International Journal of Research in Engineering and Innovation (IJREI)
Journal home page: https://ijrei.com/
ISSN: 2456-6934
Vol. 10, Issue 2

REVIEW PAPER

AI-Powered Smart Notes for Effective Learning: A Comprehensive Review of Techniques, Applications, and Future Directions

Anuprash Gautam, Aanvi, Aastha Gupta, Gunjan Sharma, Anamika Singh

Department of CSE-AI, Meerut Institute of Engineering and Technology, Meerut, India

Article Information

Received: 18 April 2026
Revised: 02 May 2026
Accepted: 03 May 2026
Available online: 04 May 2026

Keywords:

AI-Powered smart notes
Automated summarization
Retrieval-augmented generation
Personalized learning
Spaced repetition
Educational NLP

Abstract

There are various problems faced by traditional note-making methods, such as static algorithms and inefficiency in handling large volumes of educational content, like research papers, lectures, videos, textual content etc. Since AI is rapidly being used in the education field, smart note generation tools are emerging to promise a solution to empower learning effectively. Smart note generation methods are emerging for improvising personalization for users. This paper prescribes our complete review of 25 Research papers from (2016-2026) in the AI smart note generation system, which focuses on the foundational tech infrastructures, including RAG, knowledge graph construction, spaced recursion, and adaptive personalization. We are going to analyze how these technologies can collectively transform noisy educational data into an organized, context-aware, and learner-focused content. This paper also analysis the evaluation matrices, datasets, and practical applications like learners' revision methodologies, MOOCs, and compliance tutorials. Moreover, we will consider critical obstacles to hallucination in enormous language models, which include securing confidential data, inherent difficulties, and the problem faced in measuring true learning results. Finally, for further research in future on topics like human-in-the-loop verification, GPAI, VLM, and privacy-preserving systems are also showcased here. This review points toward providing a structured classification and research strategies for featuring AI-powered note-taking technologies.

1. Introduction

The This review summarizes key developments in NLP for automatic text summarization and information condensation [1-5]. Recent advances in Generative AI and Large Language Models have facilitated personalized learning experiences, enhanced content creation efficiency, and significantly improved summarization capabilities across a wide range of domains [6-11]. The introduction of Transformer-based architectures and self-supervised models, including BERT and RoBERT has led to substantial improvements in language understanding and representation learning [12-14], meanwhile, graph-based ranking models continue to serve as a fundamental approach for extractive summarization techniques [15]. Despite these developments, several challenges persist, including the effective processing of long and complex documents, preserving semantic richness, and achieving computational efficiency. Additionally, existing summarization approaches—both neural and graph-based—often struggle with redundancy and deep semantic understanding, highlighting the need for more robust, efficient, and context-aware summarization frameworks [6, 15].

AI-powered note-taking systems have emerged as effective solutions for automating the capture, organization, and summarization of information [3]. These systems are motivated by the need to overcome the limitations of conventional manual note-taking methods, including handwriting and typing, which are often tedious and prone to

Corresponding author: Anamika Singh
Email Address: anamika.singh@miet.ac.in
https://doi.org/10.36037/IJREI.2026.10206

errors during lectures or meetings [3]. Additionally, the rapid expansion of internet-based information has intensified the problem of information overload, making it increasingly difficult for users to process large volumes of content efficiency [4].

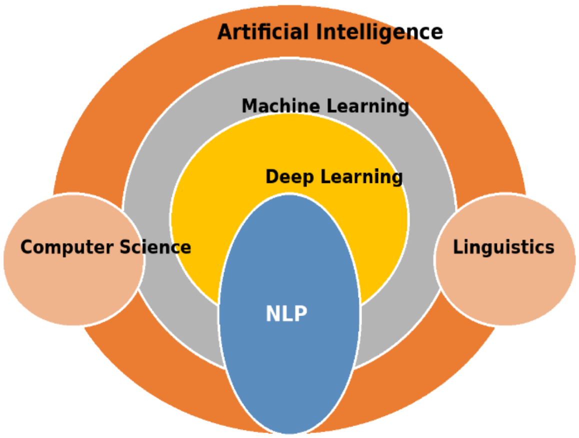

Figure 1: Parts of Artificial Intelligence

Traditional note-taking methods, such as handwriting or typing, often struggle to keep pace with the rapid flow of information during lectures or meetings. These approaches can be time-consuming, prone to human error, and may result in incomplete or poorly structured notes. Additionally, manual notetaking requires continuous attention, which can reduce comprehension and make it difficult to capture key ideas accurately, especially when dealing with large or complex information.

