

When AI Reviews Train AI Reviewers: Scientific-Judgment Collapse and Mitigation

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Large language models (LLMs) increasingly participate in scientific evaluation, both as automated reviewers and as assistants to human reviewers. As model-generated reviews enter public data and future training corpora, AI peer review can become recursive: later reviewers learn from judgments produced by earlier models. We study one step of this feedback loop in a controlled setting. Starting from Llama 3.1 8B, we first fine-tune a reviewer on official ICLR reviews from 2018–2023 and then train four successor models on ICLR 2024 data with systematically varied mixtures of official and model-generated reviews. Our study shows that introducing synthetic reviews compresses rating distributions and reduces both same-paper and corpus-level semantic diversity. We call this pattern **scientific-judgment collapse**.

To mitigate this failure mode, we introduce **TrustReviewer**, an open-source LLM-based system for generating peer reviews of AI and machine learning papers. TrustReviewer intervenes at two complementary stages. For training-time prevention, we train the core reviewer in a single stage on a curated corpus designed to reduce low-quality and semantically degenerate supervision. For test-time correction, paired activation steering aims to further mitigate residual tendencies toward collapsed judgments without further training or additional expert annotation. Together, these results characterize a concrete risk of recursive reviewer training and provide practical interventions for preserving judgment diversity and improving recommendation alignment in AI-assisted scientific evaluation.

Project Page 🏠: <https://hosytuyen.github.io/projects/TrustReviewer>

Dataset 🗃️: <https://huggingface.co/collections/hosytuyen/trustreviewer>

Code 📄: <https://github.com/hosytuyen/TrustReviewer>

1. Introduction

Large language models (LLMs) are starting to enter scientific peer review. They summarize papers, suggest critiques, predict scores, and help reviewers improve their reports. These uses can reduce reviewer workload but also create a feedback loop. Reviews written or substantially edited by an LLM may become public, enter a later training corpus, and be used to train the next LLM. The next LLM then learns, in part, from its predecessors’ judgments. Recent evidence suggests that substantial LLM modification is already present in some AI-conference review corpora, although these estimates do not identify AI use for individual reviews (Liang et al., 2024).

This feedback loop is closely related to recursive training. A known failure mode is *model collapse*: repeatedly fitting a model to generated samples can erase low-probability parts of the original distribution (Shumailov et al., 2023, Alemohammad et al., 2024). The outcome is not inevitable. If real data are retained and accumulated rather than replaced, collapse can be avoided in the settings studied by Gerstgrasser et al. (2024). Still, language-model experiments find that increasing the synthetic-data fraction can produce distributional shift and feature over-concentration (Zhu et al., 2024). These results raise a concrete question for peer review: if a reviewer is trained on generated reviews, does it express a narrower range of scientific

judgments?

We study this question in a controlled setting. Starting from Llama 3.1 8B (Meta, 2024) as the base LLM, we first fine-tune it on official ICLR reviews from 2018 to 2023. We use this model to generate reviews for ICLR 2024 papers. We then train successor reviewers on mixtures with different numbers of official and generated reviews per paper. The successor models share the same initialization, filtering, and optimization settings; the review-source mixture is the only planned difference. This is not a measurement of naturally occurring AI assistance in peer review. Rather, we hold other training factors fixed to isolate the effects of introducing a known amount of generated supervision.

Our results reveal a form of **scientific-judgment collapse**. Introducing synthetic reviews compresses rating distributions and reduces semantic diversity relative to the official-review-only baseline. Both same-paper and corpus-level semantic diversity decrease monotonically as synthetic exposure increases, with reductions of approximately 11% and 5%, respectively, from 0% to 100% synthetic exposure. This pattern reflects homogenization, a narrowing of the model’s range of judgments, rather than a systematic shift toward either leniency or harshness. Because our experiment examines only a single recursive step, whether scientific-judgment collapse compounds over multiple generations remains an important question for future work.

To mitigate this failure mode, we introduce **TrustReviewer**, an open-source LLM-based system for generating peer reviews of AI and machine learning papers. TrustReviewer intervenes at two complementary stages: training-time prevention and test-time correction. We train the core reviewer in a single stage on a curated corpus designed to reduce low-quality and semantically degenerate supervision. At inference time, paired activation steering uses contrasts between official and model-generated reviews of the same papers to further mitigate residual tendencies toward collapsed judgments without further training or additional expert annotation.

Our contributions are:

1. **A controlled experimental framework for studying recursive AI-reviewer training (Sec. 2.1).** We formalize a recursive training feedback loop in LLM-based scientific review and design a controlled experiment to study its effects. Our study varies synthetic-review exposure while holding the reviewer initialization and training setup fixed.
2. **Scientific-judgment collapse under recursive AI-reviewer training (Sec. 2.3).** We show that, after one recursive training step, introducing synthetic reviews compresses rating distributions, while increasing synthetic exposure monotonically reduces both same-paper and corpus-level semantic diversity.
3. **Open-source TrustReviewer (Sec. 3).** We introduce an LLM-based review system that intervenes at two complementary stages. For training-time prevention, the core reviewer is trained on a curated corpus designed to reduce low-quality and semantically degenerate supervision. For test-time correction, paired activation steering aims to further mitigate residual collapsed tendencies without further training or additional expert annotation.

