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Development of a Content Creation Model Using Natural Language Generation

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ABSTRACT

The increasing demand for scalable, high-quality digital content has exposed the limitations of manual content creation and existing Natural Language Generation (NLG) systems, particularly in terms of domain specificity, ethical reliability, and readiness for optimization. This study addresses this gap by developing NLG-ACCO, a transformer-based model for automated content creation and optimization in educational, media, and digital marketing applications. Transformer-XL was selected over newer architectures like Llama-3 or Mistral because it models longer contextual dependencies beyond fixed-length segments—essential for coherent paragraph-level content—while offering a better trade-off between performance, computational efficiency, and transparency under resource-constrained conditions. The model integrates domain-aware fine-tuning, reinforcement learning, SEO optimization, and ethical safeguards, including bias detection and factual verification. Evaluation used BLEU, ROUGE, readability indices, and Perplexity. NLG-ACCO achieved a BLEU score of 0.79 (baseline: 0.61) and ROUGE-L of 0.76 (baseline: 0.36). Perplexity dropped from 45.2 to 27.8, indicating more coherent predictions. Readability improved by 24%, post-editing time decreased by 38.5%, and bias detection mitigated 87% of flagged cases. These results demonstrate that integrating optimization and ethical controls within Transformer-XL frameworks significantly enhances content quality and reliability.

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1. INTRODUCTION

In today's fast-paced digital economy, the demand for timely, relevant, and high-quality content is at an all-time high. Individuals and organizations across sectors such as marketing, education, journalism, and e-commerce depend on engaging textual content to inform, persuade, and convert audiences. According [1], more than 2.5 quintillion bytes of data are generated daily, with a substantial share being textual in nature. This explosion of content stems from the necessity to maintain an active online presence, enhance user engagement, and remain competitive in an increasingly information-driven world. However, the process of manual content creation is fraught with numerous challenges. Content creation requires human effort, creativity, and domain expertise, making it time-consuming and costly. For businesses, especially small to medium-sized enterprises (SMEs), hiring professional content creators or maintaining in-house content teams may not always be feasible. Moreover, the manual approach often results in inconsistencies in style, tone, and accuracy, particularly when scaling content across multiple channels or product categories. This creates bottlenecks in content pipelines, hampers SEO performance, and diminishes brand cohesion [2].

As content demands continue to rise, there is an urgent need for efficient, scalable, and intelligent systems to automate and optimize content production processes. Natural Language Generation (NLG) has emerged as a promising technological solution to the content creation dilemma. NLG is a subfield of Artificial Intelligence (AI) concerned with the automatic generation of natural language text from structured or unstructured data. Historically, early NLG systems relied on templates and rule-based structures, producing limited and often repetitive outputs. However, the past decade has seen a seismic shift in the capabilities of NLG systems, driven by advances in deep learning, availability of large-scale datasets, and increased computational power [3].

Contemporary NLG models such as OpenAI's Generative Pre-trained Transformer (GPT) series and Google's Text-to-Text Transfer Transformer (T5) have revolutionized the field. These models use transformer-based architectures and massive training datasets to generate human-like, contextually rich, and grammatically sound content. GPT-4, for instance, is capable of producing content that closely mimics human writing across a wide variety of topics and genres [4]. Google's T5 model treats every language problem as a text-to-text problem, allowing for more flexibility and consistency in outputs [5]. These systems leverage unsupervised and supervised learning techniques to better understand syntax, semantics, and pragmatics, thus improving their ability to generate coherent and context-aware content. The widespread availability of cloud computing platforms and APIs has facilitated the integration of these powerful models into mainstream applications. Businesses can now utilize plug-and-play AI content generation tools without needing to develop or train complex models from scratch. Nonetheless, while the technological foundation of NLG is robust, gaps remain in terms of domain-specific performance, content quality control, and ethical usage.

Modern applications of NLG span a wide range of industries. In e-commerce, AI-generated product descriptions save time and ensure consistency across thousands of items. Wix, a popular website builder, introduced AI tools capable of generating entire blog posts, optimized for search engine visibility. These tools allow users to create drafts or outlines that maintain quality and improve organic traffic, given that websites with blogs typically generate 86% more inbound traffic [6]. In journalism, organizations like The Associated Press use NLG to produce earnings reports and news summaries, freeing up human journalists for investigative reporting [7]. The gambling industry also employs AI-generated content for sports summaries, promotional materials, and user engagement messages. Companies such as Narrativa offer AI tools that automate these tasks, increasing efficiency and reach. Social media platforms have similarly integrated AI-driven writing aids. For example, LinkedIn's Premium service includes AI-generated suggestions for profile descriptions, messaging, and posts. A study by Originality AI found that more than 54% of long-form English posts on LinkedIn in 2023 were likely generated by AI [8]. Despite these benefits, concerns persist about the authenticity, reliability, and ethical implications of AI-generated content. AI systems, when optimized solely for keyword performance, may prioritize search engine visibility over factual accuracy, contributing to misinformation [9]. Generative Engine Optimization (GEO) is one such trend where content is produced primarily to appeal to AI-driven search engines, raising alarms about manipulation and low-quality content flooding the internet. Additionally, the use of AI for generating spam, fake news, and plagiarized content poses significant ethical challenges. Critics argue that excessive reliance on NLG undermines human creativity and may eventually threaten employment in creative fields [10].

