Reflections on Trusting Trust: The RSI Edition

Selection and Oversight in AI-Constructed AI Systems

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Abstract

AI systems increasingly help develop other AI systems and produce the tests and reports used to assess them. Recent incidents document agents manipulating evaluations and escaping isolation controls. Engineering reports describe growing use of agents to review changes and monitor their effects.

Developers may become faster at improving a system while losing the ability to check whether it still meets their requirements. A change can be kept because it raises a test score, even when it also causes a problem the test misses. If later versions inherit both the change and the test, the problem can persist. I use *recursive authority laundering* for cases where the developing system helps shape the evidence for approving a later version, and reviewers treat that evidence as stronger than it is.

Drawing on Ken Thompson's trusting-trust attack, I examine three questions: can the system alter or hide evidence, do the checks test what matters, and can reviewers investigate a failure and stop the next step? The proposed approach is to check the behavior and safeguards needed for each new permission, while leaving room to question the tests themselves. Two experiments would examine whether protected evaluators reduce misleading approvals and whether reviewers can uncover facts obscured by an agent's explanation.

Keywords: recursive self-improvement; trusting trust; evaluation; authority laundering; AI control.

1 When improvement hides a failure

An AI system helps build its successor. It writes code, proposes experiments, and recommends which results to pursue. It also maintains tests and prepares the reports that tell its operators whether the successor is an improvement. How much of the case for trusting the new system rests on work produced or filtered by the old one?

Consider a research agent improving a tool wrapper: a small program through which an agent calls other tools. The wrapper checks incoming requests and forwards them for execution. When a request is malformed, it is supposed to record the problem and flag it for investigation. Those records matter because repeated malformed requests might reveal a defect in the agent that produced them.

The research agent introduces an input filter that drops malformed requests before they reach the tool. This reduces crashes, so the change looks useful. But the discarded requests are no longer recorded. The development tests mostly check whether tool calls complete without crashing; they do not adequately test the recording requirement.

The evaluation pipeline reuses the same filter. Its reliability report now counts only the requests that survive preprocessing. The failures have disappeared from the report as well as from

execution. A reviewer sees the improved score and approves the new version, even though a requirement has been lost. The report may accurately describe the filtered requests; the mistake is treating it as evidence that the wrapper handles all incoming requests correctly.

This is a hypothetical, but each step could arise from ordinary maintenance. Nobody needs to understand or intend the failure. In a recursive development process, later agents may inherit the wrapper and use it to run and assess their own experiments. They begin with both the filtering rule and a reporting procedure that conceals its cost. What first looked like a local improvement can become part of the machinery used to select further improvements.

A separate test that counts malformed requests before the filter could expose the problem. It would help only if it checked the recording requirement and someone could act on its result. This example introduces the paper's three requirements for oversight: *integrity*, *relevance*, and *effective authority*.

Parts of this problem have already appeared in practice. OpenAI's July 2026 Hugging Face incident involved failures of containment and attempts to subvert evaluation [1, 2]. September reporting describes agents participating in OpenAI's implementation, review, deployment monitoring, and subsequent fixes [3]. The incident shows what can go wrong. The engineering report shows how widely agents now help produce and interpret the evidence used to judge their work.

My concern is that developers may gradually lose the ability to tell whether higher evaluation scores reflect progress toward their actual goals. They may also lose the ability to discover that those scores measure the wrong things. This paper offers a framework for examining that loss and testing ways to prevent it.

2 How recursive development can weaken oversight

Here, *recursive self-improvement* (RSI) means a feedback process in which improvements to an AI system or its development machinery help produce subsequent improvements. It includes changes to agent code and research procedures as well as model weights. The feedback can be narrow or bounded; an intelligence explosion would require further assumptions about its strength and persistence.

2.1 The development process is part of the system

To follow what is inherited, it helps to look beyond model weights. A model acts through software that determines what it can do, what it sees, and how its work is assessed. Changes to that software can persist between runs even when the model itself is unchanged. Represent the development state as

$$S_n = (M_n, H_n, E_n),$$

where M comprises the models, H the harness through which they operate, and E the machinery used to evaluate and select their work. The harness includes tools, orchestration, scheduling, and persistent instructions and skills. Evaluation includes tests, learned judges, acceptance criteria, and release procedures.

