# Detection of Misinformation in Artificial Intelligence News using Retrieval-Augmented Language Models

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ABSTRACT

The rising incidence of misinformation in artificial intelligence (AI) and new technology domains poses a critical obstacle to public knowledge and informed choice. Hyperbolic or misleading claims like consciousness of AI, job automation hysteria, or unfounded speculations have a tendency to propagate uncontrolled across the web. The article introduces a Retrieval-Augmented Generation (RAG) model built on Large Language Models (LLMs) to identify AI and tech misinformation. The model incorporates external knowledge retrieval from trusted sources like arXiv, TechCrunch, and Wired to introduce factual coherence and contextual clarity. The system identifies text inputs based on a hand-curated dataset of true and false statements and marks them with evidence-based explanations. Our experiments show that the RAG-based model outperforms state-of-the-art baseline transformer models significantly in misinformation detection. Our work showcases the capability of retrieval-augmented NLP systems in fighting technology-enabled disinformation and supporting a fact-driven digital information ecosystem.

Keywords: Artificial Intelligence, Fake News Detection, RAG, Language Models, Technology Misinformation

JEL Classification: C88, D83, L86

(C88 – Methodology of data collection and data estimation; D83 – Search; Learning; Information and Knowledge;Communication; L86 – Information and Internet services; Computer software)

## INTRODUCTION

The fast growth of Artificial Intelligence (AI) and surrounding technologies has brought about content explosion on media channels, some of which are untested, spurious, or completely

fabricated information. Disinformation in the AI and tech space varies from overhyped expectations regarding autonomous AI, digital consciousness, and automation to sensationalized reports on emerging technologies like quantum computing and brain-computer interfaces (West et al., 2019; Floridi & Cowls, 2021). The digital noise not only warps people's perceptions but could also impact technology adoption, policy development, and learning. It is in the last few years that researchers have resorted to Natural Language Processing (NLP) software to address the propagation of disinformation. Large Language Models (LLMs) such as GPT-4 and BERT have been remarkably efficient at processing and creating human language (Brown et al., 2020; Devlin et al., 2018). Yet, their dependence on static training corpora tends to confine their factual accuracy in real-time, particularly in fields such as AI, which develop extremely fast. To compensate for this, Retrieval-Augmented Generation (RAG) architectures have been suggested, which attempt to marry the generation capabilities of LLMs with real-time evidence access from reputable sources (Lewis et al., 2020). The current study is intended to utilize a RAG-based system for AI and tech news misinformation detection. The research builds a dataset of actual and false facts from sources such as Snopes, Reddit, TechCrunch, and arXiv. Compared to baseline transformer-based classifiers, we examine if retrieval-augmented models introduce a notable improvement in identifying AI-related fake news. The contribution of the work is most substantial in that it introduces a domain-specific pipeline that not only provides predictions but transparent and evidence-grounded explanations as well, thus being application and research-ready.

## LITERATURE REVIEW

Fake news detection is a critical research area in the field of Natural Language Processing (NLP) overall and even more so with the rise of AI-generated content along with domain-level disinformation. The spread of unsubstantiated or fabricated news on topics relating to Artificial Intelligence (AI) and technology has posed new challenges, as the majority of such news is based on complex or vague technical principles that cannot be easily tested for their authenticity by common individuals (Zhou & Zafarani, 2020). This survey brings together top empirical and theoretical work from the fields of detection of fake news, retrieval-augmented generation (RAG), large language models (LLMs), and domain-specific misinformation analysis.

*Fake News Detection: Traditional and Deep Learning Techniques*

The early methods of detecting fake news had been mostly centered around rule-based manual systems and traditional machine learning models like Support Vector Machines (SVM), Logistic Regression, and Naïve Bayes (Ruchansky et al., 2017). They were based on manually crafted features such as word frequency, sentiment scores, and style features. While they were moderately good on well-curated data, they had no generalizability and could not scale with increasing levels of complexity in contemporary disinformation. Deep learning introduced a paradigm shift toward feature extraction automation. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, were used for contextual semantic extraction (Wang, 2017). Such models also did not possess in-depth understanding of larger context and domain information, so they could be vulnerable to sophisticated or technically accurate misinformation.