2. Recursive AI Review Training Analysis

2.1. Controlled Recursive AI Review Training Framework

We study one controlled step of recursive AI review training. Starting from a base language model, we first train a reviewer on earlier official conference reviews. We then use that reviewer to generate synthetic reviews

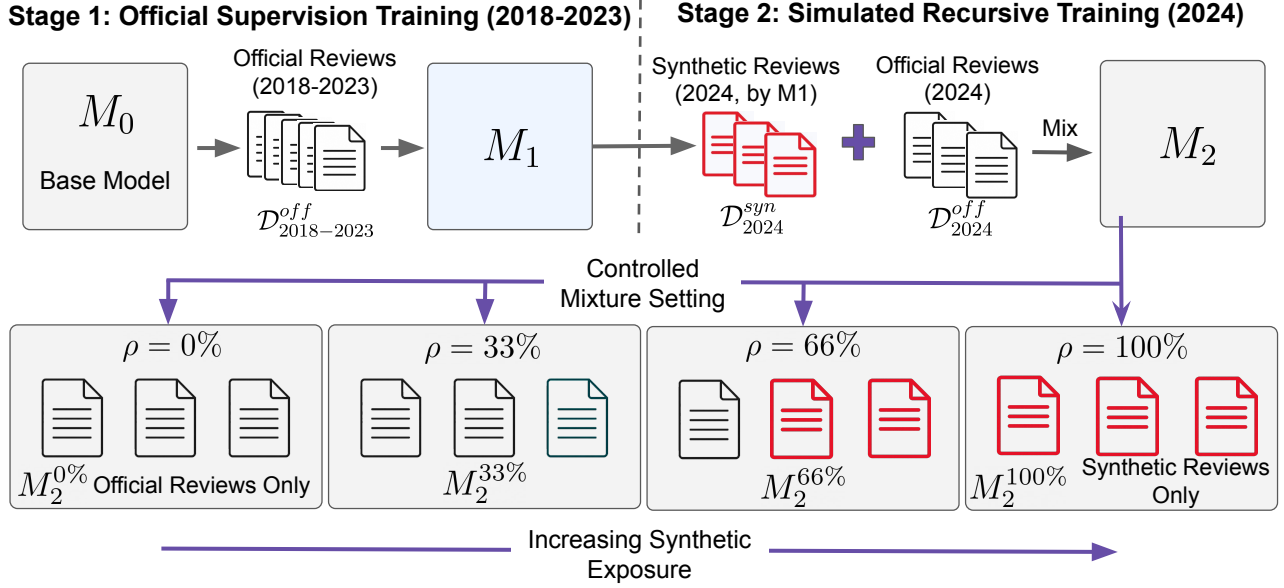


Figure 1: Our controlled experimental framework for studying recursive AI-reviewer training. The experiment varies the synthetic-review percentage p (0%, 33%, 66%, or 100%) across M_2^p variants while holding filtering, truncation, and training settings fixed.

and mix them with official reviews from the following year. This setup isolates how synthetic judgments from one reviewer affect the next training stage.

Notation. Let M_0 denote the Llama 3.1 8B base model, and let $\mathcal{T}(M, \mathcal{D})$ denote supervised fine-tuning of model M on review dataset $\mathcal{D}$. For year y , let $\mathcal{D}_y^{off}$ denote the official ICLR reviews released for submissions in that year. We use “official” rather than “human” because reviews released after ChatGPT’s launch may include unobserved AI assistance.

For recursive training, let $p \in \mathcal{P} = \{0\%, 33\%, 66\%, 100\%\}$ denote the synthetic-review percentage setting. Each paper contributes three reviews, of which zero, one, two, or three are synthetic, respectively. We use 33% and 66% as shorthand labels for one and two synthetic reviews out of three.

Stage construction. Let $\mathcal{D}_{2018:2023}^{off} = \bigcup_{y=2018}^{2023} \mathcal{D}_y^{off}$. We train the initial reviewer model on this dataset:

$$M_1 = \mathcal{T}\left(M_0, \mathcal{D}_{2018:2023}^{off}\right).$$

We end this adaptation period in 2023 for two reasons. First, these reviews largely precede widespread ChatGPT-assisted reviewing. Second, the reported training-data cutoff of Llama 3.1 8B is December 2023 (Meta, 2024). ICLR 2024 reviews therefore fall after the cutoff of M_0 , reducing the risk that the base model encountered the same reviews during pretraining.

For each $p \in \mathcal{P}$, let a be the corresponding number of synthetic reviews per submission (zero, one, two, or three) and let $h = 3 - a$ be the number of official reviews. We construct the 2024 mixture

$$\mathcal{D}_{2024}^p(M_1) = \mathcal{D}_{2024}^{off,h} \cup \mathcal{D}_{2024}^{syn,a}(M_1),$$

where $\mathcal{D}_{2024}^{off,h}$ contains h official reviews per submission and $\mathcal{D}_{2024}^{syn,a}(M_1)$ contains a synthetic reviews generated by M_1 . The corresponding M_2 variant is

$$M_2^p = \mathcal{T}\left(M_1, \mathcal{D}_{2024}^p(M_1)\right), \quad p \in \mathcal{P}.$$

Controlled recursive exposure. All M_2^p variants share the same M_1 initialization and training configuration. They differ only in the percentage of reviews generated by M_1 , denoted by p . We use $M_2^{0\%}$ as the official-review-only baseline and progressively increase synthetic exposure: $0\% \rightarrow 33\% \rightarrow 66\% \rightarrow 100\%$.

We do not assume that the official reviews used to train $M_2^{0\%}$ are entirely human-written, as they may contain unobserved AI assistance. The parameter p therefore denotes the proportion of training reviews explicitly generated by M_1 , not the total prevalence of AI assistance. By varying p while holding the training setup fixed, we isolate how increasing exposure to these synthetic reviews affects reviewer behavior after a single recursive training step.

2.2. LLM Training Setup

Data construction. We apply the same filtering pipeline at every training stage, removing malformed or follow-up reviews, structurally invalid examples, excessively short or repetitive reviews, and examples exceeding the 64k-token context limit. Appx. A gives the complete criteria and thresholds.

Training protocol. We use supervised fine-tuning in LlamaFactory (Zheng et al., 2024) with LoRA (Hu et al., 2021), using rank 64, a scaling factor of 128, dropout of 0.05, and adaptation of all target modules. Shared settings for M_1 and all M_2^p variants include a maximum context length of 64,000 tokens, a per-device batch size of 1, 16 gradient-accumulation steps, a warmup ratio of 0.05, three epochs, bfloat16 precision, and FlashAttention-2. We initialize M_1 from M_0 (Meta-Llama-3.1-8B-Instruct) and fine-tune it on filtered official reviews from 2018–2023 with a learning rate of 2×10^{-5} and cosine decay. Each M_2^p is initialized from M_1 and fine-tuned on $\mathcal{D}_{2024}^p(M_1)$ with a lower learning rate of 2×10^{-6} for $p \in \mathcal{P}$. All M_2^p variants share the same training settings, isolating the effect of synthetic-review percentage p on reviewer behavior.

