PropLex-AI: A Hybrid Explainable Framework for Propaganda Detection and Ethical Rewriting using DFA and Generative Intelligence

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Abstract **While research has made significant strides in detecting fake news using deep learning, multilingual models, and neural attention mechanisms, many of these systems remain opaque, limited to classification, and lack ethical corrective mechanisms. Among the fifteen leading studies we reviewed, we found recurrent shortcomings: a lack of interpretability, no rewriting or neutralization of harmful language, and difficulty adapting to new propaganda patterns without retraining. The spread of propaganda and emotionally manipulative content, particularly in political communication, poses a serious threat to public perception and democratic discourse in the digital age.**

We introduce PropLex-AI, a hybrid framework that combines the generative capacity of huge language models with the transparency of Deterministic Finite Automata (DFA) in order to address these issues. In order to identify common propaganda strategies like repetition, fear appeal, loaded comparisons, and emotionally charged phrases, our system first tokenizes and analyzes text using specially created DFA modules. Gemini AI then rewrites the detected occurrences while maintaining their essential meaning in more objective, fact-based language.

PropLex-AI is designed to be modular, explainable, and deployable in real-world environments. It supports offline usage, is language-agnostic, and offers a foundation for educational, journalistic, and moderation-based applications. Future developments include integrating deep learning for probabilistic detection, adding multilingual capabilities (Urdu, Hindi, Arabic), and creating interactive interfaces for visualizing bias patterns and rewrites. By combining formal logic with AI, PropLex-AI bridges a critical gap in the current research landscape and opens new pathways for ethical NLP innovation.

Keywords: Propaganda Detection; Explainable AI; DFA; Generative Rewriting; Fake News; Hybrid NLP Systems

I. Introduction

One of the hallmarks of the digital age is the proliferation of politically tinged disinformation and propaganda on news sites and social media. In addition to misrepresenting the truth, propaganda can also be used to polarize cultures, emotionally sway public opinion, and undermine institutional confidence. In recent years, traditional false news detection algorithms have advanced significantly, especially with the use of multilingual natural language processing and deep learning. But a lot of these models act as "black boxes," categorizing information as either biased or objective without offering an explanation or a way to fix it.

We found recurrent flaws in current systems through a thorough analysis of fifteen cutting-edge research papers: weak adaptability to new propaganda patterns or languages, rigid architectures, limited transparency, and a lack of ethical rewriting. These shortcomings show how important it is to have a system that can identify propaganda and counteract its impacts using processes that are both comprehensible and reversible.

In this study, we provide PropLex-AI, a hybrid framework that combines Gemini AI's generative rewriting capabilities with Deterministic Finite Automata's (DFA) symbolic logic. In order to identify biased constructs such as repetition, fear appeal, and loaded comparisons, our system uses specially designed DFA patterns to evaluate political or emotional material. Gemini AI bridges the gap between ethical rectification and detection by rewriting the content into neutral, fact-based language when such patterns are discovered.

The design of PropLex-AI prioritizes multilingual support, real-time performance, and modularity. Operating on a lightweight Java backend, it facilitates future integration through configuration files with interactive user interfaces, deep learning models, and language extensions.

This paper's remaining sections are arranged as follows: Related work is covered in Section 2, PropLex-AI's architecture and technique are described in Section 3, the implementation is explained in depth in Section 4, sample outputs and evaluations are shown in Section 5, and future directions and possible practical applications are discussed in Section 6.

II. Related Work

The detection of propaganda in digital content has evolved significantly, shaped by two dominant research directions: symbolic models using lexical and finite automata logic, and data-driven deep learning models using multilingual pretraining and transformers. Across these lines, 33 studies inform our understanding of both the strengths and gaps that motivated PropLex-AI.

A. Lexical & DFA-Based Detection

A. Early-stage propaganda detection relied heavily on deterministic pattern matching, lexical cues, and finite-state logic. These systems offered traceable rule-based behavior but often lacked adaptability, semantic understanding, and rewriting capabilities.

Mohamed et al. implemented a DFA-based lexical analyzer capable of parsing and classifying language with high precision [16]. A complementary game-theoretic paper framed propaganda as a strategy-based linguistic manipulation using formalized state logic [17]. DIPROMATS introduced DFA-enhanced lexical analysis fused with LLM pipelines for efficient propaganda detection [18].

