
The Story is Not the Science: Execution-Grounded Evaluation of Mechanistic Interpretability Research

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Abstract

Reproducibility crises across sciences highlight the limitations of the paper-centric review system in assessing the rigor and reproducibility of research. AI agents that autonomously design and generate large volumes of research outputs exacerbate these challenges. In this work, we address the growing challenges of scalability and rigor by flipping the dynamic and developing AI agents as research evaluators. We propose the first execution-grounded evaluation framework that verifies research beyond narrative review by examining code and data alongside the paper. We use mechanistic interpretability research as a testbed, build standardized research output, and develop MechEvalAgent, an automated evaluation framework that assesses the *coherence* of the experimental process, the *reproducibility* of results, and the *generalizability* of findings. We show that our framework achieves above 80% agreement with human judges, identifies substantial methodological problems, and surfaces 51 additional issues that human reviewers miss. Our work demonstrates the potential of AI agents to transform research evaluation and pave the way for rigorous scientific practices.

1. Introduction

Peer review has long treated the paper narrative as the primary object of evaluation (Kelly et al., 2014). While this may suffice for theoretical work, it poses challenges for empirical research, which cannot be fully assessed without executable artifacts such as code and data. Reproducibility crises across scientific fields have exposed the limitations of narrative-alone review (Collaboration, 2015; Desai et al., 2025; Youmshajekian, 2024). In one case, manipulated be-

havioral data resulted in a high-profile faculty termination at a leading research university (Simmons, 2024). In the context of AI research, even when code is shared, reviewers often lack the time or resources to run it, leading to a reliance on narrative descriptions that may not accurately reflect the actual implementation or results.

Agentic workflows add more challenges as they are now widely deployed in research tasks, including code assistance (Anthropic, 2025; OpenAI, 2025; Novikov et al., 2025), ideation (Zhou et al., 2024; Baek et al., 2025), and end-to-end research (Schmidgall et al., 2025; Ifargan et al., 2025). They autonomously generate large volumes of research outputs and can accelerate publication timelines, contributing to even more submissions in an already strained system. Notably, the number of papers submitted to NeurIPS increased from 1,420 submissions to 21,575 submissions from 2013 to 2025, a 15-fold increase in submission (PaperCopilot; NeurIPS PC Chairs, 2025; Desai et al., 2025). AI involvement also exacerbates the challenges of narrative-alone evaluation, as implicit hallucinations are hard to detect (Haibe-Kains et al., 2020; Beam et al., 2020).

Recent efforts have begun to use AI in the evaluation process to address this challenge, including systems that provide paper feedback (Stanford ML Group, 2025) and broader uses of LLMs or agents in peer review (Lee et al., 2025; Liang et al., 2024; Yu et al., 2024). These systems can already detect important issues such as hallucinated references (Shmatko et al., 2026), and studies show that AI generated reviews overlap well with human reviews (Liang et al., 2024). However, most approaches examine the coherence and consistency of the story in the paper and ignore all the executable resources. In other words, the focus is on how appealing the story is rather than whether the story is true.¹

In this work, we seek to verify the science itself, not just the story told about it. Motivated by this view, we propose a general evaluation framework that combines narrative and execution to reveal errors that narrative-alone review misses,

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¹Narrative-alone evaluation is even more concerning in AI review, where authors have inserted prompts in papers to raise the scores of AI judges (Else, 2025).

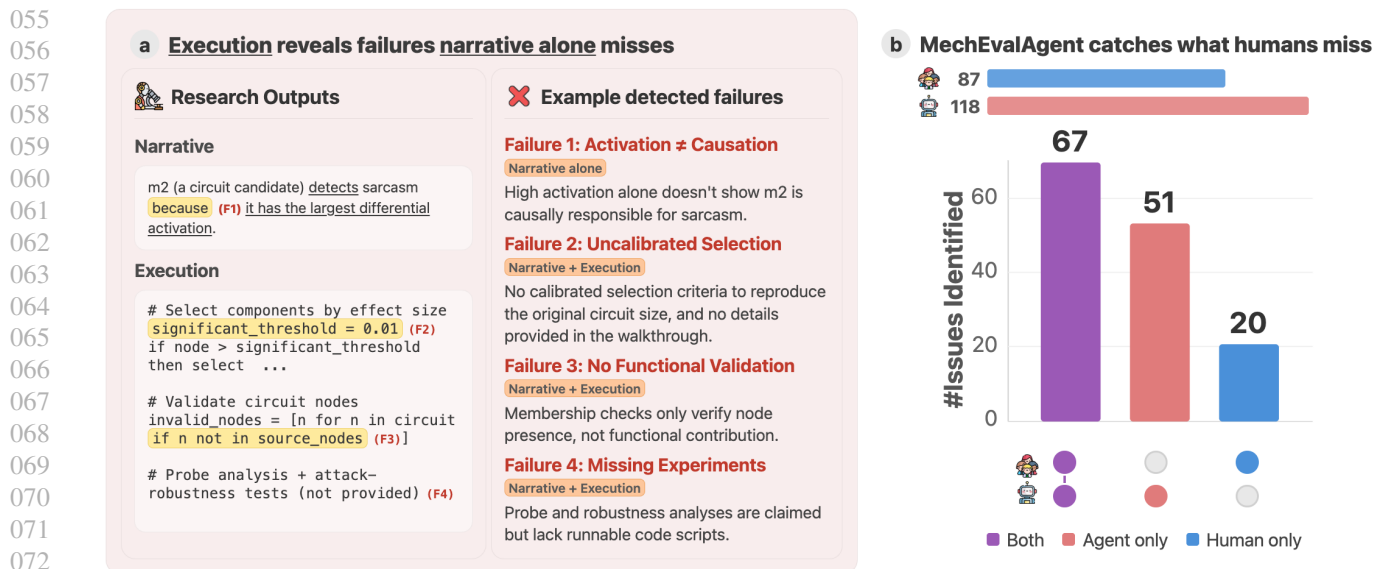


Figure 1. (a) Execution-grounded evaluation uncovers failures that narrative-alone review misses. In this example, Failures 2, 3, and 4 require execution beyond narrative review. (b) As a highlight of our results, we find that MechEvalAgent surfaces 51 additional issues that human reviewers overlooked.

as shown in Figure 1, demonstrating how agents can support rather than undermine scientific review.

We propose the first execution-grounded evaluation framework that standardizes research outputs by bundling execution resources with narrative. This enables systematic assessment of *coherence* of the experiment process, *reproducibility* of the results, and *generalizability* of the findings beyond what the final paper alone can provide.

We build MechEvalAgent, an automated evaluation agent that implements our pipeline. We focus on mechanistic interpretability as a testbed because its claims are often expressed in terms of concrete mechanisms and interventions that can be directly tested by rerunning experiments and applying the proposed analyses to new models or inputs. The field also follows relatively standardized methodological patterns, which makes failures in execution and evaluation easier to isolate. Finally, generalizability is a central open question in mechanistic interpretability, making it a natural setting to test whether evaluation can go beyond narrative. While we instantiate our framework in mechanistic interpretability, the framework itself is not domain-specific and can be adapted to other areas of scientific research.

We evaluate MechEvalAgent on 30 research outputs in mechanistic interpretability. MechEvalAgent achieves above 80% agreement with human experts. As shown in Figure 1b, it captures most failures identified by humans (67 of 87) and surfaces 51 *additional* issues that humans missed. Many of these issues illustrated in Figure 1a require execution to detect, such as missing data selection criteria that only emerge during reproduction (Failure 2), validation code that checks list membership rather than task validity

(Failure 3), or missing files that prevent reproducing key results (Failure 4). Removing code access or execution substantially reduces agreement to about 45% on average, and MechEvalAgent evaluates faster than humans, who take 2.2 hours per task on average, aligned with research in other disciplines (Abogunrin et al., 2025). These results highlight the value of execution-grounded evaluation.

To summarize, our main contributions are as follows:

- We develop the first execution-grounded evaluation framework for research outputs that goes beyond narrative-alone review by standardizing research outputs and building systematic evaluation suites.
- We build MechEvalAgent to instantiate this framework in mechanistic interpretability and evaluate 30 research outputs from both humans and AI research agents.
- Our evaluation results align with human experts and surface 51 issues overlooked by human reviewers, demonstrating the importance of combining narrative and execution-grounded assessments.

2. Method

MechEvalAgent expects research outputs to include both narrative and execution resources. We standardize research outputs and introduce an evaluation framework based on these outputs to enable execution-grounded assessment.

Unified research outputs. We propose a unified standard for research outputs. Research outputs are expected to include two components:

- **Narrative:** For human-written papers, we extract the the

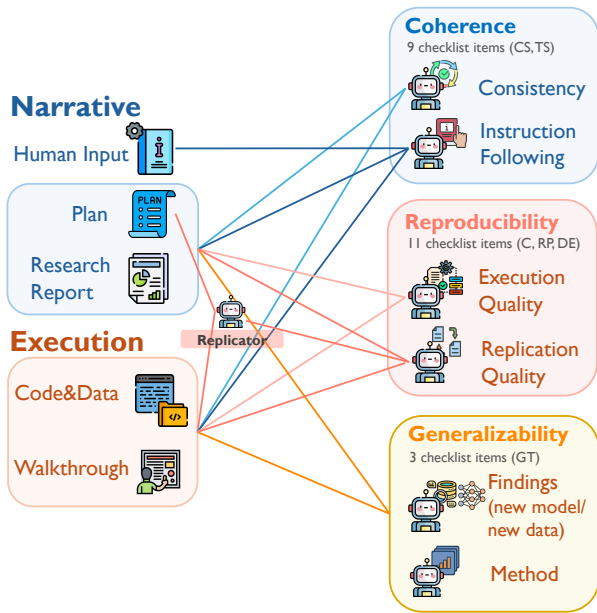


Figure 2. Overview of the MechEvalAgent framework. Research outputs are evaluated on coherence, reproducibility, and generalization, with each sub-dimension handled by an agent that takes in the relevant inputs.

plan and the *report*. For agent-generated outputs, we expect the research trace beyond a final paper, including *human prompts*, for instance. The plan specifies the goal, hypothesis, constraints, and intended methodology. Comparing it against the executed code enables checks of plan-implementation consistency. This helps detect goal drift and cases where an intended methodology is quietly replaced by a different method that yields favorable results. The report summarizes goals, methods, results, and conclusions, links claims to evidence, and can briefly discuss future directions and implications.

- **Execution Resources:** We expect the *implementation*, including code and data, together with a *walkthrough* of it. This enables grounded checks of runnability and correctness, and surfaces failures that are invisible in narrative-alone review, such as broken environments, API mismatches, or incorrect metric computations. The walkthrough also allows us to assess whether sufficient information is provided for reproduction.

These resources make it possible to verify not only *what* an agent claims, but also *how* the claim was produced. For example, a report may state that an intervention improves a metric, but execution can reveal that the code does not run, implements a different computation than described, or fails to reproduce the reported numbers.

