The Erosion of LLM Signatures: Can We Still Distinguish Human and LLM-Generated Scientific Ideas After Iterative Paraphrasing?

Sadat Shahriar, Navid Ayoobi, Arjun Mukherjee
University of Houston, Texas, USA
sadat.shrr@gmail.com, nayoobi@cougarnet.uh.edu, arjun@cs.uh.edu

Abstract

With the increasing reliance on LLMs as research agents, distinguishing between LLM and human-generated ideas has become crucial for understanding the cognitive nuances of LLMs' research capabilities. While detecting LLM-generated text has been extensively studied, distinguishing human vs LLM-generated *scientific ideas* remains an unexplored area. In this work, we systematically evaluate the ability of state-of-the-art (SOTA) machine learning models to differentiate between human and LLM-generated ideas, particularly after successive paraphrasing stages. Our findings highlight the challenges SOTA models face in source attribution, with detection performance declining by an average of 25.4% after five consecutive paraphrasing stages. Additionally, we demonstrate that incorporating the research problem as contextual information improves detection performance by up to 2.97%. Notably, our analysis reveals that detection algorithms struggle significantly when ideas are paraphrased into a simplified, non-expert style, contributing the most to the erosion of distinguishable LLM signatures.

1 Introduction

Recent advances in LLMs have demonstrated extraordinary capabilities extending far beyond mundane conversational tasks (Boiko et al., 2023; Zhao et al., 2023a). Notably, these models can even engage in complex cognitive activities traditionally reserved for human intellect, such as hypothesis generation, reasoning, and scientific inquiry (Boiko et al., 2023; Si et al., 2024). This remarkable development raises a fundamental question: Given humanity's millennia-long tradition of knowledge creation and dissemination– and the subsequent encoding into vast linguistic datasets: can we still reliably discern whether novel ideas originate from humans or are algorithmically produced by LLMs?

Si et al. showed that LLMs can generate more novel ideas compared to human experts, though these ideas are not always practically feasible (Si et al., 2024). While novelty definitions carry inherent subjectivity, on a broader scale, LLMs still exhibit significant capability in producing innovative research ideas. As such, distinguishing between ideas generated by LLMs vs humans becomes increasingly important, as it provides deeper insights into LLM cognitive patterns, ensures academic integrity, and aids in maintaining transparency by clearly attributing authorship, ultimately influencing trust in scholarly contributions and guiding responsible AI deployment in research contexts.

While prior research on detecting LLM-generated text has focused on watermarking (Zhao et al., 2023b), zero-shot methods (Yang et al., 2023; Mitchell et al., 2023), and fine-tuned classifiers (Hu et al., 2023), our study takes a fundamentally different approach. Rather than identifying LLM-generated *text*, we examine the resilience of *ideas*– which persist beyond surface-level writing styles. Unlike text, ideas are conceptually immutable; a human-conceived idea remains human in essence, even if heavily paraphrased by an LLM. We investigate whether these underlying origins: human or LLM—remain detectable after successive paraphrasing and stylistic transformations. To the best of our knowledge, this is the first study to explore scientific idea attribution in such a nuanced and dynamic setting.

Ideas manifest across diverse contexts, but in this research, we define an "idea" specifically as a proposed solution addressing a given research problem, using 'scientific idea' and 'idea' interchangeably. Scientific ideas inherently reflect nuanced thinking and careful planning, which distinguishes them from mere linguistic outputs. Formally, given a research problem RP, an idea can be represented as a response $r = f(RP)$, where f denotes either human or LLM generation. To evaluate whether the essence of human or LLM-generated ideas persists through stylistic variations,

Proceedings of Recent Advances in Natural Language Processing, pages 1118–1126
Varna, Sep 8–10, 2025
https://doi.org/10.26615/978-954-452-098-4-129

