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An AI-Assisted Research Automation System for Scholarly Paper Retrieval and Review With Workflow Orchestration

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Abstract: The rapid growth of scholarly publications has increased the complexity of conducting rigorous and reproducible literature reviews, while traditional manual review processes are increasingly constrained by information overload, time consumption, and inconsistencies in screening decisions. This study proposes an AI-assisted research automation system that integrates workflow orchestration with literature retrieval and review support mechanisms to address these challenges. The workflow supports multiple stages of the literature review process, including paper retrieval, preliminary screening, and review management, while maintaining human oversight and methodological control. Artificial intelligence, particularly natural language processing through a large language model, is employed as a supportive component to enhance efficiency and consistency rather than to replace the researcher's judgment. Implemented as a workflow-driven process, the system enhances transparency, traceability, and reproducibility in review activities. In the observed execution, the retrieval and preparation stages processed 20 papers in 21.38 seconds, while AI-assisted abstract analysis required 25.02 seconds per paper. These results indicate that workflow orchestration can reduce operational workload and support systematic literature review practices while preserving research integrity and human decision authority.

Keywords: Artificial Intelligence, Workflow-Based Automation, Literature Retrieval, Literature Review Framework, Research Automation System

Introduction

The exponential growth of scholarly publications across scientific and technological domains has fundamentally transformed academic knowledge production. While this expansion has accelerated innovation and interdisciplinary collaboration, it has also substantially increased the complexity of conducting rigorous and comprehensive literature reviews. Researchers must navigate vast volumes of heterogeneous and rapidly evolving information, making it increasingly difficult to ensure comprehensive coverage, methodological consistency, and transparency. As a result, traditional manual review approaches are becoming progressively unsustainable, particularly in multidisciplinary contexts characterized by terminological diversity and fragmented knowledge structures (Wagner et al., 2022; Zawacki-Richter et al., 2019). Empirical evidence from systematic and technology-assisted reviews further highlights persistent challenges related to information overload, inconsistent screening decisions, and the significant time and cognitive effort required to conduct rigorous reviews, underscoring the need for more scalable and transparent review methodologies (Chen et al., 2020; Wagner et al., 2022; Zawacki-Richter et al., 2019).

A substantial body of research has therefore explored the use of artificial intelligence to support and partially automate systematic literature reviews. Prior studies report that AI techniques particularly machine learning and natural language processing can reduce manual workload and improve consistency in early-stage screening tasks such as literature searching, relevance classification, and clustering (Bolaños et al., 2024; Chen et al., 2020; De la Torre-López et al., 2023; Vargas-Murillo et al., 2023; Wagner et al., 2022; Zawacki-Richter et al., 2019). More recent work demonstrates a transition from rule-based approaches toward learning-based and hybrid human AI pipelines, including active learning and prioritized screening, which improve recall and reduce the likelihood of missing relevant studies (De la Torre-López et al., 2023; Malik and Terzidis, 2025; Tomczyk, 2025). Nevertheless,

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this literature consistently emphasizes that AI performs most effectively when embedded within human-in-the-loop workflows, as human judgment remains essential for defining inclusion criteria, validating AI outputs, and mitigating risks related to bias and contextual misinterpretation (Anthuvan et al, 2025; Chen et al., 2020; Purba et al., 2025; van de Schoot et al., 2025). Collectively, existing studies reveal that AI-assisted literature review remains a maturing domain, with most approaches focusing on isolated tasks rather than integrated, end-to-end review workflows (Vargas-Murillo et al., 2023; Tomczyk et al., 2026; Zawacki-Richter et al., 2019).

Beyond literature review automation, multidisciplinary research on AI-supported decision-making highlights broader challenges associated with delegating authority to automated systems. Studies across healthcare, management, and education consistently report that while AI can enhance analytical capacity and efficiency, excessive reliance on autonomous systems introduces risks related to accountability, trust erosion, and diffused responsibility (Alzubaidi et al., 2023; Bleher and Braun, 2022; Dwivedi et al., 2021). Human-in-the-loop mechanisms are therefore critical for ensuring transparency, contextual judgement, and ethical responsibility, particularly in high-stakes or complex decision environments (Alzubaidi et al., 2023; Dwivedi et al., 2021; Kovari, 2024). Although recent frameworks for trustworthy AI formalize explainability and controllability as core principles, existing research remains largely conceptual or domain-specific, offering limited guidance on how human oversight is operationalized within integrated research workflows (Akbar et al., 2024; Bleher and Braun, 2022; Labkoff et al., 2024; Mora-Cantallops et al,. 2024; Sakowski and Parks, 2025).

