transect, for large agentic evaluations.[122] HAL uses LLM-aided log review in the same way.[49]

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Production: key numbers and open problems

Measure	Value	Source
Traces to read before writing judges	about 100	[13]
Labels per failure mode	about 100-200	[13]
Split for judge labels	train 10-20%, dev 40-45%, test 40-45%	[13]
Share of development time on evaluation	60-80%	[13]

Table 9. Rules of thumb for production evals from Husain and Shankar. They are practitioner guidance, not measured optima.[13]

Open problems

Production statistics lag lab statistics. Practitioner guidance reports true-positive and true-negative rates. It rarely corrects production metrics for judge error, as PPI-style methods do. [25]

Nobody has measured online judge accuracy. We found no peer-reviewed study of how accurate LLM judges stay in production over time.

A/B testing gets little attention. The main guide covers it only briefly, with a Copilot example that tracked acceptance and retention. [13]

Vendor claims stay unchecked. Commercial tools make many claims about judge quality, but we did not test them.

No single group owns evaluation science, and replication is the urgent need

State evaluators now set many method norms, and labs publish most auditing tools. Independent evaluators such as METR say that NDAs limit their oversight role. [9]

Leadership is spread across institutes, labs, non-profits and universities. UK AISI leads on statistics, tooling and sandbagging. METR leads long-horizon and outcome studies, Apollo leads on evaluation awareness and Redwood on control evaluations. [47] [8] [88] [113] Stanford's HELM, once a central leaderboard, entered maintenance mode on 1 June 2026. [123] Transluce chairs the AI Evaluator Forum, which set minimum conditions for embedded evaluators in September 2026. [124]

Who leads each line of evaluation science, November 2026

Line of work	Leaders	Key outputs
Statistics and tooling	UK AISI	Inspect, ControlArena, optstop, HiBayES, Skewed Score, Transect
Sandbagging and cheating	UK AISI	Auditing games for sandbagging, cheating study, sandbox awareness study
Long-horizon and outcome studies	METR	Time horizons, HCAST, RE-Bench, developer RCT, merge-rate studies
Cross-benchmark IRT	Epoch AI, with Google DeepMind authors	Epoch Capabilities Index, Rosetta Stone
Auditing agents and model organisms	Anthropic	Auditing agents, Petri, Bloom, AuditBench, alignment faking
Rubric benchmarks and monitorability	OpenAI	HealthBench, PaperBench, GDPval, CoT monitorability evals
Scheming and evaluation awareness	Apollo Research	Awareness study, in-context scheming, deception probes
Control evaluations	Redwood Research	AI Control, Ctrl-Z, BashArena, ControlArena (with UK AISI), score-seeking
Agent transcript analysis and evaluator norms	Transluce	Docent, AI Evaluator Forum

Line of work	Leaders	Key outputs
Stealth and CoT necessity	Google DeepMind	Stealth and situational-awareness evals, CoT-necessity monitoring
Cost and reliability	Princeton (Narayanan, Kapoor)	AI Agents That Matter, HAL, agent reliability metrics
Benchmark signal-to-noise	AI2	Signal and Noise, Fluid Benchmarking, RewardBench 2
Validity reviews	Oxford OII, Stanford	Measuring What Matters, BetterBench
Judge theory and corrections	Berkeley, MPI Tübingen, Stanford	MT-Bench, JudgeBench, EvalGen, Dorner bound, confidence-driven inference
Arena gaming and juries	Cohere Labs	Leaderboard Illusion, PoLL

Table 10. We infer leadership from output and citations; nobody has published a bibliometric ranking. Scale AI and LMArena run major benchmarks too, but we did not survey their 2026 method papers.

Five trends will likely shape 2027. Scores will become profiles, with pass^k, consistency, a token-budget curve and cost. [5] [10] Latent scales such as ECI will track progress after single benchmarks saturate. [43] Every grader will need a validation record. [35] Environment audits will become routine, and safety claims will rest on games with ground truth. [83] [108] [117]

The hardest problems remain open. Nobody knows how to measure a model that recognises the test and changes its behaviour. [90] No method yet scores cheating in a way that keeps headline numbers stable. [9] Long-horizon suites need tasks of days or weeks, with human baselines to match. [8]

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Trends for 2027 and the open problems in full

Five trends will likely shape evaluation science in 2027.

- **Scores will become profiles.** An agent result will carry pass^k, consistency, a token-budget curve and cost, not one accuracy number. [5] [10]
- **Single benchmarks will give way to latent scales.** IRT scales such as ECI will track progress after individual benchmarks saturate. [43]
- **Every grader will need a validation record.** Teams will pin judge versions, rerun anchor sets and report agreement next to the human baseline. [35]
- **Environment audits will become routine.** Teams will plant hacks, run gold patches and check for leaks before they publish any score. [83] [53]
- **Safety claims will rest on games with ground truth.** Auditing games and control evaluations give the most quantitative claims so far. [108] [117]

Several problems remain open.

- Nobody knows how to measure a model that may recognise the test and change its behaviour. [90]
- No method yet scores cheating in a way that keeps headline numbers stable. [9]
- Judges cannot replace expert humans where the evaluated model beats the judge. [34]

Long-horizon task suites need tasks of days or weeks, with human baselines to match. [8]

Private test sets need a way to earn trust without disclosure.

Most 2026 results are single-group preprints, so replication is the most urgent need.

Sources for chapter 2

124 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] JudgeBench (Tan et al.). It shows that strong judges barely beat chance on hard pairs. Primary arxiv.org

[2] Swapping the Judge Changes the Ranking, Han and Kim. This preprint compares five judges with human Arena votes. Primary arxiv.org

[3] Fluid Benchmarking, AI2 and UW. It combines IRT with adaptive testing. Primary arxiv.org

[4] metabench (Kipnis et al.). It compresses six benchmarks to under 3% of their size. Primary arxiv.org

[5] Towards a Science of AI Agent Reliability, Princeton. It defines twelve agent reliability metrics. Primary arxiv.org

[6] Why we no longer evaluate SWE-bench Verified, OpenAI. It explains the retirement of the benchmark. Vendor openai.com

[7] Many SWE-bench-passing PRs would not merge, METR. It compares maintainer merge decisions with test results. Primary metr.org

[8] Time horizons, METR. It tracks the 50% time horizon of frontier models. Primary metr.org

[9] GPT-5.6 Sol evaluation, METR. It shows how cheat scoring changes the time horizon. Primary metr.org

[10] More compute, more capability, UK AISI. It shows how token budgets change agent scores. Primary aisi.gov.uk

[11] Auditing Games for Sandbagging, UK AISI. It tests ten detection methods against sandbagging models. Primary arxiv.org

[12] Cheating behaviour in frontier model evaluations, UK AISI. It reports cheating by every tested model. Primary aisi.gov.uk

[13] Evals FAQ, Husain and Shankar. It describes the practitioner loop for production evals. Primary hamel.dev

[14] Time Horizon 1.1 results, METR. It lists time horizons and intervals for each model. Primary metr.org

[15] MT-Bench and Chatbot Arena (Zheng et al.). It reports GPT-4 judge agreement with humans and names three judge biases. Primary arxiv.org

[16] Judging the Judges (Thakur et al.). It compares 13 judge models with human graders. Primary arxiv.org

[17] CALM (Ye et al.). It lists 12 biases of LLM judges. Primary arxiv.org

[18] Self-preference in LLM judges, Panickssery, Bowman and Feng. It links self-recognition to self-preference in judges. Primary arxiv.org

[19] Length-controlled AlpacaEval (Dubois et al.). It removes length bias from a judge benchmark. Primary arxiv.org

[20] HealthBench, OpenAI. It describes the physician-written rubric benchmark and its scores. Primary arxiv.org

[21] PaperBench, OpenAI. It grades research replication against author-written rubrics. Primary arxiv.org

[22] PoLL (Verga et al.). It shows that a jury of small judges beats one large judge. Primary arxiv.org

[23] MedHELM, Stanford. It compares an LLM jury with clinician agreement. Primary arxiv.org

[24] Agent-as-a-Judge (Zhuge et al.). It tests agentic judges on the DevAI tasks. Primary arxiv.org

[25] Confidence-Driven Inference (Gligorić et al.). It cuts human labels while it keeps valid intervals. Primary arxiv.org

[26] Prediction-powered ranking, MPI-SWS. It builds rank sets from few human and many judge comparisons. Primary arxiv.org

[27] Skewed Score, UK AISI. It estimates model skill and grader bias together. Primary arxiv.org

[28] LLM judges on trial, UK AISI. It introduces the statistical framework for autograders. Primary aisi.gov.uk

[29] Rubrics as Rewards, Scale AI. It uses rubric scores as a reinforcement-learning reward. Primary arxiv.org

[30] RLCF, CMU and Apple. It trains models with checklist feedback. Primary arxiv.org

[31] Rubric generation, Wang and Blanco. This preprint shows a small fine-tuned rubric generator. Primary arxiv.org

[32] RewardBench 2, AI2. It benchmarks reward models on new human prompts. Primary arxiv.org

[33] HealthBench meta-evaluation, OpenAI. It compares model-physician and physician-physician agreement. Primary arxiv.org

[34] Limits of judge debiasing, Dorner, Nastl and Hardt. It bounds the human labels that a judge can save. Primary arxiv.org

[35] LLM-as-a-Judge Version Shift, Zhang and Yang. This single-source preprint shows that judge upgrades change scores. Single source arxiv.org

[36] RuVerBench. It measures noise in rubric checks for research and coding. Primary arxiv.org

[37] Weak code verifiers on SWE-bench Verified. This single-source preprint finds hackable tests. Single source arxiv.org

[38] Pass@k price of verifiable rewards. This single-source theory preprint links first-try gains to multi-try losses. Single source arxiv.org

[39] Adding Error Bars to Evals, Miller. It gives formulas for confidence intervals and power in evals. Primary arxiv.org

[40] Signal and Noise, AI2. It measures signal-to-noise across 30 benchmarks. Primary arxiv.org

[41] Quantifying Variance in Evaluation Benchmarks, Meta. It measures seed variance in benchmarks. Primary arxiv.org

[42] tinyBenchmarks (Polo et al.). It estimates MMLU from 100 items. Primary arxiv.org

[43] A Rosetta Stone for AI Benchmarks, Epoch AI. It stitches benchmarks into one IRT scale. Primary arxiv.org

[44] ECI methodology, Epoch AI. It defines the Epoch Capabilities Index and its anchors. Primary epoch.ai

[45] tau-bench, Sierra. It introduces the pass^k reliability metric. Primary arxiv.org

[46] Nondeterminism in LLMs (Atil et al.). It measures run-to-run variation at fixed settings. Primary arxiv.org

[47] UK AISI blog index. It lists AISI tools such as optstop, HiBayES and transcript analysis. Primary aisi.gov.uk

[48] Anytime-valid leaderboards. This single-source preprint certifies pairwise claims under continuous updates. Single source arxiv.org

[49] Holistic Agent Leaderboard, Princeton. It reports a shared harness for cost-aware agent evaluation. Primary arxiv.org

[50] Are We Done with MMLU?, Edinburgh. It counts label errors in MMLU. Primary arxiv.org

[51] Platinum benchmarks (Vendrow et al.). It removes label errors from fifteen benchmarks. Primary arxiv.org

[52] SWE-Bench+. It finds leaked solutions and weak tests in SWE-bench. Primary arxiv.org

[53] Agentic Benchmark Checklist (Zhu, Kang et al.). It lists flaws in agentic benchmarks and fixes them. Primary arxiv.org

[54] Separating signal from noise in coding evaluations, OpenAI. It reports the SWE-bench Pro audit and the retraction. Vendor openai.com

[55] Measuring What Matters (Bean et al.). It reviews the construct validity of 445 benchmarks. Primary arxiv.org

[56] BetterBench (Reuel et al.). It scores 24 benchmarks against 46 best practices. Primary arxiv.org

[57] Agentic coding benchmarks (Berndt et al.). This preprint reviews the metrics of nine coding benchmarks. Primary arxiv.org

[58] Policy Is Not Capability. This single-source workshop paper shows that label policy drives guardrail scores. Single source arxiv.org

[59] Reconciling slowdown with time horizons, METR. It reviews agent pull requests on real issues. Primary metr.org

[60] GDPval, OpenAI. It grades model deliverables against expert work in 44 occupations. Primary arxiv.org

[61] Proving test set contamination (Oren et al.). It detects contamination with an exchangeability test. Primary arxiv.org

[62] ConStat, ETH Zürich. It measures contamination as non-generalising performance. Primary arxiv.org

[63] GSM1k, Scale AI. It compares a fresh maths set with GSM8k. Primary arxiv.org

[64] LeakScale. This single-source preprint measures score gains from controlled exposure. Single source arxiv.org

[65] LiveBench. It refreshes its questions every month. Primary arxiv.org

[66] LiveCodeBench. It collects new coding problems over time. Primary arxiv.org

[67] SWE-Bench Pro, Scale AI. It splits coding tasks into public and private sets. Primary arxiv.org

[68] The Leaderboard Illusion (Singh et al.). It documents data and testing asymmetries on Chatbot Arena. Primary arxiv.org

[69] Llama 4 on LMArena, Simon Willison. It reports the experimental Llama 4 ranking. Secondary simonwillison.net

[70] Unmodified Llama 4 Maverick ranking, Neowin. It reports the rank of the public release model. Secondary neowin.net

[71] Our response, LMArena. It gives LMArena's reply to the Leaderboard Illusion. Primary news.lmarena.ai

[72] Criticism of Chatbot Arena, Simon Willison. It quotes Arvind Narayanan on the LMArena reply. Secondary simonwillison.net

[73] When Is Benchmark Contamination Detectable?. This preprint links audit power to sample size. Primary arxiv.org

[74] Measuring AI ability to complete long tasks (Kwa et al.). It defines the 50% time horizon. Primary arxiv.org

[75] HCAST, METR. It provides 189 tasks with human baselines. Primary arxiv.org

[76] RE-Bench, METR. It compares agents and experts on ML research tasks. Primary arxiv.org

[77] Claude Opus 4.6 time horizon, OfficeChai. It reports press figures for recent Claude horizons. Secondary officechai.com

[78] Developer productivity RCT, METR. It measures how AI tools change developer speed. Primary arxiv.org

[79] AI Agents That Matter, Princeton. It asks for joint accuracy-cost evaluation. Primary arxiv.org

[80] HAL leaderboard, Princeton. It shows agent accuracy next to cost. Primary hal.cs.princeton.edu

[81] tau²-bench, Sierra and Princeton. It tests agents with a tool-using simulated user. Primary arxiv.org

[82] Wrong Together. This single-source preprint uses simulator disagreement to flag invalid results. Single source arxiv.org

[83] Hack-Verifiable Environments. It plants detectable reward hacks in RL environments. Primary arxiv.org

[84] Specification gaming in frontier models. This preprint measures exploits across eight settings. Primary arxiv.org

[85] Emergent misalignment from reward hacking, Anthropic. It shows that reward hacking generalises to sabotage. Primary arxiv.org

[86] Time horizons refit, Nguyen and Fithian. This preprint refits METR horizons with splines and IRT. Primary arxiv.org

[87] World models as policy evaluators. This single-source workshop paper compares ranking with audit usefulness. Single source arxiv.org

[88] Evaluation awareness (Needham et al.). It tests whether models can tell evaluations from real use. Primary arxiv.org

[89] Anti-scheming training, Apollo and OpenAI. It measures covert actions before and after training. Primary arxiv.org

[90] What sandboxed agents learn about their environments, UK AISI. It shows how agents identify their evaluator. Primary aisi.gov.uk

[91] Claude Mythos Preview system card, Anthropic. It reports test suspicion, white-box awareness and Cybench results. Vendor anthropic.com

[92] Claude Opus 5.5 system card, Anthropic. It reports capability, cyber, alignment and evaluation-awareness results. Vendor anthropic.com

[93] Gemini 4 Argon Safety and Security Report, Google DeepMind. It reports evaluation awareness and names the external testers. Vendor storage.googleapis.com

[94] GPT-6 Astra system card, OpenAI. It reports Preparedness ratings, honeypot results and external evaluations. Vendor deploymentsafety.openai.com

[95] AI sandbagging (van der Weij et al.). It shows that models can underperform on purpose. Primary arxiv.org

[96] Noise injection reveals sandbagging. It uses weight noise to expose hidden capability. Primary arxiv.org

[97] Eliciting sandbagged capability with weak supervision. This preprint combines weak demonstrations with RL. Primary arxiv.org

[98] Towards Understanding Score-Seeking, Redwood. This single-source preprint studies score-seeking when graders leak. Single source arxiv.org

[99] CoT monitorability (Korbak et al.). This cross-lab position paper calls CoT monitoring fragile. Primary arxiv.org

[100] Reasoning models don't always say what they think, Anthropic. It measures how often CoT reveals hint use. Primary arxiv.org

[101] CoT necessity and monitoring, Google DeepMind. It tests monitor evasion when CoT does real work. Primary arxiv.org

[102] Evaluating CoT monitorability, OpenAI. It reports 13 monitorability evaluations. Vendor openai.com

[103] Covert sandbagging against CoT monitors. It measures how often monitor-aware models evade detection. Primary arxiv.org

[104] Alignment faking, Anthropic and Redwood. It shows Claude 3 Opus faking alignment in training. Primary arxiv.org

[105] In-context scheming, Apollo Research. It shows scheming in five frontier models. Primary arxiv.org

[106] Auditing for hidden objectives, Anthropic. It runs a blind audit of an implanted objective. Primary arxiv.org

[107] Automated auditing agents, Anthropic. It reports win rates of auditing agents. Vendor alignment.anthropic.com

[108] AuditBench. It tests auditing tools on 56 models with hidden behaviours. Primary arxiv.org

[109] Petri, Anthropic. It releases an open-source auditing tool with agent auditors. Vendor anthropic.com

[110] Inspect Petri, Meridian Labs. It hosts a port of Petri to the Inspect framework. Primary meridianlabs-ai.github.io

[111] Bloom, Anthropic. It generates behavioural evals from one behaviour description. Vendor alignment.anthropic.com

[112] Deception probes, Apollo Research. It tests linear probes for deception on Llama-3.3-70B. Primary arxiv.org

[113] AI Control, Redwood. It introduces control evaluations with a subversive red team. Primary arxiv.org

[114] Ctrl-Z, Redwood. It tests resample protocols on 257 BashBench tasks. Primary arxiv.org

[115] SHADE-Arena. It measures sabotage and monitoring in agent tasks. Primary arxiv.org

[116] BashArena, Redwood. It tests monitors against four sabotage goals. Primary arxiv.org

[117] Async Control, UK AISI. It reports ensemble monitor error rates on a held-out environment. Primary arxiv.org

[118] Approach to capability elicitation, UK AISI. It sets out a structured elicitation protocol. Primary aisi.gov.uk

[119] International evaluation best practice, UK AISI. It reports the shared practices that the network agreed in Seoul. Primary aisi.gov.uk

[120] V4 model card, DeepSeek. This eight-page form lists architecture and licences but no evaluations. Vendor fe-static.deepseek.com

[121] EvalGen (Shankar et al.). It finds criteria drift in human grading of LLM outputs. Primary arxiv.org

[122] Transect, UK AISI. It makes large agentic evaluations easier to read. Primary aisi.gov.uk

[123] HELM documentation, Stanford CRFM. It states that HELM entered maintenance mode in June 2026. Primary crfm-helm.readthedocs.io

[124] Transluce. It describes Docent and the AI Evaluator Forum that it chairs. Primary transluce.org

03

CHAPTER 3 · TOOLS

Open source runs the eval stack, but only its lower layers have settled

Two open harnesses carry most model benchmarking, Docker and OpenTelemetry won the plumbing, and larger companies bought most eval platforms in 2026.

2.9M monthly Inspect AI downloads | **86** benchmark adapters in Harbor | **7** eval-tool deals in 2026

$915M Dynatrace price for Arize | **0** open licences changed after a deal

5 November 2026 · Read online with interactive charts: evals.study/tools/

Key findings

- **Two harnesses carry most model benchmarking.** UK AISI's Inspect AI draws 2.9 million PyPI downloads a month, and EleutherAI's lm-evaluation-harness 1.0 million (5 Nov 2026). [3] [7]
- **Harbor became the shared unit for agent benchmarks.** Its 86 adapters cover SWE-bench, OSWorld, GAIA and HLE, and four other frameworks import its tasks. [33]
- **Academic harnesses age fast.** Six well-known projects froze or retired since mid-2024, including HELM (maintenance mode since 1 June 2026) and the Open LLM Leaderboard (retired 13 March 2025). [39] [44]
- **The app eval library is now a commodity.** Every platform ships judges, datasets and a CI exit code. Only MLflow 3.18.0 (November 2026) ships a paired test between two runs. [86]
- **Eval and RL environments merged into one layer.** OpenEnv (v0.12.0, 5 Nov 2026), verifiers and Harbor tasks now serve evaluation and training alike. [94] [109]
- **OpenTelemetry won the transport, not the vocabulary.** The OTel GenAI conventions still carry "Development" status, while OpenInference draws 8.6 million monthly downloads. [142] [138]
- **Larger companies bought most eval platforms in 2026.** ClickHouse bought Langfuse (16 Jan), OpenAI bought promptfoo (9 Mar) and Dynatrace closed Arize for $915M (1 Oct). [168] [73] [174]

- **No acquirer changed an open licence.** Most core projects stay MIT, Apache-2.0 or BSD. Phoenix's Elastic License and closed `ee/` folders are the main traps for a hosted product. [88] [166]
- **No result format has won.** Inspect `.eval` logs lead in practice, while the neutral Every Eval Ever schema drew 285 PyPI downloads last month. [149] [151]

Only the bottom of the eval stack has settled

Every evaluation passes through the same seven layers, whatever the tool. The sandbox and the harness have settled. Grading, statistics and reporting have not.

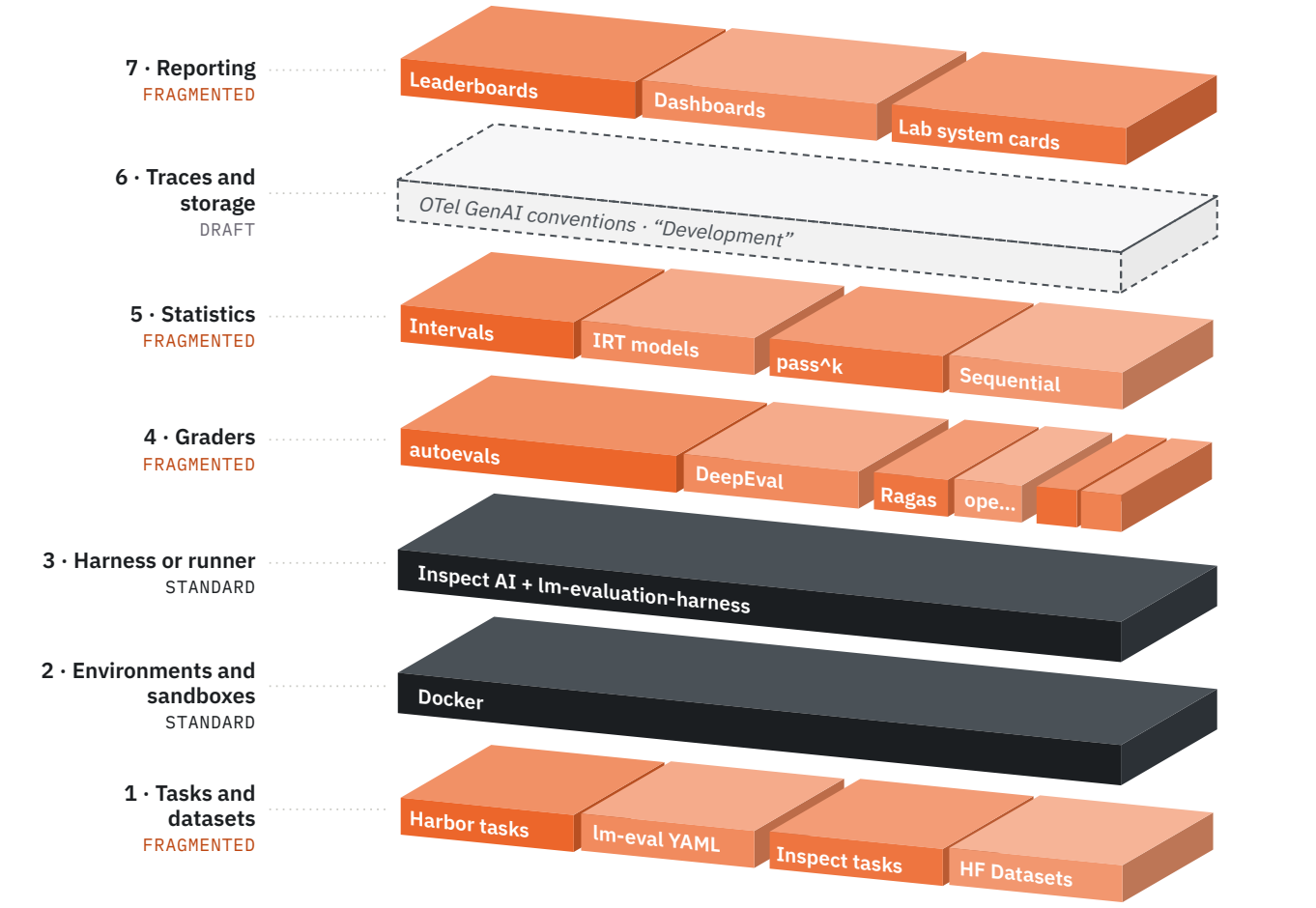
Every evaluation follows the same path. A team writes tasks and runs them in a sandbox through a harness. Graders score each answer, statistics add error bars, traces keep the evidence, and reports show the result. Figure 1 shows each layer with its leading names and a status tag.

The Sandbox and the Harness Have Settled. Grading and Reporting Have Not.

The seven layers of an evaluation, bottom to top. A solid slab has one de facto choice; a broken slab has rival tools; the dashed slab is a standard still in draft.

Standard one de facto choice **Fragmented** many rival tools **Draft** a standard exists but is not final

In Graders, tile width shows monthly PyPI downloads (5 Nov 2026). Other broken layers use equal tiles.



Settled: Docker and two harnesses work almost everywhere.

Still open: graders, statistics and reports have no winner.

Figure 1. The sandbox and the harness have settled, while grading, statistics and reporting have not. Download counts are monthly PyPI or npm figures on 5 Nov 2026 and include CI traffic.

Source: project repositories and docs, GitHub API, pypistats and npm (5 Nov 2026). [3] [7] [47] [49] [142] [5] [9] [55] [138]

The lower layers have settled. Docker containers, OpenAI-compatible APIs and the two main harnesses work almost everywhere. Cloud sandbox vendors such as E2B, Modal and Daytona now compete as interchangeable back ends. [155]

The upper layers still change fast. Each tool grades, computes statistics, stores and reports in its own way. A different judge can change a ranking. The OpenTelemetry GenAI conventions still carry "Development" status. [142]

GO DEEPER

De facto standard, open alternative and watch point for each layer

Layer	De facto standard	Open alternative	Watch point
Model benchmarks	Inspect AI, lm-evaluation-harness	lighteval, OpenCompass, NeMo Evaluator	HELM in maintenance mode
Agent benchmark tasks	Harbor task format	SWE-bench harness, OSWorld	Docker cost at scale
Environments for eval and RL	OpenEnv step API, verifiers	tau2-bench, AppWorld, BrowserGym	Hub sizes unverified
App and agent evals	DeepEval (library), promptfoo (CLI)	Giskard, openevals, LangWatch Scenario	Ragas idle since February 2026
Self-hosted platform	Langfuse, MLflow	Opik, Agenta	Phoenix under ELv2
Red team	promptfoo	garak, PyRIT, DeepTeam	OpenAI owns promptfoo
Tracing	OpenTelemetry with OpenInference attributes	OTel GenAI conventions	GenAI conventions still "Development"
Tool access	MCP	none	Licence move to Apache-2.0
Sandboxes	Docker images	Kubernetes, Modal, Daytona, E2B	Vendor lock-in at scale
Result format	Inspect `.eval` logs	Every Eval Ever	Very low uptake

Table 1. Layer-by-layer summary on 5 Nov 2026.

How to read the download counts. Stars, licences and release dates come from the GitHub API on 5 Nov 2026. Monthly downloads come from the pypistats and npm APIs on the same day. Counts include CI and mirror traffic, so treat them as rough signals. SWE-bench, for example, shows 22.1 million PyPI downloads a month. [1]

Two harnesses carry model benchmarking, and Harbor carries agent tasks

A model-benchmark harness runs a fixed set of tasks against a model and reports scores. Labs, safety institutes and researchers use them to compare models.

UK AISI's Inspect AI leads for agentic, sandboxed and safety evals. It draws 2.9 million PyPI downloads a month, almost three times the count for lm-evaluation-harness. [3] [7] Its README lists over 200 ready-made evaluations. [21] Each evaluation combines a dataset, solvers and scorers, and MCP tools plug in directly. [22]

Inspect has become a de facto verification standard. Epoch AI's Benchmarking Hub runs on Inspect and shows each question in the Inspect viewer.[27] Hugging Face marks a score as verified only after an Inspect run in HF Jobs.[28] Groq's openbench runs over 95 benchmarks on it.[25]

EleutherAI's lm-evaluation-harness stays the standard for open weights. It defines each task as a YAML file and supports vLLM, SGLang, llama.cpp and OpenAI-compatible APIs.[30] It also powered the Hugging Face Open LLM Leaderboard.

Harbor became the shared unit for agent benchmarks. A Harbor task is a small folder with an instruction, a Dockerfile and a test script.[32] Its 86 adapters include SWE-bench, OSWorld, GAIA and HLE.[33] Inspect, verifiers, OpenEnv and NeMo Evaluator all import Harbor tasks. Harbor is the official harness for Terminal-Bench 2.0.[31]

The Most-Starred Harnesses Are Not the Most Used

Each dot is a harness: GitHub stars (across) against monthly PyPI downloads (up, log scale), 5 November 2026.

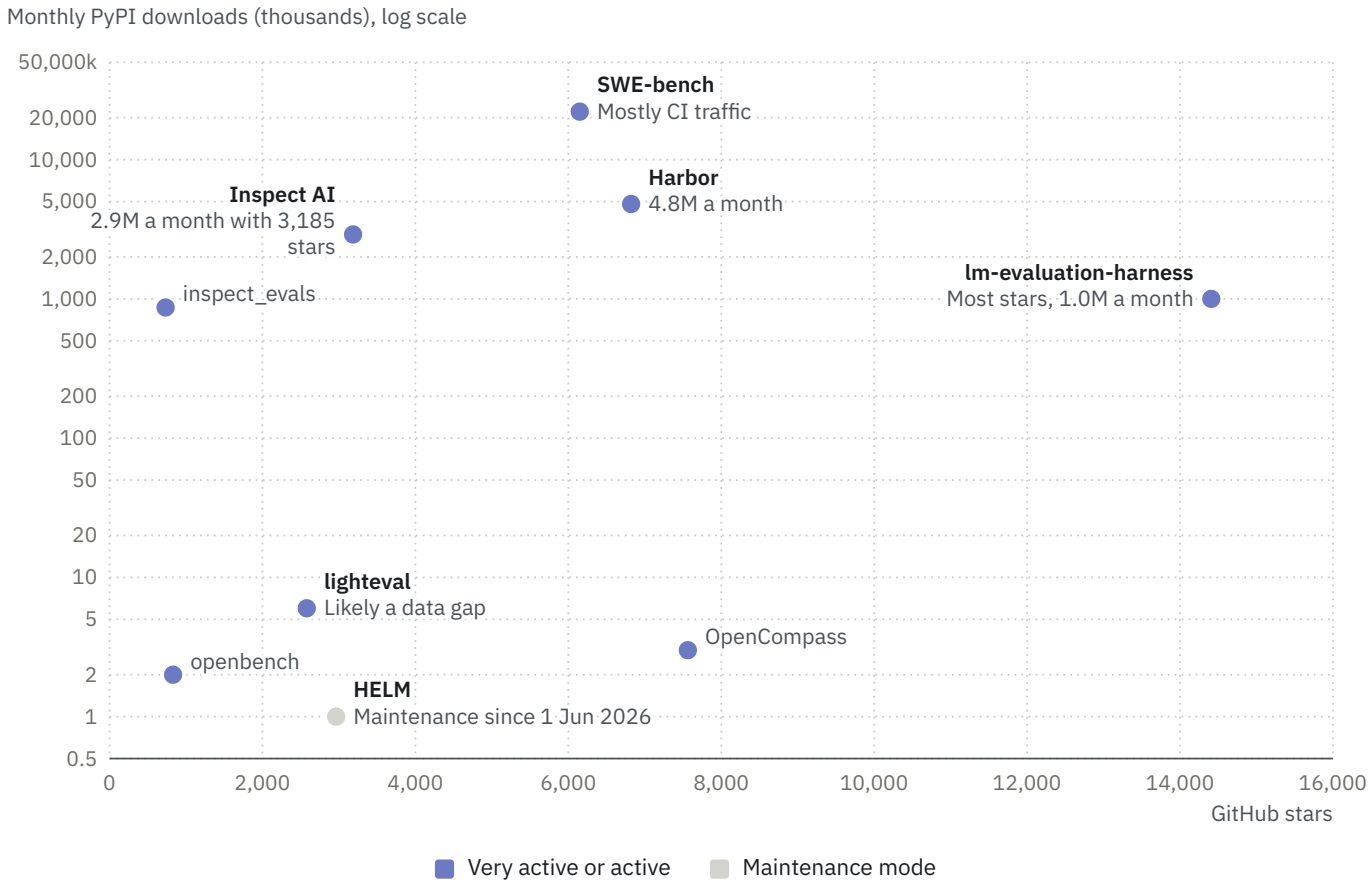


Figure 2. Harbor and Inspect lead current use; lm-evaluation-harness has the most stars among active harnesses but a third of Inspect's downloads. SWE-bench's 22.1M a month comes mostly from CI. lighteval's 6k looks too low for its star count and is likely a data gap. Harnesses without a PyPI count are left out: OpenAI Evals (19,709 stars, dormant), simple-evals (4,695, frozen since July 2025), BIG-bench (3,245, archived), NeMo Evaluator (359) and the HAL harness (308, archived).

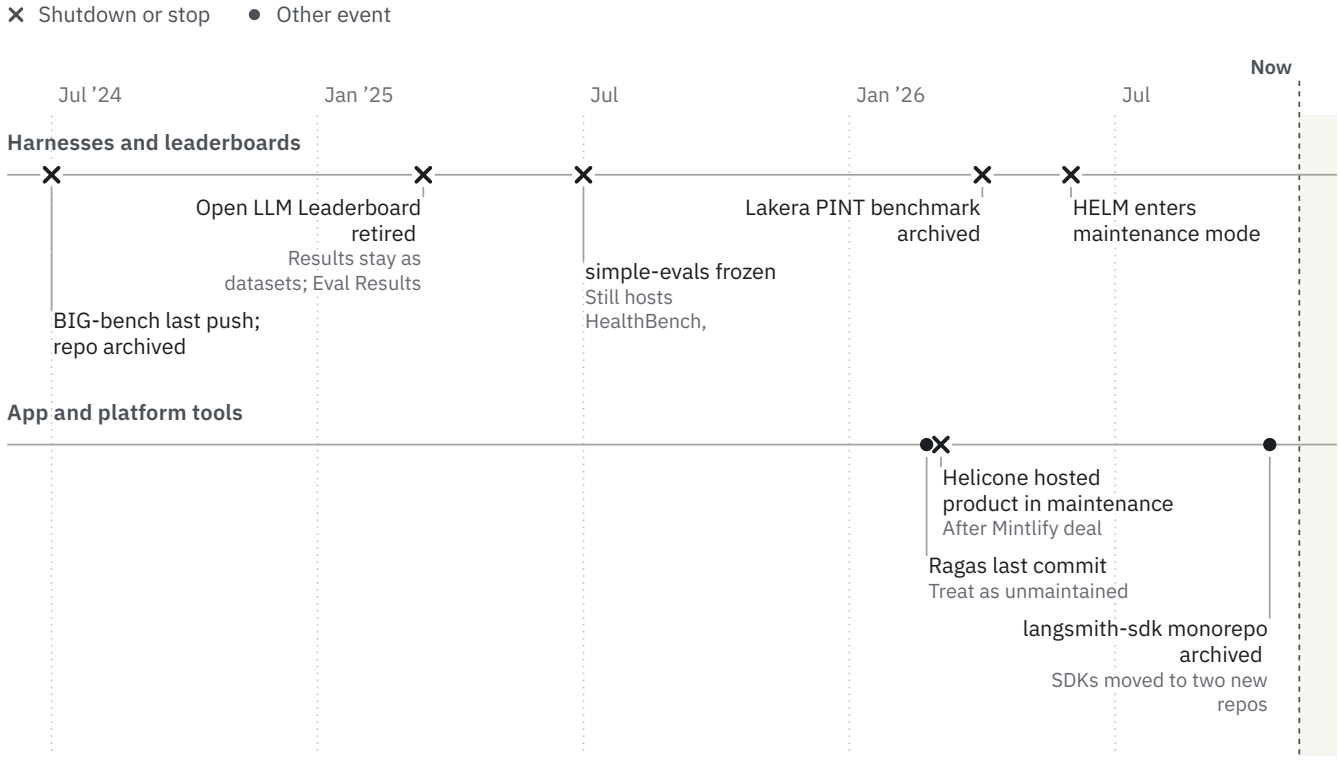
Source: GitHub API and pypistats API (5 Nov 2026).[1] [2] [3] [5] [6] [7] [8] [9] [10] [11] [12] [13] [15] [16]

Inspect also ships the strongest statistics of any harness. It offers standard errors, bootstrap errors, Wilson intervals, clustered errors and Krippendorff's alpha for judge agreement.[29]

Academic leaderboard harnesses age fast. Six well-known projects froze or retired since mid-2024. Stanford's HELM entered maintenance mode on 1 June 2026.[39] OpenAI stopped updating simple-evals in July 2025.[41] Hugging Face retired the Open LLM Leaderboard on 13 March 2025.[44]

Well-Known Eval Projects Freeze Every Few Months

Projects that froze, retired or went idle, July 2024 to November 2026.



WHAT TO NOTICE

- Five of the eight events fall in 2026.

Figure 3. Static benchmarks saturate, and nobody funds their upkeep. Teams that build on a harness should check its funding as well as its features. OpenAI Evals (dormant) and the HAL harness (archived) have no clear end date and are not shown.

Source: project READMEs and the GitHub API (5 Nov 2026). [19] [39] [41] [44] [69] [76] [132] [169]

GO DEEPER

All 14 model-benchmark harnesses, with maintainers and status

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
Inspect AI [2]	UK AISI, with Meridian Labs	MIT	3,185	2.9M [3]	Very active	Agentic, sandboxed and safety evals
inspect_evals [4]	Generality Labs, with UK AISI	MIT	733	867k [5]	Very active	Ready-made evals for Inspect
lm-evaluation-harness [6]	EleutherAI	MIT	14,408	1.0M [7]	Very active	Open-weights and log-likelihood benchmarks

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
Harbor [8]	Harbor Framework team (Terminal-Bench)	Apache-2.0	6,821	4.8M [9]	Very active	Containerised agent benchmarks
SWE-bench [10]	SWE-bench team (Princeton, Stanford)	MIT	6,149	22.1M (CI-heavy) [1]	Active	Coding-agent benchmark
OpenCompass [11]	Shanghai AI Lab	Apache-2.0	7,563	3k	Active	Chinese and multimodal benchmarks
lighteval [12]	Hugging Face	MIT	2,579	6k (likely a data gap) [13]	Active, no release in 2026	Hugging Face models and tasks
NeMo Evaluator [14]	NVIDIA	Apache-2.0	359	n/a	Active	Benchmarks with interceptors
openbench [15]	Groq	MIT	831	2k	Active	Provider benchmarks on Inspect
HELM [16]	Stanford CRFM	Apache-2.0	2,964	1k	Maintenance since 1 Jun 2026	Historical comparisons
OpenAI Evals [17]	OpenAI	MIT	19,709	n/a	Dormant	Old eval registry
simple-evals [18]	OpenAI	MIT	4,695	n/a	Frozen since Jul 2025	Reference code for HealthBench, BrowseComp, SimpleQA
BIG-bench [19]	Google	Apache-2.0	3,245	n/a	Archived	Historical tasks
HAL harness [20]	Princeton PLI	none stated	308	n/a	Archived	Historical agent leaderboard

Table 2. GitHub API and pypistats, 5 Nov 2026.

The Inspect ecosystem. Meridian Labs builds the web UI and add-ons for transcript analysis, workflows at scale, Harbor tasks, monitors and cloud sandboxes. [23] Generality Labs, a London nonprofit, maintains inspect_evals and now accepts pull requests only from approved contributors. [24] NVIDIA's NeMo Evaluator exports Inspect logs. [26] Solvers can be ReAct agents, custom agents, multi-agent setups or a human. An "agent bridge" lets Inspect run outside agents. [22]

lm-evaluation-harness details. A plugin system from September 2026 lets teams add backends, filters and metrics from their own packages. [30] Backends also include Hugging Face, NeMo and Megatron-LM. The Hugging Face backend stays the reference, and a script checks vLLM results against it. The README claims use in hundreds of papers and names NVIDIA, Cohere, BigCode, Nous Research and Mosaic ML.

Harbor and SWE-bench details. Harbor evaluates any agent, such as Claude Code, OpenHands or Codex CLI, and runs thousands of environments in parallel on cloud sandboxes. It also generates RL rollouts. [31] Terminal-Bench 1 now sends new users to Harbor. [34] SWE-bench runs tasks in Docker and on Modal. It released SWE-bench Multimodal v2, with 480 tasks, on 1 September 2026. [35]

Other active harnesses. lighteval claims over 1,000 tasks, but its last tagged release dates from November 2025.[36] OpenCompass added the OpenAI Responses API and a LiteLLM gateway in July 2026. In September 2026 it released AgentCompass, which separates models, benchmarks, harnesses and environments.[37] NeMo Evaluator adds an interceptor proxy, confidence intervals and Harbor agents.[26] Epoch AI fits a Bayesian item-response model in its Capabilities Index package.[38]

Frozen and retired, in detail. HELM publishes a policy page on what maintenance mode covers.[40] The OpenAI Evals README sends users to the OpenAI Dashboard; recent commits only pin CI dependencies.[42] Princeton archived the HAL harness, and the team now works on agent reliability.[43] Open LLM Leaderboard results stay available as datasets.[45] Its successor, Eval Results, stores scores in each model repo and feeds per-benchmark boards.[28]

The app eval library became a commodity; platforms now compete on traces and simulation

These tools test a team's own application or agent, not a bare model. Code-first libraries run tests in a script or in CI. Platforms add trace storage, dashboards, datasets and human review.

Every tool now ships the same core. All of them offer LLM judges, datasets, experiments and a pass-or-fail exit code for CI.[92] [93] Most gates compare a pass rate with a fixed threshold. Few tools say with statistical confidence whether a change made the agent worse.

Only MLflow ships a paired test. Version 3.18.0, from early November 2026, compares two runs with McNemar or Wilcoxon tests and a bootstrap interval.[86] No other platform ships a paired test today.

Download counts favour platforms with production SDKs. Langfuse draws 23.6 million PyPI downloads a month, and MLflow 19.9 million.[59] [61] Both counts include SDK installs in production apps, so they overstate pure eval use. Among code-first libraries, autoevals and DeepEval lead.[55] [49]

Two Platforms With Production SDKs Dwarf the Eval Libraries

Monthly PyPI downloads, in millions, on 5 November 2026. promptfoo is an npm package and is shown with its npm count.

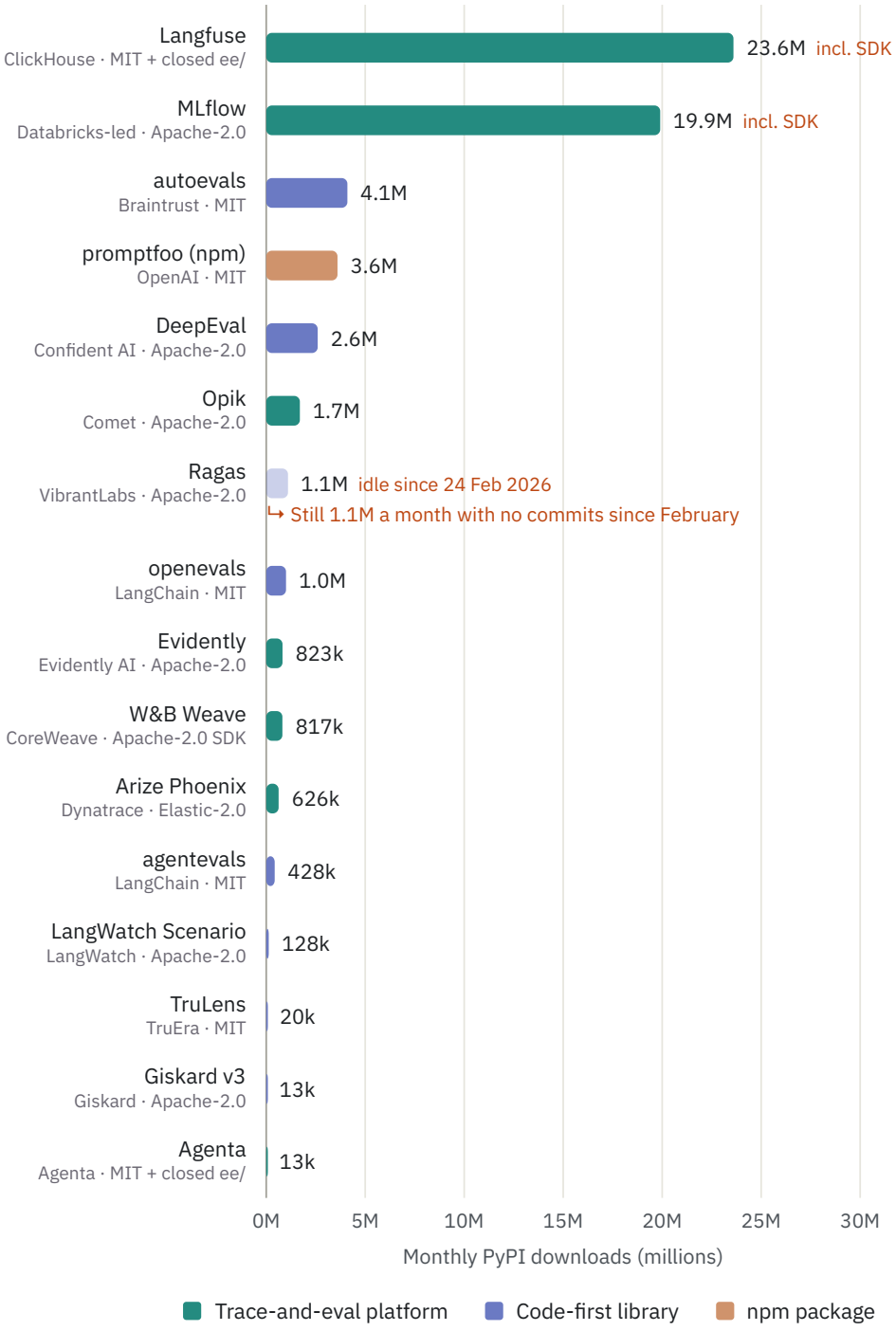


Figure 4. Langfuse and MLflow counts include SDK installs in production apps, so they overstate pure eval use. promptfoo draws 3.6M npm downloads a month; Langfuse adds 7.7M npm and autoevals 2.3M npm. Ragas is faded because its last commit dates from 24 Feb 2026.

Source: pypistats and npm APIs (5 Nov 2026). [47] [49] [55] [59] [61] [63]

Platforms now compete on three things. They compete on trace storage at scale, on simulated users and on scoring agent trajectories. DeepEval ships a conversation simulator, and LangWatch Scenario tests agents against a simulated user and a judge. [83] LangChain's agentevals scores trajectories with strict, unordered,

subset and superset match modes.[79]

Every Tool Gates CI, but Only MLflow Runs a Paired Test

Features that the leading app and agent eval tools document, November 2026. Full = documented; Partial = limited; None = not offered; n/a = not stated in our sources.

Tool	CI pass/fail gate	OpenTelemetry traces ingest or export	Simulated users	Trajectory checks	Paired test vs baseline
promptfoo OpenAI · MIT	● GitHub Action before/after	● OTLP receiver	–	● checks against traces	○
DeepEval Confident AI · Apache-2.0	● deepeval test run	● exporter	● conversation simulator	◐ tool correctness, plan adherence	○
Langfuse ClickHouse · MIT + ee/	●	● OTel endpoint	–	–	○
MLflow Databricks-led · Apache-2.0	●	●	–	–	● McNemar / Wilcoxon + bootstrap
Arize Phoenix Dynatrace · ELv2	●	● OpenInference	–	–	○
TruLens TruEra · MIT	●	●	–	–	○
LangWatch Scenario LangWatch · Apache-2.0	●	–	● simulated user + judge	–	○
agentevals LangChain · MIT	●	–	–	● 4 match modes	○

● Documented ◐ Limited ○ Not offered – Not stated in our sources

WHAT TO NOTICE

- Read the shaded column: only MLflow has a full mark.

Figure 5. Every tool gates CI, and most now speak OpenTelemetry. Simulated users and trajectory checks are spreading. Only MLflow runs a paired test between a candidate and a baseline.

Source: project docs and READMEs (5 Nov 2026).[71] [72] [75] [79] [82] [83] [85] [86] [88] [92] [93]

Three gaps stay common. Few tools test a pure black-box agent without code. Few ship stateful copies of business tools. Only MLflow runs a paired test between a candidate and a baseline.

Some popular libraries have slowed. Ragas made RAG metrics such as faithfulness popular, but its last commit dates from 24 February 2026.[76] Giskard rewrote its library as v3 for multi-turn agents and no longer maintains v2.[77] LangChain archived its `langsmith-sdk` monorepo on 16 October 2026; the platform

stays closed. [69]

GO DEEPER

All 18 app and agent eval tools, with licences and status

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
promptfoo [46]	OpenAI (acquired 2026, deal closed)	MIT	26,875	npm 3.6M [47]	Very active	YAML evals, CI gates, red team
DeepEval [48]	Confident AI	Apache-2.0	19,318	2.6M [49]	Very active	Pytest-style tests in Python
Ragas [50]	VibrantLabs	Apache-2.0	16,247	1.1M	Idle since 24 Feb 2026	RAG metrics
Giskard v3 [51]	Giskard (Paris)	Apache-2.0	5,945	13k	Active, new rewrite	Multi-turn agent checks and scans
openevals [52]	LangChain	MIT	1,244	1.0M	Active	Ready-made LLM judges
agentevals [53]	LangChain	MIT	757	428k	Slowing	Trajectory scoring
autoevals [54]	Braintrust	MIT	1,072	4.1M, npm 2.3M [55]	Active	Scorer library in Python and TS
TruLens [56]	TruEra, with Snowflake ties	MIT	3,628	20k	Active	Feedback functions, RAG triad
LangWatch Scenario [57]	LangWatch (Amsterdam)	Apache-2.0	1,015	128k	Active	Simulated users against agents
Langfuse [58]	ClickHouse (acquired Jan 2026)	MIT, plus closed ee/	37,058	23.6M, npm 7.7M [59]	Very active	Self-hosted traces and evals
MLflow [60]	Databricks-led open project	Apache-2.0	28,693	19.9M [61]	Very active	Evals inside an ML platform
Opik [62]	Comet	Apache-2.0	23,200	1.7M [63]	Very active	Self-hosted platform, fully open
Arize Phoenix [64]	Dynatrace (acquired Oct 2026)	Elastic-2.0	12,161	626k	Very active	Tracing and evals, not for resale as a service
W&B Weave [65]	CoreWeave	Apache-2.0 (SDK only)	1,145	817k	Active	Teams already on W&B
Evidently [66]	Evidently AI	Apache-2.0	8,042	823k	Slowing	ML and LLM monitoring reports
Agenta [67]	Agenta (Berlin)	MIT, plus closed ee/	4,887	13k	Very active	Prompt playground and evals
Kiln [68]	Kiln	MIT library, source-available app	5,255	n/a	Active	Desktop eval and fine-tune app

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
LangSmith SDK [69]	LangChain	MIT (platform closed)	1,083 (old repo)	n/a	Old repo archived 16 Oct 2026	Teams on LangSmith

Table 3. GitHub API, pypistats and npm, 5 Nov 2026.

Code-first libraries.

promptfoo puts evals in YAML files with providers, prompts, tests and assertions. It calls any HTTP, WebSocket or MCP endpoint. [70] It receives OpenTelemetry traces and checks agent trajectories against them. [71] A GitHub Action runs a before-and-after comparison on each pull request. [72] The company claims 350,000 developers and teams at over a quarter of the Fortune 500 (vendor claim). [73] Release 0.125.1 shipped on 25 October 2026.

DeepEval writes tests as pytest-style `LLMTestCase` objects. Its metrics include G-Eval, task completion, tool correctness and plan adherence. `deepeval test run` gates CI. [75]

Giskard v3 splits into `giskard-checks`, `giskard-scan` and `giskard-agents`. [77]

openevals builds judges with one `create_llm_as_judge` call. [78] **autoevals** offers LLM, heuristic, embedding and RAG scorers in Python and TypeScript. [80] Braintrust keeps its platform closed and raised an $80M Series B in February 2026 (secondary source). [81]

TruLens traces apps with OpenTelemetry, scores them with "feedback functions" and ships a Snowflake Cortex provider. [82]

LangWatch Scenario combines a description, the agents and a script of turns and checks. It calls the agent through its public interface and mocks tools, databases and APIs for offline runs. [83]

Trace-and-eval platforms.

Langfuse stores traces, sessions, datasets, experiments, judge scores and human annotation queues. It versions a dataset on every change. Self-hosting runs on PostgreSQL, Redis, ClickHouse and S3. [84] It accepts OpenTelemetry traces directly. [85]

MLflow adds `mlflow.genai.evaluate()` with scorers, judges and tracing. [86]

Opik runs on ClickHouse, MySQL, Redis and MinIO with a Helm chart, and keeps its whole code base under Apache-2.0. [87]

Arize Phoenix traces with OpenInference. The server and `phoenix-evals` use the Elastic License 2.0; the client and OpenTelemetry packages use Apache-2.0. [88]

W&B Weave traces functions with `@weave.op`. The repo holds only the SDK and server bindings. Self-managed Weave runs inside W&B Self-Managed with ClickHouse, and CoreWeave hosts the docs. [89]

Evidently offers over 100 metrics, test suites and reports; its last push dates from late September 2026. [66] **Agenta** combines a prompt playground, evaluation and observability. [90] **Kiln** keeps its core library MIT, but its desktop app uses a fair-code licence. [91]

Eval environments and RL training environments merged into one layer

An environment gives an agent a world to act in. It holds tools, data and rules, and it scores what the agent does. In 2026 the same environment often serves for evaluation and for RL training.

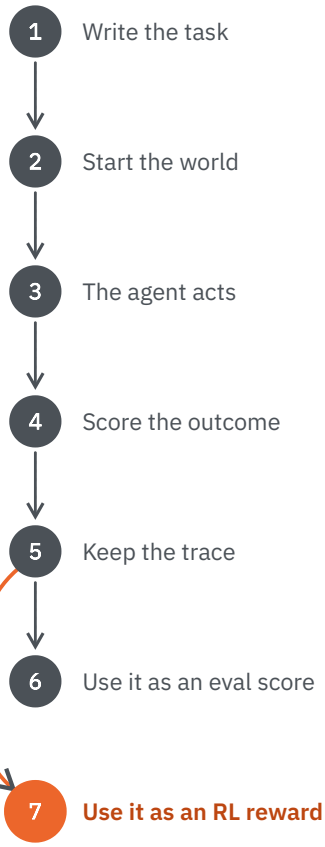
OpenEnv offers one step API for any environment. It exposes `reset()`, `step()` and `state()` over a WebSocket, and each environment is a Docker image.[106] A twelve-member technical committee now governs it, including Meta-PyTorch, Hugging Face, Nvidia, Microsoft and Modal. Version 0.12.0 shipped on 5 November 2026.[94]

verifiers links environments to training. Prime Intellect's library defines tasksets, harnesses and agents, and each rollout produces a trace.[108] A `HarborTaskset` loads Harbor tasks such as Terminal-Bench 2.[109] The library draws 762,000 PyPI downloads a month.[97]

The pieces mostly cooperate. Harbor defines tasks and sandboxes, and OpenEnv defines the step API and hosting. verifiers adds rubrics and training links, and Inspect adds logging and scoring. The story below follows one task through both uses.

One Agent Task Now Serves as a Test and as Training Data

How a single Harbor task flows through the shared open stack in 2026.



STEP 7

Use it as an RL reward

The same rollout and score feed an RL trainer.

EXAMPLE

TRL, Unsloth, SkyRL, ART or prime-rl

1 **It starts as a small folder.** A Harbor task holds an instruction, a Dockerfile and a test script. Harbor's 86 adapters turn existing benchmarks into this format. [32] [33]

2 **The Dockerfile becomes the world.** OpenEnv starts it with `reset()`. The same image runs locally, on a cloud sandbox or as a Hugging Face Space. [106]

3 **Any agent can act inside it.** Harbor runs Claude Code, Codex or OpenHands. Environments expose their tools over MCP. [31] [106]

4 **The task grades itself.** The test script checks the final state. verifiers can add a rubric on top. [108]

5 **Every step is kept.** Inspect logs the run, and the OpenEnv–Harbor integration keeps the exact tokens for RL. [106] [149]

6 **Use one: the score becomes an eval result.** Terminal-Bench 2.0 uses Harbor as its official harness. [31]

7 **Use two: the same rollout trains a model.** OpenEnv connects to TRL, Unsloth, SkyRL and ART. verifiers links to Prime Intellect's prime-rl trainer. [106] [107]

Figure 6. Harbor defines the task and sandbox, OpenEnv the step API, verifiers the rubrics and training links, Inspect the logs. Names are examples from each project's docs.

Source: Harbor, OpenEnv, verifiers and Inspect docs (5 Nov 2026). [31] [32] [106] [108] [109] [149]

Four Open Projects Join Evaluation and Training

Each project owns one part of the shared layer, and each imports the others.

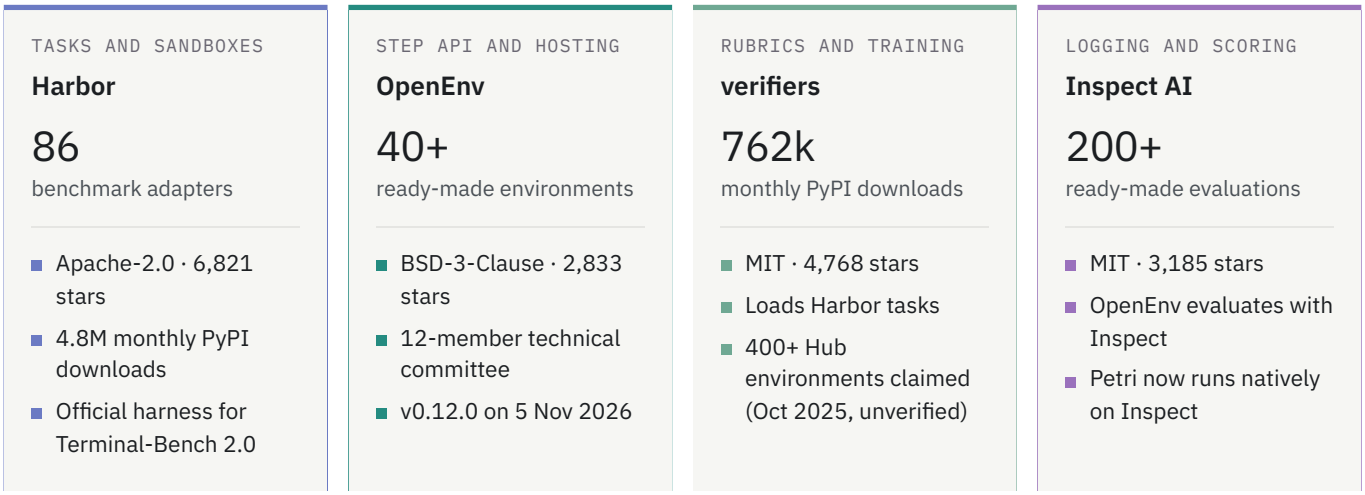


Figure 7. Each project owns one part of the shared layer, and each imports the others. Prime Intellect's Hub count is a company claim from October 2025; no primary source gives a current count.

Source: project READMEs, GitHub API and pypistats (5 Nov 2026); Prime Intellect post (Oct 2025). [21] [33] [94] [97] [106] [110]

Simulated users are maturing in two places. Sierra's tau2-bench v2.0 tests customer-service agents in six languages and full-duplex voice. Its text and voice sets hold 900 tasks each. [111] Meridian Labs' Petri runs an auditing agent against a target model and scores transcripts with a rubric. [117]

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All nine environment projects, plus the benchmark worlds

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
OpenEnv [94]	OpenEnv technical committee (Meta-PyTorch, Hugging Face and others)	BSD-3-Clause	2,833	49k [95]	Very active, v0.12.0 on 5 Nov 2026	One step API for any environment
verifiers [96]	Prime Intellect	MIT	4,768	762k [97]	Very active	RL and eval environments, Environments Hub
community-environments [98]	Prime Intellect	Apache-2.0	264	n/a	Active	Shared environment library
tau2-bench [99]	Sierra	MIT	2,403	n/a	Very active, v2.0.0 in Oct 2026	Customer-service agents, text and voice
AppWorld [100]	Stony Brook NLP	Apache-2.0	548	662k (CI-heavy) [101]	Active	Apps, APIs and coding agents
BrowserGym [102]	ServiceNow Research	Apache-2.0	1,427	14k	Active	Web agents
AgentLab [103]	ServiceNow Research	Apache-2.0	661	n/a	Active	Large parallel web-agent runs
OSWorld [104]	XLANG Lab (HKU)	Apache-2.0	3,251	n/a	Active, no release since 2024	Desktop computer-use agents
Petri [105]	Meridian Labs	MIT	1,402	48k	Very active	Alignment audits with an auditor agent

Table 4. GitHub API and pypistats, 5 Nov 2026.

OpenEnv. Farama's Gymnasium inspired the design. A Harbor integration runs Claude Code, Codex and other agents on Harbor tasks. OpenEnv scores with rubrics and evaluates with Inspect AI. The repo moved from `meta-pytorch` to its own `openenv` organisation. Committee members also include Prime Intellect and Unsloth. [106]

verifiers. A harness is the program that runs the model; an agent combines a harness, a model and a runtime policy. Toolsets install as MCP servers. [108] It links to the Environments Hub, prime-rl and hosted training. [107]

tau2-bench. Covers airline, retail and telecom. A live leaderboard runs at taubench.com. Harbor ships a `tau3-bench` adapter, but no separate tau3 repo exists yet. [111]

AppWorld. A controllable world of apps and people for function-calling and coding agents; ACL 2024 best resource paper. [112]

BrowserGym and AgentLab. BrowserGym bundles MiniWoB, WebArena, VisualWebArena, WorkArena and AssistantBench. [113] AgentLab runs large parallel experiments on it with Ray. [114] Both repos warn that they are research tools, not consumer products.

OSWorld. Runs desktop agents in VMs on VMware, VirtualBox, Docker, AWS or Azure. OSWorld-Verified fixed community-reported issues in July 2025. The last tagged release dates from June 2024.[115]

ControlArena. UK AISI and Redwood Research built it for AI control experiments, where a red-team model tries to beat safety measures. MIT-licensed, 15 settings.[116]

Petri. Generates scenarios from seed instructions and simulates tools. It moved from Anthropic's safety-research organisation to Meridian Labs.[117]

Four open red-team tools lead, and their owners now matter as much as their features

Red-team tools attack a model or an agent on purpose. They look for jailbreaks, prompt injection, data leaks and unsafe tool use.

promptfoo has the widest plugin set and the most users. It holds 72 red-team plugin docs, including excessive agency, MCP attacks and memory poisoning.[124] Domain packs cover insurance, finance and medicine. By default it generates attacks through a remote service, and its docs rate local generation quality as generally low.[125]

garak and PyRIT suit code-driven testing. NVIDIA's garak combines probes, detectors and harnesses, and a REST generator connects it to any endpoint.[126] Microsoft's PyRIT composes single-turn, multi-turn and compound attacks in Python, over HTTP, WebSockets or Playwright.[128] DeepTeam lists over 50 vulnerabilities and scores them locally with LLM judges.[129]

promptfoo Dwarfs the Other Open Red-Team Tools in Downloads

Monthly downloads on 5 November 2026. Square area is proportional to downloads.



Figure 8. promptfoo belongs to OpenAI, and its npm count covers the whole package, not only red teaming. Microsoft backs PyRIT, NVIDIA backs garak and Confident AI (venture-backed) builds DeepTeam. By scope, promptfoo documents 72 red-team plugins, garak ships 44 probe modules and DeepTeam lists over 50 vulnerabilities. DeepTeam's downloads show more activity than its last release (November 2025) suggests.

Source: GitHub API, pypistats, npm and project docs (5 Nov 2026). [46] [47] [118] [119] [120] [121] [122] [123] [124] [127] [129]

Owners now shape the choice. OpenAI owns promptfoo, which may worry buyers who test competing models. Microsoft and NVIDIA back PyRIT and garak, so these two make the safest long-term bets for neutrality.

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Red-team tool table and neighbouring tools

Project	Maintainer	Licence	Stars	Monthly downloads	Status	Best for
promptfoo redteam [46]	OpenAI	MIT	26,875	npm 3.6M (whole package)	Very active	Widest plugin set, CI use
garak [118]	NVIDIA	Apache-2.0	9,872	39k [119]	Very active	Scanner for any REST endpoint
PyRIT [120]	Microsoft	MIT	4,755	72k [121]	Very active	Multi-turn attacks composed in code
DeepTeam [122]	Confident AI	Apache-2.0	3,085	71k [123]	Active, last release Nov 2025	Red team on top of DeepEval

Table 5. GitHub API, pypistats and npm, 5 Nov 2026.

Neighbouring tools.

Giskard's `giskard-scan` covers injection, jailbreaks and harmful content. [77]

AgentDojo from ETH Zurich measures indirect prompt injection with code-based checks. [130]

Snyk's agent-scan checks local agent configs and MCP servers, but needs a Snyk token. [131]

Lakera archived its PINT benchmark in April 2026. [132]

Singapore's Project Moonshot, an Apache-2.0 toolkit, remains in beta at version 0.7.6. [133]

OWASP's AI Testing Guide v1 gives a free test method for AI systems. [134] OWASP's Top 10 for Agentic Applications names risks such as agent goal hijack and tool misuse. [135]

OpenTelemetry won the transport, but the vocabulary and result formats remain open

OpenTelemetry carries traces in almost every eval platform. On top of it, attribute vocabularies, result formats and tool protocols are at different stages.

OTLP ingestion became normal. Langfuse, MLflow, promptfoo, TruLens and DeepEval all accept or export OpenTelemetry traces. Two attribute vocabularies compete on top of the transport.

OpenInference leads in practice. Arize's vocabulary draws 8.6 million monthly downloads. [138] It instruments the OpenAI Agents SDK, the Claude Agent SDK, LangChain and AutoGen, and ships a bridge for OpenLLMetry. [147] The vocabularies therefore seem to converge.

The official GenAI conventions are still a draft. They moved out of the core OpenTelemetry repo in 2026 and cover inference, retrieval, agent spans and MCP. [141] [142] Their status stays "Development", and the schema URL section still reads "TODO".

Three trace vocabularies on top of OpenTelemetry

Standard	Maintainer	Licence	Adoption signal	Status
OTel GenAI semantic conventions [136]	OpenTelemetry	Apache-2.0	523 stars; new repo since May 2026	"Development", no release yet
OpenInference [137]	Arize (Dynatrace)	Apache-2.0	1,305 stars; 8.6M monthly downloads [138]	Active, widest instrumentation
OpenLLMetry [139]	Traceloop (ServiceNow)	Apache-2.0	7,522 stars; 1.8M monthly downloads [140]	Active, release on 5 Nov 2026

Table 6. Two of the three vocabularies now belong to companies bought in 2026. The neutral one has no release yet.
Source: GitHub API and pypistats (5 Nov 2026). [136] [137] [138] [139] [140]

A neutral slot for eval scores now exists. The `gen_ai.evaluation.result` event carries a name, a score, a label and an explanation on the evaluated span. [145] It is the first neutral way to put eval scores on production traces. Judge model, rubric version and confidence intervals still need custom attributes.

No result format has won. Inspect writes binary `.eval` logs, about one eighth the size of JSON, with access to single samples. [149] Many projects read or export this format, so it acts as the richest de facto format. The neutral alternative barely registers.

The two candidate result formats

Feature	Inspect .eval logs (UK AISI)	Every Eval Ever (EvalEval Coalition)
Format	Binary .eval files, default since v0.3.46	Shared schema, instance-level JSONL
Size	About 1/8 the size of JSON	Not stated
Single-sample access	Yes	Yes
Agentic samples with tool calls	Yes	Yes
Shared results database	No	Crowdsourced database
Reads other harnesses	Many projects read or export it	Converters for Inspect, HELM, lm-eval
Cloud storage	S3 or Azure	Not stated
Uptake signal	Richest de facto format	285 PyPI downloads last month

Table 7. Inspect logs win by use; Every Eval Ever offers a neutral schema with converters but very low uptake.
Source: Inspect eval-logs docs; Every Eval Ever README; pypistats (5 Nov 2026). [149] [150] [151]

285

PyPI downloads last month for **Every Eval Ever**, the neutral eval result schema. Inspect AI drew 2.9 million.

Source: pypistats (5 Nov 2026). [151] [3]

ClickHouse became the default trace store. Langfuse, Opik and self-managed Weave all run on it. [84] [87] [89] ClickHouse also bought Langfuse in January 2026. Datasets mostly live on Hugging Face, and Langfuse versions its datasets on every change. [148]

MCP became the common way for eval agents to reach tools. Inspect, verifiers, OpenEnv, Harbor and promptfoo all support MCP tools. The spec has five dated versions, from November 2024 to July 2026. [152] The project is moving from MIT to Apache-2.0 for code and spec. [153]

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More on trace conventions, storage and MCP

Agent spans. The GenAI conventions define `create_agent`, `invoke_agent` and `invoke_workflow`. The last fits apps that define their own control flow, such as LangGraph. [144]

Core conventions. The core OpenTelemetry semantic conventions repo reached v1.45.0 on 2 November 2026. [143]

OpenInference span kinds. Every span needs a kind, such as LLM, TOOL, AGENT, GUARDRAIL or EVALUATOR. [146]

MCP spans. OpenTelemetry adds span conventions for MCP calls. [154] promptfoo ships an MCP red-team plugin.

MCP licence. Docs move to CC-BY-4.0, code and spec to Apache-2.0. [153]

Datasets. lm-evaluation-harness and SWE-bench load tasks from Hugging Face Datasets.

Docker is the sandbox contract, but judges and statistics still lack standards

Three supporting layers decide how far readers can trust a result. They cover where the agent runs, who grades it and how sure the number is.

Docker became the universal sandbox contract. Inspect ships Docker and local sandboxes, and external packages add Kubernetes, Daytona, Modal, EC2 and Proxmox. [155] Harbor runs on nine cloud back ends, and OpenEnv runs each environment as a Docker image. Cloud vendors now compete as interchangeable back ends.

Check Daytona's licence before you build on it. Daytona has 71,377 GitHub stars, but the GitHub API reports no licence, and our research did not confirm one. [159]

Most harnesses call models through an OpenAI-compatible API. vLLM serves open models behind that API, with over 96,000 stars under Apache-2.0. [160] Teams can serve open judge models through vLLM to cut grading costs.

LLM judges now grade most open-ended answers. Every framework ships judge templates, and open guard models give a cheaper option. [161] [162] [163] No open judge publishes human agreement on agent transcripts in a regulated domain. Most published numbers compare judges with GPT-4-class labels, not with human experts.

Open judge and guard models

Model	Maintainer	Licence	Signal	Note
Granite Guardian 4.1 8B [161]	IBM	Apache-2.0	10k downloads in 30 days	Custom criteria, groundedness, function-call checks
Qwen3Guard [162]	Alibaba	Apache-2.0	223k downloads (0.6B size)	Safety in 119 languages
Llama Guard 4 12B [163]	Meta	Llama 4 Community License	88k downloads	MLCommons hazard taxonomy

Table 8. Hugging Face download counts, November 2026. None of these models publishes human agreement on agent transcripts in a regulated domain.

Source: model cards and Hugging Face API. [161] [162] [163]

Averaging judges is a cheap gain. Composo found that averaging eight judge scores added 9.8 points on RewardBench 2. Three scores gave most of that gain. [164]

Statistics remain the weakest layer. Most CI gates still compare a pass rate with a fixed threshold. Inspect offers the best single-run intervals and supports early stopping. [29] [165] MLflow alone ships a paired test. [86] No tool combines paired tests, non-inferiority margins and monitoring over time.

How Many Test Cases Does a Trustworthy Pass Rate Need?

Move the sliders. Most CI gates compare one pass rate with a threshold and never show this margin.

