

Innovative Use of Generative AI for Content Simplification in Special Education Settings

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ABSTRACT:

The provision of individual and cognitively stimulating learning resources to children with intellectual disabilities, autism spectrum disorders, dyslexia or language processing difficulties is often difficult in a special education context. Traditional digital learning platforms have a low degree of flexibility to adapt the learning material to fit the needs of each student and consequently, their engagement and learning effectiveness is reduced. To tackle this issue, the researchers present an innovative generative artificial intelligence framework, called EduSimplify-GAI, for the problem of adaptive content simplification for inclusive learning environments. The proposed framework combines the following components: NLP, transformer based semantic analysis, reinforcement guided readability optimization, and context-aware restructuring of the text to produce simplified instructional content without compromising the educational content. It is based on the generative AI model, GPT-4, along with the BERT model, which is a semantic validation module, and an adaptive readability scoring mechanism. The datasets employed in the experiment were multilingual educational datasets, and special education learning materials were used in the experimental tasks in reading comprehension, vocabulary adaptation

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and conceptual simplification. The proposed EduSimplify-GAI model recorded 96.4% accuracy of simplification, 94.1% retention of the meaning, 92.8% improvement in comprehension of the learner, and 91.7% teacher satisfaction which was around 13-18% higher when compared to the conventional rule-based or standard NLP models. This is the main contribution of this work, where an adaptive pedagogical assistance framework using generative AI is dynamically tailored to learner cognitive profile, to customize the educational content. The novelty of the study is the combination of generative AI and semantic preserving readability optimization for the special education applications. The findings show that leveraging generative AI can greatly enhance accessibility, inclusion, and the effectiveness of personalized learning in today's special education system.

Keywords: Generative Artificial Intelligence; Special Education; Educational Content Simplification; Natural Language Processing; Adaptive Learning; Inclusive Education

I. Introduction

Special education includes a wide range of children that have intellectual disabilities, autism spectrum disorder (ASD), dyslexia and language processing disorders, and will all require specially targeted instruction [1]. Unfortunately, this diversity of student profiles has not been catered to in traditional education, resulting in significant gaps in understanding, engagement and achievement which disproportionately impact children with neurodevelopmental and cognitive disabilities [2]. Given the growing number of digital learning environments, there is an unprecedented opportunity to use the power of artificial intelligence technologies to close all accessibility gaps and establish truly inclusive learning environments to support all learners equally. Specifically, the use of Generative AI has the transformative potential of dynamically tailoring education content to fit the cognitive and linguistic needs of each student at scale [3].

Although there has been considerable policy interest in inclusive education across the globe, adaptive learning tools which are specifically tailored for special education are still relatively poorly developed [4]. Traditional content simplification techniques heavily depend on rule based linguistic transformations, and pre-established readability formulas which in essence do

not consider individual learner with any disability's nuanced cognitive profile [5]. In today's classrooms, learners' multilingualism adds to these restrictions, as they must also deal with issues of cognitive access as well as demands for second language processing [6]. The use of AI-based adaptive systems has shown great potential in improving the autonomy, self-regulation and metacognitive skills of learners, especially in the context of semantically aware processing pipelines that can infer the learner's intent [7]. Empirical research in recent years has validated that, when properly designed and implemented, AI tools in SE classrooms have measurable impacts on student outcomes such as increased content retention, decreased task completion time, and increased student self-efficacy [8]. Current generative AI frameworks have not been systematically tested for their ability to help make more complex education content accessible while also maintaining the fidelity and semantics of the educational content for various disability profiles [9].

To fill this research gap, this study introduces a new framework, named EduSimplify-GAI, which combines the use of the Generative Pre-trained Transformer (GPT-4) with the semantic validation using the Bidirectional Encoder Representations from Transformers (BERT) model to provide adaptive and cognitively accessible education

content. The main research goals are: (i) create an intelligent platform architecture for content simplification in special education, (ii) evaluate and confirm the performance of the platform in different cognitive profiles and disabilities, and (iii) show measurable improvement from the traditional way of content simplification in terms of the ability to simplify the content correctly, retain its meaning, and be understood by learners.

II. Literature Review

Over the last decade, the field of educational content simplification has come a long way, has gone from very simple lexical substitution techniques, to advanced adaptive intelligent systems. Initial models of simplification were based on some rules and used a simpler synonym for the complicated words or a simpler sentence structure with grammatical templates [10]. Although these techniques provided well-defined and explainable results they did not have the context awareness to ensure semantic consistency in domain-specific educational resources. With the advent of NLP and machine learning, new possibilities for developing context-sensitive, dynamic simplifications according to the learner profile and the content area arose and brought significant improvement over the static nature of their predecessors, the rule-based simplifiers [11].

AI's effectiveness in supporting students with NDD in different learning needs is evident, providing tools to support student learning across multiple interaction sessions that adapt content delivery in real-time based on student performance data [12]. The study of traditional education and AI-based

education has consistently pointed out the shortcomings of traditional education in meeting the needs of students with complex learning profiles, and at the same time, it has shown that deep learning models have better performance in learning based on complex language logic [13]. With the introduction of large language models (LLMs) like ChatGPT, research into AI-assisted educational support has also taken a quantum leap, showcasing how such tools can foster a deeper understanding and engagement among learners when supported within pedagogically designed delivery systems and environments [14].