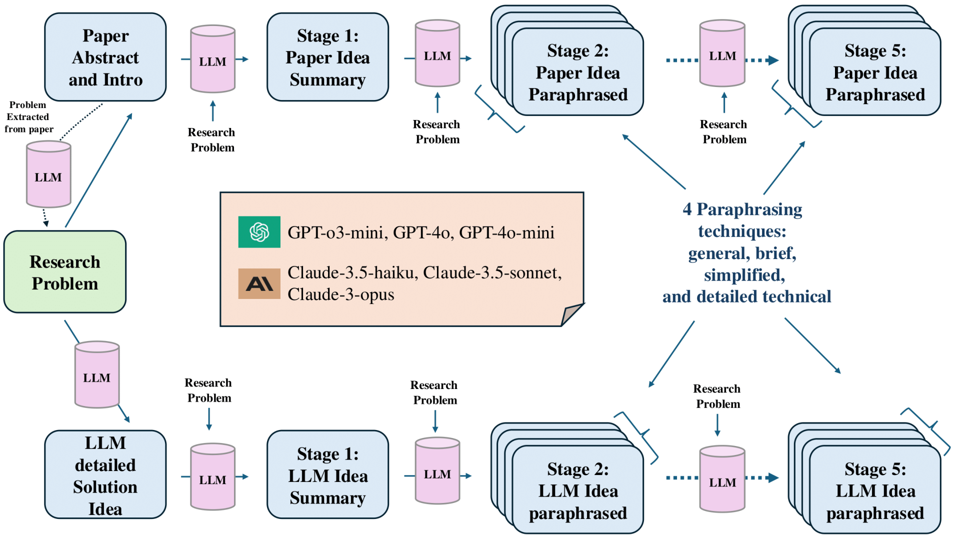


Figure 1: Idea Generation and Paraphrasing Workflow: The process begins with extracting the Research Problem from papers and then generate corresponding scientific ideas using six different LLMs. Both human and LLM-generated ideas are first summarized and subsequently paraphrased across five stages using four distinct paraphrasing techniques (To reduce visual clutter and redundancy, we abstracted Stages 3 and 4, as they represent similar paraphrasing strategies).

we iteratively paraphrase these ideas through multiple stages. At each paraphrasing stage n, the idea transforms as $r_n = f_{pn}(r_{n-1}, RP)$. Paraphrasing serves two critical purposes: firstly, in real-world scenarios, ideas are communicated through varied expressions and settings—yet retain their core meaning; secondly, without paraphrasing, classifiers might easily identify the source due to stylistic cues specific to scientific paper writing, conflating stylistic detection with genuine idea detection.

In this research, We collect 846 papers from five top CS conferences to extract their main research problems. We then prompt LLMs to generate original ideas for each problem. Human-generated (from papers) and LLM-generated ideas undergo systematic summarization and multi-stage paraphrasing using four strategies: general paraphrase, simplified summary, brief summary, and detailed technical paraphrase. Figure 1 illustrates this workflow.

We employ SOTA classifiers to assess detection performance across paraphrasing stages, revealing an average decline of 25.4% from Stage 1 to Stage 5. This deterioration suggests that characteristic "LLM signatures" initially present in earlier stages– such as specific word choices, linguistic patterns, or stylistic markers—gradually diminish through successive paraphrasing. As these superficial markers fade, traditional text-based classifiers increasingly struggle to differentiate between human and LLM-generated ideas.

Our main contributions are as follows:

- We create and release a comprehensive dataset consisting of original and multi-stage paraphrased scientific ideas, systematically generated using cutting-edge LLMs.
- Through extensive evaluation using various classification algorithms, we empirically demonstrate the inherent challenges involved in identifying LLM-generated ideas, particularly as these ideas undergo iterative paraphrasing and stylistic transformations.

2 Related Works

LLMLu et al. introduced *AI Scientist*, an end-to-end framework designed for scientific discovery using LLMs. This framework autonomously generates novel research ideas, implements experimental code, executes experiments, visualizes results, composes scientific papers, and even simulates a peer-review process to evaluate its findings (Lu et al., 2024). Similarly, Baek et al. proposed a research agent capable of automatically formulating problems, suggesting methods, and designing experiments. Their approach iteratively refines these elements through feedback provided by collaborative LLM-powered reviewing agents (Baek et al., 2024).

Li et al. developed specialized LLM-driven agents, namely *IdeaAgent* and *ExperimentAgent*, tailored for research idea generation, experimental implementation, and execution within the machine learning domain (Li et al., 2024). OpenAI's Deep Research initiative demonstrated the potential of LLMs to gather, analyze, and synthesize extensive online resources, producing comprehensive reports like those of human research analysts (OpenAI, 2025b).

Si et al. conducted a comparative study on the novelty of ideas generated by expert NLP researchers and LLM ideation agents (Si et al., 2024). Their results suggested that LLMs can generate ideas that surpass human-generated ideas in terms of novelty. However, their approach involved prompting-based idea generation across predefined NLP topics. In contrast, our research explicitly defines an idea as a response to a given research problem. This definition allows for a more unbiased comparison between human and LLM-generated ideas and reduces topic-related bias.