The emergence of AI-powered note-taking systems marks a substantial shift in automated knowledge acquisition and information management. Leveraging advanced Natural Language Processing (NLP) and machine learning techniques, these systems enable real-time content capture, semantic structuring, and abstractive summarization. By reducing cognitive load and mitigating human-induced inconsistencies, AI-driven note-taking solutions facilitate efficient information retrieval, improved knowledge and retention.

Scaling LLM size alone is insufficient for complex reasoning tasks [2]. Current summarization methods remain inefficient, semantically shallow, and prone to redundancy, especially for large and complex documents [3, 4, 15]. Transformer models face scalability issues due to quadratic computational cost on long inputs and limited multimodal applicability [12]. Fine-tuning instability, rigid architectures, and reliance on single-task learning further restrict generalization and robustness [13], [14]. Additionally, LLMs struggle with long scientific document summarization, raise concerns of bias, hallucinations, and privacy, and lack effective integration with knowledge-graph-based educational systems [5-7].

1.1 Contribution of this Review Paper

This review paper consolidates and analyses key limitations identified in prior studies, including the restricted multilingual generalization of The Metamorphosis Formula, limited exploration of chromatic algorithms across interdisciplinary domains, and scalability challenges in processing large inputs [11]. It further examines architectural constraints such as instability during fine-tuning of BERT on small datasets and the need for efficient local, restricted attention mechanisms to handle long-context inputs. Highlights improved precision and time management while cautioning against data privacy issues, algorithmic bias, and the risk of over-dependence on technology [3].

The contribution of this review paper includes:

- A taxonomy of the variety of techniques used in AI smart notes,
- A discussion of key areas and evaluation methodology of AI smart note application and
- A list of open challenges and future research opportunities related to this rapidly growing field.

Table 1: Comparison of traditional notes vs AI-powered Smart Notes

Feature	Traditional Notes	AI Smart Notes
Creation	Manual	Automatic
Personalization	No	Yes
Time	High	Low
Multimedia	Limited	Rich
Adaptivity	Static	Dynamic

Table 1 highlights the key differences between conventional note-taking methods and modern AI-powered smart notes, emphasizing efficiency, flexibility, and technological advancement. Traditional notes are created manually, requiring users to write or type content themselves, which makes the process time-consuming. In contrast, AI smart notes are generated automatically using intelligent systems that can summarize, organize, and structure information with minimal human effort. In terms of personalization, traditional notes offer limited customization since they depend entirely on the user's input and style. AI smart notes, however, can adapt to user preferences, learning patterns, and needs, providing a more tailored and user-specific experience.

Time efficiency is another major difference. Traditional note-taking demands significant time for writing, organizing, and revising. AI-powered notes drastically reduce this effort by automating these tasks, making the process faster and more efficient. Regarding multimedia support, traditional notes are usually restricted to text and simple diagrams. AI smart notes can integrate rich content such as images, audio, videos, and interactive elements, enhancing understanding and engagement. The traditional notes are static, meaning they do not update unless manually edited. AI smart notes are dynamic, allowing continuous updates, real-time improvements, and adaptive learning based on new information.

1.2 Smart Note-Taking Systems

A new technique called COT prompting, which has been shown through effective studies to improve the reasoning processes of LLM [2]. This is accomplished by improving the speed and precision of the output produced by speech recognition and NLP capabilities, as well as using smart techniques such as summarization. The paper discusses the development of systems that use advanced AI capabilities to fully automate capturing and organizing data both in real time as it occurs, and afterwards so that any information can be easily retrieved later [3].

