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AI-Powered Research Decision Support System for Scientific Literature Analysis and Research Gap Discovery

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Abstract

The number of papers is such that it's impossible to read them all. Everybody who carries out a literature review is aware of this. For each study you have to determine its aim, the methods it employed, the data and metrics it used, the limitations or omissions it had, and what the authors believe should happen next. This process is very time-consuming. Currently, most AI tools are only capable of helping with locating papers, summarising them, or answering questions. They barely deal with the task of comparing studies in an organised manner or identifying areas where further research is needed. In this seminar we present an AI-powered Research Decision Support System. The system combines Natural Language Processing, Large Language Models, and intelligent document analysis and examines a number of papers together. It extracts the key points from each paper and presents them in a structured format. It then compares the findings of the studies and compiles the evidence so that limitations which recur frequently and trends that are just beginning to appear become obvious. It also attempts to identify possible research gaps and rank them. The criteria used are intended to be transparent and based on evidence. Our aim is to reduce the amount of manual work involved in a literature review and to provide researchers with a well-organised resource on which to base their planning and decision-making.

Keywords: Artificial Intelligence, Intelligent Document Analysis, Large Language Models, Natural Language Processing, Research Decision Support, Research Gap Detection, Scientific Literature Analysis.

I. Introduction

The rapid increase in scientific publications has made it increasingly difficult for researchers to conduct literature reviews efficiently. It is now difficult for researchers to keep up with the latest literature. The primary reason for this is that an excessive number of papers are being published. When carrying out a normal review, one has to read a large number of studies and compare them study by study, looking at their objectives, methods, datasets, results, limitations, and future prospects. Carrying out such a task by hand is slow and the problem becomes even greater as the number of papers increases. Therefore, we need tools which can assist researchers in going through and understanding all this knowledge.

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Recently, progress in Natural Language Processing (NLP) and Large Language Models (LLMs) has been made, to the point where some literature analysis can now be carried out automatically. LLMs are applied in carrying out literature reviews, in information extraction, and in the analysis of scientific text [1], [2]. Studies involving the extraction of key insights or data indicate that LLMs can save effort, but accuracy and reliability remain concerns [3], [4]. Some researchers have focused on comparative literature summarization and on developing structured methods for representing scientific information [5]–[7]. OpenScholar makes use of retrieval in order to support scientific synthesis on the basis of evidence [8].

Yet the majority of such systems carry out only a single function; they retrieve, extract, or summarize. Only a small number attempt to identify research gaps from beginning to end. This is a more difficult problem since a true gap only becomes apparent when the methods, findings, limitations, and future directions of a number of studies are linked together. People have applied LLMs to the task of literature scoping and gap detection [9]. The issues of grounding claims in evidence, reliably extracting information, and getting a person to verify the results have not yet been solved.

We thus suggest an integrated decision-support approach, which combines structured information extraction, multi-paper comparison, evidence synthesis, and the identification of gaps into a single process. The papers are examined using the same criteria. On this basis, the system identifies recurring limitations, areas that have not been explored, and potential research opportunities. Then a person reviews the results.

The following points are provided by this paper: (i) the structured extraction of the important information contained in scientific papers; (ii) a comparative analysis of a number of studies; (iii) the identification of recurring limitations and possible research gaps; and (iv) a decision-support method, grounded in evidence, which assists researchers in reading the existing literature.

The paper is put together in the following way: Section II deals with related work, Section III sets out the problem and the objectives, Section IV outlines the architecture, Section V describes the methodology, and Section VI presents a use case. Following these sections are the expected outcomes, a comparison with existing approaches, the evaluation, the future scope, and the conclusion.

II. Related Work

A. LLM-Based Literature Review and Analysis

An increasing number of researchers are now considering the use of LLMs as aids in literature reviews. Agarwal and colleagues examined what is possible and what is not possible with regard to this application. They discovered that LLMs are helpful for synthesising information, but reliability and evaluation remain issues [1]. Scherbakov and co-workers investigated the way in which LLMs are being incorporated into systematic review workflows. They stated that the models are useful at a number of stages of the process [2]. Both of these studies indicate promise. At the same time, both of them assert that humans will still have to supervise the results.