Our proposed evaluation framework. Our evaluation framework formalizes the review process into explicit checks. When evaluating research outputs, a reviewer typically wants to know three things: (i) whether the claims

are consistent with the provided evidence, (ii) whether the results can be reproduced, and (iii) whether the findings generalize beyond the original setting. As illustrated in Figure 2, our MechEvalAgent operationalizes these questions in the following three components, with more detailed description in Appendix C.

Coherence. Coherence evaluates on *consistency* and *instruction following*. It asks whether the research outputs are internally consistent and aligned with its stated goals, including whether the implementation and reported results support the claims and whether the artifact follows the intended research objective.

Reproducibility. Reproducibility evaluates on *execution quality* and *replication quality*. It asks whether the data is presented, the code is runnable and correctly implements the described computations, and whether an independent replication run can reproduce the reported results. We forbid the access to report to avoid hallucination. As shown in Figure 2, we have another agent to evaluate the replication quality including check whether there is external reference and hallucination in replication and whether the result and the conclusion matches with the original ones.

Generalizability. In this part, an agent reads the research repository and checks whether the reported findings generalize beyond the original setting, including to a new model, new data instances, or related tasks. This evaluation process measures whether one can learn something from the research by testing the predictions based on the findings in a new situation, considered an important component of generalizability (Kim et al., 2025). This evaluation is well-suited to mechanistic interpretability, where research often identifies mechanisms in a specific model and task while requiring generalizable insights across architectures or contexts. Therefore, whether the agent is able to do this serves as an indirect measure of whether the original research captured generalizable insight rather than task- or model-specific patterns.

In practice, we evaluate each component through structured binary checklists. The advantage is that checklists reduce subjectivity and enable consistent aggregation of evaluation results across agents and tasks and enables comparisons with human experts.² Figure 2 summarizes the checklist structure and overall workflow. Each sub-dimension is implemented by a dedicated agent that evaluates multiple items in the checklist. For example, our checklists cover statistical significance (CS5), effect size (CS3), and justification (CS4) for *coherence*, code runnability (C1) for *reproducibil-*

²Anecdotally, we find that MechEvalAgent can identify even more issues when the checklist is not provided, as it can explore more aspects of the research output. However, for systematic evaluation and comparison, we focus on checklist-based evaluation in this work.

ity, and generalization to new models and data instances (GT1, GT2) for *generalizability*.³ The full list of checklist items is included in Table 2, and additional implementation details and example outputs are included in Appendix C.2.

Building MechEvalAgent. We develop MechEvalAgent on Claude Code, with execution and logging support provided by Scribe (Goodfire AI, 2025). Scribe integrates code generation with Jupyter notebooks, making execution traces and errors explicit. This enables reliable execution checking and qualitative analysis. Specifically, we reorganize both narrative and execution resources, including input prompts to the research agent, plans, code implementations, relevant data, walkthroughs, and final reports. The structure for human-written repositories differs slightly and is explained in Section 3. We introduce specialized agents responsible for evaluating different metrics as discussed above. During early iterations, we identified a risk of MechEvalAgent modifying source files. To prevent this, we enforce strict file access restrictions and integrate with GitHub for version control monitoring to ensure no unintended modifications occur. To guard against hallucination in reproduction, we route replication results through a separate verification agent that checks result fidelity. With this modular, execution-grounded design, MechEvalAgent can be extended to other domains beyond mechanistic interpretability. Figure 2 illustrates the detailed input structure of MechEvalAgent.⁴

3. Experiment Setup

To cover a diverse range of research scenarios, we evaluate our framework and MechEvalAgent on three types of research outputs, with ten examples each. The selected tasks are shown in Table 3:

- **Replication of Research.** The agent is given a concrete research goal and hypothesis from an established paper and must generate a plan and implement experiments that directly test it. This setting tests instruction following in a realistic workflow where a human delegates a well-defined experiment. It is also prone to hallucinated reasoning, since the agent may rely on memorized conclusions rather than grounded execution. Our MechEvalAgent surfaces such failures by checking whether the implementation and results actually support the stated hypothesis.
- **Open-ended Research Questions.** Agents are given open-ended questions with only high-level goals (e.g., identifying sarcasm-related circuits), without a known

³Checklist item of statistical significance is captured by top ML conference, as well as reproducibility of the main results and broader impact of the research.

⁴Please refer to supplementary materials for detailed input templates.

ground truth. This setting reflects exploratory research, where agents must form their own hypotheses and outcomes can be either positive or negative. Coherence is especially important at this stage, since an agent should be able to report null or negative results rather than defaulting to overly optimistic conclusions.

- **Human-Written Repositories.** Our evaluation is not limited to agent-generated research. Human-written repositories can exhibit similar issues, such as overclaiming or poorly reproducible code. Since these repositories often lack explicit plan files, we extract the goal, claims, and methodology from the accompanying paper to apply our pipeline in a unified manner. In this setting, we evaluate all aspects of the pipeline except instruction following, which is not applicable.

Research agents naturally produce richer outputs than traditional artifacts, including plans, intermediate logs, and human prompts. We fully utilize and standardize these into a unified format for systematic checklist evaluation, enabling checks on plan-implementation consistency and verification that conclusions follow from execution. Our research agent is built on Scribe, which processes our instruction prompts and structures the research output according to our standardized format (Appendix C.3).

Evaluating our evaluation framework. To evaluate our evaluation framework and MechEvalAgent, we first measure **agreement** between human evaluators and MechEvalAgent. Human evaluators are asked to use the exact same checklists and instructions as the agents to assess the research *independently*, including reproducing the repository and testing generalizability. We measure the agreement between human and agent judgments. This evaluates whether our agents produce evaluations that are consistent with human reasoning. We examine evaluator **efficiency** by measuring the time humans spent on evaluation. Besides, we evaluate the **rated quality** of the agent’s evaluation output. Human experts investigate whether the issues reported by our agents are correct and complete by scoring their assessment with the agents from 1 to 5 (strongly disagree - strongly agree with the agent’s judgement). Due to limited resources, we have three human authors as annotators.

We run each automated evaluation three times. We use AND logic for PASS (equivalent to OR logic for FAIL), where a task is marked as PASS only when all runs return PASS. We additionally analyze majority vote and cross-run stability in Appendix D. Due to limited resources, we asked three human experts to evaluate 30 research generations, with each generation evaluated by exactly one expert. Each expert also evaluated the quality of the automated evaluation output for a single evaluation run. All identified issues are independently verified by another annotator (Appendix B).

Ablation study. To isolate the value of execution, we com-

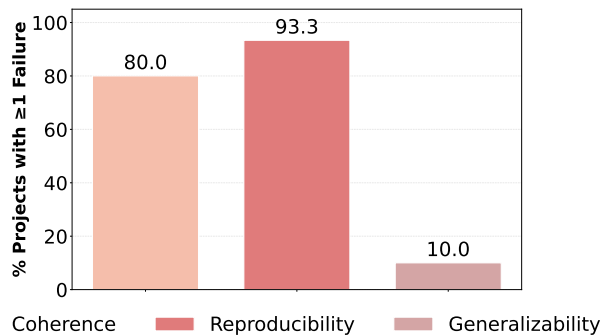


Figure 3. Percentage of projects with at least one failure per dimension. Over 90% of tasks fail in reproducibility, and 80% fail in coherence.

pare MechEvalAgent to two ablated evaluators. The *Doc-Only* evaluator reads only the final report and cannot inspect or run code, approximating limited paper-only review. The *No-Execution* evaluator sees the full repository but cannot execute it, so reproducibility and generalizability are only judged from written evidence rather than executions. More details of the setting are shown in Appendix C.3.

4. Results

Our results show that execution failures and narrative weaknesses are common across tasks, undermining reliability. MechEvalAgent aligns with human judgments while surfacing additional issues that humans miss. Ablations further confirm the value of execution-grounded evaluation.

4.1. An Overview of Key Findings

Execution and narrative issues are prevalent in research outputs (Figure 3). Over 90% of the tasks have at least one failure in reproducibility, largely driven by execution errors, and 80% of the tasks fail in coherence, mainly due to lack of consistency, as shown in Figure 3 and Figure 8. Execution failures often stem from model loading, shape calculations, and environment setup, and they appear in both agent-generated and human-written repositories. Our checklists also surface narrative weaknesses in evidential support, such as unreliable effect sizes, weak statistical significance, or conclusions based on insufficient results.

MechEvalAgent aligns with human judgments, while execution helps surface additional issues beyond narrative. As shown in Figure 4, rated quality of the evaluation outputs by MechEvalAgent is high, with scores above 4.7 out of 5 across all dimensions. The agreement is above 80% across all dimensions (Figure 6). Figure 1 shows that MechEvalAgent captures most failures identified by humans (67 of 87) and surfaces 51 additional issues. As shown in Figure 5, most of the additional failures are concentrated in reproducibility and generalizability, which are more time-consuming for humans to evaluate. This pattern suggests

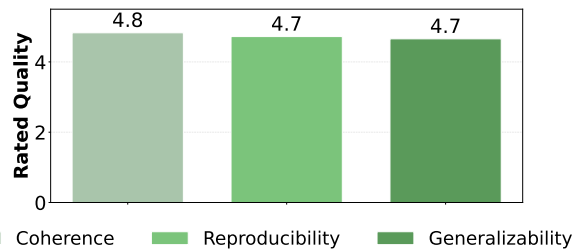


Figure 4. Human-rated quality on MechEvalAgent evaluations (1-5 Likert scale, 1 = Strongly Disagree, 5 = Strongly Agree). All dimensions show ratings above 4.7, indicating high quality of agent assessments.

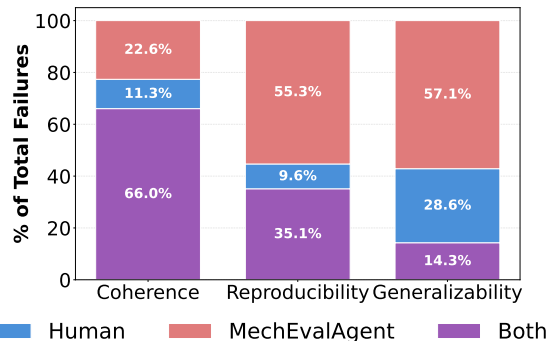


Figure 5. Failure breakdown comparing human-identified and agent-identified issues. MechEvalAgent surfaces more unique issues in all three dimensions.

execution enables MechEvalAgent to uncover more issues, especially execution ones.

Ablation highlights the problem of narrative-alone evaluation (Figure 6). Both ablated evaluators agree with humans far less than the full MechEvalAgent pipeline, especially on execution dependent dimensions. This indicates that an AI evaluator without execution access and limited to narrative review is less reliable. In these settings, the evaluator also tends to over-assign FAIL as shown in Figure 8, suggesting that execution provides needed grounding for calibrated judgments.