Unlike previous studies primarily focused on enabling research potential of LLMs, and comparing novelty, our work shifts attention toward the challenge of detection. Specifically, we investigate the inherent difficulty of distinguishing human-generated ideas from those produced by LLMs, especially as these ideas undergo multiple stages of paraphrasing.

3 Methodology

To generate research ideas, we first extract research problems from scientific papers and feed these into LLMs. Subsequently, we apply cascading paraphrasing to both human-written and LLM-generated ideas. Finally, we evaluate the distinguishability of these ideas at each paraphrasing stage using several SOTA classifiers.

3.1 Data Collection

	2017	2018	2019	2020	2021
ACL	19	15	12	35	19
EMNLP	13	27	27	43	38
ICLR	1	15	15	29	39
ICML	28	24	34	32	51
NeurIPS	37	39	56	101	97

Table 1: Conference counts by publication year.

To compile our dataset, we first sample 846 scientific papers from a larger collection drawn from five A*-rated computer science conferences—ACL, EMNLP, ICLR, ICML, and NeurIPS—spanning 2017 to 2021 (CORE: Computing Research and Education Association of Australasia, 2025). This sample size was chosen primarily due to the substantial computational and financial resources required for large-scale generation and extensive cascading paraphrasing using SOTA LLM APIs. Table 1 summarizes the sampled dataset, while detailed statistics are available in our repository.[1] We include only papers published up to 2021 to ensure the integrity of our analysis, as this guarantees that the ideas originate purely from humans, predating the release of ChatGPT in 2022 (OpenAI, 2025a).

3.2 Extracting Research Problem

We extract the research problem from the first two pages of each paper, selecting five different LLMs at random for each extraction. In general, these pages encompass the abstract and introduction, where problem statements are typically presented either explicitly or implicitly. To minimize the risk of LLMs incorporating elements of the solution, we explicitly prompt them to focus solely on the problem itself (find the prompts in Appendix) [1].

3.3 LLM Idea Generation

The extracted research problem is used as input to the LLM along with carefully designed instructions to generate potential research ideas. This process constitutes the core of LLM-driven idea generation. We employ two distinct prompting strategies. The first is a general prompting approach, where the LLM is simply instructed to provide a detailed research solution. The second approach, inspired by the idea generation technique outlined in (Si et al., 2024), involves a more structured prompt with step-by-step guidance on explaining the methodology, techniques employed, novelty, and contributions. While both approaches yielded comparable results, the latter tends to produce slightly more detailed and descriptive responses. To incorporate both prompting styles, we apply the general prompting method to half of the samples and the structured approach to the remaining half. A detailed description of both prompting strategies is provided in Appendix [1].

[1] Check the Appendix of the full paper: https://github.com/sadat1971/Erosion_LLM_Signatures/blob/main/Paper/RANLP__LLMErosion_cameraReady.pdf

3.4 Idea Paraphrasing

Since we want to differentiate ideas generated by humans from those produced by LLMs, a direct comparison between LLM-generated ideas and research papers (first two pages) is not feasible. This is primarily due to the presence of stylistic cues that algorithms can easily detect, as well as inconsistencies in formatting across these two categories. Consequently, distinguishing ideas at this stage would not be reliable.

Hence, we employ a multi-stage cascade of summarization and paraphrasing. In the first stage (Stage 1), we generate a three-paragraph summary of both the first two pages of each paper and the corresponding LLM-generated ideas. In the second stage, we apply four distinct paraphrasing strategies to each summary: (i) **general paraphrasing**, (ii) **paraphrasing for a simplified non-expert audience**, (iii) **brief summarization**, and (iv) **detailed technical paraphrasing**. This paraphrasing process continues in a cascaded manner across a total of five stages. To prevent excessive compression or the introduction of additional information, we avoid consecutive applications of the same paraphrasing type. Appendix C.3 shows the instruction prompts to generate these paraphrases.

Through this approach, we obtain 846 paraphrases in Stage 1. From Stages 2 to 5, this expands to 3,384 paraphrases for both LLM-generated and human-written ideas. In total, our process yields 28,764 paraphrased versions of research ideas. One of the authors also manually verified a 1% of the samples across all paraphrasing stages to ensure consistency.

3.5 Generative LLMs

We utilize six best-performing LLMs to generate data for research problem extraction, idea generation, and the five stages of idea paraphrasing. To ensure optimal performance, we conduct small-scale experiments and manual evaluations of the quality of generated outputs across different LLMs. Additionally, we consider the cost of API usage as a factor in model selection. Based on these trade-offs, we selected three models from OpenAI (OpenAI, 2025c) and three from Anthropic (Anthropic, 2025).