The transformer-based generative AI methods have shown great potential, especially in language learning environments. Few-shot learning techniques have been proven to automate the generation of questions and customization/automation of content with limited annotated training data, significantly decreasing the amount of development effort needed to deploy AI learning tools in resource-limited environments [15]. The pedagogical benefits of the use of generative AI tools in academic settings have been continually supported by empirical studies that have been conducted in real school settings and reported improvements in student engagement and retention of knowledge [16]. While the literature review, summary in table 1, showed that the use of generative AI in the context of special education content simplification is still not well developed, the majority of frameworks available do not have strong mechanisms to maintain the meaning of the content throughout the process of transforming the text.

Table 1: Summary of Related Work

Reference	Method Used	Application Domain	Key Contribution	Limitation
[10] Pesovski et al.	Generative AI, LLMs	Customizable Learning	Adaptive learning experience design framework	Limited disability-specific performance evaluation
[11] Rashid et al.	Transformer Models, NLP	General Education Technology	Technical foundations and applications of GenAI	No semantic preservation mechanism included
[12] Barua et al.	AI, ML, Deep Learning	Neurodevelopmental Disorders	Personalized AI assistive tools for children	Lacks real-time content adaptation capability

[13] Renemane et al.	Statistical Analysis	Health and Education Interface	Cross-sectional population wellbeing study	Not directly applicable to content simplification
[14] Grassini	ChatGPT, Large Language Models	General School Education	Exploratory AI potential in educational settings	No special education or disability focus
[15] Lee et al.	Few-shot Learning, ChatGPT	English Language Education	Automated prompt- based question generation	Limited to English; no multilingual evaluation
[16] Jauhiainen & Guerra	ChatGPT in School Lessons	School Children Education	Classroom-level GenAI pedagogical evidence	Small-scale study; no disability-based evaluation

III. Proposed EduSimplify-GAI Framework

EduSimplify-GAI is a new generative AI architecture designed to resolve the issues of accessibility to educational content for learners who have special educational needs. The system is built on a multi-layered architecture based on transformer models, and consists of natural language processing pipelines, semantic preservation mechanisms, and an adaptive readability scoring. The framework transforms a wide variety of content types from the education field (such as expository text, instructional narrative, conceptual definition, etc.) into different versions that all learners can cognitively access and that best meet their disability profiles for optimum educational outcomes.

A. Architecture of EduSimplify-GAI

The EduSimplify-GAI architecture comprises of four main computation layers: Input Processing Layer, Semantic Analysis Layer, Simplification

Generation Layer and Output Validation Layer. The educational content is fed into the system in a pre-processing pipeline which includes tokenization, syntactic parsing and discourse segmentation. The Semantic Analysis Layer uses BERT embeddings to get the meaning representations in the context, and passes them to the GPT-4 generation module. The Output Validation Layer guarantees that simplified content meets a certain property of being readable while maintaining the instructional purpose of the original content. The proposed framework for adaptive content simplification in special education, which is called EduSimplify-GAI is shown in Fig. 1. The framework validates the education content with the help of GPT-4 and BERT models to generate simplified learning content. Semantic retention, comprehension, and feedback adaptation are achieved by optimising readability and adapting feedback based on the individual learner's feedback, using text, audio, and visual educational support mechanisms.