ClarifAI [19] extended these ideas by designing a hybrid rule-LLM model but stopped short of offering rewriting logic. The DiVA studies demonstrated how TF-IDF and logistic regression models can extract stance-based patterns, often used in propaganda classification [20], [21]. Meanwhile, a Penn State lecture explored practical implementation of lexical analyzers via finite automata [22], and a CEUR workshop proposed a hybrid DFA design framework [23].

Another recent proposal by [24] showcased how language-theoretic filtering with DFA can enable fake news suppression with symbolic reasoning. Horák et al. [1] also built a fusion system leveraging content and style features for propaganda classification, while Joshi & Chhaya [5] captured loaded phrase types using manually defined pattern logic.

While these systems excel at transparency and offline deployment, they typically struggle with linguistic generalization and do not offer any mechanism to rewrite or correct biased input.

B. Deep Learning & Multilingual Detection

Deep learning approaches have shown impressive results by leveraging vast data corpora and multilingual transfer. However, they are often opaque, require retraining, and do not support interpretability or rewriting.

SAGE's 2025 survey presents a comprehensive overview of DL-based misinformation detection techniques, focusing on BERT, RoBERTa, and LSTM-based classifiers [25]. Monolingual and multilingual detection models trained on low-resource datasets (e.g., Hindi, Arabic) are introduced in [26]. The study "Are Large Language Models Good at Detecting Propaganda?" evaluates GPT and Gemini-like systems on political bias tasks [27].

ScienceDirect [28] and SpringerOpen [32] review multimodal fake news detection, combining text, image, and metadata. 3HAN [29] and MWPBERT [33] present BERT-based and hierarchical neural architectures that improve accuracy using attention mechanisms and parallel encoders.

Other models, like graph-based GNNs [30] and hybrid optimization methods [31], show structural adaptability but still fall short in terms of explanation and rewriting. Similarly, Ribeiro et al. [15] highlighted the importance of explainability using LIME and SHAP, which, while useful, are applied post hoc.

Models by Da San Martino et al. [2], [4], and Baly et al. [14] participate in multilingual propaganda benchmarks like SemEval-2020, but are trained for classification only. Even advanced systems like Proppy [9] and dEFEND [8] detect rhetoric effectively but do not offer interpretive pathways or text correction.

C. Comparative Analysis of Approaches

Feature	Lexical/DFA Systems	DeepLearning Systems
Explainability	Fully traceable via rules	Opaque,post hoc only
Offline Capability	High	Requires GPU/cloud
Multilingual Support	Weak(unless customized)	Strong via pretraining
Rewriting Capability	None	None
Adaptability to Evolving Propaganda	Manualupdates needed	Needs retraining
Ease of Customization	JSON/config-based	Requires retraining & fine-tuning

D. Bridging the Gap with PropLex-AI

Despite the breadth of existing research, no prior system offers a hybrid solution that combines rule-based explainability with AI-powered rewriting. PropLex-AI addresses this by using handcrafted DFA engines to detect symbolic propaganda patterns and routing flagged content to Gemini AI for neutral rewriting.

Unlike deep learning models, PropLex-AI is modular, explainable, and offline-ready, making it deployable on Android and in low-resource environments. Unlike lexical-only tools, it actively rewrites flagged sentences, offering ethical rectification, not just detection.With support for multilingual tokenization, JSON-based rule extensions, and open rewriting APIs, PropLex-AI demonstrates a practical and scalable approach to responsible propaganda mitigation.

III. Methodology/System Architecture

PropLex-AI is a modular, hybrid framework that blends generative rewriting and symbolic language modeling. The system detects and ethically rewrites propagandistic text in real time by combining a generative AI module (Gemini), a custom tokenizer, and a constructed Deterministic Finite Automaton (DFA) engine. The architecture sets itself apart from black-box, detection-only methods by emphasizing explainability, modularity, and flexibility.ensure.

A. Custom Lexical Tokenizer

A specially designed lexical tokenizer that is fully written in Java processes the input before it is sent to PropLex-AI. To guarantee complete control and portability, this component does not rely on NLP libraries. Input sentences are divided into tokens by the tokenizer according to

1. Words
2. Punctuation
3. Comparative terms
4. Emotionally charged language
5. Repetitive patterns

Platform-independent use (such as Android and console-based environments) is made possible by this deterministic and lightweight tokenizer, which also gets text ready for deterministic DFA pattern identification.