B. Scientific Information Extraction

If you want to convert unstructured papers into structured knowledge then you need information extraction; Song et al. developed an system based on language models which extracts key insights from scientific articles and thus it is clear that language models can automatically analyse scientific text [3]. Lee et al. carried out tests on language models with a view to extracting information for systematic reviews and they

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were concerned about accuracy and consistency [4]. Although automatic extraction can reduce the need for manual work the output should still be verified before anyone makes an evidence-based decision on it.

C. Comparative Literature Analysis

Instead, more recent research involves comparing the information from different studies rather than reading each paper individually. Li et al. developed ChatCite, combining LLM-based comparative literature summarization with advice from a human workflow [5]. Garcia et al. too carried out work on comparative summarization, using reflective mechanisms to improve the way information from different documents is analysed [6]. Although these methods do assist in comparing papers, they are mainly concerned with summarization and do not attempt to identify and prioritize research gaps in a systematic manner.

D. Structured Representation of Scientific Literature

It's simpler to compare information from papers when it's given a structured format. Wang et al. investigated how to generate tabular summaries of scientific papers using ARXIV2TABLE [7]. With such a table, the methods, the findings, and other details can be placed under common headings. However, the table doesn't show which limitations occur repeatedly or which areas represent genuine research opportunities.

E. Retrieval-Augmented Scientific Synthesis

Another method of dealing with scientific literature is through the use of retrieval-augmented language models. OpenScholar was suggested by Asai et al. and links retrieval to scientific synthesis via a language model [8]. Since the answers are derived from the papers that have been retrieved, they are more closely grounded. However, retrieval and synthesis essentially involve identifying and combining relevant evidence, even so. Systematically identifying research gaps requires more than this. The limitations, methods, findings, and future directions have to be compared across different studies.

F. Literature Scoping and Gap Identification

Certain work makes use of large language models directly in the area of literature screening and in the identification of research gaps. Pietrobon et al. applied this approach to clinical research [9]. This is important for decision support since it goes beyond simple summarising and indicates areas in which further study is required. Yet in order to obtain a reliable result it is necessary to carry out accurate extraction, to compare the evidence properly, and to read the information from a number of studies together.

G. Scientific Language Models

A language model designed for use in scientific contexts is useful as a foundation for technical writing. Beltagy et al. developed SciBERT, a model that was trained on scientific text. They found that representations tailored to a particular domain are helpful when it comes to scientific natural language processing tasks [10]. Since these models are better at understanding scientific terminology and the style of scientific writing, they assist later processes such as information extraction and document analysis.

H. LLM-Based Literature Scoping and Gap Identification

Pietrobon and others examine the use of Large Language Models for carrying out literature reviews and for identifying research gaps. They demonstrate that such LLMs can assist researchers in organising the

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evidence and in locating areas that require further investigation [9]. Their study indicates that language models are capable of going beyond simple summarisation. However, gap identification still relies on the quality of the evidence that is extracted and on how the relationships between the studies are interpreted. Our Research Gap Discovery System addresses this by first carrying out structured extraction, comparing multiple papers, and synthesising the evidence before it even suggests any potential research gaps.

I. Scientific Language Models and Document Analysis

SciBERT, which was introduced by Beltagy and others, is a language model designed for use with scientific text. It has demonstrated that domain-adapted representations are useful for scientific NLP tasks [10]. Since a scientific language model is able to deal with technical terminology and complex research documents, it provides a basis for extraction and analysis. However, on its own it does not constitute a full workflow for comparing studies or for identifying research opportunities. Our system is based on scientific NLP and makes use of it within a structured workflow for literature analysis and gap discovery

J. Summary of Research Gaps

The methodology, contribution and remaining research gap for each of the studies that we examined are given in Table I. Three gaps repeatedly appear. The first is that AI-based literature systems generally concentrate on a single task, for example retrieval, extraction or summarization, and do not address an integrated workflow spanning many papers [1]–[4]. The second is that comparative and structured analysis does not always result in a systematic determination of recurring limitations and research opportunities [5]–[8]. The third is that LLM-based gap detection still has difficulty with evidence grounding, reliable extraction and human verification [4], [9]. It is these gaps that lead to the development of the Research Gap Discovery System, which overcomes them by means of a single workflow combining structured extraction, comparative analysis, evidence synthesis and gap identification.