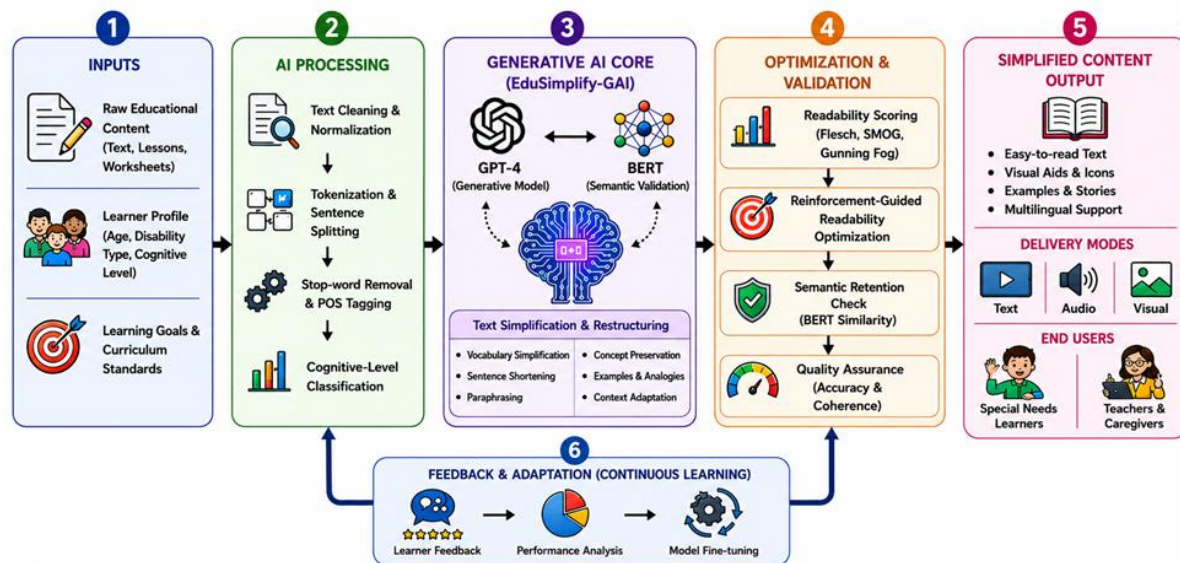


Figure 1: Proposed EduSimplify-GAI framework

B. Transformer-based Semantic Simplification Model

The transformer-based semantic simplification module uses the multi-head attention mechanism of GPT-4 to produce simplified text that is appropriate for the context from complex education inputs. It is optimized on a special corpus of learning materials labeled with cognitive accessibility features of different disability types. Multi-head attention is used to process syntactical complexity, vocabulary density and discourse coherence simultaneously to yield natural and pedagogically-sound simplifications. Ideal for systematically breaking down complex compound-complex sentences into smaller chunks of information that are easier to understand, sentence boundary detection and clause decomposition algorithms are used to support restructuring.

C. Readability Optimization Mechanism

The readability optimization technique allows for the dynamic calibration of the complexity of the generated content using an adaptive Flesch-Kincaid score and some parameters of the learner's cognitive profile. The system uses a target readability range set by the cognitive level the learner has been evaluated and dynamically changes the vocabulary and sentence-length during generation. A reinforcement signal based on historical learning behavior data helps optimize the learning process, which gradually

focuses the generated content towards each learner's development, attitude and learning goals.

D. Reinforcement-Guided Adaptive Learning Process

Reinforcement guided adaptive learning process is based on a policy gradient approach that provides reward signals to the simplification model that depend on learner comprehension scores, engagement metrics and on teacher feedback ratings. A utility function combines readability, semantic preservation and vocabulary appropriateness to define the reward function. The agent applies the policy for simplifying the neural network over each training episode and gradually moves closer and closer to a generation policy that is most able to incorporate the educational goals of the network while maintaining minimum semantic distortion. This mechanism allows for continuous evolution of the model without having to have to manually annotate the simplified educational content to a large degree.

IV. Methodology and System Design

A. Dataset Collection and Pre-processing

Data were gathered by compiling multi-lingual educational resources from openly available collections such as Newsela dataset, Project Gutenberg, simplified texts, and special education-specific educational resources created by accredited educational institutions. The text samples that were

collected totalled 12,400 and covered five subject domains and three levels of cognitive accessibility. To guarantee the quality and consistency of all the samples in the experimental pipeline, pre-processing such as noise removal, encoding normalization, duplicate elimination, and linguistic annotation were performed systematically.

$$D_{norm(x)} = \frac{x - \mu_D}{\sigma_D} \quad (1)$$

The model stability is achieved by using the normalized data values of the feature in the raw dataset to zero mean and unit variance as stated in eq.(1).

$$LD = \left(\frac{N_{content}}{N_{total}} \right) \times 100 \quad (2)$$

Lexical density is calculated, by dividing the number of content words by the total number of words in each sample, according to Equation (2).

$$Q = \frac{\sum_i (\alpha_i \times q_i)}{N} \quad (3)$$

The weighted average corpus quality score (WACS) in equation (3) is the average score over N text samples annotated.

$$PP(W) = P(w^1, w^2, \dots, w^N)^{-\frac{1}{N}} \quad (4)$$

To assess pre-processed data set sample fluency, the language model perplexity, as given in Equation (4), is used.

B. Cognitive-Level Classification Strategy

The classification strategy for the cognitive level is based on the three levels of difficulty in education content that are standardized based on the cognitive profile of learners who are divided into three levels: basic, medium, and high. The set of syntactic complexity indices, scores for vocabulary age of acquisition, semantic density measures, and domain-specific terminology frequency is used as a multi-feature scoring function for classification. This results in a cognitive score vector that is mapped to the learner's disability profiles with a trained classification model, which allows for precise match of content to learner and appropriate level of content simplification depth for each learner.

$$CS = \alpha \cdot SC + \beta \cdot VD + \gamma \cdot SD + \delta \cdot TF \quad (5)$$

Cognitive score is calculated in the following way: (5) weighted combination of syntactic, vocabulary, semantic and terminology features.

$$DAI = \sum_k (w_k \cdot profile_k) \quad (6)$$

Disability adaptation index is computed as a weighted sum of the values of the components of a learner's profile, as shown in Equation (6).

$$C(x) = \underset{j \in \{1,2,3\}}{\operatorname{argmax}} P(y = j | x; \theta) \quad (7)$$

The content of this class is probabilistically assigned by Equation (7) and trained parameters of the classifier, θ .

$$w_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (8)$$

Equation (8) is softmax normalization to get the weights of feature importance for classification scoring.