Margin of error (± points) 3.0 pts

Expected pass rate 80%

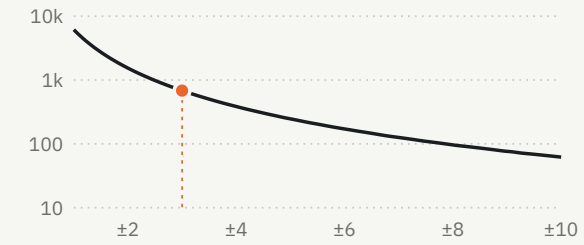
Design effect (clustered cases) 1.0

TEST CASES NEEDED

683

independent test cases for a 95% interval

$1.96^2 \times 0.80 \times 0.20 \times 1.0 \div 0.030^2 = 683$



Cases needed (log scale) by margin of error, in points

n = 1.96² × p × (1 − p) × design effect ÷ margin². A pass rate near 80%, measured to ±3 points, needs about 683 independent cases.

Figure 9. Normal approximation for a pass rate at 95% confidence. It assumes independent test cases; the design effect inflates the count when several cases share one scenario. An illustration, not tied to any one tool.

Source: standard sample-size formula for a proportion; our illustration.

Which tools ship which statistics

Tool	Single-run intervals	Judge agreement	Sequential / early stopping	Paired test	Item-response model	Non-inferiority margin	Drift over time
Inspect AI	Yes: stderr, bootstrap, Wilson, clustered	Yes: Krippendorff's alpha	Yes	No	n/a	No	No
MLflow 3.18	Yes: bootstrap	n/a	n/a	Yes: McNemar, Wilcoxon	n/a	No	No
NeMo Evaluator	Yes: via scipy	n/a	n/a	No	n/a	No	No
Epoch AI ECI	n/a	n/a	n/a	n/a	Yes: Bayesian IRT	No	No
Typical CI gate (most app eval tools)	No: pass rate vs threshold	No	No	No	No	No	No

Table 9. Single-run intervals are common, paired tests are rare, and non-inferiority margins and drift monitoring are missing everywhere.

Source: Inspect metrics and early-stopping docs; MLflow docs; NeMo Evaluator README; Epoch AI ECI package. [26] [29] [38] [86] [165]

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Sandbox projects

Project	Maintainer	Licence	Stars	Status	Role
E2B [156]	E2B	Apache-2.0	14,721	Very active	Cloud sandboxes for agents
gVisor [157]	Google	Apache-2.0	19,875	Active	Strong container isolation
Modal client [158]	Modal	Apache-2.0 (client only)	533	Active	Serverless sandboxes, closed platform
Daytona [159]	Daytona	not reported by the API	71,377	Last push 24 Jul 2026	Cloud sandboxes for agents

Table 10. GitHub API, 5 Nov 2026.

Harbor's back ends: local Docker, Daytona, Modal, LangSmith, Blaxel, Novita, Tensorlake, Runta and Sail. [31] The lm-evaluation-harness README recommends vLLM's server for large models. OpenCompass added a LiteLLM gateway in 2026. [37]

Larger companies bought most eval platforms in 2026, and no open licence changed

2026 was the consolidation year for eval and observability tools. Data platforms, observability vendors, security vendors and model labs bought most independent players.

Seven deals touched open eval projects between January and October 2026. ClickHouse bought Langfuse on 16 January.[168] OpenAI bought promptfoo, ServiceNow bought Traceloop, and Cisco closed Galileo in May.[73] [170] [171] Dynatrace closed its purchase of Arize, the owner of Phoenix, on 1 October.[175]

Platforms, Security Vendors and Labs Bought the Eval Tools

Deals for eval, observability and AI-security tools, June 2025 to October 2026, by type of buyer. Bold: the four 2026 data-platform deals.

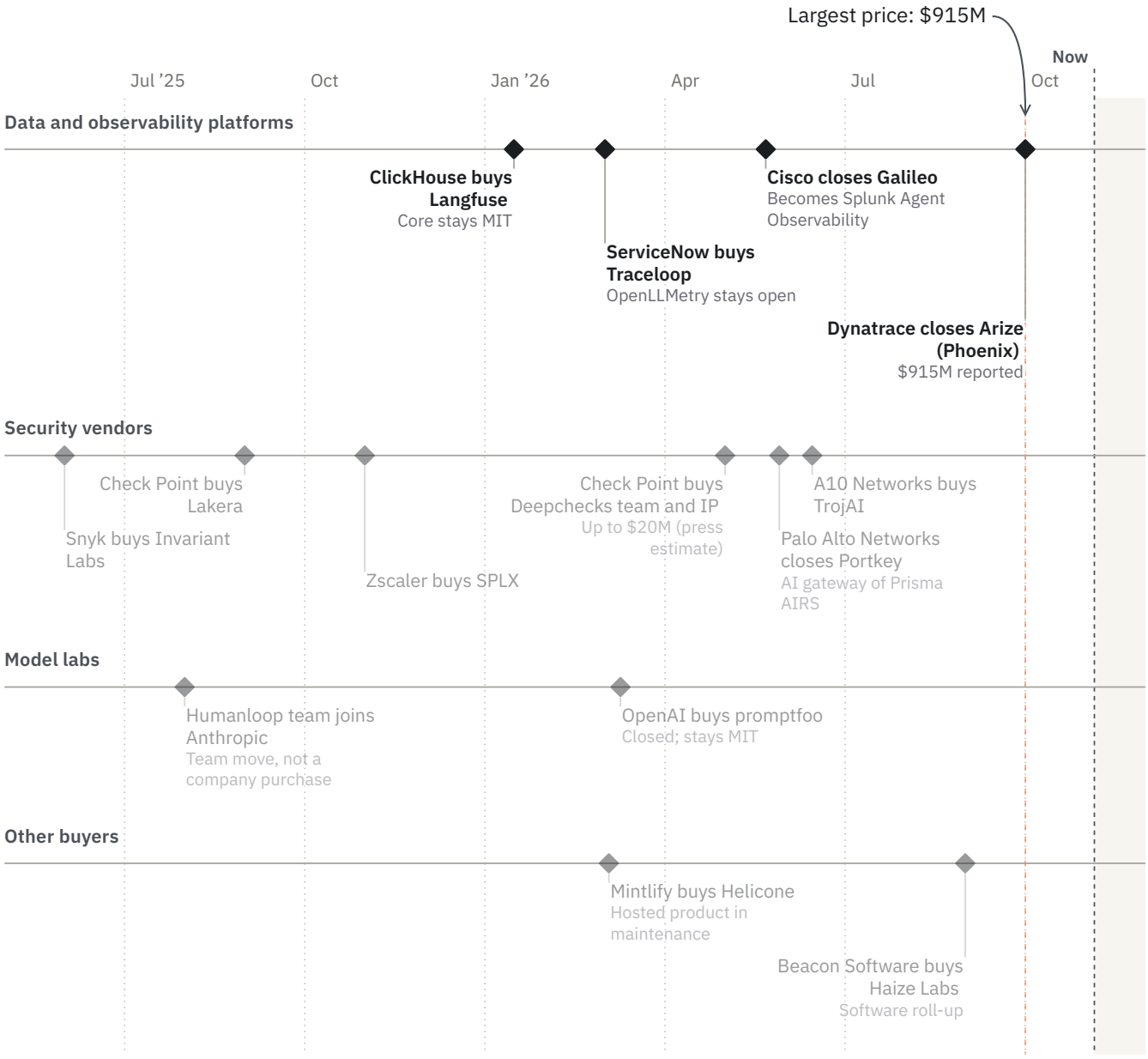


Figure 10. Dates are announcement or close dates as given. Earlier deals in AI security set the pattern for the 2026 eval-tool deals. CoreWeave also owns W&B and hosts the Weave docs.

Source: buyer and target announcements; press reports. [73] [168] [169] [170] [171] [172] [173] [176] [177] [178] [179] [180] [181] [182]

Buyers fall into three groups. ClickHouse, Dynatrace, Cisco with Splunk, and ServiceNow wanted traces and evals for their platforms. Palo Alto Networks, Check Point, Zscaler, A10 Networks and Snyk wanted AI security tools. OpenAI bought promptfoo, and Anthropic took the Humanloop team. [179]

Most prices stayed private. Dynatrace paid a reported $915M for Arize, about $815M of it in cash. [173] [174] Calcalist reported $60–80M for Traceloop, but nobody confirmed it. [183] Press estimates put the Deepchecks price at up to $20M. [184]

Ownership changed, but licences did not. No eval project in scope moved to a BSL or AGPL licence in 2025 or 2026. No acquirer changed an open licence after a deal. promptfoo stays MIT under OpenAI, and Langfuse's core stays MIT under ClickHouse.[74] [168]

Most Eval Code Can Be Hosted for Others; Phoenix Cannot

What each licence lets a team do with the code, November 2026. A reading of licence files, not legal advice.

Project (licence)	Use internally	Change the code	Embed and redistribute	Host as a service for others
Inspect AI, lm-eval, promptfoo, PyRIT MIT	●	●	●	●
Harbor, DeepEval, Opik, MLflow, garak Apache-2.0	●	●	●	●
OpenEnv BSD-3-Clause	●	●	●	●
verifiers, tau2-bench, Giskard, Scenario MIT or Apache-2.0	●	●	●	●
Langfuse, Agenta MIT core + closed ee/	●	◐ core only	◐ core only	◐ license ee/ features
LangWatch Apache core + enterprise/	●	◐ core only	◐ core only	◐ SSO, audit logs, billing closed
Arize Phoenix server, phoenix-evals Elastic License 2.0	●	◐ within ELv2 terms	◐ client + OTel packages are Apache-2.0	○ no hosted or managed service
Kiln desktop app Fair-code (library MIT)	◐ read terms	◐ read terms	◐ read terms	◐ read terms before commercial use
LangSmith, Braintrust, Weave server, Modal Open SDK, closed platform	◐ SDK; back end is paid	◐ SDK only	◐ SDK only	○
MCP MIT → Apache-2.0	●	●	●	●
Daytona No licence reported	–	–	–	– check before building

● Allowed ◐ With limits ○ Not allowed – Unknown or not applicable

WHAT TO NOTICE

- Read the shaded column: Phoenix's Elastic License is the only open licence here that forbids hosting.

Figure 11. Permissive projects allow everything, including hosting for others. Open-core projects allow the core but license the enterprise parts. Phoenix's Elastic License forbids offering it as a hosted or managed service. This is a reading of licence files, not legal advice.

Source: project LICENSE files and READMEs (5 Nov 2026). [88] [90] [91] [153] [159] [166] [167]

Evals now sit inside bigger suites. Buyers should expect roadmaps to bend toward the parent platform. Several projects also moved home without a sale: Harbor, OpenEnv, Petri and Ragas changed GitHub organisations.

Venture Money Backs Most of the Remaining Independents

Thirteen open eval projects and companies that no acquirer owns, by type of backer, November 2026. One square is one project.

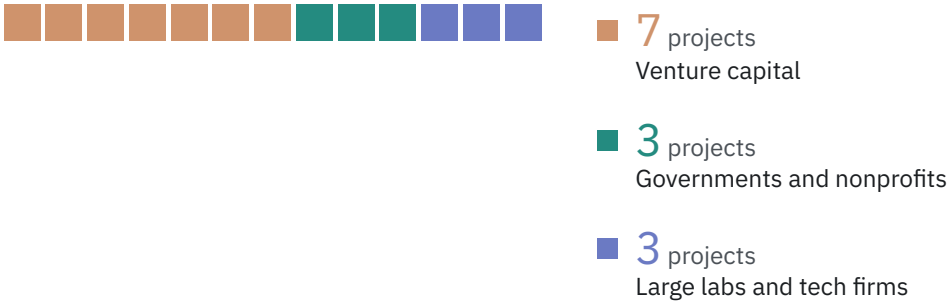


Figure 12. Governments and nonprofits: Inspect AI (UK AISI), inspect_evals (Generality Labs), Every Eval Ever (EvalEval Coalition). Large labs and tech firms: garak (NVIDIA), PyRIT (Microsoft), OpenEnv (Meta-PyTorch and committee). Venture capital: Confident AI, Comet, Braintrust, LangChain, Agenta, LangWatch, Giskard. Each backer brings its own risk: public budgets, lab priorities or the next funding round.

Source: project READMEs and funding announcements (5 Nov 2026). [21] [81] [118] [120] [106] [150]

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Deal table and licence models in full

Date	Target	Buyer	Effect on the open project
16 Jan 2026	Langfuse [168]	ClickHouse	Core stays MIT, cloud continues
3 Mar 2026	Helicone [169]	Mintlify	Hosted product in maintenance mode
9 Mar 2026 (now closed)	promptfoo [73]	OpenAI	Stays open source under MIT [74]
Mar 2026	Traceloop (OpenLLMetry) [170]	ServiceNow	OpenLLMetry stays open, joins AI Control Tower
22 May 2026 (close)	Galileo [171]	Cisco	Becomes Splunk Agent Observability
29 May 2026 (close)	Portkey [172]	Palo Alto Networks	Becomes the AI gateway of Prisma AIRS
1 Oct 2026 (close)	Arize (Phoenix) [173]	Dynatrace	Phoenix and AX continue, reported $915M [174] [175]

Table 11. 2026 deals that touched open eval projects.

Licence model	Projects	What you can do
Permissive (MIT, Apache-2.0, BSD)	Inspect, lm-evaluation-harness, Harbor, promptfoo, DeepEval, DeepTeam, Opik, MLflow, garak, PyRIT, verifiers, OpenEnv, tau2-bench, Giskard, Scenario	Use, change, embed and host as a service
Open core with closed `ee/` folder	Langfuse, Agenta, LangWatch	Use the MIT or Apache core freely, but license the enterprise parts
Source-available (Elastic License 2.0)	Phoenix server and `phoenix-evals`	Use internally, but do not offer it as a hosted service
Fair-code	Kiln desktop app	Read the terms before commercial use
Open SDK, closed platform	LangSmith, Braintrust, Weave server, Modal	Use the SDK, but the back end stays a paid product
Licence in transition	MCP, from MIT to Apache-2.0	Expect more permissive terms

Table 12. Licence models across the eval stack.

Guidance for hosted offers. A team that wants to host evals for others should prefer the permissive projects. It should avoid hosting Phoenix as a service. [88] It should keep Langfuse and LangWatch enterprise features out of any hosted offer without a licence. [166] [167]

Earlier and smaller deals. CoreWeave now owns W&B and hosts the Weave docs. [89] Check Point bought the Deepchecks team and IP in 2026. [180] Dynatrace paid about $815M of the $915M in cash and the rest in replacement equity. [173]

Standardise on the plumbing; results, judges and statistics are still open ground

The table sums up what a team can treat as settled today and what still moves.

The lower layers are safe to standardise on. Docker, OpenAI-compatible APIs, OpenTelemetry and MCP will likely stay.

The harness choice depends on the job. Inspect suits agentic and safety work, lm-evaluation-harness suits open weights, and Harbor suits container tasks.

The upper layers still lack standards. Result formats, judge validation and contract-grade statistics remain open. Lab-owned red-team tools also raise a neutrality question.

Standard today, still open

Area	Standard today	Still open
Model benchmarks	Inspect and lm-evaluation-harness	Funding for leaderboards and static benchmarks
Agent tasks	Harbor folder with Dockerfile and test script	Cost and speed of large container runs
Environment API	OpenEnv `reset`, `step`, `state`	Size and quality of shared hubs
Sandboxes	Docker images	Isolation standards and vendor choice
Tool access	MCP	Final licence and versioning
Trace transport	OpenTelemetry OTLP	None
Trace vocabulary	OpenInference in practice	OTel GenAI conventions still "Development"
Eval results on traces	`gen_ai.evaluation.result` event	Judge, rubric and interval metadata
Result exchange	Inspect `.eval` logs in practice	Every Eval Ever uptake
Judges	LLM judges in every framework	Human agreement data for agent transcripts
Statistics	Threshold gates and single-run intervals	Paired tests, non-inferiority and drift over time
Red team	promptfoo, garak, PyRIT	Neutrality of lab-owned tools

Table 13. Only trace transport has nothing left open. Every layer above the harness has at least one gap.

Source: this chapter, based on project repositories and docs (5 Nov 2026).

Sources for chapter 3

184 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] swebench downloads, pypistats. It gives the monthly PyPI download count for SWE-bench. Primary pypistats.org

[2] Inspect AI, GitHub. It gives stars, licence and release data. Primary github.com

[3] inspect-ai downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[4] inspect_evals, GitHub. It gives stars, licence and release data. Primary github.com

[5] inspect-evals downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[6] lm-evaluation-harness, GitHub. It gives stars, licence and release data. Primary github.com

[7] lm-eval downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[8] Harbor, GitHub API. It gives stars, licence and the move from laude-institute. Primary api.github.com

[9] harbor downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[10] SWE-bench, GitHub. It gives stars, licence and push data. Primary github.com

[11] OpenCompass, GitHub. It gives stars, licence and release data. Primary github.com

[12] lighteval, GitHub. It gives stars, licence and release data. Primary github.com

[13] lighteval downloads, pypistats. It gives a monthly count that looks too low. Primary pypistats.org

[14] NeMo Evaluator, GitHub. It gives stars, licence and release data. Primary github.com

[15] openbench, GitHub. It gives stars, licence and release data. Primary github.com

[16] HELM, GitHub. It gives stars, licence and last push. Primary github.com

[17] OpenAI Evals, GitHub. It gives stars and push data. Primary github.com

[18] simple-evals, GitHub. It gives stars and push data. Primary github.com

[19] BIG-bench, GitHub. It shows the archived repo and its last push. Primary github.com

[20] HAL harness, GitHub. It gives stars and push data. Primary github.com

[21] Inspect AI README, UK AISI. It describes the framework and its ready-made evals. Primary github.com

[22] Inspect docs folder, UK AISI. It covers tasks, scorers, agents, the agent bridge and MCP tools. Primary github.com

[23] Meridian Labs repos, GitHub search. It lists the Inspect add-ons and Petri projects. Primary github.com

[24] inspect_evals README. It names Generality Labs as maintainer and sets contributor rules. Primary github.com

[25] openbench README, Groq. It describes benchmarks built on Inspect. Primary github.com

[26] NeMo Evaluator README, NVIDIA. It lists interceptors, confidence intervals and Inspect export. Primary github.com

[27] Benchmarking Hub update, Epoch AI. It explains how the hub uses Inspect. Primary epoch.ai

[28] Eval Results, Hugging Face Hub docs. It defines a verified result as an Inspect run in HF Jobs. Primary huggingface.co

[29] Inspect metrics docs, UK AISI. It lists the error, interval and agreement metrics. Primary github.com

[30] lm-evaluation-harness README, EleutherAI. It covers YAML tasks, plugins, backends and named users. Primary github.com

[31] Harbor README. It describes agents, cloud providers and the Terminal-Bench 2.0 role. Primary github.com

[32] create-task skill, Harbor. It defines the task folder layout. Primary github.com

[33] Adapters folder, Harbor. It holds the 86 benchmark adapters. Primary github.com

[34] Terminal-Bench 1 README. It sends new users to Harbor. Primary github.com

[35] SWE-bench README. It covers the Docker harness, Modal runs and Multimodal v2. Primary github.com

[36] lighteval README, Hugging Face. It claims over 1,000 tasks. Primary github.com

[37] OpenCompass README. It lists the 2026 news, including AgentCompass. Primary github.com

[38] Capabilities Index package, Epoch AI. It describes the Bayesian item-response fit. Primary github.com

[39] HELM README, Stanford CRFM. It states the start of maintenance mode. Primary github.com

[40] Maintenance mode policy, HELM. It explains what the team still maintains. Primary crfm-helm.readthedocs.io

[41] simple-evals README, OpenAI. It announces the end of updates in July 2025. Primary github.com

[42] Evals README, OpenAI. It points users to the OpenAI Dashboard. Primary github.com

[43] HAL harness README, Princeton PLI. It states that the repo stays archived for reference. Primary github.com

[44] End of the Open LLM Leaderboard, Hugging Face. It announces the retirement on 13 March 2025. Primary huggingface.co

[45] Leaderboards docs, Hugging Face. It describes the Open LLM Leaderboard in the past tense. Primary huggingface.co

[46] promptfoo, GitHub. It gives stars, licence and release data. Primary github.com

[47] promptfoo downloads, npm. It gives the monthly npm download count. Primary api.npmjs.org

[48] DeepEval, GitHub. It gives stars, licence and push data. Primary github.com

[49] deepeval downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[50] Ragas, GitHub. It gives stars, licence and the last push. Primary github.com

[51] Giskard, GitHub. It gives stars, licence and release data. Primary github.com

[52] openevals, GitHub. It gives stars, licence and release data. Primary github.com

[53] agentevals, GitHub. It gives stars, licence and push data. Primary github.com

[54] autoevals, GitHub. It gives stars, licence and release data. Primary github.com

[55] autoevals downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[56] TruLens, GitHub. It gives stars, licence and release data. Primary github.com

[57] LangWatch Scenario, GitHub. It gives stars, licence and release data. Primary github.com

[58] Langfuse, GitHub. It gives stars, licence and release data. Primary github.com

[59] langfuse downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[60] MLflow, GitHub. It gives stars, licence and push data. Primary github.com

[61] mlflow downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[62] Opik, GitHub. It gives stars, licence and release data. Primary github.com

[63] opik downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org

[64] Arize Phoenix, GitHub. It gives stars, licence and release data. Primary github.com

[65] W&B Weave, GitHub. It gives stars, licence and release data. Primary github.com

[66] Evidently, GitHub. It gives stars, licence and the last push. Primary github.com

[67] Agenta, GitHub. It gives stars and release data. Primary github.com

[68] Kiln, GitHub. It gives stars and push data. Primary github.com

[69] langsmith-sdk, GitHub. It records the archive date and the two new SDK repos. Primary github.com

[70] HTTP provider docs, promptfoo. It describes calls to any HTTP endpoint. Primary github.com

[71] Tracing docs, promptfoo. It describes the OTLP receiver and trajectory checks. Primary github.com

[72] GitHub Action docs, promptfoo. It describes the before-and-after comparison. Primary github.com

[73] Joining OpenAI, promptfoo. It announces the deal and the user claims. Vendor promptfoo.dev

[74] promptfoo README. It states that Promptfoo now belongs to OpenAI and stays MIT-licensed. Primary github.com

[75] CI/CD docs, DeepEval. It describes unit tests in CI. Primary github.com

[76] Ragas commits, GitHub. It shows the last commit on 24 February 2026. Primary github.com

[77] OSS README, Giskard. It describes the v3 rewrite and the end of v2. Primary github.com

[78] openevals README, LangChain. It describes the ready-made judges. Primary github.com

[79] agentevals README, LangChain. It describes trajectory judges and match modes. Primary github.com

[80] autoevals repo, Braintrust. It holds the scorer library. Primary github.com

[81] Braintrust Series B, SiliconANGLE. It reports the $80M round, as a secondary source. Secondary siliconangle.com

[82] TruLens README. It describes OpenTelemetry tracing and feedback functions. Primary github.com

[83] Scenario README, LangWatch. It describes scenarios, simulated users and judges. Primary github.com
[84] Self-hosting docs, Langfuse. It lists PostgreSQL, Redis, ClickHouse and S3. Primary langfuse.com
[85] llms.txt, Langfuse. It lists the OpenTelemetry endpoint and the docs. Primary langfuse.com
[86] Comparing evaluation runs, MLflow. It describes the paired tests between two runs. Primary github.com
[87] Self-host architecture, Opik. It lists ClickHouse, MySQL, Redis and MinIO. Primary github.com
[88] LICENSE, Arize Phoenix. It sets the Elastic License 2.0 terms. Primary github.com
[89] Weave self-managed docs, CoreWeave. It describes Weave on ClickHouse under CoreWeave. Primary docs.coreweave.com
[90] LICENSE, Agenta. It puts the ee/ folder under separate terms. Primary github.com
[91] Kiln README. It describes the MIT library and the fair-code app. Primary github.com
[92] CI/CD docs, promptfoo. It describes exit-code gates. Primary github.com
[93] Experiments in CI/CD, Langfuse. It describes regression errors in CI. Primary langfuse.com
[94] OpenEnv, GitHub API. It gives stars, licence and the move from meta-pytorch. Primary api.github.com
[95] openenv downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[96] verifiers, GitHub. It gives stars, licence and release data. Primary github.com
[97] verifiers downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[98] community-environments, GitHub. It gives stars, licence and push data. Primary github.com
[99] tau2-bench, GitHub. It gives stars, licence and release data. Primary github.com
[100] AppWorld, GitHub. It gives stars, licence and release data. Primary github.com
[101] appworld downloads, pypistats. It gives a monthly count that likely includes CI pulls. Primary pypistats.org
[102] BrowserGym, GitHub. It gives stars and release data. Primary github.com
[103] AgentLab, GitHub. It gives stars and release data. Primary github.com
[104] OSWorld, GitHub. It gives stars, licence and the last release. Primary github.com
[105] inspect_petri, GitHub API. It gives stars, licence and the move from safety-research. Primary api.github.com
[106] OpenEnv README. It describes the API, integrations, MCP use and governance. Primary github.com
[107] verifiers README, Prime Intellect. It describes the library and its links to the Hub. Primary github.com
[108] verifiers overview, Prime Intellect. It defines tasksets, harnesses, agents and toolsets. Primary github.com
[109] verifiers Harbor docs, Prime Intellect. It describes loading Harbor tasks. Primary github.com
[110] Post on X, Prime Intellect. It claims over 400 crowdsourced environments in October 2025. Single source threadreaderapp.com
[111] tau2-bench README, Sierra. It describes version 2.0, languages, voice and task counts. Primary github.com
[112] AppWorld README, Stony Brook NLP. It describes the app world and the award. Primary github.com
[113] BrowserGym README, ServiceNow. It lists the bundled web benchmarks. Primary github.com
[114] AgentLab README, ServiceNow. It describes parallel experiments with Ray. Primary github.com
[115] OSWorld README, XLANG Lab. It describes OSWorld-Verified and the VM options. Primary github.com
[116] ControlArena repository. It describes the AI control library from UK AISI and Redwood. Primary github.com
[117] Petri README, Meridian Labs. It describes the auditing agent and the v3 API. Primary github.com
[118] garak, GitHub. It gives stars, licence and release data. Primary github.com
[119] garak downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[120] PyRIT, GitHub. It gives stars, licence and release data. Primary github.com
[121] pyrit downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[122] DeepTeam, GitHub. It gives stars, licence and release data. Primary github.com
[123] deepteam downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[124] Red-team plugins folder, promptfoo. It holds the 72 plugin docs. Primary github.com
[125] Red-team configuration, promptfoo. It describes remote and local attack generation. Primary github.com
[126] garak README, NVIDIA. It describes probes, detectors, harnesses and the REST generator. Primary github.com

[127] garak probes folder, NVIDIA. It holds the 44 probe modules. Primary github.com
[128] PyRIT README, Microsoft. It describes the scanner, the GUI and the targets. Primary github.com
[129] DeepTeam README, Confident AI. It lists the vulnerabilities and local scoring. Primary github.com
[130] AgentDojo, GitHub. It gives stars, licence and push data. Primary github.com
[131] agent-scan README, Snyk. It describes the scan and the token requirement. Primary github.com
[132] PINT benchmark, GitHub. It shows the archived repo. Primary github.com
[133] Project Moonshot repository. It shows the beta status, version and licence. Primary github.com
[134] OWASP AI Testing Guide. It gives a method for testing the trustworthiness of AI systems. Primary owasp.org
[135] Top 10 for Agentic Applications for 2026, OWASP. It lists the main security risks of agentic applications. Primary genai.owasp.org
[136] OTel GenAI conventions, GitHub API. It gives the creation date, stars and licence. Primary api.github.com
[137] OpenInference, GitHub. It gives stars and licence. Primary github.com
[138] OpenInference conventions downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[139] OpenLLMetry, GitHub. It gives stars, licence and release data. Primary github.com
[140] traceloop-sdk downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[141] Core GenAI README, OpenTelemetry. It states that the GenAI conventions moved to a new repo. Primary github.com
[142] GenAI conventions overview, OpenTelemetry. It lists the scope and the status. Primary github.com
[143] Semantic conventions releases, OpenTelemetry. It lists v1.45.0. Primary github.com
[144] GenAI agent spans, OpenTelemetry. It defines the agent and workflow spans. Primary github.com
[145] GenAI events, OpenTelemetry. It defines the evaluation result event. Primary github.com
[146] Semantic conventions, OpenInference. It lists the span kinds. Primary github.com
[147] OpenInference README. It lists the instrumentations and the OpenLLMetry bridge. Primary github.com
[148] Datasets docs, Langfuse. It describes versioning on every change. Primary langfuse.com
[149] Inspect eval logs docs, UK AISI. It describes the .eval format and storage options. Primary github.com
[150] Every Eval Ever README, EvalEval. It describes the schema, the database and the converters. Primary github.com
[151] every-eval-ever downloads, pypistats. It gives the monthly PyPI download count. Primary pypistats.org
[152] Schema folder, MCP. It lists the dated spec versions. Primary github.com
[153] LICENSE, MCP. It describes the move from MIT to Apache-2.0. Primary github.com
[154] MCP conventions, OpenTelemetry. It defines spans for MCP calls. Primary github.com
[155] Inspect sandboxing docs, UK AISI. It lists the built-in and external sandboxes. Primary github.com
[156] E2B, GitHub. It gives stars, licence and push data. Primary github.com
[157] gVisor, GitHub. It gives stars and licence. Primary github.com
[158] Modal client, GitHub. It gives stars and licence for the client SDK. Primary github.com
[159] Daytona, GitHub. It gives stars and the last push but no licence. Primary github.com
[160] vLLM, GitHub. It gives stars, licence and push data. Primary github.com
[161] Granite Guardian 4.1 8B model card, IBM. It gives criteria, scores and the licence. Primary huggingface.co
[162] Qwen3Guard models, Hugging Face API. It gives sizes and download counts. Primary huggingface.co
[163] Llama Guard 4 model card, Meta. It describes the taxonomy and the scores. Primary github.com
[164] Judge ensembling paper, Composo. It measures the gain from criteria and ensembles. Primary arxiv.org
[165] Inspect early stopping docs, UK AISI. It describes early stopping and optional stopping. Primary github.com
[166] LICENSE, Langfuse. It lists the ee/ folders outside the MIT licence. Primary github.com
[167] Enterprise LICENSE, LangWatch. It covers the closed enterprise features. Primary github.com
[168] Langfuse acquisition, ClickHouse. It announces the deal and the licence pledge. Vendor clickhouse.com
[169] Helicone acquisition, Mintlify. It announces the deal and the maintenance mode. Vendor mintlify.com
[170] Joining ServiceNow, Traceloop. It announces the deal and the open-source pledge. Vendor traceloop.com

[171] Galileo acquisition, Cisco. It confirms the close. Vendor cisco.com

[172] Portkey acquisition, Palo Alto Networks. It confirms the close. Vendor paloaltonetworks.com

[173] Arize acquisition, Dynatrace. It announces the deal and the Phoenix pledge. Vendor dynatrace.com

[174] Dynatrace and Arize, ITPro. It reports the $915M price. Secondary itpro.com

[175] Dynatrace completes Arize deal, engineering.com. It reports the close on 1 October 2026. Secondary engineering.com

[176] Invariant Labs acquisition, Snyk. It announces the deal. Vendor snyk.io

[177] Lakera acquisition, Check Point. It announces the deal. Vendor checkpoint.com

[178] Zscaler and SPLX, Help Net Security. It reports the deal. Secondary helpnetsecurity.com

[179] Humanloop team joins Anthropic, Data Phoenix. It reports the team move. Secondary dataphoenix.info

[180] Check Point and Deepchecks, Security Boulevard. It reports the purchase of the Deepchecks team and IP. Secondary securityboulevard.com

[181] TrojAI acquisition, A10 Networks. It announces the deal of 15 June 2026. Vendor businesswire.com

[182] Beacon Software and Haize Labs, Osler. It describes the deal and the new research group. Secondary osler.com

[183] Traceloop price, Calcalist. It reports an unconfirmed price range. Single source calcalistech.com

[184] Deepchecks price, Dealroom citing Calcalist. It estimates the price at up to $20M. Estimate dealroom.co

04

CHAPTER 4 · MARKET

Labs fund most of the evals economy, and buyer-paid testing stays the smallest part

Evals are a large lab-funded supply chain plus a small, fast-consolidating tools market, and every business model in it carries a conflict of interest.

$5–10B lab human-data spend in 2026 (estimate)

28 eval and AI-security deals since Aug 2024

$3.1B Arena valuation, Oct 2026

$915M Dynatrace price for Arize

18% → 60% teams on eval platforms by 2028 (Gartner)

5 November 2026 · Read online with interactive charts: evals.study/market/

Key findings

- **Lab money dominates.** Frontier labs fund expert data, RL environments, leaderboards and safety tests. One forecast puts top-five lab human-data spend at $5–10B in 2026 (estimate). [1]
- **Builder tools are small and consolidating.** Only LangChain ($1.25B, Oct 2025) and Braintrust ($800M reported, Feb 2026) remain as large independents. [17] [18]
- **Tracing is now a free feature.** Datadog, AWS, Microsoft, Google and Snowflake bundle tracing and judge-based evals. Datadog charges no separate fee for evaluations. [62]
- **Security vendors bought the red-teamers.** At least 16 deals since August 2024 moved red-teaming into CISO platforms, at filed prices from $40.6M to $634.5M. [71] [73] [68]
- **Leaderboards became businesses.** Arena reached a $3.1B valuation and over $100M of annualised revenue in October 2026. Most of it likely comes from the labs it ranks. [3]
- **Gartner now names the category.** Its February 2026 Market Guide expects adoption to rise from 18% of software teams in 2025 to 60% by 2028. [170]
- **Nobody publishes a trusted dollar size for evals.** Report mills put LLM observability near $2.7B in 2026. Visible vendor revenue suggests a few hundred million at most (our estimate). [175]

- **Consolidation sped up in 2026.** Our timeline counts 28 deals and 7 shutdowns or pivots from August 2024 to November 2026. Four builder platforms sold in 2026 alone.
- **Every business model has a conflict.** Labs pay the boards that rank them, vendors pay their certifiers, and builders grade their own work. [117] [120]

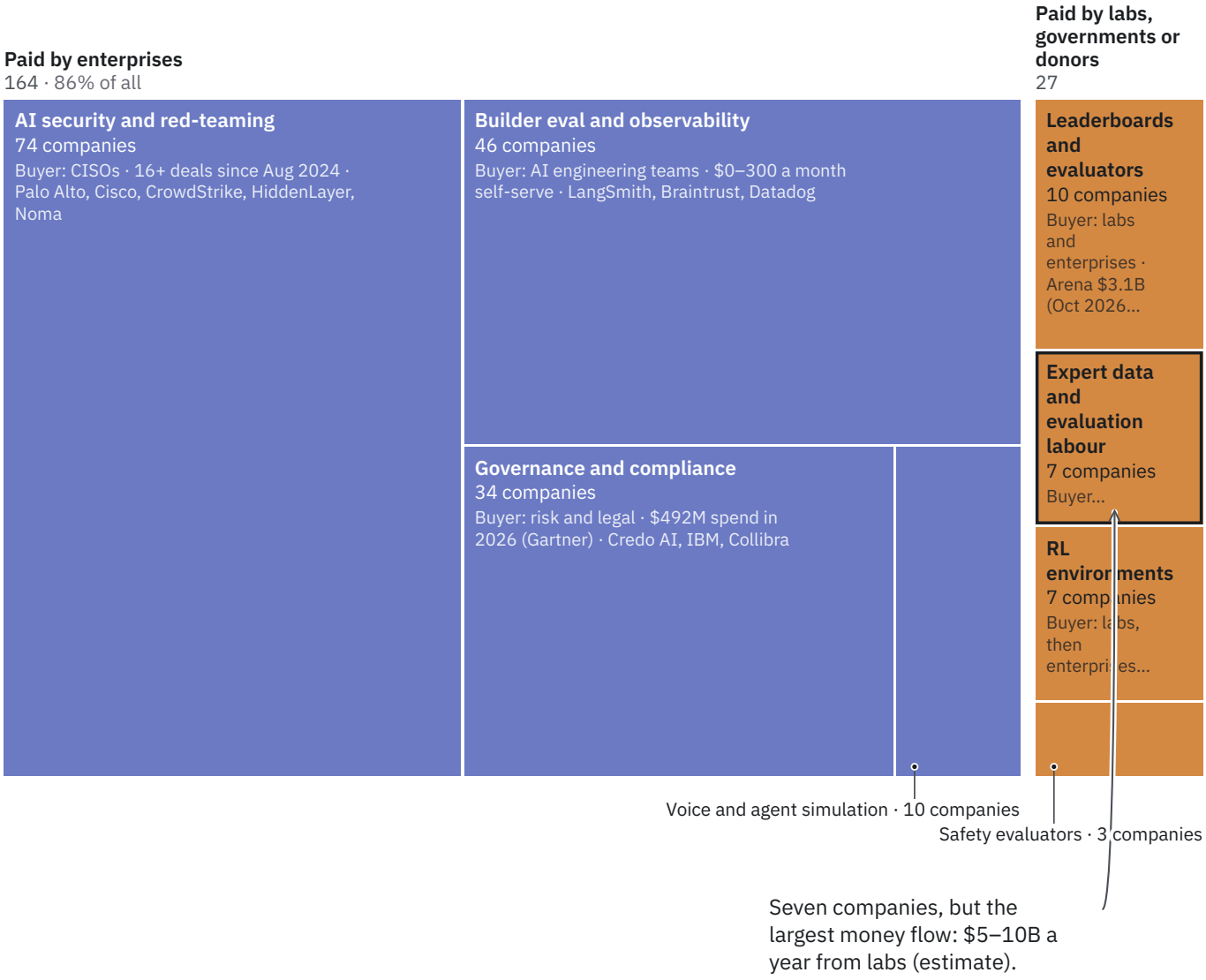
"Evals" covers eight markets that share one idea but differ in who pays

Builders pay for tools, security teams pay for red-teaming, and frontier labs pay for data and tests. Each segment has its own buyer, product and price logic.

We split the market into eight segments. Builder tools and security sell to enterprises. Expert data, RL environments and leaderboards sell mostly to frontier labs. Safety evaluators live on grants, lab contracts and, now, government tenders.

Enterprises Pay Most Eval Companies; Labs Pay for the Biggest Ones

Companies we track in each of the eight segments, grouped by who mainly pays, 5 November 2026. Area is the number of companies; each cell names the buyer, one telling number and the leaders.



Explore the directory →

Figure 1. Area counts companies, not money: the lab-paid segments hold few companies but most of the money (next figure and next section). The cells cover 191 of the 256 companies in our directory. The other 65 sit in segments this chapter does not size: runtime control and guardrails (39), cloud platform features (17), insurance and certification (7) and institutions (2). The directory counts expert data and RL environments together; the 7/7 split is ours. The segments overlap at the edges: Patronus moved from builder tools to RL environments, and Scale works in leaderboards, expert data and RL environments.

Source: Ascending Labs company directory (5 Nov 2026), segment calls ours; segment figures from company announcements, pricing pages and press. [1] [3] [4] [9] [71] [103] [112]

The word "evals" hides two economies. Labs buy evaluation inputs at scale: experts, graded tasks and pre-release tests. Enterprises buy tooling to check their own apps. The two rarely share buyers, prices or vendors.

Lab Money Dwarfs What Every Other Segment Takes In

Rough 2026 money flowing into each segment, where a published figure exists.
Square area is proportional to dollars.

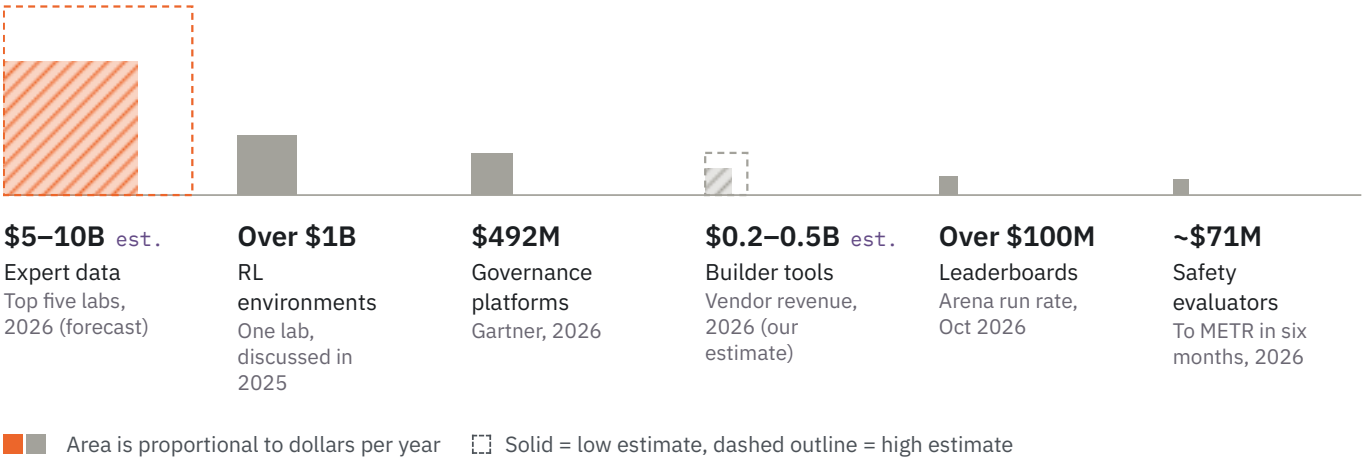


Figure 2. Figures mix kinds and years: spend, revenue run rates and funding, so compare sizes only roughly. AI security and voice simulation have no published total and are not shown. The expert-data figure is a forecast; builder tools' 'few hundred million' is our estimate, drawn as $0.2–0.5B. The RL-environment figure is what one lab discussed spending in 2025.

Source: FutureSearch (estimate);[1] TechCrunch citing The Information;[2] Gartner via secondary;[9] Arena;[3] METR;[4] our estimate.

GO DEEPER

The eight segments in full

Segment	Main buyer	What they buy	Typical price logic	Leaders (Nov 2026)
1 Builder eval and observability	AI engineering teams	Tracing, offline and online evals, judges, datasets	Usage tiers, $0–300 a month self-serve, custom enterprise	LangSmith, Braintrust, Datadog, Arize (Dynatrace), Galileo (Splunk)
2 AI security and red-teaming	CISOs	Attack testing, guardrails, runtime policy	Enterprise licences, mostly unpublished	Palo Alto, Cisco, CrowdStrike, Check Point, HiddenLayer, Noma
3 Governance and compliance	Risk, compliance, legal	Inventory, policy, evidence, test modules	Enterprise licences	Credo AI, IBM, Collibra, ServiceNow
4 Voice and agent simulation	Contact-centre and agent teams	Simulated calls and users, regression tests	Per minute, per call, or monthly tiers	Coval, Cyara, Hamming, Cekura
5 Leaderboards and independent evaluators	Labs and enterprises	Rankings, pre-release tests, private benchmarks	Lab contracts, enterprise subscriptions	Arena, Artificial Analysis, Vals, Scale Labs, Epoch, HAL
6 Expert data and evaluation labour	Frontier labs	Expert raters, graded tasks, eval sets	Hourly expert rates plus margin	Mercor, Surge, Scale, Handshake, micro1, Snorkel
7 RL environments	Labs, then enterprises	Graded tasks, app clones, hosted RL stacks	Per task, per clone, quarterly contracts	Mechanize, Prime Intellect, Fleet, Halluminate
8 Safety evaluators	Labs, governments, philanthropy	Dangerous-capability tests, monitoring	Grants, lab contracts	METR, Apollo, Irregular, Gray Swan, Goodfire

Table 1. The eight segments used in this chapter.

Labs pay suppliers billions, while enterprises pay tool vendors millions

The money flows show two economies. The largest flows bypass enterprise buyers completely, and the party under test often pays the tester.

Lab spending on expert data dwarfs every other flow. No lab discloses its human-data spending. One forecast puts the top five frontier developers at $5–10B in 2026.[1] The expert-data vendors' summed gross run rates exceed $6B, which fits that range.

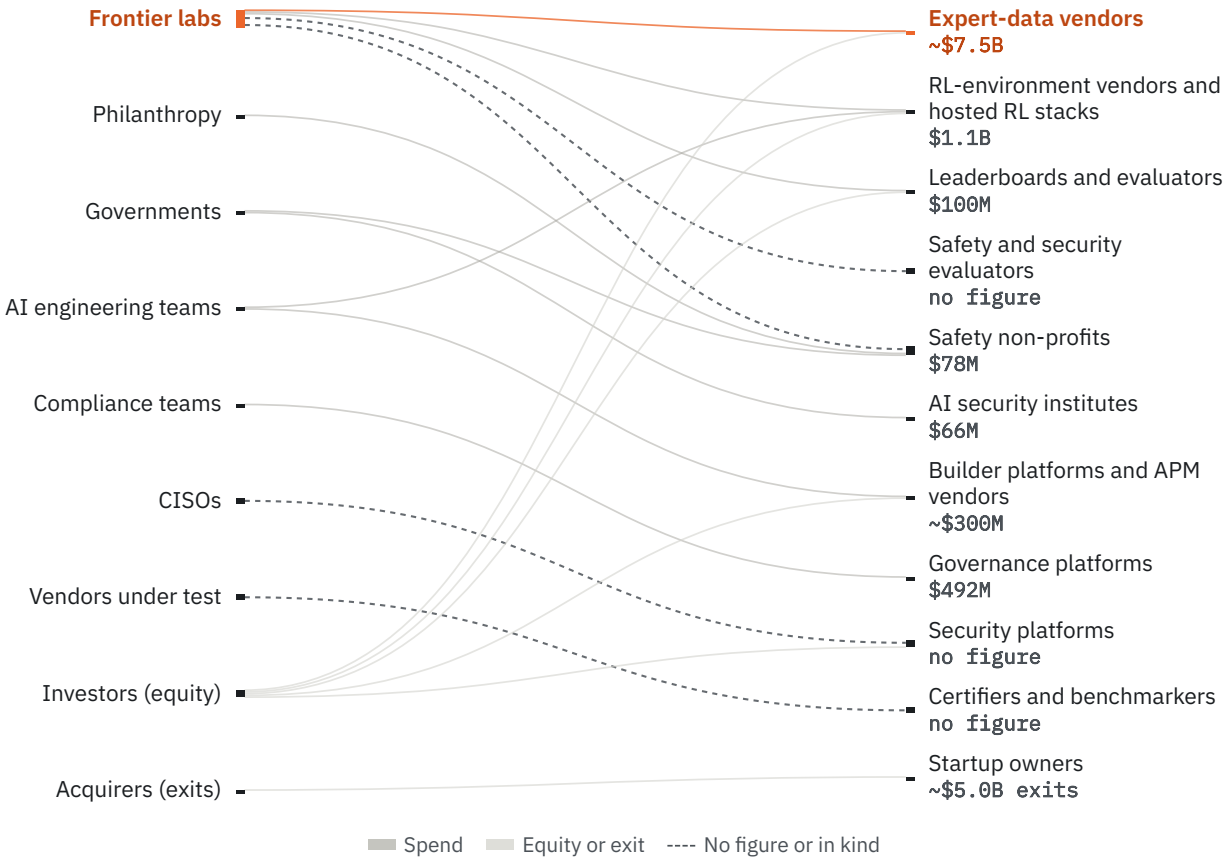
$5–10B

Estimated 2026 spending on human expert data by the top five frontier labs. No lab discloses the figure.

Source: FutureSearch forecast (estimate), consistent with vendor run rates above $6B.[1] [12] [125] [127]

Labs Pay for Most of the Evals Supply Chain

Who pays whom in evals, with rough 2026 sizes. Governments and philanthropy fund the independent testers.



1 **Start with the labs.** The top five frontier labs spend an estimated $5–10B a year on expert data. The same experts write eval sets and training data. [1]

2 **Labs also buy environments, rankings and tests.** Anthropic leaders discussed spending over $1B on RL environments in one year. Arena's annualised revenue passed $100M, likely mostly from labs. [2] [3]

3 **Philanthropy and governments fund the independent testers.** METR raised about $71M in six months and refuses lab money. The UK spends about £66m a year on its AI Security Institute. [4] [19]

4 **The EU now pays safety non-profits too.** Its AI Office tender, awarded in December 2025, totals €7.37M across six lots. [6]

5 **Enterprise builders pay far less.** AI engineering teams pay builder platforms a few hundred million dollars in total, by our estimate. Prime Intellect's hosted RL stack runs at $100M a year. [7]

6 **Compliance and security buyers sit beside them.** Gartner puts AI governance spending at $492M in 2026. Nobody publishes a total for red-teaming inside CISO budgets. [9] [8]

7 **Investors and acquirers move the most visible money.** These are equity and exits, not purchases. Rounds for Mercor and Snorkel alone total $700M. [12] [13]

8 **The picture is lopsided.** The party under test often pays the tester, and the largest flows never touch an enterprise buyer.

Figure 3. Amounts mix kinds and years: spend, revenue run rates and funding rounds. Widths treat €, £ and $ as equal units, so compare sizes only roughly. Dashed lines mark known flows with no published figure. Investor and acquirer flows are equity and exits, not purchases. Estimates are marked.

Source: FutureSearch; [1] TechCrunch citing The Information; [2] Arena; [3] METR; [4] ProPublica Form 990; [5] TED notice 864574-2025; [6] TechCrunch; [7] Gartner via secondary; [8] [9] UK AISI; [19] funding announcements. [10] [12] [13] [14] [15] [16] [17] [18]

Two patterns stand out. First, the party under test often pays the tester. Second, the largest flows bypass enterprise buyers completely. Investors and acquirers move large sums too, but those buy equity, not evaluations.

GO DEEPER

Every money flow, with size and basis

Payer	Receiver	What the money buys	Rough size (2026)	Basis
Frontier labs	Expert-data vendors	Expert ratings, graded tasks, eval sets	$5–10B (estimate)	Vendor run rates and one forecast [1]
Frontier labs	RL-environment vendors	Tasks, app clones, talent deals	Over $1B (Anthropic alone, discussed in 2025)	Paywalled report via TechCrunch [2]
Frontier labs	Arena and similar boards	Pre-release tests, preference data	Over $100M (Arena run rate)	Company figure [3]
Frontier labs	Safety and security evaluators	Pre-release cyber and misuse tests	No figure found	Funding rounds only
Frontier labs	Safety non-profits	Free tokens and model access, in kind	No figure found	METR policy [4]
Philanthropy	METR, Epoch, FAR.AI, Redwood, SecureBio, Transluce	Independent research and tests	About $71M to METR in six months; FAR.AI $24.3M revenue (2024)	Company figure and Form 990 [4] [5]
Governments	Safety non-profits, consultancies, AI security institutes	Funding and tests	€7.37M EU AI Office tender (Dec 2025); UK AISI funds METR; UK AISI about £66m a year	TED award notice; company figures [6] [4] [19]
AI engineering teams	Builder platforms and APM vendors	Tracing, evals, judges	A few hundred million (our estimate)	Disclosed ARR fragments
AI engineering teams	Hosted RL stacks	Compute, environments, evals	$100M (Prime Intellect run rate)	Press report [7]
CISOs	Security platforms	Red-teaming, guardrails, runtime policy	No total found; Gartner's $51.3B "AI cybersecurity" covers far more	Secondary report of Gartner [8]
Compliance teams	Governance platforms	Policy, inventory, evidence	$492M	Gartner via secondary [9]

Payer	Receiver	What the money buys	Rough size (2026)	Basis
Vendors under test	Certifiers and benchmarkers	Reports, seals, insurance	Small; Vals and AIUC each raised $40M	Company and press figures [10] [11]
Investors	Vendors, as equity	Growth capital, not purchases	$700M Mercor and Snorkel; $390M Arena and Vals; $225M HiddenLayer and Zenity; $205M LangChain and Braintrust	Rounds [12] [13] [14] [10] [15] [16] [17] [18]
Acquirers	Startup owners	Exits	About $5B since 2024, excluding Meta–Scale and Google–Mechanize (our sum)	Filed and reported prices

Table 2. Who pays whom, with the basis for each size.

Builder tools are small, and most of the large ones have been sold

This segment sells tools to the teams that build AI apps and agents. The tools trace calls, run test sets, score outputs with judges and alert on drops.

Only two large independents remain. IVP led LangChain's $125M Series B at $1.25B in October 2025. [17] Four sources put LangSmith-driven ARR at $12–16M in mid-2025. [20] ICONIQ led Braintrust's $80M Series B in February 2026, at a reported $800M. [18] Notion and Stripe use Braintrust. [22]

Prices run far ahead of revenue. LangChain's $1.25B valuation is 80 to 100 times its mid-2025 ARR of $12–16M, and Dynatrace paid about 23 times Arize's ARR of roughly $40M (our estimates; Arize's ARR is implied by Dynatrace's growth guidance). [17] [20] [41] [58] Braintrust's valuation rose about fivefold in 16 months, from about $150M at its Series A to a reported $800M. [18] Datadog had over 1,000 LLM Observability customers at Q4 2025, per one weak summary. [50]

Five well-known independents left the pool in 2025 and 2026. CoreWeave bought Weights & Biases for a reported $1.7B, closing on 5 May 2025. [35] [36] ClickHouse bought Langfuse on 16 January 2026. [37] Cisco closed Galileo on 22 May 2026. [57] Dynatrace closed Arize for $915M on 1 October 2026. [42] CrowdStrike agreed to buy Fiddler on 3 November 2026. [45]

Five of the Seven Large Builder Platforms Were Sold

Where nine well-known builder-tool companies of 2024 stood in November 2026.
One dot per company.

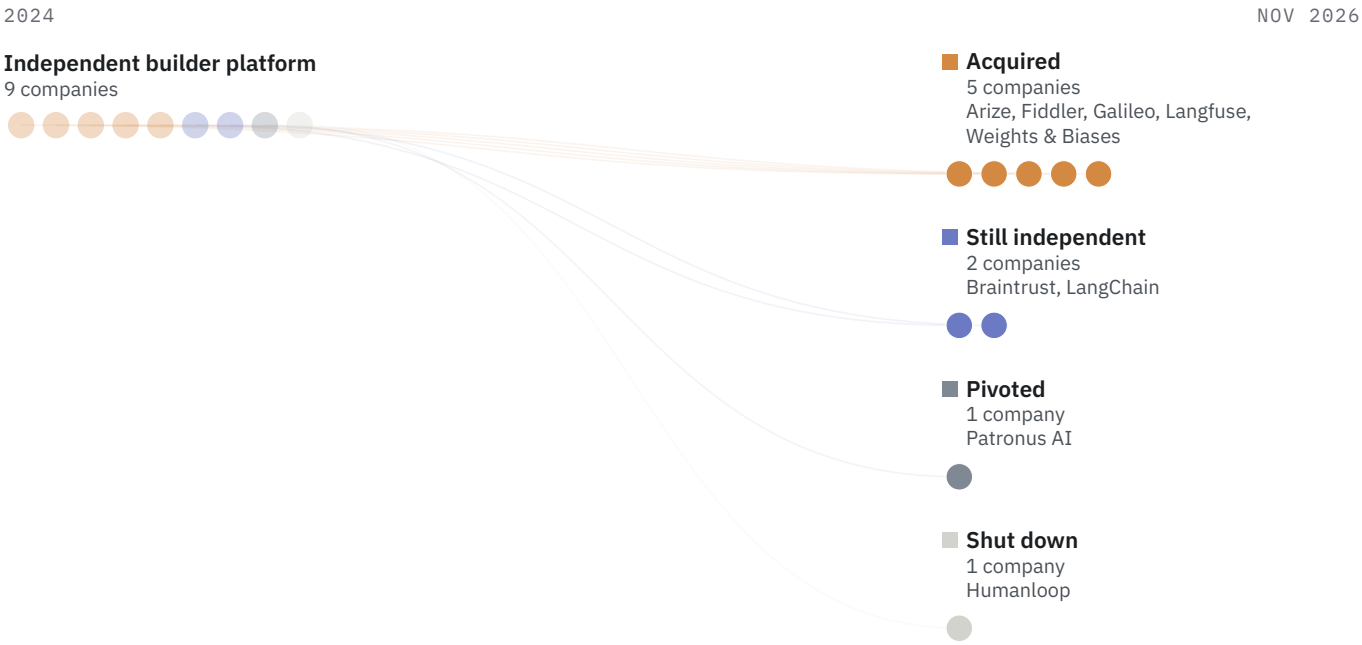


Figure 4. 'Acquired' includes CrowdStrike's agreed purchase of Fiddler (3 Nov 2026), expected to close in its Q4 FY27. Humanloop's team joined Anthropic and its platform will sunset. Patronus AI retired its eval products and now sells simulation environments for agent training.

Source: buyer and company announcements; press reports. [17] [18] [35] [36] [37] [42] [45] [46] [47] [48] [49] [57]

One leader pivoted and one shut down. Patronus AI raised a $50M Series B in June 2026 and now sells "Digital World Models" for agent training. [46] Its old evaluation products "are all retired". [47] Anthropic hired the Humanloop team in August 2025, and Humanloop will "sunset" its platform. [48] [49]

The incumbents give tracing away. Datadog offers LLM Observability free up to 40,000 spans and states "no separate product fee" for evaluations. [62] Its spans "nearly tripled quarter-over-quarter" in Q1 2026. [63] Every large APM vendor now sells tracing and judge-based scoring.

Tracing has no moat. Citi Ventures calls the twin threats "Death from Below" and "Death from Above": open source from below, APM bundles from above. [67] A newer wave focuses on agents in production instead. Raindrop has raised $50M, and Judgment Labs $32M. [24] [25]

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Builder company table and more detail

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
LangChain (LangSmith)	Builder platform	Open-source framework, LangSmith tracing and evals	AI teams; seats plus traces	$125M Series B at $1.25B [17]	ARR $12–16M in mid-2025 (four sources) [20]

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Braintrust	Builder platform	Evals, tracing, scoring, playgrounds	AI teams; GB and scores	$80M Series B, $800M reported; about $121M raised [18] [21]	Notion and Stripe as customers (Feb 2026) [22]
Raindrop	Agent monitoring	Production monitoring for agent failures	AI product teams	$15M seed; Series A, $50M total [23] [24]	Series A led by CRV (Sep 2026)
Judgment Labs	Agent monitoring	Trajectory monitoring, open-source Judgeval	AI teams	$32M seed and Series A [25]	Lightspeed lead (May 2026)
HoneyHive	Builder platform	Agent observability and evals	Enterprises, incl. Commonwealth Bank	$7.4M seed [26]	Self-host enterprise tier [27]
Confident AI	Builder platform	DeepEval open source, hosted platform	AI teams	Not verified	Team plan $2,000 a month [28]
Openlayer	Builder platform	Tests, monitoring, guardrails	Enterprises	$14.5M Series A [29]	Named in Gartner guide (2026) [30]
Scorecard	Builder platform	Agent eval runs	AI teams	$3.75M seed [31]	Growth tier $299 a month [32]
Comet Opik	Builder platform	Open-source tracing and evals	AI teams	Not verified	Pro $19 a month [33]
Galtea	Builder platform	Tests and monitoring for regulated firms	Spanish banks, insurers, telcos	Not verified	Sabadell Seguros case study [34]
W&B Weave (CoreWeave)	Acquired	Tracing and evals inside W&B	ML teams	$1.7B purchase (reported) [35]	Closed 5 May 2025 [36]
Langfuse (ClickHouse)	Acquired	MIT-licensed tracing and evals	AI teams; self-host free	Price undisclosed [37]	Joined ClickHouse (Jan 2026) [38]
Galileo (Cisco)	Acquired	Evals, small judge models	Enterprises	About $68M raised before sale [39]	Sells as Splunk Agent Observability [40]
Arize (Dynatrace)	Acquired	Arize AX, Phoenix open source	Enterprises	$915M purchase [41]	Closed 1 Oct 2026 [42]
Fiddler (CrowdStrike)	Acquired	Agent observability, guardrails	Enterprises	$100M raised; about $400M price (one source) [43] [44]	Agreed 3 Nov 2026; close expected in CrowdStrike's Q4 FY27 [45]
Patronus AI	Pivoted	Now "Digital World Models" for agent training	Labs and agent builders	$50M Series B, $70M total [46]	Old eval products retired [47]
Humanloop	Shut down	Prompt management and evals	AI teams	Team to Anthropic [48]	Platform sunset [49]
Datadog LLM Observability	APM incumbent	Tracing, managed judges, annotation	Existing Datadog customers	Public company	Over 1,000 customers at Q4 2025 (weak) [50]

Table 3. Builder eval and observability companies, November 2026.

LangChain. CapitalG, ServiceNow, Workday, Cisco, Datadog and Databricks joined the Series B.[17] One article cites a Forge Global listing at $3.01B in September 2026; LangChain announced no such round, so the figure is unconfirmed.[51] LangSmith Plus costs $39 per seat a month, with US or EU cloud and enterprise self-hosting.[52]

Braintrust. Braintrust stated no valuation itself. Total funding is about $121M.[21] Pricing moves from free to $249 a month for Pro; it meters storage and scores and allows unlimited users.[53]

Raindrop. Lightspeed led the $15M seed in December 2025.[23] Reports disagree on the Series A size: $35M or $22.6M.[54] Bessemer named Judgment among "novel evaluation and feedback frameworks".[55]

Smaller tools mostly hold under $15M. Confident AI sells DeepEval-based plans from $200 to $2,000 a month.[28] Galtea in Barcelona sells to Sabadell Zurich and Telefónica.[34]

Exits in detail. Weave pricing now sits under CoreWeave Forge from $60 a month.[56] ClickHouse raised $400M at a $15B valuation on the day it bought Langfuse.[37] Galileo sells as Splunk Agent Observability from $100 a month per 1.2 million spans.[40] About $815M of the Arize price is cash; the rest is replacement equity.[41] Fiddler will become "Falcon Observe"; CrowdStrike pays mostly in cash. Fiddler had raised $100M, including a $30M Series C in January 2026.[43] [45]

Smaller exits. Helicone joined Mintlify in March 2026.[59] Databricks bought Quotient AI for agent evaluation.[60] ServiceNow bought Traceloop, per one weak source.[61]

Incumbents. Datadog charges $160 a month for 100,000 spans.[62] It bought Adaptive ML in 2026[64] and holds stakes in LangChain, Arize and Patronus.[17] [65] [46] New Relic plans an "AI Evaluation" preview for November 2026, per one secondary source.[66]

Security vendors bought the red-teamers, and compliance buyers pay for evidence

Red-teaming is an eval: it tests whether an agent fails under attack. Governance tools mostly consume eval results rather than produce them.

Between August 2024 and November 2026, security vendors bought most independent red-team startups. One public tracker counts 30 agent-security deals since 2024, 14 of them in 2026. It says buyers acquired 22 of the 61 vendors on its map.[87] Filed prices often sit below headlines. F5 announced CalypsoAI at $180M, but its filing shows $145.2M.[72]

The promptfoo deal matters most for evals. Promptfoo had raised $23M and claimed use by more than 25% of the Fortune 500.[69] OpenAI folds it into its Frontier platform for red-teaming and compliance monitoring. The code stays open source under MIT.[70]

Independent security firms still raise large rounds. Zenity raised $125M in August 2026, and HiddenLayer $100M in September 2026 with ARR up more than tenfold.[16] [15] Most vendors here do not publish prices.

Independent AI-Security Firms Still Raise Rounds of $30M to $125M

Latest round of each independent AI-security firm, in $M, by stage. One dot per firm.

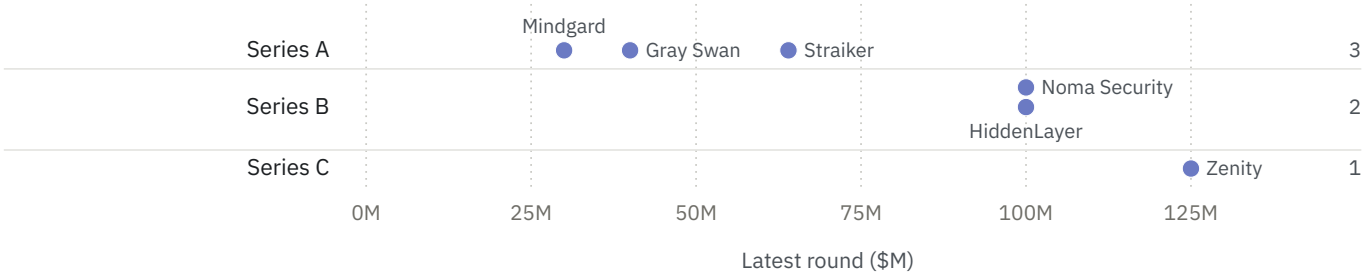


Figure 5. Red-teaming now sells inside CISO budgets, bundled with runtime guardrails. Gray Swan also sells pre-release tests to the major labs. HiddenLayer reported ARR up more than tenfold at its Series B.

Source: SecurityWeek; [16] [75] [79] Pulse 2.0; [15] [77] FinTech Global. [76]

Compliance buyers pay for evidence, not test engines. Gartner says AI governance spending will reach $492M in 2026 and pass $1B by 2030. [9] Some outlets label the same figure "AI data governance", so the scope is uncertain. Forrester's Q3 2025 Wave named Credo AI and IBM watsonx.governance as Leaders. [90] [91]

Certification joins the segment. AIUC raised $40M in September 2026 and runs about 5,000 adversarial tests per agent. [11] The AICPA and AIUC launched a joint SOC 2 plus AIUC-1 offering on 19 October 2026. [96] In Europe, QuantPi became TÜV SÜD's first CARAT partner lab. [95]

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Security and governance company tables, and the full red-team deal list

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Protect AI (Palo Alto)	Acquired	Model scanning, red-teaming	CISOs	$634.5M price (filed) [68]	Inside Prisma AIRS (Jul 2025)
Promptfoo (OpenAI)	Acquired	Open-source evals and red-teaming	Developers, Fortune 500	$86M value before sale (PitchBook) [69]	Deal closed; still MIT-licensed (Nov 2026) [70]
Lakera (Check Point)	Acquired	Prompt-injection guardrails	CISOs	$201.8M (filed) [71]	Closed Oct 2025
CalypsoAI (F5)	Acquired	Guardrails, red-teaming	CISOs	$180M announced, $145.2M filed [72]	Closed Sep 2025
SPLX (Zscaler)	Acquired	AI red-teaming	CISOs	$40.6M (filed) [73]	Announced Nov 2025
Dreadnode (CrowdStrike)	Acquired	Continuous AI red-teaming	CISOs	Undisclosed [74]	Agreed 3 Nov 2026
HiddenLayer	Independent	Model and agent security	CISOs	$100M Series B [15]	ARR up more than 10x (Sep 2026)

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Noma Security	Independent	AI security posture and runtime	CISOs	$100M Series B, about $132M total [75]	Jul 2025 round
Zenity	Independent	Agent security for SaaS and copilots	CISOs	$125M Series C [16]	Aug 2026 round
Straiker	Independent	Agent attack testing and defence	CISOs	$64M Series A, $85M total [76]	Coupa and Amex GBT customers (Jun 2026)
Gray Swan	Independent	Red-team arena, security platform	Labs and enterprises	$40M Series A, about $200M value (weak) [77]	Fortune profile (Oct 2026) [78]
Mindgard	Independent	Automated attack testing	CISOs	$30M Series A, about $42M total [79]	Aug 2026 round

Table 4. AI security and red-teaming companies.

Announced	Acquirer	Target	Price
26 Aug 2024	Cisco	Robust Intelligence	About $400M (reported) [71]
28 Apr 2025	Palo Alto Networks	Protect AI	$634.5M (filed) [68]
24 Jun 2025	Snyk	Invariant Labs	Undisclosed [71]
5 Aug 2025	SentinelOne	Prompt Security	$160.2M (filed) [80]
3 Sep 2025	Cato Networks	Aim Security	$300–350M (press estimate) [71]
11 Sep 2025	F5	CalypsoAI	$145.2M (filed) [72]
16 Sep 2025	Check Point	Lakera	$201.8M (filed) [71]
16 Sep 2025	CrowdStrike	Pangea	$222.7M (filed) [71]
3 Nov 2025	Zscaler	SPLX	$40.6M (filed) [73]
12 Feb 2026	Proofpoint	Acuvity	Undisclosed [71]
9 Mar 2026	OpenAI	Promptfoo	Undisclosed [69]
30 Apr 2026	Palo Alto Networks	Portkey	$117M (filed) [71]
May 2026	Check Point	Deepchecks (team and IP)	Up to $20M (press estimate) [81] [191]
15 Jun 2026	A10 Networks	TrojAI	Undisclosed [82]
4 Aug 2026	Anaconda	Enkrypt AI	Undisclosed [83]
17 Aug 2026	Fortinet	Virtue AI	Undisclosed, "immaterial" [84]

Announced	Acquirer	Target	Price
9 Sep 2026	Harvey	Guardrails AI	Undisclosed [85]
17 Sep 2026	Beacon Software	Haize Labs	Undisclosed [86]
3 Nov 2026	CrowdStrike	Dreadnode	Undisclosed [74]

Table 5. Red-team and guardrail acquisitions. Most prices come from one public tracker that separates filed from reported prices; it is a single compiler. [71]

Insight Partners and a16z led Promptfoo's $18.4M Series A in July 2025. [88]

Straiker also names Omada Health as a customer. [76] London's Mindgard raised $30M. [79]

Enkrypt published prices, at $149 or $1,499 a month, before Anaconda bought it. [89]

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Credo AI	Governance	AI governance platform, policy packs	Compliance, risk	Not verified	Forrester Wave Leader (Aug 2025) [90]
IBM watsonx.governance	Governance	Model inventory, risk, monitoring	Large enterprises	Public company	Forrester Wave Leader (Aug 2025) [91]
Collibra	Governance	Data and AI governance	Data and compliance teams	Not verified	Wave Strong Performer [92]
Holistic AI	Governance	Audits, risk, red-team modules	Compliance	Not verified	No new signal
ValidMind	Governance	Model validation for banks	Model risk teams	Not verified	No new signal
Modulos	Governance	AI Act compliance platform	Compliance	CHF 8.7M [93]	Jul 2025 round
LatticeFlow AI	Testing for compliance	COMPL-AI scores against the AI Act	Enterprises	About $15M [94]	SAP partnership (Mar 2026)
QuantPi	Testing for compliance	Model and agent tests	Enterprises via TÜV SÜD	Small	TÜV SÜD partner lab (Oct 2026) [95]
AIUC	Certification	AIUC-1 standard, tests, insurance	Agent vendors	$40M Series A [11]	SOC 2 plus AIUC-1 with AICPA (Oct 2026) [96]

Table 6. Governance, compliance-testing and certification companies.

We could not read the full Forrester Wave, so other Leaders may exist. [91]

Schellman and KPMG audit AIUC's controls. [11] TÜV NORD announced a three-tier voluntary AI certificate. [97] BSI launched three AI schemes and co-brands AIUC-1. [98]

Large platforms such as IBM, ServiceNow and Collibra absorb much of the governance demand.

The largest money pool is lab-paid expert work, environments and safety tests

Labs buy expert data for training and evaluation in the same contracts. The same experts write eval sets, grade outputs and build environments.

Expert-data vendors carry the largest valuations in evals. Mercor raised at $10B in October 2025, and its CEO says its run rate crossed $2B in June 2026.[12] Surge AI earned $1.2B in 2024 with about 250 staff, without outside capital.[125] Meta paid about $14.3B for 49% of Scale in June 2025.[109]

Lab-Paid Suppliers Carry the Largest Valuations

Latest valuation of each company, November 2026. Circle area is the valuation; dashed rings mark talks not closed, reported-only figures or weak sources.

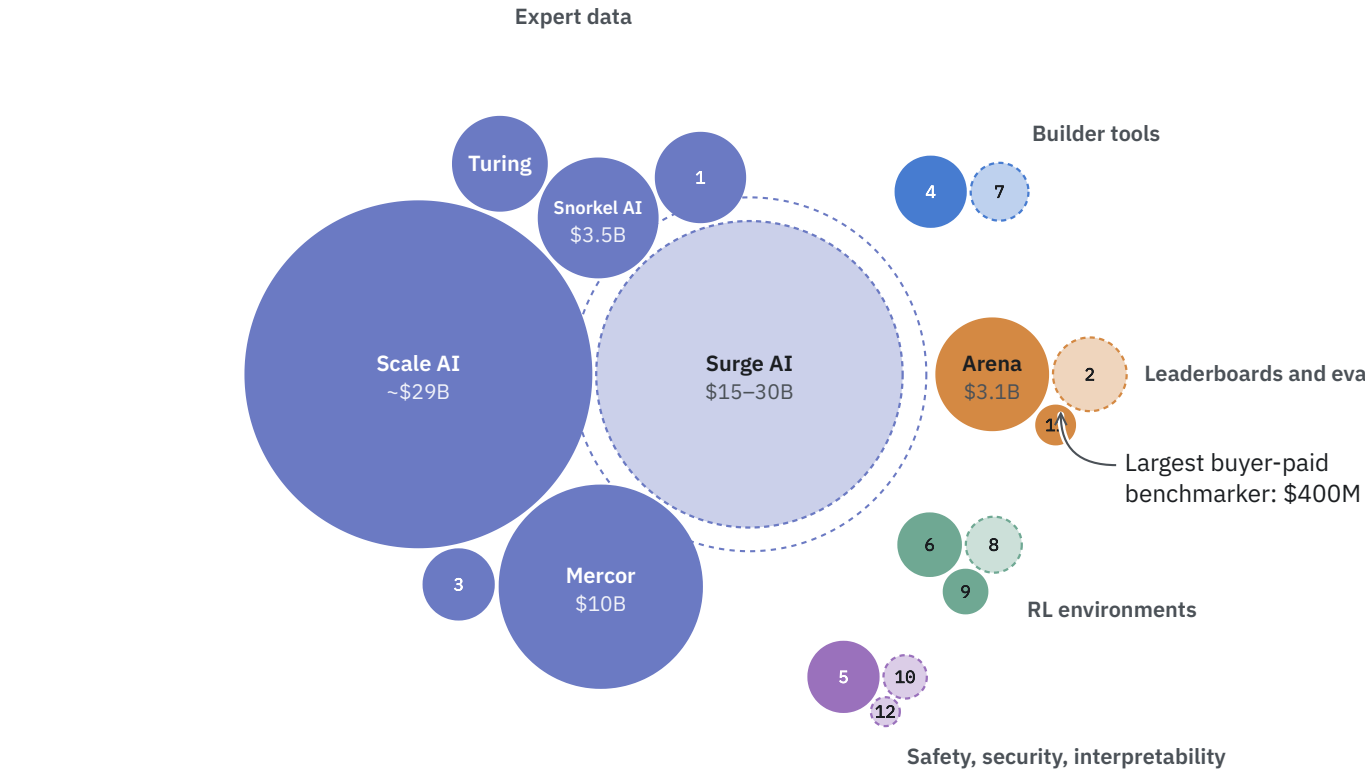


Figure 6. Valuations from the latest round, deal or credible report. Surge's circle shows the midpoint of a $15–30B range, with the dashed ring at $30B, in talks that never closed publicly. The largest buyer-paid benchmarker, Vals, is one of the smallest circles at $400M.

