WriteWizard: Collaborative Document Editing Tool

J. Shandeep
Faculty of Computing
Sri Lanka Institute of Information Technology
Colombo, Sri Lanka
shandeepsanju@gmail.com

C. Sanjayan
Faculty of Computing
Sri Lanka Institute of Information Technology
Colombo, Sri Lanka
sanjayan201@gmail.com

Krithiga D. B.
Faculty of Computing
Sri Lanka Institute of Information Technology
Colombo, Sri Lanka
krithigadb96@gmail.com

Saara. M. K. F
Faculty of Computing
Sri Lanka Institute of Information Technology
Colombo, Sri Lanka
saara.kaizer@gmail.com

Ms. Karthiga Rajendran
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
karthiga.r@sliit.lk

Lakmini Abeywardhana
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
lakmini.d@sliit.lk

***Abstract*— This paper presents an integrated, artificial intelligence-driven research designed to optimize academic writing and research workflows. Acknowledging the challenges posed by traditional, manual document editing, including inefficient citation management, rigid formatting standards, and cumbersome content organization, we propose a comprehensive solution that enhances collaboration and productivity. The research offers automated citation recommendations and IEEE-compliant formatting, an artificial intelligence-based academic writing refinement tool, and dynamic mind map generation to visually organize complex ideas. Additionally, it incorporates expertise prediction techniques to facilitate more effective contributor collaboration. By leveraging advanced natural language processing and transformer models, the research significantly reduces manual effort while ensuring high-quality, consistent academic output. Experimental evaluations demonstrate marked improvements in writing efficiency and citation accuracy, underscoring the potential of artificial intelligence-assisted methodologies to transform the academic research process.**

Keywords*— Natural Language Processing (NLP), Academic writing, AI-assisted writing, Citation management, IEEE formatting, Knowledge visualization, Mind maps, Expertise prediction, Transformer models, Sentence-BERT, LaTeX formatting.

I. Introduction

Academic research and writing encompass a complex and time-intensive process, necessitating researchers to conduct literature reviews, manage citations, structure content coherently, and adhere to stringent formatting and publication guidelines. Conventional document editing tools provide rudimentary text-processing capabilities but lack intelligent automation to assist users in dynamically organizing content, formatting documents accurately, and enhancing collaboration. The inefficiencies arising from manual efforts, tool-switching, and citation management increase cognitive load and diminish productivity.

The current study introduces several artificial intelligence-driven enhancements to streamline academic writing and knowledge management. First, an automated citation tool is proposed, which suggests relevant research papers based on user-highlighted text. By analyzing contextual information, the proposed approach retrieves sources from a database and provides IEEE-formatted citations, enhancing efficiency, accuracy, and academic integrity while reducing manual searching efforts. Second, an AI-powered academic writing refinement approach is developed to enhance grammar, structure, and formal tone while ensuring IEEE compliance. The research objective automates the conversion of research content into IEEE format, maintaining strict adherence to citation, font, and layout standards. It integrates seamlessly with a LaTeX-based formatting template, reducing manual effort and ensuring accurate structuring of sections, equations, tables, and references. Additionally, a user-friendly interface allows researchers to refine content dynamically.

Additionally, to enhance knowledge visualization, an automated approach for generating customizable mind maps from textual data is introduced. This approach bridges knowledge management and collaborative editing [1], overcoming limitations of manual mind-mapping tools. Finally, expertise prediction is improved through a transformer-based approach using Sentence-BERT and hierarchical clustering to analyze LinkedIn profiles. By recognizing skill variations, this model enhances expertise classification while addressing ethical and data privacy concerns. Subsequent sections demonstrate how these components operate in tandem to optimize the academic writing process.

II. Literature Review

A. AI-Assisted Document Formatting

The Academic writing and research paper formatting have traditionally been manual and time-consuming, requiring strict adherence to IEEE and other publication standards. The emergence of AI-driven writing assistants and automated formatting tools has improved efficiency, but existing solutions lack an end-to-end integration of academic writing enhancement, structural compliance, and LaTeX-based formatting. Studies highlight that AI-powered text refinement tools assist with basic grammar and readability but fail to enforce IEEE academic tone, citation standardization, and logical coherence, which are crucial for research writing [2]

Large language models (LLMs) like GPT-4, BERT, and T5 have shown high proficiency in NLP tasks, yet they are not optimized for research writing. The Llama 2-7B model used in this research improves academic writing by transforming informal text into structured, IEEE-compliant text while ensuring technical accuracy and coherence. However, existing models often require fine-tuning and quantization for efficient operation, especially in resource-constrained environments [3]. Research in quantization techniques has demonstrated that reducing model size while maintaining accuracy enables the deployment of large language models in constrained environments, making AI-powered academic writing more practical [4].