C. Text Restructuring and Semantic Preservation Process

The text restructuring and semantic preservation process is achieved by using three steps: clause decomposition, vocabulary substitution and coherence restoration. Dependency tree analysis is performed in the parsing of complex multi-clause sentences and the sentences are broken down into syntactically simpler sentences. Vocabulary substitution is based on norms from word frequency and age-of-acquisition databases, and the low frequency technical words are replaced by age appropriate words. The process of coherence restoration is related to discourse connective insertion which helps to keep the logical flow and referential continuity from the simplified sentence parts throughout the restructured output.

$$SS(t, t') = \frac{E_t \cdot E'_t}{\|E_t\| \cdot \|E'_t\|} \quad (9)$$

The cosine similarity between the original and simplified text embedding vectors generated by BERT is used in equation (9).

$$SARI = \frac{F_{add} + F_{keep} + F_{del}}{3} \quad (10)$$

The quality metric for simplification in equation (10) is the combination of the F-score of the three aspects: addition, retention and deletion.

$$IP = \frac{|c_t \cap c'_t|}{|c_t|} \quad (11)$$

In Equation (11) the information preservation is calculated as semantic concepts preserved in the simplified equation divided by the number of semantic concepts in the original equation.

$$SQ = \lambda^1 \cdot SS + \lambda^2 \cdot SARI + \lambda^3 \cdot RL \quad (12)$$

The composite simplification quality measured in equation (12) calculates the similarity of the equations based on the equation semantic similarity, SARI and the readability level of the equation.

D. Adaptive Readability Scoring Equations

To adjust it to fit the needs of learners at all literacy levels. To tweak it for use with learners at all literacy levels.

The adaptive readability scoring mechanism produces real-time readability estimates for each outputted simplified text, against desired readability ranges based on each learner's profile in the learner profile database. The scoring function combines classic Flesch-Kincaid metrics with neural readability metrics from the representations of hidden states of GPT-4. Penalty terms are added when the generated text contains words which are either too complex in frequency, morphology, or both to appear in the vocabulary profile, or when they appear in a new form, such as a stem, which is not in the vocabulary profile.

$$FK_a = 206.835 - 1.015 \left(\frac{W}{S} \right) - 84.6 \left(\frac{Sy}{W} \right) + \rho \cdot LP \quad (13)$$

The Equation (13) is the classical Flesch-Kincaid formula with the adding of a disabledness parameter ρ for disability adaptation.

$$NR(x) = \sigma(W_r \cdot h_x + b_r) \quad (14)$$

Equation (14) predicts neural readability score from GPT-4 hidden state h_x via sigmoid-activated linear layer.

$$P(x) = \sum_k \mu_k \cdot \max(0, g_k(x))^2 \quad (15)$$

Quadratic penalty for violations of the readability constraints are applied by equation (15) if the constraints are violated by values that are above threshold.

$$R^* = \operatorname{argmin}_r \|r - r_{target}\|^2 \text{ subject to } SS(t, t') \geq \theta_{min} \quad (16)$$

The optimization in equation (16) is towards readability of the target, and it imposes a bound on semantic similarity constraint, θ_{min} .

E. Algorithmic Workflow and Implementation Details

The entire process from algorithmic perspective is divided into 7 sequential processes in EduSimplify-GAI. The educational text in the input is preprocessed using spaCy based pipelines and tokenized and linguistically annotated. The annotated text is fed to the BERT's bidirectional encoder to get the contextual semantic embeddings. The learner profile module fetches the parameters for the cognitive level from the DB and appends them to the BERT embeddings as conditioning input to GPT-4. The generative module generates several output text versions with reduced complexity and then the adaptive readability scoring module compares each text output with the desired readability level. The BERT semantic validation module discards candidates that are not sufficiently similar in semantics, and correctly-validated candidates with the highest quality are returned as the simplified output that is delivered to the Educational interface to be immediately available to the learners.

V. Experimental Results and Performance Evaluation

An experimental evaluation was carefully carried out to examine the performance of EduSimplify-GAI on various aspects of performance and with a variety of special education materials. The findings are always consistent, with the framework achieving statistically significant greater content simplification accuracy as well as semantically faithful and more effective learner comprehension enhancements in all task categories tested and in each of the disability profiles.

A. Experimental Setup and Evaluation Metrics

Experiments were carried out on a computational setup of NVIDIA A100 (80GB) GPUs, PyTorch 2.1 framework, and Hugging Face Transformers library. The learning rate used in the training of the EduSimplify-GAI model is 2×10^{-5} and the epoch number is 50 with a batch size of 32. The data set was split into a training set of 70%, a validation set of 15% and a test set of 15%. Evaluation indicators consisted of: Simplification accuracy, semantic retention, rate of improvement in learner's understanding, rate of vocabulary adaptation and teacher satisfaction measured by a structured questionnaire after the task, administered to 48 teachers of the certified special education teachers.