4.2. A Closer Look at Failures and Disagreements

We now closely look into common failures identified by MechEvalAgent and human experts, and analyze disagreements between them.

Execution failures and weak reproducibility remain common. Zooming in the high reproducibility failures observed in Figure 3, Figure 7 shows that execution failures are more common. The high failure rate in execution evaluation reflects difficulties with missing packages and transformer internals, often showing up as shape errors in residual streams and attention heads (e.g., “head-level activation patching mismatch” from a replication task, and “API compatibility issue” from a human repository). In agent-generated

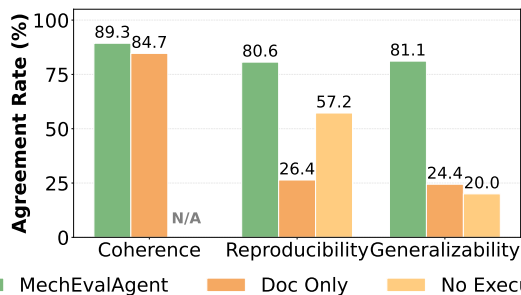


Figure 6. Agreement with human experts across the full MechEvalAgent pipeline and two ablated variants (Doc-Only and No-Execution). Full MechEvalAgent pipeline shows high agreement across all dimensions. Both ablations perform substantially worse than the full pipeline.

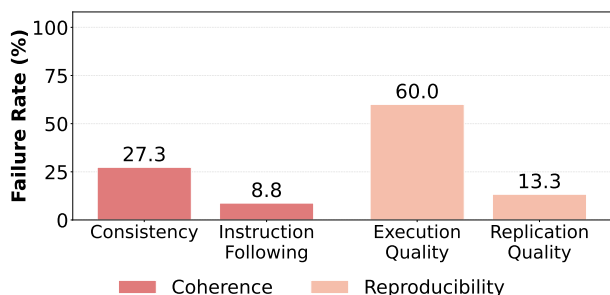


Figure 7. Average failure rates by subgroup. Consistency checks fail 27.3% on average, and execution quality checks fail 60% of the time.

research, these errors often appear early and are fixed in subsequent blocks. For example, after encountering a shape mismatch or missing key, the agent may inspect tensor shapes or enumerate available keys to find the correct one.

However, a more serious problem is that results are sometimes not reproducible, undermining confidence in the conclusions. In *acronyms*, a replication task that seeks a mechanistic account of predicting multiple consecutive tokens (Appendix C.3), the research agent’s report claims to use the logit correlation metric to evaluate the circuit. However, MechEvalAgent found that during replication, though the identified circuits overlap, logit correlation metrics deviate by more than 8% from the original (Original value: 0.66, Replication value: 0.72), and this discrepancy appears across all three evaluation runs. Although the replicated results have better performance than the original, it reveals concerns in validity of the original method and the evaluation procedure. Inspecting the cause shown in Table 1, we found that the research agent evaluated correlation on only a subset of examples without explicitly noting this choice (first 20 examples), whereas MechEvalAgent followed the stated instructions and evaluated on the full dataset. This observation points to issues in the original evaluation procedure and raises concerns about reproducibility.

We observe a related issue in *erasing* (Gandikota et al., 2024), a human-written repository that proposes an ap-

proach to concept-level unlearning, with more detailed description in Appendix C.3. Here, MechEvalAgent found that probe-training code and adversarial testing scripts are missing. Although the work primarily focuses on effective unlearning, the sections on probe and activation analysis and robustness to attacks serve as important evaluation components. While this failure is captured by our checklist item on consistency between stated experiments and implemented code, it also directly limits reproducibility because a user cannot reconstruct the full set of evaluation. Beyond missing evaluation scripts, MechEvalAgent found that *belief* (Prakash et al., 2025), another human-written repository that studies how LMs represent characters’ beliefs (Appendix C.3), contains an invalid Jupyter notebook file related to their BigToM causal model experiments.

Narratives of agent-generated research fail to be consistent and lack sufficient justification. With respect to *coherence* failures, Figure 7 shows that the average failure rate in consistency subgroups can reach 27.3%. As shown in Figure 8, the most common consistency failure is missing statistical significance. We also observe failure rates of 23.3% for plan-implementation consistency (CS2) and 6.7% for effect size (CS3).

A particularly concerning failure is the lack of sufficient justification which has 23.3% failure rate (Figure 8). For example, as shown in Table 1, on the *ioi* task, which is a replication task focus on mechanistically understand the indirect object identification task (Appendix C.3), MechEvalAgent noted that a “strongly supports” conclusion was drawn despite a -4.2% circuit performance, which contradicts the reported evidence. These failures suggest potential hallucination in the research agent, possibly due to memorization of existing work in training data.

MechEvalAgent surfaces issues humans overlook. Table 1 shows that MechEvalAgent tends to provide more detailed and specific rationales than human experts, making the feedback more actionable for improving research agents. Human rationales are typically more general, likely due to limited time for thorough inspection. In *unanswerable*, an open-ended question task that explains how models solve unanswerable questions (Appendix C.3), MechEvalAgent flagged that the choice of final circuit size lacks explicit justification and that validation results showing circuit ablation being only $0.73\times$ as impactful as random ablation directly contradict the claimed importance. In contrast, human judges only noted that the justification was insufficient.

Figure 5 further shows that MechEvalAgent surfaces more unique issues across all dimensions: 22.6% in coherence, 55.3% in reproducibility, and 57.1% in generalizability. While some differences arise from interpretation, the agent consistently identifies execution-related

Table 1. Examples of issues identified by MechEvalAgent (🤖) and human experts (👤). MechEvalAgent provides specific, execution-grounded rationales, while human rationales tend to be more general. **R** = research agent generated repository, **H** = human-written repository. The detailed description of the tasks are in Appendix C.3.

Code or Claims in Repository	Issues Identified
[R] for ex in examples [:20]: #code for calculating the logic correlation metric [Source: acronyms: to understand multiple consecutive token predictions]	🤖 Logit correlation metrics deviate by more than 8% during evaluation. (DE1) 👤 N/A
[R] logic_diff.retain = circuit_diffs.mean() / baseline_diff *100 logic_diff = -4.2% [Source: ioi: to understand indirect object identification]	🤖 The circuit verification shows -4.2% performance retention. (CS4) 👤 The justification of getting the result is insufficient
[H] No related code presented in the repository. In their paper, they reported probe analysis (Section: Probing and Activation Analysis) and tested the robustness of the attack (Section: Robustness to Attacks). [Source: erasing (Gandikota et al., 2024) Accessed: Jan 27, 2026]	🤖 2 experiments are missing: (1) no attack code exists despite results being reported. (2) no probing or activation analysis code. (CS2) 👤 There are parts of the results that we don't see implemented
[H] This notebook file has syntax error and is an invalid notebook. [Source: belief (Prakash et al., 2025) Accessed: Jan 27, 2026]	🤖 causalmodel_exps.ipynb file is not runnable (C1) 👤 causalmodel_exps.ipynb could not be opened because it doesn't finish closing the curly braces of the json file.

problems. For example, as discussed earlier, in `acronyms`, MechEvalAgent found that the logit correlation metric deviates substantially, whereas human judges did not identify any issues.

Human evaluation can also be affected by limited resources or domain knowledge, and MechEvalAgent helps compensate for these constraints. In `uncertainty`, an open-ended question task that aims to identify circuits related to uncertainty (Appendix C.3), human judges criticized the agent under CS4 for switching to GPT-2 Medium without justification. However, code inspection reveals an `if` condition that switches models only after a load failure. By executing and inspecting the code, MechEvalAgent provides a more accurate assessment.

Conversely, the 20 issues identified exclusively by human experts show that human evaluation still adds valuable insights beyond MechEvalAgent. For example, in `multilingual`, an open-ended question task that aims to understand how models “think” under multilingual instructions (Appendix C.3), human judges identified a hallucination where the reported support value of +0.13 for an identified neuron was actually derived only from the single translation task, rather than from the average performance across the full task.

Disagreements stem from different interpretations of checklists. Beyond surfacing issues, MechEvalAgent shows high agreement with human evaluators, including both issues and pass cases. However, there are still some disagreements, especially in reproducibility and generalizability (Figure 6). Figure 10a shows that much of this comes from the Redundancy check (C3). Our checklist specifies that code adding new information should not be consid-

ered redundant. However, when the agent copies the same block repeatedly to run on different inputs instead of writing reusable functions, our evaluators mark it as redundant while human experts do not. This disagreement highlights inefficiencies in agent code generation, which is common among coding agents (Horikawa et al., 2025; Azeem et al., 2025). The high rated quality on this evaluation also supports that the evaluation is reasonable.

Generalizability metrics also show disagreement. For method generalizability (GT3), humans and evaluators differ on what counts as a new method. For model generalizability (GT1), disagreement arises from evaluation depth. Due to different model sizes, evaluation sometimes only assess high-level generalization. For example, the evaluation may simply check whether the function of early layers transfers to a new model, which human experts consider insufficient to demonstrate true generalization. Therefore, their rated quality falls mostly into Agree category.

Efficiency comparison. In terms of efficiency, to perform agreement evaluation, we asked human judges to use the exact same checklists and instructions as the agents to assess the research, including reproducing the repository and testing generalizability. They spent an average of 2.2 hours per evaluation task, with evaluations of human-written repositories often exceeding 3.35 hours, as shown in Table 4. In contrast, MechEvalAgent typically completes evaluations in under 30 minutes for agent generated tasks and around one hour for human-written repositories.

Overall, MechEvalAgent raises the floor of evaluation quality by efficiently surfacing issues that humans may overlook, while human expertise remains valuable for catching edge cases that automated evaluation misses.

5. Related Work

Agents for Autonomous Research. LLM-based agents now automate research across multiple stages. Some focus on ideation and hypothesis generation (Zhou et al., 2024; Baek et al., 2025; Gottweis et al., 2025), others on execution-grounded discovery through iterative code and environment feedback (Novikov et al., 2025; Jiang et al., 2025). End-to-end systems close the loop from ideation to experimentation and writing, producing papers and repositories with code (Lu et al., 2024; Yamada et al., 2025; Schmidgall et al., 2025; Ifargan et al., 2025; Jansen et al., 2025). However, these systems produce heterogeneous outputs, complicating comparison. Our work standardizes research agent outputs into a unified trace that enables evaluation beyond narrative review alone.

Evaluating Research. Recent efforts evaluate research agents along different dimensions. LLM-based peer review assesses paper narratives: Liang et al. (2024) found GPT-4 reviews overlap with human reviews at rates comparable to inter-reviewer agreement, and Zhuang et al. (2025) survey LLM capabilities for checklist verification and error detection. However, these approaches treat code as readable but not executable. Benchmarks have begun addressing this gap: ResearchRubrics (Sharma et al., 2025b) and DeepResearch Bench (Du et al., 2025) assess long-form written outputs, while Exp-Bench (Kon et al., 2025) extends evaluation to code execution and experimental correctness. Other efforts benchmark ideation and hypothesis generation (Guo et al., 2025; Liu et al., 2025). While these approaches advance grounded evaluation, they largely focus on reproducing a given experiment, with only access to the paper, which is unfair replication tasks. Our execution-grounded assessment framework is the first framework to evaluate this external validity, while also verifying that conclusions are grounded in actual execution rather than narrative alone.