LaTeX-based tools such as Overleaf[1] and ShareLaTeX[2] provide structured templates for IEEE formatting, but they require manual coding, making them inaccessible to users unfamiliar with LaTeX. Studies suggest that while LaTeX improves document professionalism and citation management, it can be challenging for new users, leading to inefficiencies in workflow [5].

B. Research Paper Recommendation and Citation Generator

Research paper recommendation and citation management have evolved from traditional methodologies such as TF-IDF and BM25 to advanced Natural Language Processing (NLP) techniques. Early methodologies, relying on metadata filtering, encountered challenges in capturing semantic relationships within academic texts. Transformer-based models, including SciBERT and SPECTER, have enhanced context-aware retrieval but necessitate fine-tuning for specialized content [6].

Tools such as Zotero[3] and EndNote[4] provide static citation formatting, resulting in inefficiencies in research workflows. Document collaboration platforms, exemplified by Overleaf, prioritize formatting rather than intelligent citation recommendations. As shown in Table 1, these tools do not support contextual citation, semantic search for relevant papers, automated citation placement, or long-text processing for citation context, all of which are crucial for streamlining research. Deep learning approaches, including SBERT and ANN, enhance semantic search, improving document similarity detection but face limitations in processing extensive texts [7], [8].

Citation generation models, including BERT-to-BART and T5, automate formatting but frequently lack domain-specific adaptation, leading to inaccuracies. Existing tools do not integrate contextual linking, impeding efficient reference location.

C. Automated Mind Map Generation

Recent advances in NLP and machine learning have revolutionized the automation of mind map generation by addressing the limitations of manual diagramming. Early techniques, such as TF-IDF and TextRank, focused primarily on statistical keyword extraction but frequently missed the contextual nuances intrinsic to natural language. In contrast, a graph - based approach that integrates the Rapid Automatic Keyword Extraction (RAKE) algorithm with the Keyword Extraction using Collective Node Weight (KECNW) model offers enhanced performance by effectively leveraging text structure to identify candidate keywords [9]. Moreover, conventional dependency parsing methods, though useful for extracting syntactic relationships, are often vulnerable to noise that obscures deeper semantic links. To overcome this challenge, recent research has employed attentive graph convolutional networks (A-GCN) that dynamically weight dependency edges, thereby isolating relevant semantic connections from superfluous syntactic details [10]. These technical advancements underscore the importance of deep contextual analysis in achieving a more accurate and robust mind map generation.

Parallel developments in graph structuring have introduced efficient mechanisms for converting entire documents into relation graphs via sequence-to-graph transformation, which are further refined through reinforcement learning to prune redundant or noisy connections [11]. Research studies such as English2MindMap enable the generation of multilevel mind maps, wherein high-level nodes can be interactively expanded into detailed sub-maps, thereby enhancing both visualization and comprehension of complex texts [12]. In addition, sophisticated text mining algorithms have been developed to automatically extract and structure key concepts into coherent mind map representations, although preserving semantic integrity across large datasets remains challenging [13]. Other techniques, such as Latent Dirichlet Allocation (LDA) for topic modeling and transformer-based models like BERT for contextual summarization, have also been explored. However, LDA's inability to capture hierarchical structures and BERT's high computational demands limit their applicability in generating scalable and semantically rich mind maps. While these approaches show promise in improving concept extraction and semantic analysis, they still face challenges in hierarchical accuracy, scalability, and semantic consistency.