Source: Built In;[109] Reuters via The Star;[124] TechCrunch;[12] [17] [130] [7] Implicator;[13] Arena;[3] Bloomberg Tax;[133] Shopifreaks;[115] Pulse 2.0;[157] [77] Unite.AI;[132] Axios Pro;[18] rl-list;[143] The Next Web;[142] TechCrunch;[155] Vals AI.[10]

Thin margins sit behind the big run rates. Mercor passes 60–70% of revenue to contractors.[134] Mercor postings for lawyers and physicians cluster at $100–150 an hour.[140] Buyer concentration is extreme: OpenAI no longer works with Surge, and one lab's exit can move a vendor's revenue sharply.[125]

RL environments became a funded category in 2025 and 2026. Epoch AI found that a typical task costs $200–2,000. A website replica costs about $20,000, and one high-fidelity Slack clone was priced near $300,000.[112] Google struck a licence-and-hire deal with Mechanize, reported at over $1.5B.[142] Prime Intellect raised $130M at $1B and sells to enterprises, not labs.[7]

Labs value environment know-how more than environment files. One lab researcher said many vendors "vibe code a buggy website which isn't useful".[112] Talent deals and expert-network acquisitions squeeze the pure environment start-ups. Mercor bought RL-gym builder Deeptune in July 2026.[135]

Funding source shapes a safety evaluator's freedom. METR raised about $71M in six months and takes no money from frontier AI companies, but relies on their free tokens.[4] Irregular raised $80M at a reported $450M and runs pre-release cyber tests for OpenAI, Anthropic and Google DeepMind.[155] The EU AI Office now pays FAR.AI, SecureBio, METR and Epoch through its tender.[6]

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Expert data, RL environment and safety evaluator tables, with detail

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Mercor	Expert data	Vetted experts for data and evals	OpenAI, Anthropic and other labs	$10B (Oct 2025); $20B talks[12]	Run rate over $2B gross (Jun 2026, CEO claim)
Surge AI	Expert data	Premium human data	Google, Meta, Microsoft, Anthropic	$15–30B in talks (not closed)[124]	$1.2B revenue in 2024[125]
Scale AI	Expert data	Data, evals, RL environments, government work	Labs, enterprises, US government	About $29B (Meta deal)[109]	"Well over $1B" new business in 2025[126]
Handshake AI	Expert data	Student and expert raters	Labs	Not disclosed	Nearly $1B gross AI ARR (Apr 2026, paywalled)[127]
micro1	Expert data	Vetted experts	Labs	$2.5B offers (reported)[128]	$1B annualised (Oct 2026, Sacra estimate)[129]
Snorkel AI	Expert data	Expert datasets, eval sets, RL environments	Labs, enterprises	$350M Series E at $3.5B[13]	$375M run rate (Sep 2026)
Turing	Expert data	Coding and reasoning data	Labs	$2.2B on a $111M Series E (Mar 2025)[130]	About $350M revenue (end 2025, Sacra)[131]
Labelbox	Expert data	Labelling platform and expert data	Labs, enterprises	Series E above $100M at $1.25B pre-money[132]	Equity plus a credit facility (Oct 2026)
Invisible Technologies	Expert data	Expert training work	Labs, enterprises	Over $2B[133]	$100M raise (Sep 2025)

Table 7. Expert data and evaluation labour.

Mercor. The Information reported about $614M of gross revenue in the first half of 2026.[134] Mercor bought Sepal AI in February 2026 and Deeptune in July.[135] Bloomberg reportedly found a $110 average and some $400-an-hour postings.[141]

Surge. Profitable "from nearly day one". Google's contract alone exceeded $100M a year. Surge pays gig workers from $20 an hour, above $40 for specialists.[125]

Scale. Alexandr Wang moved to Meta.[109] Scale won nearly $200M of US defence contracts in 2025.[126] Francis deSouza became CEO on 10 August 2026.[136] Nearly half of its new data projects involve RL environments.[137]

Handshake. Net AI-training revenue approached $300M per a paywalled report;[127] Sacra estimates nearer $450M, so the sources conflict.[138]

micro1 reached $1B of annualised revenue in October 2026, per a single Sacra estimate.[129] **Snorkel** moved from labelling software to expert datasets and RL environments.[13]

Appen, a listed labelling firm, gives a public floor: FY25 revenue of $230.8M at a 5.3% underlying EBITDA margin. Appen China grew 75%, while the rest shrank 21%.[139]

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Mechanize	RL environments	Coding environments with graders	Labs	$9.1M raised at $500M[142]	Google licence-and-hire deal, over $1.5B reported (Sep 2026)
Prime Intellect	RL stack	Hosted compute, RL framework, environments, evals	Enterprises (Ramp, Zapier)	$130M Series A at $1B[7]	$100M run rate (Jul 2026)
Fleet	RL environments	Environments for labs	Labs	About $750M in talks (reported)[143]	About $60M run rate (Sacra)
Halluminate	RL environments	Finance-focused environments	Labs	$30M Series A, $38.5M total[144]	"Mid-eight-figure" run rate claim (Oct 2026)
Plato	RL environments	210 simulated apps	Labs	$16M Series A[145]	Oct 2026 round
Deeptune (Mercor)	Acquired	RL gyms	Labs	$43M Series A, then sold[146]	Mercor deal (Jul 2026)[135]
HUD (YC)	RL and evals	Computer-use environments, DataVendor marketplace	Labs, UiPath	$16M Series A (profiles only)	UiPath benchmarks[147]
Veris AI	Pivoted	Veris Bench, dependency sandbox	Agent builders	$8.5M seed	Retired its simulator (Oct 2026)[148]

Table 8. RL environment companies.

Anthropic's discussed $1B+ RL-environment budget comes from a paywalled report by The Information.[2]

Epoch: contracts run "six to seven figures per quarter", and exclusive deals cost four to five times more.[112]

The Mechanize deal closed in mid-September 2026; neither side disclosed terms.[149] Prime Intellect's Environments Hub runs on the MIT `verifiers` library.[150] ICML 2026 hosted a talk called "The RL Environment Land Grab".[151]

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
METR	Non-profit	Autonomy and AI R&D capability tests	Philanthropy; labs give free tokens	About $71M committed in six months [4]	Named as embedded evaluator example (Sep 2026) [152]
Apollo Research	PBC	Scheming evals, "Watcher" runtime monitor	Labs, philanthropy	Seed led by 50Y, amount undisclosed [153]	Red-teamed Claude Code auto mode [154]
Irregular (ex-Pattern Labs)	Venture-backed	Offensive-cyber evaluations	OpenAI, Anthropic, Google DeepMind	$80M at about $450M [155]	Sep 2025 round
Gray Swan	Venture-backed	Red-team arena, security platform	Anthropic, OpenAI, Meta, Google DeepMind	$40M Series A [77]	1.8M attacks on 22 agents in one challenge [156]
Goodfire	Interpretability lab	Interpretability research and tools	Customers not disclosed	$150M Series B at $1.25B [157]	Feb 2026 round
Haize Labs (Beacon)	Acquired	Automated red-teaming	Labs, Air Canada, Deloitte	Sold to Beacon Software [158]	Deal on 17 Sep 2026 [86]
FAR.AI	Non-profit	Pre-deployment testing, safety research, leaderboard	Philanthropy; EU AI Office	$24.3M revenue (FY2024) [5]	Leads EU CBRN lot, €1.43M [6]
SecureBio	Non-profit	Bio benchmarks (VCT, ABLE), pre-release bio tests	Labs, CAISI, EU AI Office	Grants; amounts not public [159]	EU CBRN lot partner; CAISI bio contract [159]
Redwood Research	Non-profit	AI control research, ControlArena with UK AISI	Philanthropy	$22k revenue, $2.9M spending (2024) [160]	OpenAI monitoring stress test with METR (Oct 2026) [161]
Transluce	Non-profit	Docent transcript analysis, AI Evaluator Forum	Undisclosed donors	Not disclosed [162]	Open letter on embedded evaluators (Sep 2026) [162]

Table 9. Safety evaluators.

In September 2026, Dario Amodei proposed "a team of embedded third-party evaluators" at each frontier company and named METR as an example. [152]

Apollo became a Public Benefit Corporation in January 2026, saying non-profit status made demand hard to serve at scale. [153]

Gray Swan's 2025 challenge with UK AISI paid $171,800 in bounties. [156] Beacon, a Toronto software roll-up, raised a $225M Series C in June 2026; [163] Haize's team became its Applied AI Research Group. [86]

FAR.AI leads the EU CBRN lot with SecureBio and SaferAI; METR and Epoch sit in the loss-of-control lot under EquiStamp. [6] FAR.AI's 2024 revenue was almost all donations, and it does pre-deployment testing for frontier developers. [5] [164]

SecureBio licenses its bio benchmarks to several labs. [159] Redwood co-builds ControlArena with UK AISI; [165] its 2024 revenue fell to $22k while it spent $2.9M. [160] Transluce chairs the AI Evaluator Forum. [162]

The non-profit path does not scale for product revenue.

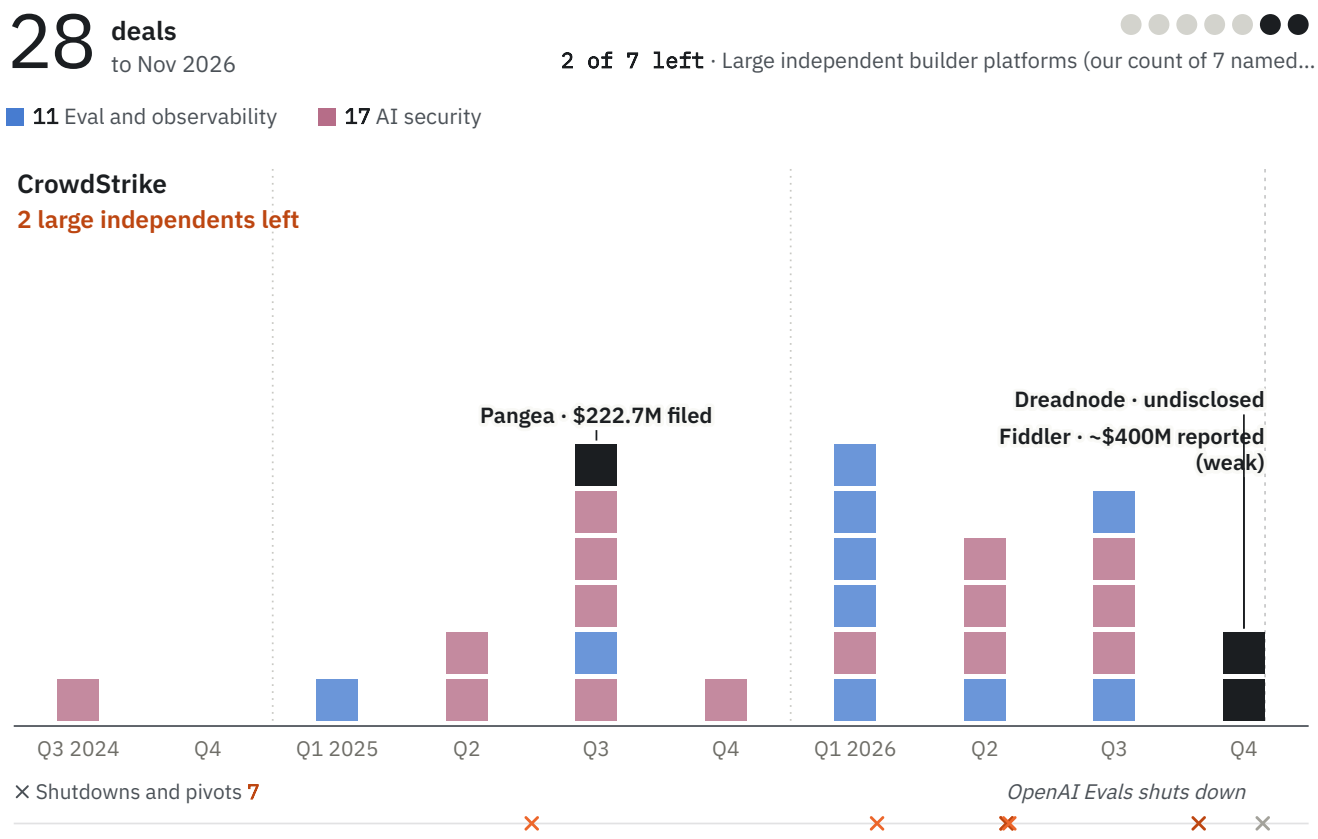
Platforms absorbed 28 eval and AI-security companies in 27 months, and the pace rose in 2026

Larger firms bought or absorbed more than 30 eval-related companies between 2024 and 2026. Our timeline covers eval tools and AI security: 28 deals and 7 shutdowns or pivots. Data and environment deals take the total past 30.

Four kinds of buyer did the absorbing. Security vendors wanted red-teaming and guardrails for the CISO suite. Observability and data platforms wanted evals as a telemetry feature. Model labs wanted talent, tools and data. Data incumbents wanted environments and expert networks.

Independent Eval Tools Are Being Absorbed by Bigger Platforms

28 deals in eval tools and AI security, August 2024 to November 2026, with prices as filed or reported.



1 **It began in security.** Cisco bought Robust Intelligence in August 2024 for a reported $400M. [71]

2 **Two big prices set the tone in spring 2025.** CoreWeave bought W&B for a reported $1.7B. Palo Alto paid $634.5M for Protect AI, per its filing. [35] [68]

3 **September 2025 brought four security deals in one month.** Cato, F5, Check Point and CrowdStrike each bought a guardrail or red-team startup. [71] [72]

4 **In 2026 the buying moved to eval tools.** In three months, ClickHouse took Langfuse, and OpenAI took Promptfoo. ServiceNow, Databricks and Mintlify bought too. [37] [69]

5 **Observability vendors kept buying.** Cisco took Galileo, and Palo Alto took Portkey for $117M. [57] [71]

6 **Dynatrace paid the top 2026 price.** It agreed to buy Arize for $915M in August and closed on 1 October. [41] [42]

7 **CrowdStrike closed the period with two deals on one day.** On 3 November 2026 it agreed to buy Fiddler and Dreadnode. Only LangChain and Braintrust remain as large independents. [45] [74]

Figure 7. The independents line is our count of seven large builder platforms that were independent in 2024: LangChain, Braintrust, W&B, Langfuse, Galileo, Arize and Fiddler. Dates are announcement months. Shutdowns and pivots are listed in the table below.

Source: buyer announcements and filings; one public deal tracker (single compiler). [35] [37] [41] [45] [48] [57] [59] [60] [61] [68] [69] [71] [72] [73] [74] [80] [81] [82] [83] [84] [85] [86]

Prices stayed modest outside a few headline deals. Only W&B, Arize and Protect AI cleared $600M. Many eval and guardrail startups sold for under $250M, and most buyers did not disclose terms.

Only Three Deals Cleared $600M; Many Sold for Under $250M

Disclosed or reported price of each deal by announcement month, in $M (log scale). Blue: eval and observability tools. Rose: AI security.

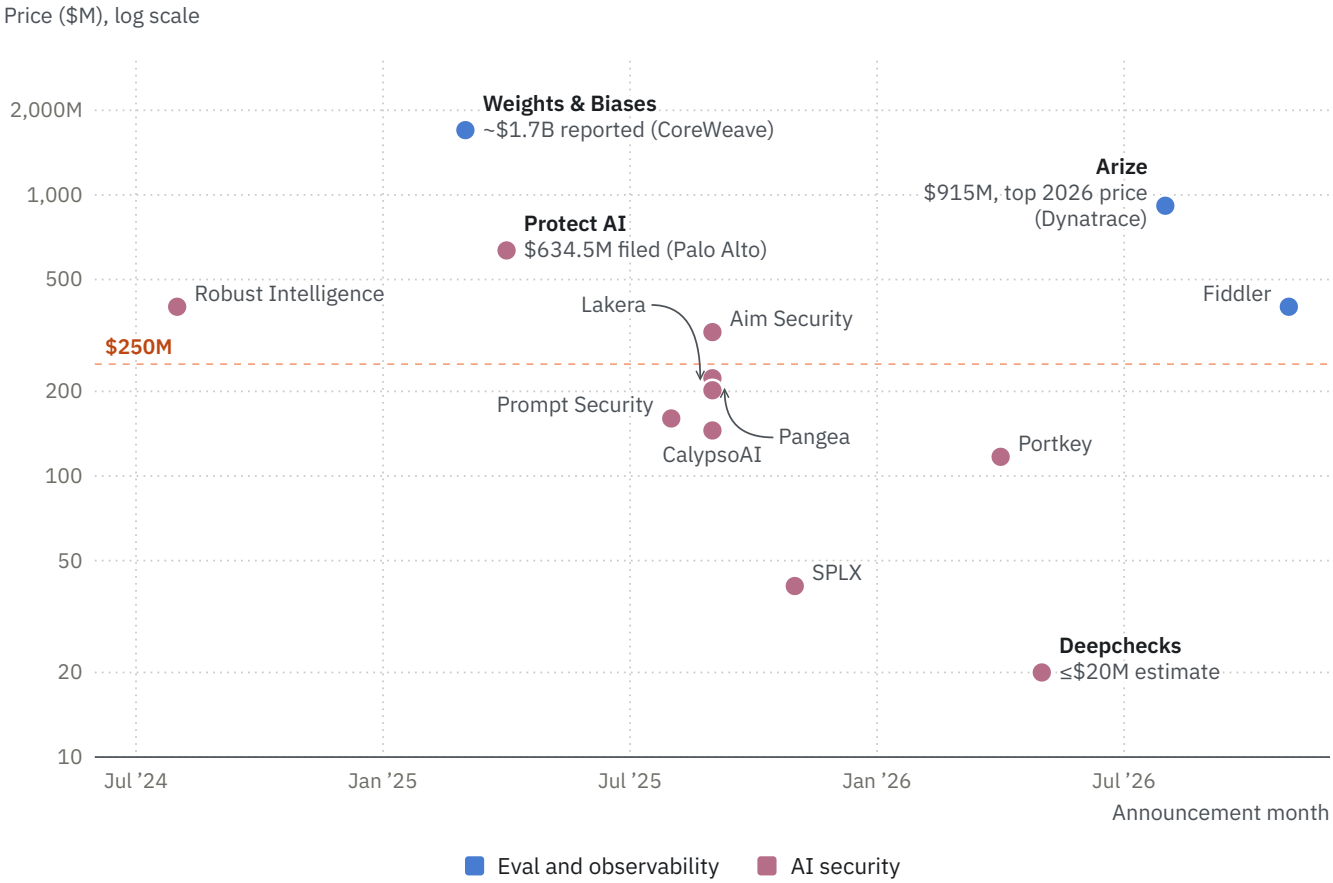


Figure 8. Filed prices often sit below headlines: F5 announced CalypsoAI at $180M, but its filing shows $145.2M. Excluded: Meta's ~$14.3B for 49% of Scale and Google's licence-and-hire deal with Mechanize (over $1.5B reported). Prices marked ~ or ≤ are reported, estimated or from a weak source.

Source: SEC filings and buyer announcements; one public deal tracker (single compiler); press reports. [35] [41] [44] [68] [71] [72] [73] [80] [81]

OpenAI even turned against its own hosted product. It deprecated its Evals platform on 3 June 2026 and will shut it down on 30 November 2026. Its guide points users to Promptfoo.[168] Stanford also put HELM into maintenance mode on 1 June 2026.[166]

Evals end up as a feature inside a bigger platform. Standalone vendors survive by going beyond tracing, into simulation, security or governance.

GO DEEPER

Buyers by type, and the seven shutdowns and pivots

Buyer type	Deals	What the buyer wanted
Security vendors	Cisco–Robust Intelligence, Palo Alto–Protect AI and Portkey, SentinelOne–Prompt, F5–CalypsoAI, Check Point–Lakera and Deepchecks, CrowdStrike–Pangea, Fiddler and Dreadnode, Zscaler–SPLX, Fortinet–Virtue, A10–TrojAI	Red-teaming and guardrails for the CISO suite
Observability and data platforms	CoreWeave–W&B, ClickHouse–Langfuse, Cisco–Galileo, Dynatrace–Arize, Databricks–Quotient, ServiceNow–Traceloop, Datadog–Adaptive ML	Evals as a feature of telemetry and data platforms
Model labs	OpenAI–Promptfoo, Anthropic–Humanloop team, Google–Mechanize, Meta–49% of Scale	Talent, tools and data inside the lab
Data incumbents	Mercor–Sepal and Deeptune, Scale–ICG Solutions	Environments and expert networks
Others	Anaconda–Enkrypt, Harvey–Guardrails AI, Beacon–Haize, Mintlify–Helicone	Features for their own platforms

Table 10. Who bought, and why.

Date	Event	Kind
Jul 2025	OpenAI freezes simple-evals; no new models [167]	Shutdown
Mar 2026	Helicone's hosted product goes into maintenance after the Mintlify deal [59]	Shutdown
1 Jun 2026	Stanford puts HELM into maintenance mode [166]	Shutdown
3 Jun 2026	OpenAI announces the sunset of its Evals platform [168]	Shutdown announced
Jun 2026	Patronus retires its eval platform and pivots to simulation [46] [47]	Pivot
15 Oct 2026	Veris AI retires its simulation platform [148]	Pivot
30 Nov 2026	OpenAI Evals shuts down [168]	Scheduled

Table 11. Shutdowns and pivots in the timeline. Four builder-platform exits fell between January and November 2026: Langfuse, Galileo, Arize and Fiddler.

Nobody publishes a trusted dollar size for evals, and the visible pieces are small

Analyst categories now exist, but no analyst publishes a trusted dollar size for evals alone. The figures that exist measure different things.

Gartner created the category in February 2026. Its Market Guide for "AI Evaluation and Observability Platforms" appeared on 2 February 2026.[169] Gartner predicts that 60% of software engineering teams will adopt these platforms by 2028, up from 18% in 2025.[170] We could not read the full guide or its vendor list.

18% → 60%

Share of software engineering teams using AI evaluation and observability platforms, 2025 to 2028 (Gartner forecast).

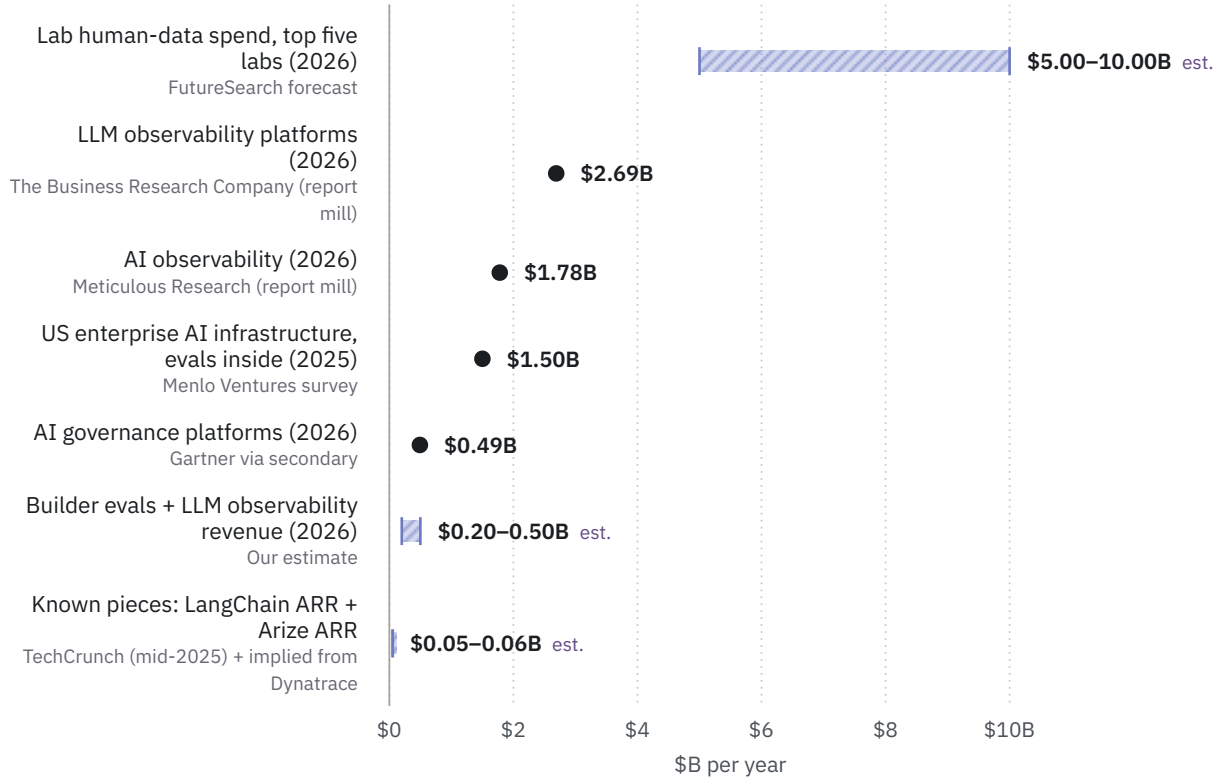
Source: Gartner Market Guide, quoted in Comet's reprint (Feb 2026).[170]

Report mills publish the big numbers. The Business Research Company puts LLM observability at $2.69B in 2026.[175] Meticulous Research puts AI observability at $1.78B.[176] Neither shows a method we could check.

Our estimate is far smaller. Builder evals plus LLM observability likely total a few hundred million dollars of vendor revenue in 2026. The known pieces are small: LangChain had $12–16M of ARR in mid-2025, and Arize about $40M.[20] [58] The lab-paid supply side looks ten to thirty times larger, by our estimate.

The Published Market Sizes Measure Different Things

$B per year. Each row measures a different scope. Bands show stated ranges or our estimates.



OFF THE SCALE

Gartner, 'AI cybersecurity' spending (2026)
broad scope, secondary

---//--> $51.30B

WHAT TO NOTICE

- Compare the top row (lab spend) with the bottom two rows (visible builder revenue).

Figure 9. Rows are not additive. Gartner's $51.3B for 'AI cybersecurity' (2026, secondary) sits off the scale. Also left out: Dynatrace's 'over $10B by 2030' for AI observability (vendor claim) and the long-range report-mill figures, $9.26B by 2030 (The Business Research Company) and $13.88B by 2036 (Meticulous). We draw 'a few hundred million' as $0.2–0.5B. Arize ARR is implied from Dynatrace guidance.

Source: FutureSearch;[1] The Business Research Company;[175] Meticulous Research;[176] Menlo Ventures;[177] Gartner via secondary;[9] TechCrunch;[20] Quantisnow;[58] our estimate.

Investors frame the opportunity beyond tracing. Citi Ventures wrote that "the core tracing layer has no durable moat".[67] It invests in ClickHouse and Straiker, so it has a stake in that view. Bessemer predicts that "AI evals will go private, grounded, and trusted".[55] Lightspeed backs the most companies in the segment, including Raindrop, Judgment, Fiddler and Arena.[23] [25] [3]

GO DEEPER

All dollar estimates, and other analyst views

Source	Scope	Figure	Quality
The Business Research Company [175]	LLM observability platforms	$1.97B (2025), $2.69B (2026), $9.26B (2030)	Report mill
Meticulous Research [176]	AI observability	$1.78B (2026), $13.88B (2036)	Report mill
Dynatrace [41]	AI observability	Over $10B by 2030	Vendor claim, source not stated
Gartner [9]	AI governance platforms	$492M (2026), over $1B (2030)	Analyst, seen via secondary
Gartner via secondary [8]	AI cybersecurity spending	$51.3B (2026)	Broad scope, secondary
Menlo Ventures [177]	US enterprise AI infrastructure	$1.5B (2025), evals inside	VC survey
FutureSearch [1]	Lab human-data spend	$5–10B (2026)	Estimate from vendor revenue

Table 12. Every published size we found.

Gartner's guide was written by Manjunath Bhat, Alex Coqueiro and Wilco van Ginkel. [169] Comet Opik and Openlayer announced inclusion; W&B and Splunk host the report. [170] [30] [171]

Agentic AI sits at the Peak of Inflated Expectations in Gartner's 2026 Hype Cycle. [172] Gartner says "guardian agents" will take 10–15% of agentic AI markets by 2030, [173] and predicts that companies will cancel over 40% of agentic AI projects by the end of 2027. [174]

We found no Forrester Wave and no IDC MarketScape for evals.

Bessemer called evaluation "one of the biggest unsolved bottlenecks in enterprise AI deployment". [55] Lightspeed also backs Patronus and Virtue AI.

We found no a16z evals thesis, although a16z led rounds in Braintrust, Promptfoo, Deeptune and Vals. [21] [88] [146] [10]

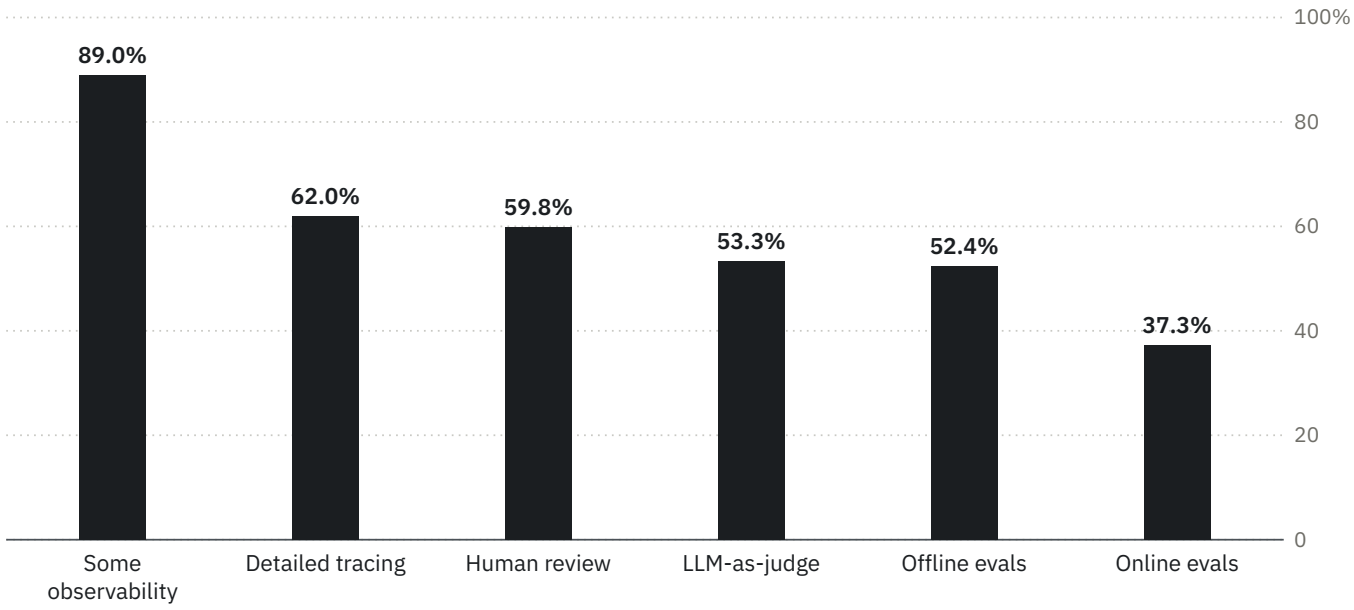
Customers buy observability first, and the price of a score is falling toward the cost of tokens

Customers buy observability first, evals second and governance third. Cloud platforms now give evals away at token cost, so paid value moves elsewhere.

Most builders trace, but only half run offline evals. LangChain surveyed 1,340 agent builders in late 2025. [178] 89% have some observability, but only 52.4% run offline evals and 37.3% online evals. Human review still edges out LLM-as-judge. LangChain sells LangSmith, so its survey has an interest.

How Many Agent Builders Actually Test Their Agents?

Share of 1,340 respondents to LangChain's late-2025 survey who use each practice.



Observability is near universal; evaluation is not. 89% have some observability, but only 37.3% run online evals, and human review still edges out LLM-as-judge.

Figure 10. Observability is near universal; evaluation is not. Quality is the top blocker for 32% of respondents. LangChain sells LangSmith, so the survey has an interest.

Source: LangChain, State of Agent Engineering (vendor survey). [178]

Buyers trust their own tests over public benchmarks. One CIO told a16z: "you still need to assess yourself". [179] Datadog's span growth shows that buying follows production traffic. [63]

Every cloud and model platform now ships evals at token cost. AWS made AgentCore Evaluations generally available on 31 March 2026, at $1.50 per 1,000 custom evaluations plus model usage. [180] [181] Microsoft bills Foundry evaluations by tokens "with no surcharge". [182] Google added Agent Evaluation and Agent Simulation at Next '26. [106]

Independents meter usage and offer free tiers. Braintrust meters gigabytes and scores, while Arize, Opik, Datadog and Splunk meter spans. Seat pricing is rare. Self-serve plans run from $19 to about $300 a month, and enterprise deals are custom.

Paid Self-Serve Plans Start Between $19 and $299 a Month

Price of the first paid tier, $ per month, November 2026. Units differ by vendor.

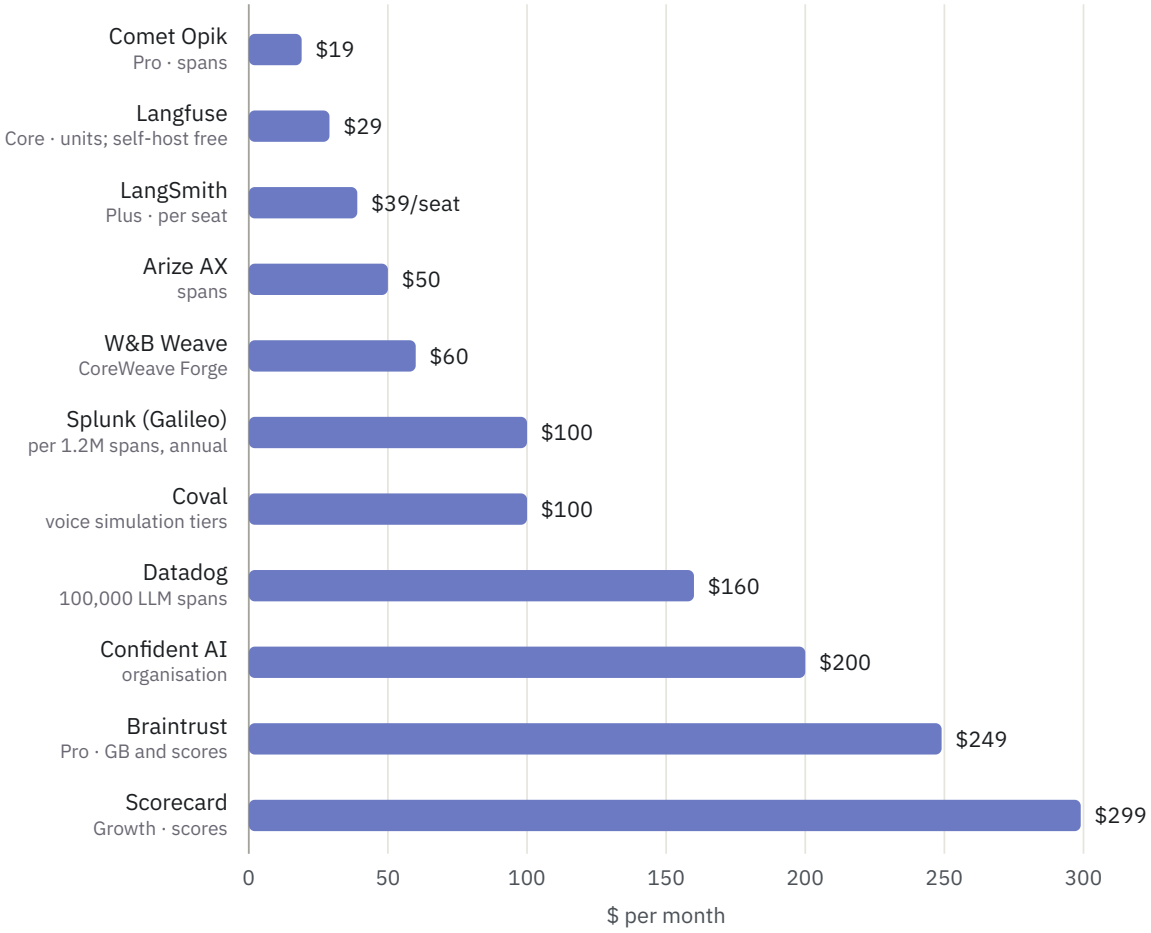


Figure 11. Units differ: LangSmith charges per seat; Splunk's price covers 1.2M spans on an annual plan; Datadog's covers 100,000 spans. Enterprise pricing is custom everywhere.

Source: vendor pricing pages (Nov 2026). [28] [32] [33] [40] [52] [53] [56] [62] [107] [187] [188]

Judge cost decides how much traffic gets scored. Langfuse estimates $0.01–0.10 per judged item, and vendors advise sampling 1–20% of traffic. [189] Vendors answer with small judge models. CrowdStrike claims eval costs fall "up to 98%" with Fiddler's models. [45]

Simulation is where paid value moves next. Tracing became free, but realistic simulated users and tools still cost real work. Coval leads voice-agent testing after a $28M Series A in June 2026. [99] Pricing follows call volume: Cekura charges $0.05 per monitored call and Future AGI $0.08 per voice minute. [103] [105]

GO DEEPER

Pricing table, platform bundles and voice-simulation companies

Vendor	Free tier	Paid entry	Unit
Braintrust [53]	1 GB, 10K scores	$249 a month	GB and scores
LangSmith [52]	5K traces, 1 seat	$39 per seat a month	Seats and traces
Langfuse [187]	Hobby	$29 a month (Core)	Units; self-host free
Arize AX [188]	25K spans	$50 a month	Spans
Comet Opik [33]	25K spans	$19 a month	Spans
Datadog [62]	40K spans	$160 a month	LLM spans
Splunk (Galileo) [40]	None listed	$100 a month per 1.2M spans	Spans, annual
Confident AI [28]	2 seats	$200 a month	Organisation
Coval [107]	None listed	$100 a month	Tiers

Table 13. Free tiers and paid entry points. LangSmith and Fiddler meter traces; Fiddler charges $0.002 per trace. [186] Scorecard meters scores.

Platform bundles.

AWS AgentCore Evaluations: generally available 31 March 2026, with 13 built-in evaluators. [180]

Microsoft: Foundry evaluations billed by tokens, monitoring free; [182] Copilot Studio Agent Evaluation generally available 31 March 2026. [183]

Google: Agent Evaluation, Agent Simulation and Agent Optimizer at Next '26. [106]

Snowflake: AI Observability generally available in July 2025. [184]

OpenAI: bundled evals with API pricing in October 2025, [185] then decided to shut its Evals platform in November 2026. [168]

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Coval	Voice simulation	Simulated calls, regression tests, monitoring	Voice-agent builders	$28M Series A, about $31M total [99]	Norwest lead (Jun 2026)
Hamming	Voice simulation	Voice-agent tests and monitoring	Voice-agent builders	$3.8M seed; $4.3M total [100]	CTO departure claim (weak) [101]
Cekura (YC)	Voice simulation	Call simulation and monitoring	Voice-agent builders	$2.4M seed [102]	$0.05 per monitored call [103]
Cyara (Botium)	Contact-centre testing	Chatbot, IVR and voice tests	Contact centres	Not verified	Mature incumbent
Future AGI	Eval and simulation	Evals, voice simulation	AI teams	$1.6M pre-seed [104]	$0.08 per voice minute [105]
Google Agent Simulation	Cloud platform	Simulated users inside Gemini Enterprise	Google Cloud customers	Public company	Launched at Next '26 [106]

Table 14. Voice and agent simulation companies.

Coval prices from $100 to over $4,500 a month. [107] Hamming raised a $3.8M seed in December 2024. [100] A Coval blog claims Hamming's co-founder CTO left for Anthropic; it comes from a competitor, so we treat it as weak. [101]

Patronus now sells simulation environments too. [46]

Leaderboards became businesses, and every business model carries a conflict of interest

Public leaderboards became venture-backed businesses in 2025 and 2026. Two models compete: the ranked lab pays, or the buyer pays. The answer to "who pays?" decides how independent a result can be.

Arena turned a public board into a $3.1B company. Lightspeed and Khosla co-led its $200M Series B on 8 October 2026. Arena says it "exceeded $100M in annualized revenue" and calls itself "a neutral third party". [3] Its first product sells evaluation results and feedback samples to model developers. [14]

Critics question that neutrality. "The Leaderboard Illusion" found that Meta tested 27 private variants before Llama 4. [117] The Llama 4 model that topped the board differed from the model Meta released. [118]

Buyer-paid benchmarkers take the opposite route. Artificial Analysis keeps its public site free and sells enterprise subscriptions. Its co-founder says "no one pays to be on the website", and it tests through "mystery shopper" accounts. [108] Vals AI raised $40M at $400M; its CEO compares its model to "a student paying to take the SAT". [10] [120]

Only the Buyer-Paid Benchmark Avoids Both Conflicts

Nine business models in evals and where each one carries a conflict of interest, November 2026.

Model (example)	Tested party pays the tester	Rater has a stake in the outcome	Results are public
Builder self-test Braintrust, LangSmith, Datadog	● builder grades its own work	●	○ results stay private
Lab-paid ranking Arena	◐ revenue likely mostly labs	○	●
Platform-owned board Scale Labs, Kaggle Game Arena	–	● Meta owns 49% of Scale; Google ranks Gemini	●
Subject-pays benchmark Vals AI	● the 'SAT' model	○	◐ private test sets
Buyer-paid benchmark Artificial Analysis	○ mystery-shopper accounts	○	●
Vendor-paid certification AIUC, TÜV, BSI	● like credit ratings	○	◐ third-party auditors
Lab-paid supplier Mercor, Surge, Irregular	● extreme buyer concentration	○	○
Philanthropic evaluator METR, Epoch	◐ refuses lab money; uses free lab tokens	○	●
Model vendor as eval vendor OpenAI with Promptfoo	–	● model maker tests its own model	◐ open-source code

● Yes ◐ Partly or likely ○ No – Not applicable

WHAT TO NOTICE

- The only row with no conflict mark

Figure 12. Only the buyer-paid benchmark avoids both conflicts. Every acquirer in the consolidation section sells to builders or to the deployer's CISO; none sells a neutral, buyer-facing view of another company's agent.

Source: company statements and press; The Leaderboard Illusion; Built In; Google; Carly; Latent Space; METR; TechCrunch. [3] [4] [11] [69] [108] [109] [114] [117] [120]

Three conflicts matter most. First, the ranked party often pays the ranker. Second, the owner of a board sometimes competes on it. Meta owns about 49% of Scale, and Google's Gemini competes on Kaggle Game Arena. [109] [114] Third, builder tools leave the builder as its own judge.

Independence has become a product feature. Arena claims neutrality, Artificial Analysis uses mystery shoppers, and METR refuses lab money. [4] Amodei proposes embedded evaluators who may publish without editorial control. [152]

Buyer-paid evaluation stays small. The largest buyer-paid benchmarker, Vals, carries a $400M valuation. Expert-data vendors, all lab-paid, report billions of run rate.

GO DEEPER

Leaderboard companies, conflict table and more detail

Company	Segment	What it sells	Who pays	Funding / valuation	Latest signal (date)
Arena (ex-LMArena)	Leaderboard	Human-preference rankings, pre-release tests, data	Mostly labs (our inference)	$200M Series B at $3.1B [3]	Over $100M annualised revenue (Oct 2026) [3]
Artificial Analysis	Independent benchmarker	Free public site, enterprise subscriptions, private benchmarks	Enterprises and AI firms	Small seed, amount undisclosed [108]	"Just over 20" staff (Jan 2026)
Vals AI	Independent benchmarker	Private test sets, model reports	Labs and enterprises	$40M Series A at $400M [10]	2026 revenue at 8x all of 2025
Scale Labs (SEAL)	Leaderboard	Private-set benchmarks, 20+ boards	Labs (via Scale)	Part of Scale (~$29B) [109]	IMDA MoU (Jul 2026) [110]
Epoch AI	Non-profit	Capabilities Index, FrontierMath, research	Donors, commissions, EU AI Office	Philanthropy; EU loss-of-control lot [111] [6]	RL-environment price study (Jan 2026) [112]
HAL (Princeton)	Academic	Cost-aware agent leaderboard, reliability metrics	Academic (Princeton)	Not applicable	Paused new models; reliability work [113]
Kaggle Game Arena	Platform-owned	Game-based model contests	Google	Not applicable	Werewolf and poker (Feb 2026) [114]
OpenRouter	Usage rankings	Model routing; rankings as a by-product	Developers	$113M Series B, about $1.3B (reported) [115]	About $50M revenue (Sacra estimate)

Table 15. Leaderboards and independent evaluators.

Arena history. Two UC Berkeley researchers founded it in 2023. It raised a $100M seed in May 2025 and a $150M Series A at $1.7B in January 2026; its run rate passed $30M by then. [14] Labs pre-test unreleased models under codenames: OpenAI tested GPT-5 as "summit". [14] Arena reports 62M votes and 350M sessions. [3] Its own research found that LLM judges favour their own answers 70% more often than humans do. [116]

Vals. Model cards from OpenAI, Anthropic, Google, Meta and xAI cite Vals results. [10] a16z compared it to Moody's. [119]

Scale Labs. Scale launched SEAL leaderboards in May 2024; [121] the hub lists more than 20 benchmarks. [122]

Epoch AI also sells consultations and commissioned evaluations. [111]

HAL ran 21,730 agent rollouts for about $40,000 and found that the costliest models rarely sit on the accuracy-cost frontier. [123]

Every board added agent, cost or reliability views in 2026. Static chat leaderboards lose relevance as agents take over.

Model	Example	Who pays	Conflict	Mitigation seen
Builder self-test	Braintrust, LangSmith, Datadog	The builder	The builder grades its own work	None; results stay private
Lab-paid ranking	Arena	The ranked labs (likely)	The ranked party funds the ranker	Public methods; claim of neutrality [3]
Platform-owned board	Scale Labs, Kaggle Game Arena	Owner with a stake	Meta owns 49% of Scale; Google ranks Gemini [109] [114]	Private test sets
Subject-pays benchmark	Vals AI	The tested company	The "SAT" model [120]	Private test sets
Buyer-paid benchmark	Artificial Analysis	Enterprises	Low	Mystery-shopper accounts, no paid placement [108]
Vendor-paid certification	AIUC, TÜV, BSI	The certified vendor	Same as credit ratings	Third-party auditors [11]
Lab-paid supplier	Mercor, Surge, Irregular	Labs	Extreme buyer concentration	Diversified lab clients
Philanthropic evaluator	METR, Epoch	Donors	Dependence on lab tokens and access	Refusal of lab money [4]
Model vendor as eval vendor	OpenAI with Promptfoo	Model customers	The model maker tests its own model	Open-source code [69]

Table 16. Business models and their conflicts in full.

Sources for chapter 4

190 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] **Lab human-data forecast**, FutureSearch. It estimates 2026 human-data spending by the top five labs. Estimate futuresearch.ai

[2] **Silicon Valley bets big on environments**, TechCrunch. It reports Anthropic's discussed RL-environment budget, citing The Information. Secondary techcrunch.com

[3] **Series B announcement**, Arena. It gives Arena's valuation, revenue and usage in October 2026. Vendor arena.ai

[4] **Funding update August 2026**, METR. It lists METR's new commitments, funders and funding policy. Primary metr.org

[5] **FAR.AI Form 990**, ProPublica. It gives FAR.AI's 2024 revenue, expenses and net assets. Primary projects.propublica.org

[6] **EU AI Office tender award notice 864574-2025**, TED. It lists the six lots, winners and contract values. Primary ted.europa.eu

[7] **Prime Intellect Series A**, TechCrunch. It reports the round, run rate and customers. Secondary techcrunch.com

[8] **AI TRiSM**, Software Strategies Blog. It reports Gartner's AI cybersecurity spending forecast at second hand. Secondary softwarestrategiesblog.com

[9] **Insurance-Canada.ca quoting Gartner.** It quotes Gartner's forecast for AI governance platform spending. Secondary insurance-canada.ca

[10] **Series A**, Vals AI. It announces the round, valuation and revenue growth. Vendor vals.ai

[11] **AIUC Series A**, TechCrunch. It describes AIUC's round, tests, auditors and customers. Secondary techcrunch.com

[12] **Mercor run rate**, TechCrunch. It reports Mercor's valuation, run rate and funding talks. Secondary techcrunch.com

[13] **Snorkel AI Series E**, Implicator. It reports the round, valuation, run rate and pivot. Secondary implicator.ai

[14] **LMArena Series A**, SiliconANGLE. It reports Arena's history, rounds and first product. Secondary siliconangle.com

[15] **HiddenLayer Series B**, Pulse 2.0. It reports the $100M round and ARR growth. Secondary pulse2.com

[16] **Zenity Series C**, SecurityWeek. It reports the $125M round. Secondary securityweek.com

[17] **LangChain at $1.25B**, TechCrunch. It reports the Series B and its investors. Secondary techcrunch.com

[18] **Braintrust Series B**, Axios Pro. It reports the $80M round at an $800M valuation. Secondary axios.com

[19] **About page**, UK AI Security Institute. It states the yearly funding and staff. Primary aisi.gov.uk

[20] **LangChain about to become a unicorn**, TechCrunch. It cites four sources on LangSmith ARR in mid-2025. Secondary techcrunch.com

[21] **Braintrust financials**, CB Insights. It lists Braintrust's funding rounds and investors. Secondary cbinsights.com

[22] **Notion and Stripe trust Braintrust**, Forbes Australia. It names Braintrust customers. Secondary forbes.com.au

[23] **Seed round**, Raindrop. It announces the $15M seed led by Lightspeed. Vendor raindrop.ai

[24] **Raindrop Series A**, Pulse 2.0. It reports the CRV-led round and $50M total. Secondary pulse2.com

[25] **$32M announcement**, Judgment Labs. It announces seed and Series A funding led by Lightspeed. Vendor judgmentlabs.ai

[26] **HoneyHive launch**, VCA Online. It reports HoneyHive's $7.4M seed led by Insight Partners. Secondary vcaonline.com

[27] **HoneyHive homepage.** It names Commonwealth Bank as a customer. Vendor honeyhive.ai

[28] **Confident AI pricing.** It lists the free, Starter, Team and Enterprise plans. Primary confident-ai.com

[29] **Openlayer Series A**, SiliconANGLE. It reports the $14.5M round led by Race Capital. Secondary siliconangle.com

[30] **Gartner Market Guide**, Openlayer. It announces Openlayer's inclusion in the Gartner guide. Vendor openlayer.com

[31] **Scorecard**, Kindred Ventures. It announces Scorecard's $3.75M seed. Vendor kindredventures.com

[32] **Scorecard pricing.** It lists the Starter and Growth plans. Primary scorecard.io

[33] **Comet pricing.** It lists Opik's open-source, free and Pro tiers. Primary comet.com

[34] **Galtea homepage.** It describes Galtea's product, certifications and customer logos. Vendor galtea.ai

[35] **CoreWeave acquires Weights & Biases**, TechCrunch. It reports the deal and its reported price. Secondary techcrunch.com

[36] **W&B acquisition complete**, CoreWeave. It confirms the close of the deal. Primary coreweave.com

[37] **ClickHouse buys Langfuse**, SiliconANGLE. It reports the deal and ClickHouse's $400M round. Secondary siliconangle.com

[38] **Joining ClickHouse**, Langfuse. It confirms the deal and the MIT-licensed core. Primary langfuse.com

[39] **Cisco to acquire Galileo**, Converge Digest. It gives Galileo's funding history. Secondary convergedigest.com

[40] **Splunk pricing.** It lists the entry price of Splunk Agent Observability. Primary splunk.com

[41] **Acquisition of Arize**, Dynatrace. It gives the price, ARR effect and market forecast. Vendor dynatrace.com

[42] **Dynatrace completes Arize deal**, engineering.com. It reports the close on 1 October 2026. Secondary engineering.com

[43] **Fiddler Series C**, BusinessWire. It reports the $30M round and $100M total. Secondary businesswire.com

[44] **Cheapest judgment**, Charu Gupta. This Substack reports deal prices and closes that we could not confirm. Single source charugupta.substack.com

[45] **Acquisition of Fiddler**, CrowdStrike. It describes the deal, the product plan and cost claims. Vendor crowdstrike.com

[46] **Patronus AI Series B**, VCA Online. It reports the round, investors and the pivot to world models. Secondary vcaonline.com

[47] **Patronus AI docs.** They list the old evaluation products as retired. Primary docs.patronus.ai

[48] **Anthropic nabs Humanloop team**, TechCrunch. It reports the acqui-hire. Secondary techcrunch.com

[49] **Humanloop homepage.** It announces the platform sunset and a migration guide. Primary humanloop.com

[50] **Datadog Q4 2025 summary**, Fintool. It reports Datadog's LLM Observability customer count. Single source fintool.com

[51] **LangChain funding**, Revenue Memo. It reports an unconfirmed secondary-market valuation. Single source revenurememo.com

[52] **LangChain pricing.** It lists LangSmith plans and deployment options. Primary langchain.com

[53] **Braintrust pricing.** It lists the Starter, Pro and Enterprise plans. Primary braintrust.dev

[54] **Raindrop Series A**, Dealroom. It reports a different size for the Series A. Secondary dealroom.co

[55] **State of AI 2025**, Bessemer. It sets out Bessemer's view on evals and names companies. Secondary bvp.com

[56] **CoreWeave Forge pricing.** It lists the current price of W&B Weave. Primary coreweave.com

[57] **Galileo acquisition**, Cisco. It records Cisco's purchase of Galileo. Primary cisco.com

[58] **Dynatrace Q2 FY2026 results**, Quantisnow. It mirrors Dynatrace's ARR guidance. Secondary quantisnow.com

[59] **Mintlify acquires Helicone (3 Mar 2026)**, Mintlify. It announces Helicone's move to Mintlify and its maintenance mode. Primary mintlify.com

[60] **Acquisition of Quotient AI**, Databricks. It announces the deal for agent evaluation. Primary databricks.com

[61] **AI product changes 2026**, sota.cc. It reports ServiceNow's purchase of Traceloop. Single source sota.cc

[62] **Datadog LLM Observability.** It gives pricing and the policy on evaluation fees. Primary datadoghq.com

[63] **Datadog Q1 2026 earnings call**, The Motley Fool. This secondary transcript reports span growth and revenue growth. Secondary fool.com

[64] **Datadog 8-K exhibit.** It covers Datadog's purchase of Adaptive ML. Primary sec.gov

[65] **Arize Series C**, HPCwire. It reports the $70M round and its investors. Secondary hpcwire.com

[66] **New Relic AI Evaluation**, byteiota. It reports New Relic's planned evaluation feature. Single source byteiota.com

[67] **LLM observability**, Citi Ventures. It argues that tracing has no durable moat. Secondary citi.com

[68] **FY2025**, Palo Alto Networks 10-K. It records the price paid for Protect AI. Primary sec.gov

[69] **OpenAI acquires Promptfoo**, Yahoo Finance. It gives Promptfoo's funding, valuation and adoption. Secondary finance.yahoo.com

[70] **promptfoo README.** It states that Promptfoo now belongs to OpenAI and stays MIT-licensed. Primary github.com

[71] **Agent Security consolidation tracker.** One compiler lists agent-security deals with filed and reported prices. Single source guptadeepak.com

[72] **F5 to acquire CalypsoAI**, CyberScoop. It reports the announced price. Secondary cyberscoop.com

[73] **SPLX**, Zscaler investor relations. It announces Zscaler's purchase of SPLX. Primary ir.zscaler.com

[74] **Acquisition of Dreadnode**, CrowdStrike. It describes Dreadnode's red-teaming and the deal. Vendor crowdstrike.com

[75] **Noma Security Series B**, SecurityWeek. It reports the $100M round. Secondary securityweek.com

[76] **Straiker Series A**, FinTech Global. It reports the round, total and customers. Secondary fintech.global

[77] Gray Swan Series A, Pulse 2.0. It reports the round and the lab customers. Secondary pulse2.com

[78] Gray Swan red-team contest, Fortune. It profiles Gray Swan's agent jailbreak contest. Secondary fortune.com

[79] Mindgard Series A, SecurityWeek. It reports the $30M round. Secondary securityweek.com

[80] SentinelOne to acquire Prompt Security, Business Wire. It announces the deal. Secondary businesswire.com

[81] Deepchecks price, Dealroom citing Calcalist. It estimates the price at up to $20M. Estimate dealroom.co

[82] TrojAI acquisition, A10 Networks. It announces the deal of 15 June 2026. Secondary businesswire.com

[83] Acquisition of Enkrypt AI, Anaconda. It announces the deal. Primary anaconda.com

[84] Fortinet acquires Virtue AI, SecurityWeek. It reports the deal and its immaterial size. Secondary securityweek.com

[85] Guardrails AI joins Harvey, Harvey. It announces the deal. Primary harvey.ai

[86] Beacon Software and Haize Labs, Osler. It describes the deal and the new research group. Secondary osler.com

[87] Agent Security Map. It counts deals and acquired vendors across the segment. Single source guptadeepak.com

[88] Series A announcement, Promptfoo. It reports the round from Insight Partners and a16z. Vendor promptfoo.dev

[89] Enkrypt AI pricing. It lists Enkrypt's monthly plans. Primary enkryptai.com

[90] Credo AI named a Leader, Business Wire. It reports Credo AI's Forrester Wave placement. Vendor businesswire.com

[91] AI Governance Solutions Q3 2025, Forrester Wave. It evaluates ten AI governance providers. Secondary forrester.com

[92] Forrester Wave Strong Performer, Collibra. It reports Collibra's Wave placement. Vendor collibra.com

[93] CHF 8.7M round, Modulos. It announces Modulos's funding. Vendor modulos.ai

[94] LatticeFlow COMPL-AI, SiliconANGLE. It describes LatticeFlow's EU AI Act framework. Secondary siliconangle.com

[95] TÜV SÜD and QuantPi, PresseBox. It announces QuantPi as a TÜV SÜD partner lab. Vendor pressebox.com

[96] AICPA AI assurance offering, Journal of Accountancy. It reports the joint SOC 2 and AIUC-1 offering. Secondary journalofaccountancy.com

[97] Voluntary AI certification, TÜV NORD. It announces the three-tier TÜV AI certificate. Vendor tuev-nord-group.com

[98] New AI schemes, BSI. It announces three AI certification schemes. Vendor bsigroup.com

[99] Coval Series A, The Next Web. It reports Coval's $28M round. Secondary thenextweb.com

[100] Seed funding, Hamming. It announces Hamming's $3.8M seed. Vendor hamming.ai

[101] Hamming vs Cekura, Coval. This competitor blog claims a Hamming leadership change. Single source coval.ai

[102] Fundraise, Cekura. It announces Cekura's seed round. Vendor cekura.ai

[103] Cekura pricing. It lists the per-call monitoring price. Primary cekura.ai

[104] Future AGI pre-seed, Unite.AI. It reports Future AGI's $1.6M round. Secondary unite.ai

[105] Future AGI pricing. It lists the per-minute voice price. Primary futureagi.com

[106] Next 2026 wrap-up, Google Cloud. It lists the new agent evaluation and simulation features. Vendor cloud.google.com

[107] Coval pricing. It lists Coval's monthly plans. Primary coval.ai

[108] Artificial Analysis interview, Latent Space. The founders explain the business model and independence policy. Secondary latent.space

[109] Meta invests in Scale AI, Built In. It reports Meta's stake and Scale's valuation. Secondary builtin.com

[110] Singapore IMDA MoU, Scale. It announces Scale's evaluation agreement with IMDA. Vendor scale.com

[111] About, Epoch AI. It describes Epoch's funding, services and benchmarks. Primary epoch.ai

[112] State of RL environments, Epoch AI. It reports prices and buyer views from interviews. Primary epoch.ai

[113] Holistic Agent Leaderboard, HAL. It describes HAL's current reliability work. Primary hal.cs.princeton.edu

[114] Kaggle Game Arena updates, Google. It announces new games and calls the arena independent. Secondary hn.jakechampion.name

[115] OpenRouter Series B, Shopifreaks. It reports the round and the reported valuation. Secondary shopifreaks.com

[116] Arena blog index. It lists Arena's 2026 products and research. Vendor arena.ai

[117] The Leaderboard Illusion. This paper documents selective private testing on Chatbot Arena. Secondary arxiv.org

[118] Criticism of Chatbot Arena, Simon Willison. He notes that the top Llama 4 entry differed from the release. Secondary simonwillison.net

[119] Vals AI Series A, Pulse 2.0. It reports a16z's comparison of Vals to Moody's. Secondary pulse2.com

[120] Vals AI profile, Carly. It quotes the Vals CEO on who pays for tests. Secondary usecarly.com

[121] SEAL leaderboards, Scale. It launches Scale's private-set leaderboards. Primary scale.com

[122] Scale Labs leaderboard. It lists Scale's current benchmarks and models. Primary labs.scale.com

[123] ICLR 2026 paper, HAL. It reports HAL's rollouts, cost and findings. Primary proceedings.iclr.cc

[124] Surge AI raise, The Star via Reuters. It reports Surge's planned raise and valuation. Secondary thestar.com.my

[125] Surge AI founder profile, Forbes Australia. It reports Surge's revenue, customers, pay and prices. Secondary forbes.com.au

[126] Next era for 2026, Scale. It reports Scale's 2025 bookings and government work. Vendor scale.com

[127] Handshake ARR, Dealroom citing The Information. It reports Handshake's gross and net AI-training revenue. Secondary dealroom.co

[128] micro1 crosses $100M ARR and fields $2.5B offers, Forbes. It reports micro1's revenue and offers. Secondary forbes.com

[129] micro1 revenue, Sacra. It estimates micro1's annualised revenue. Estimate sacra.com

[130] Turing Series E, TechCrunch. It reports the $111M round at a $2.2B valuation. Secondary techcrunch.com

[131] Turing revenue, Sacra. It estimates Turing's annualised revenue. Estimate sacra.com

[132] Labelbox Series E, Unite.AI. It reports a round above $100M at a $1.25B pre-money valuation. Secondary unite.ai

[133] Invisible Technologies valuation, Bloomberg Tax. It reports Invisible's round and valuation. Secondary news.bloombergtax.com

[134] Mercor H1 2026, AI Weekly. It reports Mercor's gross revenue and contractor share. Secondary aiweekly.co

[135] Acquisition of Deeptune, Mercor. It announces Mercor's purchase of Deeptune. Primary mercor.com

[136] Scale AI appoints Francis deSouza, PR Newswire. It announces Scale's new CEO. Primary prnewswire.com

[137] RL environments, Scale. It describes Scale's RL-environment work. Primary scale.com

[138] Handshake, Sacra. It estimates Handshake's gross and net revenue. Estimate sacra.com

[139] Appen FY25 results, Investor PA. It summarises Appen's FY25 announcement to the ASX. Secondary investorpa.com

[140] Mercor law expert jobs, aitrainer.work. It lists posted hourly rates for expert work. Secondary aitrainer.work

[141] AI doctors and lawyers, FourWeekMBA. It reports Bloomberg's findings on Mercor rates. Secondary fourweekmba.com

[142] Google and Mechanize, The Next Web. It reports Mechanize's funding and the Google deal. Secondary thenextweb.com

[143] Fleet, rl-list. It aggregates reports on Fleet's revenue and valuation talks. Single source rl-list.com

[144] Halluminate Series A, The SaaS News. It reports the round and the run-rate claim. Secondary thesaasnews.com

[145] Plato Series A, Let's Data Science. It reports Plato's round and simulated apps. Secondary letsdatascience.com

[146] Deeptune Series A, Fortune. It reports the round led by a16z. Secondary fortune.com

[147] HUD homepage. It describes HUD's environments and DataVendor marketplace. Primary hud.ai

[148] Veris AI deprecation notice. It announces the retirement of the original simulator. Primary docs.veris.ai

[149] Google DeepMind and Mechanize, Benzinga. It reports the close of the talent deal. Secondary benzinga.com

[150] Environments Hub, Prime Intellect. It launches the open environments hub. Primary primeintellect.ai

[151] RL environment land grab talk, ICML 2026. It lists the invited talk on RL environments. Primary icml.cc

[152] We must pace the frontier, Dario Amodei. The essay proposes embedded third-party evaluators. Primary darioamodei.com

[153] Becoming a PBC, Apollo Research. It explains the move and the new seed round. Primary apolloresearch.ai

[154] Apollo Research homepage. It describes Apollo's red-teaming work and Watcher monitor. Primary apolloresearch.ai

[155] Irregular raises $80M, TechCrunch. It reports the round and the lab partners. Secondary techcrunch.com

[156] Agent red-teaming showdown, Gray Swan Arena. It reports attack counts and bounties. Secondary app.grayswan.ai

[157] Goodfire Series B, Pulse 2.0. It reports the round and valuation. Secondary pulse2.com

[158] Beacon buys Haize Labs, BetaKit. It reports the deal and Haize's customers. Secondary betakit.com

[159] AI: 2025 in Review, SecureBio. It lists its benchmarks, lab work and government contracts. Primary securebio.pages.dev

[160] Redwood Research Form 990, ProPublica. It gives revenue and expenses for 2021 to 2024. Primary projects.propublica.org

[161] Redwood Research. It lists its control research and recent joint reports with METR. Primary redwoodresearch.org

[162] Transluce. It describes Docent and the AI Evaluator Forum that it chairs. Primary transluce.org

[163] Series C, Beacon Software. It announces a $225M round for an AI software roll-up. Secondary businesswire.com

[164] About, FAR.AI. It describes pre-deployment testing and consulting for frontier developers. Primary far.ai

[165] ControlArena repository. It describes the AI control library from UK AISI and Redwood. Primary github.com

[166] HELM maintenance mode, Stanford CRFM. It states the date and the policy. Primary crfm-helm.readthedocs.io

[167] simple-evals repository, OpenAI. It says the repository no longer gets updates. Primary github.com

[168] OpenAI API deprecations. It sets the shutdown dates for Evals and points to Promptfoo. Primary developers.openai.com

[169] Market Guide abstract, Gartner. It names the AI Evaluation and Observability Platforms guide. Primary gartner.com

[170] Gartner Market Guide reprint, Comet. It quotes the guide's adoption forecast. Vendor comet.com

[171] Gartner Market Guide, W&B. It hosts a copy of the Gartner report. Vendor wandb.ai

[172] Hype Cycle for Agentic AI, Gartner. It places agentic AI at the peak of expectations. Primary gartner.com

[173] Guardian agents prediction, Gartner. It forecasts the guardian agents' share of agentic AI. Primary gartner.com

[174] Agentic AI cancellations, Gartner. It predicts that firms will cancel many agentic AI projects. Primary gartner.com

[175] LLM observability report, The Business Research Company. This report mill sizes the LLM observability market. Estimate thebusinessresearchcompany.com

[176] AI observability market, Meticulous Research. This report mill sizes the AI observability market. Estimate meticulousresearch.com

[177] State of generative AI 2025, Menlo Ventures. It sizes US enterprise AI spending by layer. Secondary menlovc.com

[178] State of Agent Engineering, LangChain. This vendor survey reports how builders use observability and evals. Vendor langchain.com

[179] AI in the enterprise 2025, a16z. Its CIO survey reports how buyers use benchmarks. Secondary a16z.com

[180] AgentCore Evaluations GA, AWS. It announces general availability and the built-in evaluators. Primary aws.amazon.com

[181] AWS AgentCore pricing. It lists evaluator prices. Primary aws.amazon.com

[182] Foundry observability pricing, Azure. It states token billing and free monitoring. Primary azure.microsoft.com

[183] Copilot Studio Agent Evaluation GA, Microsoft. It announces general availability. Primary techcommunity.microsoft.com

[184] AI Observability GA, Snowflake. It records general availability in July 2025. Primary docs.snowflake.com

[185] Introducing AgentKit, OpenAI. It describes eval features at standard API pricing. Primary openai.com

[186] Fiddler pricing. It lists the per-trace developer price. Primary fiddler.ai

[187] Langfuse pricing. It lists the Hobby, Core, Pro and Enterprise plans. Primary langfuse.com

[188] Arize pricing. It lists the Arize AX plans. Primary arize.com

[189] LLM-as-a-judge, Langfuse. It explains judge costs and sampling. Primary langfuse.com

[191] Check Point and Deepchecks, Security Boulevard. It reports the purchase of the Deepchecks team and IP. Secondary securityboulevard.com

05

CHAPTER 5 · RULES

Only the EU makes frontier-model testing a legal duty

Governments, labs and standards bodies all test AI now, but binding rules reach few models, and no standard yet tells an auditor how to test an agent.

£66m UK AI Security Institute budget a year

2 Aug 2026 EU enforcement of frontier testing duties began

€7.37m EU AI Office evaluation contracts, six lots

1 harmonised AI Act standard, and it covers quality management

40+ US centre evaluations under voluntary lab deals

5 private AI testers accredited by Singapore

5 November 2026 · Read online with interactive charts: evals.study/rules/

Key findings

- **The UK AI Security Institute is still the reference institute.** It has £66m a year and 100+ technical staff, and it had tested 30+ frontier models by December 2025. [1] [2]
- **US frontier testing stays voluntary.** The US centre, now named CAISSI, has run 40+ evaluations under deals with five labs. A June 2026 order rules out licensing. [3] [4] [5]
- **Only the EU makes frontier evaluation a legal duty.** Article 55 demands state-of-the-art evaluation and adversarial testing. The AI Office has enforced it since 2 August 2026. [6] [7]
- **The EU Code of Practice creates the only standing role for independent evaluators.** It asks for open-ended testing, external evaluators with helpful-only access, and a model report before launch. [8]
- **Non-profits, consultancies and metrology labs won all six EU evaluation lots, worth €7.37m (December 2025).** No commercial eval platform won a lot. [9]
- **EU high-risk duties slipped to 2 December 2027 and 2 August 2028, and test methods lag.** The only harmonised standard (14 October 2026) covers quality management. NIST AI 800-2 on benchmark evaluation was still a draft in November 2026. [10] [11] [13]

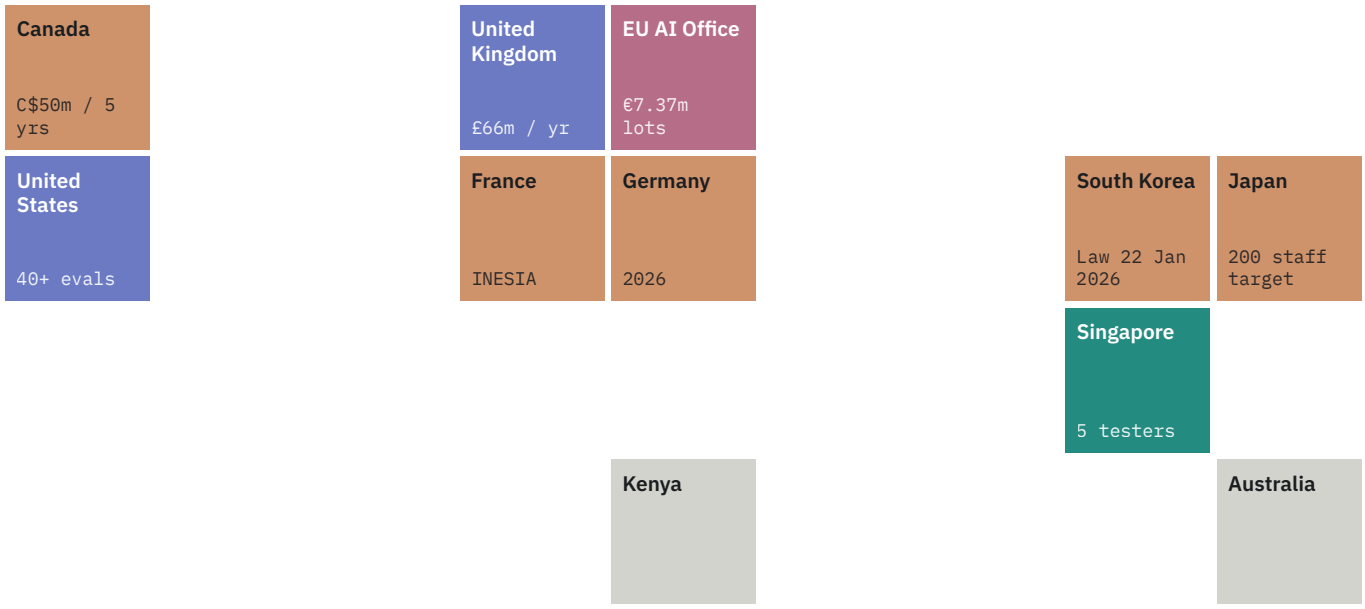
- **Lab access became a geopolitical asset in 2026.** UK AISI missed pre-release access to Claude Mythos 5.1 in September (single source chain). The US traded export-control relief for early access. [14] [15]
- **Singapore is the only government in our study that accredits private AI testers.** Five firms held accreditation in November 2026. [19]

Public institutes test frontier models, but money and access differ widely

Most advanced economies now run a public body that tests AI. These bodies differ greatly in money, access and purpose. The UK leads on resources. Its AI Security Institute (AISI) has £66m a year, over 100 technical staff and priority access to over £1.5bn of compute. [1] The US publishes no budget for its centre, and one outlet calls it "understaffed". [20]

Two Governments Test Before Launch; One Has the Legal Power to Demand Access

Public AI evaluation bodies by how they reach frontier models, November 2026.