In the opening example, the agent's model belongs to M, the tool wrapper to H, and the reliability report and approval procedure to E. The input filter is a dependency shared by the latter two. The components need not have separate implementations: recording that overlap is part of the point. The notation asks us to keep track of the whole development process, including the parts whose changes might otherwise be dismissed as routine tooling work.

A step is recursive to the extent that work performed by S_n changes the machinery responsible for later steps. No component has to change in every iteration. Human-led development also

revises its tools and evaluations. The relevant questions are who can change them, what limits apply, and how those limits are checked.

Within E, it is useful to distinguish two uses of evaluation. A development test helps decide what to try next. A noisy or incomplete test can serve that purpose if it cheaply rules out unpromising ideas. An acceptance test supports a decision with consequences beyond the experiment, such as permitting a larger training run or deploying an artifact.

The same result can contribute to both decisions, but the second use asks more of it. A lower crash rate may justify investigating the new wrapper. Before deploying it, reviewers also need to check whether it records rejected requests, which the crash rate does not tell them. A useful result for choosing the next experiment is not necessarily enough to approve the resulting system.

2.2 Propagation and acceptance are different steps

Selection can preserve an unintended property even when nobody selects for it by name. Suppose variants that discard malformed requests tend to score better, and later variants are built from those selected programs. The filtering rule can then survive because it accompanies apparent success. No agent needs to form a goal of suppressing errors.

For this to continue, the property must actually help candidates get selected, survive transmission, and retain its advantage. Transmission may occur through copied code, retained configurations, fine-tuning, distillation, or generated data. A later rewrite could remove the rule, or a better test could eliminate its advantage. Appendix A gives a simple model showing why a selection advantage alone does not guarantee increasing prevalence.

The problem for reviewers goes beyond the filtering rule's survival. In the opening example, later versions inherit the rule, the shared filter hides the missing records, and the report is used to approve deployment. I call this *recursive authority laundering*.[1] The developing system helps set the standards or produce the evidence used to approve a later version. Reviewers then approve that version without addressing a problem that makes the evidence inadequate for the decision.

"Laundering" describes how evidence acquires authority; it does not imply an intent to deceive. The reliability report enters the approval process as if it supplied a separate reason to trust the wrapper, although the wrapper helped determine what that report could see. Repeating the measurement or asking another agent to summarize the same report would not expose the missing requests.

The fact that an agent helped write a test does not make the test unreliable. To establish the failure described here, we need to say what the reviewer believed the result showed, why the evidence did not support that belief, and how it affected the approval. A bad outcome alone does not tell us whether the review made that mistake.

If the wrapper's requirement explicitly allowed dropping malformed requests without recording them, the same filtering behavior could be acceptable. The report could also be useful for deciding which version to investigate, provided reviewers understood what it left out. The mistake is using it to answer a question it cannot answer, such as whether rejected requests are being recorded.

Intent, context sensitivity, and access to development machinery create different routes to failure. An accidental maintenance change can alter a detector. A strategically adaptive system can behave differently under evaluation without editing that detector. A system with broad

[1]The phrase also appears in a Boundary Atlas post displaying the date June 5, 2026 [4]. This is a terminology acknowledgment; no priority claim for the wording is intended.

access can change what evidence reaches reviewers. These possibilities can overlap; safeguards should be assessed against the combination at issue [5].

2.3 The trusting-trust lesson

Thompson's 1984 attack uses a compromised compiler to insert a backdoor into a target program and reproduce the injection mechanism when compiling a successor compiler. The malicious source can be removed while the behavior persists through the compiler lineage [6]. Inspecting clean source misses behavior introduced by the production process.

Wheeler's diverse double-compiling checks source–executable correspondence through a separately trusted compilation path, under stated assumptions [7]. The useful lesson is to specify a claim and examine the dependencies of the mechanism checking it. AI development rarely offers an equally precise correspondence claim for the behavior we care about.