From OpenAI's suite of models, we use **GPT-4o**, **GPT-4o-mini**, and **O3-mini**. From Anthropic, we employ **Claude-3.5-Haiku**, **Claude-3.5-Sonnet**, and **Claude-3-Opus**. Across all stages of our study, 63% of the data was generated using OpenAI's models, while the remaining 37% was produced using Anthropic's models. Table 2 presents the exact distribution of data generation across the selected LLMs.

To minimize topic bias, we ensured that the same LLM was used for both summarizing the research paper and generating the summary of the corresponding LLM-generated idea. This consistency was maintained throughout the paraphrasing process as well.

LLM	% of Data
gpt-4o-mini	41.37
gpt-4o	5.91
gpt-o3-mini	17.73
claude-3-5-haiku	23.64
claude-3-5-sonnet	7.09
claude-3-opus	4.26

Table 2: Percentage of data generated by each flagship LLMs

3.6 Classifiers

We evaluated four fine-tuned language models and four text embedding methods, each coupled with downstream classification layers. First, we employed BERT (*bert-base-uncased*) as our baseline, owing to its proven ability in capturing bidirectional contextual information (Devlin et al., 2019). RoBERTa (*roberta-base*), known for its more extensive pretraining, is included as a strong comparative choice (Liu et al., 2019). Additionally, BigBird (*BigBird-RoBERTa-base*) is selected due to its efficient handling of long sequences by employing a sparse attention mechanism, thus avoiding the quadratic complexity in traditional transformers (Zaheer et al., 2020). Finally, we incorporate T5 (*t5-base*), a text-to-text transformer featuring an encoder-decoder architecture that fundamentally differs from BERT-style models by translating input text into target text (Raffel et al., 2020).

For embedding-based representations, we use the sentence-transformers' *all-MiniLM-L6-v2* as our baseline, encoding text into 384-dimensional vectors (Wang et al., 2020). Additionally, we selected three advanced embedding models—*GIST-Embedding-v0* (Solatorio, 2024), *gte-base-en-v1.5* (Zhang et al., 2024), and *stella_en_400M_v5* (Zhang et al., 2025), which consist of 109M, 137M, and 435M parameters respectively.

These specific embedding models were chosen based on initial exploratory experiments and by carefully considering the trade-offs between model size and ranking performance (Face, 2025). Each embedding representation was subsequently coupled with a downstream two-layer Feed-Forward Neural Network (FFNN).

4 Experimental Setup

For the experiments, we prepare dataset using a systematic train-test splitting approach to ensure unbiased evaluation. Initially, we have 1,692 samples in Stage 1, comprising equal portions of LLM-generated and human-generated ideas. For subsequent stages (Stage 2 to Stage 5), the dataset expanded to include 6,768 samples, incorporating four distinct paraphrasing styles for each original idea. To avoid data leakage, we perform splits such that there was no overlap between the original solution (and the research problem) in the training and test sets, meaning each problem-solution was exclusive to either the training or testing partition across all stages. This strategy ensures that all paraphrases derived from the same initial research problem statement remain consistently within the same partition, thus maintaining dataset integrity.

We conduct three random train-test splits and report the averaged results across these splits. From each training split, we further allocate 20% of the data as a validation set, specifically used for hyperparameter tuning. We perform tuning for batch size, number of epochs, dropout rate, and early stopping criteria.

For all our experiments, we use NVIDIA TITAN RTX (24 GB), Quadro RTX 8000 (48 GB), and NVIDIA GeForce RTX 2080 Ti (11 GB) GPUs. We report the macro F1-score to report the performances.

5 Results and Discussion

We evaluate the performance of various algorithms in idea-source detection (Table 3). Stage 1 achieves the highest F1-score (¿90% for BigBird, Stella) across many different models. We also find, even a simple logistic regression model attains 77%, suggesting strong lexical cues. Words like *hybrid*, *transformer*, *adaptive*, *intelligently*, *dynamically*, and *advanced* are highly correlated with LLM-generated text.