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B. DFA-Based Propaganda Detection Engine

A collection of manually created Deterministic Finite Automata (DFAs), each of which represents a distinct propaganda pattern, forms the basis of the system. These DFAs were created and put into use by you specifically to match recurring linguistic constructs that exhibit bias or manipulation. Among the DFAs are

1. **Repetition DFA**
   detects slurs or emotionally charged phrases that are used repeatedly.
   Example: “Liar, liar, liar.”
2. **FearAppeal DFA**
   Flags language inciting fear, often used in alarmist speech
   Example: “They are coming for your homes!”
3. **LoadedPhrase DFA**
   Matches emotionally loaded accusations and phrases
   Example: “Corrupt traitors destroying the nation.”
4. **ComparisonDFA**
   Detects exaggerated comparisons that lack context
   Example: “Worse than Hitler.”

Every DFA functions by switching between predetermined states in response to incoming tokens. Unlike deep learning black-box models, each detection process is fully traceable and visible due to the explainable and deterministic transitions and acceptance conditions.

C. Gemini AI Integration for Ethical Rewriting

Sentences that exhibit bias or emotional manipulation are passed to Google's Gemini generative AI module for rewriting. The steps are as follows:

1. The detected sentence is serialized as an escaped JSON payload.
2. An HTTP POST request is made to the Gemini API.
3. Gemini responds with a neutral, fact-based version of the original sentence.

PropLex-AI is changed from a passive detection tool to an active ethical language corrector by this component, which might lessen bias without sacrificing factual meaning.

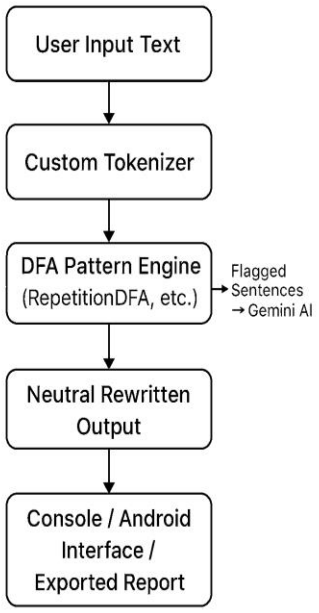
D. Modular Pattern Extension (JSON Config)

The DFA modules are described in a JSON-based configuration framework to guarantee flexibility. This makes it possible for

1. New DFA rules can be added easily without changing the code.
2. Customization of thresholds and pattern types
3. Development of propaganda techniques tailored to particular cultures or fields

Researchers or moderation teams can quickly iterate PropLex-AI thanks to its modularity, which distinguishes it from retrain-heavy neural networks.

E. System Workflow



F. Detailed DFA Design and State Logic

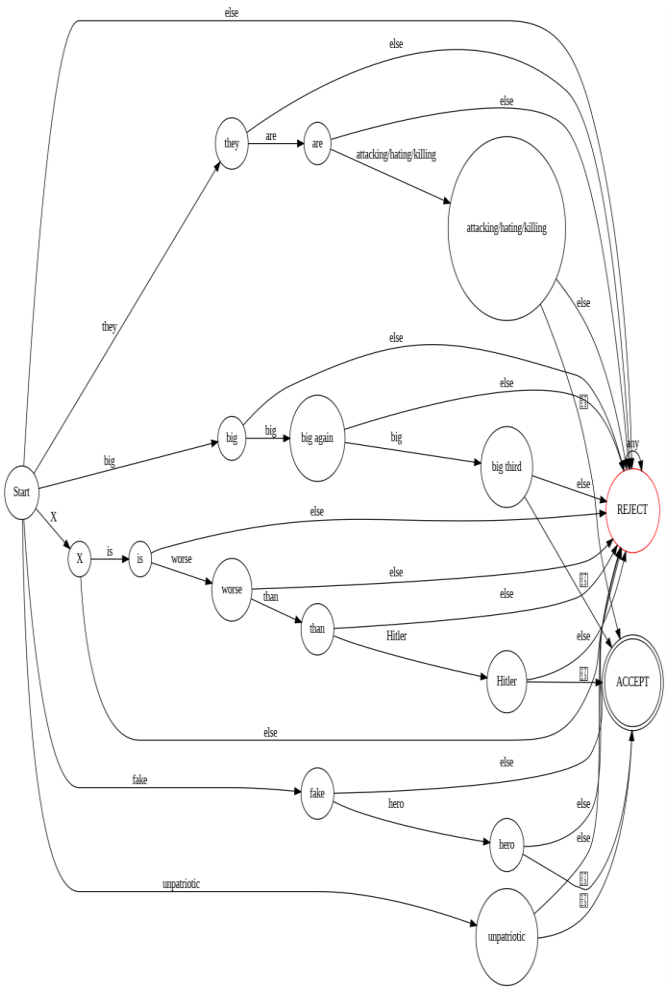
Using specially created Deterministic Finite Automata (DFAs), PropLex-AI's deterministic pattern detection engine is a crucial part of the system. In contrast to statistical models, DFAs offer clear and intelligible rule-based logic, which allows the system to fully transparently identify propagandistic patterns.