Concurrently, a growing body of literature has examined the ethical and integrity-related implications of AI-assisted research practices. Recent studies caution that generative and assistive AI systems introduce risks such as opaque content generation, hallucinated references, and blurred authorship boundaries, which challenge traditional norms of academic integrity (Chauhan and Currie, 2024; Cheng et al., 2025; Dahal, 2024; Dwivedi et al., 2023; Hsu et al., 2025; Lund et al., 2025; Luomala et al., 2025; Qadhi et al., 2024). These concerns are exacerbated by tool-centric research practices, where AI applications optimize isolated tasks such as writing assistance or screening support without providing systematic workflow integration or traceability (Kesgin and Ozer, 2025; Motahari et al., 2025; Silva et al., 2025). As a result, scholars argue that ethical challenges cannot be addressed solely through usage guidelines, but instead require system-level designs that embed accountability, documentation, and human oversight throughout the research lifecycle (Hsu et al., 2025; Qadhi et al., 2024; Silva et al., 2025).

While workflow-oriented automation has long been recognized as essential for reproducibility and transparency in complex research activities (Cuevas-Vicenttín et al., 2012; Kanwal et al., 2017), existing AI-assisted literature review systems remain largely task-centric or phase-specific (Demchenko et al., 2023; Przemysław, 2025). Limited attention has been given to coordinating AI-assisted tools across the full review lifecycle while preserving provenance tracking and methodological accountability. In response to this gap, this study proposes an AI-assisted research automation framework that integrates workflow-oriented orchestration with literature retrieval, review management, and human-in-the-loop decision control. The framework supports the entire literature review lifecycle within a unified and auditable workflow environment, offering a system-level approach to transparent, reproducible, and ethically grounded AI-assisted literature review practices.

Materials and Methods

System Architecture and Design

The proposed research automation system was developed to support end-to-end scholarly information retrieval, analysis, and organization through a workflow-based architecture. The architecture integrates several functional components, including data acquisition, processing, AI-assisted analysis, and storage, into a unified pipeline.

At the core of the architecture is a workflow orchestration engine implemented using n8n, enabling sequential and conditional execution across multiple heterogeneous data sources. This orchestration mechanism enables the automation of tasks typically performed manually, such as retrieving research articles, filtering redundant records, and extracting key insights from unstructured textual data.

As illustrated in Figure 1, the architecture is organized into four main layers:

1) User Interface Layer
2) Data Acquisition Layer
3) Processing and AI Layer
4) Storage and Output Layer

User queries are first processed by the data acquisition layer to retrieve information from multiple sources. The retrieved data are subsequently processed through normalization and deduplication before being analyzed using AI techniques and stored for further use.

The overall architecture follows a modular design, in which each component performs a distinct function within the workflow. The data acquisition layer retrieves scholarly information from multiple sources, while subsequent processing ensures data consistency through normalization and deduplication. AI-assisted analysis applies natural language processing techniques to interpret, summarize, and structure the retrieved content. The processed data are then stored for further analysis and reporting.

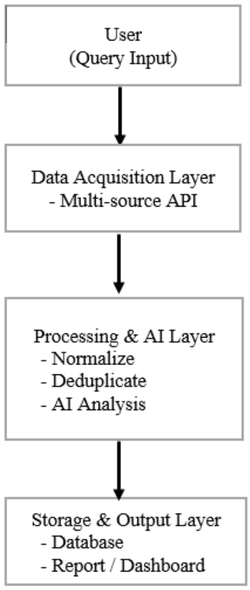

Fig. 1: Layered architecture of the proposed research automation system

To enhance flexibility and scalability, a loosely coupled architecture is adopted, allowing individual components to be updated or extended without affecting overall operation. This design is well-suited to dynamic research environments where data sources and analytical requirements frequently evolve.

In addition, the workflow-driven approach reduces repetitive manual tasks and improves operational efficiency, supporting continuous and reproducible processing of scholarly data. As a result, large volumes of information can be managed in a structured and systematic manner.

Workflow Design

The proposed research automation system consists of two primary workflows that operate sequentially to support the overall process of scholarly data retrieval and analysis.