To further analyze this, we apply Integrated Gradients (IG) Visualization with RoBERTa (Figure 2) (Sundararajan et al., 2017). IG attributes model predictions by integrating gradients from a baseline input to the actual input, quantifying feature importance. We find terms like *adaptive*, *framework*, *regularized*, and *stability* align with LLMs, likely due to their prevalence in structured academic writing, whereas domain-specific terms like *federated* and *momentum* are more indicative of human ideas.

the main idea is to develop adaptive momentum - regularized federated optimization (AMRFO) , a framework designed to enhance convergence rates and reduce communication overhead in distributed machine learning . AMRFO achieve this by employing a multi-stage adaptive regularization mechanism that includes adaptive momentum scaling, stochastic communication compression , and stability -aware gradient normalization thereby balancing communication efficiency , convergence speed , and algorithmic stability in federated learning environments .

Figure 2: Integrated Gradients Visualization: Green highlights words that contribute to classifying the text as human-written, while red highlights words that push the classification toward LLM-generated content. The overall text is LLM-idea-summarized

We observe, BigBird consistently outperforms all other models, leveraging its superior context-length capability to capture both the research problem (RP) and idea representation effectively. Among fine-tuned models (BERT, RoBERTa, T5, BigBird), RoBERTa slightly outperforms BERT, while high-quality embeddings like Stella and GTE surpass idea-only models such as BERT, RoBERTa, and T5 in most stages, highlighting the advantage of robust embedding spaces.

5.1 Learning Difficulties with the Progression of Praraphrasing Stages

As training progresses across stages, a consistent decline in performance is observed, as depicted in Figure 3. When cross-stage train-test is performed, Stage 1 shows a larger degradation, since it contains only 25% of the data compared to the later stages. In Stages 2 to 5, models generally achieve

	Single Stage Training					Combined Stage Training				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
BERT	85.8	74.1	67.1	63.2	61.1	80.7	72.6	66.1	62.4	61.2
RoBERTa	88.1	74.4	70.3	63.8	62.7	84.1	75.2	70.8	66.7	63.9
T5	84.2	65.4	59.0	54.4	49.9	89.7	81.0	72.1	67.1	64.0
Bigbird (RP+idea)	**92.3**	**83.4**	**70.9**	**65.1**	**63.2**	**90.5**	**81.4**	**72.2**	**67.2**	**64.9**
MiniLM +FFNN (idea)	81.2	66.6	59.3	57.0	55.1	75.2	64.2	59.6	57.2	56.0
MiniLM +FFNN (RP+idea)	83.2	69.4	61.6	58.0	56.3	75.9	66.3	60.1	60.0	57.0
GIST +FFNN (idea)	83.9	71.9	64.7	60.7	53.3	78.2	70.0	64.1	61.3	58.7
GIST +FFNN (RP+idea)	86.9	73.0	65.3	61.1	59.1	78.4	70.9	64.2	61.4	59.9
Gte +FFNN (idea)	89.3	72.2	63.8	61.1	56.9	78.4	66.6	62.9	59.3	56.8
Gte +FFNN (RP+idea)	89.4	73.2	64.2	61.2	57.7	79.0	69.4	63.1	59.4	57.9
Stella +FFNN (idea)	90.0	73.9	65.3	61.3	56.7	77.8	70.5	64.5	61.1	58.5
Stella +FFNN (RP+idea)	91.8	77.6	67.4	63.6	58.5	85.4	74.0	66.3	64.0	60.7

Table 3: F1-score comparison of various classifiers across different stages (S1 to S5). *Single Stage Training* involves training within a single paraphrase stage, while *Combined Stage Training* aggregates data from all stages for classification.

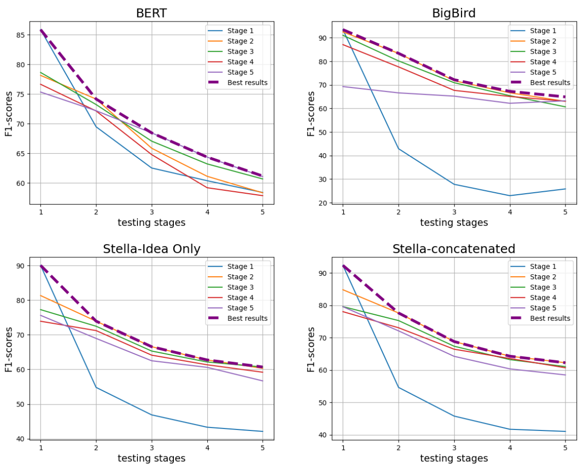


Figure 3: F1-score evaluated across different training and testing stages. The purple dashed line represents the highest performance achieved at each stage, pointing to the overall declining performance trend across the models (clockwise from top left) BERT, BigBird , Stella + FFNN (RP + Idea) (c), and Stella + FFNN (Idea Only) (d).

their highest performance within the stage they were trained on, indicating a strong stage-specific learning effect. Nevertheless, irrespective of cross-stage or within-stage, overall performance declines with the progression of stages. It also indicates that the earlier stages may still retain the "LLM signature", which aids detection but gradually diminishes in later stages.