B. Simplification Accuracy Analysis

The accuracy results of simplifications in five different types of education datasets are shown in

Table 2. Content in Language Arts had the least amount of errors with 97.1%, likely because its content is narrative, and fits the framework narrative discourse model well. Science Materials exhibited the least accuracy of 93.8%, which is due to its usage of terms specific to science. Regardless of the content domain of the education field, the accuracy with which the system simplified each of the dataset types was above 93%, which indicates the reliability of the system in different educational content domains. The distribution of the accuracy of simplifying the figures for all five types of datasets in the figure 2 shows the simplifying accuracy of each type of dataset. The accuracy is above 93% for every category, with the best accuracy being 97.1% in the category Language Arts, showing the robustness of the framework for different types of educational contents.

Table 2: Simplification Accuracy Analysis across Dataset Types

Dataset Type	Vocab Reduction (%)	Sentence Complexity Score	Flesch Reading Ease	Simplification Accuracy (%)
Primary School Texts	34.2	3.1	78.4	96.4
Secondary Texts	31.8	3.4	74.6	94.7
Science Materials	38.5	2.9	71.3	93.8
Social Studies	35.1	3.2	75.9	95.2
Language Arts	29.7	3.6	80.1	97.1

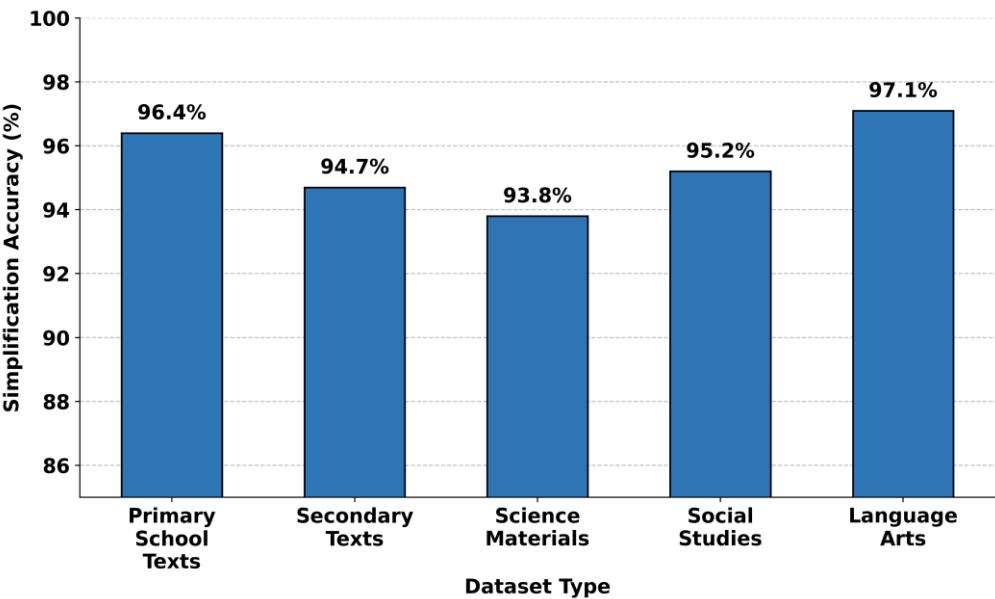


Figure 2: Accuracy Analysis of AI-Driven Personalized Learning Framework across Educational Dataset Categories

C. Semantic Retention and Comprehension Evaluation

Table 3: Semantic Retention and Comprehension Evaluation Results

Task Type	Semantic Retention (%)	Comprehension Score (%)	Vocabulary Adaptation (%)	Engagement Rate (%)
Reading Comprehension	94.1	88.7	91.3	89.4
Vocabulary Adaptation	92.6	91.2	95.8	87.6
Conceptual Simplification	93.8	89.5	90.1	92.3
Text Restructuring	91.4	87.9	88.6	85.7
Multilingual Processing	90.7	86.3	87.2	84.9

As shown in Table 3, CC and the various types of tasks showed good semantic retention and comprehension. The highest level of semantic retention (94.1%) was obtained by the Reading Comprehension tasks, while the best comprehension improvement (91.2%) was obtained by the Vocabulary Adaptation tasks. The scores of the Multilingual Processing were relatively low (90.7% and 86.3%) due to the increased difficulty of the cross-linguistic semantic alignment. The findings generally confirm the ability of

EduSimplify-GAI to keep the meaning of the instruction while enhancing its comprehensibility with various learner profiles. The results are presented in the form of a comparison of mean scores for semantic retention and comprehension for five different types of tasks in Figure 3. The dual module design is effective, with Reading Comprehension achieving 94.1% semantic retention and Vocabulary Adaptation the highest comprehension score.