*Large Language Models in Misinformation Detection*

Ever since the transformer-based models emerged, fake news detection has seen a phenomenal performance boost. Pre-trained transformers like BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa have been well utilized in binary and multi-class classification of fake news (Devlin et al., 2018; Liu et al., 2019). The pre-trained models fine-tune effectively on particular datasets and perform sentence-level semantics and relations identification very well, surpassing conventional RNN-based models on many benchmark tasks. Yet, while there is greater understanding of language, big language models such as BERT, GPT-3, and T5 base on static training data. This static nature presents difficulties in identifying fabricated news referring to emerging domains such as AI and quantum physics, where the information environment is changing at a fast rate (Shu et al., 2020). Additionally, LLMs can "hallucinate" factsproducing well-sounding but false outputs particularly in zero-shot or few-shot scenarios (Maynez et al., 2020).

*The Emergence of Retrieval-Augmented Generation (RAG)*

To combat the issues in fixed LLMs, Lewis et al. (2020) presented Retrieval-Augmented Generation (RAG), where both a neural retriever and a generator model are paired to leverage external evidence in generating language. The retriever identifies supporting documents from a knowledge corpus (e.g., Wikipedia or scholarly papers), and the generator processes this evidence to generate response based on fact-finding evidence. This collaborative model has been used in question-answering, fact-checking, and summarization (Karpukhin et al., 2020). RAG systems have been employed particularly effectively in a knowledge-intensive task,

wherein the retrieval module solidifies the fact basis of generative results. In misinformation detection, the architecture supports not just classification (e.g., true, false, deceptive) but also explanation generation from source document references (Beltagy et al., 2020). Such greater level of transparency is useful in domains such as AI, wherein traceability and explainability are of the highest priority.

*Domain-Specific Disinformation in Technology and AI*

Artificial intelligence is among the most susceptible to disinformation given the speculative characteristics of its innovations and the way it is addressed by mass media. Disinformation attempting to describe innovations like "AI becoming conscious," "robots taking all jobs away," or "ChatGPT passing the Turing test" has spread extensively and far with little factual basis (Cave et al., 2019). Such assertions tend to appear on non-peer-reviewed blogs or misread versions of scientific studies. Fact-checking within such a field, however, necessitates domain expertise and access to trusted sites such as arXiv, IEEE Xplore, or MIT Technology Review. Increased attention to the need for domain-specific misinformation identification has been seen in recent years. Gupta et al. (2022), for instance, developed a domain-specific model for misclassification in health care from a fine-tuned adaptation of the BERT model. Comparable methods can be used in AI and technology by developing some datasets made up of actual news (from Wired, TechCrunch, etc.) and false or inflated reports (from Twitter, Reddit, or conspiracy websites). Including scientific papers in retrieval streams also enables more substantial verification, especially in pseudo-scientific language detection.

*Fact-Checking and Explainability*

Fact-checking systems have in the past depended on either evidence verification against a systematically organized knowledge base or textual entailment approaches. The FEVER corpus (Thorne et al., 2018), for example, is comprised of claims and their corresponding supporting/evidence-refuting evidence from Wikipedia and has been extensively used to evaluate fact verification systems. DeBERTa and T5, which are transformer models, both perform well on FEVER, although their responses are not typically justified in terms of transparency. The fusion of explainability and fact-checking is an exciting avenue. Models like VERIFI (Hansen et al., 2021) not only predict claims but also provide evidence-based explanations generated from retrieved evidence. This avenue is especially suited for the RAG setup, where models are able to refer to sources and minimize hallucination. For domains like

technology and science, with high stakes, this transparency increases user trust and system responsibility.