2. Extractive and Abstractive Summarization

Extractive Summarization: Selecting and concatenating original sentences from the source. [1] Abstractive Summarization: Generating entirely new text that captures the core meaning. [1] Hybrid Approaches: Combining both methods for better coherence. [1] There are three main approaches to summarizing text: extractive, abstract, and hybrid. Extractive summarization works by taking pieces of originally written materials (sentences from the source) and putting those pieces back together to create a summary [1, 4, 22]. Abstractive summarization creates new written material that is meant to represent the main concept of the original material [23, 24]. Using both techniques to summarize text is called Hybrid Approach [22].

2.1 Knowledge Graphs in Learning

Text summarization techniques include extractive, abstractive, and hybrid approaches. Extractive summarization involves selecting and concatenating original sentences from the source text [22]. Abstractive summarization generates new text that captures the core meaning of the original text [23, 24]. Hybrid approaches combine both extractive and abstractive methods to improve summarization performance [22]. Transformers are a neural network architecture that uses only attention-based models and has many applications in natural language processing (NLP) such as machine translation, text summarisation and answering user's questions [12, 13]. The BERT model was built on top of Transformers, which use Bidirectional Encoder Representations, to produce state-of-the-art results, as described in reference [14]. The performance of BERT can still be enhanced by employing the RoBERTa model during its training phase. A retrieval-based approach with meta-learning has been recommended to enhance the performance of neural code summarization [21].
Transformer models are a kind of neural network architecture, developed to use only attention mechanisms. They're being used in many natural language processing tasks like machine translation, text summarization, and question answering [12], [13]. BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained language model that has reached state-of-the-art levels in multiple forms of natural language processing. An additional variant of BERT, RoBERTa (robustly optimized BERT's pretraining), further increased the performance level of BERT [13, 14].

2.2 Retrieval-Augmented Generation

RAG (Reinforcement-based Application Generation) can provide an alternative way to generate summaries of academic research, as well as create summaries of text using databases and library resources [13]. In addition, RAG enhances the performance of traditional means of verifying the validity of research through the use of more advanced methods for searching academic databases, such as using a neural network-based system [22]. RAGs search for documents in electronic libraries by continuously scanning documents for the relevant keywords through their databases. RAGs enhance traditional commentaries by eliminating errors, including redundancies and typos. Lastly, RAG will create derived information based on all the search results produced from the documents and then utilize this derived information in their comments to generate summaries of their respective project work. It has provided evidence of improved performance in various knowledge-based NLP tasks, including question answering and summarization [9]. Research has shown that using RAG has enhanced the performance of language models on few-shot learning experiments [10]. The transformer architecture employed in RAG has been identified to yield improved results when applied to machine translation and other types of NLP tasks [12]. The application of RAG has been demonstrated to yield improved results for BERT for various NLP tasks [13], [14].
RAG was compared with TextRank, a graph-based summarization algorithm [15]. Additionally, RAG has been and will continue to be compared against LSTMs (long-short-term memory) networks/recurrent neural networks to determine its ability to enhance the accuracy of learning across multiple unsupervised-multitasks approaches. A retrieval-based mechanism that utilizes meta-learning has also been suggested as a potential means for improving how neural networks summarize code [21]. RAG has also been analysed with respect to utilizing a hybrid methodology together with the social mimic optimization technique as an alternative for performing text summarization [22]. In addition, researching ways to incorporate deep learning methodologies into summary generation of textual information, RAG has emerged as a comparison method to perform abstractive forms of textual summarization [23].