Held-out evaluation set. We reserve a held-out evaluation set of 2,000 papers sampled across years: 57, 88, 136, 161, 161, 235, 449, and 713 papers from 2018, 2019, 2020, 2021, 2022, 2023, 2024, and 2025, respectively. These papers are excluded from training. Each trained reviewer model generates reviews for this fixed set, and all analysis is performed on those generated reviews. This design allows direct comparison between M_1 and the four M_2 variants.

2.3. Scientific-Judgment Collapse under Recursive AI Peer Review

2.3.1. Recursive Synthetic Exposure Compresses Rating Diversity

Goal. We first examine how recursive exposure to synthetic reviews changes the distribution of scientific judgments. In particular, we ask whether synthetic supervision causes a directional shift in recommendations. We compare the M_2 variants trained with increasing proportions of synthetic reviews using the official-only $M_2^{0\%}$ model as the controlled baseline.

Metric. For each model, we extract the overall recommendation from each generated review on the held-out evaluation set and construct the distribution over ratings from 1 to 10. We then summarize this distribution using three statistics: the mean rating, the standard deviation of ratings, and the entropy of the rating distribution. The mean captures overall leniency or harshness, the standard deviation captures how dispersed the model’s judgments are, and the entropy captures how broadly the model uses the rating scale. A lower standard deviation or entropy indicates a more concentrated judgment distribution, while higher values indicate more diverse use of the rating scale.

Observation. Fig. 2 shows that recursive synthetic exposure compresses rating diversity. Official reviews provide a broader reference distribution, with a standard deviation of 1.73 and entropy of 2.38, compared

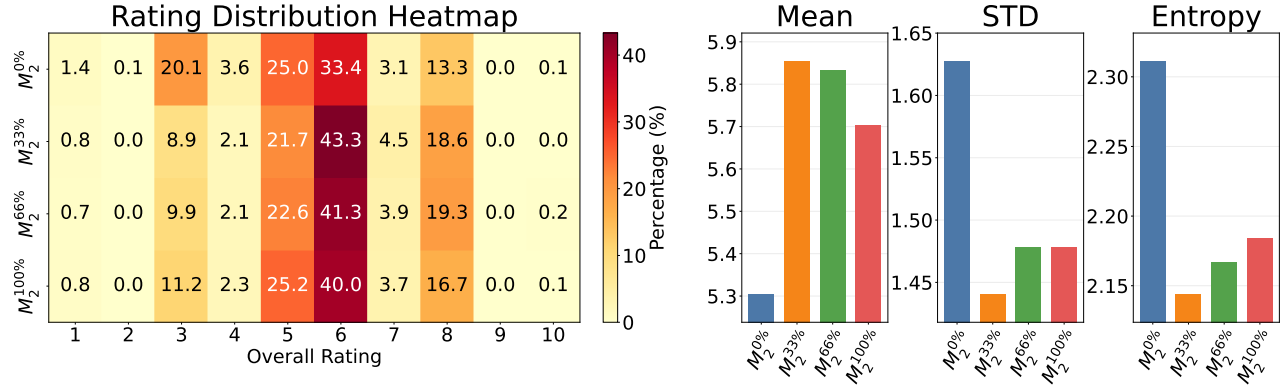


Figure 2: Introducing synthetic exposure compresses rating diversity. We compare official reviewer ratings with the M_2 variants trained using 0%, 33%, 66%, and 100% synthetic reviews. The heatmap shows the empirical rating distribution, while the remaining panels report its mean, standard deviation, and entropy. Official reviews are shown as a reference; comparisons among the M_2 variants isolate the effect of synthetic-review exposure.

with 1.63 and 2.31 for the $M_2^{0\%}$ model. More importantly, within the controlled M_2 comparison, introducing 33% synthetic reviews further reduces these values to 1.44 and 2.14, and both remain below the $M_2^{0\%}$ baseline at 66% and 100% synthetic exposure. Mean ratings change non-monotonically, rising from 5.30 at 0% synthetic exposure to 5.85 at 33% before decreasing to 5.70 at 100%. Thus, recursive exposure primarily compresses the diversity of expressed ratings rather than inducing a systematic shift toward greater leniency or harshness.

2.3.2. Recursive Exposure Reduces Same-Paper Semantic Diversity

Goal. We next examine whether recursive synthetic exposure makes independently generated reviews of the same paper increasingly alike. We hold the paper input fixed and measure variation in the judgments expressed for the same submission.

Metric. For each paper, we use up to three official reviews and model-generated reviews from three independent runs. We encode each review into a semantic embedding and compute the average pairwise cosine distance among the reviews of the same paper. Appx. B provides details of the embedding model and processing procedure. Formally, if a paper has review embeddings $\{e_1, \dots, e_n\}$, we define its same-paper semantic difference as

$$D_{\text{paper}} = \frac{2}{n(n-1)} \sum_{i < j} (1 - \cos(e_i, e_j)).$$

Larger values indicate greater semantic diversity across reviews of the same paper, while smaller values indicate greater semantic homogeneity. We report the mean D_{paper} across papers in the held-out evaluation set.

Observation. Fig. 3-right shows a monotonic reduction in same-paper semantic diversity as synthetic exposure increases. Within the controlled M_2 comparison, the mean semantic distance decreases from approximately 0.159 for the official-only $M_2^{0\%}$ model to 0.153, 0.147, and 0.142 under 33%, 66%, and 100% synthetic exposure, respectively. This corresponds to an approximately 11% reduction from 0% to 100% synthetic exposure. Thus, increasing recursive synthetic exposure makes independently generated reviews of the same submission progressively more semantically homogeneous.