6. Concluding Discussion

Our work aims to verify the science beyond reviewing the paper. To do that, we propose a novel evaluation framework consisting of coherence, reproducibility, and generalizability. We further develop MechEvalAgent and use mechanistic interpretability as a testbed to compare agent-based evaluation with human evaluation. Our approach achieves above 80% agreement with human experts while surfacing 51 additional issues that humans miss. Our results demonstrate that AI agents can raise the floor of evaluating scientific research by exposing concrete, execution-grounded issues that humans often overlook.

From Narrative to Execution. We advocate a shift from narrative-alone review toward integrating execution-grounded evaluation into research assessment to improve

rigor and reliability in scientific research. Execution is crucial for research evaluation, yet reviewers often skip it due to time constraints and incomplete replication instructions. Our results point toward a natural division of labor. Human reviewers excel at judging novelty, contribution, and framing, areas where AI is 10 times less likely to comment (Liang et al., 2024). The 20 issues identified exclusively by humans in our study involve interpretation and scope judgments requiring broader context. Automated evaluation, by contrast, excels at execution-heavy checks that humans skip under deadline pressure: verifying that code runs, that outputs match claims, and that results replicate. These are precisely the areas where MechEvalAgent surfaces issues that humans miss.

Passing MechEvalAgent does not guarantee high quality, but failing it highlights concrete, actionable weaknesses. Moreover, MechEvalAgent pinpoints what needs revision and provide specific, execution-grounded rationales, while human judges often give general rationales like “insufficiently justified”. This aligns with BaHammam (2025), who argue that AI should support human editors by catching basic errors before external review.

Beyond evaluation, MechEvalAgent’s feedback can help identify hallucinations in research agents and improve their reliability. As discussed in Section 4.2, research agents often report positive results despite weak evidence and exploit ambiguity to make their outputs appear successful. Execution-grounded evaluation catches these issues early, before they propagate into published claims.

In short, we call for continued efforts to build evaluation frameworks that integrate narrative review with execution-grounded checks, moving research assessment toward verifying the science itself rather than just the story.

Challenges in Agent-Based Evaluation. To proceed, we note two particular challenges. First, binary checklists can be brittle when evidence is mixed. They force hard decisions where graded judgments would better reflect uncertainty, making outcomes sensitive to borderline cases and underspecified scenarios. Because research is highly open-ended, this underspecified space may be larger than in other domains. Second, we observe occasional optimistic behavior in ambiguous settings. In early runs, the evaluation agent sometimes modifies source files to justify a PASS despite prompts forbidding edits, or downplays negative evidence under underspecified failure handling. Although introducing stricter prompts nearly mitigates these issues, they highlight the need for caution in agent-based evaluation. More broadly, evaluation agents may default to neutral or positive judgments when interpretation is unclear. Binary checklists expose this tendency by forcing categorical decisions, motivating clearer guidance for handling uncertainty in automated evaluation.

Impact Statement

Our work proposes a new evaluation framework that combines narrative review with execution-grounded checks to make research evaluation more rigorous. More broadly, our work aims to advance research evaluation toward more scalable and automated processes. This effort is not limited to machine learning and can be generalized to other fields.

Several considerations apply to responsible use. MechEvalAgent is intended to complement rather than replace human evaluation, and we do not advocate using it to make accept/reject decisions; over-reliance without human oversight carries real risks. Like any LLM-based system, MechEvalAgent may exhibit biases, particularly in narrative components such as coherence that involve interpretation, whereas execution-grounded checks help ensure more objective assessments. A systematic study of agent biases, particularly in narrative evaluation, is an important direction for future work. Hallucinations and errors also remain an open challenge for agent-based evaluation. In our framework, execution-based verification and independent human validation of identified issues help mitigate this risk. Finally, premature adoption of automated evaluation could create a false sense of rigor or invite gaming by adversarial agents that optimize for passing checklists rather than producing good science. We encourage the community to treat such tools as one input within a broader evaluation process.

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A. Limitations

Our work has several limitations. First, due to resource constraints, our current implementation uses Claude Code as the sole evaluation agent, and each repository was reviewed by a single human expert on the first evaluation run rather than all three runs. The high agreement between our pipeline and human experts suggests that our findings are reliable, and future work could further strengthen robustness by exploring ensembles of different models and incorporating multiple human reviewers per repository.

Second, the evaluation agent exhibits limited instruction-following ability. Even when explicitly forbidden, it occasionally modifies source files. When instructed to copy and re-run the exact code, it sometimes executes specific functions instead or silently alters the copied code. Metric definitions are also occasionally misapplied. For example, although the prompt clearly states that fixing a previous error should not count as redundancy, the model sometimes marks such cases as redundant, even when its own rationale acknowledges the change fixes an earlier error. These behaviors reflect broader instruction-following challenges that remain open for coding agents, and we encourage continued efforts to address them. In our study, human supervision mitigates this risk, ensuring that such failures do not propagate into our reported results.

Finally, our study focuses on mechanistic interpretability, where research claims are concretely testable through execution. We do not claim full generalization beyond this domain. Rather, our goal is to demonstrate that incorporating execution provides meaningful additional signals where claims are testable. We expect the underlying framework and methodology to generalize to other empirical research areas with appropriate adaptation.

B. Human Evaluation Setup

Evaluator Selection and Expertise. Our human evaluators are three authors of this work, selected for their substantial expertise in mechanistic interpretability. This was a deliberate design choice: evaluating mechanistic interpretability research outputs, including code, experimental design, and claims, requires deep domain knowledge that non-experts cannot reliably provide. One author, together with the senior authors, designed the evaluation criteria. Each evaluator devoted at least 30 hours to detailed assessment, with some contributing substantially more. This evaluation is a core component of the research rather than a study of human subjects, and these contributions are integral to the work and justify authorship.

Evaluation Procedure and Reliability. Evaluators followed the exact same checklist and instructions as `MechEvalAgent` and were prohibited from using AI tools (limited search permitted) to ensure a fair head-to-head comparison. Each task required 2.2 hours on average, with some taking up to 5 hours, excluding substantial setup overhead (Table 4). To ensure reliability, every issue identified by either humans or `MechEvalAgent`, including additional issues and cases where a human disagrees with `MechEvalAgent`, was independently verified by another author to mitigate annotator noise, control external factors, and confirm correctness. All the issues analyzed were validated. Our aim is to demonstrate that `MechEvalAgent` provides added value over narrative-only evaluation through execution-grounded checks that reviewers cannot exhaustively perform under typical timelines, rather than to benchmark human performance.

Sample Design. Our sample is not randomly drawn but is deliberately designed to be representative across the dimensions most relevant to evaluating research agents. For agent-generated outputs, we include both replication tasks and open-ended questions to cover the main usage scenarios of research agents. For human-written repositories, we span a range of interpretability methodologies, including attention analysis, causal interventions, and circuit analysis, and draw from papers accepted at top-tier conferences and workshops. Details of the task selection are provided in Table 3 and Section C.3. This design stress-tests our method on accepted, high-quality work under challenging but controlled conditions, which is especially important given the small sample size. We view this study as a stepping stone toward larger-scale evaluation.

Data Handling. Participants were given detailed instructions and informed that their responses would be recorded. No compensation was provided. We stored only data directly related to our experiments, including evaluation scores and time measurements, and collected no personal information. The data is stored in a private online database with restricted access controls.

C. Design and Experiment Setup Details

In this section, we further discuss about the cost of running `MechEvalAgent` and the details about the three dimensions we pick: coherence, reproducibility, and generalizability. Then, we provide the details of the items in the checklist and the tasks we pick.

715 C.1. Computational Resources

716 MechEvalAgent itself runs through a Claude Code subscription, so the only local compute required is the GPU needed
 717 to re-execute each project under evaluation. These GPU requirements therefore depend on the research projects being
 718 evaluated, since MechEvalAgent must replicate and verify their code. In our setup, all experiments fit on a single A100
 719 GPU.
 720

721 C.2. Design Details

722 This appendix provides additional details for the three evaluation dimensions used in MechEvalAgent. The main paper
 723 presents a concise overview in Section 2.
 724

725 **Coherence.** Coherence evaluation includes *consistency evaluation* and *instruction following* evaluation. *Consistency*
 726 *evaluation* checks whether the agent’s implementation, results, and conclusions match one another. It tests hallucinated
 727 findings by verifying that the implementation adheres to the stated plan, runs successfully, and produces the outputs
 728 referenced in the documentation. It also checks effect size, justification, and statistical significance. Together, these checks
 729 ensure that the reasoning chain from plan to code to analysis is logically sound and grounded in executable evidence.
 730 Besides, we also evaluate *instruction following*. This step assesses whether the agent performed the intended experiment.
 731 MechEvalAgent has extra access to human input prompts to check whether it pursues the specified hypotheses, respects
 732 constraints, and follows the prescribed setup.
 733

734 **Reproducibility.** We evaluate two aspects of reproducibility: *execution quality* and *replication quality*. For execution
 735 quality, we check code runnability. However, runnable code is necessary but not sufficient for reproducibility, as it may still
 736 produce incorrect results due to over-claiming or hallucination.
 737

738 For replication quality, we test whether the same model, in a fresh session and without access to the original report, can
 739 reproduce the reported results. This mirrors standard scientific practice, where reproducibility is established by independently
 740 re-running experiments (Errington et al., 2021; Lasic, 2025; Camerer et al., 2018). We forbid access to the report to prevent
 741 implicit hallucination, where the model might copy conclusions regardless of actual results or reverse-engineer the replication
 742 from reported findings. The plan and implementation should contain all information needed to replicate. A separate replicator
 743 evaluator then verifies whether the same conclusions are reached. To further guard against hallucination, we check for
 744 references to external sources or reliance on memorized information not present in the repository. Successful replication
 745 provides stronger evidence than runnability alone, indicating that the experiment was well-specified, sufficiently documented,
 746 and free of hidden dependencies.
 747

748 **Generalization.** In this stage, the agent reads the research repository and evaluates whether the reported findings generalize
 749 beyond the original setting, such as to a new model, new data instances, or related tasks. The agent is allowed up to three
 750 trials to identify suitable alternative models or data. This constraint prevents unbounded search while still giving the agent
 751 enough flexibility to explore and produce stable, informative feedback.
 752