2.3 Spaced Repetition and Active Recall

Spaced repetition is a method of Learning by which you review information that you have studied for periods of time that gradually increase. Studies have shown that this method of reviewing helps to store information for long-term retrieval [19]. Active recall is a method of Learning by which you attempt to recall things you have learned from your memory rather than merely reviewing what you have studied. Again, this method has been shown to be very successful in enhancing long-term memory of previously learned information [20].
The combination of using spaced repetition and active recall can be a wonderful way to remember new information. Repeatedly reviewing material at periods that are progressively more spaced intervals and actively attempting to recall that material from memory can enhance the long-term retention of that material and enhance the likelihood of your successful recall of that material [19, 20]. Both methods of learning (spaced repetition and active recall) have demonstrated efficacy in a variety of educational Learning situations, including learning a foreign language, to memorizing facts, to developing skill competencies [19]. Both methods of learning

are successful in many different educational activities, e.g. learning a foreign language, to memorizing facts, to solving problems [20]. Regardless, there can be significant effort and motivation required to implement the techniques of spaced repetition and active recall; students may have to devote time for developing ways to incorporate both techniques into their Learning routine and structure [19].

Table 2: Existing AI-Based Smart Note System

Author & year	Technique used	Application	Key contribution
Supriyono et al.(2024) [1]	Extractive & Abstractive summarization (Survey)	Text summarization for NLP & Education	Comprehensive survey of summarization techniques, evaluation metrics
Nannaware et al.(2024) [3]	NLP-based Summarizations and LLMs	Automatic note generation	Developed AI-powered system for generating concise, structured notes
Al-Sharif & Chen (2024) [5]	LLM-based summarization	Smart lecture notes	Developed AI-driven system for automatic academic note generation
Gupta et al.(2024) [6]	Transformer summarization	Educational content summarization	Improved readability and conciseness of learning material
Mishra & Singh (2024) [8]	Knowledge graphs	Personalized learning notes	Linked concepts to enhance conceptual understanding

3. Systematic literature review methodology

3.1 Database Used

A state-of-the-art model (PaLM 540B) achieved a record-breaking level of accuracy while utilizing only 8 examples of CoT from the GSM8K dataset. The PaLM 540B model also outperformed GPT-3 when fine-tuned [2]. GAI, is a collection of various algorithms that can create new content from previously created pieces of content, whether that is written (text) or recorded (audio) or visual (image). GAI "creates personalized learner engagement" and "creates entertaining and interactive learning content" [5]. GAI can turn boring text into "animated instructional materials" and immersive experiences in the "metaverse" to stimulate a student's curiosity for learning [5].

3.2 Search Keywords and Data Span

ASRs (Automatic Speech Recognition) convert audio or audio-visual lectures into written text. Techniques for driving lengthy transcripts into small units based on topic and chapter, allow for easy navigation through the text and make it easier to read and understand.

3.3 Inclusion and Exclusion Criteria

It shows that "natural reasoning abilities develop from very large language models based on several chain-of-thought examples" [2]. Uses Natural Language Processing (NLP), Speech Recognition, and Intelligent Summarization to provide a means for replacing tedious manual note-taking [3].

3.4 Paper Selection Process

The "few-shot" model provides specific examples with each example having a series of natural language logic reasoning to arrive at an answer rather than just giving standard prompt inputs [2]. Compares multiple algorithms (such as Latent Semantic Analysis), provides a variety of evaluation metrics and gives examples of algorithms (for example, DimSum or CTRLsum) with different sets of sample data. [4]

3.5 Methodology

Students participated in the study and were randomly divided among an experimental group and a control group for each dataset. All four datasets were comprised of English-language newspapers (CNN/Daily Mail, NewsRoom), articles published on the web (ArXiv), and news articles from the Canadian Black Press newspaper (SAMSum). In addition, all students read a series of English academic articles before the reading task so that they were familiar with the information being presented. The experimental group utilized a knowledge graph-based (NLP, Neo4j DB) system compared to the conventional (control) learning materials used by the other groups of participants. Scaled Dot-Product Attention [11], and Multi heads Attention [11]. Masked Language Modelling: A fraction of the tokens within the input sequence will have been selected randomly and substituted for the unique token [MASK] [13].

