

Large Language Models Penetration in Scholarly Writing and Peer Review

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Abstract

While the widespread use of Large Language Models (LLMs) brings convenience, it also raises concerns about the credibility of academic research and scholarly processes. To better understand these dynamics, we evaluate the penetration of LLMs across academic workflows from multiple perspectives and dimensions, providing compelling evidence of their growing influence. We propose a framework with two components: ScholarLens, a curated dataset of human-written and LLM-generated content across scholarly writing and peer review for multi-perspective evaluation, and LLMetrica, a tool for assessing LLM penetration using rule-based metrics and model-based detectors for multi-dimensional evaluation. Our experiments demonstrate the effectiveness of LLMetrica, revealing the increasing role of LLMs in scholarly processes. These findings emphasize the need for transparency, accountability, and ethical practices in LLM usage to maintain academic credibility.

1 Introduction

However, LLM-generated content often reflects lower quality and inherent biases (Brooks et al., 2024; Du et al., 2024), such as factual inconsistencies (Yang et al., 2024; Chuang et al., 2024) and

hallucinations (Tang et al., 2024; Chuang et al., 2024). Research also indicates that LLMs in the review process can lead to higher paper acceptance rates (Latona et al., 2024; Jin et al., 2024) and tend to use more positive language than human reviewers (Zhou et al., 2024). This raises concerns about the rigor of scientific research (Sun et al., 2024), highlighting the importance of ensuring transparency and accountability in the use of LLMs within academic workflows (Lund and Naheem, 2024).

To address these concerns, we propose a comprehensive evaluation framework aimed at revealing the increasing penetration of LLMs in scholarly writing and peer review. This framework takes a multi-perspective view by integrating diverse scholarly data types and employs a multi-dimensional methodology that utilizes a range of evaluation methods to provide a reliable and nuanced understanding of LLM usage trends. Figure 1 illustrates the pipeline of our work, and our **contributions** are as follows:

- We introduce ScholarLens, a curated dataset for developing technical measurement methods, comprising both human-written and LLM-generated content (§3).
 - We propose LLMetrica, a tool for assessing LLM penetration in scholarly workflows, combining rule-based metrics to analyze linguistic and semantic features with model-based detectors to identify LLM-generated content (§4).
 - Our experiments demonstrate the effectiveness of LLMetrica, consistently showing the increasing penetration of LLMs in scholarly writing and peer review from multiple perspectives and dimensions (§5).

Our findings emphasize the need for transparency, accountability, and ethical practices in LLM usage to maintain the credibility of academic research.

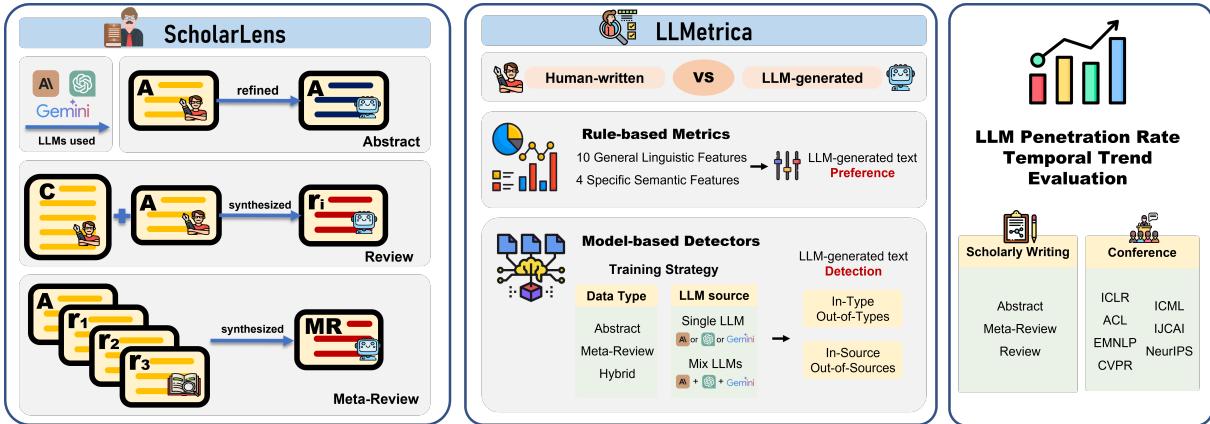


Figure 1: Pipeline Overview of Our Work: (1) **ScholarLens Curation** (§3): A designed dataset used to evaluate the effectiveness of metrics and train detection models; (2) **LLMetrica framework** (§4): The proposed method for distinguishing human-written from LLM-generated texts; (3) **Experiments** (§5): Evaluating the effectiveness of LLMetrica and applying it to real-world data to assess LLM penetration rates in scholarly writing and peer process. Symbolically, $P = \{T, A, C, R, MR\}$ represents a research paper, where T , A and C denote its title, abstract and main content, $R = \{r_i\}$ represents the individual reviews, and MR denotes the meta-review.

2 Related Work

Recent discussions in the scientific community have focused on improving the peer review process (Gurevych et al., 2024; Kuznetsov et al., 2024) to address issues like misalignment between reviewers and paper topics, as well as social (Huber et al., 2022; Tomkins et al., 2017; Manzoor and Shah, 2021) and cognitive biases (Lee, 2015; Stelmakh et al., 2021). Proposed solutions include enhancing structural incentives for reviewers (Rogers and Augenstein, 2020), using natural language processing for intelligent support (Kuznetsov et al., 2022; Zyska et al., 2023; Dycke et al., 2023; Guo et al., 2023; Kumar et al., 2023), and other policy recommendations (Dycke et al., 2022). Furthermore, some studies focus on the collection and analysis of review data (Kennard et al., 2022; Staudinger et al., 2024; D’Arcy et al., 2024).¹ However, these efforts largely focus on human reviewers: what if instead the reviewers are LLMs (Weber, 2024; Gao et al., 2024; Hossain et al., 2025)?

Previous research has demonstrated that human-written and LLM-generated texts exhibit distinct linguistic characteristics (Cheng et al., 2024; Song et al., 2025). For instance, LLM-generated texts often display the recurrent use of specific syntactic templates (Shaib et al., 2024), which largely reflect patterns learned from the training data and highlight the model’s memorization capacity (Karamolegkou et al., 2023; Zeng et al., 2024;

Zhu et al., 2024). Furthermore, some studies develop detection models to identify LLM-generated text (Antoun et al., 2024; Cheng et al., 2024; Xu et al., 2024; Kumar et al., 2024; Abassy et al., 2024). However, Cheng et al. (2024) points out that supervised detectors exhibit poor cross-domain generalizability.

Unlike previous work, we simulate LLM usage in scholarly writing and peer review, creating a comparison between LLM-generated and human-written texts. We also develop a robust framework to assess the distinctive tendencies of LLM-generated content and identify it within the scholarly domain. This framework offers a comprehensive approach to evaluating LLM penetration from multiple perspectives and dimensions.

3 ScholarLens Curation

In this section, we detail the process of curating ScholarLens, including the consideration of data types and the setup for collecting both human-written and LLM-generated text.

3.1 Data Types

We formalize a research paper as $P = \{T, A, C, R, MR\}$ where T , A , and C represent the title, abstract, and main content, respectively, and $R = \{r_i\}$ denotes individual reviews, with MR representing the meta-review summarizing feedback from multiple reviewers. Since the process of creating a research paper involves both author drafting and peer review stages, our dataset includes con-

¹ ACL Rolling Review Data Collection (ARR-DC).

tent from both the author and (meta-)reviewer roles. When creating LLM-generated text, we consider two perspectives: ‘refined’, which enhances existing drafts, and ‘synthesized’, which summarizes and generates content from provided texts.

For the author role, we focus on abstract writing, as it is a key element for summarizing the paper and is easily accessible, making it ideal for this study. Specifically, we adopt the ‘refined’ approach, where the original human-written abstract is input into the LLM to generate a refined version. For the (meta-)reviewer roles, we focus on their comment content. To simulate human-written reviews and meta-reviews, the LLM-generated version primarily adopts the ‘synthesized’ perspective. The review process requires the full text of the paper as input, while the meta-review process includes all associated reviews of the paper. All prompts used to create LLM-generated content are provided in the Appendix A.

3.2 Data Collection Setup

Considering the challenges associated with parsing full-text papers, typically in PDF format, and the high computational cost of generating LLM-based reviews from lengthy input data, the ScholarLens collection integrates pre-existing review data with self-constructed abstracts and meta-reviews.