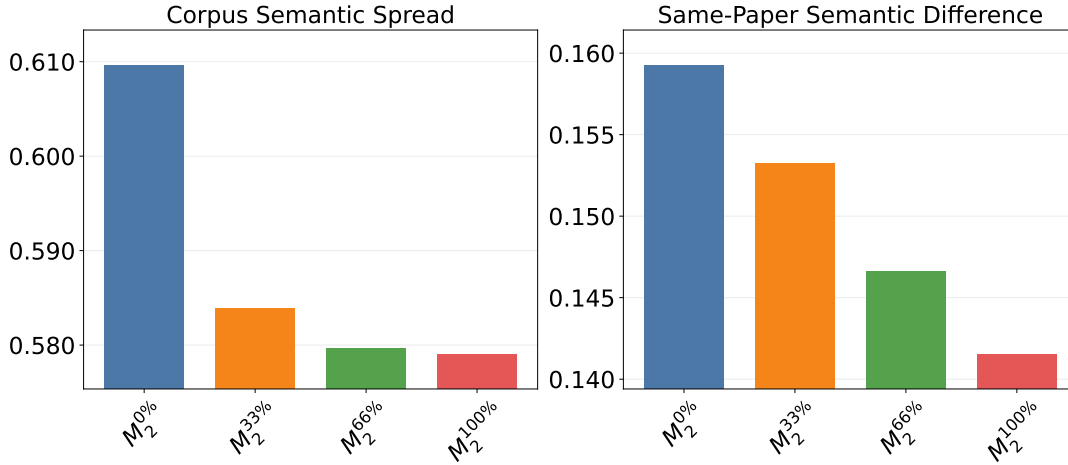


Figure 3: Recursive exposure concentrates corpus-level semantic judgments (left). The left panel reports semantic spread around the corpus centroid, which decreases under synthetic-review exposure. **Recursive exposure also homogenizes reviews of the same paper (right).** The right panel reports mean pairwise semantic distance among reviews of the same submission, which decreases monotonically as synthetic exposure increases. Official reviews are shown as a contextual reference; lower values indicate less semantic diversity.

2.3.3. Collapse of Corpus-Level Semantic Diversity

Goal. While same-paper analysis measures whether multiple reviews of the same paper become more alike, it does not capture whether the overall space of judgments across different papers also becomes more concentrated. We therefore examine whether recursive synthetic exposure contracts the corpus-level semantic distribution of generated reviews.

Metric. For each review, we encode the full review into a semantic embedding and aggregate multiple reviews of the same paper into a single paper-level embedding. We then measure how dispersed these paper-level embeddings are in semantic space. Specifically, let $\{e_1, \dots, e_N\}$ denote the normalized paper-level review embeddings for the held-out papers, and let

$$\bar{e} = \frac{1}{N} \sum_{i=1}^N e_i$$

be the corpus centroid. We compute the spread to centroid as

$$\text{Spread} = \frac{1}{N} \sum_{i=1}^N \|e_i - \bar{e}\|_2^2.$$

Larger values indicate that the review corpus occupies a broader semantic region, while smaller values indicate greater concentration around the corpus centroid.

Observation. The Fig. 3-left shows a monotonic contraction of corpus-level semantic diversity as synthetic exposure increases. Within the controlled M_2 comparison, the corpus semantic spread decreases from approximately 0.609 for the $M_2^{0\%}$ model to 0.584, 0.580, and 0.579 under 33%, 66%, and 100% synthetic exposure. This corresponds to an approximately 5% reduction from 0% to 100% synthetic exposure. Although the largest contraction occurs after introducing synthetic supervision, the spread continues to decrease as synthetic exposure increases. Together with the same-paper results, this indicates that recursive training

contracts semantic diversity both among reviews of the same submission and across the broader corpus of scientific judgments.

3. TrustReviewer: Mitigating Scientific-Judgment Collapse

Our study identifies scientific-judgment collapse under recursive AI-reviewer training: introducing synthetic reviews compresses rating distributions and reduces semantic diversity. To mitigate this failure mode, we introduce TrustReviewer, which intervenes at two complementary stages. At training time, corpus curation aims to reduce low-quality and semantically degenerate supervision in the first place (Sec. 3.1). At inference time, paired activation steering further mitigates residual tendencies toward collapsed judgments without further training or additional expert annotation (Sec. 3.2).

3.1. Training-Time Prevention via Corpus Curation

To construct the training corpus, we collect officially released ICLR reviews from 2018 to 2025:

$$\mathcal{D}_{\text{raw}} = \bigcup_{y=2018}^{2025} \mathcal{D}_y^{\text{off}}.$$

As discussed in Sec. 2, we use the term “official” rather than “human” because recent reviews may contain unobserved AI assistance. Curation therefore targets the quality and diversity of supervision rather than assuming that official reviews are entirely human-written.

Each example is a paper–review pair $z_i = (x_i, r_i)$, where x_i contains the paper content and r_i is its corresponding official review. We apply a unified filtering and curation pipeline to $\mathcal{D}_{\text{raw}}$, removing malformed, duplicated, excessively short, repetitive, and follow-up reviews, as detailed in Appx. A. By reducing repetitive and semantically degenerate supervision, this procedure aims to mitigate semantic collapse in the reviews generated by the trained model. The resulting corpus is

$$\mathcal{D}_{\text{curated}} = \mathcal{C}(\mathcal{D}_{\text{raw}}),$$

where $\mathcal{C}$ denotes the complete curation pipeline. The final corpus contains 112,743 paper–review examples, totaling approximately 1.9 billion tokens. We reserve 2,000 papers for evaluation and exclude them from corpus construction, model training, and steering-vector estimation.

Training the core reviewer. We initialize the core reviewer M_{TR} from Meta-Llama-3.1-8B-Instruct and train it on the complete curated corpus $\mathcal{D}_{\text{curated}}$, following the fine-tuning protocol described in Sec. 2.2. Unlike the controlled experiment in Sec. 2, this training aims to build the final reviewer rather than isolate the effects of synthetic-review exposure. We combine all retained reviews from 2018–2025 and fine-tune the base model in a single stage, without an intermediate reviewer model or a subsequent recursive training stage.