TABLE I

Summary of Literature Survey and Research Gaps

Ref.	Author(s) / Year	Methodology	Key Contribution	Residual Research Gap
[1]	Agarwal et al. (2025)	LLM-based literature review and synthesis	Investigated the capabilities of LLMs for supporting literature-review tasks and scientific knowledge synthesis	Requires reliable evaluation, evidence verification, and human oversight
[2]	Scherbakov et al. (2025)	LLM-assisted systematic literature-review workflow	Examined the use of LLMs across different stages of systematic literature reviews	Limited integration of multi-paper comparison with systematic research-gap identification

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Ref.	Author(s) / Year	Methodology	Key Contribution	Residual Research Gap
[3]	Song et al. (2025)	Fine-tuned open-source LLMs for scientific key-insight extraction	Automatically extracted important insights from scientific articles	Focuses on extraction rather than connecting evidence across multiple studies
[4]	Lee et al. (2025)	Evaluation of LLM-based data extraction for systematic reviews	Assessed the accuracy and reliability of LLMs in extracting research information	Extraction errors and inconsistencies can affect downstream analysis
[5]	Li et al. (2025)	ChatCite: LLM-based comparative literature summarization with human workflow guidance	Supported comparative analysis and summarization of multiple research papers	Primarily focuses on comparative summarization rather than systematic gap identification
[6]	Garcia et al. (2024)	LLM-based comparative literature summarization with reflective mechanisms	Improved comparison of information across multiple scientific documents	Does not provide a complete framework for structured gap detection and opportunity analysis
[7]	Wang et al. (2025)	ARXIV2TABLE: LLM-generated tabular summaries of scientific papers	Converted scientific-paper information into structured tabular representations for comparison	Structured summaries do not directly identify recurring limitations or research opportunities
[8]	Asai et al. (2024)	Retrieval-augmented language models for scientific literature synthesis	Combined scientific retrieval with LLM-based evidence synthesis	Emphasizes retrieval and synthesis rather than systematic research-gap discovery
[9]	Pietrobon et al. (2025)	LLM-based literature scoping and research-gap identification	Explored LLMs for literature scoping and identification of potential research gaps	Gap identification remains dependent on evidence quality and human verification
[10]	Beltagy, Lo & Cohan (2019)	SciBERT: domain-adapted language model for scientific text	Demonstrated the usefulness of scientific-domain language representations for NLP tasks	Does not provide an integrated multi-paper comparison or research-gap discovery workflow

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III. Problem Statement and Design Objectives

The analysis of scientific literature still places great reliance on people having to read and compare research papers themselves, a process which can take a lot of time particularly when the review covers a large number of studies and which may make it hard to spot connections or repeated patterns in the various papers. In order to carry out such an analysis, researchers have to look at things like the aims, the methodologies, the datasets, the findings, the limitations, and the future directions, but these details are not always given or compared in a consistent manner. An approach that involves the use of AI could be of help by extracting the relevant information, comparing the findings across the different studies, organising the supporting evidence, and pointing out possible research gaps. At the same time, the researcher must still be in charge of interpreting and verifying the results and not depend completely on automated decisions. Since this is the case, the Research Gap Discovery System proposed here is based on the following objectives:

1) *Structured Information Extraction* —Extract from scientific papers the key research details such as the objectives, the methodologies, the datasets, the findings, the limitations, and the future directions.

2) *Multi-Paper Comparison* —when using common analytical criteria to examine a number of studies, it is possible to identify similarities, differences, and patterns which might not be apparent if the papers were looked at individually.

3) *Evidence Synthesis* — arrange the relevant information from a number of research papers and combine the supportive evidence by using structured and retrieval-supported methods.

4) *Research Gap Identification* —look through the literature that has been analysed to find recurring limitations, areas that have been less explored, and potential opportunities for further research.

5) *Reliable Analysis* —enhance the reliability of automated analysis by keeping links to the supporting evidence and taking into account possible errors and inconsistencies in the extraction.

6) *Human-AI Collaboration* —Use AI as a support tool for researchers, making sure that human judgment is still involved in the review, interpretation, and validation of the findings identified and the potential research gaps.

At this stage the points in question establish the design objectives of the system in question. How the objectives are actually implemented and empirically evaluated will be dealt with in the later development and testing phases.

