LiRA: A Multi-Agent Framework for Reliable and Readable Literature Review Generation

Gregory Hok Tjoan Go[1, 2], **Khang Ly**[2], **Anders Søgaard**[3], **Seyed Amin Tabatabaei**[2], **Maarten de Rijke**[1], **Xinyi Chen**[1]
[1]University of Amsterdam
[2]Elsevier B.V.
[3]University of Copenhagen
{g.go, k.ly, s.tabatabaei}@elsevier.com, soegaard@di.ku.dk, {m.derijke, x.chen2}@uva.nl

Abstract

The rapid growth of scientific publications has made it increasingly difficult to keep literature reviews comprehensive and up-to-date. Though prior work has focused on automating retrieval and screening, the writing phase of systematic reviews remains largely under-explored, especially with regard to readability and factual accuracy. To address this, we present **LiRA** (**Li**terature **R**eview **A**gents), a multi-agent collaborative workflow which emulates the human literature review process. LiRA utilizes specialized agents for content outlining, subsection writing, editing, and reviewing, producing cohesive and comprehensive review articles. Evaluated on SciReviewGen and a proprietary ScienceDirect dataset, LiRA outperforms current baselines such as AutoSurvey and MASS-Survey in writing and citation quality, while maintaining competitive similarity to human-written reviews. We further evaluate LiRA in real-world scenarios using document retrieval and assess its robustness to reviewer model variation. Our findings highlight the potential of agentic LLM workflows, even without domain-specific tuning, to improve the reliability and usability of automated scientific writing.

Code —
www.github.com/lira-workflow/auto-review-writing
Extended version — https://arxiv.org/abs/2510.05138

1 Introduction

Since their inception, literature reviews have been consistently used to streamline the advancement of various scientific fields (Snyder et al. 2016). Of these reviews, one of the most important types is the Systematic Literature Review (SLR), which reproducibly synthesizes a significant portion of existing research relating to a specific research question being addressed (Kitchenham and Charters 2007; Bangdiwala 2024). This role has become increasingly more crucial, evidenced by how quite a few researchers consider them to be original research or potentially even a mandatory step in the scientific process itself (Kraus, Mahto, and Walsh 2023; Palmatier, Houston, and Hulland 2018).

Due to the large amount of new findings and research being disseminated through publications, it has become very difficult to release SLRs in a timely fashion (Qi, Li, and Lyu 2025; Ofori-Boateng et al. 2024; Tian et al. 2025). For example, the estimated time required to complete an SLR has increased significantly in the past few decades in the medical domain (Allen and Olkin 1999; Borah et al. 2017), which is further compounded by the necessity of using expert labor (Atkinson 2025). In tackling this, the vast majority of research relating to SLR automation focuses on the retrieval and screening of scientific papers (Orel et al. 2023; Marshall and Wallace 2019; Chen et al. 2025), as these are the most time-consuming steps (Chai et al. 2021). However, there remains the task of compiling the findings into a comprehensive review paper. Only a small number of works have been published (Kasanishi et al. 2023; Qi, Li, and Lyu 2025; Wang et al. 2024), let alone those which focus on the readability and hallucination mitigation aspects.

In this work, we present **LiRA** (**Li**terature **R**eview **A**gents), an agentic solution aimed at addressing the minimal research related to automated literature review writing. It is a Large Language Model (LLM)-based agentic workflow building upon existing relevant works and integrates some of the most recent SLR-writing guidelines to generate accurate and high-quality reviews, with an additional emphasis on readability. Moreover, it is entirely out-of-the-box, requiring no task-specific pre-training or fine-tuning. We also reduce hallucination in the outputs, which is one of the main barriers in trustworthy automated writing and a key factor preventing the widespread use of similar Artificial Intelligence (AI)-powered systems (Alkaissi and McFarlane 2023; O'Connor et al. 2024; Xu et al. 2023).

To demonstrate LiRA's capabilities, we propose the below research questions:

RQ1 *To what extent are the qualitative Systematic Literature Reviews made by LiRA similar to human-written ones compared to existing literature writing methods when all are given the same set of references?*

RQ2 *How well written are the generated articles compared to existing literature writing methods when all are given the same set of references?*

RQ3 *How well can LiRA properly use citations from the provided sources to generate qualitative Systematic Literature Reviews compared to other methods?*

RQ4 *How well can LiRA be used in real-world settings when using references returned by a scientific docu-*

ment retriever?