3.2. Test-Time Correction via Paired Activation Steering

We complement training-time curation with paired activation steering, estimating a representation direction from model-generated reviews to official reviews of the same papers and applying it during generation. Our

implementation follows Zou et al. (2023); official reviews serve as a reference rather than a guaranteed human-written or uniquely correct standard. The intervention requires neither further training nor additional expert annotation.

Steering-vector construction. We sample $K = 5,000$ paper-review pairs from $\mathcal{D}_{\text{curated}}$ and generate a review of each paper using M_{TR} . The resulting calibration set is

$$\mathcal{P}_{\text{cal}} = \left\{ (x_i, r_i^{\text{off}}, r_i^{\text{TR}}) \right\}_{i=1}^K,$$

where r_i^{off} and r_i^{TR} are the official and generated reviews of paper x_i , respectively. This pairing holds paper content fixed when estimating representational differences. The calibration set excludes all held-out evaluation papers.

We tokenize each review r as a standalone sequence and truncate it to at most 8,192 tokens. Let $H_\ell(r) \in \mathbb{R}^{T \times d}$ denote the hidden states at layer ℓ and $q(r)$ the final non-padding token’s position, determined from the attention mask. Last-token pooling yields $\phi_\ell(r) = H_\ell(r)_{q(r)}$, the final non-padding token’s hidden state. We estimate a layer-specific steering vector by averaging paired representation differences:

$$v_{\text{steer}}^{(\ell)} = \frac{1}{K} \sum_{i=1}^K \left[\phi_\ell(r_i^{\text{off}}) - \phi_\ell(r_i^{\text{TR}}) \right].$$

The saved steering vector is not unit-normalized.

Applying steering vectors during generation. Let $\mathcal{L}$ denote the selected layers. At each layer, we add the controller to the decoder block’s residual-stream output before it enters the next layer. For the last token position t in a forward pass,

$$\tilde{h}_{\ell,t} = h_{\ell,t} + \alpha v_{\text{steer}}^{(\ell)},$$

where α controls the intervention strength. The vector is added only at the last position: to the final prompt token during prefill and to the current token at every subsequent decoding step. Model parameters remain unchanged.

Steering hyperparameter selection. Using 100 separate validation pairs, we select the layer set and steering strength by exact recommendation match against the corresponding official ratings. The search selects the final decoder layer and $\alpha = 0.15$, which we use for all subsequent evaluations. Appx. C provides the full search grid and data-separation details.

Overall pipeline. TrustReviewer combines curated training with test-time steering:

$$\mathcal{D}_{\text{raw}} \xrightarrow{\mathcal{C}} \mathcal{D}_{\text{curated}} \xrightarrow{\text{one-stage SFT}} M_{\text{TR}} \xrightarrow{\text{test-time steering}} M_{\text{TR}}^{\text{steered}}.$$

Training-time curation aims to reduce low-quality and semantically degenerate supervision, while test-time steering further mitigates residual collapsed tendencies without additional parameter updates.

3.3. Experimental Evaluation of TrustReviewer

3.3.1. Evaluation setup

We evaluate generated reviews on the held-out paper set in Sec. 2.2. For locally generated reviews, we use temperature 0.6, nucleus-sampling probability 0.95, and a maximum of 4,096 new tokens. We perform three independent generation runs per paper without fixed decoding seeds. Appx. D provides the complete generation, prompting, retry, and recommendation-parsing procedures.

Baselines. For comparison, we evaluate Meta-Llama-3.1-8B-Instruct (Meta, 2024), the initialization used for TrustReviewer; OpenReviewer (Idahl and Ahmadi, 2025), an open-source specialized reviewer; and Qwen3.6-35B-A3B (Qwen Team, 2026). For each model, we report aggregate results over three generation runs.

Metrics. Following Idahl and Ahmadi (2025), we evaluate recommendation agreement using exact recommendation matching and mean absolute distance (MAD) from the average official rating. Numerical recommendations are extracted from the structured rating field; missing or unparseable ratings are not assigned default values. Higher matching and lower MAD indicate closer agreement with official recommendations; detailed parsing and metric definitions are provided in Appx. D and E. We also assess semantic diversity using corpus-level semantic spread and same-paper semantic distance, as defined in Sec. 2.3.

3.3.2. Evaluation results

TrustReviewer achieves the strongest overall recommendation agreement. Tab. 1 shows that TrustReviewer achieves the highest exact-match rate among the evaluated models at 75.40%, compared with 73.10% for OpenReviewer, 61.85% for Qwen3.6-35B-A3B, and 33.93% for its Llama initialization. Its MAD of 1.079 is also lower than that of every other baseline.

TrustReviewer mitigates judgment homogenization relative to other LLM reviewers. Its rating entropy reaches 2.18, exceeding Llama (1.53), Qwen (1.94), and OpenReviewer (2.10) and narrowing the gap to the official reference (2.38). Fig. 4 also shows greater corpus-level semantic spread and same-paper semantic distance than these baselines. OpenReviewer also exhibits strong semantic diversity in Fig. 4, which may reflect the high-quality curation of its training reviews (Idahl and Ahmadi, 2025). However, its curated training corpus is not publicly available. In contrast, we make our curated training corpus publicly available to support reproducible analysis of reviewer training and judgment diversity. The rating distributions in Appx. F provide additional context.

Test-time steering provides additional gains while preserving high semantic diversity. Relative to the same TrustReviewer checkpoint without steering, paired activation steering raises exact match from 73.85% to 75.40%, a gain of 1.55 percentage points, and increases rating entropy from 2.13 to 2.18 (Tab. 1). It also expands corpus-level semantic spread (Fig. 4), while MAD remains essentially unchanged. Same-paper semantic distance decreases slightly, remaining substantially above the general-purpose Llama and Qwen baselines but below OpenReviewer. Steering therefore improves recommendation matching and broadens aggregate judgment diversity without further training, rather than uniformly improving every diversity metric.

Table 1: Held-out reviewer evaluation. Generated-review results are reported as means $\pm$ standard deviations over three generation runs. Exact match measures whether the generated rating equals at least one official reviewer rating for the same paper. Score-based metrics exclude outputs without a valid generated rating or valid official ratings. Higher exact match and lower MAD indicate closer recommendation agreement; higher entropy indicates greater rating diversity.