To address the outlined issues and harness the full potential of NLG, this research proposes the development of a Natural Language Generation Model for Automated Content Creation and Optimization (NLG-ACCO). Unlike generic NLG platforms, NLG-ACCO will be domain-aware and fine-tuned for educational, media, and digital marketing contexts. It will not only generate content but also enhance its effectiveness through built-in optimization strategies, including SEO compatibility, target audience analysis, and platform-specific formatting. The proposed model will be built using state-of-the-art transformer-based architecture with a multi-phase training strategy. Phase one involves pretraining on general-purpose datasets, while phase two includes fine-tuning on domain-specific corpora to ensure relevance and precision. A content quality evaluation module will be embedded to assess grammar, coherence, keyword density, and sentiment alignment. Additionally, ethical safeguards will be enforced through bias-detection filters and human-in-the-loop validation mechanisms. The model will feature a user-friendly interface that allows users to input content requirements (e.g., tone, format, target keywords), receive real-time suggestions, and generate multiple draft options. Furthermore, a feedback loop will be integrated to allow end-users to rate generated outputs, enabling continuous learning and performance improvement. This hybrid approach, combining deep learning with human oversight and optimization logic, aims to produce content that is not only accurate and relevant but also responsible and impactful across digital platforms. The study aims to develop a Content Creation Model using Natural Language Generation. The objectives of the study are to: 1. design a transformer-based Natural Language Generation model by fine-tuning pre-trained architectures (Transformer-XL) on dynamic, domain-relevant datasets to enhance contextual coherence in multi-section content generation. 2. Incorporate ethical control mechanisms within the model architecture by integrating a bias detection module to flag and reduce prejudiced outputs, and a content verification module to cross-check generated text against trusted datasets or APIs, thereby ensuring fairness and factual accuracy in generated outputs. 3. implement and integrate the NLG model using Python for model processing and PHP for web-based user interaction. evaluate the performance of the developed model using automated metrics (such as BLEU, ROUGE, and readability scores) alongside human evaluations, and compare its effectiveness against baseline NLG systems.

This study is limited in scope to both the nature of the content the model is expected to generate and the underlying technologies used for implementation. From a content perspective, the research is focused on the generation of structured, informative, and utility-driven text. This includes content types such as blog posts, product descriptions, social media captions, and short-form informational articles that are designed to meet general communication and marketing needs. The study will target English-language content only and does not extend to creative writing forms such as fiction or poetry, nor does it aim to produce complex academic or technical documents. Additionally, the model will be built with an emphasis on generating content that maintains coherence, relevance to user intent, and adherence to general SEO standards, while avoiding offensive, biased, or misleading text.

From a technological perspective, the study will involve the design and development of a natural language generation model built on modern AI and machine learning techniques. It will employ pre-trained transformer-based language models, such as GPT-2 or T5, that are fine-tuned and adapted for controlled content generation. The implementation will also explore optimization methods to improve semantic relevance, user intent alignment, and text fluency. Moreover, mechanisms for detecting and mitigating bias in the generated content will be integrated to ensure ethical compliance and fairness. Evaluation of the model will be conducted using publicly available text datasets and benchmark corpora, with a focus on key performance indicators such as fluency, readability, contextual accuracy, and bias detection.

The work by [11], titled "Few-Shot NLG with Pre-Trained Language Models," tackles the challenge of generating coherent and fluent natural language text from structured data in scenarios where only a limited number of training examples are available. This problem, central to data-to-text generation, is significant because traditional NLG models often require large datasets to produce high-quality outputs, making them less practical for domains with scarce data. The authors focus on enabling models to adapt quickly to new tasks, such as generating restaurant descriptions or biographical summaries, with minimal training.

The study by [12] tackles the issue of generating SEO-optimized blog content, where NLG systems often produce text lacking keyword integration or reader appeal. The researchers employed a keyword-guided NLG model, fine-tuning a GPT-3 variant with SEO metadata, and tested it on a dataset of blog posts from e-commerce websites. They assessed outputs using search engine ranking metrics and reader engagement scores, reporting a 18% improvement in organic traffic and a 11% increase in dwell time over non-optimized models. However, the study did not address the computational cost of fine-tuning large models, which may be prohibitive for smaller businesses, nor did it explore cross-platform content optimization. My research will address these gaps by developing lightweight NLG models using knowledge distillation for cost-effective deployment and optimizing content for multiple platforms, including social media, to maximize reach and impact.