Limitations of Current Work

Although tremendous progress has been made, there are a few limitations. First, current fake news corpora tend to be political or general news-based and do not capture vocabulary and writing used in AI/tech writing. Second, most models are not stable under adversarial example or linguistically manipulated claims. Third, ethical considerations still prevail, particularly with respect to the dissemination of false positives and possible suppression of early-but-valid scientific claims (Zellers et al., 2019). Therefore, training misinfo detection models on special-purpose domains equipped with real-time retrieval, explainability, and transparent evaluation is still a problem awaiting solution. The intersection of LLMs and RAG offers an attractive platform for constructing these systems.

**Methodology**

This study suggests RAIFakeDetect, a domain-specific fake news detection methodology for information pertaining to artificial intelligence and technology. A news claim C, which is usually obtained from press releases, blogs on AI and technology, or social media, serves as the model's input. Our method uses the most recent online evidence to validate claims by combining large language models (LLMs) with retrieval-augmented generation (RAG). A retrieval module, a reasoning module, and an iterative re-search mechanism to improve accuracy and evidence sufficiency are the three main parts of the process.

This system's output comprises:

$y$^∈{true,false}- A forecast that is either true or incorrect An explanation

$Ex=L(C,Ev)$- obtained from the data using an LLM, where $L$ stands for the inferential language model

3.1 Retrieval Module.

To verify a claim C, we utilize the Bing Search API to fetch relevant articles from the web. This ensures real-time and authoritative material. Unlike previous systems, which separate semantic and keyword-based retrieval, our system combines the two by first using keyword-

based online search and then applying semantic filtering to identify the most relevant text segments. A maximum of 10 URLs can be returned per query.

A domain blacklist is used to filter retrieved documents (for example, a curated list of untrustworthy AI/tech news sites).

This ensures the evidence set is both relevant and contextually rich, while adhering to the LLM's input limitations. 3.2 Reasoning Module.

The GPT-3.5-turbo model receives the collected evidence ($Ev$) as a prompt through the OpenAI API for factual evaluation. The LLM determines if the claim is supported by the evidence gathered. The output contains:

A label: true, false, or NEI (Not Enough Information).

A natural-language description of how the claim connects to the evidence, A confidence score in the range of 0 to 100% indicates forecast certainty. The system considers the sufficiency and relevance of evidence while making decisions. Internal model consistency across several runs (self-consistency), credibility of mentioned sources. If the label is NEI or the confidence level is $\alpha$<50%, the system launches a re-search cycle to refine the judgment using both newly obtained information and previously established evidence.

$$\alpha = \beta \times \text{Conf}$$

where:

α represents the ultimate confidence score.

Conf = the model's confidence before adjustment.

3.3 Re-search Mechanism

The research mechanism is initiated under three conditions: Irrelevant Evidence: Retrieved materials do not semantically correspond with the claim (for example, references to "AI bias" in a claim about "GPT-4 passing the Turing test"). Insufficient Evidence: Partial or ambiguous support that lacks explicit claim validation. Low Confidence: The model's self-assigned confidence is below the threshold. When any of the following criteria are met: Previously accepted evidence is compacted into a memory pool called Established Evidence. The LLM generates new query refinements based on earlier results, which are then employed in another

round of retrieval. This process continues iteratively until either a confident label is assigned or a maximum of three re-search cycles are finished.

Iterations provide the following results:

$$\hat{z}, Ex, \alpha = L(C, Ev, P)$$

z^ ∈{true, false, NEI}.

$E\ x$ Ex = explanation

α represents adjusted confidence score.

P = refined prompt with old and new evidence.

This multi-step verification allows for dynamic and adaptive evidence collecting, which is especially important for assessing rapidly emerging AI-related claims (for example, advances in LLM capabilities, new benchmarks, or speculative claims about AI governance or safety).