We summarize our main contributions as follows:

- To the best of our knowledge, we propose the first agentic LLM-based automated literature review writing workflow which emulates the human writing process and integrates the findings of other relevant agentic workflows.
- We explore the usage of formally defined guidelines and techniques from relevant similar fields in the agentic workflow, such as the idea of thoroughly analyzing the existing papers before beginning the writing process, establishing a crucial link between theory and application.
- We establish several state-of-the-art baseline results for the automated literature review writing task across multiple settings, comparing between existing systems when using the same LLM type throughout.

2 Related Work

Agentic workflows Comparisons have been made between agentic LLM systems and human cognition, due to how breaking down a task into smaller steps, which these workflows often do, is commonly used to describe how humans solve more intricate problems (Flower and Hayes 1981; Correa et al. 2023). Using this concept, several works show promise in implementing agentic workflows in various fields, such as the medical sciences (Tang et al. 2024) and law (Watson et al. 2025). In some cases, this results in an improvement of more than 90% compared to a simple baseline (Watson et al. 2025).

However, for the task of automated writing specifically, only few works have been published thus far (Qi, Li, and Lyu 2025; Wang et al. 2024; Shao et al. 2024; Tian et al. 2025). Of these works, only two of them address literature reviews or a similar document type and include open-source code (Qi, Li, and Lyu 2025; Wang et al. 2024). Neither paper takes output lengths and how they relate to the readability and evaluation of each proposed system using the listed metrics into account. As a result, no works seem to exist which tackle the issues of readability, and only minimal work exists in addressing the factuality of the resulting articles.

Literature review For centuries (Lind 2014), the process of writing literature reviews has been considered crucial for the development of science (Meerpohl et al. 2012; Higgins et al. 2011; Chalmers, Hedges, and Cooper 2002), as it provides researchers valuable insight on which research questions to answer via an analysis of earlier works (Chalmers and Glasziou 2009; Eagly and Wood 1994). Moreover, improvements have been made to eliminate personal biases (Egger, Smith, and O'Rourke 2001) through the introduction of the SLR, which uses systematic methods of review for the collation and synthesis of findings (Randles and Finnegan 2023; Snyder 2019; Page et al. 2021).

Given how time-consuming (Borah et al. 2017) and costly (Michelson and Reuter 2019) this process is, a need for a viable alternative has emerged. Despite this, there is not much relevant innovation in natural language processing that tackles this issue (Mohammad et al. 2009; Kasanishi et al. 2023; Agarwal et al. 2011), let alone results indicating real-world usability. Therefore, we address all aforementioned problems by introducing an agentic workflow which uses LLMs to generate literature reviews automatically, demonstrating its potential by focusing on both readability and factuality.

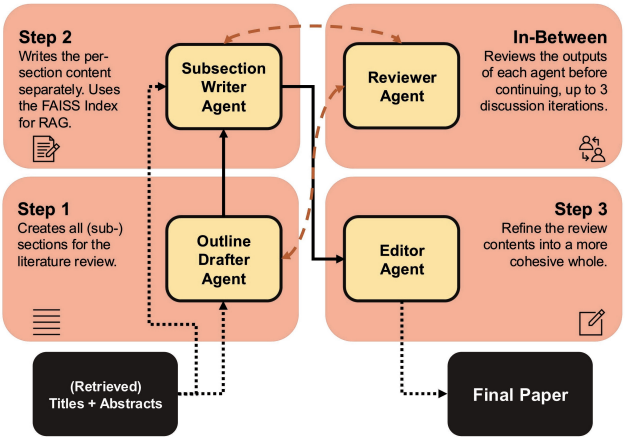

Figure 1: An overview of the LiRA architecture. The narrow dotted arrows represent document input/output, the wide dotted arrows indicate the refinement process, and the filled-in arrows signify the system's main flow. Each agent is explained in the below sections.

3 The LiRA Framework

LiRA emulates the human literature review process by decomposing it into specialized, interacting LLM-based agents. Each agent tackles a key sub-task: either structural planning, fine-grained writing, consistency refinement, or factual verification, which results in a modular and scalable pipeline. This section introduces the core agents and their design motivations.