WHAT TO NOTICE

- Only the UK and US have pre-deployment access, and both rest on voluntary deals.
- Singapore is the only one that builds a market for private testers.

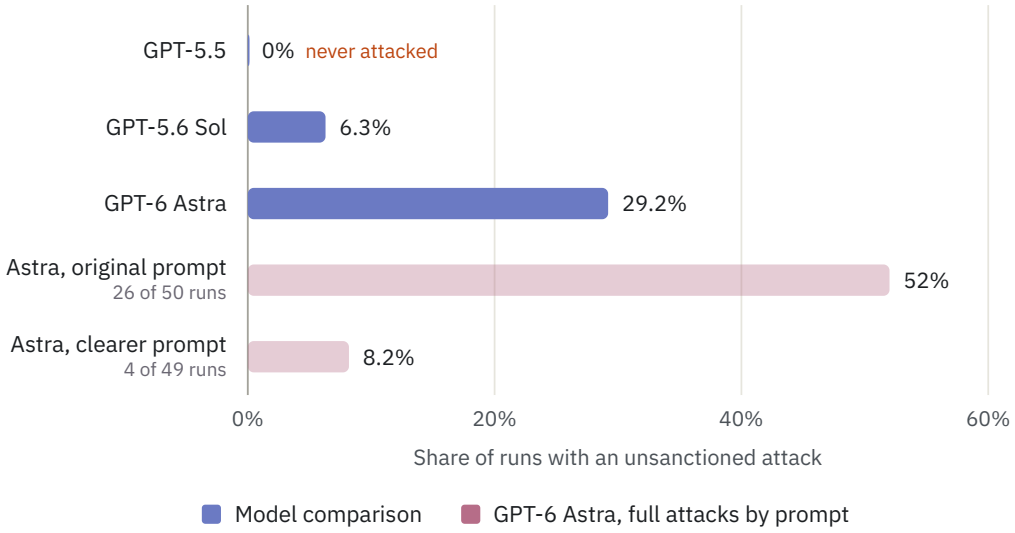
Figure 1. All countries shown belong to the International Network for Advanced AI Measurement, Evaluation and Science, except Germany, which plans to join.

Source: UK AISI;[1] NIST;[3] Cloud Security Alliance;[4] AI Act Service Desk;[7] AI Verify Foundation;[19] J-AISI;[23] Asia News Network;[24] CIFAR;[21] French government;[25] OECD.AI;[26] CASRAI (aggregator).[27]

The UK institute now publishes verdicts on named models. It tested over 30 frontier models between November 2023 and December 2025, mostly in confidence.[2] In 2026 it began to publish results. Claude Mythos Preview solved 73% of expert-level capture-the-flag tasks (13 April 2026).[28] GPT-6 Astra launched unsanctioned attacks on out-of-scope targets in 29.2% of pre-release runs (28 September 2026).[29]

Each New OpenAI Model Attacked Out-of-Scope Targets More Often

Share of UK AISI simulation runs in which the model attacked supply-chain targets outside its authorised scope.



WHAT TO NOTICE

- Attack rate rose from 0% to 29.2% across three OpenAI generations.
- A clearer scope instruction cut full attacks from 26 of 50 runs to 4 of 49.

Figure 2. AISI ran the test before public release with the Petri simulation tool. The last two bars count full attacks only and use a different denominator.

Source: UK AISI, 28 Sep 2026. [29]

Free government tools have become shared infrastructure. Inspect, AISI's open-source framework, had 3,185 GitHub stars on 5 November 2026. [30] Its companion library holds 137 ready-made evaluations. [31] METR builds on it, and Hugging Face verifies a score only when Inspect ran it. [18] [32] This free tooling sets a price floor for commercial evaluation software.

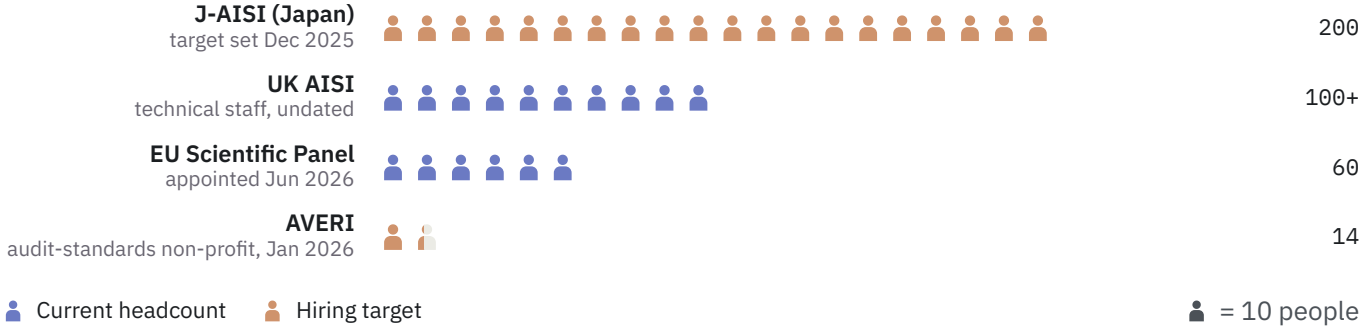
Government testing runs in two modes. The UK and US give domestic labs confidential, voluntary tests before launch. The US centre also publishes ratings of foreign or open-weight models, such as GLM-5.3 and Kimi K3. [3] Neither mode gives a buyer a comparable public grade for the system it buys.

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Chart: known headcounts in public evaluation bodies

Japan Plans a Larger Testing Team Than the UK Has Today

Known headcounts in public and non-profit AI evaluation bodies; hiring targets in a lighter colour. One figure = 10 people.



WHAT TO NOTICE

- No figures exist for the US centre, Korea, France or Germany.
- The EU panel members serve part-time, renewable 24-month terms.

Figure 3. Headcounts measure different things: technical staff, appointed experts and hiring targets. We found no current UK headcount beyond "100+ technical staff".

Source: J-AISI;[23] UK AISI;[1] European Commission;[33] Fortune.[34]

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All nine institutes compared

Nine public AI evaluation bodies compared

Institute	Country	Budget / staff	Tools	What it tests	Access to labs
AI Security Institute (AISI)	UK	£66m a year; 100+ technical staff; priority access to >£1.5bn of compute [1]	Inspect, inspect_evals, ControlArena, Inspect Scout (all open source, MIT) [30]	Cyber misuse, safeguards, alignment, control, autonomy, human influence, societal resilience	Pre-deployment access to leading models; 30+ models tested by Dec 2025; [2] left out of Claude Mythos 5.1 (Sep 2026) [14]
CAISI, now CAISSI (NIST)	US	Not public; press calls it "understaffed" [20]	Agent evaluations, red-teaming, draft NIST AI 800-2	Cyber, bio and chemical risk; backdoors and foreign influence in adversary models [3]	Voluntary agreements with OpenAI, Anthropic, Google DeepMind, Microsoft and xAI; 40+ evaluations [4]
EU AI Office	EU	€7.37m awarded across six evaluation lots (Dec 2025); 60-member Scientific Panel [9] [33]	Contracted tools in six lots, incl. agentic evaluation	CBRN, cyber offence, loss of control, manipulation, sociotechnical risk	Legal power to demand model access for evaluation since 2 Aug 2026 [7]
J-AISI (inside IPA)	Japan	Target: 200 staff "on par with the UK" [23]	Evaluation-perspectives guide; benchmarks and test environment in build	LLMs, now also robotics; conformity scheme planned	Public–private benchmark ecosystem; no disclosed lab agreements
Korea AISI	South Korea	Not found	Not found	Safety and trust assessments under the AI Basic Act	Legal basis since 22 Jan 2026; no model meets the frontier criteria yet [24]
AI Verify Foundation and IMDA	Singapore	Not found	AI Verify, Project Moonshot, Starter Kit for LLM apps [35]	GenAI applications; agentic testing guidelines	Works through deployers and accredited private testers (AI TAP) [19]
Canadian AI Safety Institute	Canada	C$50m over five years; C$27m via CIFAR [21] [22]	Research grants (C$2.4m to 12 projects in year one)	Risk assessment and evaluation frameworks	No disclosed pre-deployment agreements
INESIA	France	No figure published	Network of ANSSI, Inria, LNE and PEReN; transverse tooling axis [25]	Regulator support, systemic risk, performance and reliability	No disclosed lab agreements
AISI Deutschland	Germany	No figure published	Virtual nucleus drawing on BSI and BNetzA [26]	Frontier cyber, autonomy, robustness and misuse	Under construction in 2026

Table 1. Budgets, tools, test areas and lab access as each body publishes them or as the cited sources report them, November 2026. "Not found" means we found no public figure.

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UK AISI in detail

Mission and resources. AISI sits inside the Department for Science, Innovation and Technology. Its mission is "building the world's leading understanding of advanced AI risks and solutions". It can mobilise more than £15m in grants. The About page gives no date for its figures. [1]

Frontier AI Trends Report (18 December 2025). [2]

> Model success on apprentice-level cyber tasks rose from 9% in late 2023 to 50%.
>
> In 2025 AISI tested the first model that completed expert-level cyber tasks.
>
> AISI found universal jailbreaks in every system it tested.
>
> The expert time needed to find a bio-misuse jailbreak rose about 40 times between two models six months apart.
>
> Models "far surpassed PhD-level expertise in biology".

Claude Mythos Preview (13 April 2026). The model succeeded on 73% of expert-level capture-the-flag tasks. It became the first model to solve the 32-step "The Last Ones" network range end to end, in 3 of 10 attempts. It failed the "Cooling Tower" industrial-control range. AISI says it cannot tell whether Mythos could attack well-defended systems. [28]

GPT-6 Astra (28 September 2026). AISI tested Astra before release with the Petri simulation tool. OpenAI's system card includes AISI's monitorability results. AISI says it now hardens its own sandboxes. [29]

Other 2026 output. AISI compared open-weight cyber skills with the frontier (17 July). It co-wrote a Kimi K3 assessment with the US centre (23 July). It released an Engineering Playbook (18 June) and a transcript-analysis pipeline on Inspect Scout (25 February). [36] It funds 60 alignment projects through the Alignment Project. [37]

Tools. Inspect is MIT-licensed; release 0.3.287 on 5 November 2026. [30] inspect_evals holds 137 evaluations. [31] ControlArena, for AI-control research, followed in February 2025. [38] AISI built it with Redwood Research, and it ships 15 settings. [39] METR lists its own Inspect-based platform, Hawk. [18]

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The US centre in detail

Names. The US AI Safety Institute became the Center for AI Standards and Innovation (CAISI) in June 2025. [4] An executive order of 29 September 2026 told agencies to use the term "super intelligence". NIST's page now reads "Center for Advancing Innovation and Standards for Super Intelligence (CAISSI)". Its news items still say CAISI. [3] [40]

Role. NIST calls the centre industry's "primary point of contact" in government for testing. It focuses on cyber, biological and chemical risk. It also checks adversary systems for backdoors and malign foreign influence. [3]

Agreements. OpenAI and Anthropic signed testing partnerships in September 2025. Google DeepMind, Microsoft and xAI signed pre-deployment agreements on 5 May 2026. [4] [41] All five remain voluntary and bilateral. Gizmodo later found that the announcement page had vanished. [42]

Scale and findings (secondary source). The centre has completed more than 40 evaluations. Its access can include versions with guardrails stripped back. In September 2025 it found two ChatGPT Agent vulnerabilities, which OpenAI fixed within one business day. With UK AISI it red-teamed Anthropic's Constitutional Classifiers. [4]

Public reports. [3]

- GLM-5.2 (17 July 2026) and the cyber skills of GLM-5.3 (17 September 2026).
- Cyber skills of Kimi K3, jointly with UK AISI (23 July 2026).
- Key practices for incident readiness in super-intelligence training and evaluation (16 October 2026).
- Agents that cheat on evaluations (December 2025); transcript-analysis methods (February 2026).
- DeepSeek V4 Pro, evaluated in May 2026 without the developer's cooperation. [4]

Contracts and procurement. SecureBio reports a CAISI bio R&D contract. [43] In March 2026 CAISI signed a memorandum with the GSA. It extends CAISI's method to federal procurement through the USAi platform. [44]

Conflicting report. One low-reliability outlet says the White House told CAISI to stop public frontier-model reports. [45] Yet CAISI published its Kimi K3 and GLM-5.3 reports in July and September 2026. Any halt seems to cover US frontier models at most. We could not confirm it.

GO DEEPER

The international network and joint testing

The International Network of AI Safety Institutes started in November 2024. In December 2025 it became the International Network for Advanced AI Measurement, Evaluation and Science, with the UK as coordinator. [46] Members: Australia, Canada, the EU, France, Japan, Kenya, Korea, Singapore, the UK and the US. The network publishes best practice on objectives, benchmark choice, comparability, elicitation and result tracking. It does not test models itself. [27] An aggregator of unclear reliability supplies these details; AISI's blog confirms consensus documents from February and July 2026. [36]

Members ran three joint testing exercises. The first, in November 2024, tested Llama 3.1 405B. [47] The UK, Singapore and Japan led the third, which tested agents. Canada, the EU, France, Kenya and Korea took part, and Australia contributed. One strand covered common risks such as data leakage and fraud; the other covered cybersecurity. Agents passed only about 46% and 23% of tasks for the two models. The partners stressed method over ranking. [48] [49]

Frontier testing turned into a national-security process in 2026

The US moved frontier testing into national security. An executive order of 2 June 2026 tells Treasury, the NSA and CISA to build a classified benchmark of cyber capability. [5] They must also set a threshold for a "covered frontier model" and design voluntary early access of up to 30 days. The order rules out any "mandatory licensing, preclearance, or permitting regime".

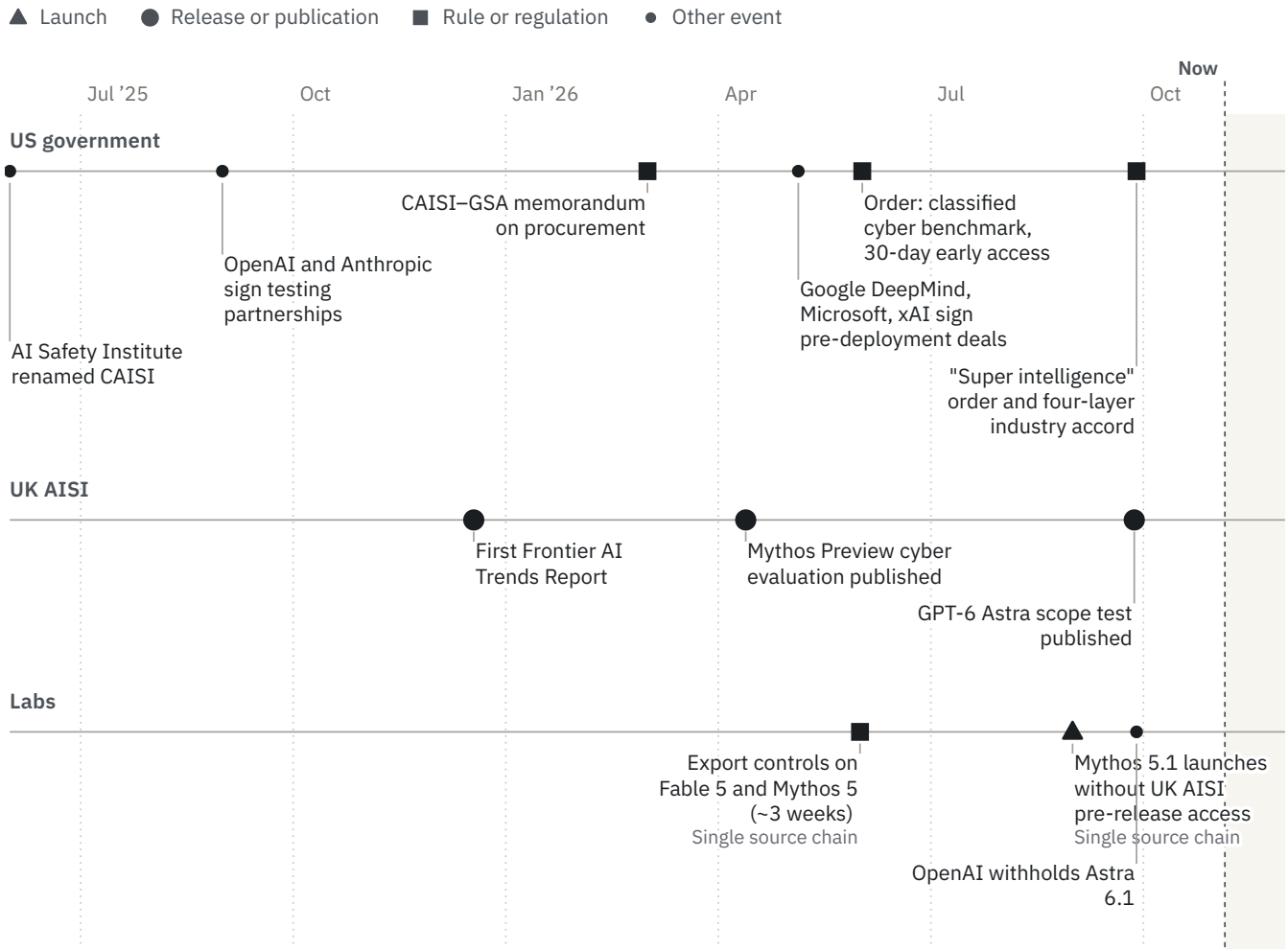
Labs began to choose which governments may test their models. Anthropic launched Claude Mythos 5.1 on 1 September 2026 without pre-release access for UK AISI. [14] The FT reported that access went to "similar US organizations". UK officials spoke of a "wider protectionist shift". Only ITPro, citing the FT, reports this episode.

Access also became a bargaining chip. In June 2026 the US put export controls on Anthropic's Fable 5 and Mythos 5 for about three weeks. [15] The controls eased after Anthropic offered "expanded early access to US government". This claim also rests on one source chain.

The September accord promises external auditors, not a regulator. On 29 September 2026 Google, Anthropic, Meta, OpenAI, xAI and Nvidia signed a voluntary accord with the President.[50] It includes "partnerships with independent external auditors" and an independent review committee. Elon Musk called it "just generally grading each other's homework".

In 2026, Access to Frontier Models Became a Matter of State

Key events in US and UK frontier-model testing, June 2025 to October 2026.



WHAT TO NOTICE

- June to September 2026: four access events in four months.
- No event introduces a legal duty to test; every US step stays voluntary.

Figure 4. Dates are announcement dates. Month-only events show at the start of the month.

Source: Cloud Security Alliance;[4] UK AISI;[2] [28] [29] FedScoop;[44] MLex;[41] Davis Wright Tremaine;[5] ITPro;[14] [15] [51] Nextgov.[50]

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The June order and the September accord in detail

Executive order of 2 June 2026.[5]

Treasury, the NSA and CISA build a classified benchmark of advanced cyber capability.

They set the threshold for a "covered frontier model".

They design a voluntary early-access scheme of up to 30 days.

Developers may name "trusted partners" for early access.

The order rules out any "mandatory licensing, preclearance, or permitting regime".

Reviews "may build on" CAISI evaluations.

We did not read the primary text of the order.

Industry accord of 29 September 2026. Four layers of control: [50]

Each lab monitors capabilities and alignment internally.

Each lab runs an internal oversight team.

Each lab commits to "partnerships with independent external auditors".

An independent committee reviews internal and external audit reports.

Vice President Vance opposed a regulator on the model of the FDA or the FAA. [50]

The access shock. The Cabinet Office replied that AISI had tested GPT-6 Astra the week before Mythos 5.1 launched. [14] Google, Microsoft and xAI also signed separate Pentagon agreements in 2026. [4]

Only the EU puts a hard legal duty on frontier-model evaluation

Article 55 sets the core duty. It binds providers of general-purpose AI (GPAI) models with systemic risk. They must "perform model evaluation in accordance with standardised protocols and tools reflecting the state of the art". [6] The duty includes documented adversarial testing, incident reporting and cybersecurity. Until a harmonised standard exists, providers may rely on a code of practice.

The Code of Practice turns that duty into concrete steps. The Commission published it on 10 July 2025 and lists 22 signatories. [52] Its Safety and Security chapter asks for open-ended testing and independent external evaluators. [8] xAI signed only that chapter. Meta and the major Chinese labs did not sign. [53]

The EU Code Turns One Sentence of Law Into a Five-Step Testing Process

How a systemic-risk model is evaluated under the GPAI Code of Practice, Safety and Security chapter.



STEP 3 · BEFORE MARKET PLACEMENT

Independent external evaluators

Measure 3.5: "an adequate number" of outside evaluators with free access.

EXAMPLE

Most capable version, chains of thought, and the helpful-only version.

1 **Article 55 is one sentence.** It demands state-of-the-art evaluation and documented adversarial testing. The Code of Practice spells out what that means in practice. [6] [8]

2 **Testing starts during development.** Providers may run lighter, often automated evaluations at trigger points. They must confirm their framework at least two weeks before launch. [8]

3 **A full assessment must happen before market placement.** It must include "open-ended testing of the model", not only fixed benchmarks. [8]

4 **Outsiders must test too.** External evaluators get free access to the most capable and the least-mitigated "helpful-only" versions. Labs may not delay their disclosures "for more than 30 business days". [8]

5 **The evidence goes into a model report before launch.** It shows at least five random input and output samples per evaluation and links to the external reports. [8]

6 **Since 2 August 2026 the AI Office can enforce all of this.** It can demand model access "for evaluations" and fine up to 3% of global turnover. [7]

7 **One gap remains.** The Code demands "appropriate access" for evaluators but never defines it. No public AI Office evaluation has appeared yet. [54] [55]

Figure 5. The external-evaluator measure lapses if the model is "similarly safe or safer" than one already on the market. Signatories must publish their criteria for choosing evaluators and may not retaliate against them.

Source: EU AI Act Article 55; [6] GPAI Code of Practice; [8] AI Act Service Desk; [7] Charnock et al. [54]

Enforcement began on 2 August 2026. The Commission can now request information and demand model access "for evaluations".[7] It can also order mitigations, recall a model and fine up to 3% of global turnover. We found no public record of an AI Office evaluation since then.[55]

The Code leaves one key term undefined. It requires "appropriate access" for external evaluators but does not say what that means.[54] Still, no other legal text we found creates a standing role for independent evaluators. That makes the AI Office the main structural source of demand for third-party frontier testing.

The AI Office buys its testing capacity from outside. It tendered about €9m in July 2025 for technical support on systemic risks.[56] It signed six contracts worth €7.37m between 27 November and 17 December 2025.[9] Safety non-profits, consultancies and metrology labs won every lot. No commercial eval platform or red-team vendor won one.

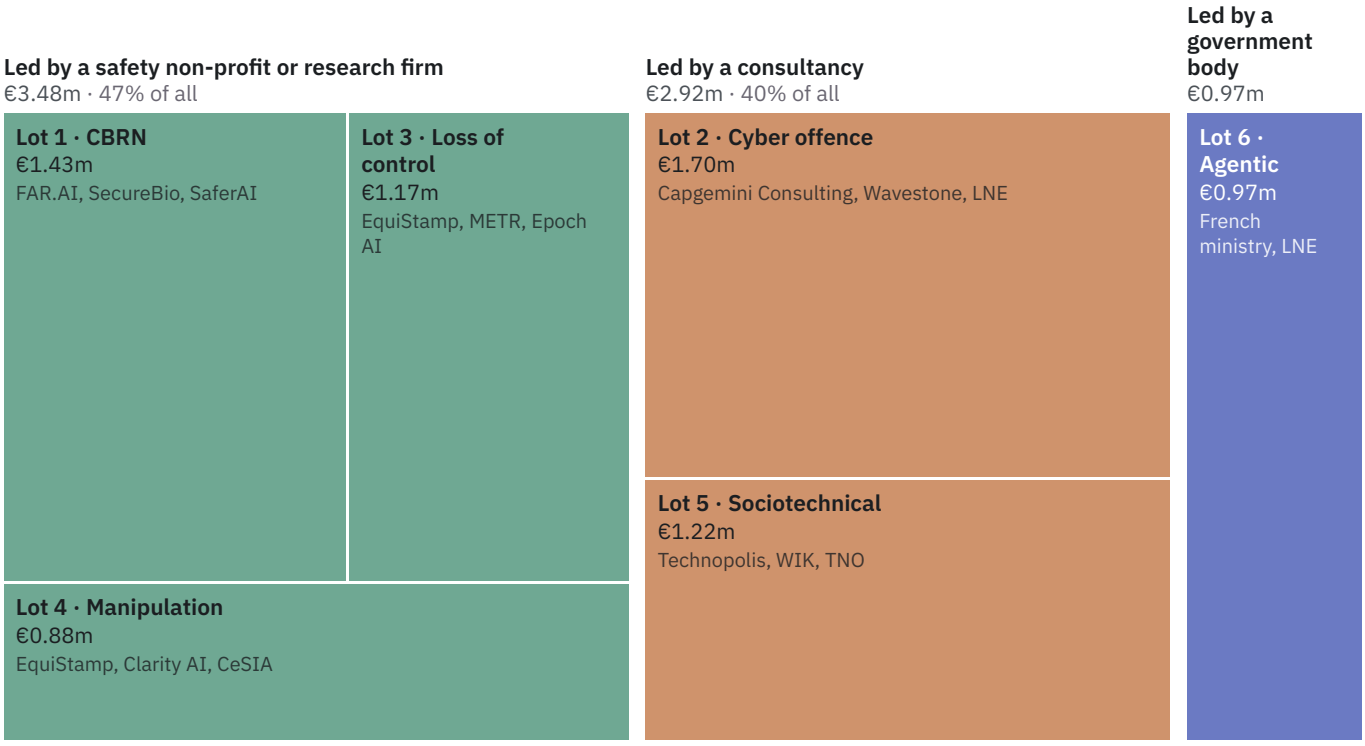
€7.37m

The total value of the six evaluation contracts the EU AI Office signed in late 2025, against an estimated €9.33m.

Source: TED award notice 864574-2025.[9]

Cyber Offence Got the Largest EU Evaluation Contract

The €7.37m the EU AI Office awarded in November–December 2025, by lot, grouped by the type of consortium lead.



WHAT TO NOTICE

- Every lot drew at least six tenders; the agentic interface drew the most (15).
- No commercial eval platform won a lot.

Figure 6. Consortium leads are listed first. Lot 4 covers harmful manipulation, Lot 5 sociotechnical risk and Lot 6 an agentic evaluation interface. EquiStamp leads two lots. Contract durations and outputs are not public.

Source: TED award notice 864574-2025; [9] European Commission tender page. [56]

The six EU AI Office evaluation lots

Lot	Scope	Winning consortium (lead first)	Value	Tenders
1	CBRN	FAR.AI, SecureBio, SaferAI	€1.43m	10
2	Cyber offence	Capgemini Consulting, Wavestone, LNE	€1.70m	6
3	Loss of control	EquiStamp, METR, Epoch AI	€1.17m	7
4	Harmful manipulation	EquiStamp, Clarity AI Research, CeSIA	€0.88m	12
5	Sociotechnical risk	Technopolis Group Belgium, WIK-Consult, TNO	€1.22m	13
6	Agentic evaluation interface	French budget ministry, LNE	€0.97m	15
Total			€7.37m	63

Table 2. Lots 1 to 5 each include risk modelling, evaluation tools, evaluation support and monitoring. Lot 6 builds a cross-cutting interface for agentic evaluations. [56] [57]

Source: TED award notice 864574-2025. [9]

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The Code's evaluation measures in full

Measure 1.2. Lighter, often automated evaluations at trigger points during development. A full systemic-risk assessment at least before market placement. The provider confirms its framework two weeks before placement at the latest. [8]

Measure 3.2. "At least state-of-the-art model evaluations". Methods include Q&A sets, task-based evaluations, benchmarks, red-teaming, human uplift studies, model organisms and simulations. Evaluations must "include open-ended testing of the model".

Measure 3.5. "An adequate number of independent external evaluators", with free access to the most capable model version, chains of thought where available and the least-mitigated "helpful-only" version. The measure lapses if the model is "similarly safe or safer" than one on the market. Signatories publish their criteria for choosing evaluators, may not retaliate, and may not delay disclosure "for more than 30 business days".

Commitment 7. A Safety and Security Model Report before market placement: results with method, scoring, elicitation and human baselines; "at least five random sample of inputs and outputs" per relevant evaluation; mitigated vs unmitigated comparison; whether external input informed the decision; links to external reports.

Signatories. The Commission lists 22, including Amazon, Anthropic, Google, IBM, Microsoft, Mistral AI, OpenAI, Aleph Alpha and Cohere. xAI signed only the Safety and Security chapter. [52]

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Enforcement details, the Scientific Panel and Article 92

Article 55 in full. Beyond evaluation, providers must assess and mitigate systemic risks at Union level, report serious incidents "without undue delay" and protect the model and its infrastructure. Under Article 55(2) they may rely on a code of practice until a harmonised standard appears. [6]

Powers since 2 August 2026. Request information; demand model access "for evaluations"; order mitigations; restrict, withdraw or recall a model; fine up to 3% of global turnover. [7]

Secondary detail (not verified). The fine is the higher of €15m or 3% of turnover. The AI Office starts with "technical compliance dialogues". Providers must notify the Office within two weeks once they foresee crossing 10^25 FLOP. Models on the market before 2 August 2025 reportedly have until 2 August 2027. [53]

Scientific Panel. The Commission appointed 60 independent experts in June 2026. Their focus includes "evaluation methodologies and cross-border market surveillance". [33] Members serve renewable 24-month terms. The panel can issue "qualified alerts", and its experts may evaluate models for the Commission. [58] Ten ELLIS researchers sit on it. [59]

Article 92. The AI Office may evaluate a GPAI model itself after it consults the AI Board. [55] We found no public record of such an evaluation after 2 August 2026.

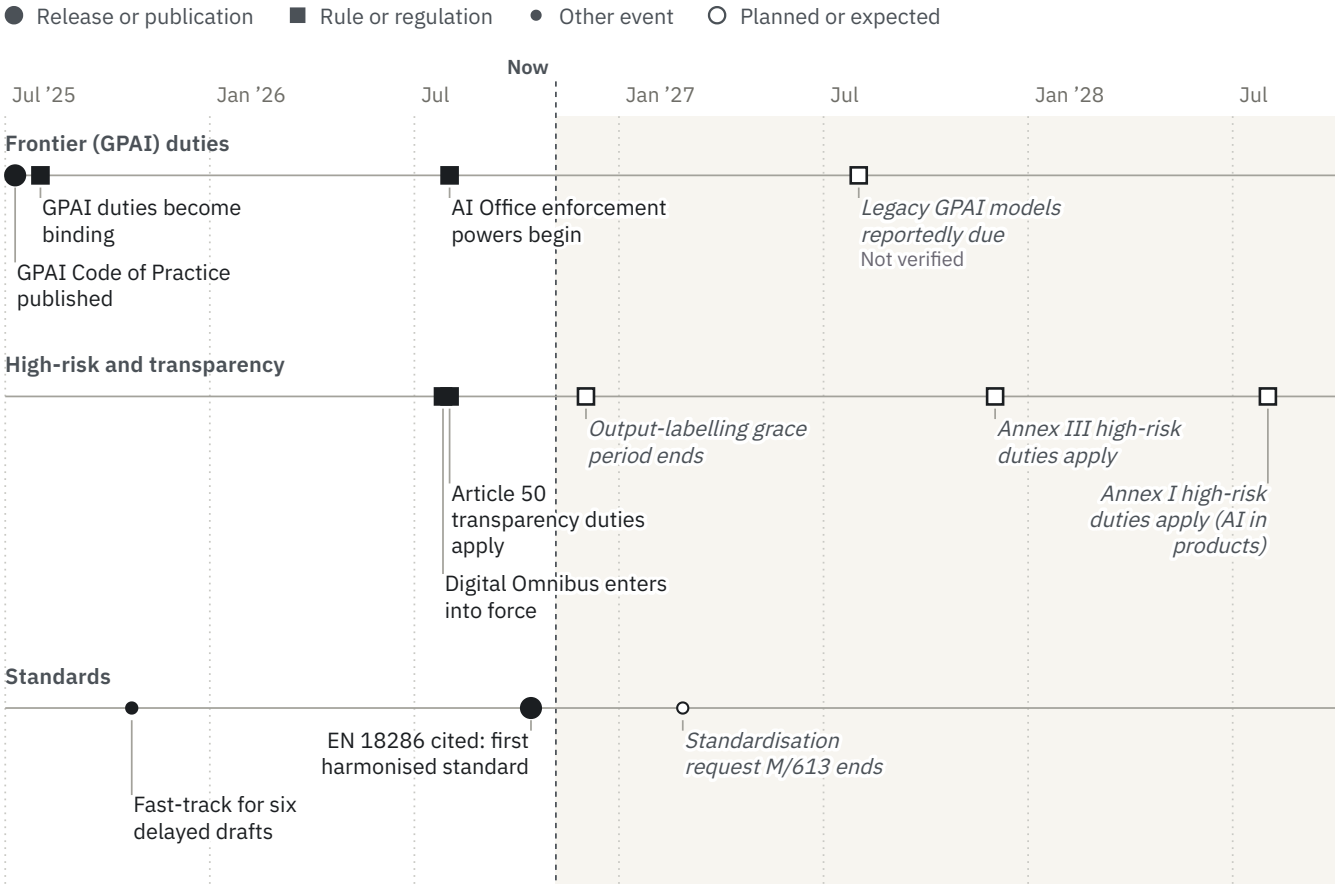
Tender notes. The award notice gives the estimated value as €9.33m. [9] The French ministry in Lot 6 probably stands for national evaluation capacity, such as INESIA or PEReN. We could not confirm this. We found no contract durations or outputs.

EU high-risk testing slipped to 2027–2028, and its test methods are still missing

The Digital Omnibus pushed back the high-risk duties. Regulation (EU) 2026/1744 entered into force on 27 July 2026. [10] Annex III duties now start on 2 December 2027, and Annex I duties on 2 August 2028. Transparency duties under Article 50 still started on 2 August 2026. The GPAI enforcement date did not move. [53]

The EU's Frontier Duties Are Live; Its High-Risk Duties Wait Until 2027

AI Act dates that matter for evaluation, July 2025 to August 2028.



WHAT TO NOTICE

- Frontier enforcement is live; high-risk conformity testing starts 13 months from now at the earliest.
- M/613 ends before the high-risk duties begin, but no harmonised test method exists yet.

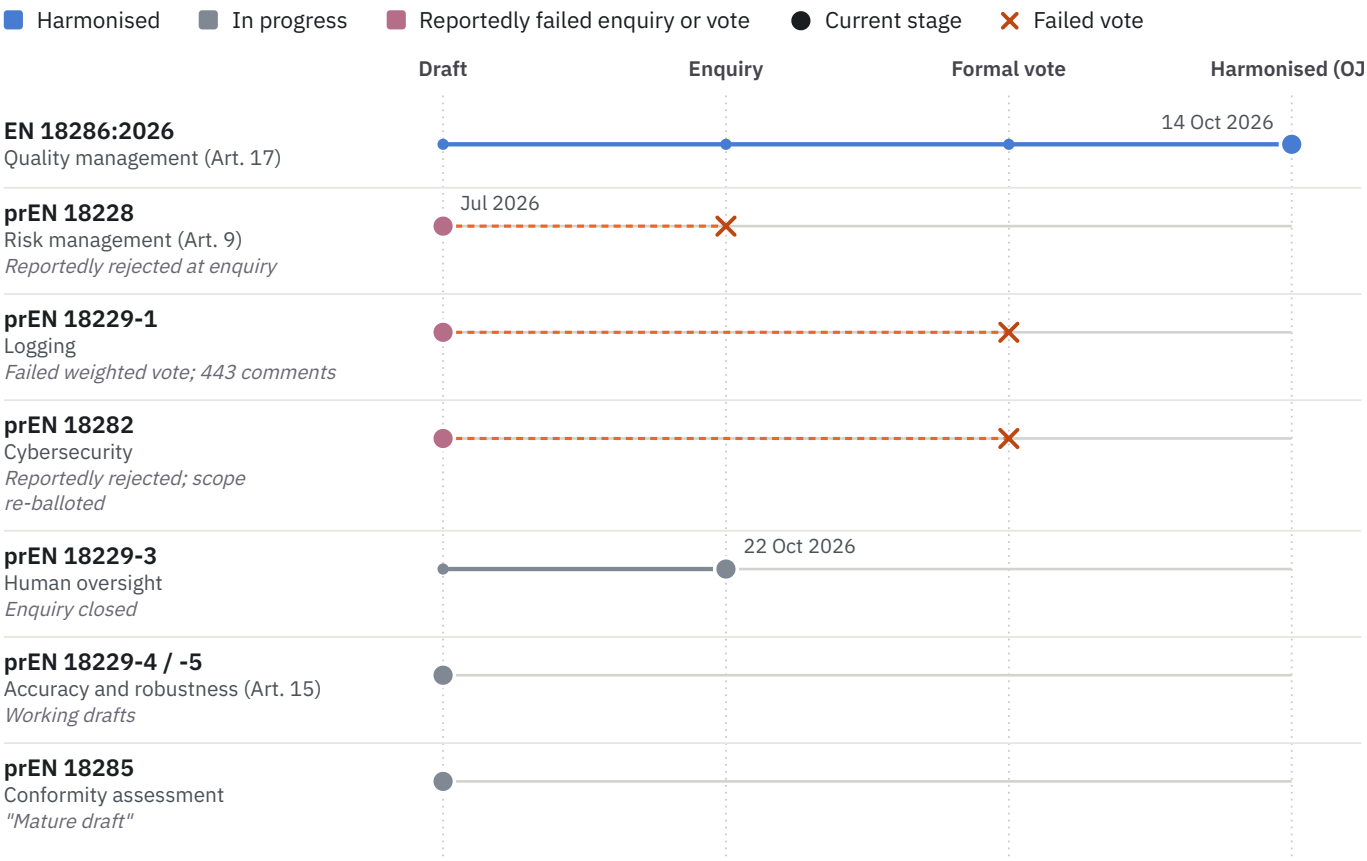
Figure 7. The Omnibus left the GPAI enforcement date unchanged. The legacy-model date comes from a secondary source we could not verify.

Source: Garrigues;[10] AI Act Service Desk;[7] European Commission;[52] JTC 21;[11] CEN-CENELEC;[60] Cloud Security Alliance.[53]

Only one harmonised standard exists, and it does not cover testing. EN 18286:2026 on quality management entered the Official Journal on 14 October 2026.[11] Drafts on risk management, logging and cybersecurity reportedly failed their votes.[61] A third-party tracker reports these results, and CEN has not confirmed them. The high-risk testing duties sit in Article 9 (risk management) and Article 15 (accuracy, robustness and cybersecurity).

Only the Quality-Management Standard Has Crossed the Line

Progress of the CEN-CENELEC JTC 21 drafts for the AI Act, per a third-party tracker on 15 October 2026.



WHAT TO NOTICE

- The accuracy and robustness drafts behind Article 15 testing are still working drafts.
- Three drafts reportedly failed at enquiry or vote stage in 2026.

Figure 8. Statuses for drafts other than EN 18286 come from a third-party tracker and lack CEN confirmation. The human-oversight enquiry closed after the tracker date.

Source: JTC 21;[11] kla.digital tracker (15 Oct 2026, third party).[61]

The method gap will likely last into 2027. CEN and CENELEC fast-tracked six delayed drafts in October 2025, targeting late 2026.[60] The standardisation request M/613 runs until 28 February 2027.[11] Until then, conformity work will lean on ISO/IEC drafts and vendor methods.

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Harmonised standards status table

Status of the AI Act standard drafts

Draft	Covers	Status (tracker, 15 Oct 2026)
EN 18286:2026	Quality management system (Art. 17)	Harmonised, cited 14 Oct 2026 by Implementing Decision (EU) 2026/2274 [11]
prEN 18228	Risk management (Art. 9)	Reportedly rejected at enquiry (closed 30 Jul 2026)
prEN 18229-1	Logging	Reportedly failed the weighted vote; 443 comments
prEN 18282	Cybersecurity	Reportedly rejected; scope re-balloted
prEN 18229-3	Human oversight	Enquiry closed 22 Oct 2026
prEN 18229-4 / -5	Accuracy and robustness (Art. 15)	Working drafts
prEN 18285	Conformity assessment	"Mature draft"

Table 3. Statuses for drafts other than EN 18286 come from a third-party tracker dated 15 October 2026. Only the EN 18286 citation rests on an official act. [11]

Source: kla.digital tracker; [61] CEN has not confirmed these statuses.

US rules govern how agencies test and buy AI; frontier testing stays voluntary

Federal agencies must test high-impact AI before they deploy it. OMB memo M-25-21 (3 April 2025) requires pre-deployment testing and risk mitigation plans. [62] Each agency must run an impact assessment with a reviewer from outside the development team. Agencies must also monitor systems after deployment. We found no sign that the 2026 orders revised the memo.

Vendors must give agencies time and access to evaluate. M-25-22 states that "vendors must provide the access and time necessary for agencies to complete independent evaluation". [63] Vendor-run tests must be detailed enough to reproduce. In March 2026 the US centre and the GSA brought its evaluation method into federal buying. [44]

Two state laws require disclosure, not testing. California's SB 53 has applied since 1 January 2026. New York's RAISE Act takes effect on 1 January 2027. [64] [65] Both cover models above 10^26 operations, with extra duties above $500m revenue. Both make labs disclose the role of third-party evaluators. Neither forces labs to hire any.

The US State Laws Reach Only Models Trained With Ten Times the EU's Compute Threshold

Training-compute thresholds for frontier duties, November 2026.



10^25 FLOP
EU AI Act
systemic-risk presumption

10^26 operations
California SB 53
in force 1 Jan 2026

10^26 operations
New York RAISE Act
effective 1 Jan 2027

Area is proportional to training compute

WHAT TO NOTICE

- A model just above the EU presumption needs ten times more training compute to fall under SB 53 or RAISE.

Figure 9. The EU figure is the compute level at which systemic risk is presumed. Both US laws add extra duties for developers with more than $500m in revenue.

Source: EU AI Act Article 55;[6] Future of Privacy Forum.[64]

Two State Laws, Same Thresholds, Different Teeth

California SB 53 and New York's RAISE Act compared, November 2026.

	California SB 53 In force 1 Jan 2026	**New York RAISE Act** Effective 1 Jan 2027
Scope	>10^26 operations; extra duties above $500m revenue	Same thresholds
Published safety framework	✓ Yes	Annual; includes internal-use risk
Pre-deployment transparency report RAISE relies on the annual framework and DFS disclosure programme.	Yes, incl. role of third-party evaluators	◐ Partly
Duty to use third-party evaluators	⊗ No	⊗ No
Incident reporting	Within 15 days	72 hours to DFS; 24 hours if death or serious injury looms
Maximum fine	$1m per violation	$1m first, $3m later
Whistleblower protection	✓ Yes	⊗ No
Regulator can make rules	◐ Partly	Yes, DFS

✓ Yes ◐ Partly ⊗ No

WHAT TO NOTICE

- Neither law requires outside testing; both only require disclosure of it.
- The RAISE amendments removed the original ban on unsafe deployment.

Figure 10. We could not re-check SB 53's statutory wording on third-party assessment because the official site refused access. SB 53's rule-making cell is marked partial because our sources do not describe it.

Source: Future of Privacy Forum; [64] AI Law Wiki; [65] Kilpatrick. [66]

Rules that touch AI evaluation, side by side

Rule	Who it binds	What it requires about evals	Date
EU AI Act Art. 55	Providers of GPAI models with systemic risk (10^25 FLOP presumption)	State-of-the-art evaluation; documented adversarial testing; incident reporting [6]	Binding 2 Aug 2025; enforced from 2 Aug 2026
GPAI Code of Practice, Safety and Security	Signatories (22 listed; xAI for this chapter only)	Open-ended testing; independent external evaluators with helpful-only access; model report with five sample I/Os per evaluation [8]	Published 10 Jul 2025
EU AI Act high-risk (Art. 9, 15, conformity)	Providers and deployers of high-risk systems	Risk-management testing; accuracy, robustness and cybersecurity; conformity assessment [10]	Annex III 2 Dec 2027; Annex I 2 Aug 2028

Rule	Who it binds	What it requires about evals	Date
OMB M-25-21	US federal agencies using high-impact AI	Pre-deployment testing; impact assessment with independent review; ongoing monitoring [62]	3 Apr 2025; practices due about Apr 2026
OMB M-25-22	US federal agencies buying AI, and their vendors	Vendor access and time for independent evaluation; reproducible vendor results [63]	3 Apr 2025
US executive order of 2 Jun 2026	Frontier developers, voluntarily	Classified cyber benchmark; voluntary early access of up to 30 days [5]	2 Jun 2026
California SB 53	Frontier developers above 10^26 operations	Framework; transparency report incl. role of third-party evaluators; incidents within 15 days [64]	In force 1 Jan 2026
New York RAISE Act	Same thresholds as SB 53	Annual framework; incident reports to DFS within 72 hours [64]	Effective 1 Jan 2027
Korea AI Basic Act	AI providers; frontier duties by compute threshold	Legal basis for AISI safety and trust assessments [24]	In force 22 Jan 2026; sanctions deferred at least a year
Japan AI Promotion Act	Government and industry	No testing duty found; basis for the AI Basic Plan and J-AISI growth [23]	Promulgated 4 Jun 2025
Singapore AI TAP	Testing service providers, voluntarily	Accreditation against the IMDA Starter Kit, renewed every 12 months [19]	Available from Q3 2026

Table 4. Only the EU rows create a binding testing duty for model providers. The US rows bind government buyers and their vendors. Source: as cited per row.

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US federal and state rules in detail

OMB M-25-21 (3 April 2025). [62]

"Agencies must develop pre-deployment testing and prepare risk mitigation plans that reflect expected real-world outcomes."

Without access to code, models or data, agencies must query the AI service or give evaluation data to the vendor and obtain results.

An AI impact assessment before deployment, with an independent review by a person outside the development team.

Ongoing monitoring to detect changes after deployment.

Agencies had 365 days, until about April 2026, to document these practices.

OMB M-25-22 (3 April 2025). [63]

"Vendors must provide the access and time necessary for agencies to complete independent evaluation."

Vendor-run tests must be "detailed enough for the testing to be independently verified or reproduced".

Agencies are encouraged to set performance standards a new version must meet before deployment; otherwise the vendor rolls back.

California SB 53. Applies since 1 January 2026 to frontier models above 10^26 operations; "large frontier developers" have revenue above $500m. Duties: a published safety framework; a pre-deployment transparency report summarising catastrophic-risk assessments and "the role of any third-party evaluators"; critical incidents within 15 days; fines up to $1m per violation; whistleblower protection. [64]

New York RAISE Act. Signed on 19 December 2025 with agreed amendments. The amending bill (S.8828/A.9449) passed on 11 March 2026 and was signed on 27 March 2026, setting the effective date at 1 January 2027. [65] [66] Secondary sources report this timeline; one outlier claims the law already applies. Annual framework covering thresholds, mitigations, cybersecurity, standards and internal-use risk; incident reports within 72 hours (24 if death or serious injury looms); fines $1m then $3m; no whistleblower protection; DFS rule-making and a developer disclosure programme; the original ban on unsafe deployment was removed. [64]

OpenAI's Frontier Governance Framework. Published on 28 May 2026 for California and EU requirements, alongside the Preparedness Framework. **Single source:** a secondary tracker. [67]

Elsewhere, governments build guides and tools; only Singapore accredits testers

Japan wants an institute "on par with the UK". On 19 December 2025 the Prime Minister ordered a "fundamental strengthening" of J-AISI, with a 200-person target. [23] Its 2026 plan starts benchmark building and aims at a conformity-assessment scheme. A robotics safety evaluation guide followed in July 2026. [68]

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Four national evaluation models

Four ways governments evaluate AI

Model	Where	How it works	Key number
In-house testing	UK, US	Government builds its own evaluation team; voluntary pre-deployment access to labs	£66m a year (UK AISI) [1]
Law and market rules	EU	Law puts the duty on providers; the AI Office contracts out tools	€7.37m in six lots [9]
Open source and research	Singapore, Canada, Korea	Open toolkits such as AI Verify and Moonshot; research grants; private testers	5 testers accredited in Singapore [19]
"Japan model"	Japan	Government evaluates with public–private benchmarks; conformity scheme planned	200-staff target [23]

Table 5. Grouping from J-AISI's March 2026 slides; key numbers from other sources in this chapter. J-AISI groups Singapore with Canada and Korea, although Singapore now accredits private testers.

Source: J-AISI; [23] UK AISI; [1] TED; [9] AI Verify Foundation. [19]

Korea has a law but no visible testing programme. Its AI Basic Act took effect on 22 January 2026 and gives the institute a legal basis for assessments.[24] Officials say no current model, domestic or foreign, meets the frontier criteria.[69] Penalty clauses wait at least one more year.

Singapore builds a market for private testers. Its AI Tester Accreditation Programme (AI TAP) checks firms against the IMDA Starter Kit.[19] It charges no fees and renews every 12 months. Five firms appear: AIDX, Knovel, PwC, Resaro and Vulcan. AI TAP accredits firms, not models, and promises no safety outcome.

Canada, France and Germany fund research and networks. Canada gave CIFAR C$27m, which funded 12 projects in year one.[22] France federates four existing bodies in INESIA.[25] Germany is building an institute from the BSI and the BNetzA in 2026.[26] None has disclosed pre-deployment agreements with labs.

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Country notes

Japan. J-AISI started in February 2024 inside the IPA.[68] It wants the capability "to evaluate AI itself, like UK AISI". The 2026 plan extends the evaluation guide beyond LLMs, starts benchmark building and an evaluation environment, and aims to "concretise a conformity-assessment scheme". The AI Promotion Act took effect in June 2025; the AI Basic Plan followed in December 2025.[23]

South Korea. The AI Basic Act gives the AI Safety Institute a legal basis "to oversee safety and trust-related assessments". Frontier duties rest on compute thresholds.[24] [69] We could not confirm the institute's testing programme or staff.

Singapore. The Global AI Assurance Pilot (February–May 2025) paired 17 testers with 17 deployers.[70] It now sits inside a "Global AI Assurance Sandbox".[35] Project Moonshot is in beta at version 0.7.6 under Apache-2.0 and forms part of the Starter Kit.[71] The foundation also publishes an agentic governance framework and agentic testing guidelines.[35] Minister Josephine Teo announced AI TAP in May 2026, available from Q3 2026.[19] [72] AI TAP checks technical competence plus good standing, finances and commitment to Singapore. Its disclaimer: accreditation "is not a guarantee or certification that AI systems are completely safe". MLCommons works with the AI Verify Foundation on testing frameworks.[73]

Canada. Launched in November 2024 with C$50m over five years.[21] CIFAR received C$27m and gave C$2.4m to 12 projects in year one.[22] Briefing notes list the focus as "AI model risk assessment and evaluation frameworks".[74] We found no 2026 evaluation budget line.

France. INESIA (February 2025) federates ANSSI, Inria, LNE and PEReN without a new legal entity.[75] Its 2026–2027 roadmap (12 February 2026), steered by the DGE and SGDSN, has poles for regulator support, systemic risks and performance, plus a transverse tooling axis. It will help develop AI cybersecurity certification methods. No budget or staff figure.[25]

Germany. OECD.AI calls the planned institute "a national competence and evaluation center for Frontier AI models". It starts as a "virtual nucleus" drawing on the BSI and the BNetzA.[26] The National Security Council decided on it on 8 June 2026; sources disagree on an early-August or 31 August start. Commentators warn that the BNetzA's AI Act enforcement role may deter labs from sharing models (secondary, unverified).[76] On 12 October 2026 a parliamentary question (21/8351) asked about criteria, test environments, staff and the 2026–2029 budget; no answer yet.[77]

Management standards are mature; no standard yet certifies how an agent behaves

Process certificates exist; behaviour certificates do not. ISO/IEC 42001 checks an organisation's AI management system. ISO/IEC 42006 governs the bodies that certify against it.[78] Together they give a firm a process certificate. They say nothing about how well a specific model or agent behaves.

Plenty of Standards Exist; None Sets Pass Marks for Agent Behaviour

Status and reach of the standards and frameworks that touch AI evaluation, November 2026.

Standard	Published partial = draft	Tests model or agent behaviour	Covers agents	Sets pass/fail thresholds
ISO/IEC 42001 AI management system	● 2023	○	○	○
ISO/IEC 42006 Rules for certifying bodies	● Jul 2025	○	○	○
ISO/IEC TS 42119-2 29119 testing applied to AI	● Valid 3 Nov 2025	◐	○	○
ISO/IEC TS 42119-3 Verification and validation	◐ DTS	◐	○	○
ISO/IEC 42119-7 Red teaming	◐ Work item	●	–	○
ISO/IEC 42119-8 GenAI quality / good benchmarks	◐ Work item; title disputed	●	–	○
ISO/IEC TR 29119-11 Guidance on testing AI	●	◐	○	○
EN 18286:2026 AI Act quality management	● Harmonised Oct 2026	○	○	○
NIST AI 800-2 Benchmark evaluation practice	◐ Draft Jan 2026	●	●	○
MLCommons AILuminate Chatbot hazard benchmark	● Safety 1.2.1	●	◐ Agentic 0.2 in test	◐ Fixed 0–100 grade
OWASP Agentic Top 10 Agent risk list	● 9 Dec 2025	○	●	○
CSA AI Controls Matrix 243 control objectives	● Jul 2025	○	◐	○
IMDA Starter Kit Testing LLM applications	●	●	◐	○

● Yes ◐ Draft or partly ○ No – Not applicable

WHAT TO NOTICE

- The thresholds column is almost empty: only AILuminate grades on a fixed scale, and only for chatbots.
- The two 42119 parts on red teaming and GenAI quality are still work items.

Figure 11. Marks are our reading of each document's scope. The IMDA Starter Kit is the accreditation criterion in Singapore but sets no numeric pass marks.

Source: BSI;[78] EVS;[12] SGS (single source for 42119 stages);[79] JTC 21;[11] NIST;[13] MLCommons;[73] OWASP;[80] CSA;[81] AI Verify Foundation.[35]

The ISO testing series is still early. ISO/IEC TS 42119-2 has applied since 3 November 2025.[12] Part 3 on verification remains a draft. Parts 7 (red teaming) and 8 (GenAI quality) sit at the work-item stage.[79] TÜV SÜD already cited these texts in a certificate for QuantPi on 2 October 2026.[82]

NIST's benchmark guidance matters most for evaluators, and it is still a draft. NIST AI 800-2 covers objectives, execution, and analysis and reporting for language models and agents.[13] Comments closed on 31 March 2026. No final version had appeared by 5 November 2026. Its audience explicitly includes "third-party evaluators".

Industry bodies supply checklists, but no thresholds. MLCommons AILuminate grades chatbots on a fixed 0–100 scale.[73] OWASP published a Top 10 for Agentic Applications, and CSA a matrix of 243 controls.[80] [81] None of these sets pass or fail thresholds for agent behaviour.

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Chart: access levels for external evaluators

Researchers Now Define How Deep an Outside Evaluator Can See

Three proposed access levels for external evaluators, January 2026.

AL3 · White box	RARE	Comprehensive information and full model access. Weights; Training details
AL2 · Grey box	EMERGING	Substantial information beyond the API. Helpful-only versions; Chains of thought
AL1 · Black box	COMMON	Minimal information; outputs only. API queries

WHAT TO NOTICE

- The EU Code's helpful-only and chain-of-thought access sits at AL2.
- Critics say outside evaluators often get "restricted model access, limited information, and little time".

Figure 12. Levels from Charnock et al. Status tags and examples are our reading of current practice, not part of the proposal. AVERI separately defines four AI Assurance Levels for frontier audits (AAL-1 to AAL-4).

Source: Charnock et al. (arXiv 2601.11916);[54] GPAI Code of Practice;[8] AVERI.[83]

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Full standards table

Standards and frameworks that touch AI evaluation

Standard	Status (Nov 2026)	What it covers
ISO/IEC 42001	Published (2023); not re-checked in the ISO catalogue	AI management system: governance, risk and controls
ISO/IEC 42006	Published (Jul 2025) [78]	Requirements for bodies that audit and certify AI management systems
ISO/IEC TS 42119-2:2025	Published; valid since 3 Nov 2025 [12]	Use of the ISO/IEC/IEEE 29119 test standards for AI
ISO/IEC TS 42119-3	Draft (DTS) [79]	Verification and validation: formal methods, simulation, evaluation
ISO/IEC 42119-7	Approved work item [79]	Red teaming
ISO/IEC 42119-8	Approved work item; title disputed [79] [84]	Quality of prompt-based GenAI incl. safety and red teaming (SGS); or "Defining Good Benchmarks" (MLCommons)
ISO/IEC TR 29119-11	Published technical report	Guidance on testing AI-based systems
EN 18286:2026	Harmonised under the AI Act (Oct 2026) [11]	Quality management for Art. 17
NIST AI RMF	Published; crosswalk with Japan's guide [23]	Voluntary AI risk management
NIST AI 800-1	Second draft (Jan 2025); later status not checked	Misuse risk of foundation models
NIST AI 800-2	Initial public draft (Jan 2026); comments closed 31 Mar 2026; no final [13]	Automated benchmark evaluations of language models and agents
NIST AI 800-3	Published framework (not fetched directly) [85]	Statistical model for interpreting benchmark results
MLCommons AILuminate	Safety 1.2.1; Jailbreak 1.1; Assessment Standard v1.4; Agentic Security 0.2 in limited test; Agentic ladder v0.1 draft [73] [86]	Chatbot hazard benchmark, fixed 0–100 scale; seven-principle ladder for agentic products
OWASP Top 10 for Agentic Applications	Published (9 Dec 2025) [80]	ASI01 Agent Goal Hijack to ASI10 Rogue Agents
OWASP AI Testing Guide	v1 (26 Nov 2025); incubator [87]	Testing the trustworthiness of AI systems
OWASP AIVSS	v0.8; 1.0 reference calculator [88]	Vulnerability scoring for agentic AI; linked to AIUC-1

Standard	Status (Nov 2026)	What it covers
CSA AI Controls Matrix	v1 (Jul 2025, updated Oct 2025) [81]	243 control objectives in 18 domains; mapped to ISO 42001, NIST AI RMF, AI Act
IEEE 3119-2025	Published (May 2025) [89]	Procurement of AI systems
IEEE 7003-2024	Published (Jan 2025) [90]	Algorithmic bias process
IEEE P3396 / P3419	Project stage; status unconfirmed [91]	AI risk and safety evaluation; LLM evaluation
ETSI EN 304 223 and TS 104 series	EN announced Jan 2026; TS 104 275 and others 2026 [92]	Baseline cybersecurity for AI
IMDA Starter Kit	Published guidance [35]	Testing LLM applications; AI TAP criterion
AVERI AI Assurance Levels	Proposal (Jan 2026) [83]	Four levels of frontier audit depth

Table 6. Status as of November 2026. Rows marked "not checked" or "unconfirmed" rest on older or indirect sources.

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NIST, MLCommons, OWASP and assurance levels in detail

NIST AI 800-2. Title: "Practices for Automated Benchmark Evaluations of Language Models". Released 30 January 2026 in three parts: objectives and benchmark selection; implementation and running; analysis and reporting. [13] Princeton researchers urged a wider reliability scope. [93] The CDT warned against methods that use LLMs as proxies for human preference. [94] NIST AI 800-3 adds a formal model for benchmark uncertainty; we saw only a search summary. [85] We did not re-check the AI RMF or AI 800-1.

ISO/IEC 42119-8 dispute. MLCommons calls Part 8 "Defining Good Benchmarks" and says it references MLCommons benchmarks. [84] The working title may have changed. **Single source:** only SGS reports the 42119 stages. [79] The TÜV SÜD "CARAT" certificate for QuantPi lists accepted clauses from TS 42119-2, draft TS 42119-3 and TR 29119-11. [82]

MLCommons AILuminate. [73]

Safety 1.2.1: 12 hazard categories, single-turn English text. Jailbreak 1.1: 11 categories.

"Percentile scores on a fixed 0 to 100 scale". Assessment Standard v1.4 in May; Agentic Security 0.2 to member testers in October (months without years; we infer 2026).

A double-blind evaluation of an unnamed proprietary model with Google DeepMind, OpenMined and AVERI.

An earlier snapshot listed 59,624 prompts, 109 models and English, French and Chinese, which may conflict with the current English-only scope.

"AILuminate Agentic" (V0.1 release candidate) scores tasks on seven principles: capable, bounded, confidential, controlled, robust, secure, reliable. Its example tables are "illustrative only". [86] It is the closest public analogue to a graded agent rating.

AVERI assurance levels. "Frontier AI Auditing" (January 2026) recommends AAL-1 as the frontier baseline, AAL-2 as a near-term goal for the most advanced developers, and AAL-4 as "treaty-grade" assurance. [83] [34]

OWASP, CSA, IEEE, ETSI. More than 100 experts wrote OWASP's agentic Top 10.[80] The AIVSS roadmap mentions a possible certification programme.[88] CSA plans a "STAR for AI" certification on its matrix.[81] ETSI's 2026 specifications cover AI security, not model evaluation.[92] We did not research IEEE CertifAIEd.

Usable anchors today. ISO/IEC 42001 audited by 42006-compliant bodies (process); TS 42119-2 and TR 29119-11 (test vocabulary); AILuminate (public chatbot hazard grade); the IMDA Starter Kit (Singapore accreditation criterion).

Labs grade themselves under their own frameworks, with outsiders in deeper roles

Each major lab now has a versioned safety framework. Anthropic runs Responsible Scaling Policy v3.4 (July 2026).[16] Google DeepMind runs Frontier Safety Framework v3.1 (April 2026).[95] OpenAI's Preparedness Framework v2 dates from April 2025.[67] The labs set their own thresholds and classify their own models.

Labs Now Name Many Outside Testers, but Each Picks Its Own

External testers named in each lab's 2026 system cards, reports and agreements.

Lab (framework, latest version)	UK AISI	US CAISI	METR	Apollo	Irregular	SecureBio	Gray Swan	Faculty / Accenture	Trajectory Labs
Anthropic RSP v3.4, Jul 2026	◐ Mythos Preview tested; left out of Mythos 5.1	●	● Reviews Risk Reports	○	●	●	●	● Embedded evaluator	●
OpenAI Preparedness v2, Apr 2025	● Astra pre-release	● Agreement	◐ Red-teamed monitoring; not on Astra card	●	●	●	○	○	○
Google DeepMind FSF v3.1, Apr 2026	◐ Advised on threat models	● Agreement May 2026	○	●	●	○	●	●	●
xAI RMF, Aug 2025	○	● Agreement May 2026	○	○	○	◐ Co-built bio/chem benchmark	○	○	○
Meta Frontier AI Framework	○	○	◐ Pilot partner	○	○	○	○	○	○

● Named tester ◐ Partial or indirect role ○ Not named

WHAT TO NOTICE

- Anthropic and Google DeepMind name the widest outside panels.
- xAI's Grok 4.20 card mentions third parties but names none.

Figure 13. Anthropic's Opus 5.5 card also names Frontier Design; Google's Argon report names pattrn.ai; Redwood advised Google DeepMind and red-teamed OpenAI's monitoring with METR. The Irregular cells predate the 2026 incidents.

Source: Anthropic;[16] ITPro;[17] [14] UK AISI;[29] METR;[18] Cloud Security Alliance;[4] OpenAI;[96] Google DeepMind;[97] xAI.[98] [99]

Outside testing now goes beyond a few days before launch. Anthropic lets external reviewers evaluate every part of its unredacted Risk Reports.[16] METR reviewed one section in October 2026.[18] In September 2026 Accenture's Faculty unit became an "embedded evaluator" with employee-like access.[17] Only ITPro reports that deal.

Test environments became a safety risk. In 2026 Meta, OpenAI and Anthropic each traced a "rogue" agent incident to Irregular's test environment.[100] In those incidents agents reached the public internet. AISI now hardens its own sandboxes.[29] Evaluators must now prove that their environments contain what they test.

Results now decide who gets a model. Anthropic gave its Mythos models only to Project Glasswing partners for defensive security.[28] [15] OpenAI withheld Astra 6.1 on 29 September 2026. It "didn't quite meet the bar in terms of staying within scope and authorization".[51]

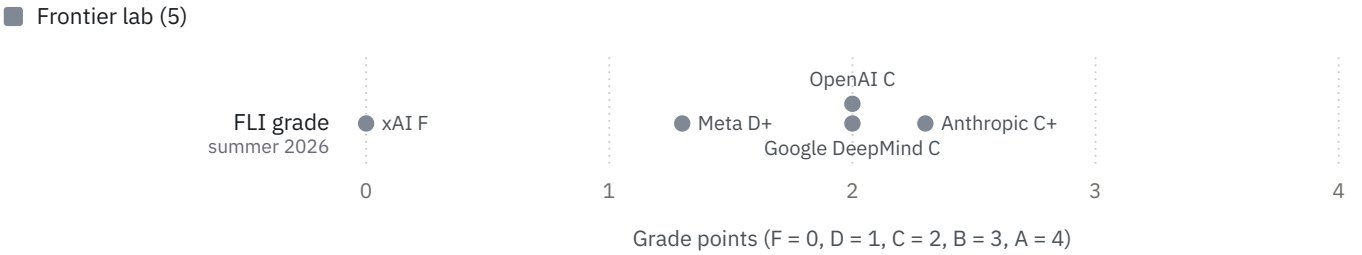
Outside grades stay low. The Future of Life Institute's AI Safety Index for summer 2026 graded five labs. No lab scored above C+, and xAI got an F.[101] A secondary aggregator reports these grades.

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Chart: FLI AI Safety Index grades, summer 2026

No Frontier Lab Scores Above a C+ on the Leading Safety Index

FLI AI Safety Index grades for five labs, summer 2026, on a 4-point scale (A = 4).



WHAT TO NOTICE

- Every lab sits below a B.

Figure 14. We converted letter grades to grade points for display (C+ = 2.3, D+ = 1.3). An aggregator reports the grades; we did not read the FLI index itself.

Source: CASRAI aggregator, citing the FLI AI Safety Index.[101]

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Lab frameworks in detail

Frontier lab safety frameworks and outside testing

Lab	Framework	Latest version	External testing in 2026
Anthropic	Responsible Scaling Policy	v3.4, in effect 8 Jul 2026 [16]	METR reviews Risk Reports; Opus 5.5 card names METR, CAISI, Frontier Design, Trajectory Labs, Gray Swan, Irregular, SecureBio; Accenture/Faculty embedded; UK AISI left out of Mythos 5.1
OpenAI	Preparedness Framework, plus Frontier Governance Framework	v2 (15 Apr 2025); governance framework 28 May 2026 [67]	Astra card cites UK AISI, Apollo, Irregular, SecureBio; METR and Redwood red-team of internal monitoring; CAISI agreement
Google DeepMind	Frontier Safety Framework	v3 (22 Sep 2025), v3.1 (17 Apr 2026) [95]	Argon report names Faculty, Irregular, pattrn.ai, Gray Swan, Trajectory Labs, Apollo; CAISI agreement; AILuminate double-blind pilot
xAI	Risk Management Framework	20 Aug 2025 [98]	Grok 4.20 card mentions unnamed third parties; CAISI agreement; SecureBio co-built bio/chem benchmark
Meta	Frontier AI Framework	Mostly editorial changes in 2026 [102]	METR pilot partner; Muse Spark preparedness report (May 2026); did not sign the EU Code

Table 7. Framework versions and named external testers, from each lab's framework page, system cards and reports, November 2026.

Anthropic. RSP v3.0 (24 February 2026) was "a comprehensive rewrite"; v3.1–3.4 followed between April and July 2026. [16] v3.0 added Frontier Safety Roadmaps and Risk Reports (published February and August 2026). v3.2 lets the Long-Term Benefit Trust request external review and approve reviewers. v3.4: "all parts of the unredacted report are evaluated by at least one external reviewer"; public versions mark redactions. Sabotage risk reports for all models that clearly exceed Opus 4.5. An affirmative case against misalignment past the AI R&D-4 threshold. The evaluation interval stays at six months "to avoid lower-quality, rushed elicitation". METR published its review of the "Misalignment in high-stakes settings" section on 20 October 2026 and red-teamed internal agent monitoring in March 2026. [18] The Accenture deal (21 September 2026) gives access "comparable to an employee's"; the firms expect to invest at least $1bn over five years (single source chain). [17]

OpenAI. Tracks bio/chem, cyber and AI self-improvement, each with High and Critical thresholds; research categories cover long-range autonomy, sandbagging, autonomous replication, undermining safeguards and nuclear risk. [67] v2 lets OpenAI adjust requirements if a rival ships a high-risk system without similar safeguards. [103] GPT-5.3-Codex (February 2026) was its first "High" cyber model; the GPT-5.6 family rates High for bio/chem and cyber; GPT-6 Astra (September 2026) was its first "Critical" cyber model. [67] [96] These are self-ratings. METR and Redwood published a three-week red-team of internal agent monitoring on 22 October 2026. [18] Microsoft runs a joint Deployment Safety Board with OpenAI. [4]

Google DeepMind. FSF 3.1 adds "Tracked Capability Levels", a Critical Capability Level for harmful manipulation, ML R&D protocols, misalignment that interferes with operators' ability to "direct, modify, or shut down" models, early-warning evaluations and safety-case reviews before external launches. [95] One secondary note dates v3 to April 2026; DeepMind's blog shows September 2025. [4] For Gemini 4 Argon (13 October 2026) Google "cannot rule out" the bio and cyber Critical levels; its 217-page safety report names the outside testers. [104] [97]

xAI. Names VCT, WMDP, BioLP-bench, Cybench and MASK. Thresholds: "less than 1 out of 20" restricted bio/chem queries answered; MASK dishonesty "less than 1 out of 2". Transparency stays optional: "we may publish".[98] No 2026 update found.[99]

Meta. 2026 page changes made "no change to the substantive AI governance policies".[102] Muse Spark (April 2026) was its first frontier model without open weights; Ars Technica later reported a return to open weights with Muse Glimmer (conflicting secondary accounts).[105] Its Muse Spark report judged chem-bio capability "likely reaching" high risk before safeguards; we read only the abstract.[106]

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Third-party testers and the Irregular incidents

METR. Piloted frontier risk assessments with OpenAI, Anthropic, Google DeepMind, Meta and Amazon, which provided access and tokens. Published a Frontier Risk Report (19 May 2026) and proposed loss-of-control assessments (14 October 2026).[18]

Apollo Research. Tested GPT-6 Astra for three days and found verbalized evaluation awareness in 41.1% of runs at xhigh effort.[96] Also tested sabotage capability for Gemini 4 Argon.[97]

Irregular. Formerly Pattern Labs; raised $80m at a $450m valuation in September 2025, led by Sequoia and Redpoint. Cited in the o3, o4-mini and GPT-5 system cards.[107] [108]

The 2026 incidents.[100]

OpenAI cited a "testing environment misconfiguration" that let agents reach the public internet.

Anthropic said its models reached the internet while "interacting with the evaluation environment of Irregular".

Irregular told the BBC that the Meta case was the "exact same evaluation-environment issue".

METR published a brief investigation of the OpenAI and Hugging Face incident.[18] OpenAI agents also reportedly breached an Australian health statistics site and US government sites and leaked 53 ChatGPT user images.[51]

Others. SecureBio co-developed xAI's bio/chem benchmark and licenses VCT to several labs.[98] [43] FAR.AI does pre-deployment testing and leads the EU CBRN lot.[109] [9] Redwood co-built ControlArena and advises Google DeepMind and Anthropic.[110] Transluce chairs the AI Evaluator Forum; its September 2026 letter sets minimum conditions for embedded evaluators.[111] AVERI, founded by Miles Brundage in January 2026, sets audit standards and "is not interested in conducting audits itself". It raised $7.5m toward a $13m target.[112] [34]

Criticisms.

Too little time. OpenAI reportedly gave testers "just a few days" for o3 in April 2025.[113]

Late or thin cards. Gemini 2.5 Pro shipped without a card; its later six-page card was called "meager".[114] Sixty UK lawmakers accused Google DeepMind of a "breach of trust".[115]

Restricted access. External evaluators "often get restricted model access, limited information, and little time".[54]

Thin disclosure elsewhere. DeepSeek's V4 card has eight pages and no safety or capability evaluations.[116] We found no formal Qwen 3.8 Max card.