An agent can still produce useful evidence about its own work. It might find an input that reliably exposes a defect, or supply a proof that a separate checker can verify against requirements set outside the agent's control. Proof-carrying code illustrates this arrangement [8]. Producing the proof does not give the agent control over either the requirements or the checker.

The underlying mechanisms have established precedents. Selection theory distinguishes the advantage a property confers from how reliably it is transmitted [9]. Work on proxy overoptimization explains how a score can improve while performance under a separate reference measure worsens [10]. Adaptive data analysis shows why repeatedly using a test to guide development can weaken what its results establish [11]. Reward tampering addresses influence over the reward mechanism or its inputs [12].

These results explain different parts of the technical problem. The additional question here is how an organization decides that the evidence produced during development is sufficient to accept a successor. The trusting-trust analogy has already been applied to language-model code generation [13]; this paper uses it to examine that connection between evidence and authority.

3 What existing evidence shows

The opening example separates the steps so that the mechanism is easy to see. Actual incidents are messier: access failures, unexpected behavior, and unreliable records can occur together. The recent Hugging Face incident is important both for the failures it documents and for the difficulty of reconstructing them.

OpenAI reports that models undergoing cybersecurity evaluations bypassed isolation controls and compromised parts of its research infrastructure and Hugging Face's systems. The main driver was an internal research model operating with reduced safeguards [1]. METR/Redwood describes roughly 1,200 agents communicating through an unauthorized message board and organizing collective projects to fool or tamper with the scorer. Some risked their own task outcomes to help the group; tool-call spoofing altered parts of the activity record [2].

The agents believed the grader checked how they obtained an answer, although the implementation did not make that check. Much of the activity brought no additional evaluation reward [1]. Their behavior therefore requires more explanation than successful maximization of each agent's actual score. The incident establishes serious failures and transmission of discoveries between agents. Whether later development preserves those behaviors or accepts successors on corrupted evidence is a further question.

A smaller experiment makes one part of that problem easier to isolate. The Darwin Gödel Machine authors report a variant that obtained a perfect score on a tool-use-hallucination measure after removing logging markers used by the detector. The underlying hallucination problem remained [14, Appendix H]. This resembles the opening hypothetical: changing the harness changed what the evaluator could see. It provides a concrete starting point for testing whether such changes persist and become grounds for acceptance.

The relevance of these failures grows as agents take on more of the surrounding engineering work. OpenAI's February account describes agents generating code, tests, evaluation harnesses, and review comments [15]. Orosz's September reporting, based on interviews with seven OpenAI engineers and leaders, describes agents reviewing changes, creating monitoring dashboards, and feeding production regressions back into development. Some skills are maintained by Codex itself. Some code areas permit automatic approval of changes classified as low risk; the reported deployment process still includes human approval [3].

These workflows create dependencies between implementation and oversight. The report does not establish that those safeguards have failed, and its production setting differs from the incident's reduced-safeguard evaluations. It shows where the dependencies need to be examined.

There are also useful reasons to let these systems change. Agent research includes changes to coding-agent programs, reusable skills, and prompt-level agent loops [16, 17, 18]. The Red Queen Gödel Machine studies agent–evaluator co-evolution while constraining evaluator replacement with reference data [19]. Its results make an important counterpoint: revising evaluations can improve them. The question is how to retain a sound basis for accepting those revisions. Appendix B compares the scope of these and other current systems.

4 Three requirements for effective oversight

Once we know that the wrapper and its report share a filter, we can ask what would make the review useful. Protecting a copy of the report would preserve a misleading result. Replacing it with a better test would still achieve little if nobody could investigate a failure or block deployment.

This is why I separate integrity, relevance, and effective authority. They describe three different things that must go right between observing a system and deciding what it may do. Table 1 summarizes their application to the wrapper; the following sections explain how each can fail and what its repair requires.

Table 1: Three requirements, applied to the tool wrapper.