3.1 Outline Drafter Agent

A key challenge in literature review writing is constructing a coherent structure from a large and unorganized set of references. Instead of relying on the model to implicitly determine the structure during generation, LiRA explicitly drafts an outline to guide the writing process. This agent takes the topic and abstracts (or alternatively the full texts) of the provided references to produce a set of candidate outlines consisting of main sections and subsections. These are then combined into a unified draft structure that includes descriptions for each section and suggested supporting papers.

To manage the context size and focus on only the most relevant content, the outline is constructed from up to 50 references. We use existing heuristics (Wang et al. 2024) that recommend generating approximately 8 sections with around 4 subsections, but the agent can adapt this amount as needed. We also include default sections such as an introduction and conclusion to ensure consistency and completeness.

3.2 Subsection Writer Agent

Generating a full review in a single pass risks superficial coverage and poor section coherence. We tackle this by hav-

ing a subsection writer agent, which writes each (sub)section individually in parallel, conditioned on the description and a selected subset of relevant references. This design encourages fine-grained generation and makes the outputs more modular and easier to revise.

Relevant references are retrieved using the FAISS index (Douze et al. 2025) based on section-level descriptions, capped at 25% of the total pool per subsection (min 3, max 150). This balances citation diversity with input tractability. Moreover, the reference titles, abstracts, or full texts can be retrieved depending on the availability. The agent outputs $\sim$1,000 words per subsection, enabling long-form synthesis while staying within model context limits. Also, the article title, abstract, and conclusion are written after the body is generated, mimicking human writing practices and avoiding the premature commitment of top-down generation.

3.3 Editor Agent

Even with structural planning and localized generation, the assembled review may exhibit issues such as redundancy, inconsistency, or stylistic mismatches across sections. These are addressed by an editor agent, which refines the entire draft with a focus on presentation and style. It performs standard editing operations, including improving transitions, enhancing vocabulary, and ensuring overall fluency and cohesion. Importantly, this agent does not alter the factual content, preserving the integrity of the generated information.

If the generated output exceeds the model's context window, the agent detects whether the text ends abruptly—typically when the maximum output length (16,384 tokens) is reached. In such cases, the model is prompted to continue the output using the original input and previously edited content as context. This mechanism effectively doubles the generation capacity, though at the cost of additional input overhead.

3.4 Reviewer Agent

To improve factual accuracy and review quality, we introduce an LLM-based reviewer agent inspired by human editorial workflows. This agent evaluates intermediate outputs (e.g., outlines) based on adapted criteria from systematic review guidelines (Snyder 2019), including content completeness, transparency, clarity, and contribution.

If a component (e.g., an outline or section) fails to meet quality thresholds, the reviewer provides structured feedback and triggers regeneration. The review loop continues up to 3 rounds before fallback progression, balancing refinement with computational efficiency.

3.5 Citation Behavior

Citation hallucination remains a major concern in automated scientific writing, as models may generate plausible-sounding but non-existent references. To address this, LiRA incorporates citation grounding directly into the generation process. Rather than relying on abstract placeholders (e.g., numbered citations), agents cite sources using full article titles, which act as semantic anchors and help the model maintain alignment with the provided references.

After generation, these in-text citations are post-processed into standard numbered references, and any hallucinated titles are redacted during evaluation to ensure fair comparison. This approach improves factual consistency and ensure fair comparison during evaluation.

3.6 Additional Implementation Details

All agents in LiRA were implemented using LangGraph. Moreover, each agent has its own memory, a standard practice for LLM-based agentic workflows to better act upon feedback (Sumers et al. 2023; Qian et al. 2024). This system of storing feedback in memory is comparable to Reflexion (Shinn et al. 2023), where the agent has to adjust its behavior based on the feedback provided. Parallelization is also included to increase the processing speed of certain steps, namely the researcher when analyzing papers and the content writer for generating the article (sub)sections.

Aspects from the design of MetaGPT (Hong et al. 2023) were adapted for more efficient inter-agent communication. Specifically, all agents are required to return their outputs as structured documents to avoid potential inefficiencies relating to information presentation, which are then sent to unique shared message pools for quick information retrieval. Moreover, the input contents are filtered based on the model's maximum context window length (128,000 tokens in our case) to prevent information overload. As a method of improving the model's output quality with minimal intervention, Zero-Shot Chain-of-Thought (Kojima et al. 2022) is included in the prompts for all agents except the researcher and editor, as they do not perform refinement.