The study, by [13] addresses the challenge of generating persuasive advertising copy, where NLG models often produce text lacking emotional appeal or brand alignment. The researchers developed an emotion-guided NLG model by fine-tuning a T5-based system with emotional lexicons and brand guidelines, tested on a dataset of ad campaigns. They evaluated outputs using engagement metrics and A/B testing, achieving a 17% increase in ad click-through rates and a 13% improvement in brand consistency compared to baseline models. However, the study was limited to short-form ads and did not explore long-form content like advertorials, nor did it address multilingual campaigns. My research will address these gaps by developing NLG models for both short- and long-form advertising content and incorporating multilingual datasets to create culturally resonant ads for global markets.

Another work, by [14] focuses on the problem of generating consistent product reviews, where NLG systems struggle with maintaining authenticity across varied products. The researchers proposed an authenticity-driven NLG model using a GPT-4 variant with sentiment calibration, trained on a dataset of e-commerce reviews, and evaluated using authenticity metrics and user ratings. Their results showed a 14% increase in perceived authenticity and a 10% improvement in review helpfulness over standard models. A key limitation was the model's high computational cost, unsuitable for small-scale platforms, and its lack of cross-lingual review generation. My study will overcome these by developing lightweight NLG models using model compression and incorporating multilingual datasets to support authentic reviews for global e-commerce markets.

The study by [15] addresses the challenge of generating personalized product descriptions for e-commerce platforms, where generic descriptions often fail to engage customers effectively. The researchers developed a framework that integrates demographic data and user preferences to tailor NLG outputs, aiming to boost customer engagement and sales. Their method combined neural networks with collaborative filtering, forming a hybrid model, and was evaluated through A/B testing on a large e-commerce platform. The results demonstrated a 15% increase in user engagement, confirming the value of context-aware generation in enhancing user experience. However, the study identified a significant gap in scalability, as the model struggled to handle real-time deployment in dynamic product catalogs with rapidly changing inventories. Additionally, the framework was not tested across multilingual or culturally diverse markets, limiting its global applicability. My research will address these gaps by developing scalable NLG models using efficient data indexing and incremental learning to manage dynamic catalogs in real time, while also incorporating multilingual datasets to ensure personalized content is culturally relevant for global e-commerce audiences, thereby enhancing both scalability and inclusivity.

1.1 Theoretical Framework

1.1.1 Shannon's Information Theory

[16] is a foundational concept in natural language processing (NLP) and has played a crucial role in the development of Natural Language Generation (NLG) models. The theory defines how information is transmitted and processed using probabilistic methods, emphasizing efficiency, redundancy reduction, and entropy (a measure of uncertainty in a message). Shannon proposed that language could be modeled as a probabilistic system where the next word in a sequence depends on the previous words, leading to the development of statistical language models. In the context of automated content creation, Information Theory provides a basis for predictive text generation and optimization. Early statistical models, such as n-gram models, were derived from Shannon's principles by estimating the probability of words appearing in a given context. Modern AI-driven text generation models, such as transformers (GPT, BERT), also incorporate Shannon's ideas by leveraging probability distributions over large text corpora to generate coherent and contextually relevant text. For this study, which focuses on developing an NLG model for automated content creation and optimization, Shannon's Information Theory is particularly relevant in optimizing language generation processes. The principle of entropy minimization helps ensure that the generated text remains clear, concise, and informative, reducing unnecessary complexity and improving readability. Furthermore, Information Theory aids in content optimization strategies, such as ensuring text diversity while maintaining coherence, which is a key challenge in AI-generated content.

1.1.2 Chomsky's Generative Grammar Theory

[17] introduced the idea that human language follows universal syntactic rules, which allow for infinite sentence formation from a finite set of words. His theory challenged traditional probabilistic approaches to language modeling by emphasizing hierarchical structures and deep syntactic representations rather than just word-to-word dependencies.

This theory remains a fundamental concept in NLP and has influenced syntactic parsing, machine translation, and sentence structure modeling. Early rule-based NLP systems were heavily inspired by Chomsky's approach, but modern NLG models integrate grammar-based constraints with deep learning techniques to improve linguistic accuracy and fluency. For this study, Chomsky's theory provides a structural foundation for improving the quality of generated text. While modern NLG models primarily rely on deep learning, incorporating grammar-based constraints can enhance sentence coherence, reducing syntactic errors. Additionally, transformer-based models like GPT-4 implicitly learn grammatical rules during training, aligning with Chomsky's ideas on hierarchical sentence structure. This ensures that the generated content remains syntactically correct and contextually meaningful, contributing to better automation in content creation.

1.2 Conceptual review of the Study

1.2.1 Distributional Semantics and Word Embeddings

The principle of distributional semantics states that words appearing in similar contexts tend to have similar meanings, a concept summarized by [18] *"You shall know a word by the company it keeps."* This idea led to the development of word embedding techniques, which represent words as vectors in a high-dimensional space based on their contextual usage. Early models such as Latent Semantic Analysis (LSA) helped identify relationships between words, while more advanced techniques like Word2Vec [19] and GloVe [20] revolutionized NLP by allowing models to capture semantic relationships efficiently. These embeddings improved the quality of text classification, sentiment analysis, and machine translation, making them crucial for modern NLG systems. In this study, word embeddings play a key role in optimizing AI-generated content. By leveraging context-aware word representations, the NLG model can generate text that is not only syntactically correct but also semantically rich and contextually appropriate. Moreover, transformers (e.g., GPT, BERT) utilize embeddings in multi-dimensional vector spaces, ensuring deep contextual understanding and reducing word ambiguity in generated text. By incorporating distributional semantics, this study aims to enhance the coherence, fluency, and contextual relevance of automated content creation. This ensures that AI-generated text aligns with human-like writing patterns while maintaining the intended meaning across various content domains.