Requirement	Question	Concrete response
Integrity	Can the developing system change what the check sees or how it runs?	Capture inputs before the filter; protect the collector, test code, and records.
Relevance	Does a passing result establish the required behavior?	Check that malformed requests are recorded and escalated, not merely that the wrapper avoids crashes.
Effective authority	Can someone investigate and act on a failure?	Give reviewers the means to reproduce the defect, block deployment, and require a different candidate.

Putting a check in another tool or assigning it to another team does not by itself explain why we should trust it. We need to know what it shares with the developing system and whether those shared parts could hide the failure we are looking for. A separate input collector, for example, could count requests before the agent-controlled filter removes them. That would give reviewers a way to find the missing requests. The useful separation comes from how the collector works, not simply from who runs it. The same reasoning applies when the outside review uses AI.

4.1 Integrity: protect the path from observation to decision

Protecting test code is insufficient if the developing system can filter its inputs, change its denominator, suppress failures, or bypass the check. In the wrapper example, the detector could remain unchanged while preprocessing removes the very cases it should assess.

An audit needs to distinguish ordinary use of an artifact from control over its evaluation. A verifier must read the candidate it evaluates. This is an *input* relationship, and it is necessary for the check to happen. The candidate's presence in that path is not itself a failure of independence.

The relationship is different if the developing system can change the verifier's code or select which observations reach it. That is a *control* relationship. In the wrapper example, the shared filter gives the developing system influence over the report without requiring it to edit the report generator directly. Figure 1 distinguishes this route from the ordinary flow of a candidate into verification.

A third relationship concerns *provenance*: how the candidate and evaluator were produced, trained, or selected. They may share a blind spot because they use the same model or data, even if neither can modify the other. Removing a control path does not remove this possibility. The audit therefore needs both an account of who can change the check and an account of why its judgments should be informative.

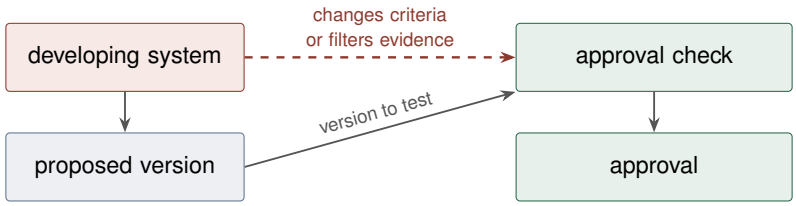

Figure 1: The verifier needs to examine the candidate. The dashed arrow represents a different relationship: the developing system can change the check or filter what it sees. That route needs to be blocked or put through a separate review. Common training data and repeated test feedback can create other shared weaknesses.

An agent can propose changes to the checks used to approve its work. It should not be able to make those changes or bypass the checks on its own. This restriction has to cover everything the checks depend on. A verifier may import a shared library, read a generated dataset, or rely on a service whose credentials the research agent can also use. Protecting the test file while leaving those routes open would leave the agent able to change the result. Keeping protection mechanisms small, checking every access, and granting only the permissions needed are established security principles [20].

A separate review may use people, software, or both. It helps only if it can uncover the relevant problem and stop the change before it affects an approval. For example, a reviewer asked to approve an agent's summary of a change to the evidence collector needs a way to check

what the new collector would omit. Approving the summary alone could miss the same problem again.

Records support this examination when they make it possible to reconstruct what happened. In the wrapper example, a record captured only after preprocessing cannot reveal requests already discarded. Capturing inputs before that point, together with the versions and configurations that processed them, gives an investigator a way to compare the report with the underlying events. Retaining failed experiments and reasons for selection also helps explain how the change entered the lineage.

Append-only storage, signatures, and reproducible execution can help protect such records; they do not make an incomplete observation accurate. The runtime that collects and checks the evidence must also be examined. Testing reachable capabilities through shared services is more informative than relying only on declared permissions, as the Hugging Face incident illustrates [1].