Model	Exact Match (%) $\uparrow$	MAD $\downarrow$	Entropy $\uparrow$
Official Reviews	–	–	2.38
Meta-Llama-3.1-8B-Instruct	33.93 ± 0.54	2.679 ± 0.010	1.53 ± 0.03
Qwen3.6-35B-A3B	61.85 ± 0.33	1.335 ± 0.012	1.94 ± 0.02
OpenReviewer	73.10 ± 1.36	1.113 ± 0.022	2.10 ± 0.05
TrustReviewer w/o Steering	73.85 ± 0.15	1.077 ± 0.005	2.13 ± 0.03
TrustReviewer	75.40 ± 0.46	1.079 ± 0.005	2.18 ± 0.01

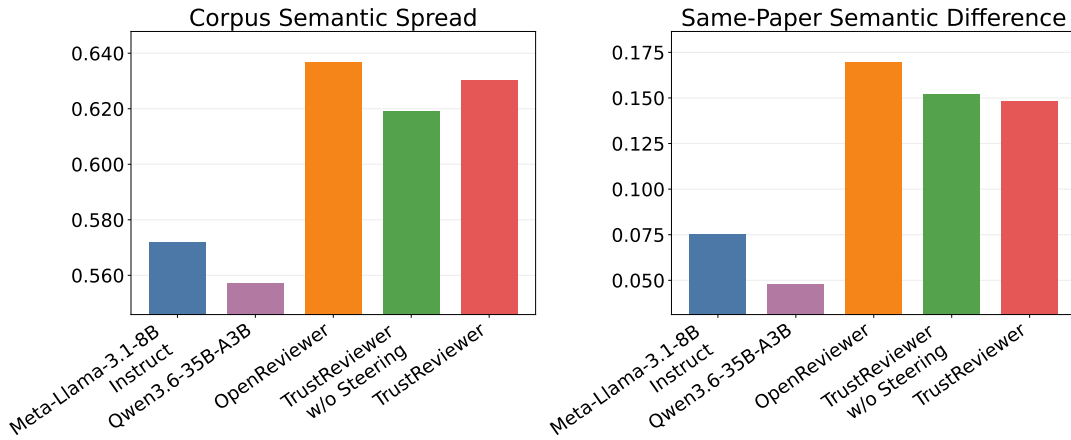


Figure 4: Semantic diversity across reviewers. The left panel reports corpus-level semantic spread, and the right panel reports mean same-paper pairwise semantic distance. We compare TrustReviewer with and without steering against the baseline models, with official reviews as a reference. Higher values indicate greater semantic diversity.

4. Related Work

Recursive training and synthetic-data feedback. The literature studies what happens when generated samples are used to train later generative models (Dohmatob et al., 2024, Fu et al., 2025). Shumailov et al. (2023) show that recursive use of generated data can erase distributional tails. Alemohammad et al. (2024) study self-consuming loops and show that fresh real data matters for retaining quality and diversity. The conclusion is conditional, not universal. Gerstgrasser et al. (2024) show that accumulating real and synthetic data can avoid collapse in their settings. For language models, Zhu et al. (2024) report increasing distributional shift and n-gram over-concentration as the synthetic fraction rises, while related work finds that the magnitude of recursive distribution shift depends on properties of the underlying training data (Kovač et al., 2025). We study a different target: conditional scientific judgment under synthetic-review exposure.

LLMs for scholarly peer review. Automated scholarly review includes score prediction, critique generation, meta-review generation, and reviewer agents to assist people. Zhou et al. (2024) evaluate GPT-3.5 and

GPT-4 on score prediction and review generation, and introduce review–revision questions. [Zhuang et al. \(2025\)](#) survey the broader area. ReviewMT organizes papers and review-process artifacts from ICLR and Nature Communications ([Tan et al., 2024](#)); Gen-Review pairs ICLR submissions and official reviews with prompt-controlled LLM reviews ([Demetrio et al., 2025](#)). Recent empirical studies find that generated reviews can be fluent and descriptive, yet generic, overly positive, limited in identifying substantive weaknesses, or unevenly grounded ([Li et al., 2025](#), [Fichtl et al., 2026](#), [Li et al., 2026](#)). We ask a different question: how does generated review text, when used as supervision, change the next reviewer model?

LLM use also changes the review process itself. [Liang et al. \(2024\)](#) estimate corpus-level rates of substantial LLM modification in reviews from several AI venues; these are not labels for individual reviews. In a randomized ICLR 2025 study, carefully guarded LLM feedback improved review specificity and actionability ([Thakkar et al., 2025](#)). These studies make an important distinction: assistance, autonomous reviewing, and training on the resulting text are different interventions. We therefore refer to these as “official” reviews rather than verified human-only reviews.

Data quality and test-time steering. Data filtering and curation are direct ways to improve supervised corpora. Prior work emphasizes the quality and diversity of instruction-tuning data ([Zhou et al., 2023](#), [Liu et al., 2024](#)). Synthetic-data work likewise emphasizes retaining reliable and diverse real-data support ([Alemohammad et al., 2024](#), [Zhu et al., 2024](#)). TrustReviewer applies these ideas to review training through uniform structural filtering and a curated official-review corpus.

Its second component is activation steering. Prior work shows that inference-time interventions on internal representations can modify behaviors including truthfulness, refusal, and instruction following without retraining the full model ([Li et al., 2023](#), [Arditi et al., 2024](#), [Kang and Kim, 2026](#)). Representation engineering provides a broader framework for identifying population-level activation directions for monitoring and control ([Zou et al., 2023](#)). Activation Addition obtains a steering direction from contrastive prompts and injects it at inference time ([Turner et al., 2023](#)); Contrastive Activation Addition averages activation differences across positive and negative behavioral examples ([Rimsky et al., 2024](#)). We adapt this family of methods to reviewing by contrasting an official review with a model-generated review of the same manuscript.