The proposed study enhances research productivity and optimizes collaboration by integrating AI-driven document structuring and advanced NLP-based citation management. Unlike traditional tools, it assigns expertise-based keywords to document sections, ensuring efficient contributor selection. Its form-based Quill.js UI facilitates structured research paper drafting, AI-powered refinements, and IEEE LaTeX formatting [14], bridging the gap between AI-assisted writing and real-time collaboration. A multi-stage NLP pipeline, incorporating high-precision retrieval, semantic matching, and context-aware reranking, enhances citation accuracy and workflow automation. Additionally, automated mind map generation improves knowledge extraction while reducing computational overhead. By leveraging transformer-based models for semantic analysis, structured content generation, automated formatting, and visual mind mapping to enhance comprehension, the system provides a comprehensive, end-to-end academic research solution.

While tools such as Zotero, EndNote, and Overleaf assist with bibliographic management and formatting, their capabilities are largely limited to static reference insertion and manual document structuring. They offer little support for semantic understanding, context-aware citation placement, or AI-assisted formatting aligned with standards such as IEEE, often requiring users to enforce compliance manually. In addition, traditional tools rely on keyword-based search mechanisms that fail to capture deeper contextual relevance. In contrast, WriteWizard introduces a paradigm shift by leveraging AI to enable contextual citation recommendations

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[1] https://www.overleaf.com/
[2] https://www.sharelatex.com/
[3] https://www.zotero.org.
[4] https://endnote.com

based on the semantic flow of a document. It performs semantic retrieval of scholarly literature and inserts citations automatically at appropriate junctures. It also supports long-form academic text, ensuring that citations remain contextually grounded within broader narrative structures. This functionality is further strengthened through a multi-stage natural language processing pipeline featuring semantic matching and context-aware reranking, which improve citation precision and relevance. Moreover, existing platforms lack integrated support for automated mind map generation, limiting their ability to facilitate knowledge visualization. These innovations streamline research workflows and enhance the coherence and accuracy of academic writing, positioning AI-assisted platforms like WriteWizard as comprehensive solutions for modern research needs.

Fig. 1 below provides a detailed comparison between existing academic tools and the proposed WriteWizard platform. It outlines the components supported by each system, the AI/NLP techniques utilized, and the corresponding functionalities.

Tool / Feature	Real-time Collaborative Edit	AI Mind-map Generator	AI writing / Refinement	Citation Management	LaTeX / IEEE Format	Reference Paper Suggester
WriteWizard	Yes	Yes	Yes	Yes	Yes	Yes
Ayoa	Yes	Yes – Organic style	Yes – Focus/brainstorm	No	No	No
Whimsical	Yes	Yes – prompt-to-map	Outline helper	No	No	No
Paperpal	Inside Word	No	Yes – Journal checks	Yes – formatted refs	Overleaf plugin	Yes – inline suggestions
Overleaf	Yes	No	Grammar tool	Yes – BibTeX only	Yes – full LaTeX	With plugins
Authorea	Yes	No	Style tips	Yes – Auto BibTeX	Yes – LaTeX/HTML	Yes – academic DB search

Fig. 1. Comparison of AI research writing tools

III. Methodology

By fusing data-driven insights with automated processes, the methodology addresses challenges in producing standardized scholarly outputs across various contexts while employing mechanisms for content refinement, reference management, and visual mapping. This balanced integration of theory and practice sets the stage for a detailed exploration of the study's core components.

A. AI-Assisted Document Formatting

The proposed AI-assisted research writing tool integrates academic text refinement, structured content generation, and automated IEEE-compliant formatting using Llama 2-7B and a collaborative user interface (UI). The methodology consists of four major components: dataset preparation, AI-driven text refinement, UI design, and LaTeX-based document formatting to create a seamless academic writing experience.

The first stage involves dataset preparation and model training. To fine-tune the Llama 2-7B model, a custom dataset was created using IEEE research papers as the primary data source. The dataset preparation involved extracting structured sections to teach the model proper research formatting [2]. Additionally, a formality style transfer technique was applied to transform formal academic paragraphs into simplified versions, creating a bidirectional dataset where the model learns to refine informal text into structured academic writing and vice versa [3]. This method ensures that the AI model accurately learns grammar rules, academic tone, citation placements, and structured argumentation, allowing it to convert general research text into IEEE-compliant writing.