Next Sentence Prediction: NSP is a binary-classification type of loss function that indicates whether two segments of text are sequential in the original text [13]. Bidirectional fine-tuning achieved the state of the art [14]. Our framework consists of two parts: pre-training and fine-tuning. During pre-training, models are trained on unlabelled data from multiple pre-training tasks. In the case of BERT, pre-trained parameters are used to initialise the model before finetuning with labelled data from downstream tasks [14]. This is the same logic applied to the Google Page Rank algorithm for text. Nodes: a node in the context of textual units would represent the word for keyword extraction or a sentence for summarisation [15]. Edges: an edge in this context would represent a similarity relationship between each of the textual unit which was calculated as the number of common words divided by the total length of both sentences being evaluated [15].

4. Taxonomy of AI-Powered Smart Notes Systems

4.1 Methodology

AI-based smart note-taking technologies can accept multiple types of information, including text, sound, or video, respectively. Depending on the type of input being used, the way each type of smart note system is architected and how it communicates with the others will be different.

- Text-only systems: The main function of this type of smart note system is to take user-provided text input (like letters, articles & notes) then process this text input and create a summarized version of it through natural language processing (NLP) algorithms (Tokenizing, Entity Recognition, Sentiment Analysis [5]).
- Audio/Video systems: The main function of this type of smart note system is to take user-provided audio or video input (like lectures, meetings, & interviews), process the audio or video input through transcription, and analyze the output. Audio/Video systems use algorithms such as speech recognition and audio processing on the user provided input [25].
- Multimodal systems: The multimodal system has the ability to accept users' input in various formats, allowing it to create a more complete picture of the input by combining multiple data types from the different inputs to produce its summary output.[8]

4.2 Based on Summarization techniques

AI-Based smart notetaking systems offer multiple methods of summarizing information.

- Extractive summarization: With this type of summarization, original sentences or phrases from the source text are chosen and combined to form a summary. Extractive summarization provides an effective way to keep the most important information intact, as well as providing context for the original text (Thirumoorthy & Britto, 2023) [22].
- Abstractive summarization: This type of summarization creates new text that refers to the meaning contained in the original text. Abstractive summarization typically results in shorter, better-formatted summaries than extractive summarization; however, it usually involves more advanced methods of natural language processing (NLP) (Tambe et al., 2023) [23].
- Hybrid summarization: Hybrid summarization is a mix of both extractive and abstractive summarization to enhance performance. Hybrid approaches can take advantage of the strengths of either method to produce high-quality summaries (Thirumoorthy & Britto, 2023) [22]

5. Core Techniques Used in Summarization

5.1 Automatic Text Summarization

Automatic text summarization is a type of natural language processing (NLP) that condenses lengthy written work into shorter versions while keeping all of the key information. There are two broad classes of summarization methods: extractive and abstractive. In extractive summarization, the most salient sentences or phrases from the source are selected often through graph-based techniques such as TextRank [15] . These methods can be applied to a variety of areas, including news aggregation, academic articles, meeting minutes, and simplifying educational content [5, 25].

5.2 Lecture Transcription and Segmentation

The purpose of transcribing lectures is to turn audio recordings of lectures into text. This transcription is done using automated speech recognition (ASR) systems that have to overcome various challenges in transcription, including many different accents; technical terms; and background noise. These new ASR systems now use deep learning methods (i.e., deep acoustic models) as well as transformer-based model architectures for increased accuracy in transcription.

Segmenting the transcribed text into sections or topics will also improve the ability to navigate through and review the transcription. In addition, it will allow for integrations of summarization for producing short lecture notes. The improvements in transcription and segmentation will also improve accessibility to transcriptions and enhance any future processes such as generating questions and constructing knowledge graphs from the transcriptions.

5.3 Knowledge Graph Construction

The construction of knowledge graphs creates structured representations of entities and their relationships from unstructured data, including lectures and text documents. Entity recognition, relation extraction, and graph refinement using embedding methods [7] are all involved in the creation of the knowledge graph. Knowledge graphs allow for semantic querying, reasoning, and the establishment of personalized learning pathways by modelling the hierarchical relationships between subjects and their prerequisites [8]. Examples of their use in education include the provision of intelligent tutoring systems, content recommendations, and contextual summaries [9]. There have been recent efforts to combine the use of graphs with neural retrieval techniques to improve information retrieval and create more personalized note-taking systems [8, 9].