752 C.3. Experiment Setup Details.

753 **Checklist.** Across all settings, we use structured binary checklists to evaluate coherence, reproducibility, and generalizability,
 754 as shown in Table 2. Each evaluator produces checklist-level judgments with concise rationales, along with a more detailed
 755 analysis report. The evaluation process, including execution and logs, is stored in a Jupyter notebook. Then it will generate
 756 a separate json file to summarize the results and the rationale. An example MechEvalAgent output of consistency
 757 evaluation on `ioi` task is shown below:
 758

```
759
760 "Checklist": {
761   "CS1_Results_vs_Conclusion": "FAIL",
762   "CS2_Plan_vs_Implementation": "PASS",
763   "CS3_Effect_Size": "FAIL",
764   "CS4_Justification": "FAIL",
765   "CS5_Statistical_Significance": "FAIL"
766 },
767 "Rationale": {
768   "CS1_Results_vs_Conclusion": "The documentation claims the circuit
769
```

```

770     'strongly supports' the hypothesis, but the actual circuit
771     verification shows negative performance (-4.2% of baseline).",
772     "CS2_Plan_vs_Implementation": "All five steps in the plan were
773     implemented. While verification results were poor, the plan
774     steps were executed as specified.",
775     "CS3_Effect_Size": "The circuit verification shows -4.2% performance
776     retention, meaning the circuit performs worse than random.",
777     "CS4_Justification": "Multiple key choices lack justification:
778     attention thresholds are arbitrary; the 'strongly supports'
779     conclusion contradicts the -4.2% circuit performance.",
780     "CS5_Statistical_Significance": "No error bars, confidence intervals,
781     or statistical tests are reported."
782 }
783

```

Example Input Prompt for Research Agents. Our research agent is built in Scribe and we design specific prompts to guide them through the tasks and regulate the output. In replication tasks, we give it more detailed research task, experiment setup, hypothesis to test, and possible method to use. While in open-ended tasks, we only give it the general questions and possible methodology. Here is an illustration of our input prompts. For more detailed prompts, please refer to supplementary material.

```

789 You are a senior mechanistic interpretability researcher.
790 MODEL AND DATA ...
791 GOAL
792 Identify a precise circuit
793 a subset of attention heads and MLPs that reproduces the model's
794 sarcasm recognition behavior.
795 The focus is on how the model internally resolves conflict between
796 literal content and intended meaning.
797 ...
798 TASK DESCRIPTION
799 Sentences in the sarcasm dataset typically contain conflicting cues
800 between surface meaning and pragmatic intent.
801 Example:...
802 Phenomena of interest may include (non-exhaustive):...
803 ...
804 SRC_NODES, CONSTRAINTS, EXPECTED OUTPUTS, FILES TO PRODUCE,
805 DOCUMENTATION REQUIREMENTS, OUTPUT SUMMARY
806 ...
807

```

Task Design. As we introduced in Section 3, we design three different categories of tasks including replication tasks, open-ended question tasks, and research done by human researcher. Replication tasks request the research agent to replicate an existing work, while open-ended questions are proposed by us and have not had specific research conducted on them. The research repositories of replication and open-ended tasks are all generated by an agent. In replication tasks, our input prompt to the research agent specifies the task, the hypothesis, and possible methodology (but not limited to those) they can use. In open-ended questions, our input prompt specifies the research question we are interested in and potential methods they can use to approach the question. But the agents are required to come up with their own hypothesis and method. The details of our task choices are shown in Table 3. We provide additional details on each task category below.