The fine-tuning process involved adapting the pretrained Llama 2-7B model using a domain-specific dataset focused on IEEE-style academic writing.[5] The model was trained on examples of structured academic content, enabling it to learn patterns in formal tone, grammar correction, and citation formatting. To ensure efficient performance, 4-bit quantization was applied using the Unsloth framework, allowing fine-tuning with significantly reduced memory usage. The process involved updating the model's internal weights based on supervised instruction learning, using pairs of informal and formal academic text. The approach focused on parameter-efficient fine-tuning, optimizing the model specifically for research paper editing without requiring extensive retraining or resource-intensive modifications.

Once trained, the model enhances research writing by identifying and correcting grammatical errors, improving sentence structure, and enforcing IEEE academic tone. The model ensures that research content follows passive voice conventions, structured argumentation, and precise technical vocabulary, maintaining coherence across sections [3]. Logical connections between paragraphs are enforced by the model to improve flow, sentence transitions, and consistency in terminology. AI also refines clarity, eliminates redundancy, and ensures adherence to IEEE writing conventions, producing publication-ready academic content.

To support research writing, a form-based UI using Quill is implemented within a collaborative environment. This UI allows researchers to create structured sections dynamically, write content interactively, and apply AI-based academic refinements in real-time [4]. Users can select text for AI enhancement or submit the entire document for comprehensive academic writing improvements. The collaborative editing feature enables multiple authors to refine content simultaneously while preserving document structure. Unlike conventional document editors, the model only refines text, while LaTeX formatting is handled separately.

The refined content is then applied to an IEEE-compliant LaTeX template to ensure proper document formatting, font consistency, and citation structuring [5]. The LaTeX template adheres to IEEE standards, using Times New Roman (10pt, double-column layout) for the body text. Section titles are formatted in bold 12pt font, while subsection titles use bold 11pt font, ensuring a clear document hierarchy. Figures, Mathematical equations and tables are automatically formatted, labeled, and numbered, ensuring compliance with IEEE publication guidelines.

Finally, a conversion process is applied, where abbreviations are replaced with their short forms using regex. The document is then automatically exported as a IEEE-compliant PDF, Fig. 2 illustrates the complete workflow, detailing how raw research content is processed, refined, and structured. providing a submission-ready research paper with minimal manual effort.

[5] https://docs.google.com/spreadsheets/d/18IWPQMXr-hyewLDQa7joMEAGmrU8_u6yP9YLCRdITN4/edit?usp=sharing

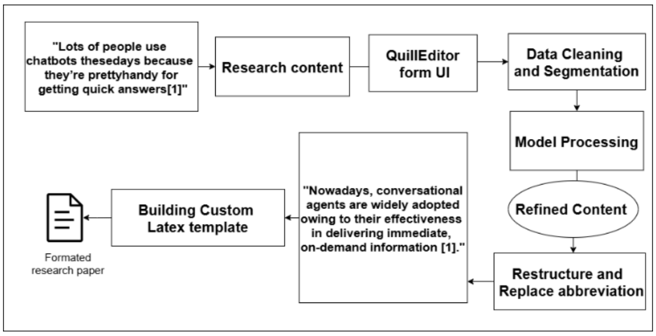


Fig. 2. AI-assisted document formatting component workflow

By integrating AI-driven academic writing enhancement with LaTeX-based formatting automation, this reduces the workload for researchers, ensures IEEE compliance, and enhances writing clarity and consistency. The proposed method bridges the gap between AI-assisted writing and structured academic publishing, making research documentation faster, more efficient, and standardized.

B. *Research Paper Recommendation and Citation Generator*

To address the limitations of conventional research paper retrieval and citation management research, the proposed study introduces an end-to-end integrated solution that combines keyword-based filtering, semantic similarity-based ranking, and automated citation generation within a collaborative document editing environment. The system is designed to support academic workflows by enhancing the relevance, accuracy, and contextuality of reference suggestions and citation placements.

The process begins with data acquisition, where a comprehensive research paper dataset is assembled by retrieving metadata and abstracts from reputable sources such as CrossRef[6], OpenAlex[7], and arXiv[8] using their respective APIs. This aggregated dataset, formatted in JSON, includes essential metadata such as titles, authors, publication sources, DOIs, and abstracts, forming the backbone of the training data for the models used in the system.