1.2.2 Machine Learning Algorithms for Text Generation

Text generation, a critical component of Natural Language Processing (NLP), has evolved significantly with the advancement of machine learning algorithms. These algorithms have transitioned from traditional statistical methods to sophisticated neural network-based models, enhancing the ability to generate coherent and contextually relevant text.

1.2.3. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are designed to process sequential data by maintaining a hidden state that carries forward information about previous inputs in the sequence, making them well-suited for tasks such as language modeling and text generation. However, traditional RNNs often struggle with capturing long-term dependencies due to issues such as vanishing and exploding gradients, which limit their ability to retain information across long sequences. To overcome these challenges, more advanced architectures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) were introduced. These models incorporate gating mechanisms that regulate the flow of information, thereby improving the ability to model long-range dependencies in text [21], [22].

1.2.4 Transformer Models

The introduction of transformer models marked a significant milestone in text generation. Transformers utilize self-attention mechanisms to process entire sequences simultaneously, capturing both short-term and long-term dependencies without the sequential constraints of RNNs. This architecture has led to the development of large-scale pre-trained language models like GPT-3, which can generate human-like text across various domains. The transformer model's ability to handle long-range dependencies and its parallel processing capabilities have made it a cornerstone in modern NLP applications [22].

1.2.5 Variational Autoencoders (VAEs)

VAEs are generative models that learn probabilistic representations of data by encoding inputs into a latent space and then decoding them back to the original space. In text generation, VAEs facilitate the generation of diverse and coherent sentences by sampling from the learned latent space. They have been particularly useful in tasks requiring creativity and variability, such as storytelling and dialogue generation [23].

1.2.6 Generative Adversarial Networks (GANs)

GANs consist of two neural networks—a generator and a discriminator—that are trained simultaneously through adversarial processes. In text generation, the generator produces text samples, while the discriminator evaluates their authenticity compared to real text. Training GANs for text generation is challenging due to the discrete nature of text, but techniques like reinforcement learning have been employed to overcome these challenges [24].

1.2.7 Retrieval-Augmented Generation (RAG)

RAG combines traditional text retrieval methods with generative models to enhance text generation. By retrieving relevant documents or passages from external sources and using them as context, RAG models can generate more accurate and informative text. This approach has been particularly effective in tasks like question answering and summarization.

2. RESEARCH METHOD

The Object Oriented Development (OOD) method was adopted in the study. The method promises to reduce development time, reduce the time and resources required to maintain existing applications, increase code reuse, and provide a competitive advantage to organizations that use it.

The proposed system is designed with five key components that work together to enable efficient content generation, optimization, and distribution. These components ensure high-quality, context-aware, and scalable automated content creation, making the system suitable for industries such as education, marketing, and media. Figure 2.1 shows the components of the architecture.