For the self-constructed data, we first collect raw data from all main conference papers in ICLR up to 2019, totaling 2,831 papers, through the Open-Review website. This selection is motivated by two factors: first, ICLR’s peer review process provides comprehensive and detailed (meta-)review data; second, by focusing on papers before 2019, we can assume that the source data remains entirely human-written, as it predates the release of ChatGPT. For each paper, we generate two types of LLM-generated content: LLM-refined abstracts and LLM-synthesized meta-reviews. Both types are created using three advanced closed-source LLMs: GPT-4o, Gemini-1.5 (Team et al., 2024), and Claude-3 Opus (Anthropic, 2024). This ensures that for every human-written version of the content, there is a corresponding LLM-generated version from each of the three models. For the pre-existing review data, we directly leverage the review data from ReviewCritique (Du et al., 2024)², which incorporates the same three LLMs. Details of ScholarLens are in Appendix B, including

²Note that ReviewCritique includes LLM-generated reviews for only 20 papers.

statistics and LLM settings.

4 LLMetrica Framework

In this section, we introduce the LLMetrica framework, designed to evaluate the penetration rate of LLM-generated content in scholarly writing and peer review. The framework includes rule-based metrics for assessing linguistic features and semantic similarity, as well as model-based detectors fine-tuned specifically to identify LLM-generated content within the scholarly domain.

4.1 Rule-Based Metrics: Preference

Rule-Based Metrics define a metric function m to measure the feature value v of an input text x , i.e., $v = m(x)$, enabling the comparison and evaluation of feature preferences in LLM-generated text. Specifically, we use 10 general linguistic feature metrics and design 4 specialized semantic feature metrics to capture both linguistic and semantic characteristics.

4.1.1 General Linguistic Features

General linguistic features are applicable to all types of text and can be categorized into word-level, sentence-level, and other related metrics. Specifically, word-level metrics include Average Word Length (AWL), Long Word Ratio (LWR), Stopword Ratio (SWR), and Type Token Ratio (TTR). Given the nature of scholarly writing, the threshold for ‘long word’ is set at 10. For sentence-level metrics, we include Average Sentence Length (ASL), Dependency Relation Variety (DRV), and Subordinate Clause Density (SCD). DRV quantifies the diversity of dependency relations within the text using Shannon entropy (Lin, 1991), while SCD focuses on dependency relations such as ‘advcl’, ‘ccomp’, ‘xcomp’, ‘relcl’, and ‘acl’ (Nivre et al., 2017). In addition, we incorporate Flesch Reading Ease (FRE) (Farr et al., 1951) to evaluate the overall readability of the text, Sentiment Polarity Score (PS, range: [-1, 1], negative → positive) to assess the sentiment, and Sentiment Subjectivity Score (SS, range: [0, 1], objective → subjective) to measure the degree of subjectivity or objectivity in the text. The implementation details of these metrics are provided in the Appendix C.

4.1.2 Specific Semantic Features

Inspired by Du et al. (2024), which shows that human-written reviews have greater diversity and segment-level specificity than LLM-generated

ones, we design four semantic metrics to analyze meta-reviews and reviews, focusing on overall semantic similarity and sentence-level specificity.

Overall Semantic Similarity We propose two semantic similarity metrics: (i) **MRSim**: measures the similarity between the MR and its reference set R, defined as the average semantic similarity between MR and each review $r_i \in R$. (ii) **RSim**: measures the similarity among reviews within R, defined as the maximum similarity among all pairs of reviews in R. The formulas are:

$$\text{MRSim} = \frac{1}{|R|} \sum_{r_i \in R} \text{sim}(\text{MR}, r_i) \quad (1)$$

$$\text{RSim} = \max_{r_i, r_j \in R, r_i \neq r_j} \text{sim}(r_i, r_j) \quad (2)$$

Using maximum similarity for RSim accounts for the fact that not all reviews in R are LLM-generated, as averaging could obscure key differences. Focusing on the maximum similarity highlights the strongest alignment, offering a more accurate measure of overall similarity.

Sentence-Level Specificity Building on ITF-IDF (Du et al., 2024)³ and the classic TF-IDF framework, we introduce the **SF-IRF** (Sentence Frequency-Inverse Reverence Frequency) metric to quantify the significance of sentences within a (meta-)review. Specifically, for a given target (meta)-review r consisting of n sentences, SF-IRF(s, r, R_{ref}) captures the importance of a sentence s in r by considering: (i) its frequency of occurrence within r (SF), and (ii) its rarity across the reference reviews R_{ref} (IRF). The metric is formally defined as:

$$\begin{aligned} \text{SF-IRF}(s, r, R_{\text{ref}}) &= \text{SF}(s, r) \cdot \text{IRF}(s, R_{\text{ref}}) \\ &= \frac{O_s^r}{n} \cdot \log \left(\frac{m}{Q_s^{R_{\text{ref}}}} \right) \end{aligned} \quad (3)$$

Here, if r represents a review, then $R_{\text{ref}} = R - r$; if r is a meta-review, then $R_{\text{ref}} = R$. O_s^r quantifies the “soft” occurrence of sentence s within the target review r , while $Q_s^{R_{\text{ref}}}$ represents the “soft” count of reviews in R_{ref} that contain the sentence s . Additionally, m denotes the total number of reviews in R_{ref} . O_s^r and $Q_s^{R_{\text{ref}}}$ are computed as follows:

$$O_s^r = \sum_{\tilde{s} \in r} \mathbb{I}(\text{sim}(s, \tilde{s}) \geq t) \cdot \text{sim}(s, \tilde{s}) \quad (4)$$

³Unlike ITF-IDF (Du et al., 2024), we only measure the SF-IRF within a single paper, considering the meta-review and review levels.

$$Q_s^{R_{\text{ref}}} = \sum_{\tilde{r} \in R_{\text{ref}}} \mathbb{I} \left(\max_{\tilde{s} \in \tilde{r}} \text{sim}(s, \tilde{s}) \geq t \right) \cdot \max_{\tilde{s} \in \tilde{r}} \text{sim}(s, \tilde{s}) \quad (5)$$

A segment s is counted when its similarity exceeds the threshold t , with the corresponding similarity score. We use SentenceBERT (Reimers and Gurevych, 2019) to calculate the all similarities, with t set to 0.5.

4.2 Model-Based Detectors: Distinction

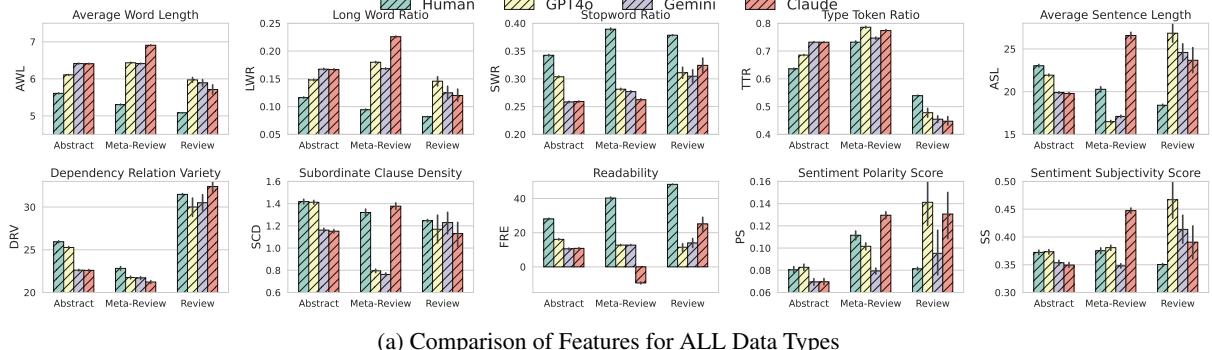
Model-based detectors are designed to train scholar-specific detection models f , capable of accurately identifying whether a scholarly input text x is human-written or LLM-generated. We use our curated ScholarLens dataset to train these models, collectively referred to as ScholarDetect.

Specifically, we split abstracts and meta-reviews data within ScholarLens into training and test sets in a 7:3 ratio, based on the human-written versions. The corresponding LLM-generated content is partitioned accordingly, ensuring that each piece of LLM-generated text is paired with its human-written counterpart. All reviews data in ScholarLens are incorporated into the test set, ensuring a comprehensive evaluation.⁴ All test sets serve as benchmarks to assess the performance of both baseline models and the trained ScholarDetect models. We create three types of detection models based on the training data: one using only abstracts, one using only meta-reviews, and one using a hybrid of both. To maintain class balance in the training data, we ensure a 1:1 ratio between human-written and LLM-generated version. We employ two strategies: one using a single LLM (GPT-4o, Gemini, or Claude), and another using a mixed-LLM approach, where each human-written piece is paired with LLM-generated content from a randomly selected model. As a result, the ScholarDetect framework involves a total of 12 distinct detection models.