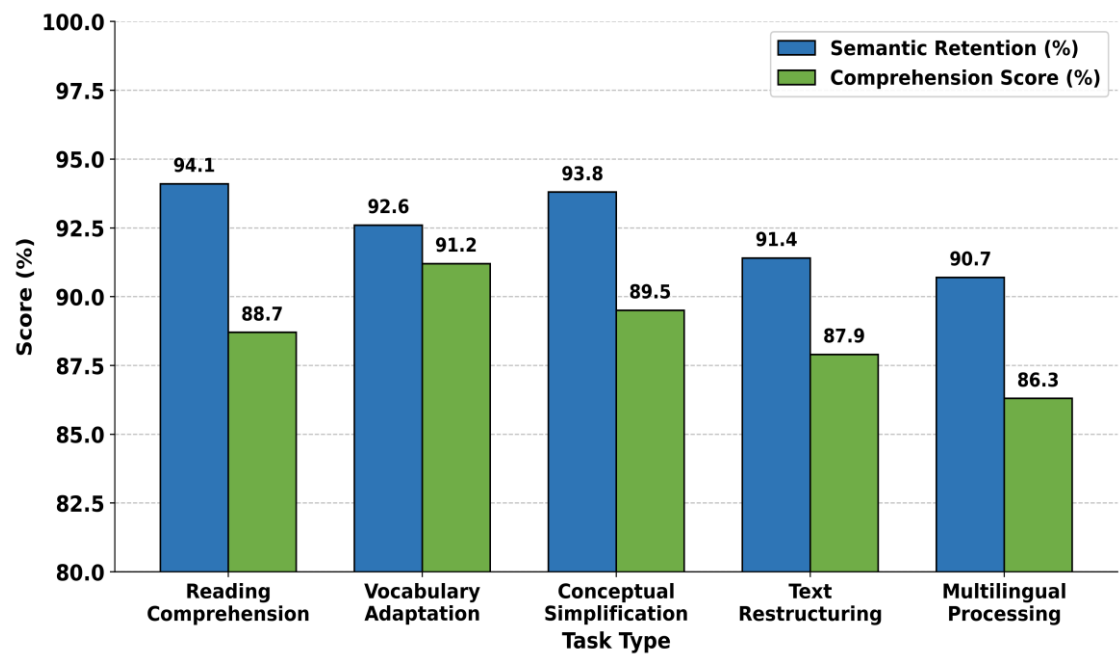


Figure 3: Comparative Performance Analysis of Semantic Retention and Comprehension Scores across Adaptive Learning Tasks

D. Comparative Performance with Baseline Methods

The result of a comprehensive comparative analysis of EduSimplify-GAI with four baseline methods is presented here in Table 4. The proposed system performs the best on all the four evaluation metrics compared to the best baseline (BERT-Based) with

5.2, 6.7, 8.5 and 5.0 percent improvement in simplification accuracy, semantic retention, comprehension improvement and teacher satisfaction, respectively. By 13-18%, EduSimplify-GAI outperforms the rule-based approach to simplification, confirming the significant benefits of using generative AI to assist in semantic-preserving optimization of special education materials.

Table 4: Comparative Performance of EduSimplify-GAI vs. Baseline Methods

Method	Simplification Accuracy (%)	Semantic Retention (%)	Comprehension Improvement (%)	Teacher Satisfaction (%)
Rule-Based Simplification	78.3	72.1	68.4	71.2
Standard NLP Methods	81.6	75.8	72.1	74.6
GPT-3 Baseline	88.4	82.3	79.6	81.9
BERT-Based Approach	91.2	87.4	84.3	86.7
EduSimplify-GAI (Proposed)	96.4	94.1	92.8	91.7