The initial stage of the model pipeline involves keyword extraction from user-highlighted content within the document. This is achieved using a Named Entity Recognition (NER) model fine-tuned on a BERT-base uncased architecture. The text undergoes preprocessing steps such as tokenization and stop word removal before being passed through the NER model. The model employs BIO-tagging to identify and extract contextually relevant keywords from the text. The extracted keywords are stored in a CSV file for downstream filtering. The BERT-based NER model was trained on scientific abstracts using BIO-tagged entities and outputs entity-level keyword phrases that serve as input to the filtering mechanism.

Following keyword extraction, the system proceeds with the retrieval of potentially relevant research papers. Keyword-based search is performed using TF-IDF and BM25 scoring mechanisms against the indexed research paper database. This initial retrieval serves as a coarse filtering mechanism to reduce the search space for semantic analysis. TF-IDF and BM25 provide lightweight, zero-shot ranked lists without requiring training.

To enhance retrieval precision, a second model is employed to conduct semantic similarity-based ranking. For this, the Sentence-BERT (SBERT) model is fine-tuned using the Semantic Textual Similarity Benchmark (STS-B) dataset, allowing for more accurate contextual matching. Abstracts from the dataset are embedded into dense vector representations using the fine-tuned SBERT model. These embeddings are stored in a pickle file and later loaded into memory for inference. For efficient approximate nearest neighbor (ANN) search, the embeddings are indexed using FAISS with the IndexFlatIP method, which supports cosine similarity-based ranking. The system calculates similarity scores between the user-highlighted content and the stored research paper abstracts and filters the most contextually relevant results for display.

The refined set of papers is presented to the user in the front-end interface as a list of cards, each showing the title, author name(s), and paper ID. When a user clicks on the 'View' button of a card, the system retrieves and displays the abstract of the corresponding paper. Additionally, it highlights the sentence within the abstract that most closely matches the selected text, using the semantic alignment output from the SBERT model.

For citation generation, the study integrates a third model that is a fine-tuned version of the Flan-T5 transformer. This model has been trained on thousands of citation examples and is capable of generating IEEE-formatted citations using the metadata retrieved from the initial dataset. When a user clicks the 'Cite' button, the system invokes this model to generate a citation based on the paper's metadata. The citation is then displayed in IEEE format.

To complete the workflow, the system allows the user to click the 'Insert Citation' button. This action automatically inserts the generated citation number in line with the highlighted text in the document and appends full reference to a dynamically maintained bibliography section in IEEE style. Citation indices are managed and updated in real time to maintain coherence and ordering within the reference list. The overall workflow of the research paper recommendation and citation generator is illustrated in Fig. 3, which outlines the sequence from keyword extraction to citation generation.

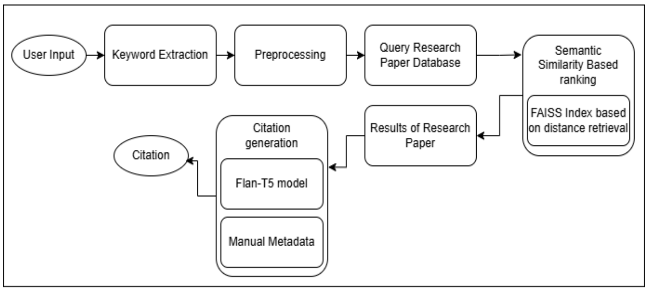


Fig. 3. Research paper recommendation and citation generator workflow

In addition to automated citation functionality, the platform also supports manual citation entry. Users can input bibliographic metadata such as reference number, title, authors, publication source, and DOI. Upon submission, this data is processed through the citation generation module to

[6] https://www.crossref.org/
[7] https://docs.openalex.org/download-all-data/openalex-snapshot
[8] https://arxiv.org/

produce a correctly formatted IEEE citation, which is then inserted into the document in the same manner as automated citations.

By integrating keyword-based search, semantic similarity matching, and dynamic citation generation into a single seamless workflow, the system minimizes manual effort and ensures high contextual accuracy. The use of transformer-based architectures like SciBERT [6], SBERT, and Flan-T5 provides a robust foundation for handling scientific text and delivering relevant, meaningful citation suggestions. This methodology not only streamlines the research and writing process but also ensures the integrity and contextual appropriateness of scholarly references in academic writing.