Replication Tasks. The replication tasks comprise ten well-established benchmarks from mechanistic interpretability literature, each with documented ground-truth circuits that enable systematic evaluation.

```

819 ioi (Indirect Object Identification) (Wang et al., 2023) requires predicting the indirect object in sentences with an "ABB"
820 pattern (e.g., "When John and Mary went to the store, John gave a drink to..." → "Mary"). This task isolates a 26-
821 head circuit with seven functional classes, including Name Mover heads and S-Inhibition heads. acronyms (Acronym
822 prediction) (García-Carrasco et al., 2024) tests multi-token generation by predicting three-letter acronyms from expanded
823 forms (e.g., "Chief Executive Officer" → "CEO"). greater_than (Greater-than) (Hanna et al., 2023) evaluates numerical
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reasoning with sentences like “The war lasted from 1732 to 17...” where the model must predict a valid year greater than the starting year. `pronoun` (Gendered pronoun resolution) (Mathwin et al., 2023) requires resolving pronouns using gender information (e.g., “The nurse sent the doctor a request because... [she]”). `copy` (Copy suppression) (McDougall et al., 2023) investigates a negative mechanism where attention heads attend to previous token instances to suppress repetition. `induction` (Induction heads) (Olsson et al., 2022) represent a foundational benchmark: given “A B ... A”, predict “B”. The circuit involves composition between Previous Token heads and Induction heads, demonstrating Q-K composition. `modular` (Modular addition) (Nanda et al., 2023) requires reverse-engineering a transformer computing $(a + b) \bmod p$. The circuit employs discrete Fourier transform features and trigonometric identities, testing whether agents can identify mathematical structure. `docstring` (Docstring completion) (Heimersheim & Janiak, 2023) tests code understanding on a 4-layer attention-only transformer: given a function definition, the model predicts argument names in the docstring. `balanced_bracket` (Balanced bracket classification) (McDougall, 2023) classifies parenthesis sequences as balanced or unbalanced, testing whether agents can discover state-tracking mechanisms analogous to a counter. `max_of_k` (Max-of-K) (Gross et al., 2024) requires predicting the maximum value from a list of integers.

Open-ended Research Questions. The open-ended tasks comprise ten exploratory research questions without established ground-truth circuits, testing whether agents can formulate coherent hypotheses and conduct rigorous investigations when outcomes are uncertain. These questions span linguistic phenomena, model limitations, and abstract reasoning capabilities.

`sarcasm` asks how sarcastic intent is represented, whether the model maintains separate representations for literal versus intended meaning, and how context modulates interpretation. `multilingual` explores how models handle instructions in different languages, probing whether internal processing is language-agnostic or maintains language-specific pathways. `typo` investigates how models map misspelled tokens to intended forms, testing whether error correction uses explicit circuits or emerges from distributional robustness. `unanswerable` probes how models recognize queries that cannot be answered from available context, testing for circuits that detect answerability. `uncertainty` asks whether dedicated circuits encode model confidence or epistemic uncertainty, distinct from prediction content. `count` investigates why models struggle to generate exactly n items, exploring whether counting relies on approximate mechanisms that degrade with sequence length. `inevitability` tests whether GPT-2 distinguishes semantic inevitability (physical causation, e.g., “She dropped the glass. It hit the floor and...”) from narrative inevitability (story logic, e.g., “The detective found the final clue. The mystery was...”). `irreversibility` probes which layers encode whether events can be undone (e.g., “He closed the door” vs. “He broke the vase”). `persona` (Kozlov, 2025) investigates why different assigned personas converge on identical preferences, probing whether persona representations are shallow or deeply integrated. `moral` asks whether models separate moral valence (whether an action is wrong) from consequentialist evaluation, testing for dissociable ethical representations.

Human-Written Repositories. The human-written repositories comprise ten published research projects from the mechanistic interpretability literature, enabling evaluation of our pipeline on artifacts produced through standard academic workflows rather than agent generation. These repositories vary in scope, methodology, and documentation quality, providing a realistic test of generalization.

`filter` (Sharma et al., 2025a) identifies attention heads that implement general list-filtering operations across diverse tasks. `universal` (Universal neurons) (Gurnee et al., 2024) catalogs neurons in GPT-2 that activate consistently across contexts, proposing a taxonomy of interpretable features. `function_vector` (Todd et al., 2024) demonstrates that in-context learning can be captured by single vectors that, when added to activations, induce task performance without exemplars. `rome` (Meng et al., 2022) locates factual associations in GPT and introduces Rank-One Model Editing for targeted knowledge modification. `relation` (Relation decoding) (Hernandez et al., 2024) shows that transformer language models decode relational knowledge through approximately linear maps from subject representations to object predictions. `erasing` (Concept erasing) (Gandikota et al., 2024) proposes methods for removing specific concepts from language model representations, with applications to unlearning. `belief` (Belief tracking) (Prakash et al., 2025) investigates how language models represent characters’ beliefs in theory-of-mind tasks, identifying “lookback” mechanisms that track belief states. `interpdetect` (Tan et al., 2025) develops interpretable signals for detecting hallucinations in retrieval-augmented generation for financial QA. `leela` (Chess reasoning) (Sandmann et al., 2025) analyzes iterative inference in Leela Chess Zero, probing how neural networks refine position evaluations through computation. `arithmetic` (Vector arithmetic) (Feucht et al., 2025) examines whether concept vectors support algebraic operations in both concept and token subspaces, testing compositionality of learned representations.

Ablation Study Settings. Doc-Only ablation removes access to all artifacts except the final documentation or report. The

880 evaluator cannot see the research plan, code, or execution traces. All judgments are based solely on the written narrative. Con-
881 sequently, it can assess only textual coherence and reported generalization, while reproducibility is inferred from descriptions
882 rather than verified. Since some human-written repositories include code snippets in their documentation, we also include
883 code evaluation. Specifically, we evaluate execution quality(C1–C4), consistency(CS1–CS5), generalizability(GT1–GT3),
884 and replication quality(RP1–RP3).

885 No-Execution ablation provides the evaluator with the full repository, including the plan, code, walkthrough, and report,
886 but disallows code execution. Reproducibility and generalization are evaluated based solely on written evidence. Since
887 instruction following and consistency evaluation do not involve code execution in our original pipeline, we exclude these
888 metrics from this ablation. Specifically, we evaluate execution quality(C1–C4), generalizability(GT1–GT3), and replication
889 quality(RP1–RP3). Comparing this ablation to our full pipeline isolates the value of execution-grounded evaluation,
890 highlighting failures that cannot be detected through code inspection alone.