5 Experiments

We first demonstrate the effectiveness of rule-based metrics (§5.1) and ScholarDetect models (§5.2) in LLMetrica, then apply these methods to real-world conference data to assess and predict LLM penetration trends (§5.3). Finally, case studies are used to explore the specific differences between human-written and LLM-generated content (§5.4).

⁴Data statistics after splitting for model training and evaluation are in Table 7.



(a) Comparison of Features for ALL Data Types

Data Type	\uparrow	\downarrow	\rightarrow
Abstract	3 (AWL, LWR, TTR)	5 (SWR, ASL, DRV, SCD, FRE)	2 (PS, SS)
Meta-Review	3 (AWL, LWR, TTR)	3 (SWR, DRV, FRE)	4 (ASL, SCD, PS, SS)
Review	5 (AWL, LWR, ASL, PS, SS)	3 (SWR, TTR, FRE)	2 (DRV, SCD)

(b) Feature preference of LLM-generated text: \uparrow indicates an increase across all LLMs, \downarrow indicates a decrease, \rightarrow indicates inconsistency. **Bold** denotes consistent trends across all data types.

Figure 2: Comparison of Human-Written and LLM-Generated Text Based on General Features in ScholarLens

5.1 Features Comparison: Human vs LLM

We apply the proposed rule-based metrics (§4.1) to ScholarLens to compare the features of human-written and LLM-generated texts, and find that the feature preferences of LLM-generated texts can be effectively compared and evaluated.

General Linguistic Features Figure 2 shows trends in the characteristics of LLM-generated texts, with slight variations across different data types. Each metric reflects the consistency of features across texts generated by the three LLMs in at least one data type, demonstrating the ‘comparability’ effectiveness of the chosen metrics. Moreover, regardless of the data type or LLM used, LLM-generated texts consistently show higher values for Average Word Length (AWL) and Long Word Ratio (LWR), and lower values for Stopword Ratio (SWR) and Readability (FRE). This suggests that LLM-generated texts tend to use longer words, avoid excessive stopwords, and have lower readability. For shorter text types, such as abstracts and meta-reviews, the observed increase in Type Token Ratio (TTR) reflects greater lexical diversity in LLM-generated texts. This may be due to the conciseness inherent in short-form LLM-generated content. In contrast, for longer reviews, TTR decreases, potentially highlighting the limitations of LLMs in producing long-form content (Wang et al., 2024; Wu et al., 2025). Longer reviews may lack specificity (Du et al., 2024), resulting in redundancy and repetitive segments. Additionally, LLM-

generated reviews tend to be more positive and subjective, suggesting a more favorable tone and less neutral objectivity. This aligns with Jin et al. (2024), who found that LLM-generated reviews generally assign higher scores and show a higher acceptance rate.

Specific Semantic Features Figure 3 shows the preferences of human-written and LLM-generated texts in both meta-reviews and reviews, based on four specific semantic features. Notably, Since each LLM generates only one review per paper in ScholarLens, while each paper usually has multiple reviews, we combine reviews from all three LLMs into a unified set, so comparisons do not distinguish between them. Comparative results show that LLM-generated meta-reviews exhibit higher semantic similarity to the referenced reviews, with lower sentence specificity. This suggests that sentences within LLM-generated meta-reviews are more semantically similar to each other (prone to redundancy) and tend to mirror the content of the referenced reviews. A similar trend is observed for reviews, where the two specific features also show consistent patterns. It is important to note that for the reviews, we assume all are LLM-generated in this experiment, which may amplify the differences in these semantic features. In reality, having more than two LLM-generated reviews per paper may be uncommon, which would likely reduce the observed disparity.

Model	LLM Source	Abstract			Meta-Review			Review			Avg.
		Human	LLM	Overall	Human	LLM	Overall	Human	LLM	Overall	
MAGE	-	40.62	35.14	38.00	40.58	33.43	37.21	92.98	57.60	87.95	54.39
RAIDetect	-	49.51	78.36	69.71	38.42	73.50	62.94	24.48	26.85	25.68	52.78
HNDCDetect	-	54.59	85.85	78.43	57.93	83.88	76.69	86.39	54.90	79.09	78.07
ScholarDetect_{Abs}	GPT-4o	97.02 \pm 0.50	99.02 \pm 0.15	98.53 \pm 0.23	87.65 \pm 3.01	95.06 \pm 1.48	92.95 \pm 2.00	97.44 \pm 0.20	79.97 \pm 1.96	95.45 \pm 0.37	95.64
	Gemini	84.40 \pm 3.11	93.48 \pm 1.59	90.80 \pm 2.13	90.62 \pm 1.98	95.06 \pm 1.21	92.93 \pm 1.63	96.41 \pm 0.64	68.68 \pm 7.26	93.56 \pm 1.19	92.43
	Claude	91.61 \pm 1.09	96.90 \pm 0.46	95.47 \pm 0.65	83.79 \pm 4.74	93.02 \pm 2.60	90.25 \pm 3.40	95.69 \pm 0.89	58.84 \pm 12.55	92.20 \pm 1.68	91.97
	Mix	97.94 \pm 0.16	99.32 \pm 0.05	98.98 \pm 0.07	93.84 \pm 0.23	97.81 \pm 0.09	96.76 \pm 0.13	97.56 \pm 0.20	81.16 \pm 1.92	95.68 \pm 0.37	97.14
ScholarDetect_{Meta}	GPT-4o	78.59 \pm 1.64	90.47 \pm 1.19	86.81 \pm 1.45	99.53 \pm 0.13	99.84 \pm 0.04	99.76 \pm 0.06	97.98 \pm 0.21	84.95 \pm 1.89	96.44 \pm 0.39	94.34
	Gemini	80.13 \pm 2.71	91.45 \pm 1.56	88.05 \pm 2.02	97.70 \pm 1.86	99.19 \pm 0.67	98.80 \pm 0.98	97.65 \pm 0.30	81.90 \pm 2.69	95.83 \pm 0.54	94.23
	Claude	62.42 \pm 13.17	69.60 \pm 16.38	66.93 \pm 15.79	86.72 \pm 7.94	94.15 \pm 3.67	91.88 \pm 5.02	97.82 \pm 0.62	83.23 \pm 5.56	96.14 \pm 1.11	84.98
	Mix	84.20 \pm 3.59	94.12 \pm 2.24	91.47 \pm 2.89	99.84 \pm 0.10	99.95 \pm 0.03	99.92 \pm 0.05	99.52\pm0.16	96.86\pm1.08	99.17\pm0.28	96.85
ScholarDetect_{Hybrid}	GPT-4o	97.69 \pm 0.35	99.23 \pm 0.13	98.84 \pm 0.19	99.33 \pm 0.17	99.78 \pm 0.06	99.67 \pm 0.08	97.73 \pm 0.16	82.72 \pm 1.42	95.98 \pm 0.28	98.16
	Gemini	85.88 \pm 0.19	94.32 \pm 0.10	91.90 \pm 0.13	97.84 \pm 1.19	99.25 \pm 0.43	98.89 \pm 0.63	97.69 \pm 0.31	82.29 \pm 2.83	95.91 \pm 0.56	95.56
	Claude	85.61 \pm 1.67	94.11 \pm 0.84	91.64 \pm 1.13	96.49 \pm 1.22	98.77 \pm 0.44	98.18 \pm 0.65	97.48 \pm 0.26	80.35 \pm 2.44	95.53 \pm 0.47	95.13
	Mix	98.11\pm0.35	99.37\pm0.11	99.06\pm0.17	99.88\pm0.00	99.96\pm0.00	99.94\pm0.00	98.06\pm0.18	85.69\pm1.53	96.59\pm0.32	98.53

Table 1: Detection performance comparison of baseline models and ScholarDetect. **Bold** denotes the best performance, and underlined denotes the second-best. “Avg.” shows the average overall score across the three test data types.

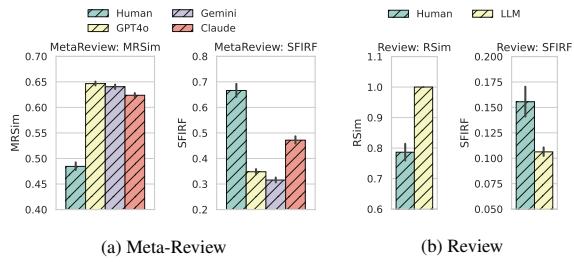


Figure 3: Comparison of Human-Written and LLM-Generated Text Based on **Specific features** for Review and Meta-Review.