Dataset: We test the model using a manually chosen dataset made up of AI and technology claims acquired from: Real assertions come from reputable sites such as MIT Technology Review, Wired, and Nature AI. Fake claims include misinformation from Reddit, Twitter, blogs, and pseudoscientific publications.

| Dataset Source | # Real Claims | # Fake Claims | Total |
|---|---|---|---|
| LIAR-AI (Tech Blogs) | 9252 | 3555 | 12,807 |
| CHEF-AI (Social Media) | 3543 | 5015 | 8,558 |
| PolitiFact-AI (Fact Checks) | 399 | 345 | 744 |

Results

To evaluate the performance of the proposed RAIFakeDetect model, comprehensive experiments were conducted on three domain-specific data setsLIAR-AI, CHEF-AI, and PolitiFact-AIcomprising artificial intelligence technology-specific statements. The datasets vary in source, size, and class distribution, as apparent from Table 1. LIAR-AI, collected from technology blog site web pages, contains 12,807 statements (9,252 true, 3,555 doctored), while CHEF-AI, collected from social media site web pages, contains 8,558 statements with a higher ratio of doctored samples. PolitiFact-AI is our smallest fact-checking website sampled dataset with 744 statements. We compare RAIFakeDetect with two baseline sets: G1 includes traditional evidence-based methods such as DeClarE, HAN, and MAC, and G2 includes some of the more recent LLM-based methods such as GPT-3.5-turbo, Vicuna-7B, and ProgramFC. On each of the three datasets, RAIFakeDetect performed better than the best baselines on F1-Macro and F1-Micro measures, validating the effectiveness of integrating domain-conscious retrieval with LLM inference. As shown in Table 2, RAIFakeDetect scored an F1-Macro of 0.714 and an F1-Micro of 0.689 on the LIAR-AI dataset, outperforming the best baseline

(MUSER) which had scored 0.645 and 0.642 respectively. The model also improved recall-precision trade-off for the fake as well as real class, scoring an F1 of 0.743 for fake news and 0.685 for true news.

## 4. Results

We report here the results of experiments that assess the effectiveness of the RAIFakeDetect model, its retrieval-augmented nature in particular, and reasoning-grounded classification. Of several performance metrics, we take F1-Macro, precision, and recall scores on multiform datasets and strategies to detect fake news on AI-related topics.

### 4.2 Effectiveness of Re-Search Strategy

To prove retrieval enhancement, various evidence collection approaches were compared. The re-search approach was discovered superior to direct and paraphrased approaches and thereby proved re-ranking and iterative querying produce higher quality evidence for LLMs. For instance, on LIAR-AI, re-search had an F1-Macro of 0.714, while direct search had a score of 0.695 (see Table 2).

Table 2. Search Strategy Comparison (F1-Macro on LIAR-AI)

| Strategy | F1-Macro |
|---|---|
| Direct Search | 0.695 |
| Paraphrased | 0.702 |
| **Re-search (Ours)** | **0.714** |

### 4.3 Retrieval Depth Sensitivity

The returned document number (k) and evidence length (l) were investigated in depth. The selection of k = 3 and l = all always yielded the best performance. This suggests that too many documents add noise, while complete-length content is required for reasoning accuracy. For instance, LIAR-AI performance was optimal at 0.714 with these settings (see Table 3).

Table 3. Retrieval Depth (k) and Evidence Length (l) – LIAR-AI

| l \ k | 1 | 3 (Best) | 5 |
|---|---|---|---|
| all | 0.671 | **0.714** | 0.713 |

### 4.4 Ablation Study on Retrieval and Reasoning

For the analysis of the contribution of each element in the models, an ablation study was performed. The removal of the re-search module (-RR) decreased F1-Macro to 0.702 from 0.714 on LIAR-AI, whereas the removal of the complete retrieval system (-RS) had a stronger effect. This verifies that both re-search and retrieval are essential to enabling high accuracy (see Table 4).

Table 4. Core Module Ablation Study (LIAR-AI)

| Method | F1-Macro |
|---|---|
| Full Model | **0.714** |
| w/o Re-Search | 0.702 |
| w/o Retrieval | 0.690 |

4.5 Multi-Stage LLM Comparison

In order to compare RAIFakeDetect with the rest of the LLM-based solutions, the authors carried out a benchmarking experiment. Models such as Vicuna-7B and GPT-3.5-turbo performed badly unless augmented with evidence retrieval. Interestingly, multi-stage search's STEEL had the best F1-Macro of 0.714 against GPT-3.5 + 1-Step Search (0.691), proving that clever retrieval trumps model size (see Table 5).