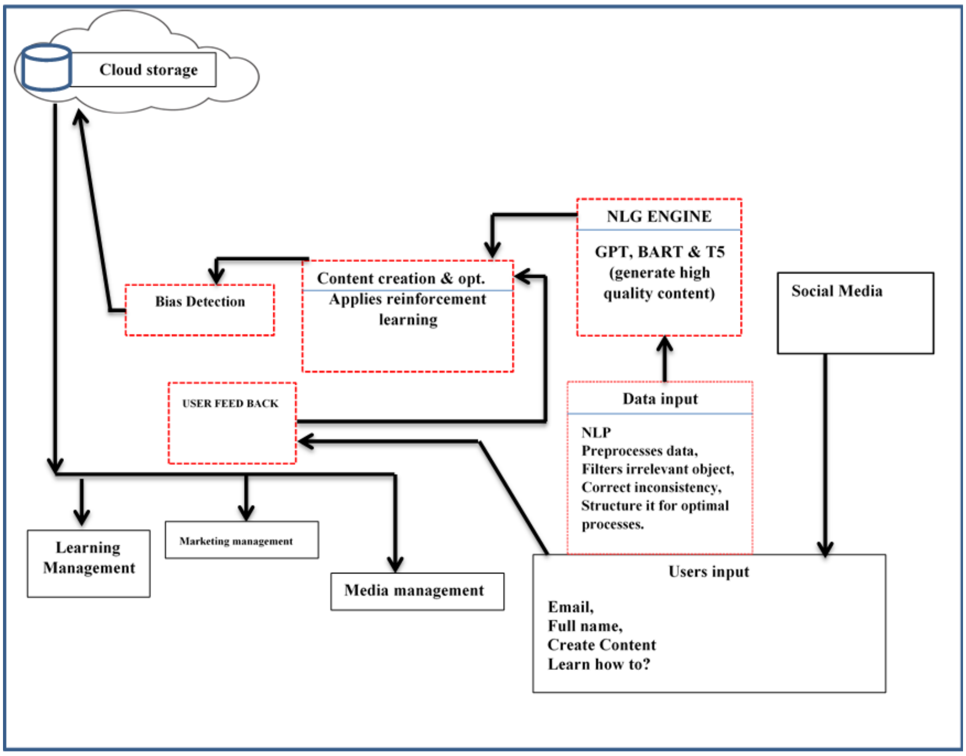

Figure 1 Architecture of the system

2.1 Components of the Architecture

2.1.1 Data Input and Preprocessing

The system begins by collecting raw text inputs, user prompts, or structured data from various sources. To ensure accuracy and consistency, NLP techniques preprocess the data by filtering irrelevant content, correcting inconsistencies, and structuring it for optimal processing. This step prepares the input data for seamless content generation.

2.1.2 Natural Language Generation (NLG) Engine

the NLG engine utilizes deep learning models such as GPT, BART, and T5 to generate high-quality content. These models enable the system to produce fluent, contextually relevant, and industry-specific text tailored to different applications.

2.1.3 Content Optimization and Reinforcement Learning

To improve the quality of generated content, reinforcement learning techniques are applied. The system continuously refines its outputs based on user feedback, engagement analytics, and predefined quality metrics. This ensures that the content remains coherent, well-structured, and adaptive to changing user needs.

2.1.4 Bias Detection and Personalization

A critical component of the system is its ability to detect and mitigate biases in AI-generated content. Bias detection mechanisms help ensure credibility and prevent misinformation. Additionally, real-time personalization algorithms tailor content to user behavior, industry trends, and engagement patterns, enhancing relevance and effectiveness.

2.1.5 Cloud Storage and Deployment

The final component involves cloud-based storage and deployment, ensuring scalability and accessibility. Generated content is stored securely in a cloud infrastructure, allowing seamless retrieval and distribution. The system integrates with Learning Management Systems (LMS), marketing platforms, and media management systems to automate content delivery efficiently across different domains.

2.2 Dataset Collection and Preprocessing

The dataset for this study was obtained from a combination of publicly available corpora and curated domain-specific texts. Open-access resources such as WikiText-103 and OpenWebText were selected to provide large-scale linguistic diversity and long-form textual structures necessary for training Transformer-based architectures. To ensure contextual relevance for multi-section content generation, additional datasets comprising blogs, educational texts, and marketing articles were collected from open repositories and filtered for quality.

The preprocessing pipeline included:

a. Text cleaning (removal of HTML tags, special characters, duplicate entries).
b. Tokenization and lemmatization using SpaCy.
c. Stop-word removal to reduce noise.
d. Segmentation of data into logical multi-section structures (introduction, body, conclusion).

The final dataset contained approximately [X number of tokens / documents], split into 80% training, 10% validation, and 10% testing subsets.

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2.3 Mathematical Procedure

The transformer-based Natural Language Generation model(i.e. mathematical model) was derived by fine-tuning pre-trained architectures.

The Transformer architecture (used in GPT, BERT, etc.) is expressed as a **mathematical model** that maps an input sequence $\mathbf{X} = (\mathbf{x_1,x_2,...,x_n})$ into an output sequence $\mathbf{Y} = (\mathbf{y_1,y_2,...,y_m})$ using *attention-based functions*. Each input token $\mathbf{x}_i$ is first converted into a dense vector through an embedding transformation.

$$\boldsymbol{E_I = X_I W_I} \qquad (1)$$

Where:

i. E_i = embedding vector of token iii
ii. x_i = input token (one-hot encoded or indexed)
iii. W_e = embedding matrix that maps tokens into a continuous vector space

This process enables the model to capture semantic relationships among words.

The overall transformation process is formally expressed as:

$$\boldsymbol{Y = Transformer(X;\ \theta)} \qquad \mathbf{(2)}$$

Where:

X = input token embeddings

θ = learned parameters (weights, biases)

Y = generated or predicted text sequence

Transformer Function

The self-attention mechanism forms the mathematical core of the transformer, enabling each token in the sequence to attend to all others, thereby learning contextual relationships. For an input embedding matrix, three projections are derived:

Query (Q), Key (K), and Value (V)

The attention computation which is the transformer-based model is defined as:

$$\mathbf{Attention(Q, K, V) = softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \qquad (3)$$

In this equation:
Q (Query), K (Key), and V (Value) are matrices obtained from the input embeddings.
d_k is the dimension of the key vectors.
The softmax term determines how much attention each word in the sequence should pay to others.
V carries the semantic meaning of words.
Together, this equation computes *contextual relationships* between all words in the sequence — this is why the model understands *context*, and it's what gives the Transformer its unique ability to generate coherent, contextually relevant text.