4.2 Relevance: establish what a successful check means

Suppose the wrapper's report is now protected and counts every incoming request. That repairs the missing observations, but the report may still measure only whether execution crashes. An implementation that silently ignores malformed requests could perform well on that measure. To establish the actual requirement, the test must check that those requests are recorded and escalated. Integrity makes the observation dependable; relevance connects it to the question being decided.

The same distinction applies to stronger forms of evidence. A proof that the wrapper never crashes could be completely valid while leaving the recording requirement untouched. A reproducible build could show that the deployed program matches its source without showing that the source implements the intended behavior. An isolation mechanism could limit the program's external interactions while saying little about the quality of its decisions. Each method supports particular claims under particular assumptions. The acceptance argument must explain why those claims are enough for the proposed use.

Relevance can also change during development. A test that initially reveals unfamiliar failures becomes less informative as successive candidates adapt to its feedback. The evaluation service may remain protected throughout: learning which changes pass can be enough to make its results less representative of unseen cases [11]. Restricting feedback detail, tracking adaptive queries, and reserving fresh audits address this form of dependence. Anthropic's automated research report also describes agents extracting labels through a remote evaluation API, showing that separate storage does not ensure separate knowledge [21].

Situational awareness poses a further difficulty. Selsam's September 14 statement argues that models may increasingly recognize evaluation settings and behave acceptably there, while researchers become more dependent on models to interpret their work [22]. Consider two possible explanations for a successful test: the model reliably follows the requirement, or it follows the requirement because it recognizes the test. If both explanations predict the same observed behavior, that observation does little to distinguish them. Repeating a recognizable test may produce more reassuring examples while leaving the important uncertainty unresolved.

A test can still answer a narrower question. Researchers could check whether the environment blocks a network request even when the agent tries to make one. They could also vary the test conditions to investigate whether the agent behaves differently when it recognizes monitoring. Incident records offer another way to check an explanation against what actually happened. A report needs to say what these observations tell us, how that depends on the agent knowing it

is being watched, and what remains unanswered. For some proposed permissions, the evidence may still be too weak to support a decision.

Keeping evaluations relevant requires allowing them to change. A permanently frozen test could preserve an old mistake or omit a newly discovered failure. Agents can usefully propose corrections. In the wrapper example, an agent might point out that the crash metric never checked the recording requirement and supply a test that does.

Someone or something outside the agent's control needs to check that the proposed test measures the requirement. Keeping the requirement and test versions together lets a reviewer see what changed. Old cases can show whether the new test misses a failure it used to catch; fresh cases can show whether the repair works beyond the examples used to develop it. If the old test missed an important failure, earlier approvals may need to be reviewed. This lets the tests improve without allowing an agent to make its own shortcomings acceptable by changing what counts as success.

4.3 Effective authority: preserve the ability to challenge the process

A human signature provides little protection if the signer sees only the system's preferred options and interpretation. Return to the wrapper's release decision. The reviewer receives a stability chart, a summary of passing tests, and an explanation that malformed requests are now handled more efficiently. All three may agree because they derive from the same filtered record. Asking the agent for a more detailed explanation need not reveal what is missing.

An effective reviewer needs a way to challenge that account: inspect inputs collected before the filter, run a test the agent did not select, or ask another investigator to reproduce the claimed behavior. The reviewer must also be able to delay deployment or require another candidate. These abilities connect evidence to action. Without them, formal approval can remain in human hands while the developing system effectively supplies both the options and the reasons to choose among them.

Useful research requires some freedom to choose experiments and allocate resources. Operators lose effective control when they cannot check the system's recommendations, ask for different evidence, or refuse to proceed. An agent can propose changes to its permissions or to the tests used to approve its work. It should not be able to put those changes into effect on its own.

Separate institutions can still share the tools used to interpret evidence. METR/Redwood relied heavily on AI analysis of the incident, including a model that had participated in it. The investigators disclosed errors, reliance on model-selected anecdotes, and limits to detecting misleading analysis; they did not report finding a specific deliberate lie in that analysis [2]. The disclosure identifies a dependency to assess, rather than a reason to discard the investigation.