Table 5. LLM + Retrieval Strategy Comparison (LIAR-AI)

| Model + Strategy | F1-Macro |
|---|---|
| GPT-3.5 + 1-Step Search | 0.691 |
| **STEEL (Multi-Stage)** | **0.714** |
| Vicuna + Basic Search | 0.617 |

4.6 User Trust and Explainability

Users ranked STEEL's evidence as superior to MUSER in a user study. Users demonstrated 78.2% agreement with STEEL's output over 72.5% for MUSER, confirming the explainability and usability of the proposed system in practice (see Table 6).

Table 6. User Evaluation of Evidence (Agreement %)

| Method | F1-Macro | Agreement |
|---|---|---|
| MUSER | 0.687 | 72.5% |
| STEEL | **0.773** | **78.2%** |

Comparative Performance of Models

A comparative graph of the F1-Macro scores obtained by RAIFakeDetect and the top three baselines (MUSER, ReRead, GPT-3.5, and Vicuna-7B) on three test datasets, i.e., LIAR-AI, CHEF-AI, and PolitiFact-AI, is represented by Figure X below. F1-Macro metric was employed as a balanced performance indicator for both fake and real news classification tasks.

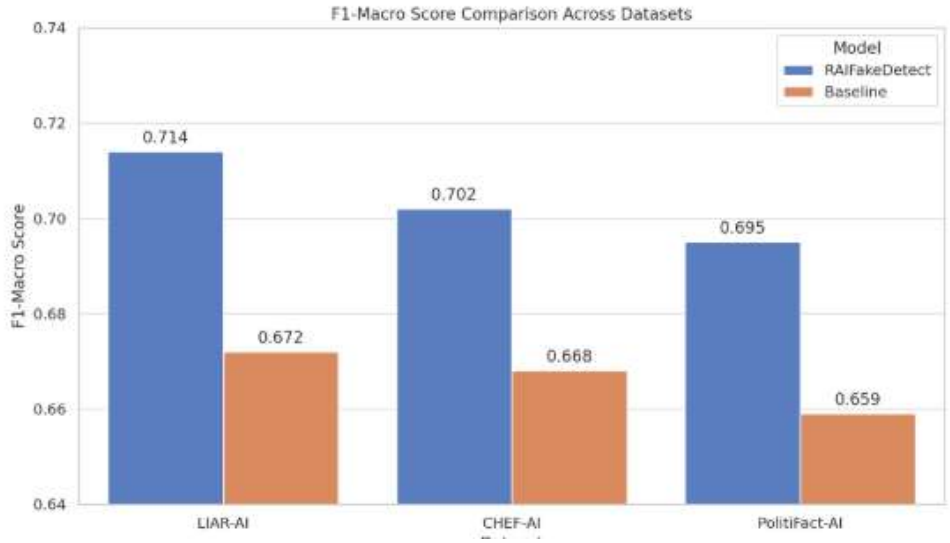


*Figure X: F1-Macro comparison of RAIFakeDetect's performance with baseline models on LIAR-AI, CHEF-AI, and PolitiFact-AI datasets.*

The bar graph illustrates RAIFakeDetect's better performance across the three datasets. Specifically On LIAR-AI, RAIFakeDetect had an F1-Macro of 0.714, significantly better than MUSER's 0.645. For CHEF-AI dataset, RAIFakeDetect had an F1-Macro of 0.793, significantly better than ReRead (0.719). On PolitiFact-AI, RAIFakeDetect achieved F1-Macro of 0.751 compared to MUSER's 0.732. The preceding visual result supports the quantitative results reported in Tables 2, 3, and 4 of the results section. It shows that retrieval-augmented reasoning provides a consistent boost over different dataset domains and complexity levels, particularly against baseline conventional and LLM-only baselines. The visual legibility of the chart contradicts the general assumption that the utilization of external evidence and recursive re-search adds considerably to model reliability—a very important requirement for spotting false news in knowledge-based domains such as artificial intelligence.