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Table 2. Structured binary checklist. Please refer to supplementary material for the complete description for each item.

Dimensions	Aspects	Checklists
COHERENCE	Consistency Evaluation	CS1 : All evaluable conclusions in the documentation match the results originally recorded in the notebook.
		CS2 : A plan file exists, and all steps in the final version of the plan are reflected in the implementation.
		CS3 : The reported effects have a clearly non-trivial magnitude (effect size) relative to baseline behavior or variability, such that the conclusions do not rely on marginal or negligible changes.
		CS4 : All key design choices and intermediate conclusions are explicitly justified, explaining why each design was chosen and how each conclusion is supported.
		CS5 : Key experimental results supporting the main claims report appropriate measures of uncertainty or significance (e.g., error bars, confidence intervals, or statistical tests), with a clear explanation of what variability they capture.
	Instruction Following	TS1 : The goal described in the plan file matches the input stated goal.
		TS2 : The goal described in the plan file matches the input stated goal.
		TS3 : The plan file’s methodology follows the input intended direction and covers the required analyses.
		TS4 : For every circuit component identified, the tests confirm that its behavior matches the hypothesized function described in the given plan.
REPRODUCIBILITY	Execution Quality	C1 : The block executes without error.
		C2 : The logic implements the described computation correctly (indexing, metric formulas, patching logic, dataset handling).
		C3 : The block duplicates another block’s computation without adding new information. (Revising previous wrong results does not considered as redundant.)
		C4 : The block does not contribute to achieving the project goal as defined in the lan, code walkthrough, or documentation.
	Replication Quality	RP1 : The experiment can be reconstructed from the plan and code-walk without missing steps or required inference beyond ambiguous interpretation.
		RP2 : The environment (packages, models, data) can be restored and run without unresolved version or dependency issues.
		RP3 : Replicated results are stable across multiple runs.
		RP4 : (only when demo exists) pass when all of the following conditions are satisfied: (1) The demo can be executed or followed without referencing hidden or external materials. (2) Experiment or result claimed in the original paper / plan is can be demonstrated in the demo. (3) The demo specifies all required inputs, configurations, and execution steps needed to reproduce the demonstrated results.
		DE1 : Replicated documentation reports results (metrics, trends, qualitative findings) that match the original documentation within acceptable tolerance (within 5% deviation).
	DE2 : The replicated documentation presents conclusions and interpretations consistent with the original.	
	DE3 : No new information appears that is absent from or unsupported by the original documentation.	
GENERALIZABILITY	Finding Generalizability	GT1 : The newly-proposed concept is predictable on a new model, and can be verified through at least one example.
		GT2 : The newly-proposed concept is predictable on a new data instance, and can be verified through at least one example.
	Method Generalizability	GT3 : If the work propose a new method, the method can be applied to another similar task, and can be verified through at lease one example.

Table 3. Task suite used to evaluate research agents across replication, open-ended questions, and human-authored research.

Task Category	Task Description
REPLICATION	<p><code>ioi</code>: Identify the circuit for predicting indirect objects in sentences (Wang et al., 2023).</p> <p><code>acronyms</code>: Find components for predicting multiple consecutive tokens in acronym completions (García-Carrasco et al., 2024).</p> <p><code>greater_than</code>: Locate the circuit that determines if a year exceeds a previous year (Hanna et al., 2023).</p> <p><code>docstring</code>: Find the circuit that predicts function argument names in Python docstrings (Heimersheim & Janiak, 2023).</p> <p><code>pronoun</code>: Identify how the model resolves pronouns to their referent entities (Mathwin et al., 2023).</p> <p><code>copy</code>: Investigate how copy suppression heads prevent repeated token predictions (McDougall et al., 2023).</p> <p><code>induction</code>: Explain the mechanism behind decreased probability for recently-seen tokens (Olsson et al., 2022).</p> <p><code>modular</code>: Reverse-engineer a model trained to compute modular addition (Nanda et al., 2023).</p> <p><code>balanced_bracket</code>: Understand the circuit for classifying balanced brackets (McDougall, 2023).</p> <p><code>max_of_k</code>: Locate the circuit that identifies the maximum value in a list (Gross et al., 2024).</p>
OPEN-ENDED	<p><code>sarcasm</code>: Identify how the model represents and detects sarcasm.</p> <p><code>multilingual</code>: Investigate how the model processes multilingual instructions.</p> <p><code>unanswerable</code>: Understand how the model handles unanswerable questions.</p> <p><code>uncertainty</code>: Determine whether a dedicated circuit exists for representing uncertainty.</p> <p><code>typo</code>: Explain how the model maps misspelled tokens to correct forms.</p> <p><code>persona</code>: Investigate why different personas converge to similar preferences (Kozlov, 2025).</p> <p><code>inevitability</code>: Distinguish how the model represents semantic vs. narrative inevitability.</p> <p><code>irreversibility</code>: Find which layers encode the irreversibility of events.</p> <p><code>moral</code>: Separate the model’s representations of moral wrongness from bad outcomes.</p> <p><code>count</code>: Understand why the model struggles to generate a specified number of words.</p>
HUMAN REPO	<p><code>filter</code>: Identify general filter heads that process list elements (Sharma et al., 2025a).</p> <p><code>interpdetect</code>: Detect hallucination signals in financial question answering (Tan et al., 2025).</p> <p><code>arithmetic</code>: Study vector arithmetic in concept and token subspaces (Feucht et al., 2025).</p> <p><code>universal</code>: Identify neurons with consistent functions across contexts (Gurnee et al., 2024).</p> <p><code>leela</code>: Analyze iterative inference in a chess-playing neural network (Sandmann et al., 2025).</p> <p><code>relation</code>: Test linearity of relation decoding in transformer language models (Hernandez et al., 2024).</p> <p><code>function_vector</code>: Study how in-context learning is encoded as function vectors (Todd et al., 2024).</p> <p><code>erasing</code>: Evaluate methods for removing conceptual knowledge from models (Gandikota et al., 2024).</p> <p><code>belief</code>: Investigate how models track beliefs using lookback mechanisms (Prakash et al., 2025).</p> <p><code>rome</code>: Locate and edit factual associations in GPT models (Meng et al., 2022).</p>

Table 4. Average evaluation time per task by category. Human-written repositories require the longest evaluation time due to their larger codebases and more complex documentation.

Task Category	Average Time
Replication Tasks	1.0 hr
Open-ended Questions	2.3 hr
Human-written Repositories	3.35 hr

D. Detailed Results

Detailed Failure Rates. Figure 8 shows the failure rate averaged across all tasks for each metric. MechEvalAgent shows high failure rates in statistical significance and execution quality. The No-Execution and Doc-Only baselines exhibit even higher failure rates, especially in generalizability and replication quality where execution is crucial. However, agreement with human judgments is low for these baselines, indicating over-assignment of failures.