The first workflow focuses on data acquisition and retrieval. It begins with user query submission through a webhook interface, which triggers workflow execution. Multi-source retrieval is then performed to collect relevant scholarly information from external platforms and APIs. This workflow is responsible for gathering raw research data and preparing it for subsequent processing. The workflow is illustrated in Figure 2.

The second workflow is dedicated to data processing and analysis. After the initial data is collected, it undergoes normalization to ensure consistency in format and structure. Duplicate records are then removed through a deduplication process to improve data quality.

Subsequently, AI-assisted analysis is applied to extract meaningful insights, summarize content, and structure the information. The processed data is then stored in a database for further use, including reporting and visualization. The workflow is illustrated in Figure 3.

For clarity, the overall workflow can be decomposed into six sequential stages, as illustrated in Figure 3.

Stage S1 – Request Intake and Validation

As shown in Figure 3 (Stage S1), the workflow begins with a controlled research request intake and validation process. Literature search requests are submitted through a structured input mechanism and undergo authorization and integrity checks. Invalid or unauthorized requests are rejected to prevent unintended workflow execution. Validated requests are logged and assigned unique identifiers to ensure idempotent behavior, thereby preventing duplicate processing. This stage establishes a secure and traceable entry point for the research automation pipeline.

Stage S2 – Multi-Source Data Retrieval

In Stage S2 (Figure 3), validated research queries are transformed into standardized search expressions and dispatched to multiple scholarly data sources. A Google Scholar-based search interface and open academic repositories are integrated to retrieve candidate publications. Search operations are executed in parallel across heterogeneous sources to enhance coverage and reduce dependency on a single bibliographic database. Retrieved records are forwarded as raw metadata for downstream processing.

Stage S3 – Integration and Deduplication

In Stage S3 (Figure 3), literature records retrieved from multiple sources are integrated, and redundancies are eliminated. Metadata from heterogeneous sources is normalized into a unified internal schema and merged into a consolidated dataset. Duplicate detection is primarily performed using DOI-based identifiers. When DOI information is unavailable, normalized title–year combinations are applied as secondary identifiers. This stage ensures data integrity and prevents redundant downstream analysis.

Stage S4 – Metadata Validation

In Stage S4 (Figure 3), retrieved records undergo metadata validation and classification. Core bibliographic attributes including title, publication year, journal or publisher, and abstract availability are examined and standardized to ensure consistency. Publisher detection and source classification are applied to support analytical grouping and filtering. Only validated records are retained in the master dataset for subsequent analysis.

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Stage S5 – AI-Assisted Analysis

In Stage S5 (Figure 3), the AI-assisted analysis component of the workflow is implemented. Records that have not yet been analyzed and that contain valid DOI information are selected for processing. Abstracts are retrieved and normalized prior to AI processing. A large language model is employed to generate structured analytical outputs, including concise summaries, thematic keywords, and methodological descriptors. At this stage, AI-generated outputs function strictly as decision-support artifacts and do not constitute final research conclusions.

Stage S6 – Persistence and Status Tracking

In Stage S6 (Figure 3), persistent storage and workflow state tracking are managed. Validated metadata and AI-generated analytical outputs are stored in structured data repositories, and explicit processing status indicators are updated for each record. This design enables incremental execution and workflow resumption, ensuring that previously processed records are not reanalyzed. The separation of AI-assisted analysis (S5) from persistence and status management (S6) reinforces transparency, accountability, and responsible use of AI.

For clarity, the stage-based structure of the proposed research automation workflow is summarized in Table 1.

Together, these stages illustrate how the framework systematically integrates workflow orchestration and AI-assisted analysis while preserving transparency and reproducibility.

Data Processing Pipeline

The data processing pipeline represents a high-level abstraction of the end-to-end transformation of scholarly data, beginning with user query submission and concluding with structured data storage and status tracking. As illustrated in Figure 4, the pipeline comprises a sequence of interconnected stages, including multi-source data retrieval, metadata normalization, deduplication, metadata validation, AI-assisted analysis, and persistent storage.

This pipeline provides an abstract, process-oriented view of how raw scholarly data are progressively refined into structured analytical records. Unlike the workflow implementation diagrams presented in Figures 2 and 3, which depict system-level execution in n8n, Figure 4 highlights the logical flow of data across the core processing components of the framework.