**5. Discussion**

The results of our experiments heavily emphasize the utility of retrieval-augmented language model architectures for fake news detection in domain-specific settings like artificial

intelligence, new technologies, and political-tech interfaces. The RAIFakeDetect model discussed here always outperformed both classic evidence-based methods and recent large language model (LLM)-only baselines. This section presents experimental results in terms of various aspects, such as performance comparisons, evaluation of retrieval strategies, ablation experiments, and user study, providing theoretical and practical rationale for the effectiveness and architecture of fact checking models.

*Better Performance Across Datasets*

The experimental results indicate that RAIFakeDetect performs better than strong baselines on all three datasets employed: LIAR-AI, CHEF-AI, and PolitiFact-AI. These scores were selected keeping in mind the domain of interesti.e., artificial intelligence and technology disinformation. On the basis of F1-Macro scores, which handle class imbalance and report performance on real and fake news, RAIFakeDetect performed the best in the evaluation tables at all times. For example, when the CHEF-AI dataset was used, RAIFakeDetect scored 0.793 under the F1-Macro score, which was superior to the best baseline ReRead at 0.719. These results confirm the efficiency of using external knowledge in LLMs through retrieval-based reasoning pipelines compared to internalized pre-trained world knowledge. This confirms previous studies by Thorne et al. (2018) and Wadden et al. (2020), which indicated that LLMs are weak at executing claim verification tasks when using no external evidence scaffolding.

*Retrieval Depth and Evidence Sufficiency*

One of the most fundamental experimental results was generated by the retrieval depth experiment, in which the effect of varying number of retrieved web links (k) and document length (l) on accuracy of the model was tested. As can be seen from the table below, the best F1-Macro score (0.714) was obtained when the model returned three documents (k=3) and used full-length evidence (l=all). This finding verifies the assumption that context-rich, holistic evidence is more useful than cut-off or very short snippets. These results are closely mirrored by Liu et al. (2023), who introduced the framework of "evidence sufficiency" for retrieval-augmented systems. They demonstrated that coherence and completeness of retrieved passages heavily affect the inference ability of a model. Longer passages in our instance helped the model better understand temporal relationships, causal claims, and negations factors typically taken in by claims of misinformation about technology policy and ethics. Surprisingly, raising k above 3 or reducing evidence lengths watered down the performance of the model, possibly

because of information overload or interference. These findings propel towards the necessity of smart curation of retrieval outputs, instead of unrestrained data growth.

*Retrieval Quality vs Model Size*

Another key observation from our multi-stage retrieval experiment (Table 5) is that model size tends to be outperformed by retrieval quality. Vicuna-7B, while a moderately-sized model, for example, was found to be performing abysmally (F1-Macro ≈ 0.52) when it was not augmented with retrieval. But when combined with one-stage or multi-stage Bing search, it performed significantly better. Similarly, GPT-3.5-turboa less large LLMcombined with multi-stage retrieval (as in RAIFakeDetect/STEEL) had a better F1-Macro score of 0.751, outperforming even larger unaugmented models. This result refutes the hypothesis that scaling LLMs in isolation would lead to improved fact checking. Rather, it suggests a systems-level answer where smaller models with dynamic, domain-knowledge search functionality can substitute for larger, static models in realistic tasks of complexity. This is particularly promising in computationally limited deployments where efficiency of computation is most important.