IV. Proposed System Architecture

A. Architecture Overview

The Research Gap Discovery System that has been proposed comprises five key stages which function together in order to carry out an analysis of scientific literature. These stages are the Literature Input Layer, the Document Processing and Information Extraction Layer, the Comparative Analysis Layer, the Evidence Synthesis and Gap Detection Layer, and the Human Verification Layer. The research papers are handled in a step-by-step manner, starting with the original documents and progressing towards structured information, the comparison of studies, and the identification of possible research gaps (Fig. 1). Although the final results are presented, the researcher has the opportunity to examine the information which has been extracted and to give verification or feedback in order to make sure that the conclusions are suitable.

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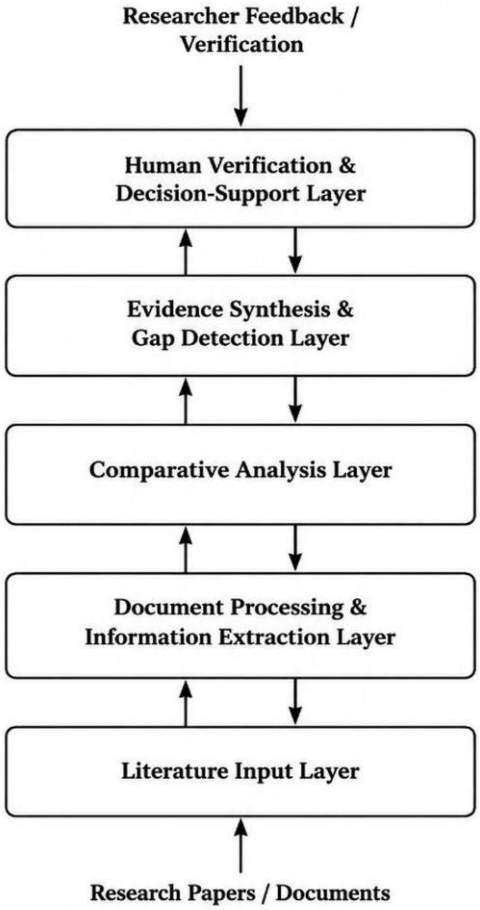


Fig. 1. Research Gap Discovery System architecture. Scientific papers flow through extraction, comparison, evidence synthesis, and gap-detection stages, with human verification applied to the generated findings.

B. Input and Document Processing Layer

The system takes as input relevant scientific papers and gets them ready for further analysis. To do this, the documents are examined in order to identify the important parts and to extract information such as the research objectives, the methodologies, the datasets, the findings, the limitations, and the future directions. The processing and understanding of the technical content of these research documents are based on NLP techniques and scientific language models [3], [4], [10].

C. Information Extraction and Comparative Analysis Core

The main part of the system carries out multi-paper analysis through four connected stages (Fig. 2):

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- *Extract* —A module based on natural language processing and large language models extracts from each research paper the information relevant to its objectives, methodology, datasets, findings, limitations, and future directions [3], [4].
- *Compare* —The information extracted from the various papers is organized based on common analytical dimensions, which makes it simpler to spot the similarities, differences, and patterns between the studies [5], [6].
- *Synthesize* —The information and supporting evidence from the selected papers are combined to produce structured summaries and comparative presentations, the synthesis process being supported by retrieval-based approaches [7], [8].
- *Identify* —The system looks at the combined information to identify recurring limitations, areas that have not been extensively explored, and the connections between the studies, and on this basis it suggests possible research gaps and opportunities [9].