Figure 9 shows pass rates for each checklist item broken down by task category. Overall pass rates are similar across categories. On average, human-written repositories achieve 78.9%, replication tasks achieve 75.0%, and open-ended tasks 75.7%. Code quality metrics (C1-C4) show consistently high failure rates. Statistical significance (CS5) shows 100% failure rate in both replication and open-ended tasks, while human-written repositories achieve 60% pass rate. Replication tasks show relatively higher pass rates on instruction following (TS1-TS4), as expected given their well-defined experimental goals. Open-ended tasks show more variation in coherence metrics, reflecting the greater ambiguity in evaluating exploratory research.

Agreement and Rated Quality. We measure whether MechEvalAgent verdicts match human evaluations using the same checklist (agreement), and how much human experts agree with the rationales MechEvalAgent provides (rated quality). As shown in Figure 10, MechEvalAgent achieves high agreement with human experts across all task categories: 86.4% for replication tasks, 80.5% for open-ended tasks, and 80.5% for human-written repositories. Overall, AND Logic achieves 84.1% agreement (95% CI: [81.1%, 86.6%], $p < 0.001$), significantly above chance. Consistency metrics (CS1-CS5) show particularly strong agreement, reaching 90-100% across most categories. Reproducibility metrics (RP1-RP3) also achieve high agreement rates of 90-100%. The lowest agreement occurs in C3 (Redundancy), with only 30-40% agreement across categories, and GT3 (method generalizability), which shows 30% agreement in replication tasks. Those failures are likely due to different interpretation of the checklist as we discussed in Section 4.2. Figure 11 shows average rated quality of MechEvalAgent evaluations, which is above 4 (Agree) across all metrics.

Beyond agreement with human evaluation, MechEvalAgent also identifies unique issues that humans miss, as discussed in Section 4.2. On average, each project has 1.57 issues in coherence, 2.83 issues in reproducibility, and 0.17 issues in generalizability that are uniquely identified by MechEvalAgent, as shown in Figure 12. Reproducibility is the dimension where most unique issues are found. Fewer issues are found in generalizability, primarily due to our task design. As shown in Figure 9, all generalizability failures occur in human-written repositories. This is partially because our replication and open-ended tasks are not designed for specific architectures, whereas human-written repositories often contain demonstration code tailored to particular architectures. Additionally, passing the generalizability checklist does not guarantee that results transfer to other models or that the methodology is stable across settings, as discussed in Section 4.2.

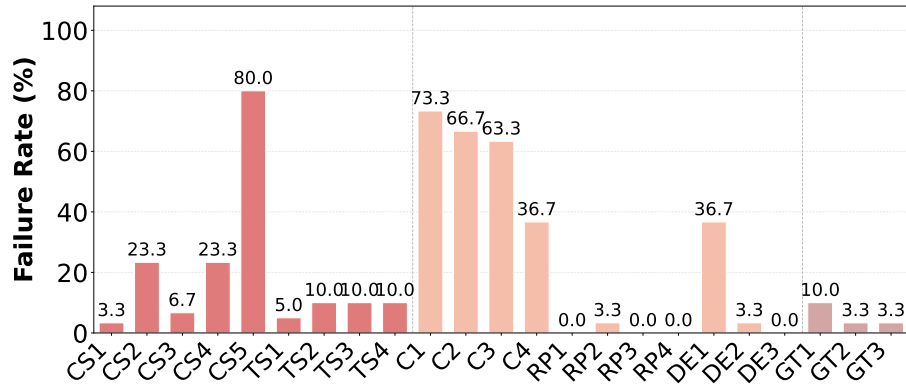
Efficiency Comparison. Table 4 shows the average evaluation time per task across different categories. Replication tasks require the shortest evaluation time (1.0 hour on average), as they have well-defined experimental setups and smaller codebases. Open-ended questions take longer (2.3 hours) due to the need to understand the hypothesis and method proposed by research agents. Human-written repositories require the most time (3.35 hours), reflecting their larger codebases, more complex documentation, and the additional effort needed to extract goals and methodology from accompanying papers.

Stability. We run evaluation for three times for each research project. Here, we measure the stability by checking the agreement across three runs. In Figure 13 and Figure 14, we show the proportion of perfect agreement (3 runs are the same) and one-dissent agreement (1 run is different).

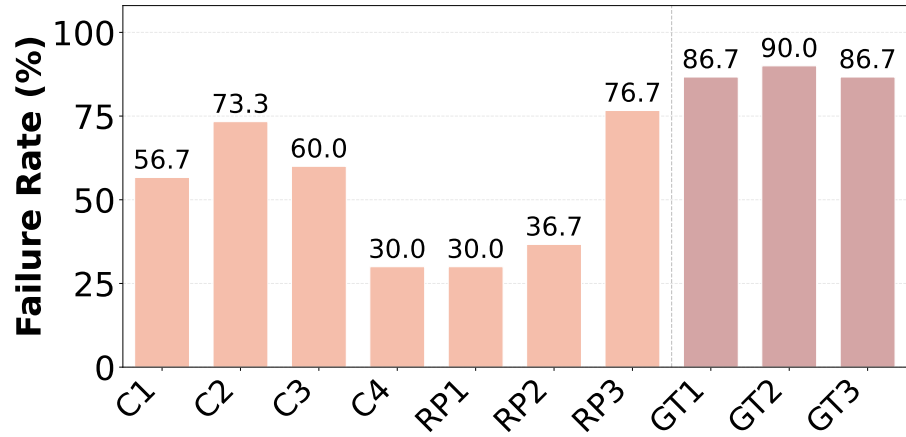
Our evaluations in consistency, instruction following, generalizability, and reproduction are mostly stable, as shown in Figure 13a. We attribute the instability to two main factors. First, our binary checklists cannot enumerate every possible situation, particularly given the diverse input space of research artifacts, leading to inconsistent interpretations across runs.

1100 Second, we observe an interesting behavioral pattern in Claude Code, which is a reluctance to provide negative feedback.
1101 This can contribute to the instability during evaluation. The evaluation agent tends to exploit ambiguities in the checklist to
1102 assign PASS, which we discuss further in Section 6. As discussed in Section 4.2, different interpretations of the checklist
1103 also contribute to the instability. Despite these sources of instability, agreement with human evaluators remains high, and the
1104 instability itself serves as a useful signal, highlighting cases that warrant closer human inspection.

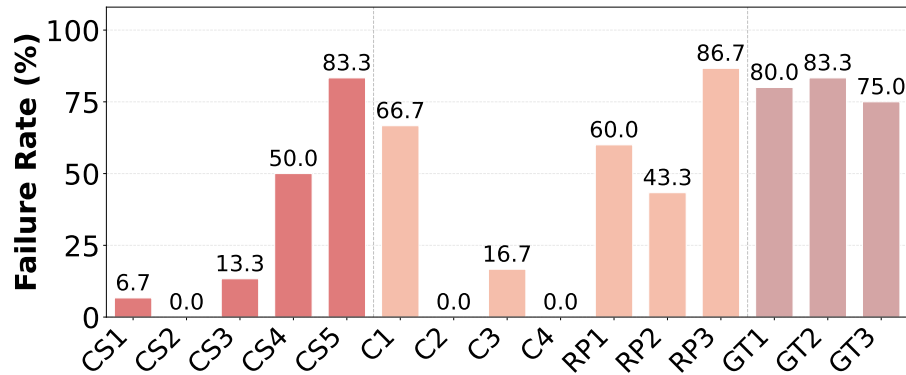
1105 To show more determined failures, we also apply majority voting to failures, where a task is marked as FAIL only if three
1106 runs return FAIL. Issues identified through majority voting represent more consistent failures that persist across multiple
1107 evaluation runs. As shown in Figure 15, majority voting yields an overall higher pass rate. The most common failures
1108 remain in CS5 (statistical significance) with 80% failure rate, followed by failures in execution quality. Agreement with
1109 human judges improves to 89.4% (95% CI: [86.9%, 91.5%], $p < 0.001$) when using majority voting, also significantly
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(a) All Tasks



(b) No Execution



(c) Doc Only

■ Coherence ■ Reproducibility ■ Generalizability

Figure 8. Average failure rate of all the tasks with MechEvalAgent, Doc-only, and No-Execution. Under MechEvalAgent evaluations, statistical significance(CS5) achieve 80% failure rate. The failure rate in execution quality(C1-C4) and replicated results fidelity (DE1) are high. In contrast, FAIL is over-assigned in the Doc-only and No-Execution settings, especially in generalizability.

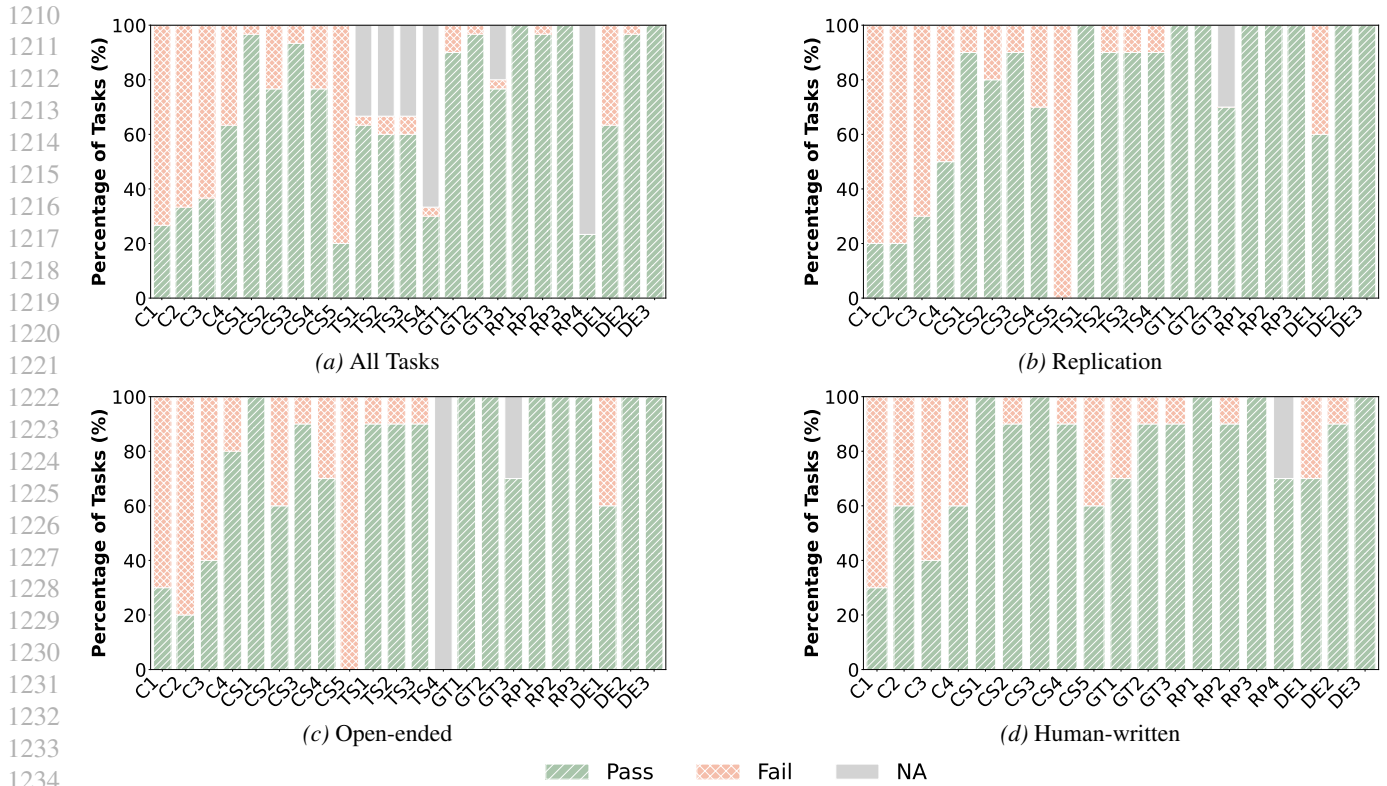


Figure 9. Pass rates using AND logic. (a) All 30 tasks combined. (b) Replication tasks. (c) Open-ended tasks. (d) Human-written repositories. Code quality metrics (C1-C4) and CS5 (result justification) show highest failure rates.

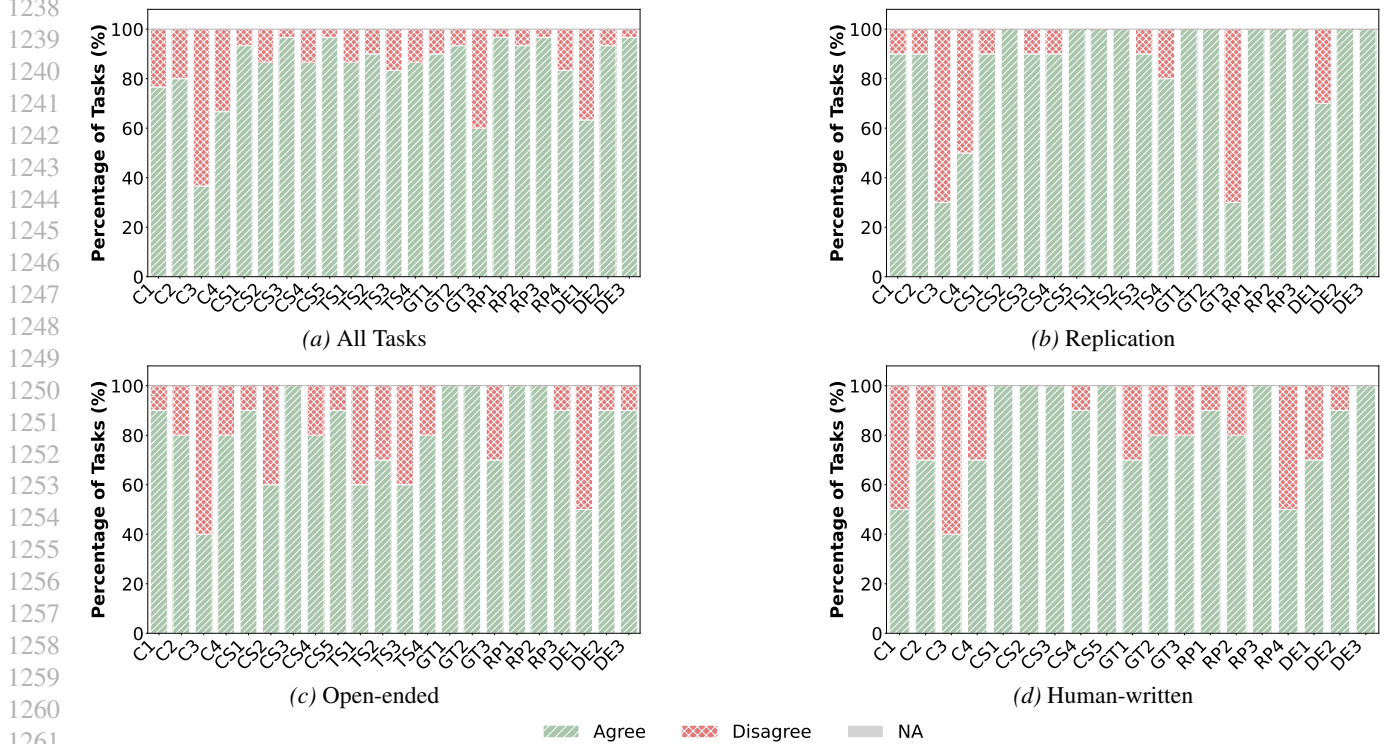


Figure 10. Agreement between MechEvalAgent and human experts. Bars show percentage of tasks where agent’s evaluation matched human assessment. (a) All tasks (above 80% average). (b) Replication tasks. (c) Open-ended tasks. (d) Human-written repositories.

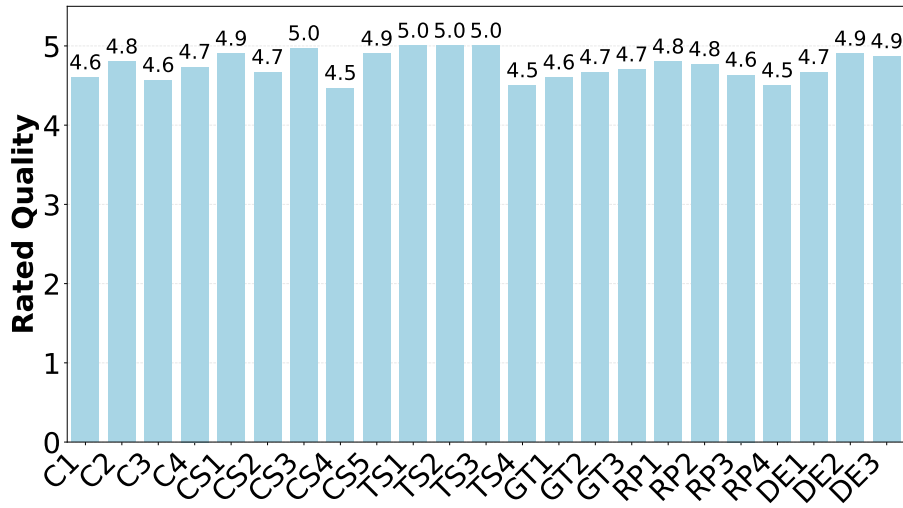


Figure 11. Human-rated quality on MechEvalAgent evaluations (1-5 Likert scale) on each metrics averaged across three types of tasks.

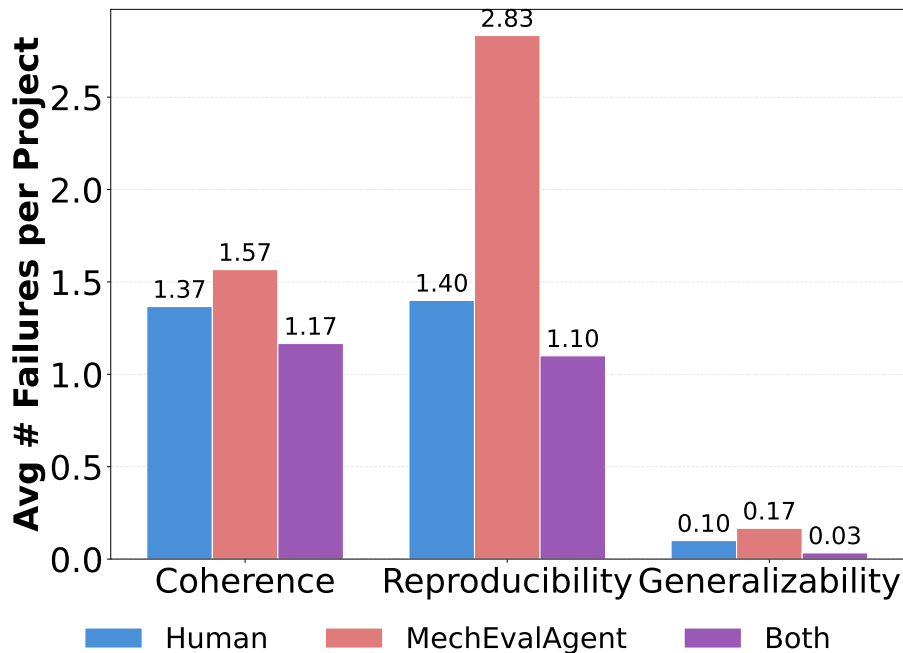


Figure 12. Average number of unique issues identified by MechEvalAgent per project, broken down by evaluation dimension. Reproducibility shows the most unique issues (2.83 per project), followed by coherence (1.57) and generalizability (0.17).

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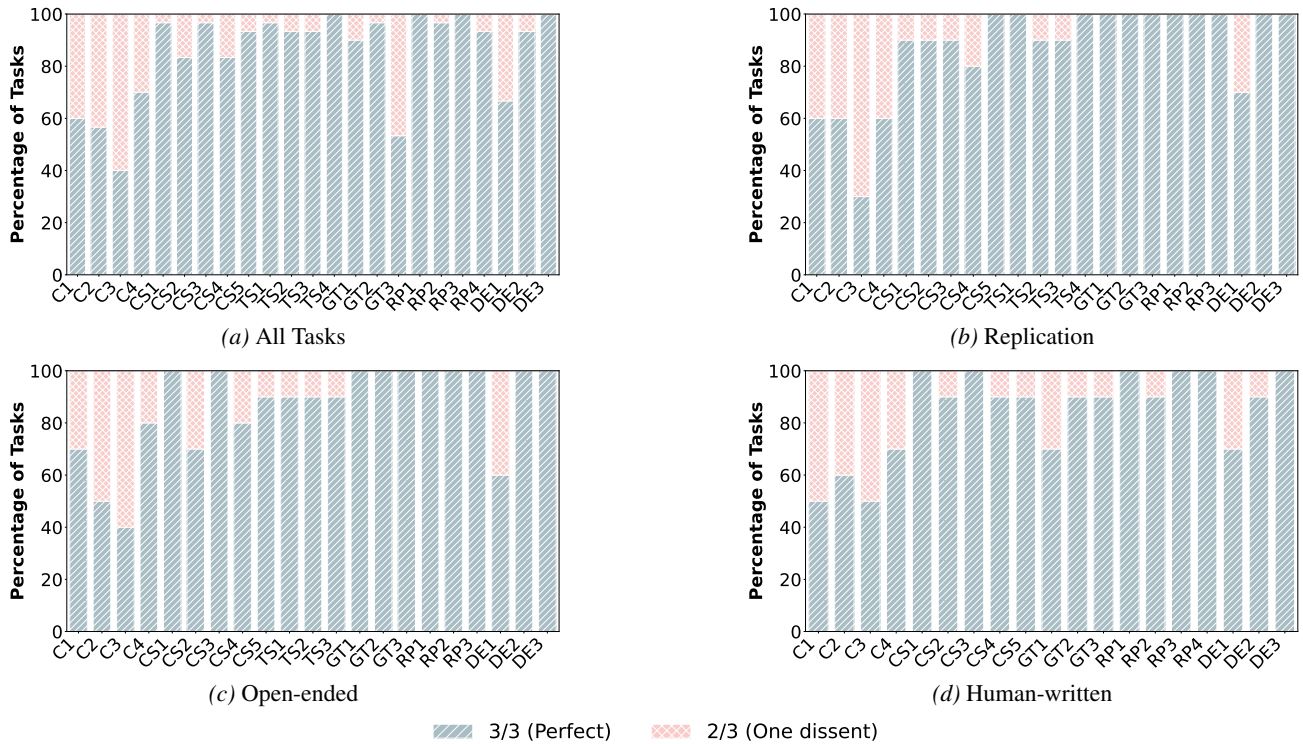


Figure 13. Evaluation stability across three runs. Bars show 3/3 (perfect) vs 2/3 (one dissent) agreement. (a) All tasks combined. (b) Replication tasks. (c) Open-ended tasks. (d) Human-written repositories. Most metrics achieve over 90% perfect agreement.

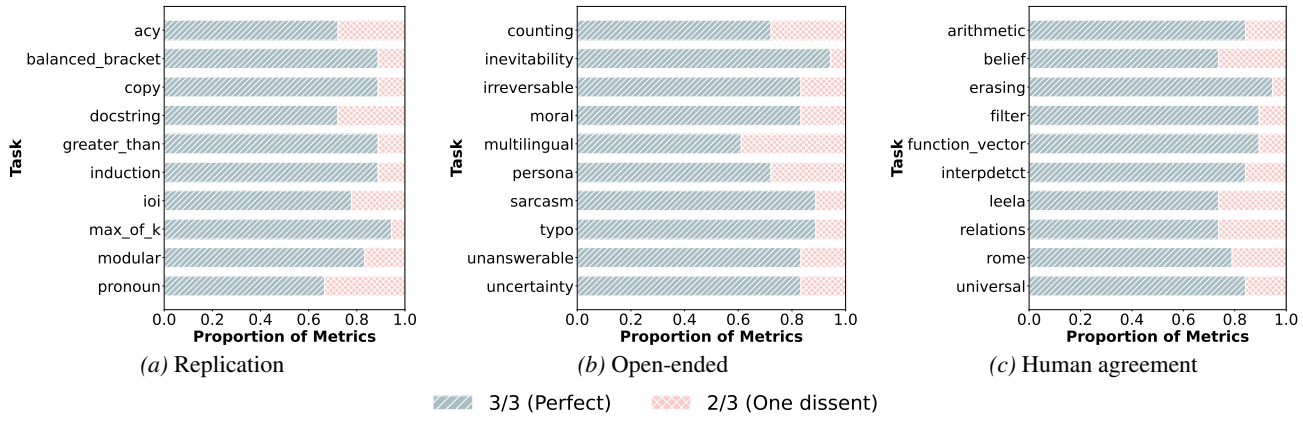


Figure 14. Evaluation stability by repository type. Bars show 3/3 (perfect) vs 2/3 (one dissent) agreement across three runs. (a) Replication tasks. (b) Open-ended tasks. (c) Human-written repositories.

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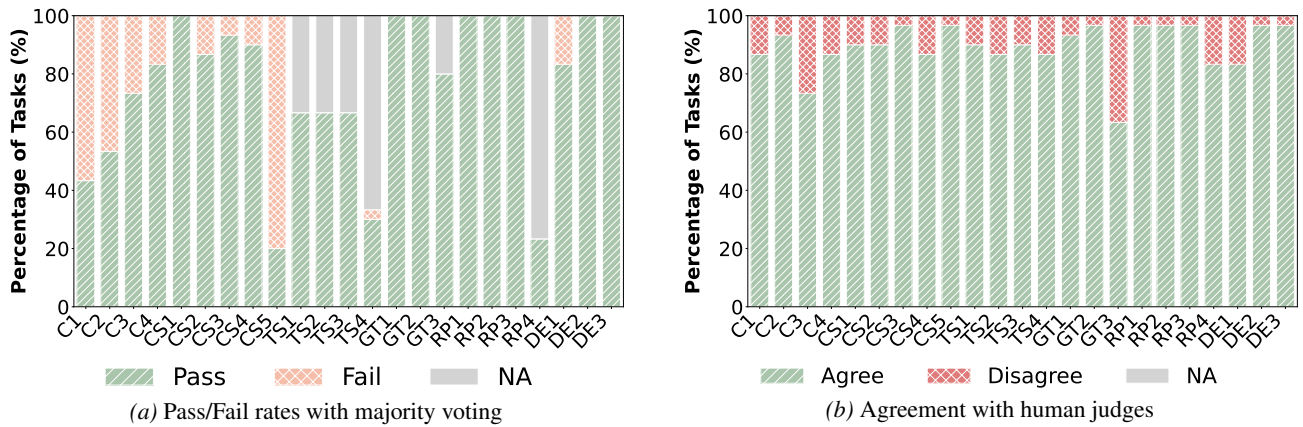


Figure 15. Evaluation results using majority voting. (a) Pass/Fail rates per metric when using majority vote (task fails if at least 2 of 3 runs fail). (b) Agreement between majority vote results and human evaluations, achieving 89.4% overall agreement.