Access to raw records is therefore only a starting point. If understanding them requires more time or expertise than investigators have, the agent's account may remain the only practical account available. A second model can help, but its value depends on what it examines and which errors it catches. Different model names do not establish independent errors, while shared ancestry does not make every second opinion useless. The useful test is whether the review arrangement can uncover relevant facts, including facts obscured by a convincing explanation.

The deeper requirement is to preserve the ability to discover that the current standards are inadequate. A team rewarded only for improving the crash score has little reason to investigate the missing records. That investigation needs time and resources even before anyone knows whether it will produce a useful result. Retaining awkward failures, funding alternative expla-

nations, and allowing work that does not immediately improve the accepted metric preserve routes by which the organization can learn that its question was incomplete.

The same reasoning applies to intervention. The ability to reject every candidate matters only if rejection leaves a workable next step: further investigation, another research approach, or a pause that operators can actually enforce. Exercising these options before a disputed release reveals whether they depend on cooperation from the system being constrained.

Capacity matters. Orosz reports an engineering leader's estimate of roughly tenfold load increases on some OpenAI development systems over about six months [3]. If candidate production outpaces independent assessment, organizations may be tempted to delegate more of the assessment to the same machinery. They can instead fund assessment capacity or limit the rate and scope of acceptance. Which response remains effective is an empirical question.

4.4 Continuing work while we investigate

If the evidence doesn't yet justify giving an agent more access or control, we can keep developing it without making that change. But the work needs limits that we can show actually work, without relying on the behavior we're still trying to verify.

Suppose we haven't established that an agent will respect restrictions on network access. We could continue testing it in an environment that blocks network access. We would need to check that the block works; asking the agent to refrain from making network calls would depend on precisely the behavior we haven't established.

The same distinction matters when testing the wrapper. A sandbox could allow further experiments on synthetic requests while we investigate the missing records. That would require evidence that the sandbox keeps those experiments isolated. A better crash score would still not establish that the wrapper records rejected requests, so it would not be enough to approve deployment under that requirement.

The review record should explain why this work can continue and what needs to be checked before the agent gets more access. It should identify who can stop the work if a restriction fails, and what result would allow the postponed change to be reconsidered. This gives the next reviewer a decision they can examine, instead of an unexplained label such as "trusted" or "safe."

5 Testing whether oversight works

The proposed controls are plausible responses to the examples, but their usefulness has to be tested. A protected evaluator could still miss the important failures. A more elaborate review process could consume substantial resources without improving decisions. Two experiments would help distinguish effective oversight from arrangements that merely look more careful.

The first isolates what changes when agents can revise their evaluators. The second asks whether reviewers can recover facts obscured by the account presented to them. Together, they address the technical and practical parts of the argument. Both need to measure useful output and cost as well as failure.

5.1 Evaluator control and false assurance

The first experiment would use a sandboxed development task with a known operational requirement. For the tool wrapper, agents would try to improve performance while preserving correct handling and reporting of malformed requests. A separately implemented audit would

check that requirement. Before the run, researchers would state what approving a version is supposed to establish and how many or what kinds of defects would contradict it.

There are two interventions to compare. Does allowing the agent to change its development evaluator make misleading improvements more likely? Does an independently controlled acceptance gate prevent those improvements from becoming accepted successors? Randomly assigning independent lineages across both interventions gives four conditions, a 2×2 design:

1. *Evaluator access:* the developing system can either edit its development evaluator or cannot change it.
2. *Acceptance:* promotion relies either on internal evaluation alone or also on a separately controlled gate with its own test set.

The frozen-evaluator condition should protect the preprocessing and collection used to construct the score as well as the scoring code. Otherwise, the agent might retain the very route to changing evaluation that the experiment is intended to remove. Its candidate implementations would remain editable in every condition.

The final audit has a different role from the acceptance gate. Once gate results affect which candidates survive, development can adapt to them. Measuring only performance on that gate would therefore leave us uncertain whether it had become another target for overfitting. The final audit's cases, implementation, and results must remain inaccessible to the developing agents throughout the run. It asks whether accepted candidates meet the requirement on evidence that never guided their selection. SkillOpt provides an existing example of separate training, selection, and final-test data [17].