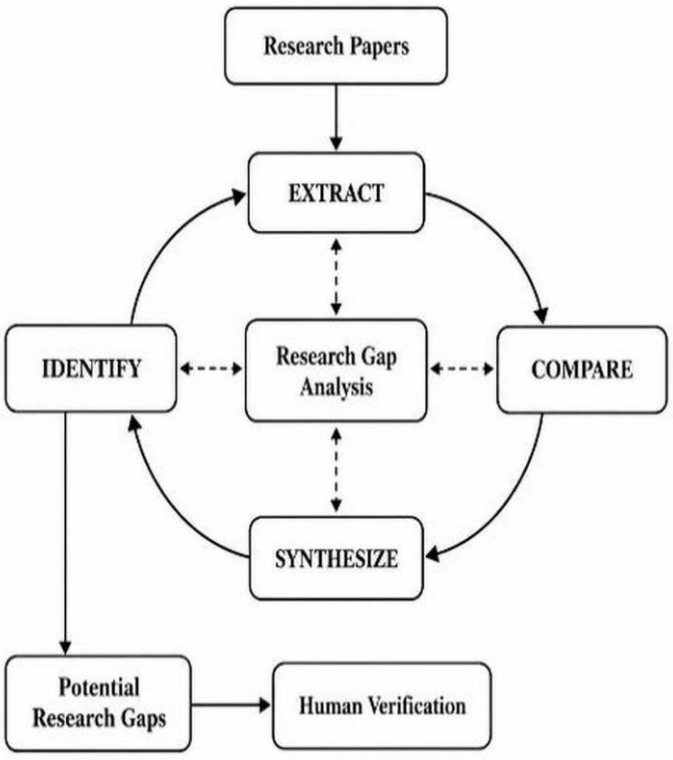


Fig. 2. The Extract-Compare-Synthesize-Identify workflow of the proposed system, transforming individual research papers into structured evidence and potential research gaps.

D. Evidence and Research Gap Detection Layer

The article looks at the evidence from various studies to determine if recurring limitations or areas that have been less thoroughly explored might point to possible research gaps. It examines patterns including repeated limitations, differences in the methods and results of the studies, and the topics which the authors have

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proposed for future research. The earlier research concerning the use of LLMs for literature screening and for identifying gaps forms the basis for this phase [9]. Moreover, retrieval-augmented synthesis can be used to link the gaps identified to the relevant evidence from the literature that has been analysed [8].

E. Human Verification and Decision-Support Layer

The last stage makes the extracted information, the comparisons, the supporting evidence and the possible research gaps available to the researcher for inspection. The researcher is then able to check the results, reject or alter any incorrect findings and look into particular areas if needed. It is important to have this human-in-the-loop method since automated information extraction and analysis based on LLMs can at times lead to errors or inconsistent interpretations [4]. The system is therefore meant to assist the researcher in making decisions rather than take over human judgment.

V. Methodology

A. Data Representation

All research papers are arranged using a standard collection of fields, for example the research objective, the methodology, the dataset, the algorithms, the evaluation metrics, the findings, the limitations, and the future directions. The details extracted are stored in a structured format in order that it may be easier to compare information from different papers. At the same time, relevant sections of the original text are kept in order to provide context for analysis based on language models. This method is in line with earlier work concerning structured scientific information and language-model-based information extraction [3], [7], [10].

B. Information Extraction Process

The component responsible for information extraction looks at each research paper and pulls out the predefined research attributes. An LLM is employed to interpret the scientific text and turn the relevant information into a structured format, in accordance with the key-insight extraction approach mentioned in [3]. Because the information generated by the LLM is not always accurate or consistent, the system also takes into account the reliability of the extracted information, as pointed out in the evaluation of LLM-based extraction for systematic reviews [4].

C. Comparative Analysis and Evidence Synthesis

The analytical dimensions in question are used to compare the information obtained from the research papers. This enables similarities and differences in various areas—such as methodologies, datasets, findings, limitations, and future directions—to be identified, thus making it easier to examine the relationships between the different studies. Comparative summarization methods [5], [6] and structured representations of scientific information [7] form the basis for organizing the results. Moreover, retrieval-augmented synthesis can be used to link the analysis with the relevant supporting evidence from the literature [8].

D. Research Gap Identification Procedure

In the research-gap identification phase, the synthesized information is examined in order to identify recurring limitations, inconsistencies between the various studies, areas that have not been explored

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adequately, and possible avenues for future research. The general procedure employed to analyze the literature and to identify possible research gaps is given in Algorithm 1.