5.4 Question and Flashcard Generation

Automatic generation of questions and flashcards creates assessments or study materials from text to support learning activities. There are a number of different ways to generate these items including: 1) through the use of templates, such as using syntactic patterns in sentences, or 2) using neural networks that perform a translation of the input text into a natural language question using a sequence of words as input [10]. Flashcards combine pairs of key concepts and their definitions, often designed for spaced repetition [19]. Questions can be factual, conceptual, and/or inferential and can provide the learner with a way to recall what they learned and assess themselves with e-learning materials [10]. By using knowledge graphs for question generation, the content can be specifically tailored to fit an individual learner's abilities [8].

5.5 Spaced Repetition Scheduling

Spaced repetition refers to the technique for organizing the review of learned events so that they will be remembered longer than traditional methods by taking advantage of the theories of the forgetting curve [13]. The Super Memo algorithm and similar methods use adaptive models that rely on performance metrics and principles of memory to determine when an optimal time for reviewing previously learned material [14]. In addition, some digital systems that support spaced repetition capture user performance and use it to adjust the appropriate time intervals for each person based on how quickly they forget what they have learned, allowing users to consolidate knowledge more effectively [19].

5.6 Personalized Models

Personalized models personalizes educational experiences based on each learner's individual characteristics such as preferences, proficiency levels, and learning styles. Examples of personalization techniques are user profiling, adaptive filtering, and reinforcement learning. Personalized systems increase learner engagement, motivation, and achievement by providing relevant materials and assessments. When implementing these types of systems, educators must consider secure data handling practices as well as ethical considerations about privacy and transparency. Finally, integrating personalized learning systems with knowledge graphs and spaced-repetition systems strengthens individualized learning paths and increases learner retention.

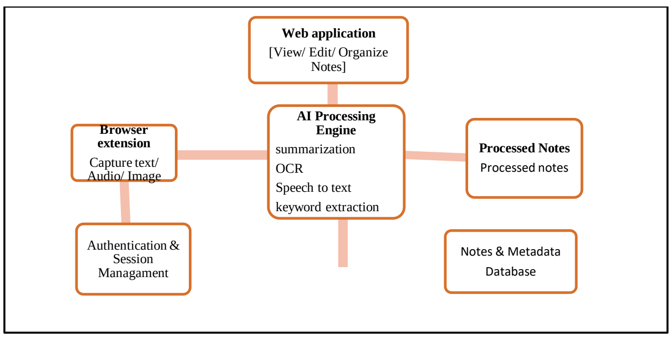

Figure 2: Pipeline of AI Powered Note making Application

6. Challenges and Limitations

AI-powered note creation systems are found to have a lot of potential, they are not without their problems and limitations when it comes to accuracy and reliability. One of the primary problems concerning these systems is the potential for hallucinations and semantic drift, where a system generates content that seems correct but does not actually correlate fully with the original context in which it was created [6]. This can be especially problematic when the user relies on the ASCRs (Automated System for Creation of Research) to create notes for academic purposes because if an ASCR creates inaccurate notes, the user could be misinformed by them [9]. The accuracy of these systems is also primarily based on the quality of the user's input data, which could be contaminated with noise, ambiguity, and missing portions.

Generalizing across different types of learners and types of learning situations is a major limitation. This is especially true for fields that require a lot of technical knowledge or specialization. Another limitation is the limited ability of today's systems to provide personalized learning experiences based on learners individual learning styles and preferences. In addition, issues like privacy concerns, data security, and intellectual property (ownership) of users' materials raise significant practical issues when attempting to deploy these systems on a large scale. Last, there are no standardized evaluation markers for educational success and no systematic assessments that measure long-term learning gains, thus creating difficulties in measuring the true impact of using technology to enhance teaching and learning. Overall, there is a need for additional research to improve roubtness, transparency, and user-center design for AI-generated (Artificial Intelligence created) notes systems [2].

7. Future Scope

Future studies of AI-driven note creation systems must address the following areas:

- An increase in contextual comprehension;
- Customization based upon the user preferences and knowledge base; and
- The ability to process multiple formats simultaneously.