4 Experiments

4.1 Baselines

To evaluate LiRA, we compare it against direct prompting and, to the best of our knowledge, the only two publicly available agentic frameworks for survey writing. For fair comparison, all systems (including LiRA) are implemented with `gpt-4o-mini` as the underlying LLM.

Direct prompting (DP) As the simplest baseline, we directly prompt the LLM with task instructions and the full set of reference titles and metadata, asking it to generate a review with the specified sections and length. When the reference list exceeds the context window, it is passed as an attached file, requiring the model's file-reading capability. This baseline tests whether a single prompt can produce a coherent review without decomposition or refinement.

MASS-Survey (MASS) Introduced in an automated survey-writing challenge (Tian et al. 2025), MASS is the only agentic framework from that challenge with publicly available code. Its workflow differs fundamentally from LiRA: Instead of decomposing the writing process into specialized roles with iterative feedback, MASS follows a strictly sequential pipeline. The system first clusters references by topical similarity to construct an outline, then generates section contents and a title directly from these clusters, and finally appends a conclusion. Long reference lists are handled by passing them as attachments.

AutoSurvey (AS) AutoSurvey (Wang et al. 2024) is a multi-stage framework for automatically generating literature surveys in computer science. Given a query (in our case, the original review title), it retrieves relevant publications and uses their titles and abstracts to construct an outline, followed by subsection drafting with refinement steps and partial use of retrieved article content (up to 1,500 tokens). While the paper claims retrieval-grounded drafting, we did not find corresponding functionality in the released code.

For fair comparison, we modified AutoSurvey to restrict retrieval to the references cited in the target human-written review. This required reducing the number of candidate documents per subsection to between 2 and 25% of the references, or falling back to 60 when the fraction exceeded this threshold (as in the original design). We also generalized system prompts from "*You are an expert in Artificial Intelligence*" to "*You are an expert in a relevant field*" to make the system better able to generate articles for multiple domains.

4.2 Metrics

To comprehensively evaluate the generated literature reviews, we consider three complementary dimensions: content similarity to human-written reviews, writing quality, and citation reliability.

Similarity to the human-written review We measure how similar the generated literature reviews are to human-written ones. Metrics include ROUGE-L, heading soft recall (*hsr*), heading entity recall (*her*), and article entity recall (*aer*). Together, these capture lexical overlap, structural alignment, and coverage of key cited works. Full definitions are provided in the extended version.

Writing quality We evaluate writing quality using both automatic and human assessments. For automatic evaluation, we use the Prometheus 2 LLM (Kim et al. 2024). It is an open-source LLM evaluator that uses the appropriate reference materials (the instruction, reference answer, and score rubric) to provide assessments which mostly align with those of human annotators. Three aspects are evaluated for all generated articles, namely the coverage, structure, and relevance. Here, coverage represents how broad the subject matter of the review is, while structure measures the organization and flow of the review, and relevance indicates how well the review is able to stay on-topic overall. Additional specifications for the model and how it measures the aforementioned aspects can be found in the extended version.

For human evaluation, we employed subject matter experts (SMEs) who helped evaluate the outputs of the system on the same aspects as mentioned above. For feasibility, the annotation was performed differently for each dataset, though the title, outline, and a section snippet were utilized in both cases. For SciReviewGen, we employed a group of 3 SMEs from Straive to select their preferences between human- and LiRA-written articles for 30 sample snippets, using a rubric as guidance for determining their choice. It must also be noted that the order in which these samples were presented was randomized for each row.

Meanwhile, a dedicated team from within the company provided scores ranging from 1 to 5 for the AutoSurvey and LiRA articles while using the human-written ones as a baseline. This grading was done using the same rubric as mentioned above. Furthermore, due to this type of annotation being more labor-intensive, only 15 article snippets were used.

Citation quality We evaluate how well generated claims are grounded in appropriate references. Our metric, Citation Quality F1-Score (CQF1), balances precision (penalizing irrelevant or hallucinated citations) and recall (capturing missing but necessary citations), serving as a proxy for hallucination in scientific writing. A full overview of the details is given in the extended version.