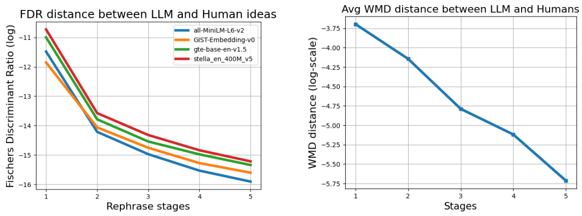
To further understand the issue, we investigate the **Fisher's Discriminant Ratio (FDR)** between LLM and Human ideas acorss different stages (Li and Wang, 2014).

$$FDR = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}$$

where μ_1, μ_2 are the means of the feature (embedding representation) for Human and LLM-generated ideas respectively, and σ_1^2, σ_2^2 are the variances of them respectively. As illustrated in Figure 4(a), the FDR steadily declines across the stages, irrespective of the embedding representation used. It suggests that as ideas undergo iterative paraphrasing or transformation, their distinguishing characteristics erode, making human and LLM-generated ideas increasingly indistinguishable.

In addition, we examine **Word Mover's Distance (WMD)**, a metric that quantifies the effort required to change one document's word embeddings into another's, serving as a measure for textual dissimilarity (Kusner et al., 2015). We employ the GloVe-wiki-gigaword-50 embedding model to compute WMD at each stage. Figure 4(b) reveals a progressive decline in WMD, further reinforcing the notion that the iterative modifications reduce the distinctiveness of LLM-generated content. As the transformation stages accumulate, the 'LLM signature' becomes increasingly elusive, making it more challenging to establish a clear boundary between human and LLM-generated ideas.

Finally, we investigate the "learning difficulty" through the analysis of the loss curves, focusing on the MiniLM + FFNN architecture trained on concatenated (RP + idea) inputs (Figure 5). Computing



(a) (b)

Figure 4: Visualization of discriminative features between human and LLM-generated ideas. (a) Four different text embedding representations illustrate the decreasing discriminability as we progress from Stage 1 to Stage 5. (b) Word Mover‘s Distance also shows a declining trend, indicating reduced differentiation between human and LLM-generated ideas over stages.

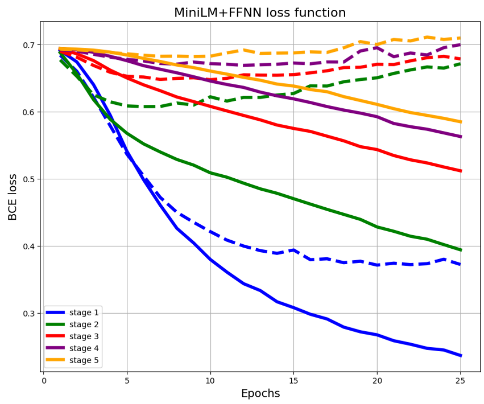


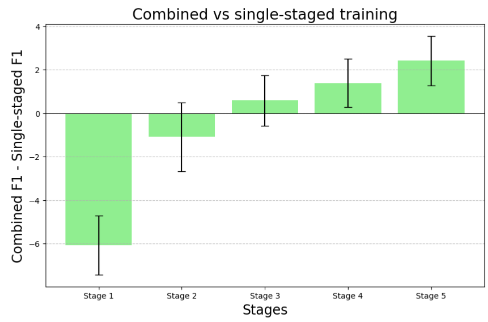
Figure 5: Visualization of the training (solid line) and validation (dashed line) loss curves for the MiniLM + FFNN model across the first 25 epochs, providing insights into learning dynamics and model convergence

the average slope of the validation loss across the initial five epochs, given by $(L(t+n-1)-L(t))/n$, reveals progressively decreasing slopes of 0.029, 0.014, 0.007, 0.003, and 0.002 from stages 1 to 5. Intuitively, as the cascaded paraphrasing stages progress, this indicates that while early stages rapidly achieve a stable, low-loss plateau, the higher stages quickly plateau at higher losses, followed by an upward drift in validation loss, clearly reflecting increased learning difficulty and poorer generalization .