5.2 ScholarDetect Evaluation: Detectability

We evaluate the trained model-based detectors, ScholarDetect (§4.2), on the ScholarLens test sets and find that scholarly LLM-generated texts can be effectively identified.

Experimental Setup **(i) Training Setup:** We adopt Longformer (Beltagy et al., 2020) as the base model for training our ScholarDetect detection models, as it has shown competitive performance among pretrained language models (Li et al., 2024; Cheng et al., 2024). Specifically, we train for five epochs in each configuration of the training set, using a learning rate of 2-e5. **(ii) Metric:** For evaluation metrics, we report the F1 score for each class (human-written and LLM-generated), as well as the overall weighted F1 score to account for class imbalance. Each experimental setup (training data type and LLM-generated text source) is evaluated through three random trials, and we report the average performance along with the standard deviation. **(iii) Baselines:** We compare the perfor-

mance of three advanced detection model baselines:

MAGE (Li et al., 2024), **RAIDetect** (Dugan et al., 2024), and **HNDCDetect** (Cheng et al., 2024). **(iv)**

Test Sets: All models are evaluated on test sets from three data types: abstract, meta-review, and review, with the first two being shorter texts and reviews being long-form. The LLM-generated data includes tasks such as refinement (for abstracts) and summarization (for meta-reviews and reviews).

Experimental Results The detection performance comparison results are presented in Table 1. Our trained ScholarDetect models consistently outperform the existing advanced baseline models, underscoring the importance of developing detection systems specifically tailored for the scholarly domain. The training approach that combines mixed LLM sources and hybrid data types yields the best overall performance, demonstrating robustness across various LLM sources and data types. Interestingly, the model trained on meta-reviews performs best when tests on reviews, likely because both data types share a similar comment-based focus and offer a “synthesized” perspective in LLM-generated text. This is further supported by ScholarDetect_{Abs}, which struggles to identify LLM-generated reviews when trained only on abstracts (F1: LLM < Human). Additionally, when trained on a single LLM source, the GPT-4o-based detectors show the strongest generalization, especially on the abstract test set. Most ScholarDetect models outperform human-written text in detecting LLM-generated content on the meta-review and review test sets, but the reverse is true for the review test set.

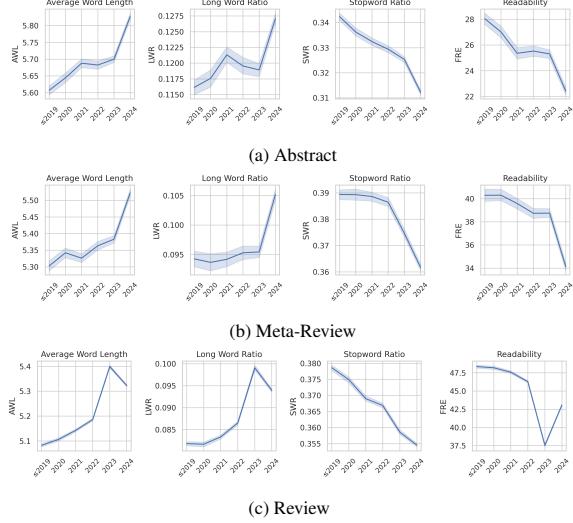


Figure 4: Temporal trends based on **four robust general linguistic metrics**.

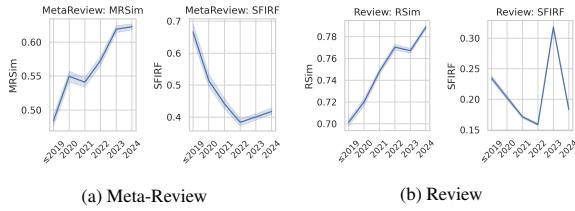


Figure 5: Temporal trends based on **specific semantic metrics**.

5.3 LLM Penetration: Temporal Analysis

We apply the proposed rule-based metrics and model-based detectors to assess and detect LLM penetration in recent scholarly texts (up to 2024), including abstracts, meta-reviews, and reviews.

Trend in Rule-based Evaluation For the general linguistic metrics, we use only the four most robust (AWL, LWR, SWR, FRE), which show consistent preferences across the three data types, and we adopt all four specific semantic metrics. Figure 4 illustrates the trend in general linguistic features across three data types in ICLR, while Figure 5 shows the trend in specific semantic features for meta-reviews and reviews. Almost all the metrics show consistent LLM preference trends across their associated data types, with an overall year-on-year increase, supporting the rising trend of LLM penetration in scholarly writing. Interestingly, among these metrics used to evaluate reviews, four show anomalous trend changes in 2023, highlighting the difficulties of using rule-based metrics to track LLM penetration in the complex and varied nature of review data.

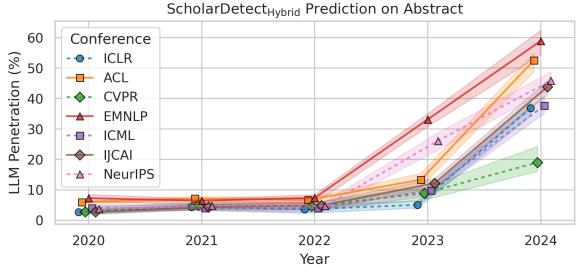


Figure 6: Abstarcet: Trend based on detection model.

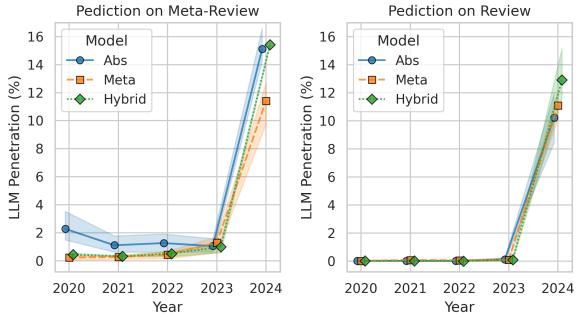


Figure 7: Abstarcet: Trend based on detection model.

Trend in Model-based Detection Based on the performance shown in Table 1 and the available evaluation data, we select ScholarDetect_{Hybrid}, which performs best on abstracts, to detect instances of LLM-assisted writing in seven conference abstracts. Additionally, we utilize three variants of ScholarDetect (Abs, Meta, Hybrid) to analyze all ICLR meta-reviews and reviews. The detected LLM penetration rates (i.e., the proportion of text predicted to be LLM-generated) are presented in Figures 6 and 7. In the abstract evaluation data, the LLM penetration rate across all involved conferences increases starting in 2023 and continues to rise in 2024, likely driven by ChatGPT’s initial release in November 2022 and its subsequent updates. In contrast, a noticeable increase appears in 2024 for comment-based data, particularly in reviews, although the overall rate remains lower than in abstracts. This may be attributed to the 2023 update of ChatGPT⁵, which enabled PDF uploads and content analysis, as well as the higher standards required for LLM-generated content in reviews, which limit the penetration rate. Specifically, ScholarDetect_{Hybrid} predicts the highest LLM penetration rate for two comment-based data types in 2024. For shorter meta-review texts, ScholarDetect_{Abs}’s rate is close to ScholarDetect_{Hybrid} but higher than

⁵ChatGPT — Release Notes

POS	Top 10 GPT-4o Preferred Words in Meta-Reviews
NOUN	<u>refinement</u> , <u>advancements</u> , <u>methodologies</u> , <u>articulation</u> , <u>highlights</u> , <u>reliance</u> , <u>enhancement</u> , <u>underpinnings</u> , <u>enhancements</u> , <u>transparency</u>
VERB	enhance, enhancing, deemed, <u>showcasing</u> , express, offering, enhances, <u>recognizing</u> , commend, praised
ADJ	<u>innovative</u> , <u>collective</u> , enhanced, <u>established</u> , <u>notable</u> , <u>outdated</u> , varied, <u>undefined</u> , <u>comparative</u> , <u>noteworthy</u>
ADV	<u>collectively</u> , <u>inadequately</u> , <u>reportedly</u> , <u>comprehensively</u> , <u>robustly</u> , <u>occasionally</u> , <u>predominantly</u> , notably, <u>innovatively</u> , <u>effectively</u>
POS	Top 10 GPT-4o Preferred Words in Abstracts
NOUN	abstract, <u>advancements</u> , realm, <u>alterations</u> , aligns, <u>methodologies</u> , clarity, <u>adaptability</u> , surpasses, <u>examination</u>
VERB	enhancing, <u>necessitates</u> , <u>necessitating</u> , featuring, revised, <u>influenced</u> , <u>encompassing</u> , enhances, <u>showcasing</u> , surpasses
ADJ	<u>innovative</u> , <u>exceptional</u> , pertinent, intricate, pivotal, <u>necessitate</u> , <u>distinctive</u> , enhanced, akin, potent
ADV	<u>inadequately</u> , <u>predominantly</u> , <u>meticulously</u> , <u>strategically</u> , notably, abstract, swiftly, <u>additionally</u> , <u>adeptly</u> , thereby

Table 2: Top-10 LLM-preferred words in GPT-4o-generated vs. human-written meta-reviews and abstracts. **Bold** denotes *long words*, and underlined denotes *complex-syllabled words*.