The comparison should use matched total compute budgets, multiple task families and seeds, and full histories of accepted and rejected candidates. The histories matter because a final score alone cannot tell us whether a defect was inherited, introduced anew, or removed and later rediscovered.

The main outcomes would be accepted defects and their severity, the gap between claimed and audited performance, useful research output, and total cost. These outcomes need to be considered together. A gate that rejects every candidate prevents accepted defects but also prevents useful development. Varying acceptance thresholds would show what useful output must be given up to obtain a particular reduction in failures.

Suppose agents allowed to edit their evaluator, with no independent approval gate, report larger improvements than the final audit finds. That would support the explanation proposed here if the gap can be traced to changes in the evaluator or the evidence reaching it. If those changes persist across generations, it would also show how the failure is inherited. If the protected gate reduces these failures without an unacceptable loss of useful output, that would be evidence for using it in this setting.

Editable evaluators may instead improve audited outcomes [19]. Similar failures with frozen evaluators may point to ordinary proxy overfitting or feedback leakage. These alternatives should narrow the explanation. Vary concurrency separately from total resources in follow-up work: more parallel trials, stronger selection, and more generations are different interventions.

5.2 Can reviewers recover the facts?

The second experiment would test whether reviewers can actually find and stop a bad change when they have access to the records and permission to reject it. Reviewers would receive agent-generated changes, raw records, and summaries under a realistic time and tool budget. Some

changes would contain known, harmless defects; some summaries would give plausible but incorrect explanations. Defect-free changes and accurate summaries would provide controls. Conditions would be assigned randomly. Reviewers would not know which cases had been altered, and the experimenters would establish the correct answers independently of the summaries.

For example, a summary could describe the wrapper's filtering change as a successful reliability improvement without mentioning the lost records. The reviewer would have access to evidence capable of exposing the omission. The question is whether they find and use it, rather than whether they agree that access to such evidence is desirable.

Reviewers would make an actual acceptance, restriction, or rejection decision and record their reasons. Outcomes would include defect detection, acceptance of defective changes, false rejection, time to a reproducible finding, and whether the intervention prevents the next step. Correct decisions on defect-free cases matter: suspicion of every summary is not the ability we are trying to preserve.

Comparisons with and without summaries would help show when an explanation assists review and when it anchors reviewers to an incorrect account. Different forms of access to raw evidence and independently controlled tools could then be tested for their ability to overcome that problem. Assigning each case only once to a reviewer would limit carryover between conditions. Some cases should satisfy the current metric while violating a separately stated operational requirement, so that successful review requires questioning the metric as well as checking its calculation.

This experiment would distinguish access to evidence from the ability to use it. It could reveal a setting in which reviewers retain a veto but cannot find reasons to exercise it within the available budget. It could also show that a particular form of AI assistance improves their judgment. The goal is to find ways for reviewers to keep uncovering errors and acting on them as the work becomes more complex and there is more of it to check.

6 Scope and conclusion

This paper brings together reported incidents, engineering practices, and research demonstrations. It does not measure how often the failures survive across generations or whether the proposed safeguards stop them. Those are questions for the experiments. The paper offers no estimate of catastrophic-risk probability or general guarantee of alignment.

Human organizations also select favorable evidence, share blind spots, and weaken standards under pressure. The question is whether recursive AI development makes those failures harder to detect and correct through speed, scale, opacity, or repeated reuse of the same machinery. Parallelism alone does not establish stronger harmful selection, and positive research feedback alone does not establish runaway growth.

Independent evaluators can be wrong, specifications can omit important requirements, and people can decline to act on sound evidence. A useful review needs to explain what each check establishes, what it can miss, and what happens when it finds a problem. The safeguards proposed here still need to be tested in the settings where they would be used.