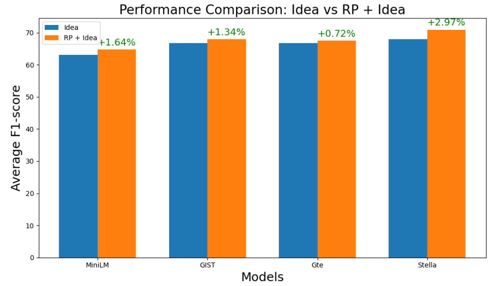
5.2 When Does Merging Data Across Stages Help ?

We investigate whether combining training examples from different paraphrase stages can improve detection performance, and Figure 6(a) reveals that this strategy unexpectedly degrades performance in earlier stages (stages 1 and 2). For stage 1 and 2, combined training declines the average performance by 6.07 and 1.08 points respectively. However, for stage 3, 4, 5, combined training imrpoves the performance by an average of 0.6, 1.4, and 2.4 points respectively, likely due to the increased volume of training data improving generalization.

In stage 1, even smaller datasets suffice to achieve high accuracy because the LLM’s distinctive “signature” remains relatively intact, making it straightforward to distinguish from human-generated content. However, as we progress to later stages (stages 4 and5), repeated paraphrasing gradually erodes these features, creating a more challenging detection task. Under these conditions, adding data from earlier stages proves beneficial because it provides subtle patterns and cues that help the model better learn residual LLM signatures.



(a)



(b)

Figure 6: (a) When combined stages and performed a holistic training, the latter stages get more benfitted, while the earlier stages decline in performance (b) When Research problem embeddings are concatenated with the Idea embedding, we observe a consistent performance increase

5.3 Improving Idea Detection by Integrating Problem Context

Through the embedding + FFNN models, we observe that RP + idea versions of training significantly outperform their idea-only counterparts 6(b), with observed performance gains of +1.64

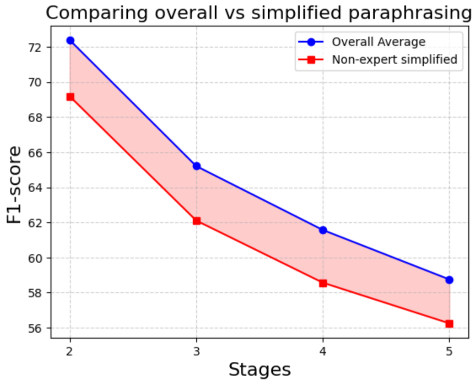


Figure 7: Detection performance (F1-score) consistently deteriorates when ideas are paraphrased into simplified, non-technical language intended for general audiences.

(p=0.00) for MiniLM, +1.34 (p=0.04) for GIST, +0.72 (p=0.02) for GTE, and +2.97 (p=0.00) for Stella.

These gains indicate how incorporating RP helps models learn structured semantic dependencies between RP and their corresponding research idea solutions, thus, leading to richer conceptual representations and reducing ambiguity. In FFNN classifiers, this additional context strengthens decision boundary formation by providing clearer distinctions between different idea categories. However, in the embedding models, RP and ideas are only concatenated at the representation level. To further enhance contextual integration, we plan to explore a cross-attention modeling structure in future work, which may better capture problem-idea interactions and improve the model's understanding of idea patterns.

5.4 Simplified Paraphrasing Significantly Reduces Detectability

Across all stages and classifiers, we observe a consistent pattern: simplified paraphrasing intended for non-expert audiences leads to the most substantial reduction in detection performance (Figure 7). The average F1-score across all algorithms and paraphrasing stages is 64.5%, while simplified non-expert paraphrasing underperforms this benchmark significantly by 2.98% (p-value = 0.03).

This phenomenon likely occurs because non-expert paraphrasing deliberately omits technical nuances, replacing them with simpler, more general language. Such simplification further diminishes the research domain specific linguistic signatures used by models to distinguish between human and LLM-generated ideas. These findings also illustrate critical limitations in current detection algorithms, suggesting they rely heavily on superficial linguistic patterns and struggle to capture deeper 'Idea Signature' when technical complexity is removed.

6 Conclusion

This paper examines the ability of SOTA textual ML models to differentiate between human and LLM-generated research ideas, revealing the challenges posed by iterative paraphrasing. Unlike direct text-based detection, idea detection is significantly harder as paraphrasing progressively erodes distinctive LLM signatures, making idea attribution increasingly unreliable. By constructing a systematic dataset from top CS conferences and leveraging advanced LLMs for idea generation and rephrasing, we find that even the best detection models struggle once ideas undergo multiple paraphrasing stages. Our results emphasize that existing classifiers rely heavily on surface-level linguistic features rather than deeply understanding the underlying idea structures, leading to substantial performance declines as paraphrasing progresses.