ScholarDetect_{meta}. We hypothesize this is due to the greater role of LLMs in refining these texts. Based on insights from Cheng et al. (2024), we propose a fine-grained LLM-generated text detection approach using three-class role recognition (human-written, LLM-synthesized, LLM-refined) for meta-reviews. Our results show that the LLM-refined role plays a more dominant part in LLM penetration.⁶

5.4 Case Study

To investigate the specific differences between LLM-generated and human-written text, we focus on GPT-4o, conducting case studies at both the word and pattern levels. (i) At the word level, we design a Two-Sample t-test based on word proportions (Cressie and Whitford, 1986; WELCH, 1947)⁷ to identify the LLM-preferred words. Table 2 shows the top 10 preferred words in four key part-of-speech (POS) categories from GPT-4o-generated abstracts and meta-reviews, compared to those in human-written versions. We find that LLMs tend to generate *long words* (≥ 10 letters) and *complex-syllabled words* (≥ 3 syllables) (Gun-

⁶Experimental details of the three-class LLM role recognition are in Appendix D.

⁷<https://www.statology.org/two-sample-t-test/>. Method details of case studies and additional results are in the Appendix E.

ning, 1952). This further supports the reliability of the four general linguistic metrics for assessing LLM penetration. Moreover, GPT-4o shows a strong preference for the word ‘enhance’ in scholarly writing and peer reviews, with its variants appearing in the top 10 list. (ii) At the pattern level, manual inspection of paired data samples from comment-based data⁸, followed by automated evaluation of the full dataset, reveals that human-written (meta-)reviews exhibit: *personability*, frequently using the first person to express opinions; *interactivity*, often incorporating questions; and *attention to detail*, citing relevant literature to support arguments.

6 Conclusion and Suggestions

Our work, including the creation of ScholarLens and the proposal of LLMetrica, provides methods for assessing LLM penetration in scholarly writing and peer review. By incorporating diverse data types and a range of evaluation techniques, we consistently observe the growing influence of LLMs across various scholarly processes, raising concerns about the credibility of academic research. As LLMs become more integrated into scholarly workflows, it is crucial to establish strategies that ensure their responsible and ethical use, addressing both content creation and the peer review process.

Despite existing guidelines restricting LLM-generated content in scholarly writing and peer review,⁹ challenges still remain. To address these, we propose the following based on our work and findings: (i) **Increase transparency in LLM usage within scholarly processes** by incorporating LLM assistance into review checklists, encouraging explicit acknowledgment of LLM support in paper acknowledgments, and reporting LLM usage patterns across diverse demographic groups; (ii) **Adopt policies to prevent irresponsible LLM reviewers** by establishing feedback channels for authors on LLM-generated reviews and developing fine-grained LLM detection models (Abassy et al., 2024; Cheng et al., 2024; Artemova et al., 2025) to distinguish acceptable LLM roles (e.g., language improvement vs. content creation); (iii) **Promote data-driven research in scholarly processes** by supporting the collection of review data for further robust analysis (Dycke et al., 2022).¹⁰

⁸Conducted by one of the authors on 100 paired meta-reviews and 20 paired reviews.

⁹Area Chair & Reviewer & Author guidelines.

¹⁰<https://arr-data.aclweb.org/>

Limitations

While this study provides valuable insights into the penetration of LLMs in scholarly writing and peer review, it may not fully represent the complexities of the real-world scenario. On one hand, the analysis focuses on peer review data from the ICLR conference, where the process is fully transparent and the quality of reviews is generally well-maintained. However, in many journals and conferences where peer review remains closed, the penetration of LLMs could be even more pronounced. On the other hand, the data simulation may not fully capture the intricate dynamics of LLM-human collaboration in real-world settings, making it difficult to distinguish between acceptable and unacceptable levels of LLM involvement, and potentially leading to a reduced ability of the model to detect LLM-generated text, which in turn lowers the assessment of LLM penetration. Therefore, the penetration of large language models in scholarly writing and peer review may be more significant in real-world scenarios than what is presented in this study.

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A Prompts for Data Construction

A.1 Prompts for abstract

To ensure diversity in the refinement process, we design five different prompts for polishing the abstract, as shown in Table 3. Each human-written abstract is randomly assigned one prompt to generate the refined content.

A.2 Prompts for meta-review

To ensure that LLM-generated meta-reviews closely mirror the writing style of human-written meta-reviews and maintain authenticity, we analyze the characteristics of human-written meta-reviews.

Id	Prompt
1	Can you help me revise the abstract? Please response directly with the revised abstract: {abstract}
2	Please revise the abstract, and response directly with the revised abstract: {abstract}
3	Can you check if the flow of the abstract makes sense? Please response directly with the revised abstract: {abstract}
4	Please revise the abstract to make it more logical, response it directly with the revised abstract: {abstract}
5	Please revise the abstract to make it more formal and academic, response it directly with the revised abstract: {abstract}

Table 3: Five distinct prompts used to refine human-written abstracts.

Based on this analysis, we provide three generation templates as guidelines for constructing LLM-generated meta-reviews, as shown in Table 4. The basic prompt does not include any formalized structures, while the other two prompts define more distinct meta-review formats. Specifically, we conduct a detailed statistical analysis of the frequencies of these two paradigms and selected the corresponding prompts based on these frequencies. The probabilities we use are shown in Table 5.

B Dataset Details

Table 6 shows the statistics of ScholarLens. The LLM versions used for data construction are: GPT-4o (gpt-4o-2024-08-06), Gemini-1.5 (gemini-1.5-pro-002), and Claude-3-Opus (claude-3-opus-20240229).

C General Linguistic Metrics Implementation

For word-level metrics, NLTK tokenization is used, and only alphabetic words are considered. For sentence-level metrics, spaCy is used to process the text and extract features such as sentence length and the dependency relation label of each word. Additionally, Sentiment Polarity Score (PS) and Sentiment Subjectivity Score (SS) are evaluated using TextBlob, while FRE is calculated using Textstat.

D Fine-Grained Detection Model

Using the existing meta-review data from ScholarLens (including both human-written and LLM-synthesized versions), we apply the LLM-refined abstract construction method to generate an LLM-refined version for each human-written meta-review. We utilize GPT-4o as the single LLM source and train a fine-grained three-class detector on the meta-reviews using the same data split. This trained detection model is then used to predict the 2024 ICLR meta-reviews, with approximately 35.32% predicted as LLM-refined and

1.39% as LLM-synthesized, which show that the LLM-refined role plays a more dominant part in LLM penetration.

E Case Study Details

E.1 Word-Level Algorithm and Experiments

E.1.1 Hypothesis Testing Algorithm

Building on the Two-Sample t-test, we propose a word-proportion-based method to identify word-level LLM preferences. Specifically, given a set of pairs of human-written and LLM-generated texts $\mathcal{D} = \{(x_i^h, x_i^l)\}$, where x_i^h represents the human-written case and x_i^l represents the corresponding LLM-generated version, our goal is to determine whether a word w is preferentially generated by the LLM.

(i) Word Proportion We define the proportion of word w appearing in the human-written set $\{x_i^h\}$ and the LLM-generated set $\{x_i^l\}$ as $\hat{p}_h(w)$ and $\hat{p}_l(w)$, respectively, representing the fraction of texts in which w occurs:

$$\hat{p}_h(w) = \frac{\text{cnt}_h(w) + \epsilon}{|\mathcal{D}|} \quad (6)$$

$$\hat{p}_l(w) = \frac{\text{cnt}_h(w) + \epsilon}{|\mathcal{D}|} \quad (7)$$

where $\text{cnt}(w) = \sum_i \mathbb{I}(w \in x_i)$ counts the number of texts in the set x_i where the word w appears, with $\mathbb{I}(w \in x_i)$ being an indicator function that returns 1 if w appears in x_i , and $\epsilon = 1$ as a smoothing constant to account for words that do not appear in a given text.

(ii) Hypothesis Setting Then, we define the following two hypotheses:

- **Null hypothesis** (H_0): $\hat{p}_h(w) \geq \hat{p}_l(w)$, suggesting that LLMs do **not** preferentially generate the word w .
- **Alternative hypothesis** (H_1): $\hat{p}_h(w) < \hat{p}_l(w)$, suggesting that LLMs preferentially generate the word w .