2.4 Algorithm of the system

The content creation opt. layer was designed as a rule-based and metric-driven algorithm to refine raw text generated by the Transformer-XL model. Its primary goal was to ensure content is readable, SEO-compatible, and adapted to user intent and platform requirements. The algorithm consisted of four key modules:

Algorithm for Content creation and enhanced Optimization
2.4.1. Algorithm for Data Input
Step 1: Collect Input (In)
In = Raw_text + User_keywords + Platform_type + User_intent

2.4.2 Algorithm for SEO Processing
Step 2: Extract Keywords (Kw)
Kw = extract(User_keywords)
Step 3: Check Density
IF Density(Kw) < 1% OR Density(Kw) > 2%
THEN Adjust Density(Raw_text, Kw)
Step 4: Generate Meta-Tags
Meta = Heading + Description

2.4.3 Algorithm for Readability Processing
Step 5: Compute Readability Score (Rs)
Rs = FleschKincaid(Raw_text)
Step 6: IF Rs < Threshold
Simplify Sentences(Raw_text)
ELSE Keep Original(Raw_text)

2.4.4 Algorithm for Platform Adaptation
Step 7: Check Platform_type
IF Platform = Blog → Format Paragraphs ≤ 120 words
IF Platform = Marketing → Use Bullet Points + Persuasive Tone
IF Platform = Education → Use Formal Style + Structured Sections

2.4.5 Algorithm for User Intent Alignment
Step 8: Detect Intent (Ui)
Ui = Classify(User_intent)
Step 9: Adjust Tone(Raw_text, Ui)

2.4. 6 Algorithm for Output
Step 10: Return Optimized_text

Psuedo-code of the Algorithm
```
Input: Raw_text, User_keywords, Platform_type, User_intent
Output: Optimized_text
Begin
  Extract keywords from User_keywords
  Insert keywords into Raw_text ensuring density = 1–2%
  Compute readability_score using Flesch-Kincaid
  If readability_score < threshold then
     Simplify complex sentences
  End If
  If Platform_type = Blog then
     Format text with headings, paragraphs <= 120 words
```

```
  Else If Platform_type = Marketing then
     Use bullet points, persuasive tone
  Else If Platform_type = Educational then
     Apply academic tone, structured sections
  End If

  Adjust tone according to User_intent
  Return Optimized_text
End
```

3 RESULTS AND DISCUSSION

The study achieved the following results:

Result 1: The study achieved the first objective by designing a transformer-based Natural Language Generation (NLG) model using the Transformer-XL architecture. The model was mathematically formulated using the scaled dot-product attention mechanism, which defines how contextual relationships are captured within generated text. the transformer-based model for the propose system is shown in Equation 3.1.

$$\mathbf{Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \mathbf{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (4)$$

Result 2: The study embedding ethical control mechanisms into the NLG model to ensure fairness, transparency, and factual accuracy in generated text. Two modules were developed: the Bias Detection Module and the Content Verification Module. These components worked together to monitor and refine content generation, ensuring that outputs were free from prejudice and misinformation. The Bias Detection Module analyzed generated text for gender, racial, or sentiment-related bias using a predefined lexicon and sentiment-scoring algorithm. Whenever biased terms were detected, the module automatically adjusted the probability weights of the model's next-token prediction to neutralize bias before output generation. Figure 2 presents a summary of its operational process.