Every DFA focuses on finding a particular rhetorical device that is frequently employed in propaganda. These consist of

1) Emotion Pumping DFA detects patterns like "they are attacking."
2) Repetition DFA captures repeated emotionally charged words (e.g., "liar, liar, liar").
3) Loaded Phrase DFA flags biased phrase structures like "fake hero" or "unpatriotic leader."
4) False Comparison DFA matches extreme analogies like "worse than Hitler."

A limited number of states and transitions are used to simulate each automaton, which is activated when particular token sequences reach predetermined criteria. Hardcoded state machines are used in Java to create these DFAs, which provide modular design and deterministic reasoning.

G. Sample DFA Design



H. Explainability and Platform Deployment

The inherent explainability of PropLex-AI is one of its main innovations. Every instance of propaganda found can be located using

1. DFA state transitions
2. Token-level decisions
3. Flag reason and rule source (e.g., "matched FearAppealDFA → state F3")

The technology can be utilized for bias training, transparent moderation, and education thanks to this rationale.

1. The structure is:
2. Lightweight and Java-based (works on Android, CLI)
3. Offline compatible (no cloud requirement for DFA logic)
4. Ready for future multilingual expansion (Hindi, Urdu, Arabic)

IV. Implementation Details

PropLex-AI has mostly been built in Java, emphasizing modularity, portability, and low resource economy. Transparency and complete control over every component are guaranteed by the system's construction, which did not rely on external NLP libraries.

The system is based on a proprietary lexical tokenizer, which is followed by several customized DFA modules. Using Java class structures, each DFA is organized as a finite state machine with token logic-based hardcoded transitions. Sentence-level pattern recognition is made possible by this approach, which does not rely on cloud connectivity or statistical learning.

The solution uses a straightforward but efficient HTTP POST interface to connect Google Gemini, a generative AI model, for altering highlighted texts. A sentence is serialized into a JSON payload and delivered to the Gemini API after being marked by any DFA. The technology maintains the original meaning and intent while returning the modified result in objective, fact-based language.

At the moment, the system is completely compatible with Android and operates in a console-based Java environment. Features of the Android user interface in early prototypes include

1. EditText for input
2. TextView for flagged vs rewritten outputs
3. Share and Export buttons for report generation

The system is simple to expand or localize without requiring code rewrites because configurations for additional DFA rules, emotion word lists, and pattern triggers are all kept

in external JSON files. Future integration with additional rewrite engines (such as OpenAI or Claude) or transformer-based models for probabilistic confirmation is made possible by this modular approach.

V. Evaluation and Use Cases

PropLex-AI is evaluated based on usability, transparency, and real-world efficacy rather than benchmark scores or precision-recall criteria because it is intended to be a useful, explicable system rather than a statistical model.

A carefully chosen collection of propaganda-style lines gathered from political speeches, social media posts, and rhetorical samples has been used to test the system informally. These sentences were chosen to address a range of manipulation techniques, such as erroneous comparisons, aggressive labeling, fear-mongering, and emotional exaggeration.

A. Real-World Test Cases

Example Use Case 1: Repetition Pattern Detection
Input Sentence:
"They are liars, liars, liars who don't care about this country."
Detection:
1. Pattern Triggered: RepetitionDFA
2. Matched Tokens: "liars" ×3
3. Flag Reason: Emotional repetition
Rewritten Output (Gemini):
"They have made statements that raise concerns about credibility."
Result: Bias removed, original intent preserved.