This abstraction aligns with the stage-based workflow (S1–S6) and provides a unified view of how scholarly data are progressively transformed across the entire pipeline.

Implementation Details

The workflow orchestration engine was implemented using n8n, a low-code automation platform that supports event-driven execution and integration with external services.

At the core, a workflow orchestration engine coordinates sequential and conditional operations across multiple stages. This engine supports event-driven execution through webhook-based triggers, allowing user queries to initiate the workflow in real time.

Table 1: Overview of Processing Stages in the Workflow

Stage	Stage Name	Primary Function
S1	Request Intake and Validation	Validates and logs research requests and prevents duplicate execution
S2	Multi-Source Data Retrieval	Retrieves candidate publications from multiple academic data sources
S3	Integration and Deduplication	Normalizes, merges, and removes duplicate records
S4	Metadata Validation	Cleans and classifies bibliographic metadata
S5	AI-Assisted Analysis	Generates AI-supported summaries and analytical attributes
S6	Persistence and Status Tracking	Stores validated data and tracks processing states for reproducibility

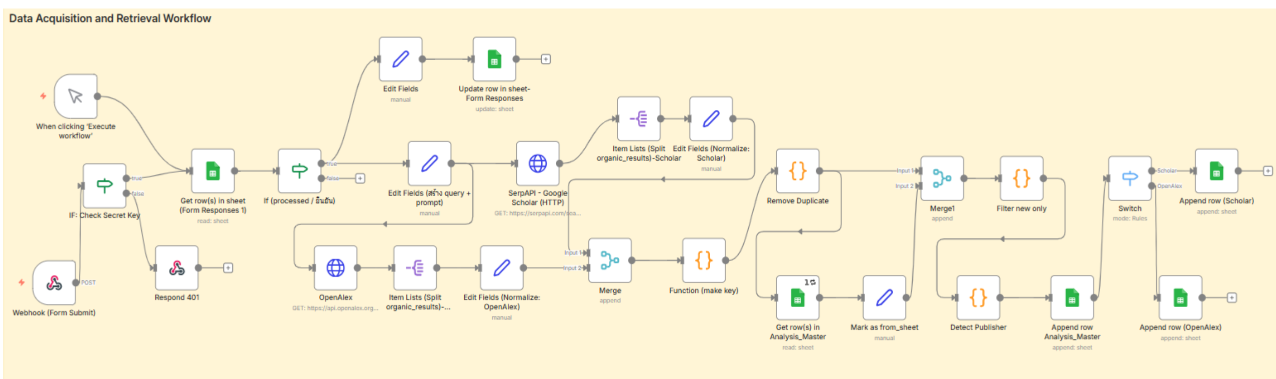

Fig. 2: Data acquisition and retrieval workflow implemented using n8n

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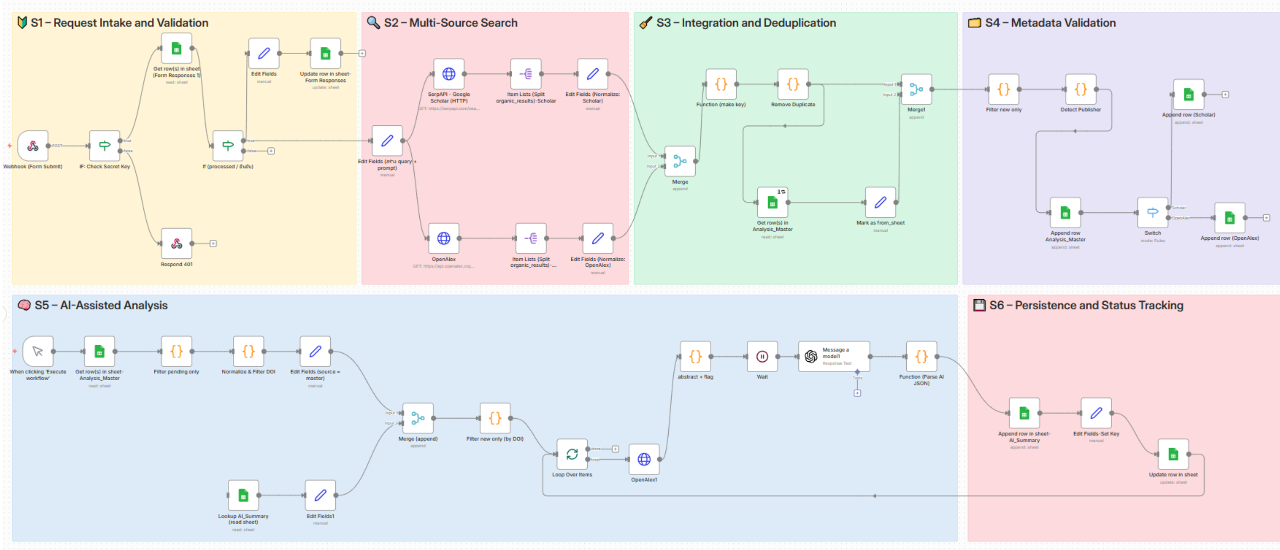