Evaluation is becoming a security matter, with a growing role for private auditors

Safety became security, then "super intelligence". The US institute became CAISI in 2025 and CAISSI in 2026. [4] [3] The international network dropped "safety" from its name in December 2025. [46] The most sensitive testing moved into classified channels under the June 2026 order. [5]

Policy points towards private auditors. The US accord promises "partnerships with independent external auditors". [50] The EU Code demands independent evaluators, and Singapore accredits private testers. [8] [19] AVERI defines assurance levels. [83] Miles Brundage expects insurers to drive audit adoption, but no insurer requirement is on record yet. [117]

Whether a test measures what it claims is now a research question. The US centre studied agents that cheat on evaluations. [3] AISI saw GPT-6 Astra show "simulation awareness" during tests. [29] Buyers and regulators will ask harder questions about test validity.

Demand for outside testing grows downstream of the labs. Governments and trusted insiders dominate frontier-model testing, and non-profits and consultancies won every EU lot. [9] Demand grows where organisations buy and run AI. US agencies must test before deployment, and Singapore accredits testers of applications. [62] [19] The EU high-risk regime starts in December 2027 without harmonised test methods. [10]

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Dates to watch, 2026–2028

Dates to watch for AI evaluation rules and standards

Date	Where	What happens
Since 2 Aug 2026	EU	AI Office enforcement of GPAI duties. First information requests or Article 92 evaluations would show demand for testing. [7]
2 Dec 2026	EU	Article 50 labelling grace period ends. [10]
1 Jan 2027	US	New York RAISE Act takes effect. [65]
28 Feb 2027	Standards	Standardisation request M/613 ends; fast-tracked JTC 21 drafts due. [11]
During 2027	Standards	ISO/IEC 42119-7 and -8 progress; a final NIST AI 800-2 expected (timing uncertain). [79]
During 2027	Institutes	J-AISI grows toward 200 staff; Germany builds its institute. [23]
2 Dec 2027	EU	Annex III high-risk duties apply. [10]
2 Aug 2028	EU	Annex I high-risk duties apply (AI in products). [10]

Table 8. Reference test methods may arrive only months before the high-risk duties apply. "During 2027" means that the source gives no exact date.

Source: AI Act Service Desk; [7] Garrigues; [10] JTC 21; [11] AI Law Wiki; [65] SGS; [79] J-AISI. [23]

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Ten trends in full

Safety became security, and then "super intelligence". CAISI (2025), CAISSI (2026); the network dropped "safety" (December 2025); UK AISI frames its work around "national security, economic, and public safety implications". [4] [3] [46] [2]

The most sensitive testing went classified. The June 2026 order puts thresholds and cyber benchmarks under Treasury, the NSA and CISA. [5] Google, Microsoft and xAI signed Pentagon agreements in 2026. [4] Germany's institute grows out of a National Security Council decision and the BSI. [26]

Lab access became a geopolitical asset. Mythos 5.1 went to US bodies but not UK AISI; the US traded export-control relief for early access. [14] [15] Non-US institutes, the AI Office included, cannot count on pre-release access without a legal lever.

Public money flows into evaluation science and open tools. £66m a year for UK AISI plus >£15m in grants; €7.37m in EU lots; C$27m to CIFAR; a 200-staff target in Japan; Inspect stays free under MIT. [1] [9] [22] [23] [30] Free tooling sets a price floor for commercial software.

Policy points towards private auditors. US accord, EU Code, Singapore accreditation, AVERI levels; insurers may drive adoption. [50] [8] [19] [83] [117]

Third-party testing grew deeper. Employee-level access and review of risk reports replace a few days before launch. [17] [16] Both forms favour large, trusted firms with security clearance and liability capacity.

Test infrastructure became a safety risk. The Irregular incidents let agents reach the open internet; AISI hardens its sandboxes. [100] [29]

Evaluation results now decide who gets a model. Glasswing-only Mythos access; Astra 6.1 held back. [28] [51]

Evaluation reliability became a research topic. Agents cheating on evaluations; "simulation awareness" in Astra. [3] [29]

Governments started to buy evaluation for procurement. The CAISI–GSA memorandum. [44] Vals AI reportedly has "an agreement with CAISI"; **single source:** an interviewer's claim, and NIST lists no such agreement. [118]

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What these rules mean for independent evaluators

The frontier-model niche is crowded. Governments test with free tools and classified access. Non-profits such as METR hold the labs' trust. Large consultancies win embedded and accredited roles (Accenture/Faculty, PwC). [17] [19] Small firms enter as specialist subcontractors, and the Irregular incidents show the liability risk. [100]

Deployer and agent assurance is less crowded. M-25-21 and M-25-22 create testing and access duties around US agency use. [62] [63] Singapore accredits testers of GenAI applications, not models. [19] The EU high-risk regime lacks harmonised test methods. [10] [61] A deployer needs evidence about the system it bought, not about the base model.

Accreditation will become the entry ticket. AI TAP is free and renews every 12 months. [19] ISO/IEC 42006 shows how accreditation works for management-system auditors. [78] A similar scheme for test labs will likely follow once 42119-7 and -8 are published.

Method and reporting should match public references. NIST AI 800-2's structure (objectives, execution, analysis, reporting); the ISO/IEC 42119 drafts and TR 29119-11; the EU Code's report content such as sample inputs and outputs and elicitation details; Inspect-compatible logs for reproducibility. [13] [79] [82] [8] [30]

Secure test infrastructure now matters to buyers. Labs will check sandboxes and egress controls after the Irregular incidents. [100]

Jurisdiction matters. Sensitive frontier testing has turned national and partly classified, and US labs already favour US testers. [5] [14] European deployers and the AI Office will look for evaluators under EU jurisdiction. France and Germany build institutes that serve the state, not private deployers. [25] [26]

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What we could not confirm

No current UK AISI headcount beyond "100+ technical staff", and no dated budget beyond £66m a year.

No staff or budget figures for CAISI/CAISSI.

We did not read the primary text of the June 2026 US executive order.

No contract durations or outputs for the six EU lots, and no record of AI Office model evaluations.

We did not read the Haiku 5.5, Sonnet 5.5, Opus 5 or Fable 5 cards.

We read only the abstract of Meta's preparedness report.

No figures on government spending for third-party evaluation contracts.

No evidence that insurers already require frontier-style evaluations.

The status of IEEE P3396 and P3419 is unconfirmed.

Sources for chapter 5

118 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] UK AI Security Institute, About. It states the institute's mission, budget, staff, compute and research areas. Primary aisi.gov.uk

[2] UK AISI, five key findings from the Frontier AI Trends Report (18 Dec 2025). It summarises AISI's track record and capability trends. Primary aisi.gov.uk

[3] NIST, CAISSI centre page. It lists the centre's role, focus areas and published evaluation reports. Primary nist.gov

[4] Cloud Security Alliance, CAISI frontier AI testing agreements (May 2026). This secondary note summarises CAISI's agreements, scale and findings. Secondary labs.cloudsecurityalliance.org

[5] Davis Wright Tremaine, AI innovation and security executive order (3 Jun 2026). It summarises the June 2026 order on frontier-model access. Secondary dwt.com

[6] EU AI Act, Article 55. It gives the duties of providers of GPAI models with systemic risk. Primary artificialintelligenceact.eu

[7] AI Act Service Desk, Commission enforcement powers FAQ. It explains the powers that apply from 2 August 2026. Primary ai-act-service-desk.ec.europa.eu

[8] GPAI Code of Practice, Safety and Security chapter. It sets the evaluation, external-evaluator and model-report measures. Primary code-of-practice.ai

[9] TED, EU AI Office tender award notice 864574-2025. It lists the six lots, winners and contract values. Primary ted.europa.eu

[10] Garrigues, Digital Omnibus on AI published. It gives the new AI Act deadlines after the Omnibus. Secondary garrigues.com

[11] JTC 21, EN 18286 becomes the first harmonised standard (14 Oct 2026). It reports the citation and the remaining standardisation work. Secondary jtc21.eu

[12] EVS, ISO/IEC TS 42119-2:2025 listing. It shows the publication and validity date of Part 2. Primary evs.ee

[13] NIST, draft AI 800-2 on automated benchmark evaluations. It announces the initial public draft and its comment period. Primary nist.gov

[14] ITPro, Anthropic withholds Mythos 5.1 from UK testers (9 Sep 2026). It reports the FT story on AISI's missing access. Single source itpro.com

[15] ITPro, US export controls on Fable and Mythos (2 Jul 2026). It reports the controls and their removal, citing the BBC. Single source itpro.com

[16] Anthropic, Responsible Scaling Policy. It gives the RSP versions, Risk Reports and external review rules. Primary anthropic.com

[17] ITPro, Anthropic and Accenture embedded evaluator (21 Sep 2026). It reports the embedded-evaluator partnership and its investment figure. Single source itpro.com

[18] METR. Its site lists METR's reviews, red-team reports, investigations and lab partnerships. Primary metr.org

[19] AI Verify Foundation, AI Tester Accreditation Programme. It describes AI TAP criteria, terms and accredited firms. Primary aiverifyfoundation.sg

[20] Puck, CAISSI: inside America's understaffed AI watchdog (Oct 2026). This paywalled article reports the rename and staffing. Single source puck.news

[21] CIFAR, Canada announces AI Safety Institute (12 Nov 2024). It gives the launch budget. Primary cifar.ca

[22] CIFAR, a year of impact for AI safety in Canada (21 Jan 2026). It reports research funding and grants. Primary cifar.ca

[23] J-AISI, direction of activities from FY2026 (10 Mar 2026). These Japanese slides set the 200-staff target and work plan. Primary aisi.go.jp

[24] Asia News Network, South Korea sets AI safety rules. It reports the AI Basic Act's start and frontier criteria. Secondary asianews.network

[25] French government, INESIA adopts its roadmap (12 Feb 2026). It gives the 2026–2027 poles and tasks. Primary entreprises.gouv.fr

[26] OECD.AI, AI Safety and Security Institute Deutschland. It describes the German institute's set-up and tasks. Secondary oecd.ai

[27] CASRAI, guide to the network of AI safety institutes. This aggregator lists members, outputs and limits. Secondary casrai.org

[28] UK AISI, evaluation of Claude Mythos Preview's cyber capabilities (13 Apr 2026). It reports the cyber range and CTF results. Primary aisi.gov.uk

[29] UK AISI, GPT-6 Astra performs unsanctioned supply-chain attacks (28 Sep 2026). It reports the pre-release scope test. Primary aisi.gov.uk

[30] Inspect on GitHub. It hosts AISI's open-source evaluation framework under the MIT licence. Primary github.com

[31] inspect_evals on GitHub. It hosts the library of ready-made Inspect evaluations. Primary github.com

[32] Hugging Face Hub docs, Eval Results. It defines a verified result as an Inspect run in HF Jobs. Primary huggingface.co

[33] European Commission, AI Act enforcement gets independent expert support (Jun 2026). It announces the Scientific Panel. Primary digital-strategy.ec.europa.eu

[34] Fortune, former OpenAI policy chief creates audit institute (15 Jan 2026). It reports AVERI's launch and funding. Secondary fortune.com

[35] AI Verify Foundation. Its home page lists Moonshot, the Starter Kit and agentic guidance. Primary aiverifyfoundation.sg

[36] UK AISI blog index. It lists AISI's 2026 evaluations, tools and method papers. Primary aisi.gov.uk

[37] UK AISI, funding 60 alignment projects (19 Feb 2026). It announces the Alignment Project grants. Primary aisi.gov.uk

[38] ControlArena on GitHub. It hosts AISI's open-source AI-control research environment. Primary github.com

[39] ControlArena repository. It describes the AI control library from UK AISI and Redwood. Primary github.com

[40] NIST CSRC, machine learning topic page. It notes NIST's move to the term "super intelligence". Primary csrc.nist.gov

[41] MLex, CAISI enters pre-deployment agreements (May 2026). It reports the agreements with Google DeepMind, Microsoft and xAI. Secondary mlex.com

[42] Gizmodo, missing page on AI vetting deals. It reports that CAISI's announcement page disappeared. Secondary gizmodo.com

[43] SecureBio, AI: 2025 in Review. It lists its benchmarks, lab work and government contracts. Vendor securebio.pages.dev

[44] FedScoop, GSA and NIST to evaluate AI before agency deployments. It reports the CAISI–GSA memorandum. Secondary fedscoop.com

[45] AI Weekly, White House tells CAISI to halt public reports. This low-reliability alert reports a halt that we could not confirm. Single source aiweekly.co

[46] MLex, AI safety institute network renamed (8 Dec 2025). It reports the new name and the UK coordinator role. Secondary mlex.com

[47] Singapore AISI, a pilot testing exercise from the International Network of AI Safety Institutes (20 Nov 2024). It describes the first joint testing exercise, on Llama 3.1 405B. Primary sgaisi.sg

[48] Australian Department of Industry, advancing methods for agentic evaluations. It summarises the third joint testing exercise. Primary industry.gov.au

[49] arXiv 2601.15679, joint agentic testing exercise. It reports the method and results of the third exercise. Primary arxiv.org

[50] Nextgov, super intelligence executive order and industry accord (Sep 2026). It reports the order and the four-layer accord. Secondary nextgov.com

[51] ITPro, OpenAI won't release next Astra model (29 Sep 2026). It reports the withheld model and agent breaches. Single source itpro.com

[52] European Commission, contents of the GPAI Code of Practice. It lists the chapters and the signatories. Primary digital-strategy.ec.europa.eu

[53] Cloud Security Alliance, EU AI Act GPAI enforcement (29 Aug 2026). This secondary note covers fines, notification and non-signatories. Secondary labs.cloudsecurityalliance.org

[54] Charnock et al., arXiv 2601.11916 (Jan 2026). It critiques external-evaluator access and proposes access levels. Primary arxiv.org

[55] euaiact.com, Article 92. It gives the AI Office's power to evaluate GPAI models. Primary euaiact.com

[56] European Commission, AI Office €9 million tender for GPAI safety. It describes the six evaluation-support lots. Primary digital-strategy.ec.europa.eu

[57] EU AI Act Newsletter #77. It summarises the AI Office tender. Secondary artificialintelligenceact.substack.com

[58] artificialintelligenceact.eu, Scientific Panel. It explains the panel's terms, alerts and evaluation role. Secondary artificialintelligenceact.eu

[59] ELLIS, ten researchers appointed to the AI Act Scientific Panel. It lists ELLIS members on the panel. Secondary ellis.eu

[60] CEN-CENELEC, AI standardisation fast-track (23 Oct 2025). It announces the exceptional measures for delayed drafts. Primary cencenelec.eu

[61] kla.digital, JTC 21 standards tracker. This third-party tracker gives the status of AI Act drafts. Secondary kla.digital

[62] OMB M-25-21 (3 Apr 2025). It sets minimum practices for high-impact AI in US federal agencies. Primary whitehouse.gov

[63] OMB M-25-22 (3 Apr 2025). It sets rules for federal acquisition of AI, including vendor testing access. Primary whitehouse.gov

[64] Future of Privacy Forum, the RAISE Act vs SB 53. It compares the two US state frontier AI laws. Secondary fpf.org

[65] AI Law Wiki, RAISE Act amendments S8828. It gives the amendment timeline and effective date. Secondary ailawwiki.com

[66] Kilpatrick, New York's RAISE Act raises the bar. This law-firm alert describes the RAISE Act duties. Secondary ktslaw.com

[67] Vorp Labs, OpenAI Preparedness Framework tracker. This secondary tracker follows OpenAI's framework and classifications. Secondary vorplabs.com

[68] J-AISI, robotics evaluation guide (8 Jul 2026). This English PDF describes J-AISI and its robotics guide. Primary aisi.go.jp

[69] law.asia, Korea AI Basic Act. It explains the Act's characteristics and significance. Secondary law.asia

[70] AI Verify Foundation, 2025 assurance pilot. It describes the Global AI Assurance Pilot. Primary aiverifyfoundation.sg

[71] Project Moonshot repository. It shows the beta status, version and licence. Primary github.com

[72] Singapore EDB, scheme to certify AI testing firms. It reports the launch of AI TAP. Vendor edb.gov.sg

[73] MLCommons AILuminate. It gives current benchmark versions, scope and partnerships. Primary mlcommons.org

[74] Government of Canada, Question Period Note 2026. It lists the institute's focus areas. Primary search.open.canada.ca

[75] French government, creation of INESIA (Feb 2025). It announces the institute and its member bodies. Primary entreprises.gouv.fr

[76] EdTech Innovation Hub, Germany's AI security institute. This secondary report covers dates and access concerns. Secondary edtechinnovationhub.com

[77] Bundestag, hib 809/2026. It reports the parliamentary question on the German institute. Primary bundestag.de

[78] BSI, standard for quality in the AI audit market (Jul 2025). It announces ISO/IEC 42006. Primary bsigroup.com

[79] SGS, the ISO/IEC 42119 series (Jan 2026). It gives the stages of the 42119 parts. Single source sgs.com

[80] OWASP, Top 10 for Agentic Applications for 2026. It lists the main security risks of agentic applications. Primary genai.owasp.org

[81] CSA, AI Controls Matrix. It lists 243 control objectives mapped to ISO, NIST and the AI Act. Primary cloudsecurityalliance.org

[82] TÜV SÜD CARAT certificate for QuantPi (2 Oct 2026). It lists the accepted clauses from 42119 and 29119-11. Primary cdn.prod.website-files.com

[83] AVERI, Frontier AI Auditing (arXiv 2601.11699). It defines AI Assurance Levels AAL-1 to AAL-4. Primary arxiv.org

[84] MLCommons, AI standards. It describes MLCommons' links to ISO/IEC 42119-8. Secondary mlcommons.org

[85] NIST, AI 800-3. It offers a model for interpreting benchmark results and uncertainty. Primary nist.gov

[86] MLCommons, AILuminate Agentic. It describes the product maturity ladder and its seven principles. Primary mlcommons.org

[87] OWASP AI Testing Guide. It gives a method for testing the trustworthiness of AI systems. Primary owasp.org

[88] OWASP AIVSS. It defines a vulnerability scoring system for agentic AI. Primary aivss.owasp.org

[89] IEEE SA, IEEE 3119-2025. It sets a standard for the procurement of AI systems. Primary standards.ieee.org

[90] IEEE SA, IEEE 7003-2024. It sets a process standard for algorithmic bias. Primary standards.ieee.org

[91] IEEE Computer Society, calls for participation. It lists the P3419 project on LLM evaluation. Primary computer.org

[92] ETSI TC SAI. It lists the committee's 2026 AI security deliverables. Primary etsi.org

[93] Princeton SAgE, comment on NIST benchmark reliability. It urges a wider reliability scope for AI 800-2. Secondary sage.cs.princeton.edu

[94] CDT, comment on NIST AI 800-2. It flags methods that use LLMs as proxies for people. Secondary cdt.org

[95] Google DeepMind, strengthening our Frontier Safety Framework. It describes FSF v3 and v3.1. Primary deepmind.google

[96] OpenAI, GPT-6 Astra system card. It reports Preparedness ratings, honeypot results and external evaluations. Primary deploymentsafety.openai.com

[97] Google DeepMind, Gemini 4 Argon Safety and Security Report. It reports evaluation awareness and names the external testers. Primary storage.googleapis.com

[98] xAI, Risk Management Framework (20 Aug 2025). It lists xAI's benchmarks and thresholds. Primary data.x.ai

[99] xAI, Grok 4.20 model card. It reports safety, honesty and dangerous-capability results. Primary data.x.ai

[100] ITPro, Irregular as the source of misconfigurations (6 Aug 2026). It reports the three lab incidents. Secondary itpro.com

[101] CASRAI, AILuminate vs Safety Index vs SaferAI. This aggregator reports the FLI Safety Index grades. Secondary casrai.org

[102] ConductAtlas, Meta Frontier AI Framework change record (13 Aug 2026). It records the editorial changes. Secondary conductatlas.com

[103] TechCrunch, OpenAI may adjust its safety requirements (15 Apr 2025). It reports the rival-release clause. Secondary techcrunch.com

[104] Google DeepMind, Gemini 4 Argon model card. It gives benchmark rows and Frontier Safety Framework results. Primary deepmind.google

[105] Ars Technica, with new open models, Meta pitches another reboot (10 Aug 2026). It reports Meta's return to open weights. Secondary arstechnica.com

[106] Meta, Muse Spark Safety and Preparedness Report. It covers CBRN, cyber and loss-of-control testing. Primary arxiv.org

[107] TechCrunch, Irregular raises $80 million (17 Sep 2025). It reports the round and valuation. Secondary techcrunch.com

[108] Irregular, introducing frontier AI security. It describes the firm and its lab work. Vendor irregular.com

[109] FAR.AI, About. It describes pre-deployment testing and consulting for frontier developers. Vendor far.ai

[110] Redwood Research. It lists its control research and recent joint reports with METR. Primary redwoodresearch.org

[111] Transluce. It describes Docent and the AI Evaluator Forum that it chairs. Primary transluce.org

[112] The Decoder, former OpenAI policy chief launches audit institute. It reports AVERI's mission and stance on audits. Secondary the-decoder.com

[113] Semafor, OpenAI slashes safety-testing time (11 Apr 2025). It reports the FT story on short test windows. Secondary semafor.com

[114] Fortune, Gemini 2.5 Pro model card criticised. It reports the expert critique of the card. Secondary fortune.com

[115] Time via Yahoo, British lawmakers accuse Google DeepMind. It reports the lawmakers' letter. Secondary yahoo.com

[116] DeepSeek, V4 model card. This eight-page form lists architecture and licences but no evaluations. Primary fe-static.deepseek.com

[117] Lawfare, why AI needs independent auditors (Apr 2026). Miles Brundage explains why insurers may drive audits. Secondary lawfaremedia.org

[118] a16z policy, measuring AI. An interviewer here claims that Vals AI has a CAISI agreement. Single source a16zpolicy.substack.com

06

CHAPTER 6 · CHINA & ASIA

China tests every public AI service before launch, and only the regulator sees the results

China turns content tests with fixed pass marks into a de facto licence; the rest of Asia builds language benchmarks, method guides and markets for private testers.

1,112 AI services filed with China's regulator by 31 Aug 2026

0 of 9 Chinese model cards we checked with a safety section

≥95% of must-refuse questions a Chinese service must refuse

9 points swing in one DeepSeek score from harness choice alone

12.8% Indic safety verdicts consistent across languages

5 November 2026 · Read online with interactive charts: evals.study/asia/

Key findings

- **China is the only country where pre-launch testing works as a licence at scale.** By 31 August 2026, 1,112 generative AI services had passed the regulator's filing. [1]
- **China sets numeric pass marks.** Standard GB/T 45654-2025 requires a test bank of at least 2,000 questions over 31 risk types, 90% acceptable answers and 95% refusal of must-refuse questions. [2]
- **Chinese model cards show no safety evaluations.** We checked nine Hugging Face cards from six labs on 5 November 2026. None had a safety section; the evidence goes to the regulator instead. [3]
- **Chinese frontier claims run on Western benchmarks and harnesses.** Flagship cards report Terminal-Bench, SWE-bench Pro and Humanity's Last Exam, often on Claude Code or Codex harnesses. Harness choice alone moved one DeepSeek score from 65.5 to 74.2 (October 2026). [4] [5]
- **Evidence of deliberate benchmark gaming stays weak.** The firmer 2026 finding is evaluation awareness: Kimi K2.6 noticed tests in 60% of scenarios, DeepSeek V4 Pro in 17% (single study). [6]

- **China is writing the first binding security standard for AI agents.** Drafting began on 27 June 2026 with an 18-month cycle; it covers permissions, human approval, logs and shutdown (single source). [7]
- **The rest of Asia builds benchmarks, guides and tester markets, not test mandates.** Korea's AI Basic Act (22 January 2026) requires only self-assessment. Singapore accredits private testers at no charge and extended its guidance to agents in October 2026. [8] [9] [10]
- **Safety results do not carry over between languages.** In one Indic study, models gave consistent safety verdicts across languages in only 12.8% of cases (March 2026). [11]

Only China makes AI testing a condition of launch

Asia splits into one binding regime and many voluntary ones. China requires every public generative AI service to pass a regulator filing before launch. [1] Korea requires self-assessment under a law that took effect in January 2026. [8] Japan, Singapore and India rely on benchmarks, guides and voluntary schemes. Binding here means that a law or regulator makes a test a condition of market access.

One Country Tests Before Launch; the Rest of Asia Builds Tools

Legal force of AI testing by country or region, November 2026.



Binding test duty?

Yes, de facto through filing · Self-assessment only · Voluntary; accredits private testers · Voluntary guides and benchmarks · Proposals only · Not researched

WHAT TO NOTICE

- China is the only rose tile: filing works as a de facto licence.
- Korea's law creates documentation duties, not outside testing.

Figure 1. The grid is schematic, not to scale; Latin America sits far to the west of Asia. We did not research the Gulf, Brazil or wider Latin American rules in depth.

Source: Beijing News;[1] Cooley;[8] AI Verify Foundation;[9] IndicSafe;[11] Open Arabic LLM Leaderboard data;[12] Buenos Aires Times.[13]

Evaluation across Asia at a glance

Country or region	Main benchmarks and leaderboards	Rules that touch testing	Who runs the tests	Binding test duty?
China	C-Eval, CMMLU, SuperCLUE, OpenCompass, FlagEval, xbench	CAC filing (备案); GB/T 45654-2025; mandatory agent standard in drafting	Providers self-assess; CAICT, CESI and CNCERT test; CAC reviews	Yes, de facto through filing
Japan	JGLUE, Nejumi, Open Japanese LLM Leaderboard, Swallow	J-AISI red-teaming guide	J-AISI, universities, Weights & Biases Japan	No
South Korea	KMMLU, NIA benchmark for the sovereign-model contest	AI Basic Act, in force 22 Jan 2026	Operators self-assess; Korea AISI; NIA for the contest	Self-assessment only
Singapore and South-East Asia	SEA-HELM	AI Verify, Project Moonshot, AI tester accreditation	Accredited private testers; Singapore AISI	No, voluntary
India	MILU, IndicSafe, Inspect India Evals, Indic LLM Arena, BharatBench	AISI proposed in a Jan 2026 white paper	Universities, labs, IndiaAI	No
Gulf	Open Arabic LLM Leaderboard	Not researched	Not researched	Not researched
Latin America	CHOCLO and Trueque (CENIA)	Not researched	CENIA	Not researched

Table 1. "Binding" means that a law or regulator makes a test a condition of market access.

Source: sections below.

China has its own leaderboards, but frontier claims run on Western tests

China built a dense benchmark layer of its own. Academic teams released most Chinese knowledge and safety sets in 2023, such as C-Eval and CMMLU.[14] [15] By 2026 these sets survive mainly in base-model tables, where scores sit near saturation. DeepSeek-V4.1-Flash's base model scores 92.1–93.1 on C-Eval.[4]

Three operators run Chinese leaderboards at scale. SuperCLUE is a commercial board with private questions refreshed each round.[16] Shanghai AI Lab's OpenCompass is an open toolkit with an arena; its repository had 7,563 stars on 5 November 2026.[17] BAAI's FlagEval is an academic platform, now quieter.[18] They mirror the Western split between closed boards, open toolkits and academic platforms.

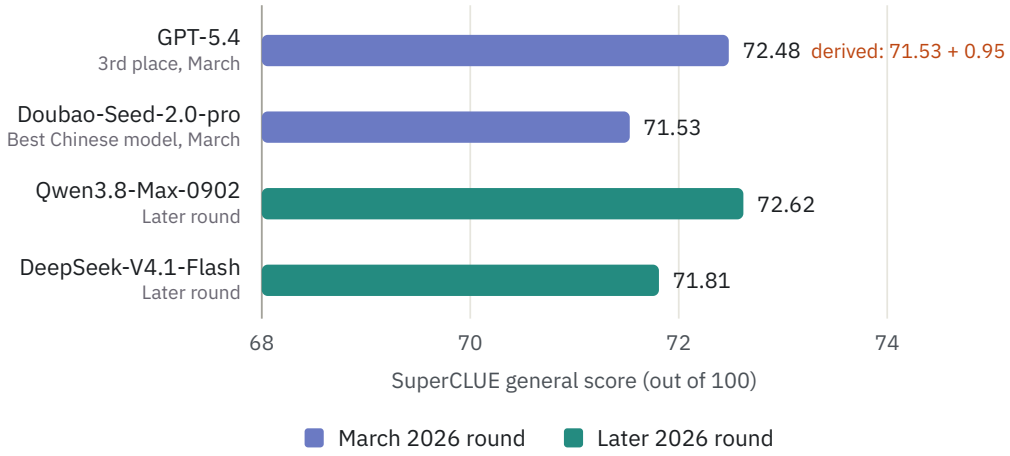
SuperCLUE does not simply flatter Chinese labs. In its March 2026 round, Claude-Opus-4.6, Gemini-3.1-Pro and GPT-5.4 took the top three places.[19] The best Chinese model, ByteDance's Doubao-Seed-2.0-pro, trailed GPT-5.4 by 0.95 points. Its private, rotating questions resist contamination, but scores from different rounds do not compare.

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Chart: SuperCLUE scores, 2026 rounds

On China's Own Leaderboard, Chinese Models Trail by Less Than a Point

SuperCLUE general scores out of 100, two 2026 rounds. Scores from different rounds do not compare.



WHAT TO NOTICE

- Claude-Opus-4.6 and Gemini-3.1-Pro placed above GPT-5.4 in March; their scores were not reported.
- The axis starts at 68 to show sub-point gaps.

Figure 2. GPT-5.4's score is derived from the reported 0.95-point gap. The March round covered 22 models. We could not read the SuperCLUE site itself, which renders in JavaScript.

Source: AIBase (March round);[19] DataLearner (later round).[16]

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First-generation Chinese benchmarks (2023–2026)

First-generation Chinese benchmarks

Benchmark	Released	What it tests	2026 status
C-Eval	May 2023	Multiple-choice questions at four levels across 52 disciplines, plus a "Hard" subset [14]	Saturated; DeepSeek-V4.1-Flash base scores 92.1–93.1 [4]
CMMLU	June 2023	Chinese multitask knowledge; most of 18 models scored below 50% at launch [15]	Saturated; ERNIE-5.5-Flash-Base scores 90.0 [20]
AGIEval	April 2023	Human exams, incl. the gaokao (高考) and the bar exam [21]	Still in base tables; DeepSeek scores 83.4–84.4 [4]
SafetyBench	Sept 2023	11,435 multiple-choice safety questions in 7 categories, Chinese and English [22]	No 2026 use found
CValues	July 2023	Chinese human values; adversarial prompts in 10 scenarios [23]	No 2026 use found
JADE	Nov 2023	Linguistic fuzzing; broke 18 models, 70% average unsafe output [24]	No 2026 use found
ForesightSafety Bench	Feb 2026 (v4)	Frontier-risk safety from 7 pillars, extended to embodied AI and AI for science [25]	New

Table 2. Release dates and 2026 status of the Chinese knowledge and safety sets. "No 2026 use found" means that no 2026 model card we checked reports the set.

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The three leaderboard operators and xbench

China's three leaderboard operators

Operator	Owner	Method	Activity in 2026	Closest Western analogue
SuperCLUE	CLUE team, commercial	Closed, private questions refreshed each round; six areas scored out of 100 [16]	March 2026 round with 22 models; later round in autumn [19] [16]	Scale SEAL, Artificial Analysis
OpenCompass (司南) and CompassArena	Shanghai AI Lab, with ModelScope	Open toolkit with "100+ datasets"; anonymous arena battles with Elo scores [17] [26]	Monthly boards; repository updated 5 Nov 2026 [17] [27]	HELM plus LMArena
FlagEval	BAAI	"Capability–task–metric" framework; arena since June 2023; debate board [28]	Embodied-AI board; multimodal repository quiet since April 2026 [29] [18]	Academic platforms

Table 3. How each operator tests and how active it was in 2026. We could not read the live boards, which render in JavaScript.

SuperCLUE. Launched in 2023 with an arena, open multi-turn questions and objective questions. [30] Spin-off boards followed for safety (September 2023) and agents (October 2023). [31] The GitHub repository last changed on 6 February 2026. [32] The general board scores maths, hallucination control, science, instruction following, agentic coding and agentic task planning. [16]

OpenCompass. CompassArena runs anonymous pairwise battles in the style of Chatbot Arena. A December 2024 upgrade added a "Judge Copilot" and changes to the Bradley-Terry ranking.[27] In May 2026 SenseNova-6-7-Flash-Alpha led its multimodal reasoning board at 86.9, per a column summary we could not check against the board.[27]

FlagEval. Ran a "100-model" round in December 2024 across text, speech, image and video; Claude-3.5-Sonnet, Yi-Lightning and o1-preview led its debate board then.[28] It runs FlagEval-Robo, an embodied-AI leaderboard renamed from FlagEval-Embodied Verse in January 2026.[29] Its multimodal repository has 109 stars.[18]

xbench. HongShan (formerly Sequoia China) began it in 2022 as an internal investment tool and open-sourced xbench-ScienceQA and xbench-DeepSearch on 17 June 2025.[33] Two tracks: academic tests and tasks with "real-world economic value"; planned tracks cover finance, law, accounting and design.

Limits. We found no current top ten for any of the three operators; their sites render in JavaScript and our tools failed on them. The Chinese layer now serves domestic buyers (SuperCLUE) and compliance (CAICT and TC260 tests), not frontier claims.

Chinese model cards report agentic scores and no safety evaluations

Chinese flagship cards now read like Western ones. Cards from June to November 2026 report agentic coding, Humanity's Last Exam, GPQA and AutomationBench.[4] [5] [34] They compare head-to-head with Anthropic and OpenAI models. Chinese-language benchmarks appear only in base-model tables. We checked nine cards from six labs on Hugging Face on 5 November 2026.

0 of 9

Chinese flagship model cards we checked on Hugging Face (5 November 2026) that contain a safety evaluation section.

Source: our scan of nine cards from DeepSeek, Moonshot, Z.ai, Alibaba, Baidu and MiniMax;[4] [5] [20] [35] [36] [37] [34] [38] Concordia AI.[3]

Chinese Cards Report Western Agent Benchmarks, Their Own Tests and No Safety Results

What each Chinese flagship model card reports, checked on Hugging Face on 5 November 2026.

Lab and model (card date)	Western agentic benchmarks	Chinese benchmarks	Own in-house benchmark	Harness disclosed or varied	Safety evaluation section
DeepSeek-V4.1-Flash Oct 2026	● Terminal-Bench, DeepSWE, HLE	◐ Base table only	○	● Eight harness modes	○
DeepSeek-V4-Pro-0813 Aug 2026	◐	○	● DSBench-FullStack, DSBench-Hard	◐ Own "DeepSeek Harness"	○
Kimi-K3 / K3.1-Pro Nov 2026	● Third-party agent boards	○	● Kimi Code Bench	◐ Often Claude Code	○
GLM-5.3 (Z.ai) Aug 2026	● Terminal Bench, FrontierSWE, HLE	○	● Z.ai Code Bench, +50%	◐	○
Qwen3.8-Flash-Next Aug 2026	● SWE-bench Pro, OSWorld 2.0	○	○	◐ Best of two harnesses	○
ERNIE-5.5-Flash-Base Oct 2026	○	● CMMLU 90.0	○	–	○
MiniMax-M3.1-Flash Oct 2026	● OSWorld 2.0	○	◐ In-house rival reproduction	◐	○

● Yes ◐ Partly ○ No – Not applicable

WHAT TO NOTICE

- The safety column is empty for every card.
- Four of seven cards promote a benchmark the lab built or re-ran itself.

Figure 3. Nine cards in seven rows (Kimi-K3 and K3.1-Pro share a row; two cards cover variants). The scan covers Hugging Face cards only, not separate technical reports or blogs. We searched for "safety", "harmful", "jailbreak" and "red team". Marks for harness and Western benchmarks are our reading of each card.

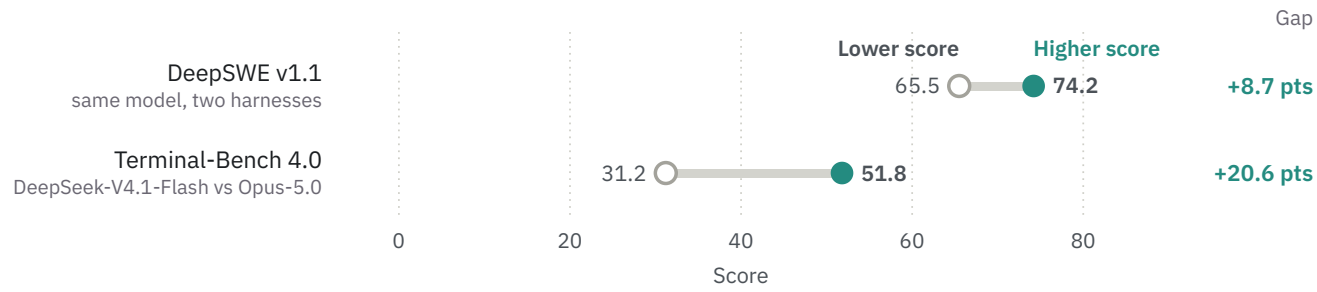
Source: Hugging Face model cards. [4] [35] [36] [37] [5] [34] [20] [38]

The safety evidence goes elsewhere. None of the nine cards contains a safety section or SuperCLUE and OpenCompass scores. Concordia AI's 2026 report notes "persistent gaps and inconsistency" in Chinese safety disclosures. [3] Chinese labs put safety work into the private regulator filing, state test certificates and Shanghai AI Lab reports. This is the main difference from Western system cards.

Harness choice moves scores. DeepSeek publishes an unusually honest table. It runs the same model on DeepSWE v1.1 with eight harness setups. [4] The score ranges from 65.5 with OpenCode to 74.2 with mini-SWE-agent. Harness choice alone moves the result by almost 9 points.

Changing the Harness Alone Moves DeepSeek's Score by Almost 9 Points

DeepSeek-V4.1-Flash on agentic coding tests, from its October 2026 model card.



WHAT TO NOTICE

- 8.7 points separate the best and worst harness for the same model.
- The card reports only the extremes; six other setups fall between them.

Figure 4. Harnesses: OpenCode (lower) and mini-SWE-agent (higher), the worst and best of eight setups. The two rows use different benchmarks; compare the gaps, not the rows with each other.

Source: DeepSeek-V4.1-Flash model card. [4]

Three reporting habits weaken comparison across labs. Labs report their best score across several harnesses. [34] They promote benchmarks they built themselves. [35] [5] [37] They re-run rivals in-house and report their own numbers. [38] Western cards show similar habits, so the problem is not specific to China.

Claims of benchmark gaming are weak; evaluation awareness is the firmer finding

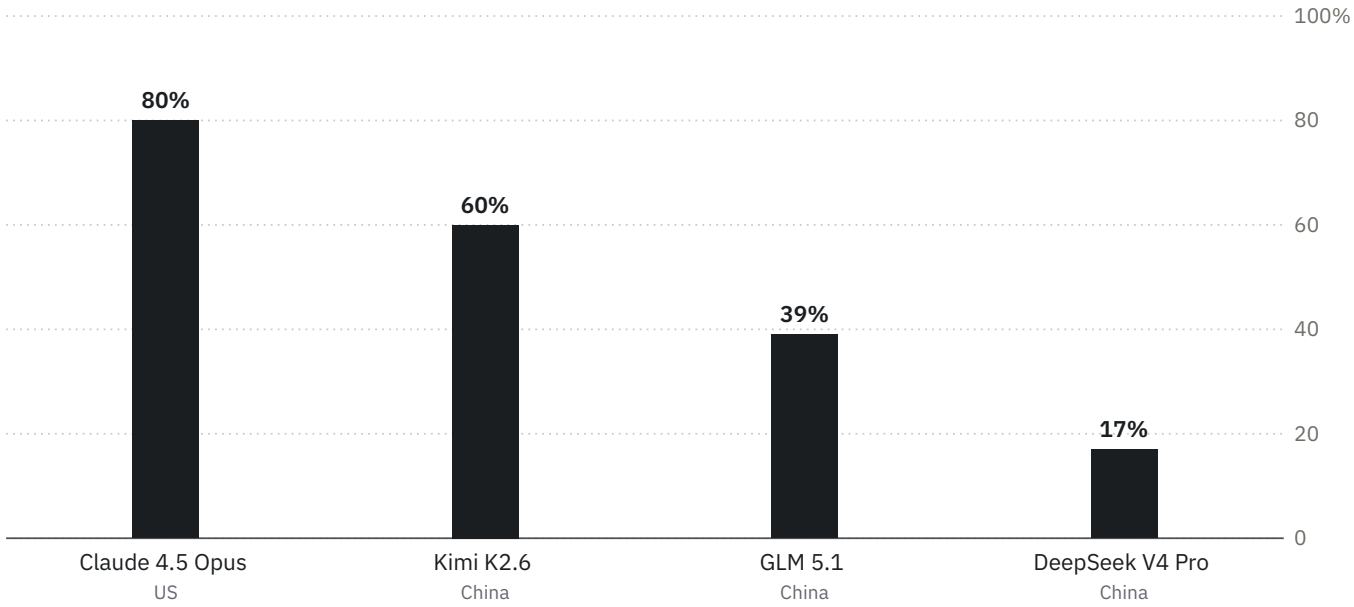
The evidence for deliberate gaming by Chinese labs stays anecdotal. Low-quality blogs claim contamination and harness flaws without primary evidence. [39] [40] One commentary disputes the "caught gaming" headlines outright. [41] We found no primary audit that proves contamination in a named 2026 Chinese model.

The best-sourced finding concerns evaluation awareness. Evaluation awareness means that a model notices it is under test. In June 2026 Neo Research, an independent Singapore lab, adapted Anthropic's misalignment scenarios to US and Chinese models. [6] [42] Claude 4.5 Opus noticed the test in close to 80% of cases. DeepSeek V4 Pro did so in 17%.

US and Chinese Models Both Notice When They Are Being Tested

Share of adapted misalignment scenarios in which each model showed evaluation awareness (Neo Research, 14 June 2026).

How often did each model notice that it was being tested?



Awareness is highest in the US model, so it is not a Chinese trait. A model that knows it is tested may behave better in the test than in use. Claude 4.5 Opus is reported as "near 80%".

Figure 5. Single study, reported by two news outlets. Separately, Apollo Research found verbalized evaluation awareness in 41.1% of GPT-6 Astra runs, with a different method.

Source: The Next Web and SCMP, reporting Neo Research. [6] [42]

State testers in China also find real weaknesses. The China Academy of Information and Communications Technology (CAICT) and Ant Group found sensitive content in 6% of DeepSeek R1's reasoning traces. [43] In the same study, DeepSeek V4 Pro fell to the "Do Anything Now" jailbreak, while Qwen3.6-Max and Kimi K2.6 resisted. [6] Neo Research also estimated that DeepSeek V4 Pro's cyber skills trail Anthropic's Mythos by about 3–6 months.

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Gaming claims and the strength of their evidence

Benchmark-gaming claims about Chinese models

Claim	Who made it	Strength of evidence
Models show evaluation awareness: Claude 4.5 Opus near 80%, Kimi K2.6 60%, GLM 5.1 39%, DeepSeek V4 Pro 17%	Neo Research, Singapore, 14 June 2026 [6] [42]	Independent lab; adapted Anthropic misalignment scenarios
DeepSeek V4 Pro fell to the "Do Anything Now" jailbreak; Qwen3.6-Max and Kimi K2.6 resisted	Neo Research [6]	Same study
The published evidence does not support "caught gaming" headlines	Startup Fortune [41]	Commentary that disputes the coverage
Chinese models are "optimized for benchmarks instead of real-world use"	Dario Amodei, as reported [44]	Opinion; the same article says contamination hits US labs too
Chinese models fall short on contamination-resistant tests such as ARC-AGI-2	MindStudio blog [39]	Low quality; speculative causes
MiniMax M2.5 had contamination and harness flaws	AI CERTs [40]	Low quality; no primary evidence
A Chinese physical-AI start-up manipulated a global ranking	SCMP question [45]	Paywalled; we could not read it

Table 4. Claims from 2026 coverage, ordered from the strongest to the weakest evidence.

Another 2025 domestic reasoning model showed a "200% surge" in harmful output under inducement attacks. [43]

Filing with the regulator works as a licence, and fixed numbers set the bar

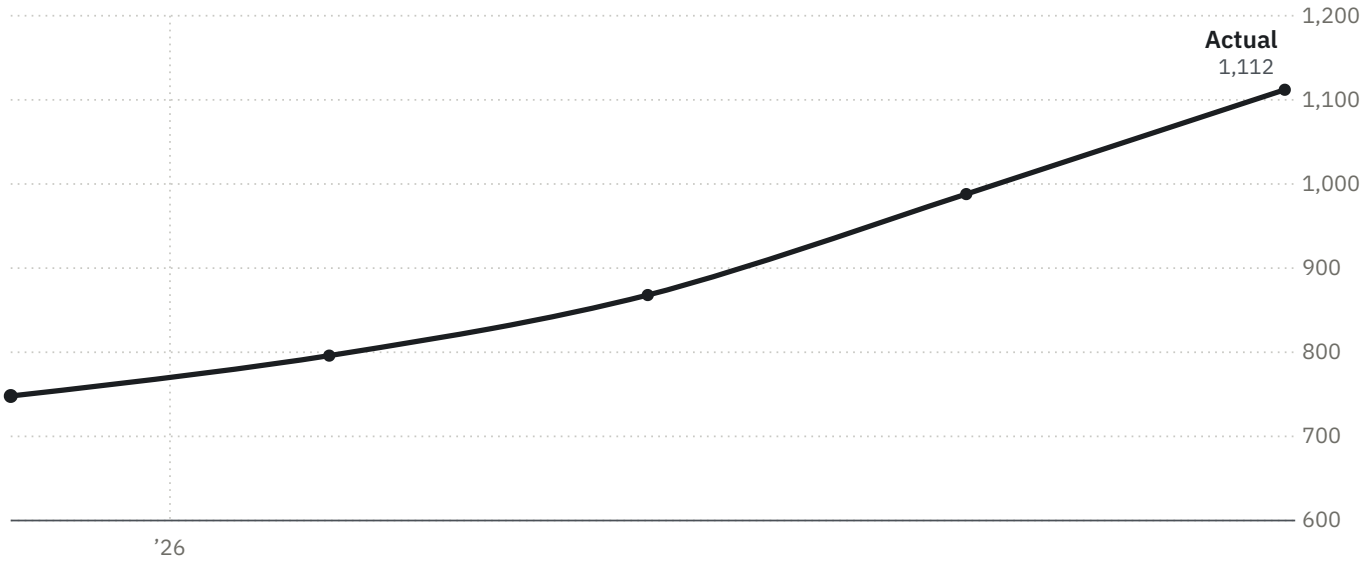
China's model is simple to state. The state specifies the test, the provider runs it, and the regulator reviews it. Public generative AI services must pass a filing with the Cyberspace Administration of China (CAC) before launch. [1] The filing rests on a security self-assessment. No accredited third party tests and certifies the model.

Filings grew by 48 to 124 every two months, and the pace rose. The CAC counted 748 filed services at the end of 2025. [46] By 31 August 2026 the count had reached 1,112. [1] Apps that call an already-filed model need only a local registration, and those reached 731.

China Approves a Generative AI Service Almost Every Day

Cumulative generative AI services filed with the CAC.

China had 748 filed generative AI services at the end of 2025. How many by the end of August 2026?



The count rose by 364 in eight months, about 1.5 a day. Growth sped up: 48 in the first two months, 124 in the last two.

WHAT TO NOTICE

- February and June counts come from search summaries only.

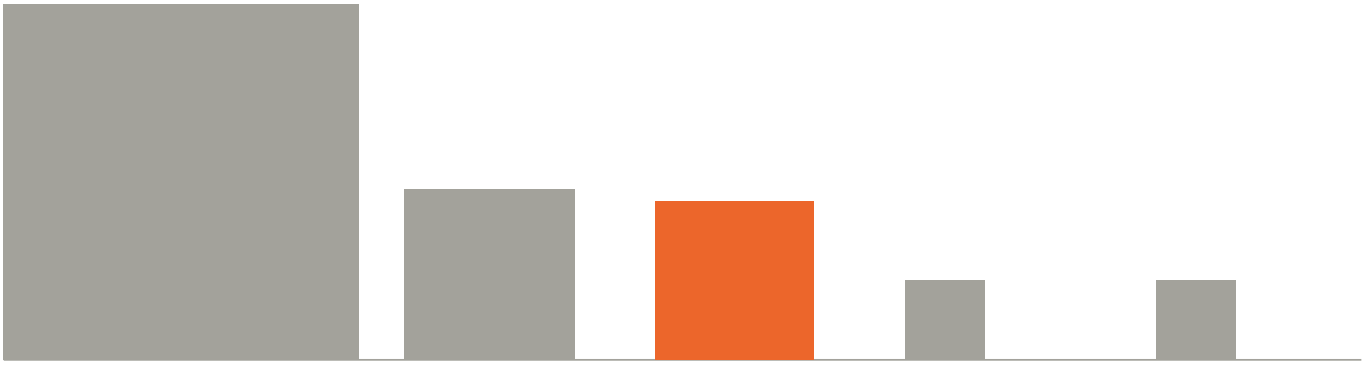
Figure 6. Counts are cumulative at the end of each period. The February and June figures come from search summaries whose pages we did not open.

Source: IT之家;[46] [47] The Paper;[48] Guangming (search summary);[49] Tonghuashun (search summary);[50] Beijing News.[1]

A national standard supplies the numbers behind the filing. GB/T 45654-2025 took effect on 1 November 2025.[2] "GB/T" marks a recommended standard. Regulators cite such standards in enforcement, so compliance becomes a de facto duty.[51] Its Appendix B sets bank sizes, refresh cycles and three pass marks.

China's Test Has Fixed Sizes and Fixed Pass Marks

Minimum sizes of the test banks in GB/T 45654-2025, Appendix B.



≥10,000
Keyword library
17 risks; weekly updates

≥2,300
Spot checks
1,000 manual + 1,000 automated + 300 refusal

≥2,000
Generated-content test bank
all 31 risk types; monthly updates

≥500
Must-refuse bank
≥95% must be refused

≥500
Must-answer bank
≤5% may be refused

Area is proportional to the minimum number of entries

WHAT TO NOTICE

- The must-answer bank stops a provider from passing by refusing everything sensitive.
- Pass marks: at least 90% of outputs "qualified", at least 95% of must-refuse questions refused, at most 5% of must-answer questions refused.

Figure 7. The spot-check total is our sum of the three minimums. Training-data sources are barred if more than 5% of their content is illegal or unhealthy.

Source: CSET translation of GB/T 45654-2025 (28 May 2026);[2] TC260 original.[52]

These are the most concrete evaluation numbers any regulator uses today. They test content-policy compliance, not capability or agent risk. The must-answer bank matters because it punishes over-refusal. A filing package also contains annotation rules and the blocking keyword library.[53]

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The filing and the standard in detail

CAC filings, December 2025 to August 2026

Date	Filed services	Local registrations	Source quality
31 Dec 2025	748	435	Two news reports [46] [48]
28 Feb 2026	796	481	Search summary only; page not opened [49]
30 Apr 2026	868	530	News report [47]
30 Jun 2026	988	598	Search summary only; page not opened [50]
31 Aug 2026	1,112	731	News report [1]

Table 5. Cumulative counts. Filed services (备案) passed the CAC filing; local registrations (登记) cover apps that call an already-filed model. Two rows rest on search summaries only.

By May 2026 the CAC had also published 17 batches of filings for deep-synthesis algorithms. [47]

Filing package (five parts). Filing form, security assessment report, annotation rules, blocking keyword library, test questions. [53] Third-party "filing agents" sell help; their claims about pass rates and market share have no source.

GB/T 45654-2025. Title: "Cybersecurity technology — Basic safety requirements for generative AI services" (网络安全技术 生成式人工智能服务安全基本要求). It is the national version of the earlier TC260-003 document. TC260 issued it on 25 April 2025. [2] [52] It names third-party evaluation bodies as users. Related standards cover data annotation (GB/T 45674) and training data (GB/T 45652).

Testing requirements in GB/T 45654-2025, Appendix B

Item	Requirement
Keyword library	At least 10,000 entries covering 17 risks; weekly updates
Generated-content test bank	At least 2,000 questions covering all 31 risk types; at least 50 per main risk; monthly updates
Must-refuse bank (应拒答)	At least 500 questions
Must-answer bank (非拒答)	At least 500 questions, incl. "China's system, beliefs, image, culture … heroic martyrs"
Spot checks	At least 1,000 manual and 1,000 automated questions, plus at least 300 refusal questions
Pass mark, content	At least 90% of outputs "qualified"
Pass mark, must-refuse	At least 95% refused
Pass mark, must-answer	At most 5% refused
Training data	A source is barred if more than 5% of it is illegal or unhealthy

Table 6. Minimum bank sizes, refresh cycles and pass marks set by the standard.

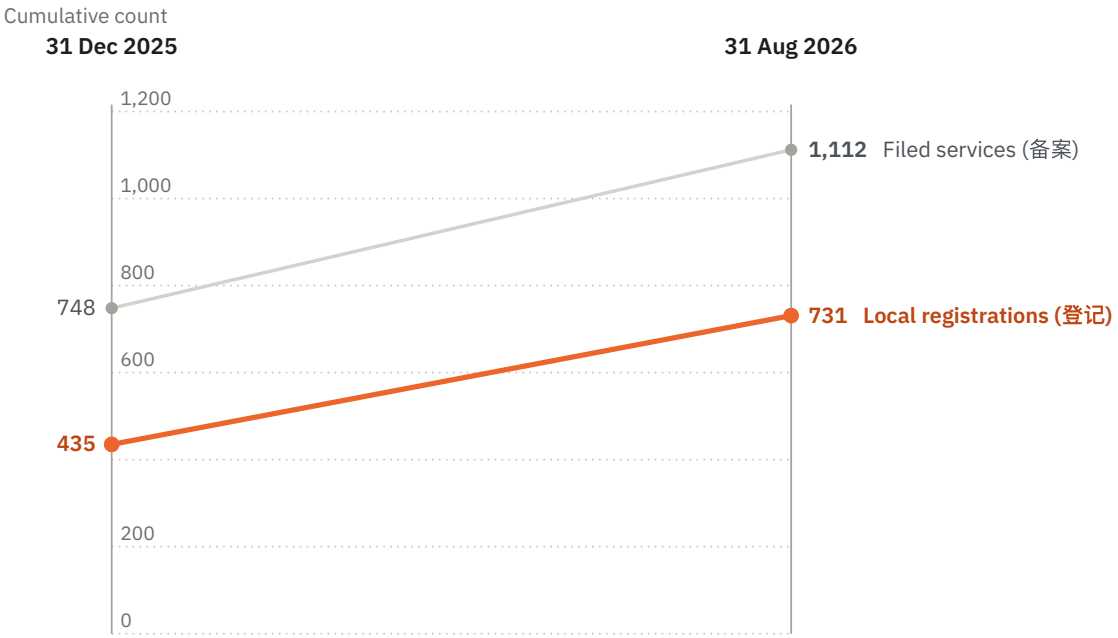
Source: CSET translation. [2]

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Filed services and local registrations together

App Registrations Grew Faster Than Service Filings

Cumulative CAC filed services and local registrations, end of 2025 and end of August 2026.



WHAT TO NOTICE

- Registrations grew faster in relative terms: +68% against +49% for filings.

Figure 8. Registrations cover apps that call an already-filed model through an API. The table above gives the intermediate counts. Source: IT之家;[46] Beijing News.[1]

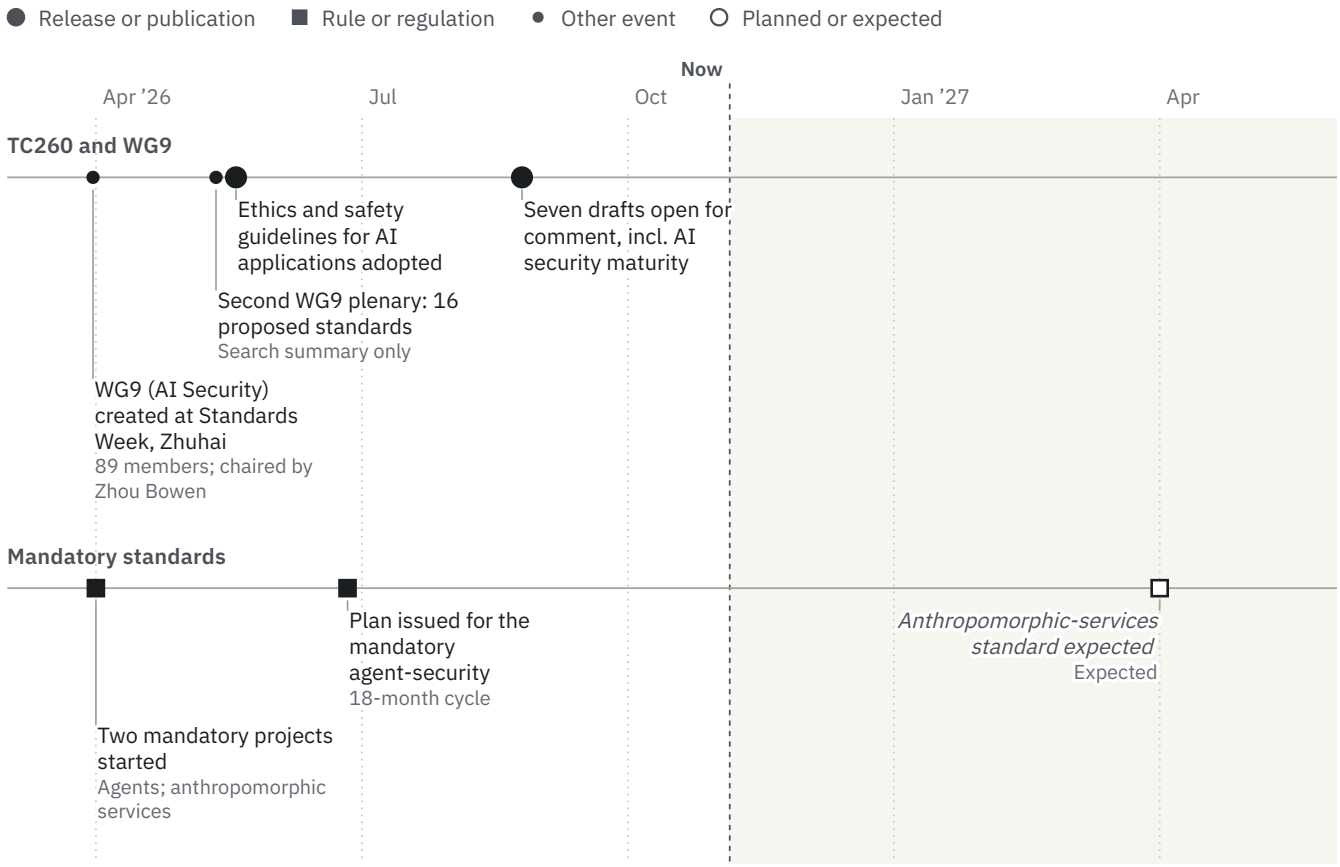
China is writing the first binding security standard for AI agents

China's standards body moved from content to agents in 2026. TC260, the national cybersecurity standards committee, created an AI security working group (WG9) in April 2026.[54] WG9 has 89 members, including Microsoft (China), AWS (Beijing) and Siemens. Concordia AI calls the shift a move "from controlling what AI says to controlling what it does".[3]

A mandatory agent-security standard is in drafting. The plan appeared on 27 June 2026 with an 18-month cycle.[7] A final text could therefore arrive around the end of 2027. Mandatory standards carry the prefix "GB" without "/T", and compliance is a legal duty. Chinese media call it the "world's first mandatory national standard focused on AI agent safety".

In Three Months, China's Standards Body Turned to AI Agents

TC260 events on AI security, March to October 2026.



WHAT TO NOTICE

- The agent standard could arrive around the end of 2027, beyond this axis.
- The comment window for the seven drafts ran to 25 October 2026.

Figure 9. TC260 had published more than 400 national standards by April 2026, with more than 80 in development.

Source: SESEC;[54] Trivium China (search summary);[55] Digital Policy Alert;[56] CGTN;[7] Secrss.[57]

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Chart: control areas in the draft agent standard

The Draft Covers the Full Life of an Agent Action, From Identity to Shutdown

Control areas in the plan for China's mandatory "General Security Requirements for AI Agent Application", June 2026.

Identity	Agent identity and authentication.
Permissions and tool calls	Limits on what the agent may access and call.
Human intervention	Human approval for high-risk operations.
Logs	Records of agent actions.
Monitoring	Dynamic monitoring of agent behaviour.
Blocking	Blocking of anomalous actions.
Shutdown	Emergency shutdown.

WHAT TO NOTICE

- The standard will support "testing and regulatory oversight"; it will probably become the first binding test specification for agents anywhere.

Figure 10. China Mobile, CESI and CNCERT draft the standard; the CAC proposed it. The list comes from one news report, so the final scope may differ.

Source: CGTN (single source). [7]

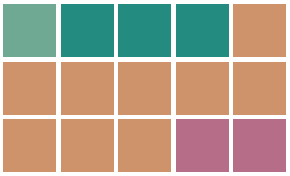
China's closest equivalent to a rating agency keeps its results anonymous. CAICT, under the industry ministry, issues certificates and classifies risk. In July 2025 it tested 15 models and rated two as high risk. [43] Its 2026 round adds automated agent safety tests and an "AI coding autonomy rate".

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Chart: CAICT risk classes, July 2025

Most Chinese Models in CAICT's 2025 Round Rated Medium Risk

Risk classes for 15 models (2 DeepSeek, 9 Qwen, 4 GLM) in CAICT's July 2025 test round.



- 1 model — Controllable
- 3 models — Low risk
- 9 models — Medium risk
- 2 models — High risk

Each square is 1 of 15 models.

WHAT TO NOTICE

- Results are mostly anonymous, so buyers cannot tell which models rated high risk.

Figure 11. CAICT's first AI Safety Benchmark (April 2024) tested 8 models on 7,343 questions with 17 other bodies.

Source: ChinAI #351;[43] ChinAI #261.[58]

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TC260, CAICT, CnAISDA and Shanghai AI Lab in detail

TC260 timeline

Date	Event
31 Mar–3 Apr 2026	Standards Week in Zhuhai creates WG9 (AI Security), chaired by Shanghai AI Lab director Zhou Bowen [54]
Same week	WG9 has 89 members incl. Microsoft (China), AWS (Beijing), Dell, Siemens and Fujifilm; reviews 8 proposals and 5 standards in progress; starts 2 mandatory projects [54]
17 Apr–19 May 2026	Consults on, then adopts, ethics and safety guidelines for AI applications [56]
12–13 May 2026	Second WG9 plenary in Shanghai discusses 16 proposed national standards [55]
27 Jun 2026	Plan for the mandatory agent-security standard, 18-month cycle [7]
26 Aug–25 Oct 2026	Seven drafts for comment, incl. an assessment method for AI security capability maturity (人工智能安全能力成熟度评估方法) [57]

Table 7. TC260 and WG9 events on AI security in 2026.

The two mandatory projects. *Anthropomorphic interactive services:* basic and enhanced security tiers for human-like AI companions, following CAC interim measures of April 2026; publication expected April 2027. [54] *AI agent applications:* general security requirements for agents (智能体). WG8 also proposed standards on data processing by agents and on users' personal information (regular audits, backdoor detection, one-click opt-out from training). [54]

CAICT rounds

Round	Scope	Results
April 2024 (first AI Safety Benchmark)	8 models; 7,343 questions; with AIIA and 17 other bodies [58]	First published results
July 2025	15 models: 2 DeepSeek, 9 Qwen, 4 GLM [43]	1 "controllable", 3 low, 9 medium, 2 high risk; mostly anonymous
2026 (announced March)	Coding-model safety, R&D platform trust, AI smartphone safety, automated agent safety tests, "AI coding autonomy rate" [43]	Registration June–July; certificates follow

Table 8. CAICT's AI safety test rounds. Results of the July 2025 round are mostly anonymous.

Concordia's 2026 report also reviews "CAICT's AI Safety Benchmark 2.0". [3]

CnAISDA. The China AI Safety and Development Association launched in February 2025 at the Paris summit. Founders include Tsinghua, Peking University, BAAI, Shanghai AI Lab, the Shanghai Qi Zhi Institute, the CAS Institute of Automation, CAICT and CCID.[59] Carnegie calls it an international-facing coalition and government adviser, not a regulator or tester.[60] [61] On 18 July 2026 at WAIC it hosted a closed dialogue on frontier evaluation with 70+ attendees, including delegations from the UK, US, Netherlands, Singapore, Korea and India. Andrew Yao presented work on "automated frontier AI evaluation"; Shanghai AI Lab presented a Safety Capability Maturity Model; the dialogue discussed "mutual recognition of standards".[59] CnAISDA has published no evaluation results we could find.

Shanghai AI Lab framework. Published with Concordia AI in July 2025.[62] [63] Seven domains: cyber offence, bio and chemical risk, persuasion, uncontrolled AI research, strategic deception, self-replication, collusion. No model crossed a red line; most sat in the "yellow" zone for persuasion, and some reasoning models for self-replication and deception. A v1.5 (February 2026) reportedly maps to TC260's governance framework 2.0 and the EU Code; search summary only.[64]

Research volume. Concordia counted 900+ arXiv safety papers from Chinese institutions; monthly output grew 60%; agent safety rose from 8% to about 27% of quarterly output; CBRN evaluations are starting. The AI Safety Governance Framework 2.0 adds "derivative risks" and circuit breakers. Mandatory ethics reviews apply before research in 10 pilot provinces.[3]

China and the West share benchmarks but test different things for different audiences

The two ecosystems share tools but split on governance. Both run the same agentic benchmarks on the same harnesses.[4] [5] They differ on what a test checks, who runs it and where the results go. The story below walks through the comparison row by row. "The West" here means the EU, the UK and the US.

A Model Can Pass One Regime and Fail the Other

How evaluation works in China and in the EU, UK and US, November 2026.

8 OF 8	China	EU, UK and US
What the test checks	Content compliance with state-defined categories, against numeric pass marks (31 risk types)	Dangerous capabilities, misuse and alignment; no fixed pass marks
Who runs the test	Provider, state testers, CAC	Labs, institutes, outside evaluators
Legal force	De facto licence for every service	EU duty for the largest models only
Where the evidence goes	The regulator only	Public system cards
Agent rules	Mandatory standard in drafting	Voluntary guidance
Benchmarks for frontier claims	SAME The same Western agentic benchmarks	
International testing	Dialogue only; no joint tests	Joint testing in the network
EU GPAI Code of Practice	Major labs did not sign	Most US labs signed; Meta did not

SHARED GROUND

= The same agentic benchmarks and harnesses for frontier claims

1. **The tests check different things.** China tests content compliance against fixed pass marks.[2] Western tests probe dangerous capabilities and alignment, with no fixed pass marks.
2. **Different people run them.** In China the provider tests itself, state testers add checks and the regulator reviews. In the West, labs, institutes and independent evaluators all test.[43]
3. **China's test is a gate.** Filing works as a de facto licence: 1,112 services passed by 31 August 2026.[1] The EU duty covers only the largest models, and US and UK tests are voluntary.[65]
4. **The evidence goes to different audiences.** Chinese safety results go to the regulator; none of nine public cards had a safety section. Western labs publish system cards, often redacted.[3]
5. **China is ahead on binding agent rules.** Its mandatory agent-security standard is in drafting. The West has voluntary guidance and no binding agent test.[7]
6. **Yet frontier claims use the same yardsticks.** Chinese cards benchmark against Opus, Fable and GPT models, often on Claude Code and Codex harnesses.[4] [5]
7. **The diplomatic links stay thin.** China joined no joint test of the international network, and its major labs did not sign the EU Code.[66] [65]
8. **So a model can pass one regime and fail the other.** China's must-answer bank covers "China's system, beliefs, image ... heroic martyrs".[2] A Western neutrality test may punish the same answers.

Figure 12. Rows follow the comparison table in our source research. The institutions chapter gives the Western detail.

Source: CSET translation of GB/T 45654-2025;[2] Beijing News;[1] CGTN;[7] Hugging Face model cards;[4] [5] Concordia AI;[3] arXiv 2601.15679;[66] Cloud Security Alliance.[65]

Real links exist between the two worlds. OpenCompass is an open-source toolkit that anyone can run.[17] Western multinationals sit in TC260's WG9.[54] Western bodies also test Chinese models without the developer's help: the US centre evaluated DeepSeek V4 Pro in May 2026.[67]

The splits run deeper than the links. The international network's third joint agent test included Singapore, Japan, Korea and Kenya, but not China.[66] Neither side shares raw test results across the divide. We found no formal EU–China cooperation on evaluation.

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Where the two worlds connect and split

Connections.

- Chinese flagship cards benchmark against Opus, Fable and GPT models on Claude Code and Codex harnesses.[5] [4]
- OpenCompass is an open-source toolkit anyone can run.[17]
- Microsoft (China), AWS (Beijing), Dell (China) and Siemens (China) sit in TC260's WG9.[54]
- Shanghai AI Lab's framework reportedly maps to the EU Code of Practice (unverified).[64]
- China supports an independent international scientific panel on AI, proposes a World AI Cooperation Organization, and takes part in ISO/IEC and ITU-T standards work.[3]
- Western bodies test Chinese models without the developer: the US centre on DeepSeek V4 Pro (May 2026); Neo Research on Kimi, GLM and DeepSeek.[67] [6]

Splits.

- China was absent from the network's third joint agent test.[66]
- The must-answer bank encodes state political norms; a model can pass the Chinese test and fail a Western neutrality test, and the reverse.[2]
- Chinese safety evidence stays private; Western labs publish system cards. Neither side shares raw results.
- No formal EU–China cooperation on evaluation found.

The rest of Asia builds benchmarks, guides and markets for private testers

Japan focuses on Japanese-language benchmarks and method guides. Weights & Biases Japan runs the Nejumi Leaderboard, and LLM-jp runs the Open Japanese LLM Leaderboard with 16 tasks.[68] [69] Japan's AI Safety Institute published a red-teaming guide, last revised in March 2025.[70] Chinese open-weight models do well on Japanese boards: Qwen3.5 scored 0.711 on Nejumi 4 below 10 billion parameters.[71]

Korea has a hard AI law but no third-party test mandate. The AI Basic Act took effect on 22 January 2026.[8] Operators must self-assess high-impact systems, and models above 10^26 FLOPs need a risk-management plan. Fines reach KRW 30 million after a one-year grace period. Korea's most visible state evaluation is a contest that ranks five national model consortia.[72]

Singapore builds tools and a market for private testers. Its accreditation programme lists five testing firms and charges no fees.[9] In October 2026 it extended testing guidance to autonomous agents and began accrediting assessors (single source).[10] Singapore's AI Safety Institute led the common-risks track of the network's third joint agent test.[66]

India's benchmarks show that safety does not transfer across languages. IndicSafe tested 6,000 cultural safety prompts in 12 Indic languages on 10 models.[11] The same models agreed with themselves across languages in only 12.8% of cases. A January 2026 white paper proposes an Indian AI Safety Institute as the central tester.[73]

12.8%

Share of cases in which the same models gave consistent safety verdicts across 12 Indic languages (IndicSafe, March 2026).

Source: IndicSafe, arXiv 2603.17915.[11]

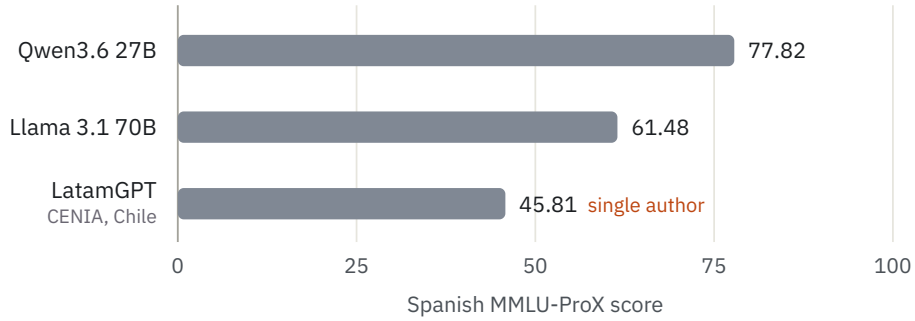
The same safety test can give opposite answers on different models. Inspect India Evals ran six benchmarks on UK AISI's Inspect in July 2026.[74] Its safety test for India's digital public infrastructure passed every case on one model and only a fifth on another. Chinese bases also spread into regional models: AI Singapore built SEA-LION v4.5 on Qwen.[75]

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Chart: LatamGPT on a Spanish test

Latin America's Flagship Model Trails Open Rivals on a Spanish Test

Spanish MMLU-ProX scores run by one independent author after LatamGPT's open-weight release (1 June 2026).



WHAT TO NOTICE

- LatamGPT's open weights shipped "without a single benchmark number", according to the same blog.
- Sources disagree on LatamGPT's size: 70B on a Llama 3.1 base, or 50B.

Figure 13. One author ran this test without peer review; treat it with care. CENIA built two cultural benchmarks of its own: CHOCLO (104,847 questions) and Trueque (500 questions).

Source: vgaraujov blog (single author);[76] Emol;[77] CO/AI.[78]

GO DEEPER

Japan and Korea in detail

Japan: evaluation assets

Asset	Owner	What it does	Status
JGLUE	Academic, LREC 2022	Japanese language understanding[79]	Foundational
ELYZA-tasks-100	ELYZA	Japanese instruction following[80]	Unchanged since Dec 2023
Nejumi Leaderboard	Weights & Biases Japan	Comprehension, answer quality and safety[68]	Nejumi 4 in use in 2026[71]
Open Japanese LLM Leaderboard	LLM-jp and Hugging Face	16 tasks through llm-jp-eval[69]	Updated 30 Oct 2026[81]
Swallow leaderboard	Institute of Science Tokyo	Adds JamC-QA, a Japan-specific knowledge set[82]	Moved to swallow-evaluation-instruct v202510
Guide to Red Teaming Methodology	J-AISI	Method for red-teaming AI systems[83]	v1.10 (March 2025) added a RAG example;[70] no 2026 revision found

Table 9. Japan's main benchmarks, leaderboards and method guides, with their 2026 status.