4.3 Datasets

We evaluate the effectiveness of the LiRA framework using two datasets. The primary dataset is SciReviewGen (Kasanishi et al. 2023), a publicly available benchmark built on the Semantic Scholar Open Research Corpus (S2ORC) (Lo et al. 2020). It contains 10,000 review articles in computer science, referencing approximately 690,000 papers. Each review is annotated with structured metadata, including titles, section headers, full texts, and references. Following the setup in Shao et al. (2024), we randomly sample 125 reviews, ensuring each selected article contains a sufficient number of references—averaging around 70 per paper.

To assess the generalizability beyond computer science, we additionally evaluate on an internal dataset of 125 expert-written reviews from ScienceDirect, covering 23 subject areas including business, microbiology, and materials science. The dataset is matched in size to the SciReviewGen subset to support direct cross-domain comparison.

4.4 Results

Across both datasets, LiRA consistently outperforms baseline systems on the majority of evaluation metrics, demonstrating stronger alignment with human-written reviews, higher writing quality, and more reliable citation use.

Similarity to human-written review LiRA achieves the highest ROUGE scores, indicating stronger lexical alignment with human-written reviews. AutoSurvey attains slightly higher heading/entity recall, but largely due to verbosity: on average, AutoSurvey produces 50,000 tokens per article compared to only 22,000 for LiRA. Since recall-based metrics do not normalize for length, longer outputs are naturally favored. Crucially, this shows that LiRA generates concise yet information-dense reviews, rather than inflating scores by producing excessive text.

Writing quality LiRA achieves the best overall writing quality, with a clear advantage in structural coherence. AutoSurvey performs marginally better in coverage, again reflecting its longer outputs, but at the cost of organization and readability. SME evaluations align with these trends: on ScienceDirect, experts strongly preferred LiRA for structure, while AutoSurvey received marginally higher scores for coverage and relevance, suggesting a trade-off between breadth and coherence. On SciReviewGen, SMEs favored LiRA over the human-written reviews, noting its broader and more balanced coverage given the outlines.

Metric	DP	MASS	AS	LiRA
SciReviewGen				
ROUGE	0.06 ± 0.0	0.09 ± 0.0	0.09 ± 0.0	**0.13 ± 0.0**
hsr	0.69 ± 0.1	0.66 ± 0.1	**0.92 ± 0.4**	0.82 ± 0.1
her	0.06 ± 0.0	0.05 ± 0.0	**0.15 ± 0.0**	0.10 ± 0.0
aer	0.06 ± 0.0	0.09 ± 0.0	**0.34 ± 0.0**	0.27 ± 0.0
ScienceDirect				
ROUGE	0.02 ± 0.0	0.04 ± 0.0	**0.13 ± 0.0**	0.13 ± 0.0
hsr	0.24 ± 0.2	0.22 ± 0.2	0.24 ± 0.4	**0.25 ± 0.1**
her	0.03 ± 0.0	0.03 ± 0.0	**0.13 ± 0.0**	0.05 ± 0.0
aer	0.03 ± 0.0	0.05 ± 0.0	**0.25 ± 0.0**	0.17 ± 0.0

Table 1: Results for similarity to the human-written reviews with the baseline settings.

Metric	DP	MASS	AS	LiRA
SciReviewGen				
Coverage	3.53 ± 0.4	4.30 ± 0.3	**4.50 ± 0.1**	4.45 ± 0.1
Structure	3.15 ± 0.9	2.47 ± 1.2	2.30 ± 1.3	**3.38 ± 0.9**
Relevance	4.49 ± 0.2	**4.74 ± 0.2**	4.55 ± 0.2	4.57 ± 0.2
Average	3.72	3.83	3.78	**4.13**
ScienceDirect				
Coverage	3.08 ± 1.0	3.44 ± 1.0	**4.10 ± 0.1**	3.90 ± 0.3
Structure	3.23 ± 1.0	2.59 ± 1.1	2.21 ± 1.3	**3.42 ± 0.9**
Relevance	3.98 ± 0.7	4.15 ± 0.7	4.29 ± 0.3	**4.33 ± 0.3**
Average	3.43	3.39	3.53	**3.88**

Table 2: Writing quality results for the baseline settings.

Dataset	DP	MASS	AS	LiRA
SciReviewGen	0.14	0.13	0.63	**0.76**
ScienceDirect	0.06	0.33	0.55	**0.73**

Table 3: Citation quality results for the baseline settings.