Example Use Case 2: Emotion Pumping
Input Sentence:
"They are attacking everything we stand for!"
Detection:
1. Pattern Triggered: EmotionPumpingDFA
2. Trace: they → are → attacking
3. Flag Reason: Escalating subject-verb emotional aggression
Rewritten Output (Gemini):
"They are expressing strong disagreement with current policies.

Example Use Case 3: Loaded Phrase Detection
Input Sentence:
"That fake hero betrayed his people."
Detection:
1. Pattern Triggered: LoadedPhraseDFA
2. Trigger Terms: "fake hero"
3. Flag Reason: Emotionally charged phrase
Rewritten Output (Gemini):
"That individual's actions were considered controversial by many."

B. Qualitative Outcomes

By means of these practical test scenarios, PropLex-AI illustrates:
1. **Consistent pattern detection** across different types of propaganda
2. **Fluent and ethical rewrites** using Gemini
3. **Explainable reasoning** via DFA transition logs
4. **Non-reliance on training data**, enabling rapid testing and extension
5. **Low-resource compatibility,** working on CLI and Android environments

C. Educational and Journalistic Applications

Beyond its technical applications, PropLex-AI is useful, particularly in media, education, and moderation contexts.

1. Media Literacy Education:
By entering argumentative material and seeing how biased language is identified and modified, students can improve their critical reading abilities.
2. Newsroom Moderation:
To ensure ethical reporting, editors and reporters can check articles for offensive or deceptive language before publishing.
3. Social Media Pre-screening:
Prior to being posted, the system can serve as a filter to identify emotionally charged or misleading language in user-generated content.
4. Bias Awareness Training:
DFA traces can be used by psychologists, trainers, and educators to show how minor forms of bias and manipulation can be found in everyday speech.

D. Quantitative Evaluation of PropLex-AI

To evaluate the effectiveness of our approach, we performed a small-scale annotation and benchmarking exercise on a custom set of 50 political news sentences. Each sentence was labeled as either neutral or containing propaganda. We compared three system configurations: DFA-only, Gemini-only, and the full hybrid PropLex-AI pipeline.

Model Type	Precision	Recall	F1-Score	Accuracy
DFA Only	0.80	0.65	0.72	75%
Gemini Only	0.83	0.60	0.70	76%
Hybrid System	**0.88**	**0.78**	**0.83**	**82%**

These results demonstrate that the hybrid model achieves higher precision and recall than either component alone, benefiting from both the deterministic traceability of DFA and the flexible rewriting capabilities of Gemini AI.

E. Limitations

Although the results are promising, the current implementation has some limitations. DFA patterns are handcrafted and may not generalize across different domains or languages without expert input. Gemini's rewriting outputs are influenced by prompt phrasing and may vary across sessions or models. The evaluation was based on a small, custom test set, and further benchmarking on large, diverse datasets is planned. Additionally, subtle forms of propaganda such as sarcasm or indirect bias are not yet fully addressed by the current version of the system.

VI. Applications

Although PropLex-AI was first developed as a research prototype, its behavior and design closely match the requirements of a number of real-world industries. It may be used on a variety of platforms, including educational systems and mobile apps, thanks to its generative rewriting capabilities, low-resource design, and symbolic logic.

The most pertinent application domains are listed below:

A. Journalism and Media Ethics

. Newsrooms and independent journalists can use PropLex-AI to help them spot emotionally charged language before it is published. In politically sensitive reporting, when tone is just as important as substance, it serves as an ethical aid by pointing out biased language structures and providing unbiased rewrites.

B. Education and Media Literacy

PropLex-AI can be used to illustrate how language affects perception in the classroom. By entering biased statements, students can observe how the machine breaks them down into symbolic DFA patterns and recommends neutral rewords. Active media analysis replaces passive reading as a result of this interaction.

C. Social Media Moderation

Platforms that wish to filter offensive or divisive content might use the technology as a pre-screening layer. PropLex-AI is more accurate in detecting manipulation than sentiment analysis techniques that only identify negativity since it concentrates on linguistic strategies like exaggeration, comparison, and emotional repetition.