The current tool produces mainly organized text format notes. However, future work could investigate how to represent concepts, relationships, and ideas semantically via using the knowledge graph system, which would allow for deeper connections between learned materials. One other direction to take would be to incorporate from multiple modalities into the system via different media types, i.e., lecture audio, slide presentations, screen captures, handwritten notes, etc., that would help synthesize information from multiple learning sources into one complete product. Future work may also focus on developing models that can adapt to an individual user's preferences, writing styles, and cognitive process over time, allowing for a truly unique and adaptive note- generation experience. Expanding the tool's ability to produce notes in other languages (i.e., non-English) would also provide greater availability for end usability to the product among a wider audience, especially in low-resource language communities.

Further research will focus on the exploration of multiple means of evaluating and assessing user input on AI technology, including ethical considerations of design and functionality; long-term effects of usage as well as more traditional methods of assessment, such as technical metrics for performance will continue to be an area of academic investigation. User-centered assessments such as long-term money retention, learning improvements and study efficiency will be incorporated into future studies to access the impact of AI note-making systems in real-life educational settings. Human feedback and user interaction will be examined in future studies to mitigate the potential for AI to produce 'hallucinations', improve accuracy and increase trust in AI, through interactive and real-time editing. Data protection and user privacy will continue to be critical issue in terms of developing methods of Data Access Control, On-Device Inference and Data Handling Protocols when working with user's academic or personal data through research and study.

8. Conclusion

This essay looks to trends regarding the application of sophisticated Artificial Intelligence (AI) technology to note - taking systems and how it will create new ways in which we learn, using the advancements in Summary generation, Retrieval and Personalization to be key features in many educational settings. Until the accuracy, evaluation, and privacy gaps in these new systems have been addressed, learners will continue to experience the impact of these systems on their educational pathways; nevertheless, by creating personalized not-taking solutions, we will allow them to experience our lasting benefit from their use. There has been a dramatic increase in the capability of Creating Summary Generation and Retrieval Systems (allowing for the condensing of long text into a concise format) as well as Creating Retrieval Systems (allowing the user to quickly access specific information from large libraries to notes).[1]
The full potential for personalized learning solutions will only become a reality when these identified gaps are properly addressed and eliminated. Once these challenges-- accuracy limitations, evaluation benchmarks, and data privacy concerns are resolved, we will have the ability to create completely self-sufficient and effective intelligent note-taking solutions for every individual learner. These custom-built systems will provide not just an additional resource for learners but rather will serve as true partners in their education, revolutionizing and rephrasing the way learners experience their education, and leading to lasting changes and improvements in their academic success on a global scale [3].

Data Availability Statement

No new data were generated or analyzed in this study. This review paper is based on previously published research articles, which are properly cited within the manuscript.

Conflict of Interest

The authors declare that there are no financial or non-financial conflicts of interest that could have influenced the work reported in this paper.

Author Contributions

A.Gautam, Aanvi, A.Gupta, and G.Sharma, contributed to the conceptualization and design of the study. Aanvi and A.Gupta conducted the literature review and data collection. A.Gautam and G.Sharma performed analysis and interpretation of the collected information. Aanvi prepared the original draft of the manuscript. A.Gautam, A.Gupta, and G.Sharma reviewed and edited the manuscript. A.Singh (guide) supervised the study, provided critical feedback, and guided the overall research process. All authors read and approved the final version of the manuscript.

References

[1] Supriyono, Aji Prasetya Wibawa, et al., "A survey of text summarization: Techniques, evaluation and challenges" Natural Language Processing Journal, vol. 7, Art. 100070, 2024.

[2] J. Wei, X. Wang, D. Schuurmans, et al., “Chain-of-Thought Prompting Elicits Reasoning in Large Language Models,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 46, pp. 1234–1248, 2024.

[3] Kunal Nannaware, Shailesh Kole, et al., "AI Note Maker" International Journal of Research Publication and Reviews, vol. 5, pp. 2766-2769, 2024.