C. *Hierarchical Text-to-Mind Map Conversion via NLP*

The proposed approach for mind map conversion automates hierarchical mind map generation from raw text by leveraging a fine-tuned transformer-based language model. The training dataset was built using publicly available academic content in the machine learning domain. Text snippets from various document sections served as inputs for mind map generation. The selected samples varied in length and structure, and each snippet was manually paired with a JSON mind map reflecting its semantic structure and topical flow. Earlier attempts to construct the dataset included automated methods such as keyword pair generation with weightage and curated relation-based graphs, but these were replaced due to lack of structural consistency. This JSON format explicitly encodes hierarchical parent-child relationships, serving as the ground truth for the mapping task. The schema follows a strict single-root format, where each node can recursively contain nested children, enabling depth in semantic representation.

Initial investigations explored multiple natural language processing techniques, including coreference resolution, keyword extraction, relation extraction, dependency parsing, and named entity recognition, to structure text into coherent mind maps. However, these combinations did not yield sufficient connectivity or capture the hierarchical structure required. Consequently, the Mistral-7B-v0.3 model was selected for its extended vocabulary of 32,768 tokens, which delivers superior domain-specific language comprehension and a robust capacity to model inter-sentence dependencies. Comparative evaluations with alternative models such as SciBERT, Phi-2, and LLaMA-2-7B confirmed that these alternatives fell short in preserving hierarchical data and in reliable JSON parsing.

A minimal preprocessing pipeline including sentence segmentation, tokenization, coreference resolution, and stop word removal was applied to improve data quality without altering its intended meaning. Data augmentation through paraphrasing and summarization further enhances training diversity and robustness.

During fine-tuning, an adapted pipeline was implemented in which the model's final transformer layers were modified to output node-level representations aligned with the JSON mind map structure, effectively replacing the default language modeling head. Transformer-based self-attention layers capture intricate inter-sentence dependencies and preserve subtle contextual cues essential for hierarchical representation. The model was further trained on modified input text to produce both extended and simplified mind map representations, addressing different levels of detail. Quantization is performed using Unsloth and 4-bit precision, ensuring computational efficiency while maintaining accuracy. Postprocessing steps validate the generated JSON structure by enforcing token limit constraints and proper syntax, ensuring that the output adheres to the desired schema. The workflow for this module is depicted in Fig. 4, illustrating the process by which the model directly generates hierarchical mind maps from raw text.

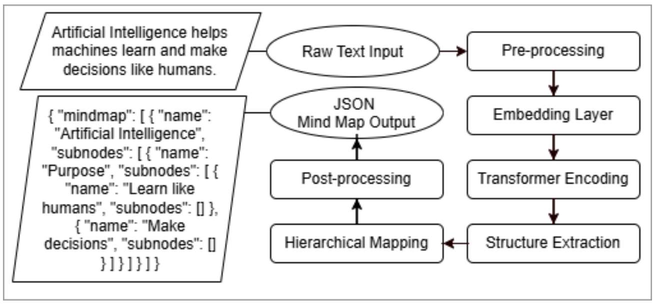


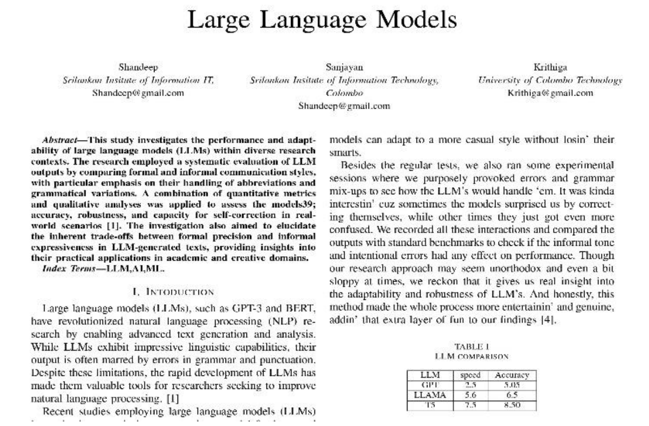
Fig. 4. Hierarchical mind map generation workflow

Additionally, the approach processes any given topic by generating pertinent content and producing an accurate hierarchical mind map. For complete documents, topics, subtopics, and corresponding content are extracted, with the paper title designated as the root node and subsequent layers capturing the detailed structure. The generated JSON mind maps incorporate images through a hybrid image matching technique that employs contextual analysis and cosine similarity. A matching score is computed between the image description and the node text, and the image is integrated only if the score exceeds a predefined threshold, which was empirically tuned to avoid semantic drift. A brief visualization module based on D3.js renders interactive, tree-based outputs with customization options for compact integration into the overall workflow.