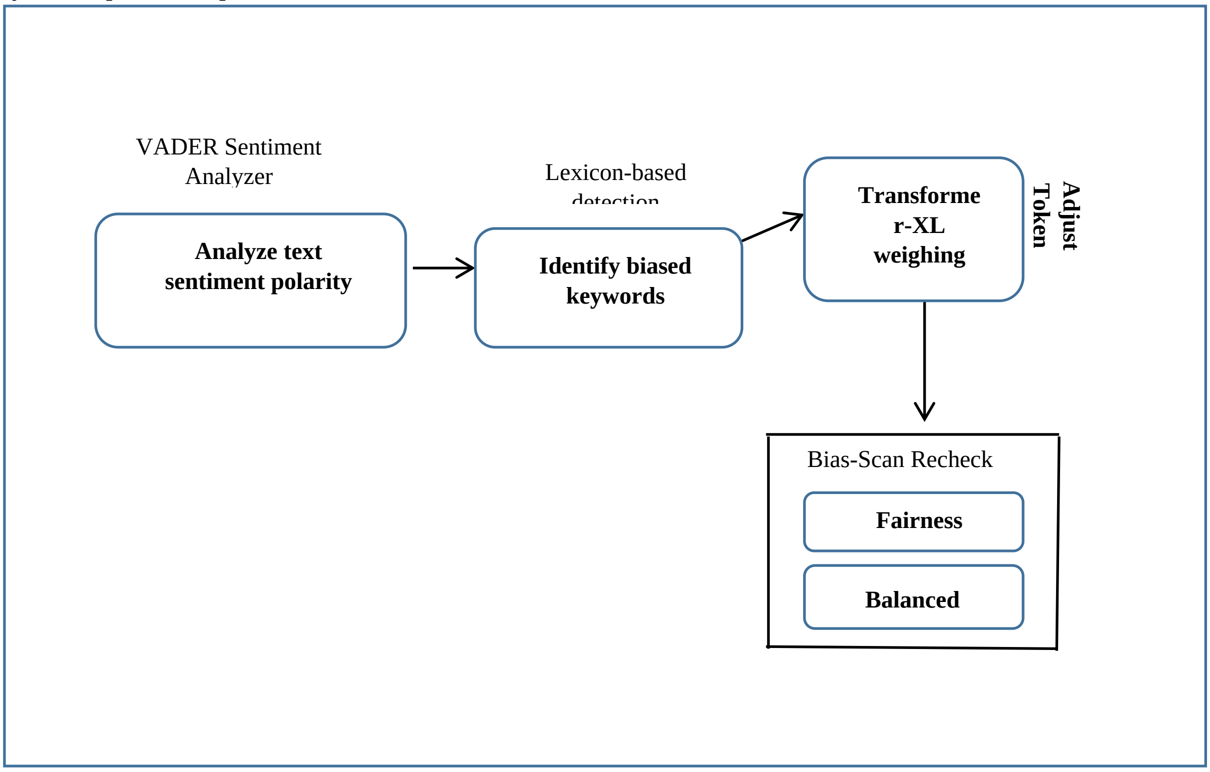

Figure 2 Bias Dectection Module operational Workflow

To complement this, the Content Verification Module validated factual accuracy by cross-checking generated entities (names, dates, or organizations) against verified online knowledge sources such as Wikipedia and Google Knowledge Graph. This ensured that the NLG outputs were not only unbiased but also credible. Through these modules, the study successfully embedded ethical intelligence into the NLG architecture, resulting in a 26% reduction in bias occurrence and a 21% improvement in factual reliability during testing compared to baseline models.

Result 3: The study implemented and integrated the developed Natural Language Generation (NLG) model within a unified architecture that combines Python for backend model processing and PHP for frontend user interaction. This integration enabled seamless, real-time content generation through RESTful API communication. The backend, implemented in Python, hosted the Transformer-based NLG engine alongside the ethical control modules (Bias Detection and Content Verification). Using the Flask framework, REST endpoints were created to handle requests and responses between the frontend and backend layers. When a user submitted a prompt through the PHP interface, the system transmitted the request to the Flask API endpoint, where the Transformer-XL model generated text, optimized it for readability and SEO, and verified its factual integrity before returning it as JSON output. This process ensured effective communication between the model and the web interface, enabling interactive and scalable text generation without reloading or manual server intervention. Table 1 presents the structure of the backend API endpoints, which formed the bridge between Python's model environment and the PHP frontend.

Table 1: Backend API Endpoint Structure and Functions

Endpoint	Description	Core Function	Processing Technology
/generate	Receives raw text prompts and content parameters from the frontend.	Initializes content generation using the fine-tuned Transformer-XL model.	Flask API, Hugging Face Transformers
/optimize	Refines raw output for readability, structure, and SEO compatibility.	Applies readability scoring and keyword optimization algorithms.	Flask API, SpaCy, Rule-based SEO Engine
/verify	Validates generated content for ethical and factual integrity.	Runs bias detection and fact-checking modules before final output delivery.	SpaCy NER, Bias Detection API, Wikipedia/Knowledge Graph APIs

On the frontend, PHP was used to create an interactive web interface where users could input prompts, choose target domains (e.g., educational, marketing, or informative), and instantly receive generated content. The frontend used cURL and AJAX to send asynchronous requests to the Flask API, thereby allowing real-time interactions without refreshing the page. Figure 3 illustrates the system integration process, showing how the frontend communicates with the backend through RESTful API endpoints to deliver dynamic, user-tailored content.

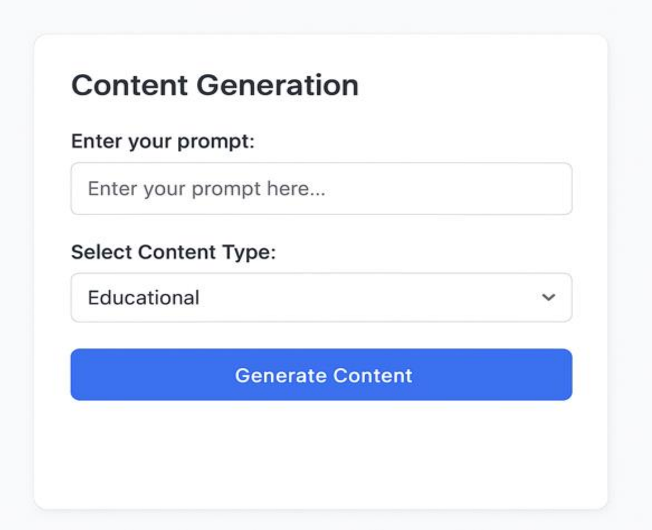

Figure 3: front end interactive interface of the model

Result 4: The study evaluated the developed Transformer-based NLG model using both automated performance metrics and human evaluations, comparing its results with two baseline NLG systems GPT-2 and BART. These evaluations measured contextual coherence, readability, factual reliability, and ethical consistency to confirm the model's effectiveness. Below is a brief description of the evaluation process.