Basic Prompt Guideline

You are an AI assistant tasked with generating meta-reviews from multiple reviewers' feedback.

Please write a meta review of the given reviewers' response around $\{n\}$ words.

Do not include any section titles or headings. Do not reference individual reviewers by name or number. Instead, focus on synthesizing collective feedback and overall opinion.

Abstract: {abstract}

Reviewers' feedback:{review_text}

Formatted Prompt Guideline 1

You are an AI assistant tasked with generating meta-reviews from multiple reviewers' feedback.

Please write a meta review of the given reviewers' response around $\{n\}$ words.

Do not include any section titles or headings. Do not reference individual reviewers by name or number. Instead, focus on synthesizing collective feedback and overall opinion.

Please include the given format in your meta review:

Give a concise summary here.

Strength: [List the strengths of the paper in points based on reviews.]

Weakness: [List the weaknesses of the paper in points based on reviews.]

Abstract: {abstract}

Reviewers' feedback:{review_text}

Formatted Prompt Guideline 2

You are an AI assistant tasked with generating meta-reviews from multiple reviewers' feedback.

Please write a meta review of the given reviewers' response around $\{n\}$ words.

Do not include any section titles or headings. Do not reference individual reviewers by name or number. Instead, focus on synthesizing collective feedback and overall opinion.

Please include the given format in your meta review:

Give a concise summary here.

Pros: [List the strengths of the paper in points based on reviews.]

Cons: [List the weaknesses of the paper in points based on reviews.]

Abstract: {abstract} ### Reviewers' feedback:{review_text}

Table 4: Three prompts as guidelines for constructing LLM-generated meta-reviews. Here, n represents the approximate word length for the generated content.

(iii) Hypothesis Testing Considering that the variance of word proportion may differ between the two text groups, we adopt Welch's t-test to quantify the difference. Specifically, the test statistic and degrees of freedom are computed as follows:

$$t(w) = \frac{\hat{p}_l(w) - \hat{p}_h(w)}{\sqrt{\frac{s_h^2 + s_l^2}{|\mathcal{D}|}}} \quad (8)$$

$$df(w) = \frac{\left(\frac{s_h^2 + s_l^2}{|\mathcal{D}|}\right)^2}{\frac{(s_h^2/|\mathcal{D}|)^2 + (s_l^2/|\mathcal{D}|)^2}{|\mathcal{D}|-1}} \quad (9)$$

where s_h and s_l represent the standard deviations of the corresponding word proportions, calculated as follows:

$$s = \sqrt{\frac{\hat{p}(1-\hat{p})}{|\mathcal{D}|}} \quad (10)$$

(iv) Hypothesis Decision We define the critical t-value, t_c , as the threshold for rejecting or accepting the null hypothesis. It is calculated using the inverse of the cumulative distribution function (CDF) of the t-distribution:

$$t_c(w) = t_{\alpha, df(w)}^{-1} \quad (11)$$

where $\alpha = 0.05$ is the significance level. If $t(w) > t_c(w)$, we reject the null hypothesis and conclude that the word occurs significantly more often in LLM-generated texts than in human-written texts. In this way, we can identify the words favored by LLMs.

E.1.2 Experimental Setup

To address part-of-speech variability of the same word (e.g., ‘record’ functioning as both a noun and

Word Count	Basic Prompt	Formatted 1	Formatted 2
$n \leq 50$	1.000	0.000	0.000
$50 < n \leq 110$	0.800	0.100	0.100
$110 < n \leq 160$	0.400	0.300	0.300
$160 < n \leq 220$	0.550	0.225	0.225
> 220	0.250	0.375	0.375

Table 5: The statistical distribution of word lengths observed for each involved meta-review format.

Academic Aspects	Human (Size)	LLM Source(Size)	Data Source
Abstract	2831	GPT-4o (2831) / Gemini-1.5 (2831) / Claude-3 Opus (2831)	Ours
Meta-Review		GPT-4o (2831) / Gemini-1.5 (2831) / Claude-3 Opus (2831)	
Review	$20 \times R $	GPT-4 (20) / Gemini-1.5 (20) / Claude-3 Opus (20)	ReviewCritique

Table 6: Statistics of ScholarLens: $20 \times |R|$ represents 20 papers, each with $|R|$ reviews, where $|R|$ varies by paper.

Data Type	Data Source	Train	Test
Abstract	Human		850
	LLM	1981	2550
Meta-Review	Human		850
	LLM		2550
Review	Human	-	20
	LLM		60

Table 7: Dataset split for training detection models.

a verb in a sentence), we adopt (word, POS) pairs as the fundamental unit for analysis rather than isolated words. We use SpaCy for POS tagging, and stopwords are excluded from consideration. Using the proposed Hypothesis Testing Algorithm (§E.1.1), we filter the LLM-preferred word set and rank these words based on their Word Usage Increase Ratio (WUIR), defined as follows:

$$\text{WUIR}(w) = \frac{\text{cnt}_l(w) - \text{cnt}_h(w)}{\text{cnt}_h(w) + \epsilon} \quad (12)$$

E.1.3 Results: LLM-Preferred words

Tables 8 and 9 display the top-30 preferred words across four key part-of-speech (POS) categories in GPT-4o-generated abstracts and meta-reviews, with long words accounting for 40.48% and 39.96%, and complex-syllabled words for 73.45% and 67.82%. Furthermore, Tables 10 and 11 show the top-30 preferred words in four key POS categories for Gemini-generated abstracts and meta-reviews, while Tables 12 and 13 display the same for Claude-generated abstracts and meta-reviews.

All show a high proportion of long words and complex-syllabled words.

E.2 Pattern-Level Feature Statistics

We identify the following pattern-level features in human-written (meta-)reviews: *personability*, characterized by frequent use of the first person to express opinions; *interactivity*, marked by the inclusion of questions; and *attention to detail*, demonstrated by citing relevant literature to support arguments. To compare these pattern-level features between human-written and LLM-generated content, we calculate two metrics for each pattern in both meta-reviews and reviews within the ScholarLens dataset: **Feature Proportion (FP)** and **Feature Intensity (FI)**. FP is defined as the proportion of instances exhibiting the feature within the target data group, while FI is the average number of occurrences of the feature within instances that exhibit it. We report the FP and FI values for each pattern in meta-reviews and reviews across different data types—Human-written, GPT-4-generated, Gemini-generated, and Claude-generated—as shown in Table 8. The results show that, in both meta-reviews and reviews, the FP and FI values for each pattern feature in the Human-written data type are significantly higher than those in the LLM-generated versions.

E.3 Validation of Detection Model Reliability

We use our filtered full LLM-preferred word set and the identified pattern-level features to validate the reliability of our detection models. Specifically, we classify all meta-reviews from ICLR 2024

into two groups based on the fine-grained detection results in Appendix §D: human-written and LLM-generated (including LLM-refined and LLM-synthesized prediction). For each meta-review, we calculate the proportion of words that belong to the full GPT-4-preferred word set, defined as the ratio of matching words to the total number of words in the set. The average ratios for the human-written and LLM-generated groups are 35.15% and 44.95%, respectively. We then compute the FR and FI values for each pattern feature in each group, with results shown in Table 9. The FR and FI values for predicted LLM-generated text are lower than those for predicted human-written text. These results provide evidence of the reliability of our model’s detection capabilities.

Data Type	Resource	FR (%)	FI
Meta-review	Human	32.00	1.62
	GPT4o	0.07	1.00
	Gemini	0.11	1.33
	Claude	0.07	1.00
Review	Human	76.32	2.07
	GPT4o	0.00	0.00
	Gemini	0.00	0.00
	Claude	0.00	0.00

(a) Personability

Data Type	Resource	FR (%)	FI
Meta-review	Human	2.01	1.54
	GPT4o	0.00	0.00
	Gemini	0.00	0.00
	Claude	0.00	0.00
Review	Human	17.11	1.85
	GPT4o	0.00	0.00
	Gemini	0.00	0.00
	Claude	0.00	0.00

(b) Interactivity

Data Type	Resource	FR (%)	FI
Meta-review	Human	1.48	1.60
	GPT4o	0.00	0.00
	Gemini	0.00	0.00
	Claude	0.00	0.00
Review	Human	7.89	3.17
	GPT4o	0.00	0.00
	Gemini	0.00	0.00
	Claude	0.00	0.00

(c) Attention to Detail

Figure 8: Comparison of Pattern Features of Meta-Reviews and Reviews in ScholarLens.