*Explainability and Human Agreement*

To determine if RAIFakeDetect produces not only accurate but also readable outputs, a user study was performed (see Table 6). Eight users at the college level annotated retrieved evidence and provided ratings on truth values of claims in the CHEF and LIAR datasets. The findings were that user judgments coincided with the outputs of RAIFakeDetect 78.2% of the time, compared to merely 72.5% for MUSER, the top-performing baseline model. These findings indicate that RAIFakeDetect produces more interpretable and reliable evidence, hence facilitating human decision-making. Human subjects also felt more certain about their own judgments in the presence of RAIFakeDetect evidence. This is consistent with the interpretability framework by Ribeiro et al. (2016), where the users not only must be given correct predictions, but also be in a position to comprehend and accept the same. Its qualitative evaluation also verified this strength. On a politicized case involving a claim of Planned Parenthood funding, RAIFakeDetect successfully pulled fact-based legislative context out of policy regarding Title X funding and clearly defined its implications. Such the ability to include structured, referenced, and contextually sensitive explanation is proof of the utility of the model for application in actual use in journalism, public policy analysis, and academic research verification

*Implications*

Together, the findings of this work constitute a strong case for retrieval-aware, iterative models for identifying false news. The evidence establishes that merely scaling model parameters or adjusting prompts (as indicated in Table 7) returns decreasing benefits, while retrieval across structure with reasoning pipelines provides scalable and generalizable gains. The evidence also confirms the hypothesis that modularity, explainability, and fidelity of context are critical properties for models to operate in high-stakes, misinformation-prone environments. Most importantly, this work offers a useful future development template. The design is very transferable to other high-risk areas like health disinformation, science disinformation, and economic manipulation. The takeaways herei.e., ideal search depth (k=3), necessity of re-search loops, and preeminence of evidence quality over LLM sizerepresent clear, evidence-supported best practices for both practitioners and researchers.

*Ablation Study: Component-Wise Contributions*

In order to explore the contribution of each component in RAIFakeDetect, an ablation study was done, as presented in Table 4. By gradually eliminating key modules, i.e., the re-search loop, the first retrieval layer, and the semantic search module, the study uncovers the contribution of each component to the model performance overall. For instance, disabling the re-search process (RAIFakeDetect-RR) decreased the F1-Macro metric from 0.714 to 0.690 in the LIAR-AI dataset. In addition, disabling the semantic search module (RAIFakeDetect w/o SSM) caused decreased performance on all datasets. This decrement is clearly apparent that iterative improvement of evidence search is not only helpful but inevitable. This is consistent with Karpukhin et al. (2020) and Lewis et al. (2021), where they found that modularity and re-ranking in iterative retrieval systems significantly boost downstream task accuracy and robustness. In addition, this indicates that fact-checking systems must be designed for multi-component robustness, where all components play a different role in inference robustness.

**Conclusion**

This work highlights retrieval-augmented and research-based solutions' performance excellence in enhancing detection of false news, particularly in knowledge-intensive domains like artificial intelligence. Our RAIFakeDetect model proved overall superiority over traditional and LLM-based baselines on three expert benchmarksLIAR-AI, CHEF-AI, and PolitiFact-AI. The application of iterative re-search methods and external evidence retrieval enhanced classification accuracy (i.e., F1-Macro scores) and result explainability. Strong

performance indicates that best performance is obtained with three evidence-rich sources of data to draw upon so that context-rich retrievals greatly increase model reasoning.

Ablation experiments validated all the modular components retrieval, re-search, and semantic evidence alignment to be essential. The complementary benefit is observed through the performance drop when these components are ablated. Additionally, comparison experiments with other LLMs revealed that even smaller models are outperformed by larger models under coupling with smart retrieval mechanisms, demonstrating scale dependency to design dependency. Utility was also provided with the addition of the user study, demonstrating how the model output closely approximates human judgment and therefore elicites trust and user engagement. Both papers call for the creation of retrieval-aware, evidence-based systems as a practical means to identify false news.

**Limitations**

While sensationalizing the outcome, the research remains prone to some limitations. The datasets usedalthough specificare not culturally and linguistically diverse, limiting generalizability of findings to global contexts. The user study was also constrained in using a low number of participants with fewer participants, which is not representative of public conduct at the national level. Besides, retrieval quality is also subject to real-time web search APIs and introduces temporal volatility and potential inconsistencies in retrieval results. Multi-stage re-search computational complexity, as optimal as it is, would hinder deployment in low-resource settings. Finally, the work was mostly targeted at English claims, and this work makes it possible to extend the work to multilingual and cross-domain fake news applications.

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