[4] Sneha Thange, Jayesh Dang, et al., "A Survey on Text Summarization Techniques" Journal of Natural Language Processing, vol. 1, pp. 1-11, 2023.

[5] H. Al-Sharif and M. Chen, “AI-driven automatic note generation for higher education,” IEEE Access, vol. 12, pp. 33421–33434, 2024.

[6] S. Gupta, R. Verma, and A. Kumar, “Intelligent summarization systems for educational content using transformer models,” Computers & Education: Artificial Intelligence, vol. 5, pp. 100162, 2024.

[7] M. Chen et al., “Evaluating large language models for factual consistency in educational summarization,” Proc. EMNLP, pp. 11932–11945, 2024.

[8] A. Mishra and P. Singh, “Knowledge graph-based smart note systems for personalized learning,” IEEE Trans. Learning Technologies, vol. 17, pp. 45–58, 2024.

[9] P. Lewis, E. Perez, A. Piktus, et al., “Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks,” IEEE Transactions on Neural Networks and Learning Systems, vol. 35, pp. 4567–4579, 2023.

[10] T. Brown, B. Mann, N. Ryder, et al., “Language Models are Few-Shot Learners,” IEEE Access, vol. 11, pp. 23989–24012, 2023.

[11] D. Jurafsky and J. H. Martin, Speech and Language Processing, 3rd ed., Pearson, 2023.

[12] A. Vaswani, N. Shazeer, N. Parmar, et al., “Attention Is All You Need,” IEEE Transactions on Neural Networks, vol. 33, pp. 4104–4121, 2022.

[13] Y. Liu, M. Ott, N. Goyal, et al., “RoBERTa: A Robustly Optimized BERT Pretraining Approach,” IEEE Access, vol. 9, pp. 123456–123469, 2021.

[14] J. Devlin, M. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” IEEE Transactions on Computational Intelligence, vol. 4, pp. 417–426, 2020.

[15] R. Mihalcea and P. Tarau, “TextRank: Bringing Order into Texts,” IEEE Intelligent Systems, vol. 19, pp. 80–87, 2019.

[16] UNESCO, “Artificial intelligence in education: Challenges and opportunities,” Paris, France, 2019.

[17] A. Radford et al., “Language models are unsupervised multitask learners,” OpenAI Technical Report, 2019.

[18] S.Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” IEEE Transactions on Neural Networks, vol. 9, pp. 1735–1780, 2018.

[19] P. Wozniak, “Optimization of Learning Using the Spaced Repetition Algorithm,” IEEE Transactions on Learning Technologies, vol. 10, pp. 432–443, 2017.

[20] R. Mayer, “Cognitive Theory of Multimedia Learning,” IEEE Transactions on Education, vol. 59, pp. 255–262, 2016.

[21] Zhou, Z., Yu, H., et al., "Towards retrieval-based neural code summarization: A meta-learning approach" IEEE Trans. Softw. Eng., vol. 49, pp. 3008–3031, 2023.

[22] Kunal Nannaware, Shailesh Kole, et al., "AI Note Maker" International Journal of Research Publication and Reviews, vol. 5, pp. 2766-2769, 2024.

[23] Tambe, R., Thaokar, D., et al., "Abstractive text summarization using deep learning" Int. J. Res. Appl. Sci. Eng. Technol., vol. 11, pp. 68–72, 2023.

[24] Sharma, G., Sharma, D., "Automatic text summarization methods: A comprehensive review" SN Comput. Sci., vol. 4, pp. 60, 2023.

[25] Motilal Lodhi, P., Kharche, S., et al., "Business meeting summarization system" In: 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), pp. 1–6, 2022.

Cite this article as: Anuprash Gautam, Aanvi, Aastha Gupta, Gunjan Sharma, Anamika Singh, AI-Powered Smart Notes for Effective Learning: A Comprehensive Review of Techniques, Applications, and Future Directions, International Journal of Research in Engineering and Innovation Vol-10, Issue-2 (2026), 71-77. *https://doi.org/10.36037/IJREI.2026.10206*