Role	FR (%)	FI
LLM-synthesized	6.12	1.00
LLM-refined	34.32	1.53
LLM-generated	32.61	1.53
human-written	39.50	1.77

(a) Personability

Role	FR (%)	FI
LLM-synthesized	0.00	0.00
LLM-refined	2.02	1.53
LLM-generated	1.89	1.53
human-written	4.87	1.88

(b) Interactivity

Role	FR (%)	FI
LLM-synthesized	0.00	0.00
LLM-refined	1.57	1.13
LLM-generated	1.47	1.06
human-written	3.77	2.25

(c) Attention to Detail

Figure 9: Comparison of Pattern Features in Each Prediction Data Group for ICLR 2024 Meta-Reviews.

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	abstract	40.00	advancements	28.50	realm	24.00
	alterations	20.00	aligns	19.00	methodologies	18.80
	clarity	17.00	adaptability	13.00	surpasses	13.00
	examination	10.00	competitiveness	9.00	aids	9.00
	reliance	8.75	necessitating	8.00	assurances	8.00
	necessitates	8.00	assertions	8.00	threats	8.00
	assessments	7.33	advancement	7.25	enhancements	7.25
	demands	7.00	findings	6.91	standpoint	6.00
	oversight	6.00	study	5.42	exhibit	5.33
	enhancement	5.00	adjustments	5.00	capitalizes	5.00
VERB	enhancing	73.00	necessitates	58.00	necessitating	50.00
	featuring	47.00	revised	46.00	influenced	40.00
	encompassing	31.00	enhances	30.10	showcasing	29.00
	surpasses	19.50	underscoring	19.00	facilitating	18.67
	necessitate	18.00	managing	18.00	concerning	15.33
	garnered	14.50	employing	14.06	surpassing	14.00
	adhere	14.00	neglecting	14.00	comprehend	14.00
	underscore	13.00	discern	13.00	examines	12.00
	accommodates	11.00	detail	11.00	utilizing	10.87
	enhance	10.82	begins	10.50	integrating	10.21
ADJ	innovative	34.17	exceptional	24.00	pertinent	22.00
	intricate	16.33	pivotal	16.00	necessitate	12.00
	distinctive	11.00	enhanced	10.80	akin	10.40
	potent	10.00	adaptable	9.67	unfamiliar	9.00
	straightforward	8.42	accessible	8.00	versatile	7.13
	adept	7.00	devoid	7.00	advantageous	6.80
	extended	6.67	prevalent	6.00	underexplored	6.00
	commendable	6.00	contingent	6.00	foundational	5.75
	comprehensive	5.09	strategic	5.00	renowned	5.00
	attributable	5.00	unidentified	5.00	numerous	4.82
ADV	inadequately	17.00	predominantly	16.67	meticulously	16.00
	strategically	14.00	notably	12.60	abstract	12.00
	swiftly	12.00	additionally	9.08	adeptly	8.00
	thereby	7.52	conversely	7.40	traditionally	7.33
	initially	7.10	innovatively	7.00	subsequently	6.06
	unexpectedly	6.00	excessively	5.00	historically	5.00
	seamlessly	4.50	nonetheless	4.25	primarily	4.00
	markedly	4.00	short	4.00	infrequently	4.00
	effectively	3.97	solely	3.80	consequently	3.78
	inherently	3.40	concurrently	3.33	particularly	3.09

Table 8: Top-30 LLM-preferred Words in **GPT-4o**-generated vs. human-written **abstracts**, with long words making up 40.48%, and complex-syllabled words 73.45%.

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	refinement	284.00	advancements	88.00	methodologies	58.50
	articulation	50.00	highlights	41.00	reliance	39.50
	enhancement	39.00	underpinnings	37.00	enhancements	28.33
	transparency	26.00	complexities	25.00	skepticism	24.67
	adaptability	24.00	narrative	24.00	integration	23.43
	persist	22.00	acknowledgment	22.00	differentiation	21.67
	advancement	21.33	contextualization	21.00	foundation	20.50
	inconsistencies	20.00	reception	20.00	demands	20.00
	backing	19.50	sections	18.71	refinements	17.50
	credibility	16.50	benchmarking	16.00	reliability	15.50
VERB	enhance	239.00	enhancing	120.50	deemed	79.33
	showcasing	66.00	express	52.17	offering	50.50
	enhances	45.00	recognizing	41.00	commend	37.25
	praised	37.20	integrating	36.25	criticized	32.00
	hindering	32.00	utilizes	31.00	highlights	28.00
	surpass	27.00	bolster	26.00	emphasizing	25.33
	substantiate	25.00	integrates	24.50	solidify	23.00
	questioning	22.67	arise	21.17	expanding	20.67
	faces	20.67	weakens	20.00	recognized	19.71
	criticize	19.00	illustrating	19.00	critique	19.00
ADJ	innovative	114.50	collective	99.00	enhanced	45.00
	established	30.00	notable	28.00	outdated	22.00
	varied	16.00	undefined	15.00	comparative	14.70
	noteworthy	14.50	broader	14.10	comprehensive	13.67
	clearer	13.61	intriguing	13.50	foundational	13.00
	organizational	13.00	typographical	12.50	contextual	12.00
	traditional	11.83	advanced	11.00	inadequate	10.89
	diverse	9.84	insightful	9.56	prevalent	9.50
	spatiotemporal	9.00	engaging	9.00	adaptable	9.00
	illustrative	8.50	robotic	8.50	commendable	8.33
ADV	collectively	223.00	inadequately	38.00	reportedly	18.00
	comprehensively	13.00	robustly	12.00	occasionally	10.00
	predominantly	9.00	notably	8.38	innovatively	8.00
	effectively	7.81	insufficiently	6.71	additionally	6.59
	particularly	5.09	creatively	5.00	distinctly	5.00
	positively	4.71	overall	4.30	primarily	3.32
	convincingly	3.07	elegantly	3.00	marginally	2.93
	selectively	2.50	conclusively	2.33	especially	2.26
	favorably	2.20	universally	2.00	theoretically	1.71
	overly	1.71	consistently	1.65	potentially	1.59

Table 9: Top-30 LLM-preferred Words in **GPT-4o**-generated vs. human-written **meta-reviews**, with long words making up 39.96% and complex-syllabled words 67.82%.

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	abstract	40.00	advancements	28.50	realm	24.00
	alterations	20.00	aligns	19.00	methodologies	18.80
	clarity	17.00	adaptability	13.00	surpasses	13.00
	examination	10.00	competitiveness	9.00	aids	9.00
	reliance	8.75	necessitating	8.00	assurances	8.00
	necessitates	8.00	assertions	8.00	threats	8.00
	assessments	7.33	advancement	7.25	enhancements	7.25
	demands	7.00	findings	6.91	standpoint	6.00
	oversight	6.00	study	5.42	exhibit	5.33
	enhancement	5.00	adjustments	5.00	capitalizes	5.00
VERB	enhancing	73.00	necessitates	58.00	necessitating	50.00
	featuring	47.00	revised	46.00	influenced	40.00
	encompassing	31.00	enhances	30.10	showcasing	29.00
	surpasses	19.50	underscoring	19.00	facilitating	18.67
	necessitate	18.00	managing	18.00	concerning	15.33
	garnered	14.50	employing	14.06	surpassing	14.00
	adhere	14.00	neglecting	14.00	comprehend	14.00
	underscore	13.00	discern	13.00	examines	12.00
	accommodates	11.00	detail	11.00	utilizing	10.87
	enhance	10.82	begins	10.50	integrating	10.21
ADJ	innovative	34.17	exceptional	24.00	pertinent	22.00
	intricate	16.33	pivotal	16.00	necessitate	12.00
	distinctive	11.00	enhanced	10.80	akin	10.40
	potent	10.00	adaptable	9.67	unfamiliar	9.00
	straightforward	8.42	accessible	8.00	versatile	7.13
	adept	7.00	devoid	7.00	advantageous	6.80
	extended	6.67	prevalent	6.00	underexplored	6.00
	commendable	6.00	contingent	6.00	foundational	5.75
	comprehensive	5.09	strategic	5.00	renowned	5.00
	attributable	5.00	unidentified	5.00	numerous	4.82
ADV	inadequately	17.00	predominantly	16.67	meticulously	16.00
	strategically	14.00	notably	12.60	abstract	12.00
	swiftly	12.00	additionally	9.08	adeptly	8.00
	thereby	7.52	conversely	7.40	traditionally	7.33
	initially	7.10	innovatively	7.00	subsequently	6.06
	unexpectedly	6.00	excessively	5.00	historically	5.00
	seamlessly	4.50	nonetheless	4.25	primarily	4.00
	markedly	4.00	short	4.00	infrequently	4.00
	effectively	3.97	solely	3.80	consequently	3.78
	inherently	3.40	concurrently	3.33	particularly	3.09