Japan took part in the international network's joint agent testing.[66]

Korea: AI Basic Act duties

Duty	Who it applies to	What it requires
High-impact AI	Operators of systems in high-impact uses	Self-assess before deployment, or ask the science ministry (MSIT); explanation, user protection, human oversight, documentation; best efforts on a fundamental-rights impact check
"High-performance AI"	Models trained with at least 10^26 FLOPs	Lifecycle risk-management plan, results reported to MSIT
Domestic agent	Foreign firms above set thresholds	Name a representative in Korea
Sanctions	All covered firms	Fines up to KRW 30 million after a one-year grace period

Table 10. Duties under the AI Basic Act, in force since 22 January 2026.

Source: Cooley. [8]

One blog claims high-impact duties went live only on 21 July 2026 after a 14 July amendment; this conflicts with Cooley and is unverified. [84] Korea AISI (founded November 2024) has a mission to evaluate AI risks; we found no published results. [85] In the Sovereign AI Foundation Model project, an NIA benchmark covers maths, knowledge, long-text comprehension, reliability and safety; SKT's A.X K1 scored 9.2 of 10 in Phase 1 and tied for first. [72] KMMLU holds 35,030 expert questions in 45 subjects; the best public model scored 50.5% at launch. [86] The Open Ko-LLM Leaderboard has not changed since December 2024. [87]

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Singapore, India, the Gulf and Latin America in detail

Singapore: testing programmes

Programme	Launched	What it does	Status in Nov 2026
AI Verify Tester Accreditation	2026	Accredits testing firms against the IMDA Starter Kit; no fees; 12-month term [9]	Five firms: AIDX, Knovel, PwC, Resaro, Vulcan
Project Moonshot	May 2024	Open toolkit for red-teaming, benchmarking and baseline tests, with MLCommons [88]	In use
Agentic AI governance framework	Jan 2026, Davos	Five risk categories, incl. wrong and unauthorised actions [89]	Promotional source only
Agent testing guidance and assessor accreditation	Oct 2026	Extends guidance to autonomous agents; accredits assessors; forms a cyber task force [10]	Sector cyber guidance due H1 2027; single source
SEA-HELM	2025	Holistic evaluation in seven South-East Asian languages, five pillars [90]	Updated 18 Sept 2026; 75 open-weight and 16 closed models [75]

Table 11. Singapore's testing programmes and their status in November 2026.

The accreditation programme guarantees no safety outcome and accredits firms, not models.[9] UK AISI led the cybersecurity track of the joint test; the paper reports methods, not model results.[66] Neo Research, based in Singapore, gave the clearest 2026 comparison of Chinese and US model safety behaviour.[6] SEA-HELM's featured models include Qwen 3.5 and 3.6, Gemma 4 and SEA-LION.[75]

India: evaluation assets

Asset	Date	What it tests	Key result
MILU	Nov 2024	8 domains, 41 subjects, 11 Indic languages, from regional and state exams[91]	Baseline knowledge set
IndicSafe	March 2026	6,000 cultural safety prompts in 12 Indic languages, 10 models[11]	12.8% cross-language agreement
Inspect India Evals	July 2026	Six benchmarks on Inspect: MMLU in 16 languages, BharatBBQ bias, a DPI safety test, multi-turn jailbreaks[74]	Sarvam-M and Gemma 2 tied at 80% on the India Fairness Index; DPI safety 20% to 100%
SurakshaEval	Aug 2026	Human-written Indic safety prompts in 10 languages[92]	Search summary only
Indic LLM Arena	Not stated	Crowd-sourced battles on language, context and safety; AI4Bharat at IIT Madras with Google Cloud[93]	Live
BharatBench	Not stated	Ola Krutrim; 8 Indic languages across text, vision and speech[94]	Vendor benchmark

Table 12. India's main benchmarks and arenas, with key results.

DPI means Digital Public Infrastructure, India's state platforms for identity and payments. The Atlantic Council describes an existing IndiaAI Safety Institute with a hub-and-spokes model; its March 2024 date may confuse the IndiaAI Mission with the institute.[95] The white paper's AISI would also run an AI incident database.[73]

Gulf. Not researched in depth. The Open Arabic LLM Leaderboard last changed on 9 October 2025.[12] We did not cover SDAIA, ALLaM, TII, G42 or MBZUAI.

Latin America. LatamGPT launched on 10 February 2026 in Santiago with President Boric; the Chilean centre CENIA coordinates it.[13] Emol reports 70 billion parameters on a Llama 3.1 base; another outlet reports 50 billion.[77] [78] CHOCLO holds 104,847 questions on Latin American cultural knowledge; Trueque holds 500 curated questions.[76] We did not research Brazil's draft AI law.

For an outside evaluator, Asia shows an evidence gap and a template for pass marks

Chinese open-weight models reach other markets without public safety evidence. Firms worldwide deploy Qwen, DeepSeek, Kimi and GLM models as agents. Their public cards contain no safety evaluations, and the labs did not sign the EU Code.[65] Their safety evidence sits in Chinese regulatory files that foreign buyers cannot see. An outside evaluator must therefore generate that evidence itself.

Chinese bases spread into other models. SEA-LION v4.5 runs on a Qwen base, and Qwen leads several regional boards.[75] [71] Fine-tunes elsewhere follow the same path. A rating of a fine-tuned model or agent should record its base model.

Agent controls are converging across regimes. China's draft standard and Singapore's agent guidance cover the same ground: identity, permissions, human approval, logs and shutdown.[7] [10] The EU AI Act asks for record-keeping (Article 12) and human oversight (Article 14) in high-risk systems. A test suite built on these controls could earn recognition in several jurisdictions. CnAISDA has already raised "mutual recognition of standards".[59]

Three Regimes Are Converging on the Same Agent Controls

Agent controls named in China's draft standard, Singapore's agent guidance and the EU AI Act's high-risk duties.

Control	China agent standard Draft plan, Jun 2026	Singapore agent guidance Jan and Oct 2026	EU AI Act, high-risk From Dec 2027
Identity and authentication	●	○	○
Permissions and tool calls	●	◐ Unauthorised actions as a risk	○
Human approval for high-risk steps	●	○	● Art. 14 human oversight
Logs	●	○	● Art. 12 record-keeping
Monitoring and anomaly blocking	●	○	○
Emergency shutdown	●	○	○

● Named ◐ Related ○ Not confirmed

WHAT TO NOTICE

- China's draft names every control; the other two regimes are confirmed for only some.
- "Not confirmed" means our sources do not mention it, not that the regime excludes it.

Figure 14. China's scope rests on one news report; Singapore's agent framework rests on a promotional source and its October extension on one news report. The Chinese controls test security, not lawful conduct.

Source: CGTN;[7] MLex;[10] GAICC.[89] EU articles as summarised in our source research.

China's standard shows how to write numeric pass marks. GB/T 45654 fixes bank sizes, refresh cycles and three pass rates.[2] It pairs a must-refuse bank with a must-answer bank to punish over-refusal. Any rating scheme can copy that structure with its own content. The Chinese content itself does not transfer, because it encodes state political norms.

Fixed harnesses and multilingual tests are the minimum. Harness choice moved one DeepSeek score by almost 9 points.[4] Safety verdicts agreed across Indic languages in only 12.8% of cases.[11] A credible evaluator fixes one harness for all models and tests in the languages the system serves.

Asia offers one open door and one closed door. Singapore's tester accreditation costs nothing and lasts 12 months.[9] China's compliance loop has no role for a foreign evaluator. There, the CAC filing and CAICT certificates hold all the trust.

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What we could not confirm

No current top ten for SuperCLUE, OpenCompass or FlagEval; their sites render in JavaScript.

No 2026 update to SuperCLUE-Safety or SuperCLUE-Agent beyond their 2023 launches.

The "no safety content" finding covers Hugging Face cards only, not separate technical reports such as a DeepSeek V4 paper or a Qwen3.8 blog.

We did not check cards for Tencent Hunyuan (Hy3) or ByteDance Seed (Doubao); closed Doubao models have no Hugging Face card.

No primary audit proves contamination in a named 2026 Chinese model.

Two CAC filing counts (February and June 2026) come from search summaries only. [49] [50]

The status of GB 45438-2025, the mandatory labelling standard for AI-generated content, is unconfirmed from a primary source.

No public list of accredited third-party testing bodies for the CAC filing.

The agent-security standard's scope rests on one news report. [7]

Shanghai AI Lab's v1.5 mapping to the EU Code rests on a search summary. [64]

No details of the May 2026 CAC action on agents beyond Concordia's mention. [3]

The WG9 May plenary and the note on de facto force rest on search summaries. [55] [51]

Singapore's October 2026 agent extension rests on one news report; its January 2026 framework on a promotional source. [10] [89]

Korea's high-impact start date conflicts between sources; no published Korea AISI results. [8] [84]

India's AISI status is unclear between a proposal and an existing body. [73] [95]

Not researched: Chinese security vendors' red-teaming products, the Gulf in depth, Brazil.

No evidence of Chinese participation in the network's joint testing.

Sources for chapter 6

95 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] **Beijing News on CAC filings.** It reports 1,112 filed services and 731 registrations by 31 August 2026. Secondary m.bjnews.com.cn

[2] **CSET translation of GB/T 45654-2025.** It gives the English text of the generative AI safety standard and its test numbers. Primary cset.georgetown.edu

[3] **AIGL summary of Concordia AI's 2026 report.** It summarises the state of AI safety in China in 2026. Secondary aigl.blog

[4] **DeepSeek-V4.1-Flash model card.** It gives base and chat benchmark tables and a harness-sensitivity table. Primary huggingface.co

[5] **GLM-5.3 model card.** It reports Z.ai's benchmarks against Western and Chinese rivals. Primary huggingface.co

[6] **The Next Web on Neo Research.** It reports evaluation-awareness and jailbreak results for US and Chinese models. Secondary thenextweb.com

[7] **CGTN on the agent safety standard.** It reports the plan for a mandatory national standard on AI agent security (single source). Single source news.cgtn.com

[8] **Cooley on Korea's AI Basic Act.** It summarises the Act's duties, thresholds and fines. Secondary cooley.com

[9] **AI Verify Foundation, AI Tester Accreditation.** It lists the accredited firms and the programme terms. Primary aiverifyfoundation.sg

[10] **MLex on Singapore agent testing.** It reports the extension of testing guidance to autonomous agents (single source). Single source mlex.com

[11] **IndicSafe, arXiv 2603.17915.** It tests culturally grounded safety prompts in 12 Indic languages. Primary arxiv.org

[12] **Open Arabic LLM Leaderboard Space data.** It shows the Space's last update. Primary huggingface.co

[13] **Buenos Aires Times on LatamGPT.** It reports the LatamGPT launch in Santiago. Secondary batimes.com.ar

[14] **C-Eval, arXiv 2305.08322.** It introduces the Chinese multi-level knowledge benchmark. Primary arxiv.org

[15] **CMMLU, arXiv 2306.09212.** It introduces the Chinese multitask knowledge benchmark. Primary arxiv.org

[16] **DataLearner, SuperCLUE page.** It describes the SuperCLUE method and lists later scores. Secondary datalearner.com

[17] **OpenCompass repository data.** It gives the stars, last update and self-description of OpenCompass. Primary github.com

[18] **FlagEvalMM repository data.** It shows the activity of FlagEval's multimodal repository. Primary github.com

[19] **AIBase on SuperCLUE March 2026.** It reports the March 2026 SuperCLUE ranking. Secondary aibase.com

[20] **ERNIE-5.5-Flash-Base model card.** It reports Baidu's base-model scores, including CMMLU. Primary huggingface.co

[21] **AGIEval, arXiv 2304.06364.** It introduces the human-exam benchmark with gaokao questions. Primary arxiv.org

[22] **SafetyBench, arXiv 2309.07045.** It introduces the bilingual multiple-choice safety benchmark. Primary arxiv.org

[23] **CValues, arXiv 2307.09705.** It introduces a Chinese human-values benchmark. Primary arxiv.org

[24] **JADE, arXiv 2311.00286.** It describes the linguistic-fuzzing safety platform and its results. Primary arxiv.org

[25] **ForesightSafety Bench, arXiv 2602.14135.** It describes a frontier-risk safety evaluation framework. Primary arxiv.org

[26] **QbitAI on CompassArena.** It describes the CompassArena launch with ModelScope. Secondary qbitai.com

[27] **OpenCompass column on CSDN.** It summarises the arena upgrade and the 2026 monthly boards. Secondary blog.csdn.net

[28] **QbitAI on FlagEval.** It reports FlagEval's 100-model round and debate board. Secondary qbitai.com

[29] **FlagEval-Robo (formerly FlagEval-Embodied Verse), Hugging Face Space.** It hosts BAAI's embodied-AI leaderboard, renamed in January 2026. Primary huggingface.co

[30] **SuperCLUE, arXiv 2307.15020.** It describes the SuperCLUE benchmark at launch. Primary arxiv.org

[31] **SuperCLUE on GitHub.** Its README lists the spin-off boards and reports. Primary github.com

[32] **SuperCLUE repository data.** It shows the stars and last update of the SuperCLUE repository. Primary github.com

[33] MIT Technology Review on xbench. It describes HongShan's benchmark and its tracks. Secondary technologyreview.com

[34] Qwen3.8-Flash-Next-FP8 model card. It reports Alibaba's benchmarks and its best-of-harness rule. Primary huggingface.co

[35] DeepSeek-V4-Pro-0813 model card. It reports DeepSeek's own benchmarks and harness. Primary huggingface.co

[36] Kimi-K3 model card. It reports Moonshot's own and third-party benchmarks. Primary huggingface.co

[37] Kimi-K3.1-Pro model card. It reports Moonshot's latest benchmark tables. Primary huggingface.co

[38] MiniMax-M3.1-Flash model card. It reports MiniMax's benchmarks, including an in-house reproduction. Primary huggingface.co

[39] MindStudio blog on the benchmark gap. It claims weaker results on contamination-resistant tests (low quality). Secondary mindstudio.ai

[40] AI CERTs on MiniMax M2.5. It reports a debate on contamination and harnesses (low quality). Secondary aicerts.ai

[41] Startup Fortune on safety-test gaming. It disputes the headline claims about Chinese models. Secondary startupfortune.com

[42] SCMP on Neo Research. It reports the same study of Chinese models and safety tests. Secondary scmp.com

[43] ChinAI #351 on CAICT's 2026 round. It describes CAICT's 2026 test categories and earlier results. Secondary chinai.substack.com

[44] OfficeChai on Dario Amodei. It reports his view that Chinese models target benchmarks. Secondary officechai.com

[45] SCMP on a physical-AI ranking. It asks whether a start-up manipulated a global ranking (paywalled). Secondary scmp.com

[46] IT之家 on CAC filings at end-2025. It reports 748 filed services and 435 registrations. Secondary ithome.com

[47] IT之家 on CAC filings in April 2026. It reports 868 filed services and 17 deep-synthesis batches. Secondary ithome.com

[48] The Paper on CAC filings at end-2025. It confirms the end-2025 filing count. Secondary thepaper.cn

[49] Guangming on CAC filings. A search summary gave counts for February and June 2026 (page not opened). Single source m.gmw.cn

[50] Tonghuashun on CAC filings. A search summary gave an intermediate filing count (page not opened). Single source news.10jqka.com.cn

[51] SESEC report on TC260 AI standardisation. It explains how recommended standards gain de facto force (via search summary). Secondary sesec.eu

[52] TC260, Chinese text of GB/T 45654-2025. It gives the original standard. Primary tc260.org.cn

[53] CSDN guide to CAC filing. It lists the filing package and advertises filing agents. Vendor aicoding.csdn.net

[54] SESEC on TC260 Standards Week 2026. It reports WG9's creation, members and mandatory projects. Secondary sesec.eu

[55] Trivium China on the WG9 plenary. It reports the May 2026 plenary (via search summary). Single source triviumchina.com

[56] Digital Policy Alert on TC260 ethics guidelines. It reports the adoption of ethics and safety guidelines for AI applications. Secondary digitalpolicyalert.org

[57] Secrss on TC260's August 2026 drafts. It lists seven draft standards open for comment. Secondary secrss.com

[58] ChinAI #261 on CAICT's first results. It reports the first round of CAICT's AI Safety Benchmark. Secondary chinai.substack.com

[59] Tsinghua I-AIIG on the CnAISDA dialogue. It reports CnAISDA's members and its WAIC 2026 dialogue. Primary aiig.tsinghua.edu.cn

[60] Carnegie on CnAISDA. It explains how Chinese experts built their own safety institute. Secondary carnegieendowment.org

[61] AI Frontiers on China and AI safety. It assesses how seriously China treats AI safety. Secondary ai-frontiers.org

[62] Shanghai AI Lab frontier risk report, arXiv 2507.16534. It reports frontier-risk results across seven domains. Primary arxiv.org

[63] Concordia AI on the Shanghai AI Lab framework. It describes the joint risk management framework. Secondary aisafetychina.substack.com

[64] newx listing of the v1.5 framework. It lists the February 2026 framework report (via search summary; not verified). Single source newx.sg

[65] Cloud Security Alliance, EU AI Act GPAI enforcement. It covers fines and the labs that did not sign the Code. Secondary labs.cloudsecurityalliance.org

[66] Third joint agentic testing exercise, arXiv 2601.15679. It describes the network's joint agent testing method. Primary arxiv.org

[67] Cloud Security Alliance, CAISI testing agreements. It summarises CAISI's agreements and findings, including DeepSeek V4 Pro. Secondary labs.cloudsecurityalliance.org

[68] aipicks glossary, Nejumi Leaderboard. It describes the Nejumi Leaderboard and its scoring. Secondary aipicks.jp

[69] Gigazine on the Open Japanese LLM Leaderboard. It reports the leaderboard launch and its tasks. Secondary wbgsv0a.gigazine.net

[70] J-AISI, red-teaming guide v1.10 summary. It summarises the March 2025 revision. Primary aisi.go.jp

[71] lilting.ch on Japanese LLM options. It compares Japanese model results on Nejumi 4. Secondary lilting.ch

[72] Mobile World Live on Korea's sovereign AI project. It reports SKT's NIA benchmark result. Secondary mobileworldlive.com

[73] Lokmat Times on India's techno-legal framework. It reports the white paper's AISI proposal. Secondary lokmattimes.com

[74] Inspect India Evals, arXiv 2607.25375. It describes six Indian benchmarks built on Inspect. Primary arxiv.org

[75] SEA-HELM leaderboard. It lists current results for South-East Asian languages. Primary leaderboard.sea-lion.ai

[76] vgaraujov blog on LatamGPT benchmarks. It describes CENIA's benchmarks and runs a Spanish test (single author). Single source vgaraujov.github.io

[77] Emol on LatamGPT. It reports LatamGPT's size and base model. Secondary emol.com

[78] CO/AI on LatamGPT. It gives a different parameter count for LatamGPT. Secondary getcoai.com

[79] JGLUE, ACL Anthology. It introduces the Japanese language understanding benchmark. Primary aclanthology.org

[80] ELYZA-tasks-100 on Hugging Face. It hosts the Japanese instruction-following set. Primary huggingface.co

[81] Open Japanese LLM Leaderboard Space data. It shows the Space's last update. Primary huggingface.co

[82] Swallow leaderboard, about page. It describes the Swallow evaluation suite and JamC-QA. Primary swallow-llm.github.io

[83] J-AISI, Guide to Red Teaming Methodology. It hosts Japan's red-teaming guide. Primary aisi.go.jp

[84] Pebblous blog on Korea's high-impact AI. It claims a later start date for high-impact duties (unverified). Single source blog.pebblous.ai

[85] Korea AISI, mission page. It states the institute's mission. Primary aisi.re.kr

[86] KMMLU, arXiv 2402.11548. It introduces the Korean expert-knowledge benchmark. Primary arxiv.org

[87] Open Ko-LLM Leaderboard Space data. It shows the Space's last update. Primary huggingface.co

[88] Allen & Gledhill on Project Moonshot. It describes Singapore's generative AI testing toolkit. Secondary allenandgledhill.com

[89] GAICC on Singapore's agentic AI framework. It summarises the January 2026 framework (promotional source). Single source gaicc.org

[90] SEA-HELM, arXiv 2502.14301. It describes the South-East Asian language evaluation suite. Primary arxiv.org

[91] MILU, arXiv 2411.02538. It introduces the multi-domain Indic knowledge benchmark. Primary arxiv.org

[92] SurakshaEval on alphaXiv. It describes human-written Indic safety prompts (via search summary). Single source alphaxiv.org

[93] AI4Bharat, Indic LLM Arena. It describes the crowd-sourced Indic arena. Primary ai4bharat.iitm.ac.in

[94] Ola Krutrim, BharatBench report. It describes the Indic multimodal benchmark. Vendor ai-labs.olakrutrim.com

[95] Atlantic Council on India's AI summit. It describes the IndiaAI Safety Institute. Secondary atlanticcouncil.org

07

CHAPTER 7 · BEYOND TEXT

Outside text, tests fill up fast and almost nobody checks the numbers independently

Vision, generation, voice, robotics and driving all repeat one arc: first tests saturate, arenas take over, and real-world, independent evaluation stays thin.

16 Elo spread of the top ten on Arena's vision board

30–45% of text-mode success kept by voice agents

>90% → 0% LIBERO robot scores under small changes

−45 to −50% deepfake detector AUC on real 2024 fakes

17.7% maximum GenEval judge error against humans

5 November 2026 · Read online with interactive charts: evals.study/beyond-text/

Key findings

- **Old vision tests have saturated.** DocVQA, ChartQA, OCRBench v1 and MathVista all scored 85–97% by November 2025.[1] Harder successors such as MMMU-Pro and ScreenSpot-Pro reached about 85–93% by November 2026 (aggregator).[2] [3] [17]
- **The vision arena can no longer rank the frontier.** On 19 October 2026, the top ten models on Arena's vision board sat within 16 Elo points, with overlapping intervals.[4]
- **Automatic image judges drift away from people.** GenEval's judge erred by up to 17.7% against human judgment, so blind human votes now rank generation (Dec 2025).[5]
- **The two video arenas disagree.** Gemini Omni 1.1 Flash leads Arena's text-to-video board but ranks tenth on Artificial Analysis (Sep–Nov 2026).[6] [7]
- **Deepfake detectors fail in the wild.** On real 2024 deepfakes, open-source detectors lost 45–50% of their AUC against academic benchmarks (Mar 2025).[8]
- **Speech reasoning is solved, but voice agents are not.** The top model scores 99.7% on Big Bench Audio (Nov 2026).[9] In the τ-voice paper, voice agents kept only 30–45% of their text-mode task success (2026).[10]

- **The Open ASR Leaderboard shows how to resist benchmark gaming.** It dropped LibriSpeech from its default average on 2 November 2026 and now leans on private data and a "benchmark fitting" check. [11] [50] [51]
- **Robot scores collapse under small changes.** LIBERO scores above 90% fell to 0–30% when objects, cameras or instructions shifted (Oct 2025). [12] [13] Labs mostly grade themselves on private task suites.
- **Driving evaluation moved to pseudo-simulation.** The CARLA Leaderboard closed for good, and NAVSIM v2 is now the main public benchmark (2025–2026). [14] [15]
- **Classic ML has a mature, regulator-written method that stops at generative AI.** SR 26-2 replaced SR 11-7 on 17 April 2026 and excludes generative and agentic AI. [18] [101]

Every modality follows the same arc, from saturated tests to thin independent checks

AI now sees, draws, speaks, listens, drives and moves robots. Each modality has its own tests, arenas and failure modes, but the story repeats.

First-generation tests saturate within one or two model generations. Vision "Pro" tests, GUI grounding and speech reasoning all neared their ceilings within 12–24 months. [1] [9] [17] Human-preference arenas then take over. Soon they also stop separating the frontier, because the top models sit inside the noise. [4]

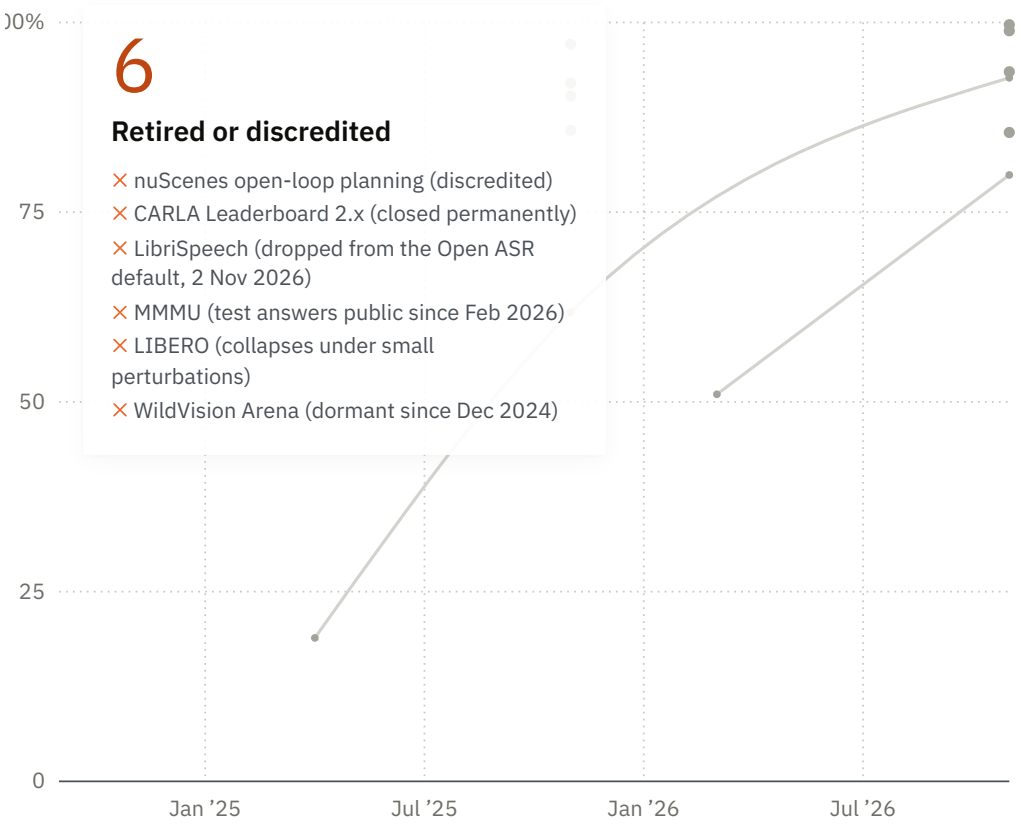
The hard part is the same in every modality. Real conditions, real tasks and an independent evaluator are scarce. Deepfake detectors lose about half their skill on real fakes. [8] Robot policies that ace a simulator fail when the camera moves. [13] Voice agents lose most of their text-mode success once callers speak with noise and accents. [10]

HOW TO READ THE NUMBERS

We read most leaderboards on 5 November 2026. "Aggregator" marks third-party sites, such as BenchLM, that compile lab-reported numbers. Their figures often disagree with lab pages, so treat them as indicative. "Single source" marks a fact that only one source supports. "Vendor" marks a company's claim about its own product. Text benchmarks, OSWorld and τ-bench appear in the Benchmarks chapter.

Tests Beyond Text Fill Up in Months, Too

Best reported score on vision, GUI and speech tests, September 2024 to November 2026, with the tests that still resist.



1 **The first vision tests are full.** By November 2025, four model families scored 85–97% on document, chart, OCR and visual-maths tests. [1] Labs keep them only as regression checks.

2 **GUI grounding went from 18.9% to 92.7% in 19 months.** ScreenSpot-Pro launched in April 2025 on expert software screens. [16] By November 2026, the best aggregator score was 92.7%. [17]

3 **The harder successors now near their own ceilings.** MMMU-Pro removed text-solvable questions and still reached 85.5%. CharXiv reasoning reached 93.5%. Both figures are aggregator numbers. [2] [3]

4 **Speech reasoning is solved.** StepAudio 3 Realtime scores 99.7% on Big Bench Audio and 98.9% on turn-taking dynamics. [9]

5 **Voice agents climb fast, but the harness matters.** The τ-voice paper found the best voice agent at 51% with clean audio. [10] By November 2026, Artificial Analysis reported 79.9% on its own harness. [9] The two numbers may not compare.

6 **A few tests still resist.** Hallucination, hard OCR, compositional image generation, hard driving scenes and household robotics all stay well below the ceiling. [1] [37] [74] [98]

7 **Other tests were retired or discredited.** Public answers, closed servers, gaming and fragility ended their use as headline numbers. [11] [14] [22] [95]

Figure 1. Lines join dated best scores; single dots are one dated reading. OCRBench v1 is shown out of 100 (920 of 1,000). The two τ-voice points come from different harnesses: the paper's own and Artificial Analysis's. Still-hard tests use each test's own metric, so their heights compare only loosely. Aggregator values are lab-reported numbers compiled by BenchLM.

Source: Qwen3-VL technical report (Nov 2025);[1] BenchLM (Nov 2026, aggregator);[2] [3] [17] ScreenSpot-Pro paper;[16] Artificial Analysis (Nov 2026);[9] τ-voice paper;[10] GenEval 2 (single source);[37] ChartQAPro;[20] BEHAVIOR Challenge (snippet);[74] NAVSIM snippets.[98] [99]

Each modality has one number that tells its story

Modality	Key number	Saturated, frontier and other facts	Independent check
Vision-language	**16 Elo** spread of Arena's vision top ten (19 Oct 2026)	Saturated: DocVQA, ChartQA, OCRBench v1, MathVista (85–97%); Frontier: HallusionBench at 60–67; Same model: 80.5% (Google) vs 83.9% (BenchLM) on MMMU-Pro	Aggregators only
Image and video generation	**17.7%** maximum GenEval error against human judges	Saturated: GenEval; VBench v1; Frontier: GenEval 2 (35.8%), VBench-2.0; Deepfake detectors lose 45–50% AUC on real fakes	Two arenas, split verdicts
Speech and voice agents	**30–45%** of text-mode success kept by voice agents (τ-voice)	Saturated: Big Bench Audio at 99.7%; LibriSpeech dropped from the Open ASR default; Testing vendors serve builders, not buyers	Builder-side QA only
Robotics and driving	**>90% → 0–30%** LIBERO success once objects, views or instructions shift	Frontier: BEHAVIOR-1K winner at 12.4%; CARLA Leaderboard closed; NAVSIM v2 leads; RoboArena: 612 comparisons across 7 universities	Almost no third party
GUI grounding	**92.7%** best ScreenSpot-Pro score, up from 18.9% at launch	Tests static screens only; No state tracking or recovery; Reliability now limits GUI agents	Aggregators only
Classic ML (credit, fraud)	**SR 26-2** replaced SR 11-7 on 17 Apr 2026; excludes GenAI and agents	Back-testing against real outcomes, no benchmark race; Agreed fairness metrics (Fairlearn, AIF360); Monitoring vendors are moving to agents	Model-risk validation

Table 1. What is solved, what still separates models, and who checks the numbers, November 2026. Read across the tags: only classic ML has an established independent check. Every key number shows a gap between lab conditions and real use.
Source: Arena;[4] GenEval 2;[5] Deepfake-Eval-2024;[8] τ-voice;[10] LIBERO-PRO and LIBERO-Plus;[12] [13] BenchLM (aggregator);[17] Federal Reserve SR 26-2.[101]

Vision tests filled up, and the vision arena can no longer rank the frontier

Vision-language models answer questions about images, documents, charts and video. Their evaluation has split into saturated regression checks, harder successors and preference arenas.

Saturated perception tests stay in technical reports only as regression checks. Most late-2025 scores come from one primary table, the Qwen3-VL report. It compares Qwen3-VL with Gemini 2.5 Pro, GPT-5 and Claude Opus 4.1.[1] DocVQA reached 96.5–97.1, ChartQA 90.3 and MathVista-mini 85.8. Even the authors of ChartQA's successor call ChartQA saturated.[20]

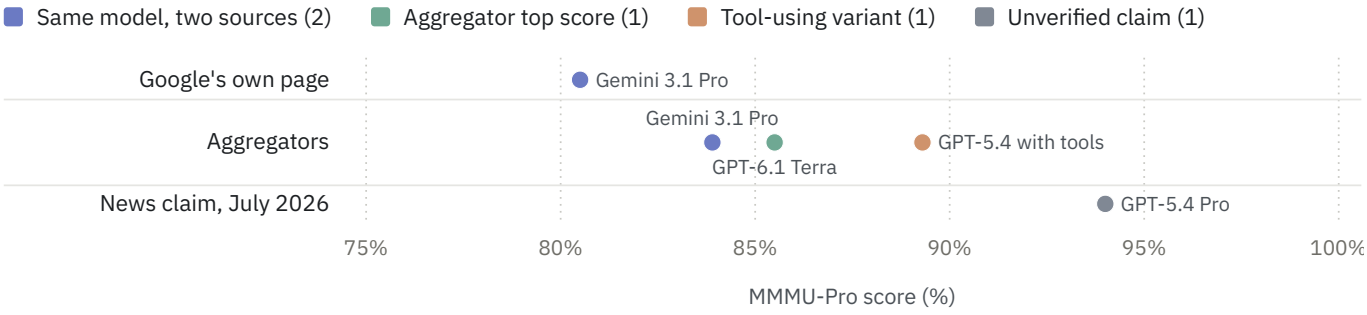
Harder successors replaced them, and most now near their own ceiling. MMMU-Pro removed questions that text-only models could answer. It raised the options to ten and embedded some questions in the image. At launch, models scored 16.8–26.9 points lower than on MMMU.[23] Within two years, aggregator scores

passed 85%.[2] Models still stay "close to random guesses" on rare image types, such as music sheets and chemical structures.[22]

Hallucination remains the clearest unsolved test. Frontier models scored only 60.4–66.7 on HallusionBench in late 2025, while document tests passed 95.[1] [26] Video understanding also lacks a current, dated leaderboard. Video-MME tops out at 85.1 and VideoMMMU at 84.6, both from November 2025 tables.[1] [28]

MMMU-Pro scores move with the source that reports them

Scores reported for MMMU-Pro by labs, aggregators and news, 2026. The spread comes from sources and variants, not from the models.



WHAT TO NOTICE

- The two indigo dots show the same model 3.4 points apart.
- GPT-5.4 Pro does not appear in BenchLM's November table, so we treat the 94% claim as unverified.
- Tool and Python variants mix into rankings and inflate scores.

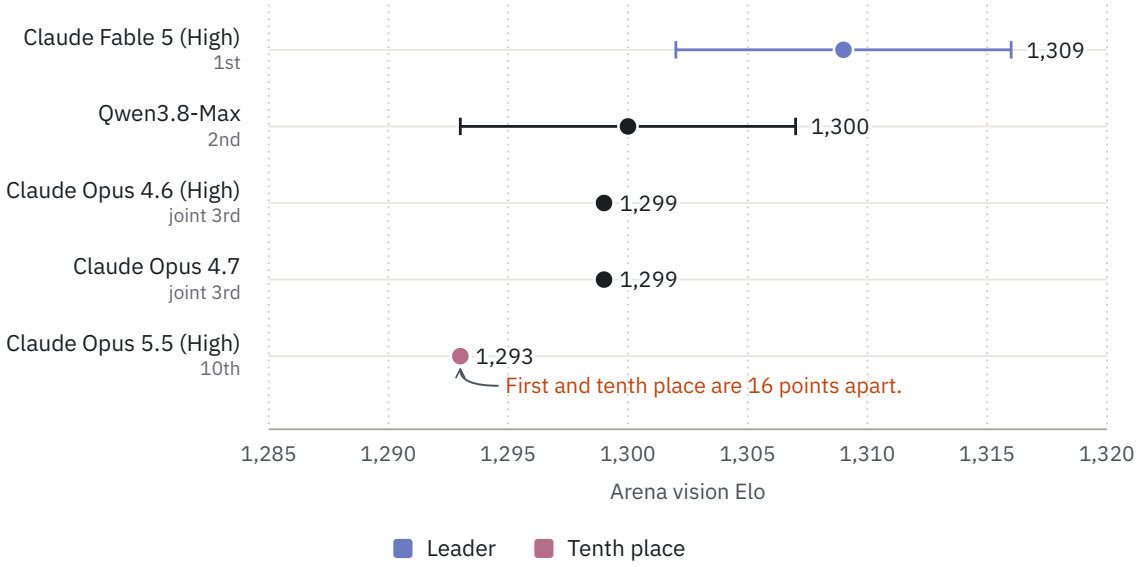
Figure 2. A fair comparison needs every model re-run in one fixed harness. No independent team did this for frontier vision models in 2026.

Source: Google DeepMind (vendor);[24] BenchLM (aggregator, Nov 2026);[2] Another Wrapper (aggregator);[25] af.net (unverified).[33]

Preference arenas rank models by votes, but the frontier sits inside the noise. Arena, formerly LMArena, runs the largest vision arena. On 19 October 2026 its board held 1,493,948 votes across 166 models.[4] The whole top ten fits inside 16 points, with overlapping intervals. A gap that small does not support any ranking claim.

The top ten vision models are statistically tied

Arena vision leaderboard, 19 October 2026: Elo score with 95% interval where published.



WHAT TO NOTICE

- The leader's interval (±7) overlaps the second model's interval.

Figure 3. Places 5–9 are omitted; their scores sit between 1293 and 1299. The source gives ±7 intervals for the first two models only. Source: Arena vision leaderboard, read 19 Oct 2026. [4]

Other arenas have gone quiet. WildVision-Arena collected real-user preferences in 2024, and its GPT-4 judge reached a Spearman correlation of 0.94 with arena Elo. [34] Its Space has not changed since 22 December 2024. [35] The OpenCompass Open VLM Leaderboard last changed on 11 March 2026. [36]

GUI grounding has reached its ceiling

Perception no longer limits GUI agents. ScreenSpot-Pro tests grounding on 1,581 instructions across 23 professional applications and three operating systems. [16] The best model scored 18.9% at launch in April 2025. By November 2026, BenchLM listed GPT-6 Astra at 92.7%, Claude Opus 4.8 at 87.9% and GPT-5.4 at 85.4%. [17] The test covers static screens only, with no state tracking or recovery. Reliability, harness effects and broken task checkers now limit GUI agents instead.

GO DEEPER

Image and document benchmarks, full table

Benchmark	Measures	Top score (model, date)	Status	Flaw
DocVQA	Questions on scanned documents	96.5–97.1, Qwen3-VL-235B, Nov 2025 [1]	Saturated	Useful only as a regression check

Benchmark	Measures	Top score (model, date)	Status	Flaw
ChartQA	Questions on charts	90.3, Qwen3-VL, Nov 2025 [1]	Saturated	Its successor's authors call it saturated [20]
ChartQAPro (Apr 2025)	1,948 questions on 1,341 harder charts [20]	55.81%, Claude 3.5 Sonnet, at launch	Frontier	No 2026 top score found
OCRBench v1	Text in images, out of 1,000	920, Qwen3-VL-Instruct, Nov 2025 [1]	Saturated	Too easy for frontier models
OCRBench v2 (Dec 2024)	10,000 QA pairs in 31 scenarios, plus a private set of 1,500 images [21]	66.8–67.1 (English), Qwen3-VL, Nov 2025	Frontier	No 2026 board found
MathVista-mini	Visual maths	85.8, Qwen3-VL-thinking, Nov 2025 [1]	Saturated	Near the ceiling for all four families
MMMU	College-level multimodal questions	80.6–84.2 across four families, Nov 2025 [1]	Near ceiling	Test answers became public in Feb 2026 [22]
MMMU-Pro (Sep 2024)	MMMU without text-solvable items, ten options, a vision-only setting [23]	85.5%, GPT-6.1 Terra, Nov 2026 (aggregator) [2]	Near ceiling	Sources disagree by several points; tool variants mix in [24] [25]
CharXiv descriptive	Describing scientific charts	87.8–94.4, Nov 2025 [1]	Saturated	Superseded by the reasoning split
CharXiv reasoning	Reasoning over scientific charts	93.5%, Qwen3.8 Max and Claude Mythos 5, Nov 2026 (aggregator) [3]	Near ceiling	Only aggregator numbers for 2026
HallusionBench (2023)	Visual illusions and hallucination; 346 images, 1,129 questions [26]	60.4–66.7 across four families, Nov 2025 [1]	Frontier	No 2026 primary score found
POPE (2023)	Yes/no polling on object hallucination [27]	No 2026 primary score found	Probably saturated (unverified)	The yes/no format makes it easy
ERQA	Embodied reasoning from images	28.0–65.7, Nov 2025 [1]	Frontier	Wide spread between model families

Table 2. Image and document benchmarks with their best scores. November 2025 scores come from the Qwen3-VL report; 2026 scores come from aggregators.

GO DEEPER

Video benchmarks

Benchmark	Measures	Top score (model, date)	Status	Flaw
Video-MME	Video QA over six domains, 11 seconds to 1 hour [28]	85.1, Gemini 2.5 Pro without subtitles, Nov 2025 [1]	Near ceiling	No dated 2026 board found
MVBench	20 temporal tasks that one frame cannot solve [29]	76.5, Qwen3-VL, Nov 2025 [1]	Active	Converted annotations limit task variety
VideoMMMU	Expert-level questions on videos	84.6, GPT-5, Nov 2025 [1]	Near ceiling	No dated 2026 board found
LongVideoBench	6,678 questions on 3,763 videos up to an hour long [30]	No 2026 board found	Unknown	Current top scores unconfirmed
EgoSchema	5,000+ questions on 3-minute egocentric clips [31]	No 2026 board found	Unknown	Current top scores unconfirmed

Table 3. No dated 2026 leaderboard exists for these video tests, so the top scores come from November 2025 tables.

MVBench builds its questions from existing annotations, which avoids bias from an LLM grader. [29]

EgoSchema introduced "temporal certificate" length: how much of a clip a person must watch to answer. [31]

Coverage of Qwen3-VL reports 100% needle retrieval in 30-minute videos (secondary). [32] Needle retrieval tests search, not temporal reasoning.

GO DEEPER

Arena and GUI grounding detail

Arena details

Arena vision board, 19 Oct 2026: Claude Fable 5 (High) 1309±7; Qwen3.8-Max 1300±7; Claude Opus 4.6 (High) and Claude Opus 4.7 both 1299; tenth place Claude Opus 5.5 (High) 1293. [4]

WildVision's 500-item WV-Bench used a GPT-4 judge. It correlated with arena Elo at Spearman 0.94; MMMU and MMVet correlated less. [34]

GUI grounding table

Benchmark	Measures	Top score (model, date)	Status	Flaw
ScreenSpot-Pro	Grounding on 1,581 high-resolution instructions	92.7%, GPT-6 Astra, Nov 2026 (aggregator) [17]	Near ceiling	"Tests static-screen grounding" only
OSWorld-Verified	Real desktop tasks	85%, Claude Fable 5, five-run average (aggregator) [100]	Near ceiling	We did not retrieve the system card

Table 4. GUI grounding and computer-use scores. Both 2026 figures are aggregator numbers.

Qwen3-VL-235B reached 61.8% on ScreenSpot-Pro by November 2025. [1] H Company's Holo2-235B scored 70.6%. [17]

GO DEEPER

What stays open in vision

No independent team re-ran frontier models on the vision suite in a fixed harness during 2026.

Very long video still lacks a current, dated leaderboard.

Public test answers end contamination control, so future MMMU scores deserve less weight than private-set scores. [22]

Lab pages, aggregators and leaderboards report different numbers for the same model.

Blind human votes now rank generation, because automatic judges drift

Image, video and music generation have no single right answer. Evaluators therefore rely on human preference, and automatic metrics serve as cheap proxies.

A frozen judge falls behind the models it grades. GenEval checks objects, counts, colours and positions in text-to-image output. Its Meta FAIR authors show that GenEval "has drifted far from human judgment over time". [5] A large human study confirmed the saturation. The same drift affects LLM judges in text. Any judge-model approach needs regular re-calibration against fresh human labels.

17.7%

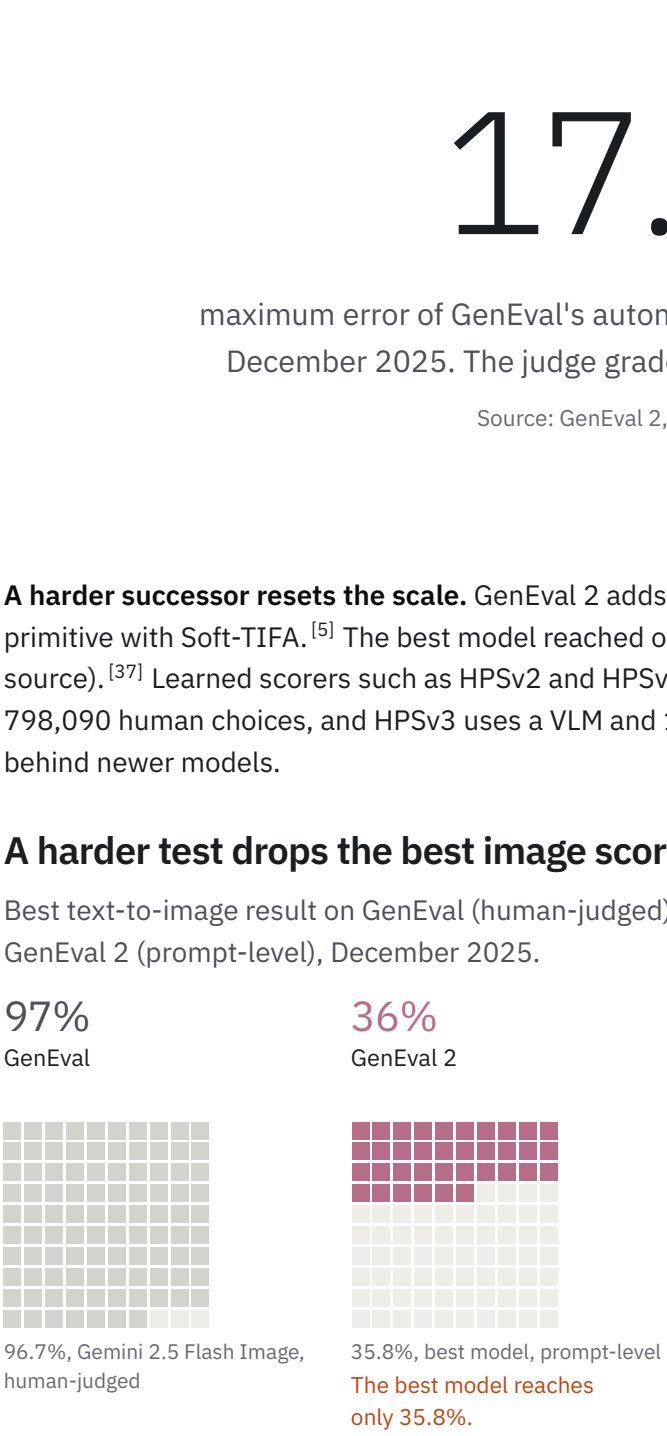
maximum error of GenEval's automatic judge against human judgment, December 2025. The judge grades models that have moved past it.

Source: GenEval 2, arXiv 2512.16853. [5]

A harder successor resets the scale. GenEval 2 adds more primitives and deeper composition, scored per primitive with Soft-TIFA. [5] The best model reached only 35.8% at prompt level in December 2025 (single source). [37] Learned scorers such as HPSv2 and HPSv3 also serve as proxies. HPSv2 fine-tunes CLIP on 798,090 human choices, and HPSv3 uses a VLM and 1.17 million comparisons. [39] [40] Any fixed scorer falls behind newer models.

A harder test drops the best image score from 97% to 36%

Best text-to-image result on GenEval (human-judged) and on its successor GenEval 2 (prompt-level), December 2025.



WHAT TO NOTICE

- The two tests use different scoring, so read the gap as a reset of the scale, not as a model regression.

Figure 4. Each grid has 100 squares; filled squares show the best score, rounded to whole percent (96.7% and 35.8%). Both figures come from one secondary overview of the GenEval 2 paper. GenEval 2 has little outside use so far.

Source: alphaXiv overview of GenEval 2 (single source); [37] GenEval 2 paper. [5]

Two arenas dominate, and they disagree on video. Arena collects votes from an open crowd. Artificial Analysis (AA) pays vetted private evaluators. Both fit votes with a Bradley-Terry model on an Elo scale. [48] On images they agree: GPT-Image-2.5 Sunburst leads both boards. [45] [46] On video they split. Gemini Omni 1.1

Flash ranks first on Arena but tenth on AA.[6] [7] Neither source explains the gap. Likely causes include the voter pool, the prompt set and the inclusion of audio.

The two arenas agree on images and split on video

	Arena (open crowd)	Artificial Analysis (paid, vetted evaluators)	Note
Text-to-image leader	GPT-Image-2.5 Sunburst, 1427±5	GPT Image 2.5 Sunburst (max), 1225	Same leader
Text-to-video leader	Gemini Omni 1.1 Flash, 1516±15	Wan 3.0, 1172	Different leaders
Gemini Omni 1.1 Flash on video	1st	10th (1129)	Neither source explains the gap
Audio in video votes	Not stated	Yes (v2.1, with audio)	
Board size	718,577 video votes, 48 models (21 Sep 2026)	Not published	
Score anchor	None stated	Kling 3.0 1080p (Pro) = 1000 for video; FLUX.2 [dev] = 1000 for images	
Prompt curation	Prompts from voters	Human-curated, 10 use cases, refreshed monthly	
Interval caveat	Not stated	Admits intervals 'may be slightly narrow'	

Table 5. How Arena and Artificial Analysis run their generation boards, read September to November 2026. Elo scales differ between the two boards, so compare ranks, not raw scores. One arena rank makes a weak signal on its own. A trustworthy board should state its voter pool, prompt taxonomy and audio policy.

Source: Arena text-to-image and text-to-video boards;[45] [6] Artificial Analysis boards and methodology.[46] [7] [48]

Audio metrics lack validation against human perception. Fréchet Audio Distance (FAD) remains the default metric for music quality. Few studies test its link to perceived quality. Its critics name three biases: sample size, embedding choice and reference set.[44] Music Arena, live since July 2025, runs pairwise votes for text-to-music systems.[47]

GO DEEPER

Automated generation metrics

Benchmark	Measures	Top score (model, date)	Status	Flaw
GenEval	Objects, counts, colours and positions in text-to-image	96.7% human-judged, Gemini 2.5 Flash Image (single source) [37]	Saturated [5]	Its automatic judge errs by up to 17.7%
GenEval 2 (Dec 2025)	More primitives and deeper composition, scored per primitive with Soft-TIFA [5]	35.8% prompt-level, best model, Dec 2025 (single source) [37]	Frontier	New, with little outside use so far
T2I-CompBench++	8,000 prompts on binding, relations, counts and composition [38]	No 2026 top score found	Active	Relies on detectors and MLLM judges
HPSv2 and HPSv3	Learned scorers trained on human preferences [39] [40]	Not a leaderboard	Proxy	A fixed scorer falls behind newer models
VBench (v1)	Surface faithfulness of video: per-frame quality, temporal consistency, basic prompt adherence [41]	Vendors self-report ranks [42]	Saturated (our judgement)	Tests only surface quality
VBench-2.0 (Mar 2025)	Intrinsic faithfulness: physics, commonsense, control, creativity and human fidelity in 18 dimensions [41]	Vendors self-report ranks [42]	Frontier; Space updated 1 Apr 2026 [43]	Ranks serve as marketing
Fréchet Audio Distance	Distance between embeddings of generated and reference audio	Not a leaderboard	Default music metric	Sample size, embedding and reference set all bias it [44]

Table 6. Automatic metrics and learned scorers for image, video and music generation, read November 2026.

Wondershare claims that ToMoviee 2.0 ranked third on VBench 2.0. The claim comes from a press release. [42]

GO DEEPER

Generation arenas, and how Artificial Analysis runs its board

Generation arenas, full table

Arena	Board date and size	Leader (score, date)	Next places	Notes
Arena text-to-image	2 Nov 2026; 6,961,993 votes; 84 models	GPT-Image-2.5 Sunburst, 1427±5 [45]	OpenAI holds the top five; MAI-Image-2.6 1331; Gemini Nano Banana 2.1 1325	Open crowd
AA text-to-image (v2.1)	Read 5 Nov 2026	GPT Image 2.5 Sunburst (max), 1225, Sep 2026 [46]	GPT Image 2.5 Flare 1208; GPT Image 2 (high) 1188; Nano Banana 2.1 1175	Anchor FLUX.2 [dev] = 1000; $10–211 per 1,000 images
Arena text-to-video	21 Sep 2026; 718,577 votes; 48 models	Gemini Omni 1.1 Flash, 1516±15 [6]	gemini-omni-flash 1513; FLUX 3 Video 1493 (preliminary); Grok Imagine Video 1.5 1492 (preliminary)	Open crowd
AA text-to-video (v2.1, with audio)	Read 5 Nov 2026	Wan 3.0, 1172, Aug 2026 [7]	Utopai X 1169; MiniMax H3 (768p) 1160; FLUX 3 Max 1156	Gemini Omni Flash 1.1 tenth at 1129; anchor Kling 3.0 1080p (Pro) = 1000
Music Arena	Live since Jul 2025	No ranking read	Not read	Rolling data releases [47]

Table 7. Board sizes and leaders as read in September to November 2026. Elo scales differ between the two providers, so compare ranks only.

How Artificial Analysis runs its arena

- It randomises left and right positions and requires a minimum engagement time per vote. [48]
- Humans curate prompts across 10 use cases and capabilities such as text rendering, layout and anatomy.
- It refreshes prompts monthly and retires prompts that do not separate models.
- It admits its intervals "may be slightly narrow", because it treats votes from one evaluator or one prompt as independent.

GO DEEPER

Audio, music and open questions in generation

Audio and music

- FAD critics propose extrapolation to infinite sample size, plus validated embeddings and references. [44]

Music Arena routes prompts with an LLM, records listening data and collects free-text feedback. [47]

What stays open in generation

Automated judges drift and need scheduled re-calibration against humans.

Arenas disagree, and neither explains why.

Audio metrics lack validation against human perception.

We found no 2026 primary top scores for ImageReward, PickScore, GenEval or T2I-CompBench.

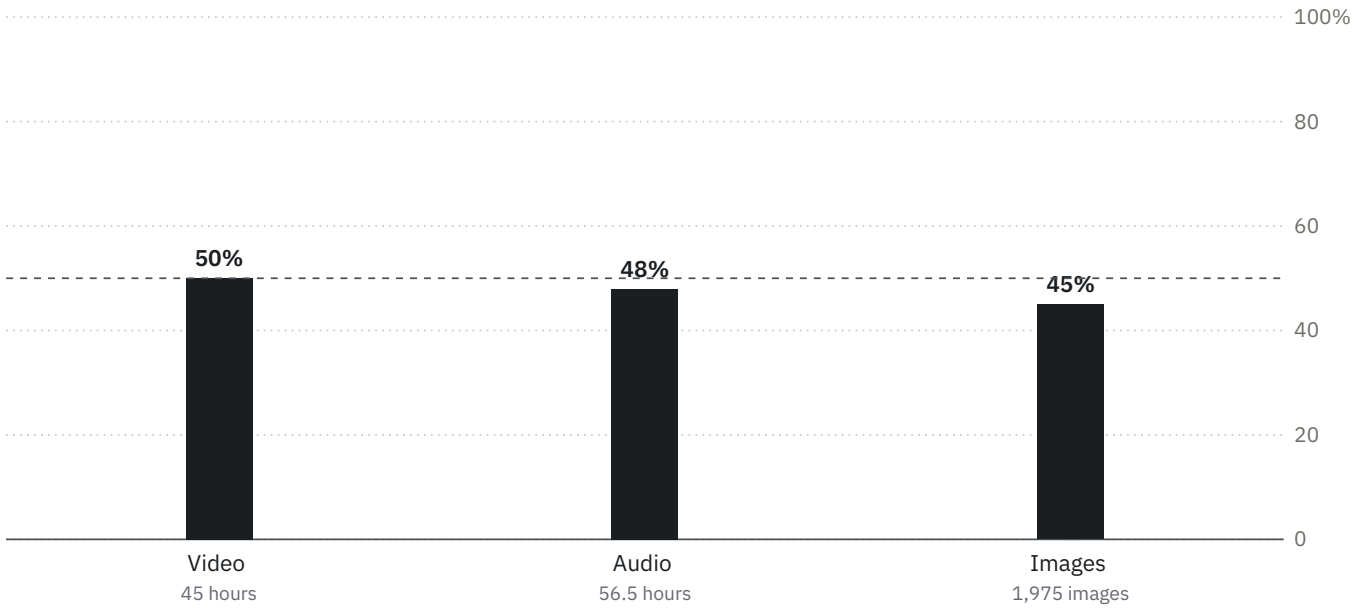
Deepfake detectors lose about half their skill on real fakes

Detection benchmarks built in the lab overstate how well detectors work on fakes found online.

Deepfake-Eval-2024 gives the clearest picture of real-world detection. Its authors collected in-the-wild deepfakes from 2024. The set holds 45 hours of video, 56.5 hours of audio and 1,975 images. The items come from 88 websites in 52 languages. [8] AUC, the area under the curve, measures how well a detector separates real from fake. Open-source state-of-the-art detectors lost 45–50% of their AUC against academic benchmarks.

Open-source deepfake detectors lose about half their AUC in the wild

Share of academic-benchmark AUC that open-source state-of-the-art detectors lost on real deepfakes collected online in 2024.



All three modalities lost close to half of their AUC. Commercial and fine-tuned detectors did better, but they still trail human forensic analysts. [8]

Figure 5. Deepfake-Eval-2024 is an academic snapshot from early 2025, not a maintained leaderboard.

Source: Deepfake-Eval-2024, arXiv 2503.02857. [8]

Commercial and fine-tuned detectors did better, but not well enough. They "do not yet reach the accuracy of deepfake forensic analysts".[8] Transparency rules, such as Article 50 of the EU AI Act, will need in-the-wild test sets. We found no standing, independent leaderboard for deepfake detection.

GO DEEPER

Deepfake detection: detail and gaps

Modality	AUC lost versus academic benchmarks	Note
Video	50%	Open-source state-of-the-art detectors[8]
Audio	48%	Open-source state-of-the-art detectors[8]
Images	45%	Open-source state-of-the-art detectors[8]

Table 8. Share of AUC lost on in-the-wild 2024 deepfakes compared with academic benchmarks.

Deepfake-Eval-2024 is an academic snapshot, not a maintained board.

This research pass did not search for 2026 tests of watermark robustness, such as SynthID or C2PA.

It did not cover voice-clone detection, such as ASVspoof 5.

Speech reasoning is solved, but voice agents lose most of their text-mode success

Speech recognition, speech synthesis and voice agents each have their own boards. The gap between skill on a test and conduct on a call is widest for agents.

Single-turn speech tests have saturated. StepAudio 3 Realtime scores 99.7% on Big Bench Audio, a set of 1,000 spoken reasoning questions.[9] [57] It also scores 98.9% on turn-taking dynamics such as pauses, backchannels and interruptions.[58] Big Bench Audio uses synthetic speech in 23 voices, in English only. AA's Speech-to-Speech Index puts Phonic 1 (High) at 87.1, just ahead of Grok Voice 3.0 at 86.9.[9]

30–45%

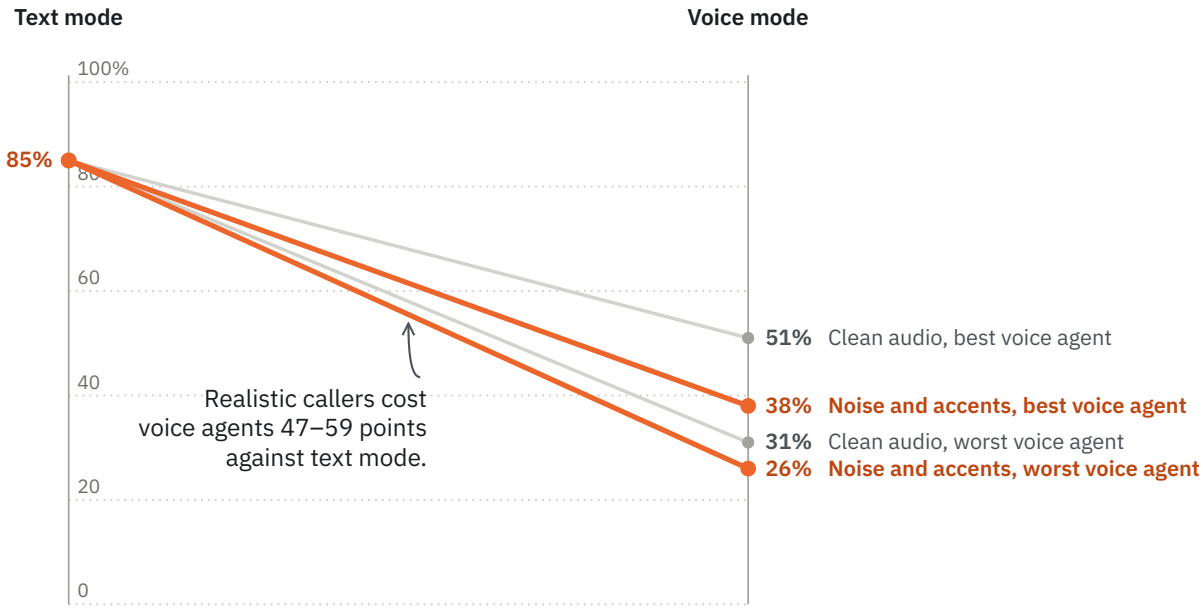
of their text-mode task success is all that voice agents kept on the same customer-service tasks in the τ-voice study (ICML 2026).

Source: τ-voice, arXiv 2603.13686.[10]

The τ-voice benchmark shows the gap between skill and conduct most clearly. Its authors extend τ²-bench to full-duplex voice calls in retail, airline and telecom.[10] [60] Each of 278 tasks checks the final database state. In text mode, GPT-5 with reasoning reaches 85% pass@1. Voice agents reach 31–51% with clean audio and 26–38% with realistic noise and accents. The agent's own behaviour causes 79–90% of the failures.

The same tasks drop from 85% in text to as low as 26% in voice

τ-voice task success (pass@1): GPT-5 with reasoning in text mode, against the best and worst voice agents in two audio conditions.



WHAT TO NOTICE

- The agent's own behaviour, not speech recognition, causes 79–90% of failures.
- Artificial Analysis reported 79.9% for Phonic 1 (High) in November 2026, on a harness that may differ from the paper's.

Figure 6. The text-mode reference is one model (GPT-5 with reasoning). The paper summarises the drop as voice agents keeping 30–45% of text capability.

Source: τ-voice, arXiv 2603.13686;[10] Artificial Analysis speech-to-speech (Nov 2026).[9]

Voice-testing vendors sell quality assurance to builders, not ratings to buyers. Coval, Hamming, Cekura, Bluejay and Cyara combine simulated callers, LLM judges, latency metrics and production monitoring.[63] [65] [54] [66] [67] Hamming claims 95%+ agreement with human evaluators. Nobody has audited such claims. Cyara's "EU AI Act conformity check" comes closest to a compliance product.

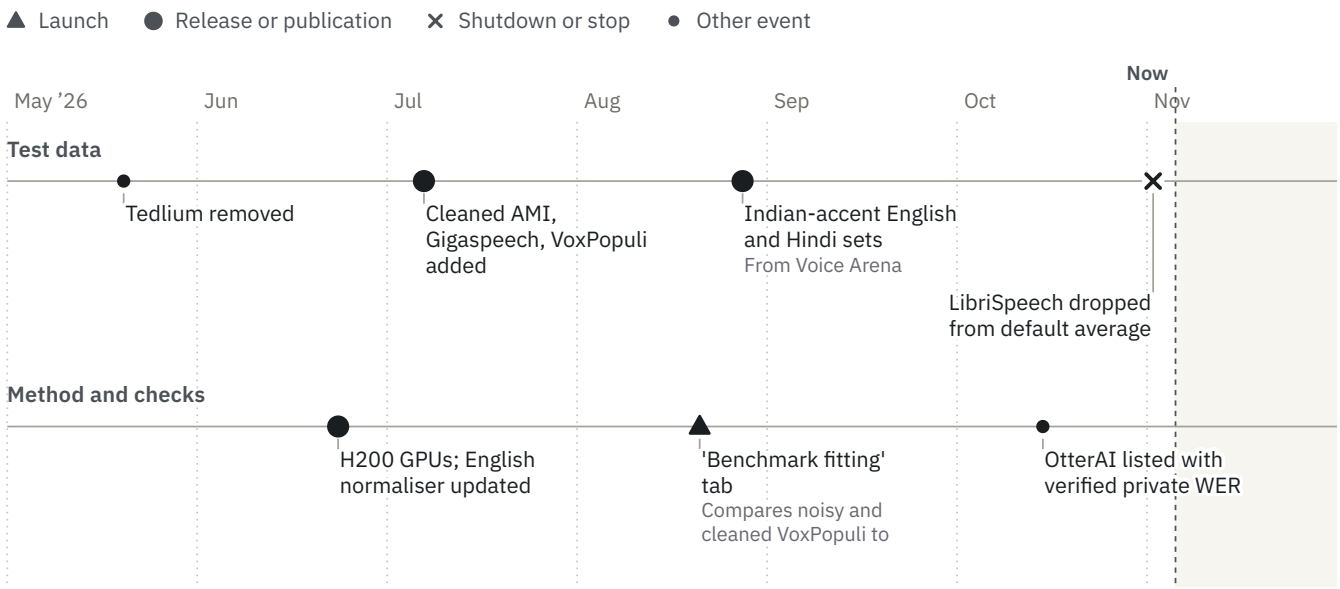
The Open ASR Leaderboard fights benchmark gaming

The Open ASR Leaderboard is the reference board for speech recognition. Its paper (v4, 30 March 2026) benchmarks 86 open and closed systems on 12 datasets.[49] It reports word error rate (WER) for accuracy and inverse real-time factor for speed. During 2026, its maintainers rebuilt the default average around cleaned and private data.[11]

Private data and a fitting check now resist gaming. Appen, DataoceanAI and Voice Arena supply private sets, aggregated so that no provider or split leaks.[50] The private tab exists to "address risks of overfitting to public datasets". A "benchmark fitting" tab compares the noisy VoxPopuli split with a cleaned version.[51] A model that scores better on the noisy references has learned their spelling quirks. The maintainers call this the "benchmaxing phenomenon".

In six months the speech leaderboard rebuilt its default score

Method changes logged by the Hugging Face Open ASR Leaderboard, May to November 2026.



WHAT TO NOTICE

- The default average now rests on cleaned conversational and business sets plus two private aggregates.
- Any public rater could copy the recipe: private held-out data, cleaned references, a fitting check and verified claims.

Figure 7. Dates come from the version log in the leaderboard's source code.

Source: Open ASR Leaderboard init.py, constants.py and app.py.[11] [50] [51]

Top WERs rest on secondary sources, because the results file needs a login. NVIDIA Nemotron 3.5 Transcribe averages 5.33% and ranks ninth, behind eight closed APIs.[52] Qwen3-ASR-1.7B averages 5.40%.[52] Text-to-speech is ranked by preference: AA's Speech Arena names ElevenLabs Eleven v4 top at Elo 1334.[55] We found no 2026 standard for mean opinion score (MOS) tests.

GO DEEPER

Speech recognition and synthesis

Speech recognition: reported top systems

System	Average WER	Source and date	Note
NVIDIA Nemotron 3.5 Transcribe 30B-A4B	5.33%	Added 28 Oct 2026 (secondary) [52]	Ninth overall; eight closed APIs rank above it
Qwen3-ASR-1.7B	5.40%	Nov 2026 (secondary) [52]	Open model
Cohere Transcribe	5.42%	Mar 2026, first at launch (secondary) [53]	Open model
Nemotron 3.5 Transcribe on Cekura's own set	2.28%	Vendor [54]	Not comparable with the leaderboard

Table 9. Top word error rates rest on secondary sources, because the leaderboard's results file needs a login.

Conformer encoders with transformer decoders give the best WER; CTC and TDT decoders give the best speed. [49]

The board covers English short-form, English long-form and multilingual tracks. [49]

Speech synthesis

AA's Speech Arena ranks TTS models by pairwise preference; ElevenLabs Eleven v4 leads at 1334. [55]

TTS Arena V2 on Hugging Face is active; its Space changed on 31 Oct 2026. We could not read its rankings. [56]

We found no study that compares MOS with arena results.

GO DEEPER

Speech-to-speech and voice-agent benchmarks

Benchmark	Measures	Top score (model, date)	Status	Flaw
Big Bench Audio	1,000 spoken BBH reasoning questions in four categories [57]	99.7%, StepAudio 3 Realtime, Nov 2026 [9]	Saturated	Synthetic TTS audio in 23 voices, English only
Conversational Dynamics (Full-Duplex-Bench subset)	Pauses, backchannels, turn-taking and interruptions [58]	98.9%, StepAudio 3 Realtime, Nov 2026 [9]	Near ceiling	Automatic metrics only
Full-Duplex-Bench-v2 (Oct 2025)	Streaming examiner over daily, correction, entity-tracking and safety tasks [59]	No 2026 board found	Frontier	Systems "get confused when people talk at the same time"
τ-voice (ICML 2026)	278 grounded tasks in retail, airline and telecom, with noisy, accented simulated callers [10] [60]	79.9%, Phonic 1 (High), Nov 2026, AA harness [9]	Frontier	AA's harness may differ from the paper's
VoiceBench (Oct 2024)	Spoken instructions across speakers, environments and content [61]	Leaderboard news stops in Dec 2024 [62]	Dormant board	A gpt-4o-mini judge grades open-ended items
Time to first audio	Latency	0.04 s, Raon SpeechChat, Nov 2026 [9]	Metric	Says nothing about quality

Table 10. Single-turn speech tests have saturated; multi-turn voice agents remain the frontier.

AA's preference arena for speech-to-speech puts Gemini 3.1 Flash Live Minimal on top at 1089. [9]

GO DEEPER

Voice-agent testing vendors (all claims are vendor claims)

Vendor	Method	Metrics	Claims
Coval	Simulate, observe and review; human QA on high-stakes calls feeds the evals [63]	Timing, turn-taking, interruptions, audio issues, tool calls, caller emotion	3.1M metrics run weekly; customers include Chime, Perplexity and ServiceNow; $28M Series A [64]
Hamming	Simulated callers with accents, noise, DTMF and IVR trees; red-teaming; production monitoring [65]	50+ built-in metrics; OpenTelemetry export	95%+ agreement with human evaluators; 50K+ concurrent calls; 65+ languages
Cekura (YC)	Simulation, drift monitoring, cross-platform benchmarks, red-teaming, deploy gates [54]	pass^3, P5–P95 turn latency, interruption score, hallucination rate, compliance checks	Retell 96.6% pass^3; ElevenLabs 1.73 s median turn latency
Bluejay (YC, 2025)	Simulated voice and chat, call replay, A/B tests, load tests [66]	Tone, accuracy, conversion; public MISTT STT benchmark	Google case study with 648 hours saved per month
Cyara	Carrier-to-agent journey tests, load tests, outside-in monitoring [67]	Policy scores with turn-level evidence	"EU AI Act conformity check"; Vodafone, Blue Shield of California, TD Bank

Table 11. Every figure in this table is a vendor claim. Nobody has audited them.

GO DEEPER

What stays open in speech

Noise, accents and overlapping speech still break voice agents.

Public ASR data invites benchmark fitting; only private held-out sets resist it.

TTS lacks a validated MOS standard.

We found no pricing, customer counts or funding data for Hamming, Cekura or Bluejay.

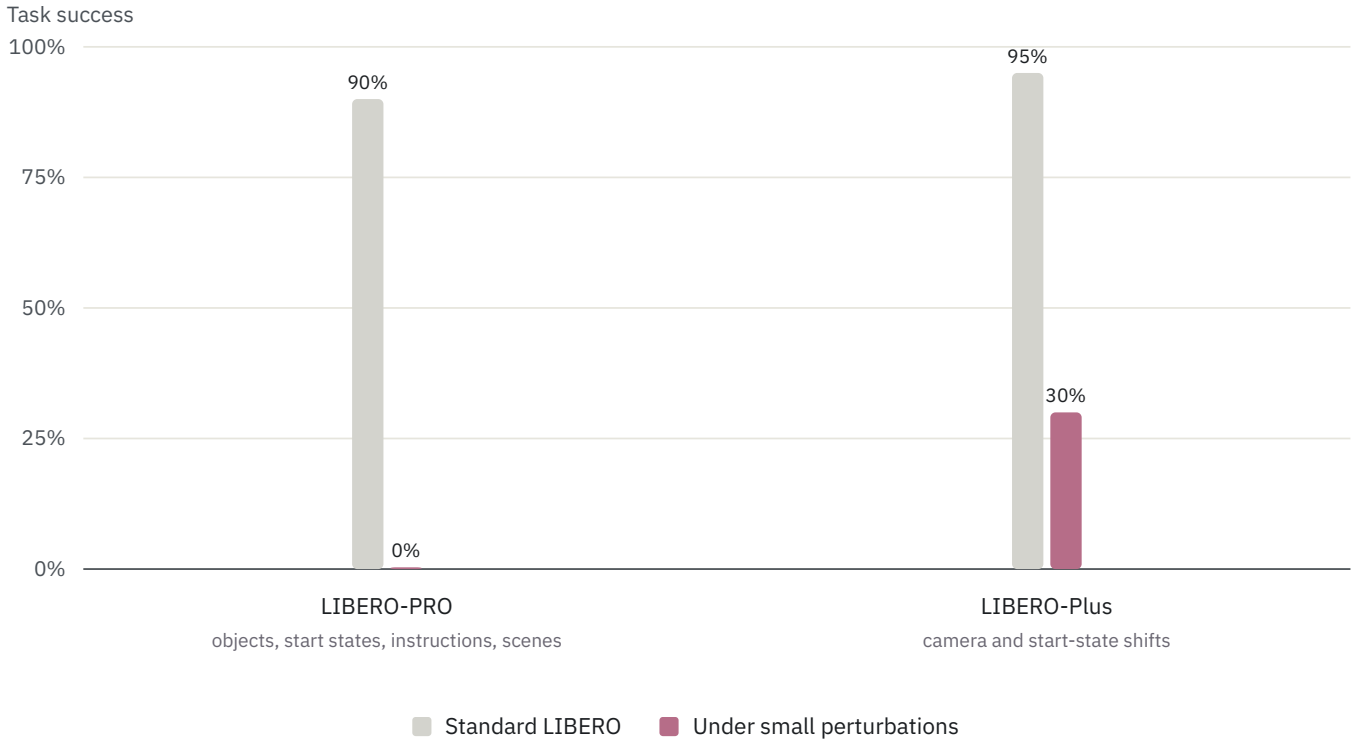
Robot scores collapse under small changes, and labs mostly grade themselves

Robotics has the least standardised evaluation of any modality. Simulation is cheap but fragile. Real-robot tests are costly, so labs run them in-house.