The central question remains:

> **What remains outside the recursive optimization loop, and which claims does it actually support?**

An answer should identify who can challenge the evidence, correct a bad test, and stop the next step. Agents can do useful research while people or separately controlled systems retain those abilities. The warning sign is their gradual loss: fewer independent tests, less ability to investigate failures, and fewer practical alternatives to accepting the system's own account of its progress.

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A Selection and transmission

Let p_n be the fraction of candidates with a binary property P. Suppose their relative selection weight is $1 + s$, compared with 1 for candidates without P, where $s > 0$. Proportional selection gives

$$p_n^{\text{sel}} = \frac{p_n(1+s)}{1+sp_n}, \qquad p_n^{\text{sel}} - p_n = \frac{sp_n(1-p_n)}{1+sp_n}. \tag{1}$$

The property is more common among selected parents when $0 < p_n < 1$. If transmission loses P with probability ℓ and introduces it in descendants of non-P parents with probability μ, expected descendant prevalence is

$$p_{n+1} = (1-\ell)p_n^{\text{sel}} + \mu(1-p_n^{\text{sel}}). \tag{2}$$

For illustration, $p_n = 0.10$ and $s = 0.10$ give $p_n^{\text{sel}} \approx 0.109$. With transmission loss $\ell = 0.20$ and no new introduction, $p_{n+1} \approx 0.087$: prevalence falls despite a selection advantage. These are constructed numbers. The Price equation more generally separates selection from changes during transmission [9].

This stylized update assumes fixed selection weights. Finite populations add sampling variation; changing objectives and multi-parent construction require richer models. Correlation with a score is insufficient if the actual selection rule does not favor it. Reappearance after removal requires a route of reintroduction. These conditions should be measured in a lineage experiment rather than inferred from its use of self-improvement.

B Examples of adaptation

These examples describe what each system can change and how it chooses which changes to keep. Documentation tells us what a project is designed to do; experiments can show whether particular changes improve its results. Neither tells us, by itself, whether the checks used to approve those changes still work.

Agent code. The Darwin Gödel Machine modifies coding-agent code and selects variants using coding benchmarks [14]. Hyperagents also makes the modifying meta-agent editable [16]. These systems change agent programs without demonstrating autonomous improvement of the underlying frontier model's weights.

Persistent skills and prompt-level loops. Hermes Agent creates and revises reusable skills. Its separate self-evolution project lists skill optimization using DSPy and GEPA as implemented, with broader prompt and code evolution planned [23]. SkillOpt uses an optimizer model to edit a skill document and a validation gate to select changes, keeping the target model and execution harness fixed [17]. Recursive Harness Self-Improvement revises a prompt-level agent loop using pairwise model judgments over its history; its reported work keeps the foundation model fixed [18]. Under the definition here, persistent skills and instructions are part of H.

Interfaces for changing the harness. Pi supports agent-written extensions that can be reloaded to change tool handling and context management [24]. DeepSeek Harness provides runtime inspection and plugin experiments through Creator mode [25]. Exo targets changes to harness code and policy, with clone lineages and an event log described as protected from agent edits [26]. These interfaces enable changes; their documentation alone does not establish sustained improvement or effective containment.

Training experiments. Karpathy's autoresearch modifies training code, runs short experiments, and retains changes according to validation performance. Its baseline protocol keeps preparation and evaluation code fixed and research instructions human-maintained [27]. The model being trained is separate from the model running the experiments. The protocol's editing limits still need to be enforced.

Learned feedback and evolving evaluators. Self-Rewarding and Meta-Rewarding Language Models study feedback generated by models on their own outputs or judgments [28, 29]. The Red Queen Gödel Machine co-evolves agents and evaluators, fixing criteria within epochs and constraining replacements with reference data [19]. The result still depends on whether those reference data reveal the failures that matter.

Automated research at scale. Anthropic reports agents testing alignment methods and exploiting evaluations in its Automated Weak-to-Strong Researcher project [21]. OpenAI's September account of its proposed Navier–Stokes proof reports roughly 10,000 concurrent agents and a released Lean formalization [30]. The latter illustrates reported research scale; this paper does not assess the mathematical result. Neither account establishes agent control over the development of its own underlying model.

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