5. Conclusion

We study how recursive AI-reviewer training affects scientific judgment. In our controlled experiment, increasing synthetic-review exposure compresses rating distributions, monotonically reduces same-paper semantic diversity, and modestly contracts corpus-level semantic diversity. These results reveal a form of *scientific-judgment collapse*. We discuss the study’s limitations in Appx. G.

To mitigate this failure mode, we introduce TrustReviewer, an open-source LLM-based system that intervenes at two complementary stages: training-time corpus curation and test-time activation steering. TrustReviewer achieves stronger recommendation agreement and greater judgment diversity than the evaluated external baselines, while activation steering provides additional gains without further model training or additional expert annotation. Moreover, official reviews serve as a practical reference rather than a verified human-only or uniquely correct standard. Together, our results characterize a concrete risk of recursive reviewer training and provide practical mechanisms for building more diverse and better-aligned AI-assisted scientific evaluation systems.

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Appendix

AI Use Disclosure

Generative AI was used as part of the research methodology to generate synthetic reviews and model outputs, as described in the paper. Separately, generative AI assisted with language editing, manuscript organization, title development, and presentation of existing results. It did not derive results or create citations. The authors verified all revisions and take responsibility for the text, claims, and artifacts.

A. Detailed Data Curation

Paper inputs. We collect ICLR papers and their reviews from 2018 to 2025 via the OpenReview API. We then use Marker¹ to convert the paper PDFs to Markdown. We retain only the main paper text and discard appendix content.

System prompt and review forms. Following the guideline template in Idahl and Ahmadi (2025), the system prompt assigns the model the role of an AI-conference reviewer and provides general instructions for constructive, evidence-based evaluation. It asks the model to assess the paper’s objective, strengths, weaknesses, correctness, novelty, significance, and supporting evidence.

The requested review fields are not fixed across all examples. We insert the ICLR form corresponding to the submission year into the system prompt. For example, earlier forms request a free-form review and overall rating, while later forms additionally specify structured fields such as correctness, technical and empirical novelty, soundness, presentation, contribution, strengths, weaknesses, questions, and ethics concerns. The rating scale and permitted rating values are likewise taken from the corresponding annual form. Thus, the model is trained to follow the review structure that was used for the original supervision.

User prompt. The user prompt is deliberately minimal:

Please review the following paper according to the ICLR reviewing guidelines.
{paper text}

Data filtering. We apply the same two-stage filtering pipeline to every review dataset before training.

Quality and structural filtering. In the first stage, we retain a review only if it contains a parseable rating and follows the year-specific review structure derived from the corresponding conference form. We exclude reviews that satisfy any of the following conditions:

- contain follow-up response markers such as “follow-up comment” or “revision”;
- contain fewer than 600 characters;
- contain at least 8 duplicated lines;
- contain at least 4 repeated 30-grams, indicating degenerate repetition; or
- fail the required year-specific review structure.

¹<https://github.com/datalab-to/marker>

Token-length filtering. In the second stage, we format each paper–review pair as the complete training chat sequence and retain it only if its length is strictly below 64,000 tokens. Applying these criteria consistently yields a more structurally uniform corpus while reducing malformed, noisy, repetitive, and overlength supervision.

B. Semantic Embedding Details

For all semantic embedding analyses, we use the `jinaai/jina-embeddings-v3` (Sturua et al., 2024) with its symmetric `text-matching` encoding task. This model supports sequences of up to 8,192 tokens. We set the maximum embedding length to 8,192 tokens. All 37,681 held-out official and generated reviews used in our semantic analyses fit within this limit (maximum 5,940 tokens). Therefore, no review is truncated.

We obtain one L2-normalized embedding per review using the model’s task-aware `encode` interface. Cosine similarity between two review embeddings is computed as their dot product.

For corpus-level analyses, we embed each review independently. When multiple official reviews are available for the same paper, we average their normalized review embeddings and L2-normalize the resulting paper-level vector before computing corpus-level semantic distances. The same-paper analysis instead computes pairwise cosine distances directly between normalized embeddings of individual reviews generated for the same paper.

C. Steering Hyperparameter Selection

We select the steering layer set $\mathcal{L}$ and strength α using 100 validation paper–review pairs sampled from $\mathcal{D}_{\text{curated}}$. These pairs are separate from the 5,000 calibration pairs used to construct the steering vectors, and neither set contains papers from the held-out evaluation set. The selection criterion is exact recommendation match against the corresponding official review ratings.

We first fix $\alpha = 0.10$ and compare steering at all decoder layers, progressively later layer ranges (16–31, 20–31, 24–31, and 28–31), and the final layer alone (layer 31). This search selects $\mathcal{L}^* = \{31\}$. We then evaluate $\alpha \in \{0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.40, 0.50\}$ with $\mathcal{L} = \mathcal{L}^*$, selecting $\alpha^* = 0.15$. All reported steering evaluations use $(\mathcal{L}^*, \alpha^*) = (\{31\}, 0.15)$.

D. Review Generation and Recommendation Parsing

Generation settings. For locally generated reviews, we sample with temperature 0.6, `top_p` 0.95, a repetition penalty of 1.0, and a maximum of 4,096 new tokens. The scripts do not explicitly set `top_k`. We generate three samples per paper in three separate runs. The generation scripts do not use fixed decoding seeds, which also affects paper order and the selection of alternative user-prompt phrasing. The reported variation therefore reflects three independent generation runs rather than deterministic, seed-labeled replications. Fixed seeds used by downstream analysis scripts for sampling, grouping, or bootstrapping are separate from the generation process.

Prompt and paper text. The review prompt combines a general system prompt, the year-specific ICLR review form, and a user prompt containing the paper text. Papers are converted to Markdown and truncated

after the references section. Local baselines receive the same held-out paper identifiers, Markdown paper text, prompt structure, and default decoding settings unless a model-specific wrapper overrides a setting.

Recommendation parsing and invalid outputs. The strict parser locates a line containing the structured `## Rating` heading, with an optional colon, and reads the beginning of the immediately following line as either an integer rating or NA. During generation, a malformed response is retried up to 10 times, and a review is written only when the strict parser finds a valid numerical rating. If all attempts fail, the paper is recorded as failed for that generation run.