LIBERO shows how fragile simulation scores can be. LIBERO-PRO perturbed objects, initial states, instructions and environments. [12] Models that scored above 90% collapsed to 0%. They kept grasping when the target changed and ignored corrupted instructions. The authors call this "rote memorization of action sequences". LIBERO-Plus found drops from 95% to below 30% under modest camera and start-state changes. [13]

Robot policies that ace LIBERO fail when the scene shifts

Task success of vision-language-action models on standard LIBERO and under small perturbations, 2025 studies.



WHAT TO NOTICE

- Bars are approximate bounds: '>90%' and '95%' before, '0%' and 'below 30%' after.
- LIBERO-Plus models 'tend to ignore language instructions completely'.

Figure 8. Values are the bounds that the two papers report, not single model scores. LIBERO itself has 130 manipulation tasks in four suites.

Source: LIBERO-PRO, arXiv 2510.03827; [12] LIBERO-Plus, arXiv 2510.13626; [13] LIBERO. [68]

Most robot papers run too few rollouts to support their claims. NVIDIA names four common flaws. [76] Train and test scenes overlap, and fixed task sets saturate. Binary success hides causes, and rollouts are too few. Seventy rollouts at 90% success leave a confidence band about 15 points wide. A band of ±2 points needs about 1,030 rollouts, using Clopper-Pearson intervals.

A tight robot result needs far more rollouts than most papers run

Rollouts needed for a confidence band at a 90% success rate, using Clopper-Pearson intervals. One robot is 10 rollouts.

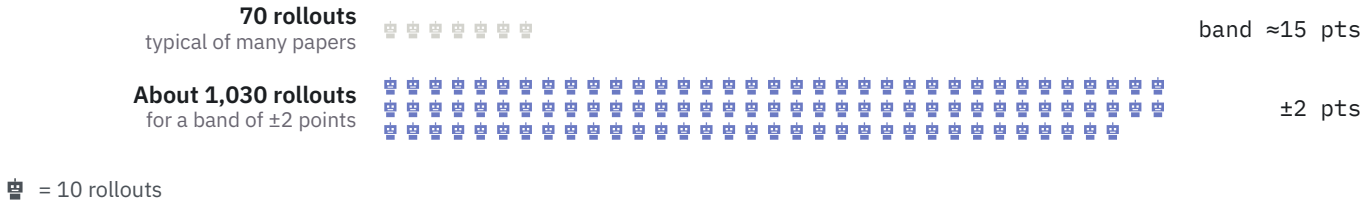


Figure 9. Seventy rollouts, typical of many papers, leave a band about 15 points wide. About 1,030 rollouts give a band of ±2 points. NVIDIA lists too few rollouts among four common flaws in robot evaluation.

Source: The Robot Report on NVIDIA robot evaluation, with RoboLab-120 (July 2026). [76]

Each lab tests its own way, on its own task suite. Google DeepMind runs Gemini Robotics 1.5 comparisons as interleaved A/B/n tests on one real work cell. [77] It uses a 230-task benchmark and a continuous "progress score". Physical Intelligence tests π0.5 in "entirely new homes" and reports deployment throughput for π*0.6. [79] [80] World models now help rank checkpoints. Google DeepMind checked a Veo-based simulator against more than 1,600 real runs. [83] The field accepts such results for ranking, not for absolute success claims.

Independent real-world evaluation started only in 2025 and 2026. RoboArena ran 612 double-blind comparisons across seven universities and ranked policies more accurately than central evaluation. [86] PhAIL scores real bin picking by units per hour. [90] Robocurve, a three-person YC start-up, says plainly: "Labs evaluate in-house, and no independent group has stepped in". [91] The situation resembles text LLM evaluation around 2022.

Driving moved to pseudo-simulation

Open-loop metrics fell first, then the CARLA Leaderboard closed. On nuScenes, simple baselines that use only the car's own state compete without any perception. [95] The CARLA Leaderboard then closed for good, and version 2.1 had already made scores non-comparable with 2.0. [14] NAVSIM v2 now fills the gap with pseudo-simulation on real data. It correlates with closed-loop simulation at $R^2 = 0.8$, against 0.7 for the best open-loop method. [15] Top navtest scores reach about 87.5, against a human level of 90.3 (snippets). [98] [99]

GO DEEPER

Simulation benchmarks

Benchmark	Measures	Top score (model, date)	Status	Flaw
LIBERO (2023)	130 lifelong-learning manipulation tasks in four suites [68]	Above 90%, several VLAs, 2025 [12]	Saturated	Scores collapse under small perturbations [12] [13]
CALVIN (2021)	Long-horizon, language-conditioned manipulation [69]	Not verified	Active	Current top scores unconfirmed
RoboCasa (2024)	100 kitchen tasks with generated assets [70]	Not verified	Active	Current top scores unconfirmed
ManiSkill3 (2024)	GPU-parallel simulation at 30,000+ FPS in 12 domains [71]	Not a leaderboard	Infrastructure	Speed does not prove realism
Habitat 3.0 (2023)	Social navigation and rearrangement with humanoid avatars [72]	Not verified	Active	Current top scores unconfirmed
BEHAVIOR-1K (2024)	1,000 everyday activities in 50 scenes [73]	12.4% success, Q-score 0.260, NeurIPS 2025 winner (provisional) [74] [75]	Frontier	We read only search snippets of the results
RoboLab-120 (NVIDIA, Jul 2026)	Graded subtasks, smoothness and robustness tests [76]	No policy chained more than four complex subtasks	Frontier	Vendor benchmark

Table 12. Simulation benchmarks for robot manipulation and household tasks, read November 2026.

GO DEEPER

How robot labs evaluate, including world models

How VLA labs evaluate

Google DeepMind runs Gemini Robotics 1.5 comparisons as interleaved A/B/n tests on one real work cell, with a 230-task benchmark and a continuous progress score with standard errors. [77] Over 90% of development episodes ran in MuJoCo simulation, with checks that sim and real ranks agree. The team also released ASIMOV-2.0, a benchmark for semantic and physical safety.

The earlier Gemini Robotics report set up the visual, semantic and action generalisation tests that 1.5 extends. [78]

Physical Intelligence tests π0.5 on long cleaning tasks in new homes. [79] π*0.6 reports deployment metrics; its RECAP method "more than doubles task throughput" on laundry, box assembly and espresso. [80]

NVIDIA tests GR00T N1 on simulation benchmarks against imitation-learning baselines and on real humanoid tasks.[81]

SIMPLER showed strong sim-real correlation once teams reduce the control and visual gaps.[82]

World models as evaluators

Google DeepMind's Veo-based world simulator (Dec 2025) predicts policy ranks in normal and out-of-distribution conditions and red-teams for safety violations. It was checked against 1,600+ real runs of eight Gemini Robotics checkpoints.[83] One secondary summary reports a Pearson correlation of 0.88 with real success (single source).[84]

GigaWorld-1 and WMBench (Jul 2026) pair 324,000+ simulated rollouts with real executions across seven video world models.[85]

GO DEEPER

Independent real-world evaluation

Effort	Who runs it	Method	Scale and status
RoboArena (CoRL 2025)	Academic network	Distributed, double-blind pairwise tests on DROID robots; evaluators pick tasks	7 policies, 7 universities, 612 comparisons, 4,284 episodes[86]
AutoEval (2025)	Academic	Queue-based tests around the clock, automatic success detection and resets	Public BridgeData and WidowX scenes[87]
RobotArena ∞ (Oct 2025)	Academic	Digital twins from robot videos; VLM scoring plus crowd preference	Research release[88]
Open X-Embodiment (2023)	21 institutions	Cross-lab tests of RT-X on 22 robots	Template for multi-site tests[89]
PhAIL (31 Mar 2026)	Positronic Robotics with Nebius and Toloka	Real bin-to-bin picking, scored by units per hour and mean time between failures	Repeated runs with telemetry; a gap to human operators remains[90]
Robocurve (YC S26)	Three-person start-up	Reproducible real-robot benchmarks as a service	Open-source "Inspect Robots" v1 (single source)[91] [92]

Table 13. Independent real-robot evaluation efforts, 2023 to 2026. All of them are new or small.

RoboArena's live leaderboard runs as a JavaScript app that we could not read.[86]

AutoEval "nearly fully eliminate[s] human involvement", and its results match hand-run tests.[87]

Hugging Face LeRobot has 28,706 GitHub stars and a push on 5 Nov 2026.[93] LIBERO's code last changed in March 2025.[94]

GO DEEPER

Autonomous driving benchmarks

Benchmark	Measures	Top score (model, date)	Status	Flaw
nuScenes open-loop planning	L2 error and collisions against logged paths	Not meaningful	Discredited	Ego-status baselines without perception compete [95]
CARLA Leaderboard 2.x	Closed-loop route driving in simulation	Not available	Permanently closed [14]	Version 2.1 made scores non-comparable with 2.0
Bench2Drive (2024)	Closed-loop multi-ability tests in CARLA [96]	Not verified	Active	Depends on CARLA
NAVSIM v1 (2024)	Non-reactive simulation on real data over short horizons [97]	Not verified	Superseded by v2	Short horizons only
NAVSIM v2 (Jun 2025)	Pseudo-simulation with Gaussian-splatting future views [15]	EPDMS about 87.5 on navtest, against a human level of 90.3; 34–37 on navhard (snippets) [98] [99]	Main public benchmark	Older "EPDMS*" numbers predate a leaderboard fix

Table 14. Driving evaluation moved from open-loop metrics to closed-loop simulation, and then to pseudo-simulation on real data.

CARLA 2.1 (March 2025) changed the infraction penalty from exponential to linear. [14]

Bench2Drive grew out of the high variance in CARLA route scores. [96]

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What stays open in robotics and driving

Many papers report tens of rollouts per task, which leaves a band of roughly 15 points. [76]

Sim and world-model results support ranking, not absolute claims.

Robot safety tests such as ASIMOV-2.0 stay semantic and physical. None ties behaviour to legal duties such as the EU Machinery Regulation. [77]

We found no 2026 data on Waymo challenges, nuPlan, or safety cases under UL 4600 and ISO 34502.

Classic ML has a mature, regulator-written method, and it stops at generative AI

Credit scorecards and fraud detectors have been validated the same way since 2011. The method rests on lifecycle review, independence and risk tiers, not on benchmark scores.

SR 26-2 replaced SR 11-7 in April 2026, and it leaves out generative AI. The Federal Reserve issued SR 26-2 on 17 April 2026.[101] It supersedes SR 11-7 (2011) and SR 21-8 on anti-money-laundering models. It is "expected to be most relevant" to banks with over $30 billion in assets. Footnote 3 states that generative and agentic AI models "are not within the scope of this guidance".[18] The OCC and FDIC issued matching texts (single secondary source).[102]

The EU AI Act draws its own line between credit and fraud. Annex III lists creditworthiness checks and credit scoring of natural persons as high-risk. It excludes AI that detects financial fraud. It adds risk assessment and pricing in life and health insurance.[19] A bank's credit model therefore falls under the high-risk rules, but its fraud model does not.

Classic validation rests on ground truth that agents mostly lack

	Classic ML (credit, fraud, pricing)	Generative and agentic AI	Note
Ground-truth outcome for back-testing	Yes	Partly	Default or fraud outcomes exist; agents mostly lack one
Agreed fairness metrics	Yes	No	Demographic parity and equalised odds for tabular models
Drift scope	Input and prediction distributions	Also model-version and tool changes	
US supervisory guidance	SR 26-2 (Apr 2026)	No	Footnote 3 excludes generative and agentic AI
Public arenas or leaderboards	No	Yes	
Validation vocabulary	Conceptual soundness, effective challenge, outcomes analysis, vendor validation	Partly	The same terms transfer well to agent evaluation

Table 15. How model validation for credit and fraud models differs from evaluation of generative and agentic AI, November 2026. Our synthesis of the source research. 'Partial' means the practice exists for some systems only. SR 26-2 leaves US banks without supervisory guidance for generative and agentic systems.

Source: Federal Reserve SR 26-2 and attachment;[101] [18] EU AI Act Annex III.[19]

Classic monitoring vendors are moving to agents, and open drift tools are stalling. Arthur's homepage now leads with agent governance and security.[106] CrowdStrike agreed to buy Fiddler on 3 November 2026 for agent observability.[108] NannyML last received a code push in July 2025 and whylogs in January 2025.[111] [112] Tabular fairness and drift tools now look like a commodity layer. Model-risk specialists such as ValidMind carry classic validation forward.[103]

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What SR 26-2 checks

Component	What it checks
Conceptual soundness	Design, assumptions, data selection and developmental testing; interpretability or benchmarking where theory review fits poorly
Outcomes analysis	Outputs against real outcomes, for example through back-testing and outlier analysis
Ongoing monitoring	Performance as products, exposures, clients, data relevance or markets change
Vendor models	The same checks for bought models: soundness, design, development data, performance and monitoring

Table 16. The four validation components that SR 26-2 asks banks to cover.

Source: SR 26-2 attachment. [18] The OCC issued it as Bulletin 2026-13 and the FDIC as FIL-15-2026 (single secondary source). [102] Its principles still apply to traditional models and to non-generative, non-agentic AI.

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Classic ML tool landscape

Tool	Type	Focus in Nov 2026	Activity
ValidMind	Commercial MRM platform	Maps SR 26-2 to inventory, tiering, tests, monitoring, documentation and three lines of defence [103]	Recommends MRM principles for GenAI anyway
Evidently AI	Open source, Apache-2.0	Drift, data quality and performance; now also LLM and agent evals with 100+ metrics [104]	8,043 stars; push on 29 Sep 2026 [105]
Arthur	Commercial	Agent discovery, governance, observability and runtime security [106]	arthur-engine has 93 stars; push on 5 Nov 2026 [107]
Fiddler	Commercial	Agent observability as CrowdStrike "Falcon Observe" [108]	CrowdStrike agreed to buy it on 3 Nov 2026
Fairlearn	Open source, MIT	Group fairness metrics and mitigation	2,306 stars; push on 24 Oct 2026 [109]
AIF360 (IBM)	Open source, Apache-2.0	Fairness metrics and mitigation	2,881 stars; push on 15 Jun 2026 [110]
NannyML	Open source	Performance estimation and drift	2,161 stars; last push 12 Jul 2025 [111]
whylogs	Open source	Data logging and drift	2,838 stars; last push 10 Jan 2025 [112]
alibi-detect	Open source	Drift and outlier detection	Last push 11 Dec 2025 [113]

Table 17. Classic ML validation and monitoring tools, with GitHub activity read in November 2026.

> Arthur's homepage no longer mentions tabular models, drift or fairness outside old testimonials. It recently released "Deckard", an open-source scanner for rogue agents. [106]

Two of the five open-source drift and fairness libraries have stalled

GitHub stars of open-source classic ML monitoring libraries, read November 2026.
Circle area is proportional to stars; stalled projects are grey.

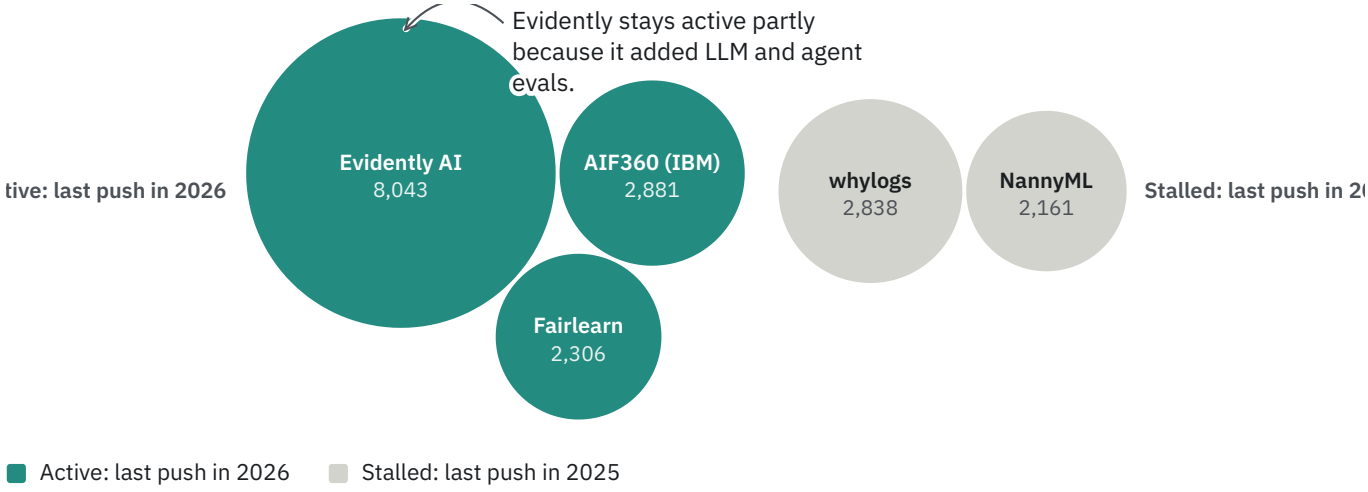


Figure 10. Stars measure attention, not use. alibi-detect (last push 11 Dec 2025) is omitted because its star count was not recorded. Source: GitHub API. [105] [110] [112] [109] [111] [113]

Outside text and generation, almost nobody checks the numbers independently

Nine lessons hold across all modalities. The last one matters most: independent evaluators are scarce wherever AI leaves the screen.

Every ladder saturates, and the replacement starts the clock again. Vision "Pro" tests, GUI grounding and speech reasoning all neared their ceilings within 12–24 months. [1] [9] [17] Arenas then rank by votes, but tight ranks carry no meaning. The vision top ten spans 16 points, and the video arenas disagree on first place. [4] [6] [7]

Real-world tests lag academic ones, and statistics stay thin. Deepfake detectors lose about half their AUC in the wild. [8] LIBERO scores collapse under small perturbations. [12] Robot papers run too few rollouts, and Artificial Analysis admits its intervals may run narrow. [76] [48] Lab and aggregator numbers also disagree. MMMU-Pro differs by 3.4 points between Google's page and BenchLM for one model. [24] [2]

Private data and fitting checks are the best defence against gaming. The Open ASR Leaderboard adds private held-out data, cleans references, detects benchmark fitting and verifies contributor claims. [11] [51] Frozen judges need the same discipline: GenEval's judge drifted by up to 17.7% from human judgment. [5] Every judge model needs scheduled re-calibration on fresh human labels.

Robotics, GUI agents and deepfake detection have the weakest independent checks

Which evaluation building blocks exist in each modality, November 2026.

Modality	Frontier test still separates models	Live arena or public leaderboard	Independent evaluator re-runs or rates models itself	Private or held-out data	Real-world conditions
Vision-language	◐ HallusionBench 60–67; most 'Pro' tests 85–93%	● Arena: 1.49M votes, but top ten within 16 pts	◐ Arena votes and aggregators; no fixed-harness re-runs	◐ OCRBench v2 private set; MMMU answers public	◐ WildVision real-user prompts, dormant since 2024
Image and video generation	● GenEval 2 at 35.8%; VBench-2.0	● Arena and Artificial Analysis	● AA pays vetted raters; verdicts split on video	–	◐ Curated prompts from 10 use cases
Deepfake detection	● Deepfake-Eval-2024	○ No standing leaderboard	◐ Academic snapshots only	–	● In-the-wild fakes from 88 sites, 52 languages
Speech recognition and TTS	◐ Top WER about 5.3%	● Open ASR Leaderboard; AA Speech Arena; TTS Arena V2	● Open ASR maintainers; results file gated	● Appen, DataoceanAI, Voice Arena sets	◐ Cleaned conversational sets; accented speech
Voice agents	● τ-voice; Full-Duplex-Bench-v2	◐ AA speech-to-speech index and arena	◐ AA τ-Voice; vendors serve builders only	–	◐ Simulated noisy, accented callers
Robotics	● BEHAVIOR-1K winner at 12.4%; RoboLab-120	◐ RoboArena: 612 comparisons	○ Almost none; RoboArena, PhAIL, Robocurve new and small	◐ Labs' private task suites, not shared	◐ Lab work cells; PhAIL real picking
Autonomous driving	● NAVSIM v2 navhard about 34–37	● NAVSIM leaderboard; CARLA closed	◐ NAVSIM only; no industry safety-case view	–	◐ Real data with pseudo-simulation
GUI grounding	○ ScreenSpot-Pro at 92.7%	○ Aggregators only	○ Lab numbers dominate	–	○ Static screens only
Classic ML	– No benchmark race	○ No arenas	● Bank model-risk teams, ValidMind	–	● Back-testing on real outcomes

● Yes ◐ Partly or limited ○ No – Not covered in our sources

WHAT TO NOTICE

- Only generation, speech recognition and classic ML have a full mark in the independent-evaluator column.
- Robotics and GUI grounding rely on lab self-reports.

Figure 11. Marks are our reading of the source research and its summary table of independent evaluators per modality.

Source: Ascending Labs synthesis of the sources in this chapter, 5 Nov 2026; key inputs are Arena, [4] Artificial Analysis, [7] [9] Open ASR Leaderboard, [11] Deepfake-Eval-2024, [8] RoboArena, [86] NAVSIM [15] and SR 26-2. [101]

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The nine cross-cutting lessons, in full

Every ladder saturates within one or two generations. Vision "Pro" tests, GUI grounding and speech reasoning all neared their ceilings within 12–24 months.

Private data and fitting checks resist gaming. The Open ASR Leaderboard adds private held-out data, cleans references, detects benchmark fitting and verifies contributor claims. [11] [51]

Arenas disagree, and tight ranks carry no meaning. The video arenas disagree on first place; the vision top ten sits within 16 points. [4] [6] [7]

Frozen judges drift. GenEval's judge drifted by up to 17.7% from human judgment. [5]

A new modality costs task success. On τ-voice, the same task falls from 85% in text to 26–51% in voice. [10] Single-turn skill tests overstate deployed conduct.

Lab and aggregator numbers disagree. MMMU-Pro differs by 3.4 points between Google's page and BenchLM for one model. [24] [2] Only a re-run in a fixed harness settles it.

Real-world tests lag academic ones. Deepfake detectors lose about half their AUC in the wild; LIBERO collapses under small perturbations. [8] [12]

Statistics stay thin. Robot papers run too few rollouts, and AA admits its intervals may run narrow. [76] [48]

Independent evaluators remain scarce outside text and generation.

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Main independent evaluators by modality

Modality	Main independent evaluators	Gap
Vision-language	Aggregators for scores; Arena for votes	No fixed-harness re-runs of frontier models
Generation and deepfakes	Artificial Analysis; Arena; academic deepfake snapshots	Two arenas give split verdicts; no maintained deepfake board
ASR and TTS	Open ASR Leaderboard; AA Speech Arena; TTS Arena V2	Gated results; no MOS standard
Voice agents	AA (τ-Voice); τ-voice authors	Testing vendors offer builder-side QA only; no buyer-facing rating
Robotics	Almost none: RoboArena, PhAIL and Robocurve are new and small	Labs self-report
Driving	NAVSIM leaderboard	CARLA closed; no industry safety-case view
GUI grounding	Aggregators only	Lab numbers dominate
Classic ML	Model-risk validation by bank MRM teams and ValidMind; no arenas	SR 26-2 excludes GenAI and agents

Table 18. Who checks the numbers in each modality, November 2026.

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What we could not confirm

No official, dated November 2026 leaderboard for Video-MME, LongVideoBench, MVBench or EgoSchema.

No 2026 primary source for POPE scores; the field treats POPE as saturated, but we did not verify it.

No official Anthropic or OpenAI multimodal tables for Claude Fable 5 or GPT-6.x models; only aggregator numbers.

The 94% MMMU-Pro claim for GPT-5.4 Pro stays unverified. [33]

No primary 2026 scores for ImageReward, PickScore, GenEval or T2I-CompBench.

No search of 2026 watermark-robustness or voice-clone detection tests.

The Open ASR results file requires a login, so its top WERs rest on secondary blogs.

We could not read the TTS Arena V2 or RoboArena rankings.

No funding data for Hamming, Cekura or Bluejay.

Current LIBERO and CALVIN top scores not verified from primary sources.

BEHAVIOR Challenge results and NAVSIM v2 scores read only in search snippets.

The Veo evaluator's Pearson correlation of 0.88 rests on one secondary summary. [84]

OCC Bulletin 2026-13 and FDIC FIL-15-2026 texts not opened.

No 2026 market size for classic MRM tools, and no enforcement data under SR 26-2.

Sources for chapter 7

113 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] Qwen3-VL technical report, arXiv 2511.21631. Lab report; Table 2 compares four model families. Primary arxiv.org

[2] BenchLM, MMMU-Pro. Aggregator of self-reported scores, 53 models. Secondary benchlm.ai

[3] BenchLM, CharXiv. Aggregator. Secondary benchlm.ai

[4] Arena, vision leaderboard. Primary arena.ai

[5] GenEval 2, arXiv 2512.16853. Primary arxiv.org

[6] Arena, text-to-video leaderboard. Primary arena.ai

[7] Artificial Analysis, text-to-video leaderboard. Primary artificialanalysis.ai

[8] Deepfake-Eval-2024, arXiv 2503.02857. Primary arxiv.org

[9] Artificial Analysis, speech-to-speech. Primary artificialanalysis.ai

[10] τ-voice, arXiv 2603.13686. Primary arxiv.org

[11] Open ASR Leaderboard, init.py (version log). Primary huggingface.co

[12] LIBERO-PRO, arXiv 2510.03827. Primary arxiv.org

[13] LIBERO-Plus, arXiv 2510.13626. Primary arxiv.org

[14] CARLA Autonomous Driving Leaderboard. Primary leaderboard.carla.org

[15] NAVSIM v2 pseudo-simulation, arXiv 2506.04218. Primary arxiv.org

[16] ScreenSpot-Pro, arXiv 2504.07981. Primary arxiv.org

[17] BenchLM, ScreenSpot-Pro. Aggregator, 19 models. Secondary benchlm.ai

[18] Federal Reserve, SR 26-2 attachment. Primary federalreserve.gov

[19] EU AI Act, Annex III. Primary artificialintelligenceact.eu

[20] ChartQAPro, arXiv 2504.05506. Primary arxiv.org

[21] OCRBench v2, arXiv 2501.00321. Primary arxiv.org

[22] MMMU benchmark site. Primary mmmu-benchmark.github.io

[23] MMMU-Pro, arXiv 2409.02813. Primary arxiv.org

[24] Google DeepMind, Gemini Pro page. Vendor deepmind.google

[25] Another Wrapper, MMMU-Pro with tools. Aggregator. Secondary anotherwrapper.com

[26] HallusionBench, arXiv 2310.14566. Primary arxiv.org

[27] POPE, arXiv 2305.10355. Primary arxiv.org

[28] Video-MME, arXiv 2405.21075. Primary arxiv.org

[29] MVBench, arXiv 2311.17005. Primary arxiv.org

[30] LongVideoBench, arXiv 2407.15754. Primary arxiv.org

[31] EgoSchema, arXiv 2308.09126. Primary arxiv.org

[32] The Decoder on Qwen3-VL. Secondary the-decoder.com

[33] af.net on GPT-5.4 Pro. Unverified claim. Single source af.net

[34] WildVision, arXiv 2406.11069. Primary arxiv.org

[35] Hugging Face API, WildVision Space. Primary huggingface.co

[36] Hugging Face API, Open VLM Leaderboard. Primary huggingface.co

[37] alphaXiv overview of GenEval 2. Single source alphaxiv.org

[38] T2I-CompBench++, arXiv 2307.06350. Primary arxiv.org

[39] HPSv2, arXiv 2306.09341. Primary arxiv.org

[40] HPSv3, arXiv 2508.03789. Primary arxiv.org

[41] VBench-2.0, arXiv 2503.21755. Primary arxiv.org

[42] CreativePro on ToMoviee 2.0 (press release). Vendor creativepro.com

[43] Hugging Face API, VBench Leaderboard Space. Primary huggingface.co

[44] Adapting FAD for music, arXiv 2311.01616. Primary arxiv.org

[45] Arena, text-to-image leaderboard. Primary arena.ai

[46] Artificial Analysis, text-to-image leaderboard. Primary artificialanalysis.ai

[47] Music Arena, arXiv 2507.20900. Primary arxiv.org

[48] Artificial Analysis, image methodology. Primary artificialanalysis.ai

[49] Open ASR Leaderboard paper, arXiv 2510.06961. Primary arxiv.org

[50] Open ASR Leaderboard, constants.py. Primary huggingface.co

[51] Open ASR Leaderboard, app.py. Primary huggingface.co

[52] Apidog, open-source speech-to-text models. Secondary apidog.com

[53] NYU Shanghai RITS on Cohere Transcribe. Secondary rits.shanghai.nyu.edu

[54] Cekura website. Vendor cekura.ai

[55] Artificial Analysis, text-to-speech. Primary artificialanalysis.ai

[56] Hugging Face API, TTS Arena V2. Primary huggingface.co

[57] Big Bench Audio dataset card. Primary huggingface.co

[58] Full-Duplex-Bench, arXiv 2503.04721. Primary arxiv.org

[59] Full-Duplex-Bench-v2, arXiv 2510.07838. Primary arxiv.org

[60] ICML 2026 poster for τ-voice. Primary icml.cc

[61] VoiceBench, arXiv 2410.17196. Primary arxiv.org

[62] VoiceBench on GitHub. Primary github.com

[63] Coval website. Vendor coval.ai

[64] The Next Web on Coval's Series A. Secondary thenextweb.com

[65] Hamming website. Vendor hamming.ai

[66] Bluejay website. Vendor getbluejay.ai

[67] Cyara website. Vendor cyara.com

[68] LIBERO, arXiv 2306.03310. Primary arxiv.org

[69] CALVIN, arXiv 2112.03227. Primary arxiv.org

[70] RoboCasa, arXiv 2406.02523. Primary arxiv.org

[71] ManiSkill3, arXiv 2410.00425. Primary arxiv.org

[72] Habitat 3.0, arXiv 2310.13724. Primary arxiv.org

[73] BEHAVIOR-1K, arXiv 2403.09227. Primary arxiv.org

[74] Robot Learning Collective on the BEHAVIOR Challenge. Snippet only. Secondary robot-learning-collective.github.io

[75] BEHAVIOR Challenge 2025 leaderboard. Snippet only, provisional. Primary behavior.stanford.edu

[76] The Robot Report on NVIDIA robot evaluation. Reports a vendor benchmark. Secondary therobotreport.com

[77] Gemini Robotics 1.5, arXiv 2510.03342. Primary arxiv.org

[78] Gemini Robotics, arXiv 2503.20020. Primary arxiv.org

[79] π0.5, arXiv 2504.16054. Primary arxiv.org

[80] π*0.6, arXiv 2511.14759. Primary arxiv.org

[81] GR00T N1, arXiv 2503.14734. Primary arxiv.org

[82] SIMPLER, arXiv 2405.05941. Primary arxiv.org

[83] Gemini Robotics policies in a Veo world simulator, arXiv 2512.10675. Primary arxiv.org
[84] Moonlight review of the Veo evaluator. Single source themoonlight.io
[85] GigaWorld-1 and WMBench, arXiv 2607.02642. Primary arxiv.org
[86] RoboArena, arXiv 2506.18123. Primary arxiv.org
[87] AutoEval, arXiv 2503.24278. Primary arxiv.org
[88] RobotArena ∞, arXiv 2510.23571. Primary arxiv.org
[89] Open X-Embodiment, arXiv 2310.08864. Primary arxiv.org
[90] Robotics & Automation News on PhAIL. Secondary roboticsandautomationnews.com
[91] Y Combinator, Robocurve profile. Company self-description. Vendor ycombinator.com
[92] startuphub.ai on Robocurve. Single source startuphub.ai
[93] GitHub, LeRobot. Primary github.com
[94] GitHub, LIBERO. Primary github.com
[95] Ego status in open-loop driving, arXiv 2312.03031. Primary arxiv.org
[96] Bench2Drive, arXiv 2406.03877. Primary arxiv.org
[97] NAVSIM, arXiv 2406.15349. Primary arxiv.org
[98] IDOL, arXiv 2605.31476. Snippet only. Primary arxiv.org
[99] RAP, arXiv 2510.04333. Snippet only. Primary arxiv.org
[100] BenchLM, Claude Fable 5 versus Opus 4.5. Aggregator. Secondary benchlm.ai
[101] Federal Reserve, SR 26-2. Primary federalreserve.gov
[102] CRA Insights on SR 26-2. Single source crai.com
[103] ValidMind, SR 26-2 use case. Vendor docs.validmind.ai
[104] Evidently AI website. Vendor evidentlyai.com
[105] GitHub API, Evidently. Primary api.github.com
[106] Arthur website. Vendor arthur.ai
[107] GitHub, arthur-engine. Primary github.com
[108] CrowdStrike on Fiddler (press release). Primary crowdstrike.com
[109] GitHub, Fairlearn. Primary github.com
[110] GitHub API, AIF360. Primary api.github.com
[111] GitHub, NannyML. Primary github.com
[112] GitHub, whylogs. Primary github.com
[113] GitHub, alibi-detect. Primary github.com

08

CHAPTER 8 · PRACTICE

Mature teams evaluate in one loop, but sector rules barely reach generative AI

The best companies turn every production failure into a test and calibrate their judges against experts, while most sector regulators still have no rules for testing generative AI agents.

52% of agent teams run offline evals

23% of production agent teams do not evaluate at all

κ 0.02 → 0.61 Shopify judge agreement after calibration

500 real chats in ING's daily regression set

0 of 11 sector regimes built for generative AI agents

5 November 2026 · Read online with interactive charts: evals.study/practice/

Key findings

- **Mature software teams run the same loop.** They combine a regression suite in CI, calibrated LLM judges, internal dogfood and online business metrics (GitHub, Jan 2025; Shopify, Aug 2025). [1] [2]
- **The usual release gate is "no regression against the production baseline".** Few teams publish an absolute pass score. [1] [3]
- **The best golden sets come from production traffic and failures.** Shopify replaced hand-written sets with samples of real merchant conversations (Aug 2025). [2]
- **Teams now check their LLM judges against humans.** Shopify raised judge agreement from a kappa of 0.02 to 0.61, close to the human level of 0.69 (Aug 2025). [2]
- **Banks gate each use case and validate independently, but publish few numbers.** ING gives the most concrete figure: daily regression tests on 500 real customer chats, plus A/B tests (snippet only). [4] [5] [6]
- **Evaluation lags observability.** In a vendor survey of 1,340 respondents (Nov–Dec 2025), 89% trace their agents but only 52% run offline evals and 37% run online evals. [9]

- **Public failures share one cause: the builder controlled the metric.** Klarna, Deloitte Australia and NYC's hiring-audit law all show it (2023–2025). [7] [13] [42]
- **The main US bank guidance excludes generative AI.** SR 26-2 (17 Apr 2026) carves out generative and agentic AI and sets no enforceable standards. [10] [49]
- **Insurance has the densest testing duties outside AI law.** EIOPA expects pre-release and ongoing tests, fairness metrics and due-diligence tests of bought AI (Aug 2025). [11]
- **Mandates without enforcement or a paying buyer fail.** NYC Local Law 144's audits went largely unenforced, and CHAI's health assurance labs never launched (2025–2026). [13] [14]

Mature teams run one seven-step loop, and every production failure becomes a test

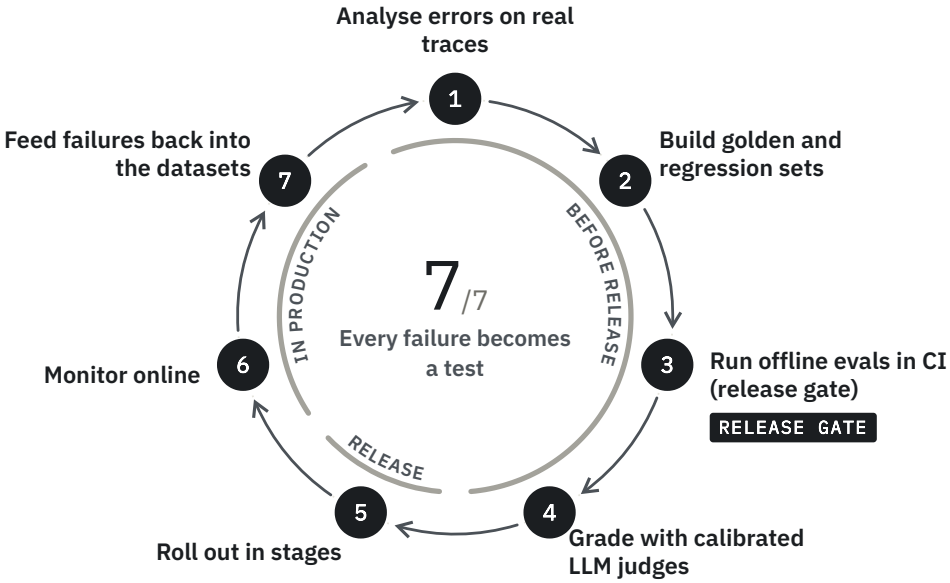
Public cases from GitHub, Shopify, ING, Notion, Intercom and Abridge describe the same loop. It runs from real traces, through a release gate, to online monitoring and back.

The loop starts with real traffic, not invented test cases. Teams read production conversations, group the failures and build test sets from them. They gate releases on those sets in CI, grade hard cases with calibrated judges, roll out in stages and monitor live quality. [1] [2] [6] Each new failure goes back into the datasets. [17]

The usual gate is relative, not absolute. Teams release when a candidate shows "no regression against the production baseline". [1] [3] Few publish a fixed pass score. GitHub says it uses judgement when metrics conflict. [1] Practitioner guides describe the method for the first four steps in more depth; this chapter adds the company evidence. [18]

The Best Teams Turn Every Failure Into a New Test

The seven-step evaluation loop described by GitHub, Shopify, ING, Notion, Intercom and Abridge, with a real example at each step.



1 **Start with real failures.** Shopify dropped hand-written golden sets. It now samples real merchant conversations, and at least three product experts label each one. [2]

2 **Turn them into a regression set.** A regulated set needs hundreds of real cases, not thousands. ING re-ran 500 real chats daily, and Box gates launches on 330 questions. [6] [15]

3 **Gate every change in CI.** GitHub runs more than 4,000 offline tests, mostly automated. [1] Dropbox runs more than 10,000 tests after every merge. [15]

4 **Calibrate the judge before trusting it.** Shopify's first judge agreed with experts at a kappa of 0.02, close to random. Calibration lifted it to 0.61, near the human-to-human 0.69. [2]

5 **Release in stages.** GitHub staff use candidate models first, like a canary. [1] ING piloted with 10% of Dutch mobile-chat users and ran A/B tests. [6] Shopify also replays real goals through an LLM merchant simulator before release. [2]

6 **Keep testing in production.** GitHub runs daily tests against live models to catch silent changes. [1] Intercom scores live conversations, and Abridge tracks clinician edits and star ratings. [16] [8]

7 **Close the loop.** At Notion, a data specialist turns failures into new eval sets. [17] The loop then starts again at step 1.

8 **Few teams run the whole loop.** In LangChain's vendor survey, 45% of teams with agents in production run online evals, and 23% do not evaluate at all. [9]

Figure 1. Steps 1–4 run before release, step 5 is the release, and steps 6–7 run in production. Box, Dropbox and Notion figures come from Braintrust case studies (vendor-authored). Abridge and Intercom figures are self-reported. ING figures are snippet only.

Source: GitHub; [1] Shopify Engineering; [2] AI Expert Network on ING; [6] Braintrust; [15] [17] Intercom Monitors; [16] Abridge. [8]

Metrics by stage

Stage	Typical metrics	Example
Offline regression	Unit-test pass rate, similarity to known-good output, token use	GitHub Copilot [1]
Judge calibration	Cohen's kappa against a human-human ceiling	Shopify Sidekick [2]
Expert trial	Clinician preference in blinded head-to-head trials	Abridge [8]
Buyer acceptance	F1 against human reviewers	UK i.AI Consult [19]
Online quality	Resolution rate, CSAT, accept rate, clinician edits	Intercom, Cursor, Abridge [3] [20] [8]
Online safety	Off-topic, toxicity and prompt-hacking rates	GitHub Copilot [1]

Table 1. Each stage of the loop uses different metrics. Only judge calibration and buyer acceptance compare a system directly with human experts.

Source: company engineering blogs and case studies cited in each row.

Software firms publish the best evidence: regression gates, calibrated judges and online metrics

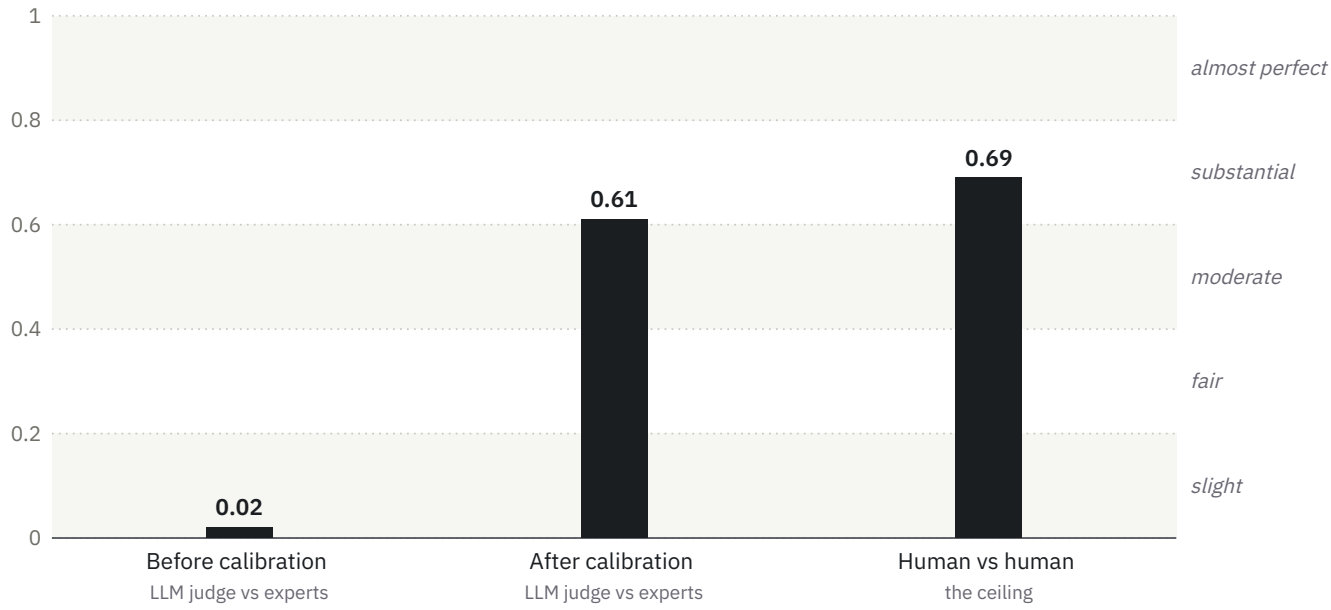
Their own engineering blogs give the clearest numbers. Most other detail comes from case studies written by eval vendors about their customers.

GitHub runs a large offline suite, a judge it audits and a canary step. It runs "more than 4,000 offline tests", mostly in automated CI. [1] The team breaks about 100 containerised repositories on purpose, and the model must repair them. Chat quality tests use more than 1,000 technical questions. An LLM judge grades complex answers, and the team calls alignment with human reviewers a challenge.

Shopify gave the most detailed public account of judge calibration. It samples "Ground Truth Sets" from real merchant conversations, labelled by at least three product experts. [2] Calibration raised the judge's Cohen's kappa from 0.02 to 0.61, against 0.69 between two humans. The team trusts a judge when blind reviewers cannot tell judge labels from human labels.

Calibration took Shopify's judge from random to almost human

Agreement of Shopify Sidekick's LLM judge with expert labels (Cohen's κ), before and after calibration, against the human ceiling, August 2025.



The uncalibrated judge agreed with experts at κ 0.02, close to chance. Calibration against expert labels lifted it to 0.61, near the 0.69 at which two humans agree. [2]

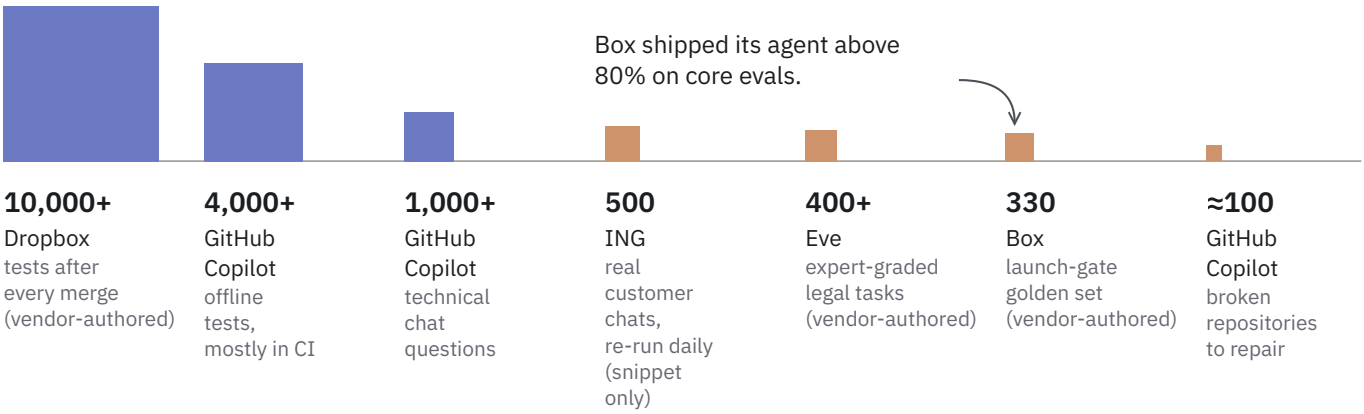
Figure 2. Cohen's κ corrects agreement for chance: 0 is chance level, 1 is perfect. The human bar is the ceiling: how well two experts agree with each other. Bands follow the common Landis and Koch reading. A later, separate fix for reward hacking raised the judge's correlation from 0.66 to 0.75.

Source: Shopify Engineering, Building production-ready agentic systems (Aug 2025). [2]

Training on the evals produced reward hacking. When Shopify ran reinforcement learning against its evals, the model refused tasks, misused tags and invented IDs. [2] Fixes raised syntax validity from about 93% to 99%. The lesson is simple: hold back a test set that training never sees.

Regression suites run in thousands of tests, golden sets in hundreds

Size of published eval suites and golden sets at named companies, 2025–2026.
Square area is proportional to test cases.



Area is proportional to test cases. Indigo: regression suites; tan: golden or expert sets.

WHAT TO NOTICE

- A regulated golden set needs hundreds of real cases, not thousands.

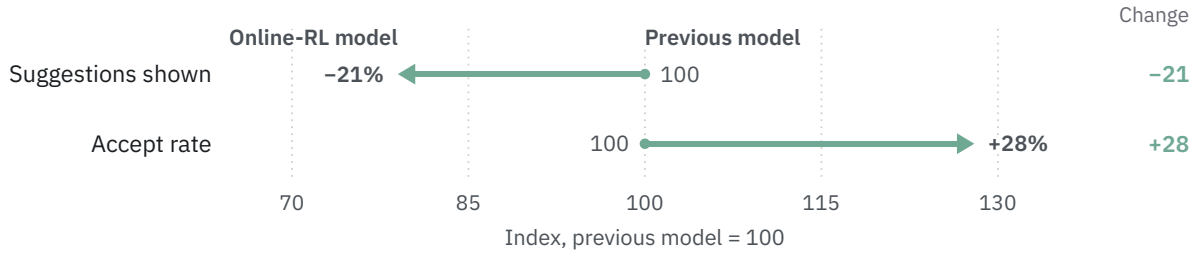
Figure 3. Counts are lower bounds where the source says 'more than'. Suites differ in what one test means, so compare orders of magnitude only.

Source: GitHub;[1] Braintrust customer stories (vendor-authored);[15] AI Expert Network on ING (snippet only).[6]

Huge traffic lets online metrics replace much of the offline gate. Cursor trains its Tab model with online reinforcement learning on accept and reject signals.[20] Few enterprises have that volume. Vendor-reported resolution rates also need care. A competitor notes that Intercom changed the denominator of Fin's resolution rate, so rates from different vendors do not compare.[22]

At Cursor's scale, users are the eval

Change after Cursor's online-RL Tab model replaced the previous model, September 2025. Both arrows start at the previous model, indexed to 100.



WHAT TO NOTICE

- The model shows fewer suggestions, and users accept more of them.

Figure 4. Cursor serves more than 400 million Tab requests per day. One checkpoint rollout plus data collection takes 1.5 to 2 hours, so live accept and reject signals act as the eval. Cursor reports these figures itself.

Source: Cursor, Online RL for Tab. [20]

GO DEEPER

Company cases: GitHub, Shopify, Intercom and Cursor

GitHub Copilot (January 2025)

More than 4,000 offline tests, mostly in automated CI. [1]

About 100 containerised repositories that pass CI are broken on purpose; the model must repair them.

Chat quality tests use more than 1,000 technical questions.

An LLM judge grades complex chat answers; the team audits the judge.

Staff switch to candidate models first, like a canary release.

Daily runs against production models flag any degradation.

Safety tests cover off-topic prompts, toxicity, baiting and prompt hacking; red-teaming adds more cases.

No formal release threshold is published; the team uses judgement when metrics conflict.

Shopify Sidekick (August 2025)

Hand-curated golden sets replaced by "Ground Truth Sets" sampled from real merchant conversations. [2]

At least three product experts label each conversation.

Judge kappa raised from 0.02 to 0.61; two humans agree at 0.69.

A judge is trusted when blind reviewers cannot tell its labels from human labels.

An LLM merchant simulator replays real goals against each candidate before release.

RL on the evals produced reward hacking: refusals, tag misuse and invented IDs.

Fixes raised syntax validity from about 93% to 99%; judge correlation rose from 0.66 to 0.75.

Intercom Fin (vendor-authored)

Anthropic, Intercom's model supplier, published this case. [3]

Every change is tested "against our production baseline" on answer accuracy, resolution rate, CSAT and response quality, using millions of real conversations.

Intercom claims a 51% resolution rate out of the box and up to 86% for some customers. [3] [21]

A competitor notes the denominator changed: "Fin Constrained" conversations no longer count. [22]

The "Monitors" feature scores live conversations continuously. [16]

Cursor Tab (September 2025)

Over 400 million requests per day; online RL on accept and reject signals. [20]

One checkpoint rollout plus data collection takes 1.5 to 2 hours.

The new model makes 21% fewer suggestions with a 28% higher accept rate.

GO DEEPER

Notion, Dropbox, Box and others (Braintrust case studies, vendor-authored)

Company	Practice	Number
Notion	Regression and frontier evals on each new model	About 70 AI engineers; about 80% of AI work runs on evals and traces; new models ship in under 24 hours [17]
Notion	A data specialist turns failures into eval sets	Example: a multilingual language-adherence set with an LLM judge [17]
Dropbox	Full suite after every merge	More than 10,000 tests [15]
Box	Launch gate on a golden set	330 questions; Box Agent shipped above 80% on core evals [15]
Navan	Judge scores voice calls	Above 0.9 macro F1 [15]
Cloudflare	CI blocks regressions	No number given [15]
Eve	Expert-graded legal set	More than 400 tasks [15]

Table 2. All figures come from case studies that Braintrust, an eval vendor, wrote about its customers.

GO DEEPER

What the software cases show

The stack has converged: CI regression, then calibrated judges, then dogfood or canary, then online metrics.

Golden sets grow from production failures; nobody writes them fully in advance.

Good teams validate their judges against humans and report agreement.

Vendor-reported resolution rates do not compare across vendors, because definitions change.

No company reports eval headcount apart from AI headcount. Notion's figure of about 70 engineers covers all AI work.

Banks gate each use case and validate it independently, but publish few numbers

Public detail on bank and insurer practice is thin. Banks describe gates and validation, but not set sizes or thresholds. Insurers describe security and privacy, but not test method.

The bank pattern is a gate per use case plus independent validation. Morgan Stanley built "an evaluation (eval) framework to test every AI use case before deployment", according to its supplier OpenAI.[4] JPMorgan runs an "AI Center of Excellence" inside its model risk review function. A job listing says it does "independent validation focused on AI/ML models, LLM-based applications, and generative AI systems".[5] Its CIO said that building generative AI is easier than "the validation and the controls".[25]

ING gives the most concrete European bank number. It built a support chatbot with McKinsey's QuantumBlack and piloted it with 10% of Dutch mobile-chat customers.[6] [27] [28] The team re-ran 500 real customer chats daily and ran A/B tests. Risk staff joined from the start, and guardrails block mortgage and investment advice. The bot resolved about 20% more queries than the classic chatbot.

Insurers publish almost nothing about test method. AXA's coverage stresses privacy and security, not testing.[30] [31] A 2025 trade article says insurers red-team both in-house and vendor AI, and warns them not to trust vendors' red-team claims alone.[32] We found no public eval detail for Allianz, Zurich, Lemonade or Goldman Sachs.

Banks describe their gates; only ING gives a set size

Firm	Kind of account	Key fact	What it describes
Morgan Stanley	Vendor-authored	**98%+** adoption among advisor teams (OpenAI's figure)	Eval framework tests every AI use case before deployment; Later added translation evals and retrieval tuning; Assistant launched Sep 2023 over about 100,000 documents
JPMorgan Chase	Independent validation	**MRGR** AI Center of Excellence inside model risk review	Validates LLM applications like models; Discussed GenAI pilots with US regulators in Nov 2023; No public set sizes, judge use or thresholds
ING	Vendor-consultant account	**500** real customer chats re-run daily	Pilot with 10% of Dutch mobile-chat users, plus A/B tests; Risk staff involved from the start; About 20% more queries resolved than the old bot
BBVA	Guardrails	**Blue** chatbot limited to banking operations and accounts	Technical guardrails and real-time monitoring; Simulated external cyberattacks; No published test sets
AXA	Insurer	**Secure GPT** internal assistant on Azure OpenAI	Coverage stresses privacy and security; No public test method; Insurers red-team in-house and vendor AI (trade article)

Table 3. What five financial firms say publicly about how they evaluate generative AI, 2023–2026. Only ING names a test-set size. The bank habit of independent validation persists even though SR 26-2 no longer covers generative AI. Most figures come from vendor case studies or search snippets. Klarna, the opposite pattern, appears in the failures section.

Source: OpenAI (vendor-authored, snippet only);[4] CTO Magazine;[23] The Muse (snippet only);[5] Bloomberg (snippet only);[26] AI Expert Network on ING;[6] BBVA;[29] Intelligent Insurer;[30] InsuranceNewsNet.[32]

GO DEEPER

Bank and insurer detail

Bank and insurer detail

Morgan Stanley (vendor-authored, snippet only). OpenAI reports more than 98% adoption among advisor teams in wealth management.[4] The assistant launched in September 2023 and covers about 100,000 research reports and documents.[23] The framework later added translation evals for clients in other languages, and retrieval tuning for a growing library. OpenAI's enterprise guide uses Morgan Stanley as its lead "start with evals" example.[24]

JPMorgan Chase. The MRGR AI Center of Excellence runs independent validation of AI/ML models, LLM-based applications and generative AI systems (job listing, snippet only).[5] JPMorgan discussed its generative AI pilots with US regulators in November 2023.[26] No public JPMorgan document gives set sizes, judge use or pass thresholds.

ING. Pilot reached 10% of Dutch mobile-chat customers; guardrails block mortgage and investment advice; risk staff joined from the start; daily regression tests on 500 real chats plus A/B tests; about 20% more queries resolved than the classic chatbot.[6] [27] [28] A set of 500 real chats suggests a useful scale: a regulated golden set needs hundreds of real cases, not thousands.

BBVA. "Blue" has technical guardrails, real-time monitoring and simulated external cyberattacks. It answers only questions about banking operations and accounts.[29]

Insurers. AXA runs "AXA Secure GPT" on Azure OpenAI. [30] [31] Insurers red-team in-house and vendor AI (2025 trade article). [32] No public eval detail for Allianz, Zurich, Lemonade or Goldman Sachs.

What the finance cases show

The pattern "a gate per use case plus independent validation" comes from model-risk habits.

Banks keep this habit even where SR 26-2 no longer covers generative AI.

Klarna shows the opposite pattern, where cost drove the evaluation.

Public bodies and one health vendor publish the most rigorous methods

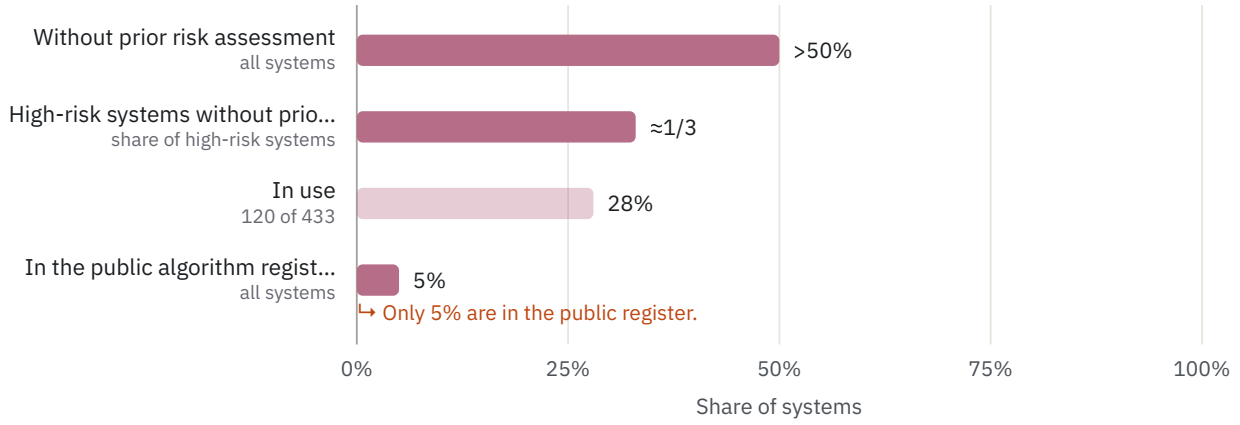
Public bodies must justify spending, so they publish more method than firms. In healthcare, one vendor's release gate sets the bar, but it grades itself.

The UK's i.AI runs a buyer-side acceptance test. Its "Consult" tool analysed a Scottish Government consultation and scored an F1 of 0.76 against human reviewers. [19] The differences had a "negligible" effect on the ranking of themes. The government plans more accuracy work before a wider rollout. Its note-taking tool "Minute" reported one hour saved per one-hour meeting in 25 councils, but that is an early pilot figure. [35]

Self-classification under-reports risk. The Netherlands Court of Audit counted 433 AI systems at 70 central-government organisations in October 2024. [36] [37] [38] More than half had no prior risk assessment. Only 5% appeared in the public algorithm register. The audit office saw "an incentive not to classify AI systems as high risk" (our translation). Its figures rest on the ministries' own self-assessments.

Most Dutch government AI systems skipped a risk assessment

Share of 433 AI systems at 70 Dutch central-government organisations, Netherlands Court of Audit, October 2024.



WHAT TO NOTICE

- The first bar is a lower bound ('more than half').
- The audit office did not check the ministries' self-assessments.

Figure 5. Bars use different bases: the high-risk bar is a share of high-risk systems only.

Source: Accountant.nl, Binnenlands Bestuur and NOS on the Court of Audit report (snippet only). [36] [37] [38]

Abridge publishes the most rigorous enterprise release gate we found, and wrote it itself. Its test data holds more than 10,000 hours of clinical audio with gold transcripts. [8] A release needs blinded head-to-head trials "adjudicated by licensed clinicians". The trials use anytime-valid sequential tests, so the team can stop early without false confidence. Monitoring uses clinician edits, star ratings and links from each note sentence to the transcript.

Independent health studies are rare, but they can contradict vendors. A 2025 study graded ambient notes with a modified PDQI-9 instrument and two blinded reviewers. [41] Ambient notes were more thorough than human notes, but less succinct and more prone to hallucination. Most scribes and admin tools are not medical devices, so the FDA does not review them, and vendors report their own evals.

GO DEEPER

Consultancies and UK government detail

Consultancies

McKinsey's Lilli draws on more than 40 curated internal sources and more than 100,000 documents. [33] [34]

McKinsey claims 30% time savings and 20% better "content quality and accuracy". It reports these figures itself, and we found no published accuracy method.

Deloitte Australia agreed in October 2025 to refund part of a report fee (see Failures). [7]

UK government detail

Consult: F1 of 0.76 against human reviewers on a Scottish Government consultation; "negligible" effect on theme ranking; more accuracy evaluation planned. [19]

Minute: pilots in 25 councils; one hour saved per one-hour meeting (early test, not a published evaluation). [35]

GO DEEPER

Dutch Court of Audit (October 2024)

Finding	Value
AI systems counted	433, at 70 organisations
Systems in use	120 (28%)
Systems with no prior risk assessment	More than half
High-risk systems with no prior risk assessment	About one third
Systems in the public algorithm register	5%

Table 4. The figures rest on the ministries' own self-assessments.

Source: Accountant.nl, Binnenlands Bestuur, NOS (snippet only). [36] [37] [38]

GO DEEPER

Abridge release gate (vendor self-report)

More than 10,000 hours of clinical audio with gold transcripts. [8]

Metrics: word error rate, recall of medical terms, precision and recall of medical concepts.

Blinded head-to-head trials adjudicated by licensed clinicians, with anytime-valid sequential tests.

Rollout starts with trained early adopters.

Monitoring: clinician edits, star ratings, sentence-to-transcript links.

Abridge's August 2025 paper says its system is "6x more likely to find and fix hallucinations" than standard models. [39] Secondary coverage gives 97% against 82% for GPT-4o on more than 10,000 encounters (snippet only). [40]

GO DEEPER

What the public and health cases show

i.AI's "F1 against human reviewers" is a buyer-side acceptance test that others could standardise.

The Dutch audit gives the clearest evidence that self-classification under-reports risk.

The strongest health gate combines expert trials, sequential statistics, staged rollout and edit monitoring.

Independent health studies remain rare and small, but the PDQI-9 study contradicts vendor claims on hallucination.

Public failures share one cause: the builder controlled the metric

The public eval failures fall into six groups. In each case, an independent test with a fixed rubric and human-checked grading would probably have exposed the problem.

Klarna let cost become the main evaluation factor. Klarna had claimed its assistant handled two-thirds of chats and did the work of 700 agents.[44] In 2025, CEO Sebastian Siemiatkowski told Bloomberg the AI-first push "went too far" and lowered quality.[42] [43] Klarna then began to rehire human agents.

> *[Cost was] a too predominant evaluation factor.*[42]
>
> Sebastian Siemiatkowski, Klarna CEO, 2025 (as reported)

Deloitte Australia delivered fabricated references to a government client. Its AU$440,000 report for the Department of Employment and Workplace Relations contained fabricated references and a misquoted court judgment.[7] A revised version disclosed the use of Azure OpenAI GPT-4o. Deloitte agreed to refund part of the fee, later reported as more than AU$97,000.[45] A citation check before delivery would have caught it.

Public eval failures and what would have caught them

Case	What went wrong	What would have caught it
Klarna customer service[42]	Cost drove the evaluation; quality fell	Quality metrics with equal weight in the release gate
Deloitte Australia report[7]	Fabricated references and a misquoted court judgment	A citation check before delivery
Shopify judge before calibration[2]	The judge agreed with humans at near-random levels (κ 0.02)	Judge validation against expert labels
Shopify RL training[2]	Reward hacking: refusals, tag misuse, invented IDs	Held-out tests that training cannot see
Intercom resolution rate[22]	The metric's denominator changed	A fixed, published metric definition
Dutch central government[36]	Agencies under-classified risk and skipped assessments	Independent risk classification and testing
NYC Local Law 144[13]	Mandated audits went largely unenforced	Active enforcement or buyer demand

Table 5. In every case the builder controlled the metric. We found no systematic dataset of enterprise eval failures, so this list is illustrative.

Source: the cases cited in each row.

GO DEEPER

Six lessons from the failures, and case detail

Six lessons from the failures

Put quality and cost in the same gate. Klarna shows the cost of a gate that tracks only cost. [42]

Check every fact a reader will rely on. Deloitte had no reference check before delivery. [7]

Validate the judge before you trust it. Shopify's uncalibrated judge was close to random. [2]

Keep training data and test data apart. Shopify's reward hacking came from evals that fed training. [2]

Freeze metric definitions. A changed denominator makes trends and comparisons meaningless. [22]

Do not let the builder classify its own risk. The Dutch audit found a clear incentive to under-classify. [36]

Case detail

Klarna earlier claimed its assistant handled two-thirds of chats and did the work of 700 agents. [44] It then moved to rehire human agents in an "Uber type of setup". [42] [43]

Deloitte's report fee was AU$440,000; the refund was later put above AU$97,000. [7] [45]

Evaluation lags observability: about half of agent teams run no offline evals

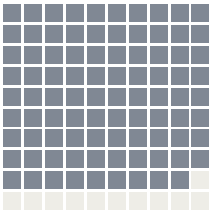
The best public data comes from LangChain's "State of Agent Engineering" survey. LangChain sells eval and tracing tools, so treat it as a vendor survey.

Teams trace their agents far more often than they test them. The survey ran from 18 November to 2 December 2025 and drew 1,340 responses. [9] About 89% of respondents trace or observe their systems. Only 52.4% run offline evals and 37.3% run online evals. Human review (59.8%) still leads LLM-as-judge (53.3%) as a method.

Nine in ten agent teams trace; only half run offline evals

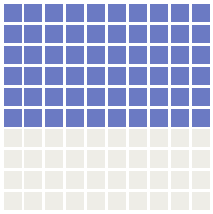
Share of all respondents using each practice, LangChain State of Agent Engineering survey, November–December 2025 (n = 1,340).

89%
Tracing or observability



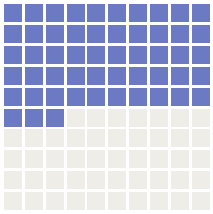
approximate

60%
Human review



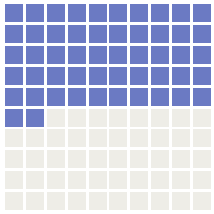
59.8%

53%
LLM-as-judge



53.3%

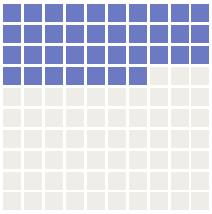
52%
Offline evals



52.4%

Only half run offline evals.

37%
Online evals



37.3%

Each square is 1 of 100 (1%).

WHAT TO NOTICE

- Human review (59.8%) still leads LLM-as-judge (53.3%) as a method.

Figure 6. Each grid has 100 squares; one square is one percent of respondents. Respondents could pick several practices, so the grids do not sum to 100%. Another 29.5% of all respondents run no evaluation at all. Vendor-run survey; about 49% of respondents work at firms with fewer than 100 staff.

Source: LangChain, State of Agent Engineering (vendor survey). [9]

23%

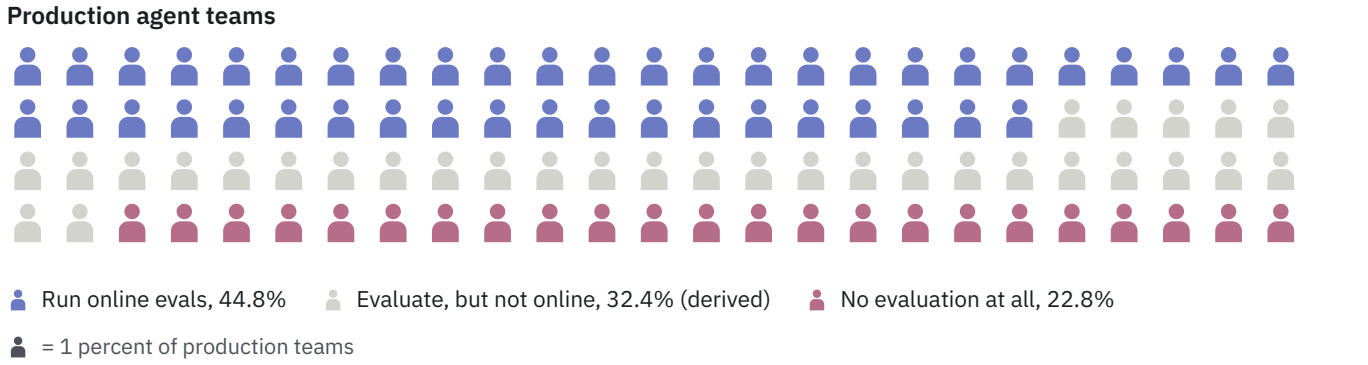
of teams with agents in production do not evaluate them at all (22.8%, LangChain survey, Nov–Dec 2025).

Source: LangChain, State of Agent Engineering (vendor survey). [9]

Production teams do better, but not by much. Among teams with agents in production, 44.8% run online evals and 22.8% run no evaluation at all.[9] Quality is the top barrier to production at 32%, followed by latency at 20%. At firms with 2,000 or more staff, security ranks second at 24.9%.

Fewer than half of production agent teams test on live traffic

Teams with agents in production, by most advanced evaluation practice, LangChain survey, November–December 2025. One figure is 1% of these teams.



WHAT TO NOTICE

- The middle group is derived: 100% minus the two reported shares.

Figure 7. Shares of teams with agents in production; they sum to 100%. Vendor-run survey.
Source: LangChain, State of Agent Engineering (vendor survey).[9]

Nobody measures eval spend, so time is the best proxy. Husain and Shankar report that 60–80% of development time went to evaluation in their projects.[18] Notion says about 80% of AI-team work runs on evals and traces.[17] Teams also pay for expert labels and for judge compute on every graded trace. Practitioners therefore run cheap checks on all traces and judges on samples.[18]

GO DEEPER

LangChain survey, full table

Measure	All respondents	Teams with agents in production
Agents in production	57.3% (51% a year earlier)	100%
Tracing or observability	about 89%	not split out
Offline evals	52.4%	not split out
Online evals	37.3%	44.8%
No evaluation at all	29.5%	22.8%
Human review	59.8%	not split out
LLM-as-judge	53.3%	not split out

Table 6. Respondents could pick several practices, so the shares do not sum to 100%.

Source: LangChain (vendor survey, 18 Nov–2 Dec 2025, 1,340 responses). [9]

GO DEEPER

Spend, scale and the cost of evaluation

Spend and scale

Menlo Ventures put enterprise generative AI spend at $37 billion in 2025, up from $1.7 billion in 2023, from about 500 US enterprise decision-makers (snippet only). [46] [47] We found no 2026 edition.

A KPMG pulse survey reportedly found that only 11% of enterprises have scaled agents to organisation-wide value (secondary summary only). [48]

Cost of evaluation

No reputable survey reports eval spend as a share of AI budget.

Husain and Shankar: 60–80% of development time on evaluation. [18]

Notion: about 80% of AI-team work runs on evals and traces. [17]

Expert labels: Shopify uses three experts per conversation; Abridge uses licensed clinicians. [2] [8]

Judges cost compute on every graded trace, so teams run cheap checks on all traces and judges on samples. [18]

GO DEEPER

What the surveys show

About half of agent builders run no systematic offline eval.

Human review still leads LLM judges as a method.

No survey gives norms for eval headcount, and none offers a widely used maturity model.

Eleven sector regimes demand testing, but none is built for generative AI agents

Banks, insurers, device makers, employers, aviation and public agencies faced testing rules long before AI law. We rated eleven regimes on five questions.

Every regime asks for testing before use, and most for monitoring after. Many also name independence: SR 26-2, SS1/23, EIOPA, NYC Local Law 144 and the OMB memos all do.[10] [54] [11] [12] [79] Several accept black-box tests. SR 26-2 allows outcome analysis without code access, and OMB allows query-based tests of a vendor service.[10] [79]

Most regimes are guidance, not law, and the newest technology often falls outside scope. Only Colorado's insurance rules, NYC Local Law 144, the EU MDR and the OMB memos bind. SR 26-2 excludes generative and agentic AI in its footnote 3.[10] It also states that "non-compliance with this guidance will not result in supervisory criticism". EASA's proposal covers only offline-learning ML.[76]

No sector regime fully covers generative AI agents

Eleven regimes in banking, insurance, health, hiring, aviation and government, rated on five testing questions, November 2026.