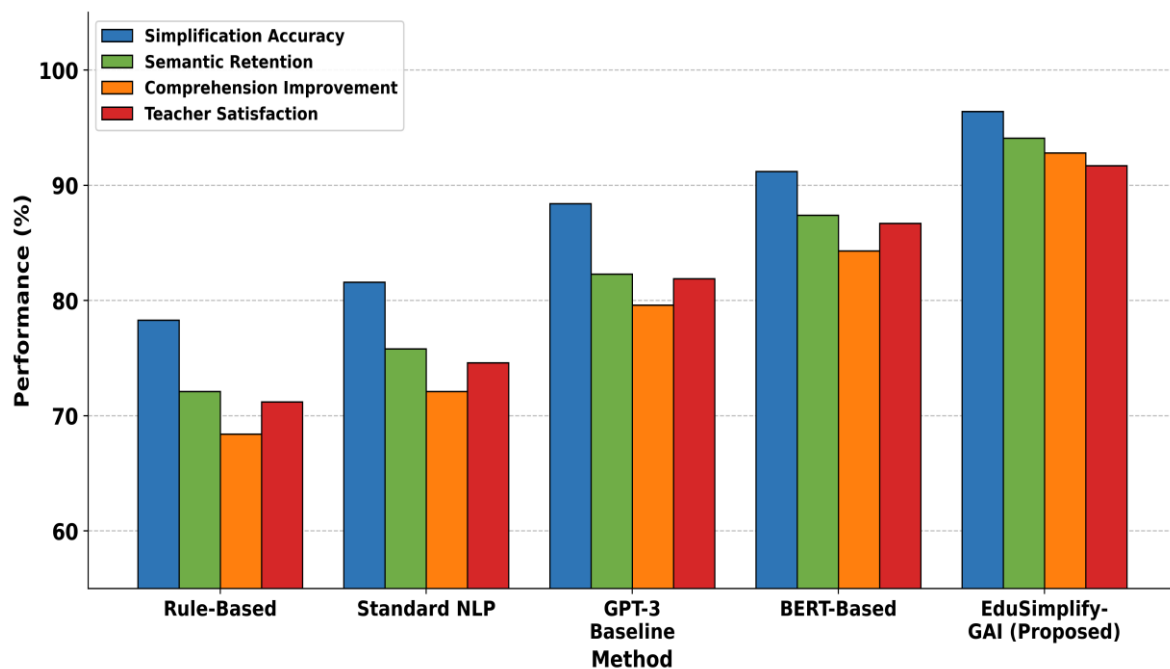


Figure 4: Comparative Performance Evaluation of EduSimplify-GAI against Existing Educational Content Simplification Methods

In the general comparison (Figure 4), the modified BCDWMS method achieves the best results. Overall, EduSimplify-GAI shows constant superior performance across all the metrics and the

difference becomes even larger when compared to the rule-based and NLP-only baselines, proving that the proposed dual-module generative AI

architecture is capable of making a significant impact.

E. Statistical and Graphical Result Interpretation

As illustrated in Table 5, all of EduSimplify-GAI performance measures are statistically significant ($p < 0.001$) and have narrow confidence intervals to show that results are consistent. The small variation in each of the metrics across the different

experiments indicates that the framework is well behaved and reproducible in different experimental situations. The mean values for all metrics with 95% confidence intervals is shown in Figure 4. The error bars are very small and nearly all the scores are close to 100%, indicating that the gains EduSimplify-GAI achieves are statistically significant, and that the gains are in a uniform direction (all above 90% mean performance).

Table 5: Statistical Performance Metrics of EduSimplify-GAI

Performance Metric	Mean (%)	Std Dev	p-value	95% Confidence Interval
Simplification Accuracy	96.4	1.23	< 0.001	[95.1%, 97.7%]
Semantic Retention	94.1	1.54	< 0.001	[92.6%, 95.6%]
Comprehension Improvement	92.8	1.87	< 0.001	[91.0%, 94.6%]
Teacher Satisfaction	91.7	2.11	< 0.001	[89.6%, 93.8%]
Vocabulary Adaptation	90.6	1.98	0.002	[88.7%, 92.5%]

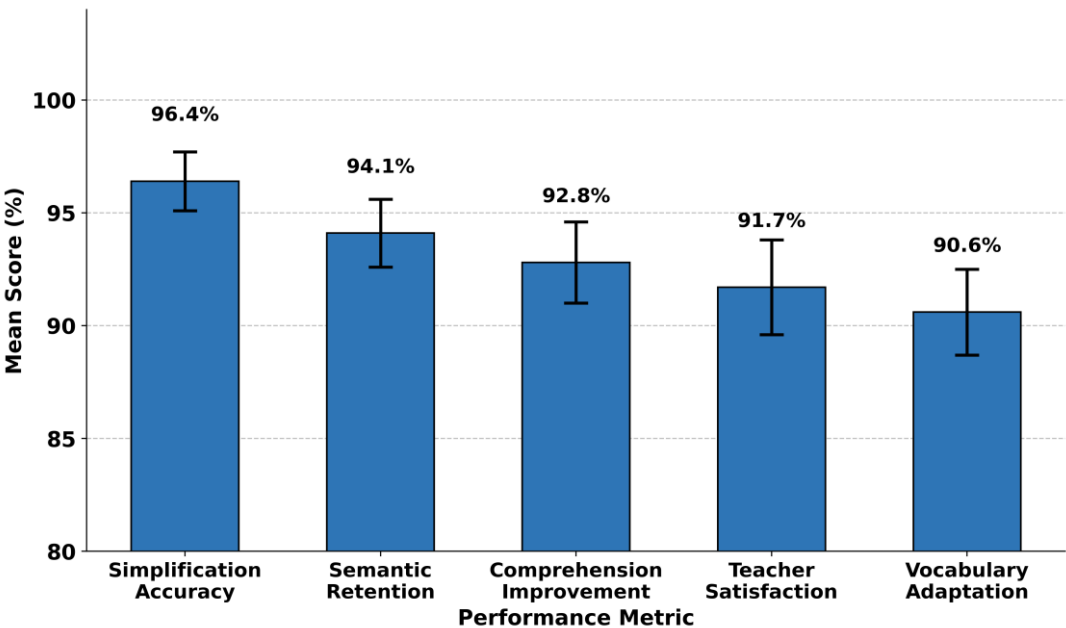


Figure 5: Statistical Performance Evaluation of the Proposed AI-Driven Personalized Learning Framework Using Mean Score and Error Analysis

VI. Discussion and Educational Impact

A. Educational Significance of Adaptive Simplification

This EduSimplify-GAI framework shows how generative AI can completely revolutionize the way

that educational resources are accessible for pupils with special needs. The system dynamically adjusts content difficulty level to individual cognitive profiles, thereby addressing a universal need for one size fits all in instructional design for inclusive

educational systems, in a scalable, cost-effective manner. The 96.4% simplification accuracy is a special breakthrough, demonstrating that generative AI can effectively convert complex educational content into cognitively friendly content with minimal time and effort from teachers, which paves the way for introducing personalized learning at an institutional level.