In future, we aim to extend this study beyond CS to other scientific disciplines, exploring whether similar challenges persist across diverse knowledge domains. A key direction for improvement involves incorporating the reasoning trajectory of LLMs during idea generation, as tracing the thought process may provide a more robust signal for detection. Additionally, integrating structured knowledge-based embeddings could help models capture deeper conceptual patterns, reducing their dependence on linguistic artifacts and enhancing their ability to differentiate between human and LLM-generated ideas.

References

Anthropic. 2025. Claude ai models. Accessed: March 14, 2025.

Jinheon Baek, Sujay Kumar Jauhar, Silviu Cucerzan, and Sung Ju Hwang. 2024. Researchagent: Iterative research idea generation over scientific literature with large language models. *arXiv preprint arXiv:2404.07738*.

Daniil A Boiko, Robert MacKnight, and Gabe Gomes. 2023. Emergent autonomous scientific research capabilities of large language models. *arXiv preprint arXiv:2304.05332*.

CORE: Computing Research and Education Association of Australasia. 2025. Core conference portal. Accessed: 2025-03-09.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, pages 4171–4186.

Hugging Face. 2025. Mteb leaderboard - hugging face spaces. Accessed: 2025-03-14.

Xiaomeng Hu, Pin-Yu Chen, and Tsung-Yi Ho. 2023. Radar: Robust ai-text detection via adversarial learning. *Advances in neural information processing systems*, 36:15077–15095.

Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From word embeddings to document distances. In *International conference on machine learning*, pages 957–966. PMLR.

Cheng Li and Bingyu Wang. 2014. Fisher linear discriminant analysis. *CCIS Northeastern University*, 6.

Ruochen Li, Teerth Patel, Qingyun Wang, and Xinya Du. 2024. Mlr-copilot: Autonomous machine learning research based on large language models agents. *arXiv preprint arXiv:2408.14033*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, and David Ha. 2024. The ai scientist: Towards fully automated open-ended scientific discovery. *arXiv preprint arXiv:2408.06292*.

Eric Mitchell, Yoonho Lee, Alexander Khazatsky, Christopher D Manning, and Chelsea Finn. 2023. Detectgpt: Zero-shot machine-generated text detection using probability curvature. In *International Conference on Machine Learning*, pages 24950–24962. PMLR.

OpenAI. 2025a. Chatgpt. Accessed: March 14, 2025.

OpenAI. 2025b. Introducing deep research. Accessed: 2025-03-14.

OpenAI. 2025c. Openai platform - model documentation. Accessed: 2025-03-14.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67.

Chenglei Si, Diyi Yang, and Tatsunori Hashimoto. 2024. Can llms generate novel research ideas? a large-scale human study with 100+ nlp researchers. *arXiv preprint arXiv:2409.04109*.

Aivin V Solatorio. 2024. Gistembed: Guided in-sample selection of training negatives for text embedding fine-tuning. *arXiv preprint arXiv:2402.16829*.

Mukund Sundararajan, Ankur Taly, and Qiqi Yan. 2017. Axiomatic attribution for deep networks. In *International conference on machine learning*, pages 3319–3328. PMLR.

Wenhui Wang, Furu Wei, Li Dong, Hangbo Bao, Nan Yang, and Ming Zhou. 2020. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. *Advances in neural information processing systems*, 33:5776–5788.

Xianjun Yang, Wei Cheng, Yue Wu, Linda Petzold, William Yang Wang, and Haifeng Chen. 2023. Dna-gpt: Divergent n-gram analysis for training-free detection of gpt-generated text. *arXiv preprint arXiv:2305.17359*.

Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, et al. 2020. Big bird: Transformers for longer sequences. *Advances in neural information processing systems*, 33:17283–17297.

Dun Zhang, Jiacheng Li, Ziyang Zeng, and Fulong Wang. 2025. Jasper and stella: distillation of sota embedding models.

Xin Zhang, Yanzhao Zhang, Dingkun Long, Wen Xie, Ziqi Dai, Jialong Tang, Huan Lin, Baosong Yang, Pengjun Xie, Fei Huang, et al. 2024. mgte: Generalized long-context text representation and reranking models for multilingual text retrieval. *arXiv preprint arXiv:2407.19669*.

Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023a. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 1(2).

Xuandong Zhao, Yu-Xiang Wang, and Lei Li. 2023b. Protecting language generation models via invisible watermarking. In *International Conference on Machine Learning*, pages 42187–42199. PMLR.