Taken together, this sets the stage for further analysis, leading to a discussion on implementation outcomes and practical impacts.

IV. Results and Discussions

The evaluation of the proposed research demonstrates significant enhancements in various aspects of academic research workflows. The tool as whole was evaluated for academic writing quality, formatting accuracy, user efficiency, and IEEE compliance. For this task LLaMA 2-7B is well-suited due to its strong contextual understanding, advanced language modeling capabilities, and efficient text transformation. The AI effectively transforms informal text into IEEE-compliant writing, ensuring consistency in technical terminology and logical coherence, while preserving the original meaning. The model's performance was evaluated using ROUGE and BLEU scores, measuring content preservation. User testing in a collaborative Quill.js interface revealed a 60% reduction in editing time, as the tool streamlined content refinement. Additionally, the LaTeX template automated IEEE formatting by ensuring proper font selection, section hierarchy, and reference structuring, so that users simply create arbitrary sections, add content, and generate a fully formatted PDF with refined content. An example output is shown in Fig. 5. so that the final PDF output required no manual adjustments. Future improvements will expand AI support for domain-specific writing, enhance citation accuracy, and support additional formatting standards.



Large Language Models

Shandeep
Srilankan Insitute of Information IT,
Shandeep@gmail.com

Sanjayan
Srilankan Insitute of Information Technology,
Colombo
Shandeep@gmail.com

Krithiga
University of Colombo Technology
Krithiga@gmail.com

***Abstract*—This study investigates the performance and adaptability of large language models (LLMs) within diverse research contexts. The research employed a systematic evaluation of LLM outputs by comparing formal and informal communication styles, with particular emphasis on their handling of abbreviations and grammatical variations. A combination of quantitative metrics and qualitative analyses was applied to assess the models39; accuracy, robustness, and capacity for self-correction in real-world scenarios [1]. The investigation also aimed to elucidate the inherent trade-offs between formal precision and informal expressiveness in LLM-generated texts, providing insights into their practical applications in academic and creative domains.**

***Index Terms*—LLM,AI,ML.**

I. INTODUCTION

Large language models (LLMs), such as GPT-3 and BERT, have revolutionized natural language processing (NLP) research by enabling advanced text generation and analysis. While LLMs exhibit impressive linguistic capabilities, their output is often marred by errors in grammar and punctuation. Despite these limitations, the rapid development of LLMs has made them valuable tools for researchers seeking to improve natural language processing. [1]

Recent studies employing large language models (LLMs)

models can adapt to a more casual style without losin' their smarts.

Besides the regular tests, we also ran some experimental sessions where we purposely provoked errors and grammar mix-ups to see how the LLM's would handle 'em. It was kinda interestin' cuz sometimes the models surprised us by correcting themselves, while other times they just got even more confused. We recorded all these interactions and compared the outputs with standard benchmarks to check if the informal tone and intentional errors had any effect on performance. Though our research approach may seem unorthodox and even a bit sloppy at times, we reckon that it gives us real insight into the adaptability and robustness of LLM's. And honestly, this method made the whole process more entertainin' and genuine, addin' that extra layer of fun to our findings [4].

TABLE I
LLM COMPARISON

LLM	speed	Accuracy
GPT	2.5	5.05
LLAMA	5.6	6.5
T5	7.5	8.50

Fig. 6. Result from the automated IEEE format converter

In addition to writing, the study also evaluated research paper recommendation and citation generation. In the semantic retrieval phase, a fine-tuned SBERT model was assessed using cosine similarity to ensure improved semantic alignment. SBERT, combined with FAISS-based nearest neighbor retrieval using the IndexFlatIP index, enhanced the relevance of returned results by accurately matching embedded sentence meanings. For keyword-based retrieval, a fine-tuned SciBERT filter achieved an F1 score a precision of 0.7696, and F1 score of 0.7565, effectively balancing precision and recall. The automated IEEE citation module, leveraging a fine-tuned Flan-T5 model, was validated using cosine similarity, confirming high accuracy in citation formatting. These advancements streamline academic research workflows by ensuring precise literature recommendations and high-quality citations, significantly reducing manual efforts in research retrieval and formatting. Fig. 6 shows the citation generation interface showing automated IEEE formatting (via Flan-T5) and a sidebar with retrieved reference papers, improving literature selection and citation accuracy.