Fig. 3: Data processing and AI-assisted analysis workflow implemented using n8n

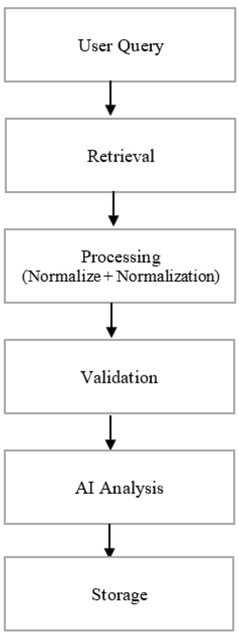

Fig. 4: Abstract data processing pipeline of the research automation system

The orchestration mechanism enables modular design, where individual components can be independently configured, monitored, and extended.

For data acquisition, multiple scholarly sources are integrated through web-based search interfaces and open metadata repositories. Queries are programmatically transformed into standardized search expressions and dispatched to these sources. Retrieved data are collected in structured formats to facilitate downstream processing.

The data processing component performs normalization and deduplication to ensure consistency and data quality. Metadata from different sources is mapped into a unified schema, and duplicate records are identified primarily using DOI-based matching. In cases where DOI information is unavailable, alternative matching strategies based on title and publication year are applied.

The AI-assisted analysis component leverages a large language model to process textual information, particularly abstracts. Prior to analysis, textual data are normalized and validated to ensure input quality. The model is then used to generate structured outputs, including summaries, keywords, and methodological descriptors. These outputs are intended to support research analysis and are not treated as definitive conclusions.

For data storage and management, structured data repositories are used to persist both raw and processed information, with each record linked to processing status indicators for incremental tracking. Each record is associated with processing status indicators, enabling incremental execution and preventing redundant analysis. This design supports workflow resumption and enhances system reliability.

Overall, the implementation emphasizes modularity, scalability, and reproducibility. The integration of workflow orchestration with AI-assisted analysis enables the automation of complex research tasks while maintaining transparency and explicit control over each processing stage.

Results and Discussion

This section reports the observed results of the implemented workflow and discusses their implications

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for AI-assisted literature review practice. The discussion focuses on system behavior, workflow effectiveness, and methodological contributions rather than domain-specific research findings, as the primary objective of this study is to evaluate the performance and design of the research automation framework.

Workflow Execution and System Outputs

The stage-based workflow was successfully executed across all processing stages (S1–S6), demonstrating the feasibility of the end-to-end literature review pipeline. The workflow execution consistently handled structured research requests, multi-source retrieval, metadata processing, AI-assisted analysis, and persistent storage without redundant execution.

Using the query keywords “Artificial Intelligence” and “Internet of Things,” the workflow retrieved and processed 20 scholarly records during the retrieval and preparation stages (S1–S4). These stages required a total execution time of 21.38 seconds. A summary of execution outcomes and stage-level processing times is presented in Table 2.

Overall, the results show that the workflow can reliably automate core literature review tasks while maintaining transparency and explicit control across processing stages.

Multi-Source Retrieval and Coverage

During Stage S2, the workflow performed a multi-source scholarly search by querying Google Scholar and OpenAlex. This design enabled the retrieval of heterogeneous publication records spanning different publishers, venues, and publication years. In the observed execution, a total of 20 candidate papers were retrieved and normalized into a unified data schema.

The integration of multiple scholarly sources reduced reliance on a single bibliographic repository and enhanced coverage diversity. The retrieval and normalization processes were completed within approximately 15 seconds, demonstrating the effectiveness of workflow-based orchestration for scalable and repeatable literature discovery.