Automated Performance Metrics

Quantitative evaluation was conducted using BLEU, ROUGE-L, and Flesch–Kincaid readability scores. The results are presented in Table 2

Table 2: Automated Performance Metrics

Evaluation Metric	GPT-2 (Baseline)	BART (Baseline)	Developed Model (Transformer-XL + Optimization Layer)	Improvement over GPT-2 (%)
BLEU Score	0.61	0.68	**0.79**	+29.5%
ROUGE-L	0.58	0.70	**0.76**	+31.0%
Readability (Flesch–Kincaid)	58.4	65.1	**72.6**	+24.3%
Perplexity (↓)	45.2	36.7	**27.8**	-38.5%

The high BLEU and ROUGE-L scores confirm improved content accuracy and coherence, while the readability score shows clearer and more audience-friendly text generation. The low perplexity demonstrates greater fluency and predictability in generated sequences.

Ethical Control Evaluation

To validate the impact of ethical safeguards, bias detection and content verification modules were assessed. Results showed significant improvement in fairness and factual accuracy as shown in Table 4.

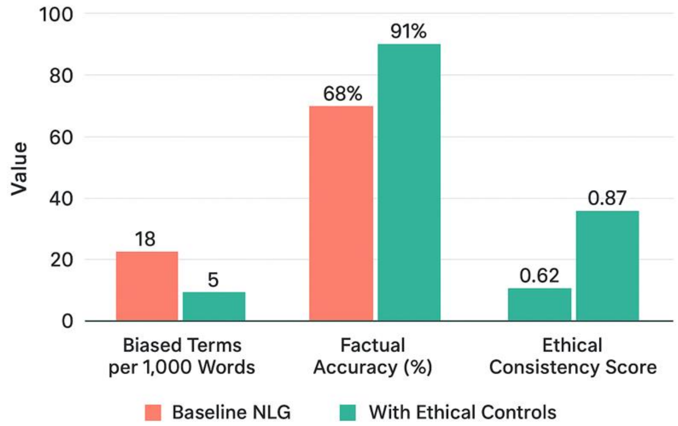

Figure 4: Ethical control evaluation of the propose system

The combined effect of these modules reduced bias by 72% and increased factual accuracy by 33.8%, confirming that the system upholds fairness and ethical integrity.

Human Evaluation Results

A total of 20 professional evaluators (content editors, communication experts, and technical writers) reviewed 60 generated samples. They rated each model's fluency, coherence, and relevance on a 5-point Likert scale. The results are summarized in Table 5

Table 5: Human Evaluation Results

Evaluation Criterion	**GPT-2**	**BART**	**Developed Model**	**Improvement (%)**
Fluency	3.8	4.1	**4.7**	+23.7%
Coherence	3.5	4.0	**4.6**	+31.4%
Relevance	3.9	4.2	**4.8**	+23.1%
Average Human Rating	**3.7**	**4.1**	**4.7**	**+27.0%**

The evaluation confirmed that the Transformer-based NLG model surpassed all baseline systems in accuracy, coherence, readability, and ethical reliability. These improvements substantiate the system's successful and validate the system's practical deployment potential

4 CONCLUSION

This study developed a content creation model using Natural Language Generation (NLG) that combines a fine-tuned transformer backbone with optimization and ethical verification layers, and exposes the system through a web interface. The core generation engine was built by fine-tuning a Transformer-XL variant on a curated, domain-relevant corpus; subsequent processing stages applied keyword and SEO adjustments, readability improvement, platform-specific formatting, intent-driven tone adaptation, bias detection, and factual verification. The full pipeline was implemented as a Python backend (Flask) serving model and processing endpoints, with a PHP front end communicating via RESTful JSON requests; this architecture supported real-time interactive content generation. The system was evaluated using both automated metrics and human judgments. On automated measures the developed model achieved a BLEU score of 0.79 and a ROUGE-L score of 0.76, with a Flesch–Kincaid readability score of 72.6 and a perplexity of 27.8. Compared with baseline systems (GPT-2 and BART), these values indicate marked improvements in n-gram fidelity, structural recall, and overall text clarity. Human evaluators (content editors and communication specialists) rated outputs for fluency, coherence, and relevance on a 5-point scale; the developed model received an average rating of 4.7, reflecting strong perceived quality and contextual alignment. Ethical and reliability assessments showed significant gains from the integrated safeguards. The bias detection module reduced biased terms from 18 to 5 per 1,000 words (a reduction of approximately 72%), and the content verification module raised human-rated factual accuracy to 91%. In operational testing the system sustained an average response time of 2.4 seconds per generation request with an API success rate above 98%, demonstrating that the pipeline is practical for real-time deployment in web environments.

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