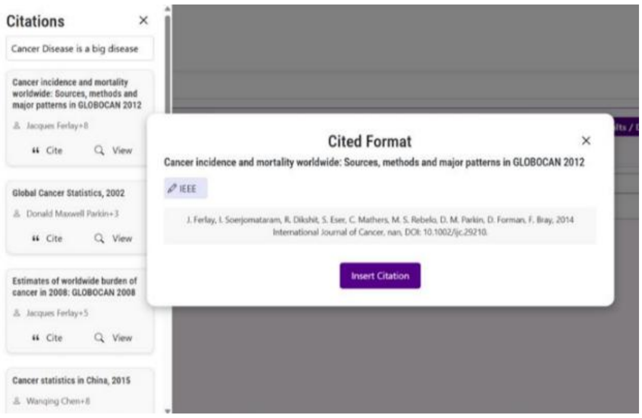


Fig. 7. Interface from reference suggester & citation generator

The study also evaluated the automated mind map generation module as a core component. The fine-tuned Mistral-7B-v0.3 model achieved a BLEU score of 78.2% and an F1 score of 76.6% on the test set, demonstrating strong alignment with manually created JSON mind maps. Due to the open-ended nature of mind maps, purely quantitative evaluation was limited, making qualitative benchmarking essential. Forum-based assessments confirmed improvements in semantic coherence and structural accuracy. Comparisons with a fine-tuned LLaMA-2-7B model and the pre-trained GPT-4 showed that the fine-tuned model produced more accurate mind maps with clearer semantic structure, supported by both metric results and qualitative reviews. The D3.js-based visualization module supports interactive expansion, node editing, and real-time customization, with features such as image embedding and export options enhancing usability. Users can generate mind maps by entering raw text into an editor or selecting documents from a curated database, typically consisting of abstracts, introductions, or other semantically rich academic sections. An example of a generated mind map is shown in Fig. 7, illustrating the model's capability to produce structured and meaningful visual outputs.

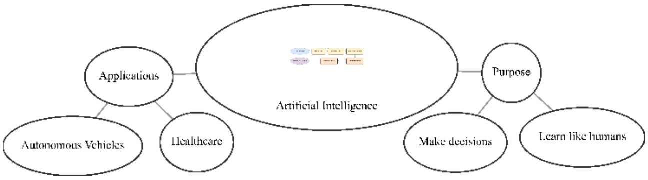


Fig. 5. Mind map generated using the proposed system

Together, these components form a cohesive, AI-driven ecosystem that not only elevates academic writing and research processes but also streamlines collaboration in a natural and efficient manner. The improvements in efficiency, accuracy, and IEEE compliance have significantly reduced the manual workload. Complementing these benefits, the entire tool is implemented as a MERN-based web application that seamlessly unifies advanced AI-driven functionalities with real-time collaborative editing, scalable data management, and interactive features powered by WebSockets.

V. CONCLUSION AND FUTURE WORK

The integrated solutions introduced in this research show significant advancements in research paper recommendation, citation management, automated mind mapping, and academic writing refinement. The synergy of specialized transformer-based models such as fine-tuned SciBERT, SBERT, Flan-T5, Mistral-7B-v0.3, and Llama 2-7B underscores the growing importance of NLP-driven pipelines for efficient discovery of knowledge. By leveraging semantic similarity, contextual analysis, real-time automation, and interactive visualization, each component delivers robust performance while reducing manual effort, thus enhancing user productivity in educational and professional settings.

Future work involves expanding reference databases to encompass major research hubs, refining expertise-ranking methodologies, and integrating advanced image recognition, ontology-based visualization, and domain-specific writing improvements. Supporting multiple citation styles like APA and MLA, along with additional standards such as ACM and Springer, will foster greater accessibility and compliance. Real-time updates, deeper LaTeX integration, and personalized recommendations can further streamline collaboration and knowledge sharing. Together, these enhancements promise broader scalability, richer contextual insights, and a more seamless user experience for researchers worldwide.

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