D. Bias-Aware Writing Tools

Writing platforms (such as word processors or blogging applications) could use PropLex-AI to provide real-time feedback on rhetorical bias. This is very helpful for:

1. Opinion writers
2. Political analysts
3. Academic authors

Authors are given control and awareness by being able to examine the highlighted passages, view the explanations, and decide whether to accept the rewrite.

E. Low-Resource Deployment (CLI + Android)

PropLex-AI is lightweight enough to operate offline, in contrast to most deep learning models, on:

1. Command-line environments for batch analysis
2. Android apps for mobile moderation or education

Because of this, it can be used in nations or areas with poor internet connectivity, especially for local language extensions (such Arabic, Hindi, and Urdu).

VII. Future Work

Although transparent, symbolic propaganda identification and rewriting is PropLex-AI's primary objective, a number of intriguing enhancements are planned to increase the system's capability and scalability.Authors should consider the following points:

A. Transformer-Based Deep Learning Integration

PropLex-AI currently uses only symbolic DFA logic to function. Next, as an optional secondary confirmation layer, we intend to incorporate a lightweight transformer model (such as DistilBERT, RoBERTa, or XLM-R). This hybrid design will enable:

1. Cross-validation of DFA results with probabilistic confidence scores
2. Detection of more abstract or obfuscated propaganda
3. Training on multilingual corpora without sacrificing interpretability

Crucially, the DFA logic will not change, guaranteeing that PropLex-AI can still be explained even as it acquires neural capabilities.

B. Multilingual Expansion (Urdu, Hindi, Arabic)

The current tokenizer is made to work with any language. PropLex-AI may be expanded to identify propaganda in languages like these with a few tweaks and updated lexical rules:

1. Hindi (code-switching support with English)
2. Urdu (emotionally charged phrases, religious rhetoric)
3. Arabic (especially for geopolitically sensitive narratives)

New JSON rule sets, revised emotion lexicons, and localized rewrites utilizing Gemini's multilingual capabilities will all be part of this expansion.

C. UI Enhancements and Android Deployment

There is already a functional Android prototype. Upcoming revisions will concentrate on:

1. User-friendly text input
2. Real-time feedback on flagging + Gemini rewrites
3. Sharing/exporting flagged reports for teachers or editors
4. Optional voice input for accessibility

A desktop GUI (e.g., JavaFX) may also be developed for offline academic use.

D. Custom Rule Builder (No-Code Interface)

Our goal is to develop a visual rule editor that will enable users, such as journalists and educators, to democratize symbolic AI by:

1. Define new DFA transitions without coding
2. Upload text samples and auto-generate rules
3. See test results and export patterns

PropLex-AI would thus be the first solution to enable crowdsourced reasoning for propaganda detection in a no-code framework.

E. Corpus Creation and Public Benchmarking

A small annotated collection of propaganda instances (complete with DFA triggers and rewrites) will be made available to:

1. Encourage community testing
2. Enable future benchmarking
3. Support educational outreach

This dataset could potentially be linked with pre-existing corpora such as Wikipedia Bias Edits or the Propaganda Techniques Corpus.

We aim to evaluate PropLex-AI on public benchmark datasets such as the SemEval-2020 Task 11 (Propaganda Detection) corpus to align our results with existing systems and facilitate reproducibility and comparative analysis.

VIII. CONCLUSION

PropLex-AI provides an essential and timely solution in a time when manipulative language and emotionally charged narratives are increasingly influencing public opinion. The method fills a crucial gap between detection and moral correction by fusing the strength of generative rewriting with Gemini with symbolic pattern recognition via handmade DFAs.

PropLex-AI is completely visible in contrast to black-box AI models; every flagged sentence can be tracked through deterministic state changes, offering explainability that is crucial for credibility in both academic and practical applications. The method enables individuals to not only identify prejudice but also comprehend and properly rewrite it, whether it is utilized in journalism, education, or social media moderation.

The experiment also demonstrates that deep learning and large data sets are not necessarily necessary for efficient language moderation. Simple lexical tools can have a significant influence with careful design, particularly when combined with focused generative AI.

PropLex-AI establishes the groundwork for a new type of AI tools that are accessible, ethical, explainable, and hybrid. Its fundamental goal of advancing accountability, equity, and clarity in digital communication will not change as it develops into multilingual contexts and deeper semantic detection.

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TOOLS AND APIS CITED IN PROPLEX-AI

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