Deduplication and Metadata Validation

Following retrieval, the workflow integrated results from multiple sources and applied DOI-based deduplication in Stage S3. In the observed execution, no duplicate records were detected, resulting in a clean dataset of 20 unique publications. This outcome reflects the robustness of DOI-based key generation and the effectiveness of pre-filtering mechanisms.

Subsequently, metadata validation and classification were conducted in Stage S4. Bibliographic attributes, including publication year, journal or publisher name, and abstract availability, were standardized and verified. The validated records were stored in a master dataset, forming a reliable foundation for downstream AI-assisted analysis and ensuring data consistency and integrity.

AI-Assisted Abstract Review Performance

Stage S5 evaluated the AI-assisted abstract analysis module using a representative paper. The AI review process, including abstract verification, bilingual summarization (Thai and English), and structured output parsing, required 25.02 seconds per paper, inclusive of a 2-second intentional delay for API rate regulation.

Robust handling of incomplete metadata was observed. When abstracts were unavailable, the AI module explicitly documented this limitation and generated context-aware summaries based on available bibliographic information. Key characteristics of the AI-assisted abstract analysis are summarized in Table 3.

These observations suggest that AI-assisted analysis can support qualitative literature review, although its effectiveness remains dependent on metadata completeness and input quality.

Table 2: Observed execution outcomes and processing time across workflow stages (S1–S6)

Stage	Description	No. of Records	Execution Time (Observed)
S1	Research request intake and validation	1 request	< 1 s
S2	Multi-source scholarly search	20	~15 s
S3	Result integration and deduplication	20 → 20	~3 s
S4	Metadata validation and classification	20	~2 s
S5	AI-assisted abstract analysis	1	~25.0 s
S6	Knowledge persistence and status tracking	1	< 1 s
Total (S1–S4)	Retrieval and preparation	20 papers	21.38 s
Total (S5–S6)	AI review pipeline	1 paper	25.02 s

Table 3: Characteristics of AI-assisted abstract analysis

Aspect	Observation
Input type	Abstract text (or metadata-only if abstract unavailable)
Output languages	Thai and English
Handling of the missing abstract	Explicitly documented by AI
Average processing time	~25 s per paper
Execution mode	Incremental, per-record

While the workflow demonstrates stable execution, its current design prioritizes process transparency over analytical depth, which may limit its effectiveness in complex domain-specific reviews.

Incremental Processing and Knowledge Persistence

Upon completion of AI-assisted analysis, processed records were persistently stored with explicit status indicators in the knowledge base. Stage S6 recorded each paper's processing state, enabling incremental execution and preventing redundant reprocessing in subsequent workflow runs.

The separation between retrieval-intensive stages (S1–S4) and AI-intensive stages (S5–S6) allows selective re-execution of AI analysis without repeating earlier retrieval steps. This design supports iterative literature review workflows and facilitates continuous monitoring of newly retrieved publications.

Overall, the workflow supports transparent processing, enables traceability of analytical states, and facilitates efficient management of repeated executions.

In practice, variations in metadata quality and abstract structure across different data sources occasionally resulted in inconsistent AI-generated outputs. For example, records with incomplete abstracts or ambiguous terminology led to summaries that required manual verification before being used in further analysis. This observation indicates that, while the workflow can automate large portions of the review process, certain edge cases still require human intervention to ensure analytical reliability.

Limitations and Future Directions

Although the workflow was successfully implemented and demonstrated stable end-to-end execution, several limitations should be acknowledged.

First, the current implementation does not include a formal mechanism for detecting misinformation or verifying the factual correctness of AI-generated outputs. The analysis is constrained by the availability and quality of input metadata, particularly abstracts. This dependency introduces a risk of incomplete or potentially misleading interpretations when source information is limited. This limitation indicates that the current workflow lacks an explicit mechanism for verifying factual correctness, which may affect analytical reliability in real-world review settings.

Second, the evaluation conducted in this study is primarily feasibility-oriented. The reported execution times reflect observed system behavior under a specific configuration rather than optimized or benchmarked performance. For example, the retrieval and preprocessing stages (S1–S4) processed 20 papers in approximately 21.38 seconds, while the AI-assisted analysis stage (S5) required approximately 25.02 seconds per paper, including an intentional delay to regulate API requests. These results indicate that AI-assisted analysis is the dominant factor in overall processing time and should be interpreted as descriptive rather than comparative performance evidence.