Algorithm 1

Research Gap Discovery Workflow

Step	Operation
Input	Research papers P, analysis criteria C
1	papers ← Preprocess(P)
2	information ← Extract(papers, C) // LLM-based extraction [3], [4]
3	structuredData ← Organize(information)
4	comparison ← Compare(structuredData) // comparative analysis [5], [6]
5	evidence ← Synthesize(comparison) // structured synthesis [7], [8]
6	patterns ← IdentifyRecurringPatterns(evidence)
7	gaps ← IdentifyGaps(patterns, limitations, future directions) // [9]
8	evidence ← VerifySupportingEvidence(gaps)
9	Present (gaps, evidence, comparison) to researcher
10	researcher ← Validate(gaps)
Output	Structured comparison, evidence-supported research gaps, and potential research opportunities

E. Human Verification Mechanism

In the final stage, the researcher is given the extracted information, the comparative results, the supporting evidence, and the potential research gaps for verification. They have the opportunity to go through each finding and decide whether to accept it, make modifications to it, or reject it before the results are used for further investigation. This stage is especially important since LLM-based extraction and the identification of gaps may at times lead to inconsistencies or may necessitate additional context in order to be interpreted correctly [4], [9]. The system thus acts as a decision-support tool, with the automated analysis helping to organise and examine the literature while the final interpretation is left to the researcher.

VI. Illustrative Case Study: Research Gap Discovery

To illustrate how the system is intended to function, let us look at a hypothetical study of AI-driven predictive maintenance in IoT systems. This example only depicts the workflow and is not based on an actual implemented or evaluated system, with no results being reported.

Imagine that a researcher uploads a group of papers which deal with machine-learning-based predictive maintenance, IoT sensor systems, and edge analytics. The Literature Input Layer takes them in and the Document Processing Layer extracts from each paper its objectives, the datasets it used, the methods and algorithms employed, the evaluation metrics, the findings, the limitations, and the future directions that

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were stated. In the Comparative Analysis stage, these attributes are then presented side by side, making it easy to see the differences in the datasets, the model choices, and the deployment environments.

Evidence Synthesis brings together the findings and their limitations from the various studies in order to identify patterns in the existing literature. Although a number of the studies may show strong predictive performance, several of them acknowledge the same drawbacks: a lack of real-world data diversity, high computational demands, or no testing under changing operating conditions. Individually, these admissions appear to be minor, but when read as a group they indicate a common problem.

Recognising this, Gap Detection suggests an opportunity—for instance, a lightweight predictive-maintenance approach which operates on edge devices with limited resources and is trained using more diverse real-world data. The system then displays the proposed gap along with the relevant papers, the extracted limitations, and the comparison results. The researcher can examine this evidence, either accept or alter the interpretation, and determine if the gap is worth pursuing.

That is the function which the system is designed to carry out. Researchers no longer need to manually compare dozens of papers in order to identify recurring limitations, since the system arranges the evidence and highlights potential gaps. It is up to the researcher to decide whether a gap is a worthwhile direction.

VII. Expected Outcomes and Discussion

The Research Gap Discovery System has not yet been fully implemented or subject to empirical evaluation, which is why this paper includes no measured performance figures. The benefits mentioned here are based on expectations derived from previous work; studies involving the use of language models for literature reviews indicate that such models can assist with scientific analysis and synthesis [1], [2], and research into automated information extraction shows that it is possible to extract relevant details from scientific papers and put them in a structured format [3].

Other related work indicates the same thing. ChatCite demonstrates that it is possible to compare information from a number of studies [5], ARXIV2TABLE illustrates how scientific content can be systematically organised [7], and retrieval-augmented approaches aid in linking the analysis to relevant evidence [8]. Research into the use of language models for literature scoping and for identifying gaps suggests that they can assist in finding areas that require further study [9].

The fact that reliability problems have been reported in the extraction literature [4] is also the reason why the workflow includes a human participant. All of these findings indicate that combining structured extraction, multi-paper comparison, evidence synthesis, and gap identification could usefully assist researchers when they are carrying out a literature analysis. It is only by putting the system into practice and testing it empirically that we can determine whether it is actually effective, accurate and reliable.

VIII. Comparison with Existing Approaches

Table II compares the proposed Research Gap Discovery System with the approaches discussed in Section II based on five key capabilities required for systematic scientific literature analysis: structured information extraction, comparison of multiple papers, evidence synthesis, research-gap identification, and human verification.