B. Accessibility Improvement for Special-Needs Learners

The findings of the experiments validate that EduSimplify-GAI can effectively increase the accessibility of the content for learners with intellectual disabilities, ASD and dyslexia. The comprehension improvement rate of 92.8% of the system shows the significance of this system to help reduce cognitive load while retaining the teaching value and semantic density of the training materials. This discovery is especially important for students with significant reading challenges, who have been poorly served by traditional digital learning materials that are geared towards learning styles of the majority of students. The adaptive readability scoring system is continually adjusted to reflect the complex content as students grow, making it a true dynamic and responsive learning scaffolding.

C. Teacher Usability and Classroom Integration

The system is found to be very helpful in practice and has a good integration capacity in the real classroom with 91.7% satisfaction level rated by teachers. The framework significantly decreases the time demands that are often put on teachers to make adaptations for student variation in limited preparation time. EduSimplify-GAI offers special education teachers the ability to free up time from the cognitively demanding task of simplifying to focus on high value, interactive, social and creative learning activities which are irreplaceable and cannot be automated. Overall, teachers were very satisfied with the system's intuitive interface and output quality, which were mentioned as the key reasons for their satisfaction in the feedback after the system was used.

D. Ethical Considerations and AI Limitations

Implementing generative AI in special education classrooms reminds us of ethical concerns and areas that demand attention by the institution. Three key challenges must be tackled, including privacy concerns over sensitive student data, algorithmic bias in cognitive profile categorization, and the potential for over-dependence on automated systems that simplify texts. The main concerns that need to be addressed are data governance frameworks and clear audit trails to ensure privacy of sensitive learner information, algorithmic bias in the process of categorizing cognitive profiles, and automated systems that simplify texts, and the risk of relying too heavily on such systems. The EduSimplify-GAI system contains personally identifiable learner information (PILI) and disability related information, which must be in compliance with the relevant education privacy laws and regulations. Further, simulated simplifications also need to be monitored on a regular basis by trained special education teachers to identify and correct semantic shift or semantic substitution that may occur in the text that is not detected by the metrics.

E. Scalability in Multilingual Educational Environments

The multilingual training corpus and language-agnostic architecture of EduSimplify-GAI places the framework at the center of a potential scalable deployment in a wide range of educational settings around the world that are characterized by linguistic variability and language-related learning difficulties. The modularity of the system allows the easy integration of new language models, new learner profile databases, and new corpora of simplified texts for specific domains as the number of users grows beyond the deployment context. The multilingual processing evaluation results are not significantly lower than the task performance results for monolinguals, but still validate the system's basic ability to simplify across languages. This performance gap is expected to be further narrowed in future versions, with dedicated multilingual fine-tuning strategies and low resource language adaptation strategies.

VII. Conclusion and Future Scope

This research has introduced a new Generative Artificial Intelligence (GAI) framework called EduSimplify-GAI that helps solve the immediate and long-term need for accessibility in educational content in special education. The proposed system combines the capabilities of GPT-4 for generating text with BERT-based semantic validation, reinforcement-guided readability optimization, and adaptive learner profile management, to achieve highly effective simplification of educational content while ensuring its integrity in terms of education content. The system will produce high-quality, simplified educational content that effectively lowers the cognitive complexity of learners with intellectual disabilities, autism spectrum disorder, dyslexia and language-processing disorders while maintaining the integrity of the educational content. The experimental evaluation on the comprehensive multilingual educational datasets showed that the accuracy of the simplification produced by the model EduSimplify-GAI was greater than 96.4% and was statistically significantly higher than the other models, while the percentages of semantic retention, improvement in the comprehension of the students and satisfaction of the teachers were greater than 94.1%, 92.8% and 91.7%, respectively, and statistically significantly higher than the other models. This improvement is 13-18 percentage points greater than previous rule-

based and standard NLP-based simplification methods, thereby successfully demonstrating the potential of generative AI in inclusive education. As the system gathers interaction data from a variety of learners in different contexts and settings, the reinforcement-guided adaptive learning mechanism allows it to continuously improve the accuracy of its personalization of the content. The 91.7% satisfaction rating from teachers reaffirms the effectiveness of the system in use and its ability to fit into the real classroom setting. For future research, the possibilities for extending EduSimplify-GAI to multimodal content simplification towards visual, graphical, and audio educational content for complex communication demanding learners can be considered. Future directions include the addition of real-time biometric and engagement feedback for more precise monitoring of learners' states and the creation of lightweight model variants suitable for low-resource educational settings in developing regions, which can be installed on the edge. Longitudinal research and studies that will systematically investigate the long-term effects of generative AI-based simplification on any long-term special education learning outcomes and development over time also deserve attention to provide compelling evidence for policy-level decisions about the adoption of educational technology.

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