Third, the AI-assisted analysis was performed on a limited number of records in the current experiment. Although the workflow supports incremental and resumable execution, the cumulative processing time of AI-intensive stages is expected to increase proportionally with dataset size. This suggests that scalability may become a constraint in large-scale applications unless optimization strategies such as batching, parallel processing, or adaptive scheduling are introduced.

Fourth, the effectiveness of the analysis is inherently dependent on the completeness and consistency of metadata across data sources. Variations in abstract structure, missing fields, and inconsistencies between sources were observed during system execution. While the workflow includes mechanisms to handle missing data, the analytical depth and consistency of AI-generated outputs may still be affected. Future extensions may incorporate full-text analysis, citation context extraction, or structured knowledge integration to address these limitations.

Finally, this study focuses on system design and operational feasibility rather than comparative evaluation. The absence of controlled benchmarking against manual review processes or alternative automation approaches limits the ability to generalize the observed performance advantages. Future research should include comparative experiments to assess time efficiency, consistency, and reviewer workload across different review methods. In addition, broader validation across diverse research domains and larger datasets would provide stronger evidence of the generalizability and practical applicability of the approach.

Conclusion

This study proposes and demonstrates a stage-based AI-assisted research automation workflow designed to support transparent, reproducible, and systematically controlled literature review processes. By integrating workflow orchestration with multi-source literature retrieval, AI-assisted abstract analysis, and persistent state tracking, the framework positions artificial intelligence as a structured decision-support mechanism rather than an autonomous replacement for human researchers.

The empirical results confirm the feasibility of executing an end-to-end literature review pipeline within a workflow-oriented environment. Specifically, the retrieval and preparation stages (S1–S4) processed 20 scholarly records within 21.38 seconds, while the AI-assisted analysis stage (S5) required approximately 25.02 seconds per paper. These findings highlight that, although AI-assisted analysis introduces additional computational overhead, it provides structured analytical outputs that enhance consistency and reduce manual effort in early-stage review activities.

From a methodological perspective, the stage-based architecture represents a deliberate design choice aimed at improving traceability and controllability across the research workflow. The explicit separation between retrieval-intensive stages and AI-intensive stages enables incremental execution and prevents redundant processing, while also allowing human intervention at critical decision points. However, this modular design introduces trade-offs, particularly in terms of increased orchestration complexity and processing latency in AI-dependent stages.

Furthermore, the study acknowledges that the effectiveness of AI-assisted analysis is inherently constrained by the availability and quality of metadata, especially abstracts. In cases of incomplete data, the depth of AI-generated insights may be limited, reinforcing the importance of maintaining human oversight. Additionally, the absence of automated mechanisms for validating the factual correctness of AI-generated outputs highlights an important area for future development.

Compared with existing approaches that focus on isolated tools or task-level automation, the framework contributes a system-level perspective by embedding AI within a structured, auditable, and reproducible workflow. This approach supports iterative literature review, continuous data integration, and long-term research monitoring while preserving methodological rigor.

In conclusion, this work demonstrates that workflow-based orchestration provides a practical foundation for integrating AI into scholarly review processes in a responsible and controlled manner. Rather than maximizing automation autonomy, this work emphasizes transparency, accountability, and human-in-the-loop decision-making as core design principles. Future research may further explore optimization strategies, full-text analysis, and validation mechanisms to strengthen both the efficiency and reliability of AI-assisted research workflows.

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Author’s Contributions

Sompoch Tongnamtiang: initiated the study and led the overall system development, including the architectural design of the stage-based AI-assisted research automation workflow. He implemented the workflow, performed system execution and operational analysis, synthesized the findings, and drafted the manuscript with all associated figures and tables.

Manirath Wongsim: Offered theoretical and methodological insights related to research automation and AI-supported review processes, supported the interpretation of system-level implications and limitations, and critically reviewed the manuscript to enhance clarity, structure, and completeness.

Natarpha Satchawatee: Contributed to shaping the research direction and methodological alignment, examined the coherence and validity of the design, and provided substantive editorial revisions to strengthen the analytical depth and scholarly presentation of the manuscript.

Ethics

This study does not involve human participants or personal data. All analyses are based on publicly available bibliographic metadata and scholarly abstracts, and artificial intelligence is used solely as a decision-support tool under human oversight.

Conflicts of Interest

The authors declare that there are no conflicts of interest associated with this research.

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