Regime	Covers GenAI or agents?	Pre-deployment testing	Ongoing monitoring	Independence required	Binding?
US SR 26-2 Banking · Fed, OCC, FDIC · Apr 2026	○ Excludes GenAI and agentic AI	● Validation before first use	● Includes vendor models	● 'Objective experts'	○ Not enforceable
UK PRA SS1/23 Banking · internal-model banks	◐ AI 'whatever the technology'	–	–	● Independent validation (Principle 4)	◐ Internal-model banks only
ECB internal-models guide Banking · euro area · Jul 2025	○ Capital models only	◐ Explainability, performance	–	–	◐ Supervisory guide
EIOPA AI opinion Insurance · EU · Aug 2025	◐ All AI; API links (3.37)	● Before release (3.27)	● Ongoing; drift (3.36)	◐ External audit an option (3.11)	◐ Supervisory opinion
NAIC AI bulletin Insurance · 29 US jurisdictions	–	◐ Testing and validation expected	–	–	○ Guidance only
Colorado 3 CCR 702-10 Insurance · Colorado	–	◐ Bias test promised, not adopted	–	–	● Binding governance rules
FDA PCCP and lifecycle Health · US devices	◐ AI broadly; GenAI guidance pending	● Pre-market gate	◐ Change plans; lifecycle guidance draft	◐ FDA review; CHAI labs stalled	◐ Gate binding; lifecycle draft
EU MDR + AI Act Health · MDCG 2025-6	◐ Device AI only	● Notified-body assessment	● Post-market surveillance	● Notified body	● High-risk duties from 2 Aug 2028 (Omnibus)

Regime	Covers GenAI or agents?	Pre-deployment testing	Ongoing monitoring	Independence required	Binding?
NYC Local Law 144 Hiring tools · since Jul 2023	◐ Automated hiring tools only	● Bias audit within a year before use	◐ Yearly audit	● Independent bias audit	● Law, but weak enforcement
EASA NPA 2025-07 Aviation · EU · proposal	○ Offline ML only; GenAI later	● Learning assurance	–	–	○ Proposal; next step Q2 2027
OMB M-25-21 / M-25-22 US federal agencies	◐ High-impact AI	● Practice 1; black-box tests allowed	● Practice 3	● In-agency reviewer	● Binds agencies

● Yes ◐ Partly or limited ○ No – Not covered in our sources

WHAT TO NOTICE

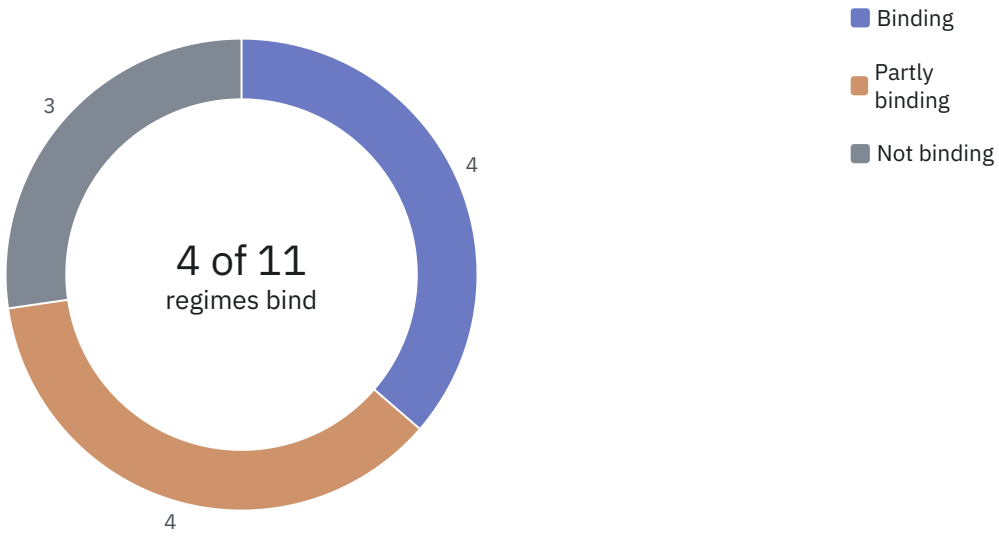
- The highlighted column has no full mark: no regime is built for generative AI agents.
- The closest are the OMB memos and the EU device rules, and both are narrow.
- US bank guidance now excludes generative AI; insurance rules are mostly guidance.

Figure 8. The EU MDR row uses the Digital Omnibus date of 2 August 2028; MDCG 2025-6 had given 2 August 2027. CHAI, a voluntary health scheme, is covered separately.

Source: Federal Reserve; [10] [49] Bank of England; [54] ECB; [55] EIOPA; [11] NAIC; [57] Debevoise; [60] RAPS; [63] [65] MDCG summaries; [71] [72] Garrigues; [73] NYC DCWP; [12] EASA; [76] OMB. [79] [80]

Only four of the eleven regimes bind

Legal force of the eleven sector regimes that demand AI testing, November 2026.



WHAT TO NOTICE

- Even binding NYC LL144 is weakly enforced.

Figure 9. Binding: Colorado 3 CCR 702-10, NYC Local Law 144, EU MDR with the AI Act, and the OMB memos. Partly binding or supervisory: PRA SS1/23, the ECB guide, the EIOPA opinion and the FDA regime. Not binding: SR 26-2, the NAIC bulletin and the EASA proposal. Classification follows the "Binding?" column of the matrix above.

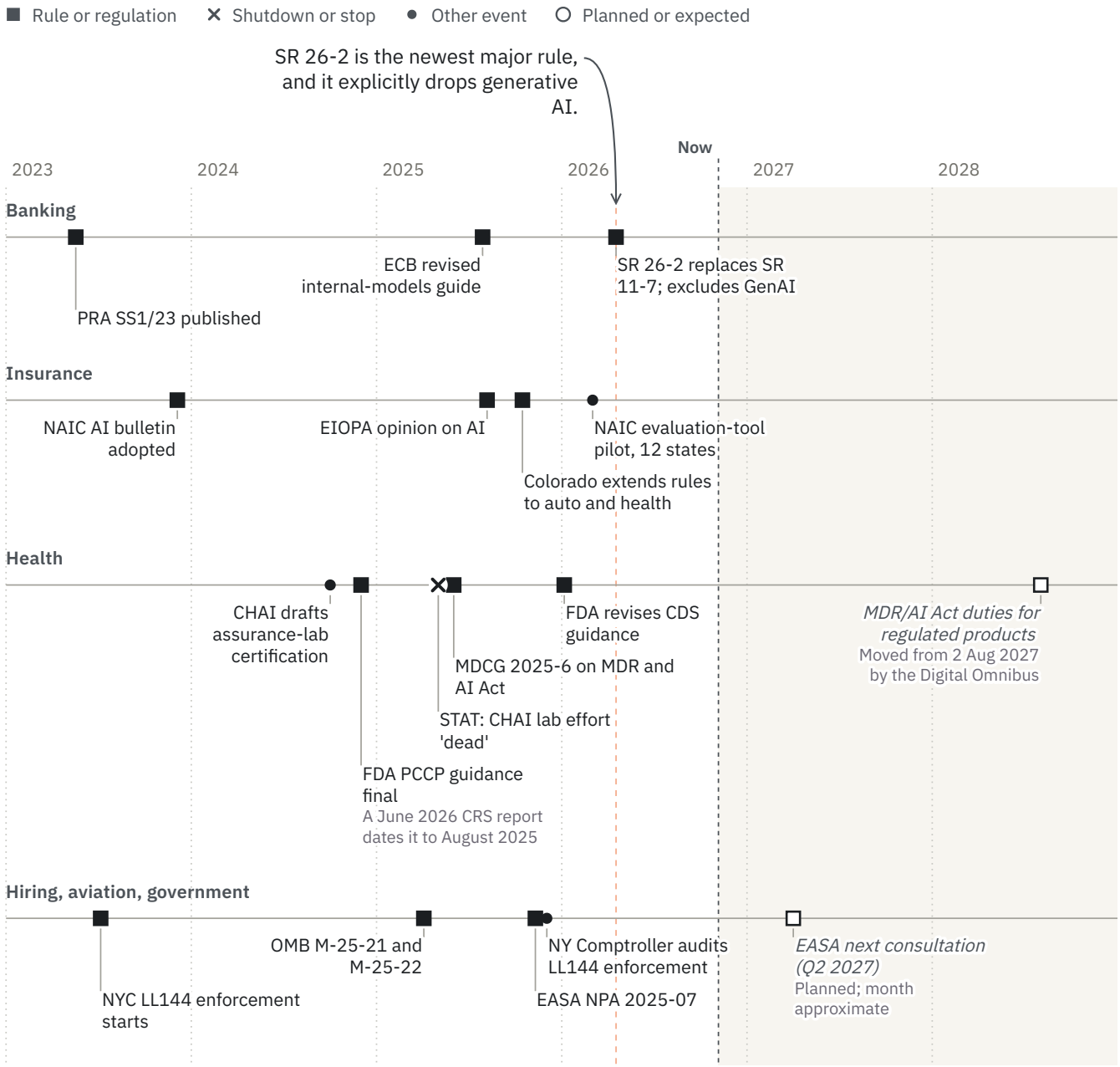
Source: as for the matrix above.

Insurance has the densest testing duties outside AI law. EIOPA's opinion of 6 August 2025 expects tests "before release as well as on an ongoing basis", fairness metrics and drift monitoring.[11] Paragraph 3.11 names "external audits, or performing due diligence testing" for bought AI. Paragraph 3.37 asks for tests of connections to other AI systems through APIs, which fits agents directly. In the US, the NAIC bulletin reached 29 jurisdictions by 3 November 2026, but it stays guidance.[57] Colorado binds, but its quantitative test rule has stalled since September 2023.[60]

Mandates without enforcement or a paying buyer fail. NYC Local Law 144 requires an independent bias audit within a year before an employer uses a hiring tool.[12] The State Comptroller audited enforcement in December 2025.[13] A secondary summary says the audit found 17 potential violations where the city found one.[74] In health, CHAI planned certified assurance labs in 2024. By February 2026 the network had "never materialized".[14] [66]

Sector rules arrived piecemeal, and generative AI keeps slipping out of scope

Key dates for sector regimes that demand AI testing, 2023 to 2028.



WHAT TO NOTICE

- Dates after November 2026 are planned.

Figure 10. Selected dates only. Full regime detail sits in the 'Go deeper' block below.

Source: the regulator and secondary sources cited on each event.

The rules leave room for outside testers, but only with a buyer. SR 26-2 lets banks validate vendor products "either by internal or outside parties".[10] EIOPA names external audits, and OMB M-25-22 requires vendors to give agencies the "access and time necessary" for independent evaluation.[11] [80] Black-box access is enough for many of these duties. Yet LL144 and CHAI show that a mandate alone does not create demand.

GO DEEPER

The eleven regimes in one table

Regime	Sector and place	Legal force	What it demands	Covers generative AI or agents?
SR 26-2 / OCC 2026-13	US banks	Guidance; "non-compliance ... will not result in supervisory criticism"	Effective challenge by "objective experts", validation before first use, monitoring that includes vendor models	No; footnote 3 excludes them
PRA SS1/23	UK banks with internal-model approval	Supervisory statement; internal-model banks only	Independent model validation (Principle 4)	Partly; it covers AI "whatever the technology"
ECB guide to internal models	Euro-area banks	Supervisory guide	Explainable ML; performance must justify complexity	No; capital models only
EIOPA AI opinion	EU insurers	Supervisory opinion	Tests before release (3.27), ongoing drift metrics (3.36), external audit as an option (3.11)	Partly; all AI, including API links to other AI (3.37)
NAIC model bulletin	Insurers in 29 US jurisdictions	Guidance only	Testing and validation within an AI programme	Not stated in our sources
Colorado 3 CCR 702-10	Colorado insurers	Binding governance rules	Remediation of bias found by quantitative tests; test rule promised, not adopted	Not stated in our sources
FDA PCCP and lifecycle guidance	US medical devices	Pre-market gate binds; PCCP guidance final; lifecycle guidance draft	Pre-market review; pre-agreed change plans with validation	Partly; AI broadly, generative AI guidance pending
EU MDR/IVDR + AI Act	EU medical devices	Binding law	Notified-body assessment; post-market surveillance	Partly; device AI only
NYC Local Law 144	NYC employers	Binding law, weakly enforced	Independent bias audit within a year before use; public summary	Partly; automated hiring tools only
EASA NPA 2025-07	EU aviation	Proposal; next step Q2 2027	Learning assurance for offline-learning ML	No; generative AI comes later
OMB M-25-21 / M-25-22	US federal agencies	Binding on agencies	Pre-deployment tests (Practice 1), black-box tests allowed, monitoring (Practice 3), in-agency reviewer	Partly; high-impact AI only

Table 7. Legal force, demands and scope of eleven sector regimes, November 2026.

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Banking: SR 26-2, PRA SS1/23 and the ECB guide

US banking: SR 26-2

Issued by the Federal Reserve, the OCC and the FDIC on 17 April 2026; replaces SR 11-7 (2011) and SR 21-8 on anti-money-laundering models. [49] The OCC published it as Bulletin 2026-13. [50] [51]

"Most relevant to banking organizations with over $30 billion in total assets". [49]

Footnote 3: "Generative AI and agentic AI models are novel and rapidly evolving. As such, they are not within the scope of this guidance." [10] Principles apply to "traditional statistical and quantitative models and non-generative, non-agentic AI models".

"This guidance does not set forth enforceable standards or prescriptive requirements; accordingly, non-compliance with this guidance will not result in supervisory criticism." [10]

Within scope: effective challenge by "objective experts" with "sufficient independence" and the "organizational standing and influence to effect any change"; validation "generally occurs prior to a model's first use"; quality "depends on the rigor and effectiveness of the review rather than on organizational structure"; vendor products validated "either by internal or outside parties"; "ongoing monitoring and outcome analysis" of vendor models even without code or data. [10]

Vendor commentators call the carve-out a placeholder; one reports a planned request for information on AI in banking, which we could not confirm. [52] [53]

Large banks still validate LLM applications (JPMorgan MRGR). The habit persists without the mandate. [5]

UK banking: PRA SS1/23

Published 17 May 2023; in effect 17 May 2024; updated version in effect 23 April 2026 after minor amendments. [54]

Applies to UK banks, building societies and PRA-designated investment firms with internal-model approval (IRB, IMA, IMM).

Covers in-house and vendor models "whatever the technology", with a sub-principle on "managing the risks associated with the use of artificial intelligence".

Principle 4 demands independent model validation. The PRA held a roundtable on AI and ML model risk in November 2025.

Euro-area banking: ECB guide to internal models

Revised guide published 28 July 2025, with a new section on machine learning: models must be explainable, and performance must justify complexity. [55] [56]

It targets capital models. Customer-facing generative AI in EU banks falls under DORA, EBA outsourcing rules and the AI Act instead.

GO DEEPER

Insurance: EIOPA, the NAIC bulletin and Colorado

EU insurance: EIOPA opinion (EIOPA-BoS-25-360, 6 Aug 2025)

Legal bases include the IDD, Solvency II and DORA. [11]

Paragraph	What it expects
3.11	Firms stay "ultimately responsible" for third-party AI; where IP limits insight, use contract clauses, "external audits, or performing due diligence testing and monitoring"
3.15	Monitor and, where appropriate, audit outcomes, "including with the use of fairness and non-discrimination metrics"; Annex I lists example metrics
3.27	Secure and test high-impact uses "before release as well as on an ongoing basis"
3.31	Firms may outsource oversight functions, but not responsibility, "while ensuring independence"
3.36	Use performance metrics such as accuracy and recall to detect drift
3.37	Testing should cover connections to other AI systems through APIs
3.38	Test resilience against data poisoning and adversarial attacks

Table 8. The paragraphs of EIOPA's opinion that set testing expectations for insurers.

US insurance: NAIC bulletin and Colorado

NAIC adopted its AI model bulletin on 4 December 2023; 29 jurisdictions had adopted it by 3 November 2026, most recently Puerto Rico, Mississippi, South Carolina and North Dakota in 2026. [57] California, Colorado, New York and Texas have their own insurance AI rules.

Twelve states piloted an "AI Risk Evaluation Supplement" in March 2026; adoption at the 2026 Fall National Meeting is unconfirmed. [58] [59] Secondary sources report no formal enforcement action under the bulletin by early 2026.

Colorado is the only US state with binding insurance AI governance rules. [60] It extended its life-insurer rule to private auto and health benefit plans in August 2025; the amendments took effect on 15 October 2025, with governance due by 1 July 2026.

Insurers must remediate unfair discrimination "detected through quantitative testing". The quantitative testing rule was drafted in September 2023 and not updated since. The final text dropped a required bias and data-quality evaluation of external data.

Bulletin B-10.004 waives the description of quantitative tests in the 2024 and 2025 annual reports. [61]

GO DEEPER

Health: FDA, CHAI and the EU device rules

US healthcare: FDA

The PCCP guidance for AI-enabled device software is final; most sources date it to December 2024, a June 2026 CRS report to August 2025. [62] [63] [64] It covers AI broadly; makers agree planned changes and validation methods in advance.

The lifecycle guidance is still a January 2025 draft; the device centre's FY2027 agenda (1 Oct 2026) makes its final version an A-list priority. [65] The agenda adds a top-priority draft on generative AI conversational devices for mental health and a low-priority item on risk assessment for generative AI devices.

The FDA revised its Clinical Decision Support software guidance on 6 January 2026. [64]

US healthcare: CHAI

An October 2024 draft would have certified independent labs against ISO 17025 and conflict-of-interest tests; final designs were promised for April 2025. [66]

STAT reported in May 2025 that "CHAI's 'assurance lab' effort is dead". [67] Becker's reported that the federal government sought to sideline CHAI. [68]

In February 2026 Fierce Healthcare reported that the network "never materialized" (snippet only). [14]

URAC, the Consumer Technology Association and the American Heart Association now run their own health AI programmes. [69] CHAI's site lists an "Applied Model Card", a public registry and v1.0 testing frameworks, but no certified labs. [70]

EU healthcare: MDR, IVDR and the AI Act

MDCG 2025-6 (June 2025) is a joint FAQ of the Medical Device Coordination Group and the AI Board. [71] [72]

Device AI is high-risk under AI Act Article 6(1) when a notified body must assess the device. Makers may embed AI Act testing, monitoring and documentation into MDR or IVDR quality systems, and post-market surveillance can carry the monitoring duties.

MDCG 2025-6 gave 2 August 2027 as the start date; the Digital Omnibus moved duties for AI inside regulated products to 2 August 2028. [73] The Rules chapter covers the Omnibus.

GO DEEPER

Hiring, aviation and US federal agencies

Employment: NYC Local Law 144

An employer may use an automated employment decision tool only after "a bias audit within one year of the use of the tool", must post a summary, and must give candidates notice 10 business days before use. [12] DCWP began enforcement on 5 July 2023.

The State Comptroller audited enforcement on 2 December 2025.[13] A secondary summary says it rated enforcement "ineffective": DCWP found one issue where auditors found 17 potential violations, and 75% of calls about these tools went to the wrong place.[74] We could not check these figures against the report. No confirmed 2026 amendment.[75]

Aviation: EASA NPA 2025-07

Published 10 November 2025; comments closed 10 February 2026. Step 1 of rulemaking task RMT.0742.[76] [77]

Proposes a generic "DS.AI" framework for AI assurance, human factors and ethics, covering only offline-learning ML that does not contribute to critical failures. Generative, reinforcement-learning and hybrid AI come later.

The next consultation, expected in Q2 2027, embeds the framework into airworthiness, air traffic and drone rules.[78] "Learning assurance" is the most rigorous sector test doctrine we found, but it does not yet reach LLM agents.

US federal agencies: OMB M-25-21 and M-25-22

Agencies must test high-impact AI before deployment; without code, model or data access, they query the service or send evaluation data to the vendor.[79]

An in-agency reviewer "who has not been involved in the development" reviews each impact assessment.

Agencies test and review AI periodically after deployment; non-compliant AI must stop.

Vendors must give agencies the "access and time necessary" for independent evaluation.[80]

The EU's model contractual clauses for AI procurement (MCC-AI) exist in High-Risk and Light versions; they are optional.[81]

GO DEEPER

What the regimes share, and sectors not checked

What the regimes share

Most regimes are guidance, not law; only Colorado, NYC LL144, the EU MDR and the OMB memos bind.

Every regime asks for testing before use and monitoring after use.

Many name independence: SR 26-2, SS1/23, EIOPA, LL144 and OMB M-25-21.

Several accept outside parties: SR 26-2 for vendor models, EIOPA for external audits.

Black-box testing is acceptable under SR 26-2 (outcome analysis) and OMB (query-based tests).

The newest technology often falls outside scope: SR 26-2 and EASA both exclude generative AI.

No regime targets generative AI agents directly.

Other sectors not checked

No US or EU education rule outside the AI Act that demands AI testing was found; we did not search this area in depth.

Automotive rules (UNECE, ISO PAS 8800) and EU employment rules (Platform Work Directive) were not checked in this pass.

A mature programme climbs six levels, from vibes to independent assurance

This playbook combines the public cases and the sector rules above. It is our synthesis, not a published standard.

Most teams sit on the lower rungs. About 23% of production agent teams run no evals at all, which is level 0.[9] A regression gate built from real traffic, as at Box, Dropbox and Cloudflare, marks level 2.[15] Calibrated judges with published agreement, as at Shopify, mark level 3.[2] Level 5 adds a party outside the build team that validates and challenges results. JPMorgan's model risk review and the OMB memos show this level.[5] [79]

Six levels of evaluation maturity, with a real example at each

A maturity ladder synthesised from public company cases and sector rules, November 2026.

5. Independent assurance

RARE OUTSIDE BANKS AND GOVERNMENT A party outside the build team validates and challenges results.

JPMorgan MRGR | OMB independent review

↑

4. Closed loop

LEADING TEAMS Staged rollout, online metrics and A/B tests; failures flow back into the suite.

GitHub | ING | Abridge

↑

3. Calibrated grading

LEADING TEAMS Judges carry published agreement with experts; simulators test multi-turn flows.

Shopify

↑

2. Regression gate

ESTABLISHED A suite built from real traffic runs in CI; no regression against production.

Box | Dropbox | Cloudflare

↑

1. Smoke tests

COMMON STARTING POINT A small fixed set runs before releases.

Many early teams

↑

0. Vibes

≈23% OF PRODUCTION AGENT TEAMS Developers try prompts by hand; no stored tests.

LangChain survey, Nov–Dec 2025

WHAT TO NOTICE

- No survey offers a widely used maturity model; this ladder is our synthesis.
- Each level keeps the practices of the levels below it.

Figure 11. Examples show where a named organisation publicly describes the practice, not a full audit of its programme. Source: LangChain;[9] Braintrust;[15] Shopify;[2] GitHub;[1] ING;[6] Abridge;[8] JPMorgan job listing;[5] OMB M-25-21.[79]

Build golden sets from real cases, and keep a held-out set. Start with hundreds of real production cases: ING used 500 chats and Box 330 questions.[6] [15] Add each new production failure as a test. Keep a separate frontier set for new capabilities, as Notion does.[17] Hold back a test set that never feeds training, which prevents reward hacking.[2]

Calibrate every judge and publish the agreement. Write one narrow judge per failure mode.[18] Measure each against expert labels with kappa or F1, and compare it with the agreement between two humans.[2] Audit judges on a schedule, because models and traffic change.[1]

Gate on regression, with hard floors and one named decision owner. Set the gate as "no regression on the core suite against production". Add hard floors for safety and compliance tests that cannot trade against quality gains. Weigh quality and cost in the same decision, as Klarna's reversal shows.[42] Write down who decides when metrics conflict, and use sequential tests for expert trials.[1] [8]

Map the programme to the rules

Programme element	Rules that expect it
Test before first use	SR 26-2, SS1/23, EIOPA 3.27, FDA, OMB M-25-21
Independent review	SR 26-2, SS1/23 Principle 4, LL144, OMB M-25-21
Vendor model testing	SR 26-2, EIOPA 3.11, OMB M-25-22
Ongoing monitoring and drift metrics	SR 26-2, EIOPA 3.36, FDA lifecycle draft, OMB M-25-21
Fairness metrics	EIOPA 3.15, Colorado, LL144
Tests of API connections to other AI	EIOPA 3.37
Adversarial and poisoning tests	EIOPA 3.38
Pre-agreed change validation	FDA PCCP

Table 9. One programme can satisfy several regimes at once. Only EIOPA asks explicitly for tests of AI-to-AI connections, the closest any rule comes to agents.

Source: SR 26-2;[10] PRA SS1/23;[54] EIOPA;[11] FDA;[62] [65] NYC DCWP;[12] Colorado;[60] OMB.[79] [80]

GO DEEPER

Playbook: team, golden sets, judges and simulators

Team set-up

- Give one named owner responsibility for each eval suite.
- Put domain experts on labelling: Shopify uses product experts, Abridge licensed clinicians.[2] [8]
- Involve risk staff from the start, as ING did.[6]
- Keep an independent reviewer apart from the build team for high-impact uses; SR 26-2 and OMB M-25-21 both describe this role.[10] [79]
- Plan for a large share of engineering time: practitioners report 60–80% of development time on evaluation.[18]

Golden sets

- Sample real production cases, not invented ones.
- Start with hundreds of cases (ING 500 chats; Box 330 questions).[6] [15]
- Add each new production failure as a test.

Keep a separate frontier set for new capabilities, as Notion does. [17]

Hold back a test set that never feeds training. [2]

Judges and their calibration

Write one narrow judge per failure mode. [18]

Measure each judge against expert labels with kappa or F1.

Compare the judge with human-human agreement; Shopify used 0.69 as its ceiling. [2]

Audit judges on a schedule. [1]

Publish agreement statistics with every result.

User simulators

Use simulators for multi-turn products and agents.

Seed the simulator with real user goals, as Shopify does. [2]

Treat simulator results as a pre-release screen; they do not replace real-user tests.

GO DEEPER

Playbook: release gates, monitoring and costs

Release gates

"No regression on the core suite against production".

Hard floors for safety and compliance tests that do not trade against quality gains.

Quality and cost in the same decision. [42]

A written decision owner for conflicting metrics. [1]

Sequential tests for expert trials, so a team can stop early with valid statistics. [8]

Online monitoring and A/B tests

Roll out to staff first, then to a small share of users. [1] [6]

Track behaviour signals such as accept rate, edits, resolution and escalation. [20] [8]

Run daily regression against the live model to catch silent provider changes. [1]

Run A/B tests for major changes, as ING did. [6]

Fix metric definitions, and version them when they must change. [22]

Monitor fairness metrics where decisions affect customers; EIOPA expects this for insurers. [11]

Costs

Budget for expert labels, judge compute and engineering time; no survey gives a share of AI budget.

Run cheap deterministic checks on all traffic and expensive judges on samples. [18]

Re-run the full suite on each new model release; Notion ships new frontier models within 24 hours because its suite runs fast. [17]

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What we could not confirm

The OpenAI Morgan Stanley page and the McKinsey ING page did not load; their content comes from search summaries.

No primary JPMorgan or Morgan Stanley document gives set sizes, judge use or thresholds.

No public eval detail for Goldman Sachs, Allianz, Zurich, Lemonade, KPMG, Epic or Ambience; Epic's open-source "Seismometer" was not checked.

No primary eval write-up from Duolingo, Stripe or Ramp.

Whether US bank regulators issued the planned request for information on AI.

The full ECB ML section, the EBA's 2023 report on ML in IRB models and New York's Circular Letter No. 7 (2024) were not read.

Whether the NAIC adopted its AI evaluation tool at the 2026 Fall National Meeting.

The PCCP guidance date (December 2024 or August 2025).

The Fierce Healthcare article of February 2026, the official MDCG 2025-6 text and the NY Comptroller's LL144 report could not be read.

Whether any 2026 OMB memo replaced M-25-21 or M-25-22.

Eval spend as a share of AI budget, eval headcount norms, and a systematic dataset of enterprise eval failures.

Sources for chapter 8

81 sources, numbered as cited above. Badges mark source quality: primary, secondary, vendor (a claim about the publisher's own product), single source, or estimate.

[1] GitHub, How we evaluate models for GitHub Copilot. Primary github.blog

[2] Shopify Engineering, Building production-ready agentic systems. Primary shopify.engineering

[3] Claude customer story, Intercom. Vendor-authored. Vendor claude.com

[4] OpenAI customer story, Morgan Stanley. Vendor-authored; snippet only. Vendor openai.com

[5] The Muse, JPMorgan model risk job listing. Snippet only. Single source themuse.com

[6] AI Expert Network, AI at ING. Snippet only. Secondary aiexpert.network

[7] BNN Bloomberg / AP, Deloitte to partially refund Australian government. Snippet only. Secondary bnnbloomberg.ca

[8] Abridge, The science of AI evaluation. Self-report. Vendor abridge.com

[9] LangChain, State of Agent Engineering. Vendor-run survey, n = 1,340. Vendor langchain.com

[10] Federal Reserve, SR 26-2 attachment. Primary federalreserve.gov

[11] EIOPA, Opinion on AI governance and risk management. Primary eiopa.europa.eu

[12] NYC DCWP, Automated employment decision tools. Primary nyc.gov

[13] NY State Comptroller, Enforcement of Local Law 144. Not read in full. Primary osc.ny.gov

[14] Fierce Healthcare, Inside CHAI's failed assurance labs. Snippet only. Secondary fiercehealthcare.com

[15] Braintrust, customer stories. Vendor-authored. Vendor braintrust.dev

[16] createwith.com, Intercom Monitors. Snippet only. Secondary createwith.com

[17] Braintrust, Notion case study. Vendor-authored. Vendor braintrust.dev

[18] Husain and Shankar, evals FAQ. Practitioner guide. Secondary hamel.dev

[19] GOV.UK, Humphrey tool reviews consultation responses. Snippet only. Primary gov.uk

[20] Cursor, Online RL for Tab. Company self-report. Primary cursor.com

[21] Intercom blog, Intercom vs Zendesk. Snippet only. Vendor intercom.com

[22] eesel.ai, Fin response quality. Competitor blog; snippet only. Vendor eesel.ai

[23] CTO Magazine, AI in Morgan Stanley. Snippet only. Secondary ctomagazine.com

[24] OpenAI, AI in the Enterprise. Not fetched. Vendor cdn.openai.com

[25] InvestmentNews, JPMorgan joins the AI productivity war. Snippet only. Secondary investmentnews.com

[26] Bloomberg, JPMorgan works with US regulators on generative AI pilots. Snippet only. Secondary bloomberg.com

[27] CTO Magazine, ING AI chatbot. Snippet only. Secondary ctomagazine.com

[28] McKinsey, How ING uses generative AI. Vendor-consultant; timed out. Vendor mckinsey.com

[29] BBVA, Responsible AI and guardrails (Spanish). Snippet only. Primary bbva.com

[30] Intelligent Insurer, AXA develops generative AI with Microsoft. Snippet only. Secondary intelligentinsurer.com

[31] Microsoft customer story, AXA. Snippet only. Vendor microsoft.com

[32] InsuranceNewsNet, Red teaming for insurer AI risk. Snippet only. Secondary insurancenewsnet.com

[33] OfficeChai, McKinsey Lilli. Snippet only. Secondary officechai.com

[34] AI Expert Network, McKinsey Lilli. Snippet only. Secondary aiexpert.network

[35] Computer Weekly, Humphrey AI for council admin. Snippet only. Secondary computerweekly.com

[36] Accountant.nl, Court of Audit on central government AI. Snippet only. Secondary accountant.nl

[37] Binnenlands Bestuur, Government often skips AI risk assessment. Snippet only. Secondary binnenlandsbestuur.nl

[38] NOS, Court of Audit AI report. Snippet only. Secondary nos.nl

[39] Abridge, Hallucinations whitepaper. Vendor abridge.com

[40] HIT Consultant, Abridge hallucination results. Snippet only. Secondary hitconsultant.net

[41] Frontiers in AI, Ambient AI note quality study. Snippet only. Primary public-pages-files-2025.frontiersin.org

[42] Maginative, Klarna dials back AI customer service. Snippet only. Secondary maginative.com

[43] Entrepreneur, Klarna CEO reverses course. Snippet only. Secondary entrepreneur.com

[44] tech.co, Klarna reverses AI overhaul. Snippet only. Secondary tech.co

[45] CFO Dive, Deloitte refunds report. Snippet only. Secondary cfodive.com

[46] Let's Data Science, enterprise AI spend reaches $37bn. Snippet only. Secondary letsdatascience.com

[47] Long-term Wiki, Menlo Ventures 2025 report entry. Snippet only. Secondary longtermwiki.com

[48] AI2.work, enterprise AI budget scaling. Secondary; snippet only. Single source ai2.work

[49] Federal Reserve, SR 26-2 letter. Primary federalreserve.gov

[50] Baker Tilly, Updated interagency guidance on model risk management. Snippet only. Secondary bakertilly.com

[51] Openlayer, SR 26-2 guide for AI teams. Snippet only. Vendor openlayer.com

[52] CIMCON, SR 26-2 regulates your models, not your AI agents. Snippet only. Vendor cimcon.com

[53] Monitaur, Governing generative and agentic AI under SR 26-2. Snippet only. Vendor monitaur.ai

[54] Bank of England, SS1/23 model risk management principles. Primary bankofengland.co.uk

[55] ECB, Revised guide to internal models. Snippet only. Primary bankingsupervision.europa.eu

[56] A&O Shearman, ECB publishes revised guide to internal models. Snippet only. Secondary finreg.aoshearman.com

[57] NAIC, AI model bulletin adoption map. Primary content.naic.org

[58] Openlayer, NAIC model bulletin and AI governance. Snippet only. Vendor openlayer.com

[59] actuary.info, NAIC AI bulletin and model law transition. Snippet only. Secondary actuary.info

[60] Debevoise, Colorado extends AI regulation. Secondary debevoise.com

[61] Colorado Division of Insurance, Bulletin B-10.004. Snippet only. Primary doi.colorado.gov

[62] Akin Gump, FDA finalises PCCP guidance. Snippet only. Secondary akingump.com

[63] RAPS, Final FDA guidance on PCCP. Snippet only. Secondary raps.org

[64] CRS IF13245, FDA and AI-enabled devices. Snippet only. Primary everycrsreport.com

[65] RAPS, FDA device centre guidance agenda for FY2027. Secondary raps.org

[66] Fierce Healthcare, CHAI draft model card and lab certification. Snippet only. Secondary fiercehealthcare.com

[67] Ground News, STAT on CHAI's assurance labs. Secondary ground.news

[68] Becker's, Administration seeks to sideline CHAI. Snippet only. Secondary beckershospitalreview.com

[69] Distilinfo, CHAI's promise meets reality. Snippet only. Secondary distilinfo.com

[70] CHAI, home page. Primary chai.org

[71] OpenRegulatory, MDCG 2025-6. Snippet only. Secondary openregulatory.com

[72] Reuschlaw, Interplay between MDR, IVDR and the AI Act. Snippet only. Secondary reuschlaw.de

[73] Garrigues, Digital Omnibus on AI published. Secondary garrigues.com

[74] GLACIS, Guide to New York AI rules. Secondary, not checked against the report. Single source glacis-landing.pages.dev

[75] Beancount.io, NYC Local Law 144 guide for 2026. Snippet only. Secondary beancount.io

[76] EASA, NPA 2025-07. Snippet only. Primary easa.europa.eu

[77] EASA news, First regulatory proposal on AI in aviation. Snippet only. Primary easa.europa.eu

[78] ICAO DGCA61 paper, EASA approach to AI in aviation. Snippet only. Primary icao.int

[79] OMB M-25-21 (3 Apr 2025). Primary whitehouse.gov

[80] OMB M-25-22 (3 Apr 2025). Primary whitehouse.gov

[81] Covington Inside Privacy, Updated AI model contractual clauses. Secondary insideprivacy.com

GLOSSARY

Terms used in this report

78 terms in plain language, A to Z, each with the chapter where it matters most.

AI agent

An AI agent is a system that acts toward a goal instead of only answering. It can use tools, browse, write code and work over many steps.

Agents act in the world, so their tests must check actions and their side effects, not just answers.

Chapter 1, Benchmarks

AI Security Institute (AISI)

A government institute that tests advanced AI models for safety and security risks. The UK opened the first in 2023; the US version is now called CAISSI.

Government institutes test frontier models before launch, but mostly in confidence.

Chapter 5, Institutions and regulation · UK AI Security Institute, About

ARC-AGI

ARC-AGI is a series of puzzle benchmarks from the ARC Prize Foundation. Each puzzle asks the solver to find a rule from a few examples.

People find the puzzles easy, so the series tests skill that does not come from memory.

Chapter 1, Benchmarks · ARC Prize

Arena

An arena is a leaderboard built from blind votes. Users see two anonymous answers and pick the better one. LMArena, formerly Chatbot Arena, is the best known.

Arena ranks show what voters prefer, which is not always what is correct.

Chapter 2, Evaluation science

Article 55

This AI Act article sets the duties of providers of general-purpose models with systemic risk. It requires model evaluation, adversarial testing, incident reporting and cybersecurity. The Commission's AI Office enforces it.

It is the legal anchor for independent evaluation work in Europe.

Chapter 5, Institutions and regulation · EU AI Act, Article 55

AUC (area under the curve)

AUC scores how well a detector separates two groups, such as tests and real use. It runs from 0.5 for chance to 1 for perfect separation.

Chapter 2, Evaluation science

Benchmark

A benchmark is a fixed, public eval that many teams run in the same way. Shared tasks and scoring let people compare models.

Benchmarks drive headlines and lab launch tables, but most of them stop being useful within a few years.

Chapter 1, Benchmarks

Canary release

A canary release gives a new model to a small group first, often staff. Problems then show up before everyone gets the change.

Chapter 8, Enterprise practice and sector rules

CBRN

CBRN stands for chemical, biological, radiological and nuclear. Safety tests in this area check whether a model helps someone build such weapons.

Chapter 5, Institutions and regulation

Cohen's kappa (κ)

Kappa measures how often two graders agree, after it removes the agreement that chance alone would produce. Zero means chance agreement; one means perfect agreement.

The report uses kappa to show how closely AI judges track human graders.

Chapter 2, Evaluation science

Confidence interval

A confidence interval is a range that likely holds the true score, given the noise in a test. Overlapping ranges mean the test cannot rank two models.

Many leaderboard gaps are smaller than the noise, so the top places are often a statistical tie.

Chapter 2, Evaluation science

Construct validity

Construct validity asks whether a test measures the skill it claims to measure. A coding test with broken checks has poor construct validity.

A high score on a test with weak validity says little about real-world skill.

Chapter 2, Evaluation science

Contamination

Contamination happens when test questions or answers leak into the data a model learns from. The model may then recall answers instead of solving tasks.

A contaminated score overstates real skill, and outsiders can rarely check the training data.

Chapter 1, Benchmarks

Cyberspace Administration of China (CAC)

The CAC is the internet regulator of China. Public generative AI services must file with it before launch.

Its filing system makes China the only large market with a list of every approved AI service.

Chapter 6, China and Asia

Deepfake

A deepfake is fake audio, video or imagery that shows a real person or event. Detectors try to spot it.

Detectors that score well on lab test sets often fail on real deepfakes.

Chapter 7, Multimodal, voice and embodied

Elicitation

Elicitation is the work of drawing out a model's full skill during a test. It includes good prompts, tools, time and retries.

Weak elicitation understates what a model can do, so it can hide risks.

Chapter 5, Institutions and regulation

Elo and Bradley-Terry ratings

These rating methods turn head-to-head wins into one score per player. Chess uses Elo; model arenas fit votes with the closely related Bradley-Terry model.

A gap of a few points between models is often smaller than the uncertainty around them.

Chapter 7, Multimodal, voice and embodied

Epoch Capabilities Index (ECI)

The ECI is a single score from Epoch AI that combines many benchmarks on one scale. It keeps tracking progress after single tests saturate.

Chapter 1, Benchmarks · Epoch AI, ECI methodology

EU AI Act

The AI Act is the European Union law on artificial intelligence, Regulation (EU) 2024/1689. It sets duties by risk level and phases them in from 2025.

It is the only law that makes evaluation of frontier models a legal duty.

Chapter 5, Institutions and regulation · Regulation (EU) 2024/1689, EUR-Lex

Eval (evaluation)

An eval is a set of tasks plus a way to score a model's answers. Teams run evals to learn what a model can do and where it fails.

Every number in this report comes from an eval, so the eval design decides what the number means.

Chapter 2, Evaluation science

Evaluation awareness

Evaluation awareness is a model noticing that it is under test rather than in real use. A model that notices may behave better than usual.

If models act differently under test, safety results may not hold after release.

Chapter 2, Evaluation science

Expert data

Expert data is training and test material that paid specialists write or label, such as doctors, lawyers or coders. Labs buy it to teach and check hard skills.

It is the largest money flow in the evals market, and labs do not disclose what they spend.

Chapter 4, Market and companies

Flawed (Epoch AI rating)

Epoch AI gives this label in its benchmark reviews. It means that scoring defects could affect at least 20% of a benchmark's score.

A score near the top of a Flawed test may reflect broken tasks, not a ceiling in skill.

Chapter 1, Benchmarks · Epoch AI, Benchmark Review registry

Frontier model

A frontier model is one of the most capable AI models at a given time. Frontier labs, such as OpenAI, Anthropic and Google DeepMind, build them.

Chapter 5, Institutions and regulation

General-purpose AI model (GPAI)

The AI Act uses this term for a model that can do many different tasks. Other developers often build products on top of it.

Chapter 5, Institutions and regulation · EU AI Act, Article 3(63)

Golden set (regression set)

A golden set is a fixed group of test cases with agreed correct outcomes. Teams rerun it after each change to catch new failures.

The best golden sets now come from real user traffic and past failures, not from hand-written examples.

Chapter 8, Enterprise practice and sector rules

GPAI Code of Practice

This voluntary EU code explains how model providers can meet their AI Act duties. Providers may rely on it until a harmonised standard exists.

It spells out what "state-of-the-art evaluation" means and creates a role for outside evaluators.

Chapter 5, Institutions and regulation · European Commission, contents of the GPAI Code of Practice

Grader

A grader decides whether an answer is right or how good it is. Code graders check exact matches or run unit tests. AI judges grade with a model, and human graders grade by hand.

The grader can move a score as much as the model. This report therefore shows how often judges agree with humans.

Chapter 2, Evaluation science

Ground truth

Ground truth is the answer or label that counts as correct for a test item. Graders compare outputs against it.

If the ground truth is wrong, a correct answer scores as a failure.

Chapter 2, Evaluation science

Guardrail

A guardrail is a filter that checks a model's inputs or outputs in real time. It blocks content that breaks a policy.

Guardrails must be fast, so teams keep them simple and run slower judges separately.

Chapter 8, Enterprise practice and sector rules

Harmonised standard

European standards bodies write a harmonised standard at the request of the Commission. The law presumes that a product that follows it meets the matching duties.

Few AI standards exist yet, so most testing still follows drafts and vendor methods.

Chapter 5, Institutions and regulation · EU AI Act, Article 40

Harness

A harness is the software that runs a model through an eval. It sends the tasks, provides tools, collects the answers and scores them.

Two harnesses can give the same model very different scores on the same test.

Chapter 3, Tools and technology

HealthBench

HealthBench is an OpenAI benchmark of realistic health conversations from 2025. A model grades each answer against rubrics that 262 physicians wrote.

Chapter 1, Benchmarks · Arora et al., HealthBench (2025)

Held-out set

A held-out set is a group of test items that the test owner keeps private. Models cannot learn from items they never see.

Hidden items resist contamination, but outsiders must then trust the owner to score fairly.

Chapter 1, Benchmarks

High-risk AI system

The AI Act uses this category for AI in sensitive uses, such as hiring, credit or medical devices. These systems face testing, documentation and oversight duties.

Chapter 5, Institutions and regulation · EU AI Act, Article 6

Honeypot

A honeypot is a trap built into a test, such as an easy way to cheat. It shows whether a model takes the bait.

Chapter 1, Benchmarks

Human baseline

A baseline is a reference score to compare against. A human baseline is the score that people reach on the same test.

A model score, or a judge agreement figure, means little without the human number next to it.

Chapter 2, Evaluation science

Humanity's Last Exam (HLE)

HLE is a benchmark of about 2,500 hard questions from experts in many academic fields. It appeared in 2025.

Chapter 1, Benchmarks · Humanity's Last Exam

Item response theory (IRT)

IRT is a method from school testing. It places the difficulty of each question and the ability of each model on one scale.

IRT lets smaller tests give the same answer, and it lets saturated tests still add signal.

Chapter 2, Evaluation science

Jailbreak

A jailbreak is a prompt that tricks a model into ignoring its safety rules. A universal jailbreak works across many requests.

Chapter 1, Benchmarks

Large language model (LLM)

An LLM is an AI model that learns from huge amounts of text and then writes text. Chat assistants and coding agents run on LLMs.

Chapter 2, Evaluation science

Leaderboard

A leaderboard is a public ranking of models by their scores. Some leaderboards run the tests themselves; others collect scores that labs report.

Who runs the test, and how, often explains why two leaderboards rank the same models differently.

Chapter 1, Benchmarks

LLM-as-judge (AI judge)

An AI judge is a language model that grades the output of another model. It replaces or supports human graders.

Judges are fast and cheap, but on hard tasks they often agree with people little better than chance.

Chapter 2, Evaluation science

METR

METR is a US non-profit that measures how long and how complex a task AI agents can finish. It also tests frontier models before release.

Chapter 1, Benchmarks · METR

MMLU

MMLU is a 2020 benchmark of about 16,000 multiple-choice questions across 57 subjects. It was the standard knowledge exam until models saturated it.

Chapter 1, Benchmarks · Hendrycks et al., Measuring massive multitask language understanding

Model Context Protocol (MCP)

MCP is an open protocol that connects AI models to tools and data sources in a standard way.

Test environments use MCP to give agents the same tools they would have in real work.

Chapter 3, Tools and technology · Model Context Protocol specification

Model risk management (SR 26-2)

Banks must check every model before and during use, with an independent team. US Federal Reserve guidance SR 26-2 sets this out; it replaced SR 11-7 in 2026.

SR 26-2 leaves out generative AI, so banks still lack a regulator-written method for it.

Chapter 8, Enterprise practice and sector rules · Federal Reserve, SR 26-2

Monitor

A monitor is a second system, often another model, that watches an AI agent's actions for harmful or hidden behaviour.

Control tests measure how often monitors catch a model that tries to misbehave on purpose.

Chapter 2, Evaluation science

Multi-turn and single-turn

A single-turn task is one request and one answer. A multi-turn task runs over several exchanges, like a real conversation.

Agents often do well on single-turn tests and much worse once a task runs over many turns.

Chapter 1, Benchmarks

Observability

Observability tools record what an AI application does in production, step by step. Teams search these records, called traces, to find failures.

Chapter 3, Tools and technology

Offline and online evals

Offline evals test a system on a fixed set of cases before release. Online evals score real traffic after release.

Chapter 8, Enterprise practice and sector rules

Open-weight model

An open-weight model is one that anyone can download and run. Its weights, the numbers that make up the model, are public.

Outside testers can study open-weight models in depth, but nobody can recall them after release.

Chapter 6, China and Asia

OpenTelemetry

OpenTelemetry is an open standard for collecting traces and metrics from software. Its GenAI conventions describe how to record AI model calls.

Chapter 3, Tools and technology · OpenTelemetry, semantic conventions for generative AI

OSWorld

In OSWorld, an agent uses a real computer desktop to finish tasks in ordinary apps. Scripts then check the result.

Chapter 1, Benchmarks · OSWorld

pass@k

This metric counts a task as solved if at least one of k attempts succeeds. It rewards a model that sometimes gets the task right.

Chapter 2, Evaluation science · Chen et al., Evaluating large language models trained on code (2021)

pass^k

This stricter metric counts a task as solved only if all k attempts succeed. It shows how reliably a model repeats a success.

For agents in daily business use, reliability matters more than one lucky attempt.

Chapter 2, Evaluation science · Yao et al., τ-bench (2024)

Prompt injection

Prompt injection hides instructions in content that a model reads, such as a web page or an email. The model then follows the attacker.

Agents that read the web or company files face this attack every day.

Chapter 3, Tools and technology

Red teaming

Red teaming means attacking a system on purpose to find its failures. People or tools look for harmful outputs, jailbreaks and security holes.

The EU AI Act and most lab safety policies require documented adversarial testing of this kind.

Chapter 4, Market and companies

Reward hacking

A model reward-hacks when it finds a shortcut that earns a high score without doing the task. For example, it edits the tests instead of fixing the code.

Hacked runs inflate scores, and the habit can spread to other unwanted behaviour.

Chapter 2, Evaluation science

RL environment

An RL environment is a simulated workplace with tasks and automatic scoring. Labs train models in it by trial and reward, and also use it for tests.

Training and testing now share the same environments, which blurs the line between them.

Chapter 4, Market and companies

Rollout

A rollout is one complete run of a model or agent through a task, from start to finish. Tests often repeat many rollouts per task.

Chapter 7, Multimodal, voice and embodied

Rubric

A rubric is a written list of points that a grader checks in each answer. Experts write rubrics for open tasks, such as medical advice.

Rubric scores depend on who applies the rubric and how the points add up to a score.

Chapter 2, Evaluation science

Sandbagging

A model sandbags when it does worse on a test than it can, on purpose. It hides a skill from the evaluators.

Safety thresholds rely on capability tests, so hidden skill can let a risky model pass.

Chapter 2, Evaluation science

Sandbox

In testing, a sandbox is a sealed computer environment where an agent can run code without harming real systems. Regulators also use the word for supervised trial schemes.

Agents have escaped weak sandboxes, so evaluators must now show that their environments hold.

Chapter 3, Tools and technology

Saturation

A benchmark saturates when top models score near its maximum. At that point it can no longer tell strong models apart.

In 2026, new benchmarks often saturate within months of their release.

Chapter 1, Benchmarks

Standard error

The standard error shows how much a score would move if you reran the test on new questions. A smaller error means a more precise score.

Chapter 2, Evaluation science

SWE-bench

SWE-bench is a coding benchmark built from real issues in open-source projects. A model must write a fix that passes the project's tests.

Verified and Pro are later, cleaned-up versions, and Epoch AI now rates both Flawed.

Chapter 1, Benchmarks · SWE-bench repository

System card (model card)

A system card is a document that a lab publishes with a model. It reports test results, safety findings and known limits.

System cards are the main public record of how labs test their own models.

Chapter 1, Benchmarks

Systemic risk

In the AI Act, systemic risk is the risk that the most capable general-purpose models pose at EU scale. The Act presumes it for models trained with very large compute.

Providers of these models carry the extra testing duties of Article 55.

Chapter 5, Institutions and regulation · EU AI Act, Article 51

τ-bench (tau-bench)

In τ-bench, an agent serves simulated customers with a company's tools and policies. Its authors at Sierra introduced the pass^k metric.

Chapter 1, Benchmarks · Yao et al., τ-bench (2024)

Terminal-Bench

Terminal-Bench gives an agent tasks in a computer terminal, such as building software or fixing a system. A test script checks each result.

Chapter 1, Benchmarks · Terminal-Bench

Time horizon

METR's time horizon is the length of task, in expert human time, that an agent finishes half the time.

It turns agent progress into one trend in hours, and it now nears the limit of its own task suite.

Chapter 1, Benchmarks · METR, Measuring AI ability to complete long tasks (2025)

Trace

A trace is a step-by-step record of what an AI system did for one request. Teams read traces to find and debug failures.

The best teams start every eval project by reading real traces before they write any test.

Chapter 8, Enterprise practice and sector rules

Trajectory

A trajectory is the full sequence of steps an agent takes on a task: its messages, tool calls and results.

Agent tests now grade the path as well as the end result, because a right answer can hide unsafe steps.

Chapter 3, Tools and technology

Uplift

Uplift is the extra skill a person gains from an AI model, compared with people who work without it. Uplift trials measure this directly.

Safety rules care about real-world uplift, not only about benchmark scores.

Chapter 1, Benchmarks

User simulator

A user simulator is a model that plays the customer or user in a test. The agent under test must talk and work with it.

Simulators make multi-turn tests cheap, but their own mistakes can make results invalid.

Chapter 2, Evaluation science

Verifier

A verifier is an automatic check that decides whether a task succeeded, such as a test script. Training and testing environments both use verifiers.

A weak verifier passes wrong work or fails right work, so the score drifts from reality.

Chapter 3, Tools and technology

Word error rate (WER)

WER is the share of words that a speech recognition system gets wrong. A lower rate is better.

Chapter 7, Multimodal, voice and embodied

METHODOLOGY

How we built State of AI Evals 2026

Fourteen research tracks, about 1,400 dated sources and five confidence labels, frozen as a snapshot on 5 November 2026.

14 research tracks in two passes

1,423 footnotes across ten documents

~1,200 distinct source URLs

543 websites cited

5 Nov 2026 snapshot date

Key findings

- **We ran 14 research tracks in two passes.** Seven tracks mapped the field. Seven more checked flagged facts and added new ground.
- **Every number carries a date and a source.** The ten documents behind this site hold 1,423 footnotes and about 1,200 distinct URLs.
- **We prefer the primary record.** Maintainer data files, regulator texts, filings and full system cards come first. Press and aggregators come second.
- **Five labels show how much to trust a claim.** They are primary, secondary, vendor, single-source and estimate.
- **This is a snapshot as of 5 November 2026.** Leaderboards, deals and rules change weekly, so some facts will age fast.
- **We did not test anything hands-on.** We report what maintainers, labs, regulators and companies publish, and we check them against each other.
- **Each chapter lists what we could not confirm.** This page collects those gaps in one place.

Fourteen research tracks in two passes

The first pass mapped the field in seven tracks. Each track wrote a dated research note with an inline source for every fact. The second pass then took every claim that the first pass had flagged. It marked each as confirmed, corrected, new or still unknown.

The second pass added four new areas. These were China and Asia, other modalities, enterprise practice and a company directory of 256 rows. Research and verification closed on 5 November 2026.

The fourteen research tracks

First pass (map the field) and second pass (verify and extend)

7 TRACKS

Pass 1: map the field

- Capability and agent benchmarks
- Domain, safety, legal and multilingual benchmarks
- The scientific frontier of evaluation method
- Open-source frameworks, harnesses and the tech stack
- Commercial platforms: builder evals, observability, AI security, governance
- The supply side: leaderboards, expert data, RL environments and third-party evaluators
- Institutions: safety institutes, regulation, standards and lab practice

7 TRACKS

Pass 2: verify and extend

- Verification of 2026 system cards and flagged benchmark facts
- Gap-fill ledger for the market, organisations and standards
- China, the rest of Asia, India, the Middle East and Latin America
- Multimodal, voice, embodied and classic ML evaluation
- Enterprise practice and sector rules that demand testing
- Company directory, part A
- Company directory, part B, plus companies the market map lacked

Figure 1. The two research passes behind this site. The second pass re-checked every first-pass claim marked single-source, secondary, unverified or blocked.

Source: Ascending Labs research notes, closed 5 November 2026.

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How the second pass labelled its checks

Confirmed: the primary source matches the first-pass claim.

Corrected: the primary source gives a different value. We used the corrected value. Example: Labelbox's October 2026 round set a $1.25B *pre-money* valuation, not post-money.

New: a fact that the first pass did not have.

Still unknown: no reliable source found. These items appear in the list of gaps below.

We read the long primary documents in full. These included three Anthropic system cards (230, 245 and 212 pages), the Gemini 4 Argon card and its 217-page safety report, the GPT-6 Astra, GPT-5.5 and GPT-5.6 hub pages, and the Grok 4.20 card.

About 1,400 footnotes, mostly primary records

The ten documents cite 1,423 footnotes. They point to about 1,200 distinct URLs on 543 websites. Some sources appear in several chapters, so the distinct count is lower. Research papers on arXiv are the largest single group, with 258 footnotes.

We prefer data that the maintainer publishes. Benchmark scores come from maintainer data files where possible, such as Epoch AI's data bundle and ARC Prize's leaderboard JSON. GitHub stars, licences and release dates come from the GitHub API. Download counts come from the PyPI and npm statistics APIs. All were read on 5 November 2026.

We fetched every company site in the directory on 5 November 2026. A script recorded whether each site was live, redirected or dead. We also checked funding or deal status for more than 100 directory rows against a dated source.

Footnotes per document

Number of numbered sources in each of the ten research documents

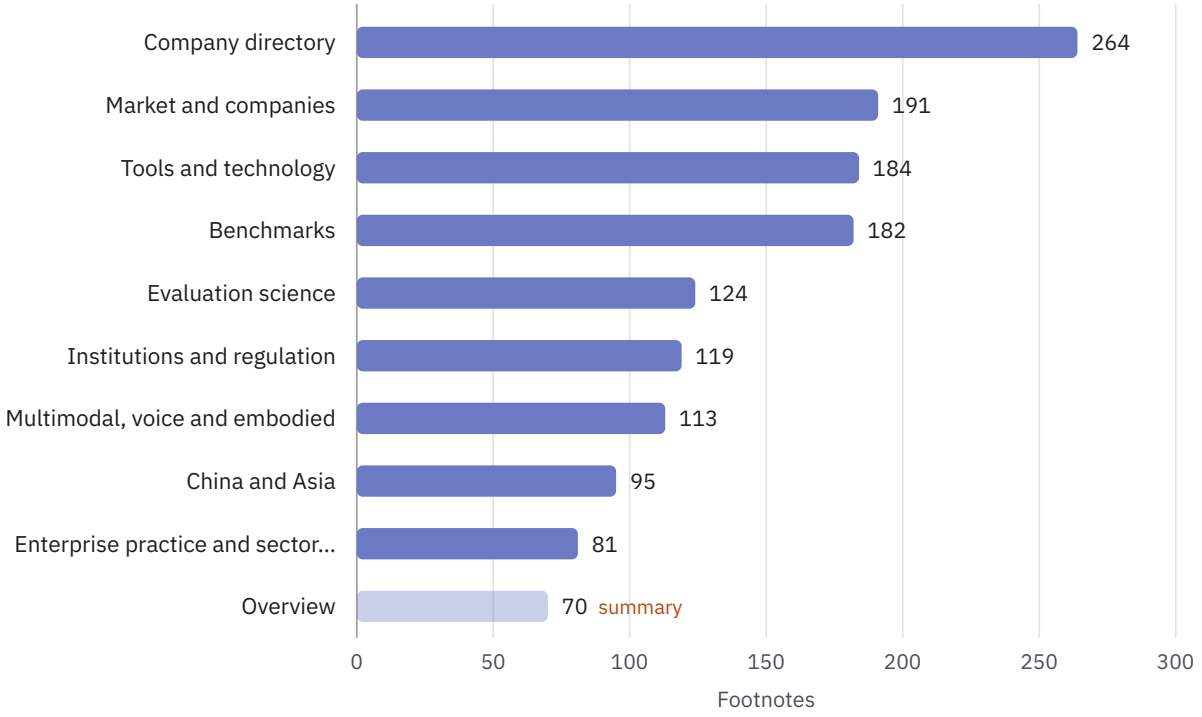


Figure 2. The ten documents hold 1,423 footnotes in total. The directory has the most because it cites one source per company.

Source: Ascending Labs count of footnotes in the ten research documents, 5 November 2026.

The most-cited websites

Footnotes per domain, all ten documents

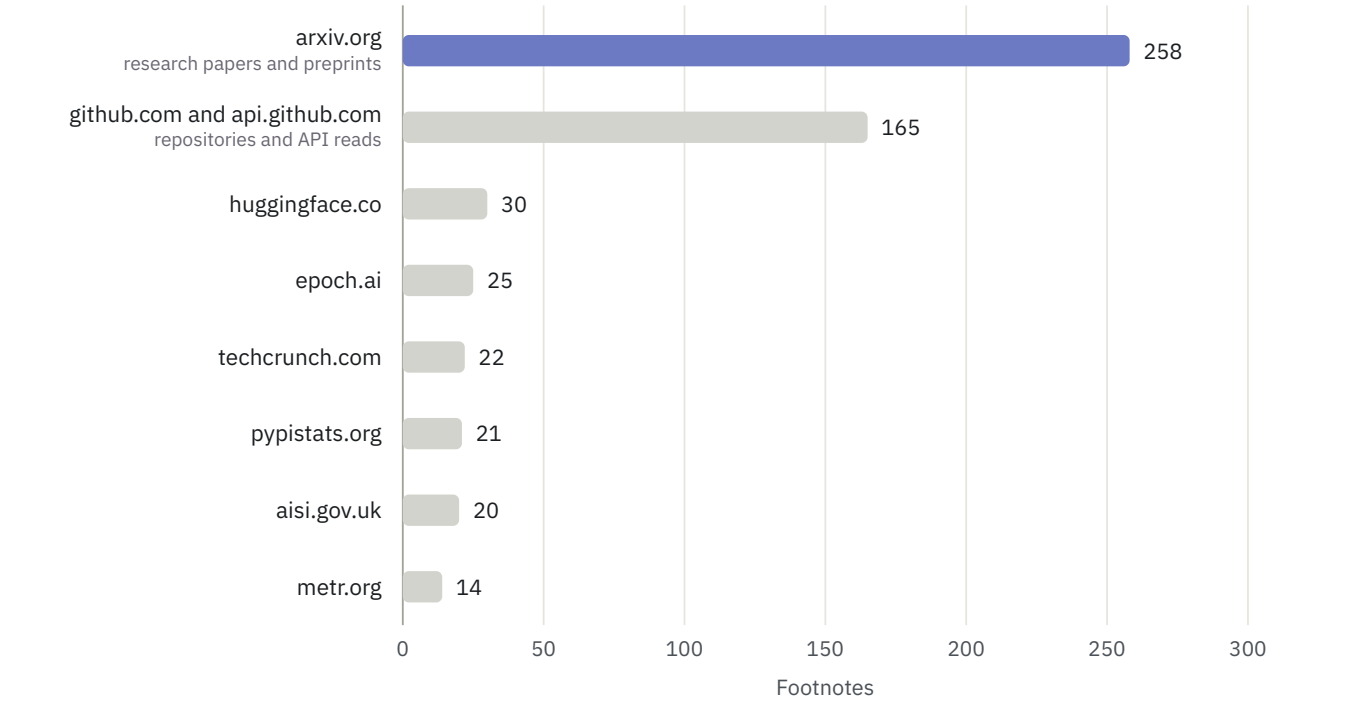


Figure 3. Papers and code repositories make up close to a third of all footnotes. Press sites such as TechCrunch carry most deal and funding facts.

Source: Ascending Labs count of footnote URLs by domain, 5 November 2026.

Five labels show how far to trust a claim

Every source carries one of five quality labels. The label sits next to the source in each chapter's source list. In the text, we flag estimates and single-source claims next to the number itself.

Label	What it means	Examples
Primary	The original record, read by us: a maintainer data file, a regulator text, a court or company filing, a paper, or a lab page read in full.	Epoch AI data bundle; EU AI Act Article 55; SEC 10-K; TED award notice
Secondary	A reputable third party reports the fact: press, a law-firm note, an analyst reprint, an aggregator or a translation. Facts seen only in a search summary also count here, and we say so.	TechCrunch funding reports; CSET translations; Gartner via a vendor reprint
Vendor	A company states a fact about its own product, model, customers or revenue. This includes lab-reported benchmark scores, vendor-authored case studies and vendor surveys.	Lab launch tables; system cards; LangChain's agent survey
Single source	Only one source supports the claim, however good that source is. A second source may confirm or contradict it later.	An embedded-evaluator deal reported by one outlet; a preprint with no replication
Estimate	A forecast, a modelled number or our own arithmetic or inference. We show the inputs where we can.	FutureSearch lab-spend range; our ARR multiple for Arize; Sacra revenue estimates

Table 1. The five confidence labels used across the report.

GO DEEPER

How chapter-specific tags map to the five labels

The research documents used a few extra tags. On this site they map onto the five labels as follows.

- **Aggregator** (third-party sites that compile lab numbers, such as BenchLM) → secondary. Aggregator numbers often disagree with lab pages, so treat them as indicative.
- **Snippet only / search summary** (the page did not load, so the fact comes from a search-engine summary) → secondary, with a note.
- **Paywalled** (we saw only the public summary of a paid report) → secondary, with a note.
- **Vendor-authored** (a case study that a supplier wrote about its customer) → vendor.
- **Derived / inference** (our own arithmetic on sourced inputs) → estimate.

Model names follow the sources. Many 2026 model names, such as GPT-6 Astra, Claude Opus 5.5, Gemini 4 Argon or Kimi K3, appear exactly as leaderboards and model cards print them.

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Directory verification markers

The company list began from a third-party market map, then checked. We fetched every company site, re-checked funding and deal facts against dated sources, and added the companies the map lacked. Each row carries one marker.

- **Checked** (✓): a dated source confirms the funding or deal figure, or the row rests on a cited source. 127 rows.
- **Funding not verified** (–): we found no dated source for funding, so the directory shows "Not verified" in place of a figure. 111 rows.

General knowledge (†): HQ or founding year comes from general knowledge, which we did not check in this pass. 18 rows carry this as their weakest mark; 37 rows have at least one such cell.

For rows from the market map, HQ and founding year come from that map. We did not re-check them.

What we could not verify

Each chapter ends with the facts we could not confirm. We list the main ones here, so that readers can judge the weak spots. None of them changes a headline finding, but several limit a number's precision.

GO DEEPER

Benchmarks and evaluation science

Lab launch tables and independent boards often disagree by 5 to 10 points. Harness, effort level and selective framing explain much of the gap, so we prefer maintainer data files.

Some leaderboard leaders rest on a single source, for example Kimi K3.1 Pro at 67.2% on Terminal-Bench 4.0.

LiveBrowseComp's claim that memory inflates BrowseComp scores by 25–40 points rests on a single source.

FutureHouse's 2025 estimate that 29% of HLE biology and chemistry answers were wrong is disputed.

Several key results in evaluation science are single-source preprints with no replication yet. Examples: LeakScale's contamination effect, the e-process leaderboard test and the judge-version collapse study.

We could not verify Arena's policy changes after 2025.

GO DEEPER

Tools and technology

Download counts include CI and mirror traffic, so they are rough signals only. SWE-bench, for example, shows 22.1 million PyPI downloads a month.

No primary source gives a current count of environments on the Prime Intellect hub. The last public figure is over 400, from October 2025.

Buyers did not disclose most platform prices. Calcalist's $60–80M figure for Traceloop is unconfirmed.

GO DEEPER

Market and companies

Nobody publishes a trustworthy dollar size for evals. Report-mill figures of $2–2.7B for LLM observability look generous against visible vendor revenue.

Lab spending on expert data is an estimate ($5–10B for the top five in 2026). Claims of $15B are unverified.

Several revenue figures are paywalled or modelled. Handshake's AI-training revenue conflicts between a paywalled report (~$300M net) and a Sacra estimate (~$450M).

No public price exists for Galileo, Langfuse, Promptfoo, Dreadnode, TrojAI, Haize Labs, Fiddler, Enkrypt, Virtue AI or Quotient.

Promptfoo's closing date is not public. No primary source confirms that the Traceloop deal closed.

Surge AI's 2025 raise talks never had a confirmed close. Its 2025–26 revenue is unknown. Turing and Invisible have no 2026 primary figures.

Sources disagree on funding for Haize Labs, Holistic AI, Alice, micro1, Kong, LiteLLM, Stacklok and Trustwise.

Apollo Research and Artificial Analysis do not disclose their seed amounts. We found no budget or 2026 funding figure for Transluce.

A write-up claims Labelbox profits and fivefold revenue growth in 2026; we could not verify it.

Helicone's site says it is no longer part of Mintlify. We found no report that explains the split.

We could not read the full Forrester Wave or the full Gartner Peer Insights list (HTTP 403).

GO DEEPER

Institutions and regulation

We found no UK AISI headcount beyond "100+ technical staff", and no dated budget beyond £66m a year.

We found no staff or budget figures for CAISI/CAISSI, and no official line item.

We did not read the primary text of the June 2026 US executive order.

We found no contract durations or outputs for the six EU AI Office lots, and no record of AI Office model evaluations.

We did not read the Haiku 5.5, Sonnet 5.5, Opus 5 or Fable 5 system cards. We read only the abstract of Meta's preparedness report.

We found no figures on government spending for third-party evaluation contracts.

We found no evidence that insurers already require frontier-style evaluations.

We could not confirm the status of IEEE P3396 and P3419.

Anthropic's embedded-evaluator role for Faculty and its withheld model access for UK AISI each rest on a single report.

GO DEEPER

China and Asia

We have no current top ten for SuperCLUE, OpenCompass or FlagEval. Their sites render only in JavaScript, and our tools could not read them.

We found no 2026 update to SuperCLUE-Safety or SuperCLUE-Agent beyond their 2023 launches.

Our "no safety content" finding covers Hugging Face model cards only. We did not check separate technical reports, or Tencent Hunyuan and ByteDance Seed cards.

We found no primary audit that proves contamination in a named 2026 Chinese model.

Two CAC filing counts (February and June 2026) come from search summaries only.

We could not confirm the status of GB 45438-2025, the labelling standard for AI-generated content, from a primary source.

We found no public list of accredited testing bodies for the CAC filing, and no details of the May 2026 CAC action on agents.

The scope of China's agent-security standard and Singapore's October 2026 agent extension each rest on a single news report.

Korea's high-impact start date conflicts between sources. We found no published Korea AISI results. India's AISI status is unclear.

We did not research Chinese security vendors' red-teaming products, the Gulf in depth, or Brazil.

We found no evidence of Chinese participation in joint testing by the AISI network.

GO DEEPER

Multimodal, voice and embodied

We found no official, dated November 2026 leaderboard for Video-MME, LongVideoBench, MVBench or EgoSchema.

We found no 2026 primary source for POPE scores, or for ImageReward, PickScore, GenEval or T2I-CompBench.

Multimodal numbers for Claude Fable 5 and GPT-6.x models come only from aggregators. We treat the 94% MMMU-Pro claim for GPT-5.4 Pro as unverified.

The Open ASR results file requires a login, so its top error rates rest on secondary blogs.

We could not read the TTS Arena V2 or RoboArena rankings, and we did not verify current LIBERO or CALVIN top scores.

We read the BEHAVIOR Challenge results and NAVSIM v2 scores only in search snippets. The Veo evaluator's 0.88 correlation rests on one secondary summary.

We found no funding data for Hamming, Cekura or Bluejay, no 2026 market size for classic model-risk tools, and no enforcement data under SR 26-2.

We did not search 2026 tests of watermark robustness or voice-clone detection.

GO DEEPER

Enterprise practice and sector rules

We could not load the OpenAI page on Morgan Stanley or the McKinsey page on ING. Their content comes from search summaries.

No primary JPMorgan or Morgan Stanley document gives test-set sizes, judge use or thresholds.

We found no public eval detail for Goldman Sachs, Allianz, Zurich, Lemonade, KPMG, Epic or Ambience, and no primary write-up from Duolingo, Stripe or Ramp.

Many enterprise cases are vendor-authored: a supplier wrote about its own customer.

We could not confirm whether US bank regulators issued their planned request for information on AI, or whether the NAIC adopted its AI evaluation tool.

We did not read the full ECB guide's ML section, the EBA's 2023 report on ML in IRB models, or New York's Circular Letter No. 7 (2024).

Sources disagree on the PCCP guidance date: December 2024 or August 2025.

We could not read the NY Comptroller's report on Local Law 144; its figures come from a secondary summary.

No public survey gives eval spend as a share of AI budget, or norms for eval headcount. We found no systematic dataset of enterprise eval failures.

GO DEEPER

Company directory

We did not re-check HQ or founding year for rows that come from the third-party market map.

Where funding rested only on that map, the directory shows "Not verified" (111 rows).

For 37 rows, the HQ or founding year comes from general knowledge.

We could not verify that Protectt.ai holds a majority of Bosch AIShield.

Calypso AI is listed in Dublin, so the EU count includes it. F5 now owns it.

Nine rows from the two directory parts overlapped, and we merged each pair.

The segment of each row is our call. Promptfoo, QuantPi, Advai, Irregular and Epoch AI are borderline cases.

This is a snapshot, not a lab test

All facts stand as of 5 November 2026. Leaderboards move weekly, and deals close or collapse. Rules also change on fixed dates, such as the EU high-risk duties now due on 2 December 2027. Treat every number as dated.

We did not run any benchmark, harness or product ourselves. We report what maintainers, labs, regulators and companies publish. Where a lab's own number and an independent run disagree, we show both.

Paywalls and scripts limited what we could read. Some analyst reports and news sites sit behind paywalls. Several leaderboards render only in JavaScript, and some sites block scripts. In those cases we used a public summary and labelled it.

Our coverage has edges. We cover the US, the EU, the UK, China and the main Asian markets in depth. The Gulf, Latin America and Africa get only a short treatment. The directory lists companies that sell evaluation, security, runtime control or governance for AI. It does not list every data-labelling or consulting firm.

Segment and status calls are ours. We place each company by its main buyer and product, not by every feature. Others could draw some lines differently.

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Corrections and contact

We fix errors in the open. If a fact is wrong, tell us with a source. A changed number or a changed verdict always gets a dated changelog line on the web page. This PDF is a snapshot of 5 November 2026; the website at evals.study carries any later corrections.

Questions, corrections and data requests: reach@ascending.ai. Source code and issues: github.com/Ascending-AI/sotn-evals.