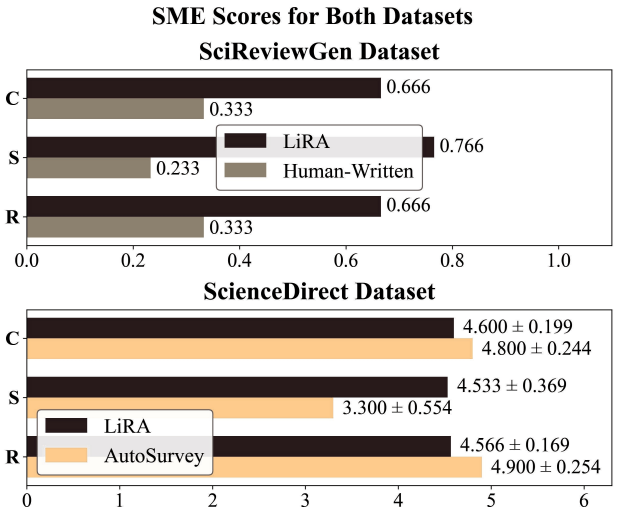

Figure 2: SME evaluation results. Here, **C** indicates Coverage, **S** indicates Structure, and **R** indicates Relevance.

These results highlight LiRA's strength in generating well-structured, concise, and expert-aligned reviews, in some cases even being favored over human-written baselines.

Citation quality LiRA demonstrates the largest gains in citation reliability, achieving the highest Citation Quality F1 (CQF1) scores across both datasets (0.76 on SciReviewGen, 0.73 on ScienceDirect) and substantially outperforming AutoSurvey ($\leq$0.63) and all other baselines. This indicates that LiRA is more effective at grounding claims in appropriate references, avoiding both omissions (recall errors) and hallucinations (precision errors), which stem from LiRA's citation-grounded generation design that explicitly enforces reference anchoring during drafting and refinement.

From this, it can be seen that LiRA overall produces literature reviews that are concise, structurally coherent, and citation-faithful, while maintaining competitive coverage. This balance between quality and reliability highlights LiRA as a more trustworthy and practically useful framework for automated survey writing. achieves the highest ROUGE scores, indicating stronger lexical alignment with human-written reviews. AutoSurvey attains slightly higher heading/entity recall, but largely due to verbosity: on average, AutoSurvey produces 50,000 tokens per article compared to only 22,000 for LiRA. Since recall-based metrics do not normalize for length, longer outputs are naturally favored. Crucially, this shows that LiRA generates concise yet information-dense reviews, rather than inflating scores by producing excessive text.

5 Potential Modifications on LiRA

In this section, we discuss the adjustments tested on LiRA to evaluate its performance more robustly. This involves the usage of a different LLM type for the reviewer agent to potentially mitigate self-bias amplification in the refinement process, and document retriever usage to evaluate if LiRA can be deployed in real-world settings.

5.1 Using a Different Reviewer Model

Method Based on concerns stemming from self-bias amplification (Xu et al. 2024), experimentation was performed using a reviewer model type different from the one used during generation for each component, which is based on existing suggestions. To this end, the `gemma3:4b` model was used through `ollama` (Kamath et al. 2025). This model was chosen because it is open-source, has a context window similar to `gpt-4o-mini`, and has lower hardware requirements compared to most other models. In addition, `ollama` was the selected model provider because of its accessibility and ease of use, with LangGraph already being compatible with it. The parameter values used by `gemma3:4b` were the default `ollama` ones aside from the context window size (128,000) and seed (42).

Metric	SciReviewGen		ScienceDirect	
	LiRA	LiRA +gemma3	LiRA	LiRA +gemma3
ROUGE	**0.13 ± 0.0**	**0.13 ± 0.0**	**0.13 ± 0.0**	**0.13 ± 0.0**
hsr	0.82 ± 0.1	**0.83 ± 0.1**	0.25 ± 0.1	**0.25 ± 0.1**
her	0.10 ± 0.0	**0.10 ± 0.0**	**0.05 ± 0.0**	0.05 ± 0.0
aer	**0.27 ± 0.0**	0.26 ± 0.0	**0.17 ± 0.0**	0.17 ± 0.0
CQF1	0.76	**0.77**	**0.73**	0.73
Coverage	**4.45 ± 0.1**	4.45 ± 0.1	**3.90 ± 0.3**	3.89 ± 0.4
Structure	3.38 ± 0.9	**3.47 ± 0.9**	**3.42 ± 0.9**	3.26 ± 1.0
Relevance	**4.57 ± 0.2**	4.64 ± 0.2	**4.33 ± 0.3**	4.29 ± 0.3

Table 4: The gemma3 results for the ScienceDirect dataset. Note that if both numbers in a row are bolded, it means they returned the exact same value.