For downstream analysis, the optional relaxed parser additionally searches the rating block for expressions such as `Rating: 6`, `Score: 6`, `6 out of 10`, or `overall score of 6`. A missing, unparseable, or NA rating yields no numerical recommendation and is never mapped to a default value. Such cases are recorded as an invalid generated rating, missing official reviews, or no valid official ratings, as applicable, and are excluded from score-based metrics.

E. Recommendation Agreement Metrics

Following [Idahl and Ahmadi \(2025\)](#), we measure agreement between generated recommendations and official reviewer ratings using two metrics. For each generation run, the valid evaluation set contains papers with both a parsed numerical recommendation and at least one valid official rating. Let N be the size of this set and m_i the number of valid official ratings available for paper i .

- Recommendation matching. Let $\hat{s}_i$ denote the generated recommendation for paper i , and let $S_i = \{s_{i1}, \dots, s_{im_i}\}$ denote its official reviewer ratings. We measure exact recommendation matching as

$$\text{Match} = \frac{1}{N} \sum_{i=1}^N \mathbf{1}[\hat{s}_i \in S_i].$$

- To capture the magnitude of disagreement, we also report the mean absolute distance from the average official rating:

$$\text{MAD} = \frac{1}{N} \sum_{i=1}^N \left| \hat{s}_i - \frac{1}{m_i} \sum_{j=1}^{m_i} s_{ij} \right|.$$

Higher matching and lower MAD indicate closer agreement with the official recommendations. These metrics assess recommendation alignment rather than the factual correctness or completeness of the review text. We compute each metric separately for the three generation runs and report the mean and standard deviation across runs.

F. Reviewer Rating Distributions

G. Limitations

Our controlled recursive-training experiment covers one recursive step, one base-model family, and one scientific-review domain. The observed effects may differ across additional generations, model scales and families, scientific fields, conferences, or review formats.

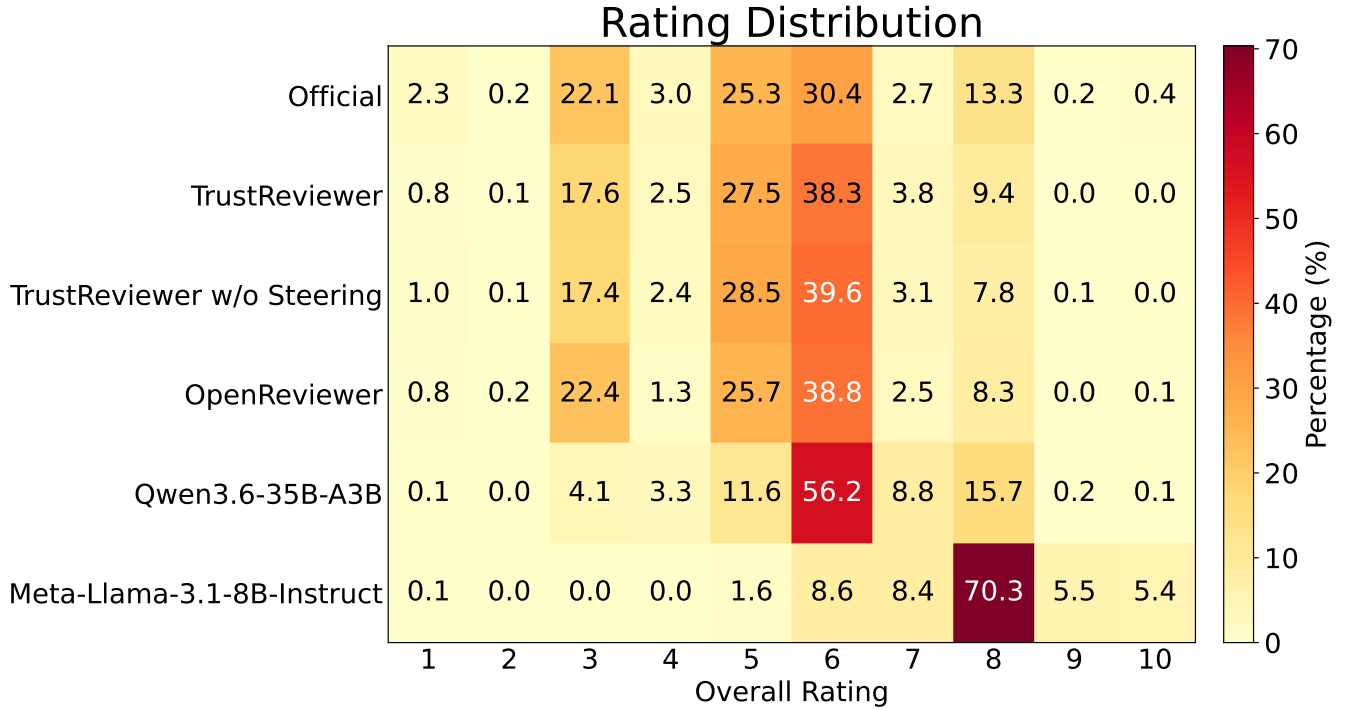


Figure 5: Rating distributions across reviewers. The heatmap reports the percentage of reviews assigned to each overall rating for TrustReviewer with and without steering and the baseline models. Official reviews in the plot provide a reference distribution.

Our evaluation measures should also be interpreted narrowly. Greater judgment diversity is not necessarily greater review quality: a diverse set of reviews can be incorrect, while a homogeneous set can be accurate. Similarly, exact recommendation match and MAD measure agreement with the distribution of official ICLR ratings, not the correctness of a scientific judgment. Official reviews are an institutional reference rather than ground truth; they may contain errors, disagreement, or unobserved AI assistance.

Finally, embedding-based distances are proxies for substantive diversity. They capture variation in the representations produced by a particular embedding model but do not directly establish that reviews identify different valid scientific concerns, contain factually correct critiques, or provide useful evidence. Human evaluation of critique correctness, specificity, and substantive coverage would provide an important complementary assessment.