Table 10: Top-30 LLM-preferred Words in **Gemini**-generated vs. human-written **abstracts**, with long words making up 44.35%, and complex-syllabled words 74.80%

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	refinement	59.00	leans	55.00	reliance	45.50
	generalizability	37.00	handling	35.00	advancements	28.00
	achieves	24.00	explores	23.00	inconsistencies	20.33
	underpinnings	17.00	core	16.38	clarification	16.29
	hinder	16.00	contingent	16.00	implications	14.42
	articulation	14.00	calculations	14.00	typos	13.86
	quantification	13.00	testing	12.71	availability	12.50
	efficacy	12.33	referencing	12.00	mitigation	12.00
	contextualization	12.00	duration	12.00	investigation	11.97
	practicality	11.43	grounding	11.25	overfitting	11.00
VERB	deemed	153.67	solidify	94.00	hindering	66.00
	criticized	63.67	praised	52.20	weakens	42.00
	exceeding	41.00	praising	40.33	questioned	37.68
	leans	32.57	recognizing	32.00	drew	31.00
	leaned	29.50	enhance	28.00	offering	27.25
	mitigating	27.00	weakened	26.50	utilizes	25.00
	showcasing	23.00	hinders	23.00	arose	21.67
	expanding	20.67	recurring	19.00	challenged	17.00
	leverages	16.75	desired	15.46	raising	15.33
	promoting	15.00	termed	15.00	differing	15.00
ADJ	core	65.25	established	29.00	undefined	17.00
	nuanced	16.00	cautious	16.00	presentational	15.00
	absent	13.00	combined	12.00	innovative	11.62
	outdated	11.00	simplified	9.25	robotic	9.00
	benchmark	8.56	inconsistent	8.50	illustrative	8.50
	diverse	8.26	adaptable	8.00	dataset	7.44
	insightful	7.33	grammatical	7.29	observed	7.20
	comprehensive	7.03	spatiotemporal	7.00	repetitive	7.00
	certain	6.98	rigorous	6.86	deeper	6.64
	superior	6.55	compact	6.50	unconvincing	6.30
ADV	definitively	9.00	solely	8.43	reportedly	8.00
	particularly	7.35	purportedly	7.00	primarily	6.89
	positively	5.43	generally	5.02	straightforward	5.00
	adaptively	5.00	specifically	4.96	favorably	4.80
	demonstrably	4.00	locally	3.50	consistently	3.41
	incrementally	3.25	potentially	3.21	visually	3.00
	furthermore	2.93	theoretically	2.58	overhead	2.50
	effectively	2.35	publicly	2.29	additionally	2.15
	fine	1.88	especially	1.76	computationally	1.71
	finally	1.62	insufficiently	1.50	overly	1.47

Table 11: Top-30 LLM-preferred Words in **Gemini**-generated vs. human-written **meta-reviews**, with long words making up 34.58%, and complex-syllabled words 62.07%

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	abstract	40.00	advancements	28.50	realm	24.00
	alterations	20.00	aligns	19.00	methodologies	18.80
	clarity	17.00	adaptability	13.00	surpasses	13.00
	examination	10.00	competitiveness	9.00	aids	9.00
	reliance	8.75	necessitating	8.00	assurances	8.00
	necessitates	8.00	assertions	8.00	threats	8.00
	assessments	7.33	advancement	7.25	enhancements	7.25
	demands	7.00	findings	6.91	standpoint	6.00
	oversight	6.00	study	5.42	exhibit	5.33
	enhancement	5.00	adjustments	5.00	capitalizes	5.00
VERB	enhancing	73.00	necessitates	58.00	necessitating	50.00
	featuring	47.00	revised	46.00	influenced	40.00
	encompassing	31.00	enhances	30.10	showcasing	29.00
	surpasses	19.50	underscoring	19.00	facilitating	18.67
	necessitate	18.00	managing	18.00	concerning	15.33
	garnered	14.50	employing	14.06	surpassing	14.00
	adhere	14.00	neglecting	14.00	comprehend	14.00
	underscore	13.00	discern	13.00	examines	12.00
	accommodates	11.00	detail	11.00	utilizing	10.87
	enhance	10.82	begins	10.50	integrating	10.21
ADJ	innovative	34.17	exceptional	24.00	pertinent	22.00
	intricate	16.33	pivotal	16.00	necessitate	12.00
	distinctive	11.00	enhanced	10.80	akin	10.40
	potent	10.00	adaptable	9.67	unfamiliar	9.00
	straightforward	8.42	accessible	8.00	versatile	7.13
	adept	7.00	devoid	7.00	advantageous	6.80
	extended	6.67	prevalent	6.00	underexplored	6.00
	commendable	6.00	contingent	6.00	foundational	5.75
	comprehensive	5.09	strategic	5.00	renowned	5.00
	attributable	5.00	unidentified	5.00	numerous	4.82
ADV	inadequately	17.00	predominantly	16.67	meticulously	16.00
	strategically	14.00	notably	12.60	abstract	12.00
	swiftly	12.00	additionally	9.08	adeptly	8.00
	thereby	7.52	conversely	7.40	traditionally	7.33
	initially	7.10	innovatively	7.00	subsequently	6.06
	unexpectedly	6.00	excessively	5.00	historically	5.00
	seamlessly	4.50	nonetheless	4.25	primarily	4.00
	markedly	4.00	short	4.00	infrequently	4.00
	effectively	3.97	solely	3.80	consequently	3.78
	inherently	3.40	concurrently	3.33	particularly	3.09

Table 12: Top-30 LLM-preferred Words in **Claude**-generated vs. human-written **abstracts**, with long words making up 42.81%, and complex-syllabled words 74.80%

POS	Word	WUIR	Word	WUIR	Word	WUIR
NOUN	refinement	604.00	center	151.00	demonstrates	108.00
	foundations	99.00	articulation	70.00	relies	62.00
	generalizability	60.57	tier	38.00	reservations	37.43
	sentiments	37.00	critiques	34.00	explores	31.00
	vulnerabilities	29.00	transparency	27.00	achieves	27.00
	promise	25.67	advancement	25.67	substantiation	25.00
	introduces	24.00	benchmarking	23.00	leans	23.00
	underpinnings	22.00	capabilities	21.00	skepticism	21.00
	shows	20.00	challenges	19.53	ambiguities	19.00
	narrative	19.00	highlights	19.00	differentiation	18.67
VERB	synthesizes	984.00	recognizing	153.00	view	131.33
	critique	92.00	express	91.83	revealing	81.33
	appreciating	73.67	praising	56.67	expanding	52.67
	highlighting	47.53	offering	42.50	acknowledging	39.92
	center	37.50	mitigating	36.00	substantiate	32.67
	persist	27.00	enhance	26.50	deemed	26.00
	conducting	24.00	reveals	24.00	graph	23.00
	handling	20.67	contexts	20.00	emerge	19.75
	recognize	19.43	generative	17.50	represents	17.10
	praised	16.80	offers	16.66	bridging	16.00
ADJ	collective	1049.00	nuanced	292.00	innovative	109.50
	cautious	46.00	comprehensive	40.22	comparative	36.30
	revolutionary	33.00	definitive	31.00	meta	27.84
	methodological	22.28	rigorous	22.24	transformative	21.00
	noteworthy	18.50	substantive	18.00	presentational	18.00
	notable	17.75	clearer	17.06	scholarly	17.00
	academic	16.00	undefined	15.00	intriguing	14.00
	addresses	14.00	robotic	14.00	core	13.38
	diverse	12.11	adaptable	12.00	primary	11.26
	scientific	10.69	deeper	10.64	broader	10.17
ADV	collectively	1112.00	definitively	54.00	comprehensively	37.00
	positively	25.14	conclusively	16.00	critically	16.00
	consistently	15.24	scientifically	12.00	marginally	8.57
	predominantly	7.00	cautiously	6.50	unanimously	5.94
	robustly	5.00	adaptively	5.00	particularly	4.59
	incrementally	4.50	meaningfully	4.33	generally	4.11
	fully	3.95	primarily	3.61	overhead	3.50
	short	3.38	potentially	3.37	genuinely	3.33
	dynamically	2.78	fundamentally	2.71	technically	2.54
	methodologically	2.50	semantically	2.33	dramatically	2.33

Table 13: Top-30 LLM-preferred Words in **Claude**-generated vs. human-written **meta-reviews**, with long words making up 43.93%, and complex-syllabled words 70.49%