Results The results for this setting can be found in Table 4. Though the extent of bias mitigation itself cannot be measured properly with the current metrics, we can remark how using `gemma3:4b` has little impact on the scores overall across all metrics. This suggests that alternative model configurations may not significantly alter the article output quality, therefore indicating potentially that the pipeline can work well even when using different LLMs in the process.

5.2 Retrieval Usage

Method All prior experiments assumed the availability of gold references from a reference article to generate a review. This is not the case for real-world settings, however, as novel literature reviews are required to keep up with current developments. Therefore, we evaluate if the system can generate reviews similar enough to the human-written ones when provided with retrieved references instead, hence the inclusion of **RQ4**. Specifically, an internal API for embedding-similarity search was used, which can be called to retrieve as many references as listed in the human-written review.

Results We examined if the results when using retrieval differed significantly compared to the baseline researcher setting, which was tested using the appropriate statistical tests. From the results (shown in Table 5), we note that only two results were significantly different compared to the baseline, indicating that LiRA is capable of performing similarly despite the different references used. More details on the statistical tests can be found in the extended version.

6 Deployment

The deployment of LiRA will use the following steps. First, it will be developed using the Python version of LangGraph, which is an open-source and production-ready agentic framework. Furthermore, the `gpt-4o-mini` LLM from AzureOpenAI will be used, with the possibility of using other models given LangGraph's extensive support for various other endpoints such as form `ollama`.

As the use case of LiRA requires it to generate novel literature reviews not based on existing reviews, a document retrieval system will be added on to the system. It would function by asking the user for a review topic as input, which would then be enriched using an LLM (i.e., `gpt-4o-mini`) and afterwards used for embedding-based retrieval using an internal API. This API by default has access to a large collection of scientific articles, and can be replaced depending on the specific circumstances.

Metric	LiRA	LiRA +retriever
ROUGE	**0.130 ± 0.021**	0.128 ± 0.019
hsr	**0.257 ± 0.130**	0.251 ± 0.116
her	**0.056 ± 0.043**	0.054 ± 0.044
aer	**0.170 ± 0.057**	0.152 ± 0.054*
Coverage	**3.892 ± 0.407**	3.839 ± 0.415*
Structure	3.264 ± 1.049	**3.411 ± 1.023**
Relevance	**4.296 ± 0.389**	4.270 ± 0.372

Table 5: The ScienceDirect retrieval results. The stars indicate results significantly lower than the baseline.

7 Conclusion, Limitations, and Future Work

This work introduces **LiRA**, an agentic workflow designed for the automatic writing of literature reviews, which integrates the concepts of research before writing and refinement in its core pipeline. The results obtained show that LiRA is capable of performing the task of automated literature review quite well, outperforming all tested open-source methods when accounting for the varying output lengths, indicating a positive result for essentially every research question proposed. Moreover, it reduces hallucination through improved citation behavior and can demonstrably be used in real-world settings.

Several improvements could be made, mainly regarding the irreproducibility of results due to the usage of `gpt-4o-mini` for all experiments. This can be solved by using seedable models instead, which should be feasible given current LLM availability. In addition, there is a lack of open-source datasets for this task specifically, which hinders the generalizability of all results to other scientific fields. Therefore, we encourage authors to create additional datasets, ideally in a similar format to SciReviewGen, to facilitate the evaluation of similar systems in the future.

Furthermore, opportunities exist to create more end-to-end pipelines, as the current project does not take into account factors such as primary studies and risk of bias in randomized trials (i.e., the implementation of automated tools based on Higgins et al. (2024)). Doing this would allow for the integration of more steps within the literature review writing process, namely the screening and search criteria definition steps, which would allow for better paper reproducibility.

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