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TABLE II

Qualitative Comparison of Scientific Literature Analysis Approaches

Approach	Structured Information Extraction	Multi-Paper Comparison	Evidence Synthesis	Research-Gap Identification	Human Verification
LLM Literature Review [1], [2]	Yes	Partial	Yes	Partial	Yes
Scientific Key-Insight Extraction [3]	Yes	No	Partial	No	Partial
LLM Data Extraction for Reviews [4]	Yes	Partial	No	No	Yes
ChatCite [5]	Partial	Yes	Yes	Partial	Yes
Comparative Literature Summarization [6]	Partial	Yes	Yes	Partial	Partial
ARXIV2TABLE [7]	Yes	Yes	Partial	No	Partial
OpenScholar [8]	Partial	Yes	Yes	Partial	Partial
LLM Literature Scoping & Gap Identification [9]	Partial	Yes	Yes	Yes	Yes
SciBERT [10]	Yes	No	No	No	No
Proposed Research Gap Discovery System	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

IX. Ethical, Safety, and Explainability Considerations

Since tools used in the analysis of literature can influence the way that researchers read and interpret the existing evidence, it is essential that they are reliable and used responsibly. The system is based on four principles, each of which stems from problems mentioned in the reviewed literature.

There is human oversight since there are known reliability concerns regarding literature analysis based on LLMs [1], [4]; therefore, the system assists researchers and does not on its own determine whether a gap is valid or significant. It is up to the researcher to reach a final interpretation.

A justification based on evidence is required, and each proposed gap must be linked to the papers and to the specific findings or limitations from which it originated. [8] Retrieval-augmented synthesis can be used to connect the analysis that is generated to the source literature.

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The explainability and traceability features ensure that each gap is accompanied by the findings that support it, along with its limitations and the source papers; this enables researchers to understand why a gap was identified and to trace the conclusion back to its original sources.

Verification is required before adoption. Since LLM-based extraction and analysis may result in inaccurate or inconsistent output [4], researchers should verify the generated results before proceeding with further work on them.

These principles together ensure that the system remains transparent and is under the control of the researcher; it serves as a decision-support tool rather than as an independent source of scientific conclusions.

X. Evaluation Plan and Future Work

The system will be developed as a prototype and will be tested using a sample of scientific publications. The evaluation will consist of several components. The first of these is extraction accuracy, which involves checking the objectives, methods, datasets, findings, limitations, and future directions against annotations that have been verified by researchers [3], [4]. The second component is cross-paper analysis, and this will be judged according to how effectively it identifies relationships, differences, and recurring patterns among the studies [5], [7].

We shall also look at how reliably the system combines evidence, in particular by checking that the conclusions and the suggested opportunities can be linked to the correct source papers [8]. The quality of gap identification will be assessed by comparing the gaps and underexplored areas identified by the system with those pointed out by researchers or domain experts [9]. Lastly, we will investigate whether the explanation and verification features are of any real help, that is to say, whether researchers are able to easily examine the evidence and then accept, alter, or reject what the system produces [1], [4].

Future research will focus on finding improved methods for basing the output on evidence from the source, on using scientific-domain language models such as SciBERT [10], and on ranking the potential opportunities according to their consistency across studies, their relevance to the research area, and the strength of the evidence supporting them.

XI. Conclusion

The paper describes an AI-driven Research Decision Support System whose purpose is to make the processes of carrying out literature reviews and identifying research gaps more systematic and easier to manage. The literature examined includes LLM-assisted review and synthesis [1], [2], scientific information extraction [3], [4], comparative analysis of papers [5], [6], structured scientific representations [7], retrieval-augmented synthesis [8], literature scoping and gap identification [9], and scientific language models [10]. A common limitation applies to these methods in that most of them focus on a single task and do not provide an integrated workflow which links extraction, multi-study comparison, evidence-based gap identification, and researcher verification. The proposed system overcomes this shortcoming by means of a pipeline consisting of document processing, structured extraction, multi-paper comparison, evidence synthesis, gap identification, and human validation. The paper also includes a conceptual example illustrating how the workflow might be carried out, together with a plan for evaluating a future prototype.

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To sum up, the framework provides a practical means of combining NLP and LLM techniques with a structured analysis of evidence and human supervision. It is not intended to replace the researcher, since it helps to organize the literature, makes it easier to examine the relationships between different studies, and in a more traceable and systematic manner identifies possible research opportunities. However, further implementation and empirical evaluation are required in order to demonstrate how well the approach performs in actual research settings.

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