Context-Aware Hate Speech Detection via Post–Comment Joint Modeling

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***Abstract*—Hate speech detection systems deployed in real-world moderation pipelines predominantly operate on isolated textual inputs, ignoring the conversational context in which language is produced. This context-blind design leads to systematic misclassification, frequently conflating emotionally charged disagreement with malicious intent and failing to distinguish provoked hostility from standalone abuse. This paper presents a context-aware framework that redefines hate speech detection as a post–comment interaction problem rather than an independent classification task. We introduce a reaction-based taxonomy that jointly analyzes a parent post and its corresponding response to categorize behavior into four distinct classes: Neutral, Heated Reaction, Standalone Hate, and Reactionary Hate. To support this formulation, we constructed a dataset of real-world post–comment pairs centered on politically and socially sensitive topics. Addressing the inherent noise in conversational data, we implemented a rule-driven sanitization strategy to objectively separate benign emotional outbursts from toxic content prior to training. We trained a Transformer-based classifier on these paired inputs to learn interaction-aware representations. Our experimental results demonstrate that modeling the dependency between a post and its comment significantly reduces false positives associated with "heated" disagreement while maintaining high recall for genuine hate speech. This approach not only enables more granular and proportional moderation decisions but also provides the necessary semantic grounding for downstream interventions, such as automated counterspeech generation and escalation prediction.**

. ***Index Terms*—Hate Speech Detection, Context-Aware NLP, Post–Comment Interaction, Social Media Moderation, Reaction Classification, Transformer Models.**

I. Introduction

The exponential growth of user-generated content on social media platforms has necessitated the widespread deployment of automated moderation systems to mitigate hate speech, harassment, and toxic discourse [8], [11]. These systems operate at massive scale, serving as the first line of defense by filtering millions of user interactions daily to reduce psychological harm and limit the escalation of online hostility.

Despite significant advances in natural language processing, the dominant paradigm in automated hate speech detection remains largely context-blind [5], [8], [11]. Most state-of-the-art systems-including Transformer-based architectures-process comments as isolated textual units[5], [8], without incorporating the conversational context in which they are produced. While this design choice enables efficient inference, it fundamentally conflicts with the reactive nature of social media discourse, where comments are often responses to prior content, news events, political statements, and other users' opinions [6], [13] and are instead responses to prior content such as news events, political statements, or other users' opinions.

Ignoring this parent–child dependency introduces a critical semantic failure mode in moderation systems [6], [13]. Context-free systems frequently conflate emotionally charged disagreement with malicious intent. For example, a response such as "This is absolute madness!" directed at a controversial policy reflects political dissent rather than hate, yet may be flagged due to high-arousal language. Conversely, a superficially neutral statement like "They get what they deserve" may carry severe hateful intent when reacting to content describing humanitarian suffering. Without access to the triggering context, moderation systems are unable to distinguish between provoked emotional reactions and unprovoked abusive behavior.

This limitation results in what can be characterized as oversensitive or disproportionate moderation, a challenge repeatedly highlighted in recent surveys of hate speech detection and online harm mitigation systems [8], [11], [12], where legitimate expression is over-penalized while context-dependent abuse remains undetected. Such behavior not only undermines user trust but also limits the applicability of automated moderation systems in real-world deployment scenarios [8], [11].

To address these challenges, this paper introduces a Context-Aware Hate and Reaction Understanding Framework that builds upon prior work in contextual conversational modeling while extending it toward moderation-oriented reaction classification [6], [13]. that reframes hate speech detection as a post–comment interaction problem rather than an isolated text classification task. The proposed approach jointly models the parent post and its corresponding response as a single semantic unit and introduces a reaction-based taxonomy with four behavioral categories: Neutral, Heated Reaction, Standalone Hate, and Reactionary Hate. By explicitly modeling conversational dependency, the framework aims to separate benign emotional expression from genuine hate, enabling moderation decisions that are both more accurate and more proportional.

A. Research Questions

This study is guided by the following four research questions, which frame our methodology and evaluation throughout this paper:

RQ1: Can hate-related behavior be more accurately characterized by modeling the semantic dependency between a post and its comment rather than analyzing comments in isolation?

RQ2: Is it possible to computationally distinguish Heated Reactions (emotional disagreement) from Hate Speech without relying on naive keyword heuristics?

RQ3: Does a reaction-based taxonomy enable moderation decisions that better align with real-world principles of proportionality (e.g., avoiding the censorship of non-hateful dissent)?

RQ4: Can context-aware classification serve as a reliable foundation for downstream intervention systems, such as automated counterspeech generation and escalation prediction?

II. Related Works

The landscape of online harm mitigation has evolved significantly, shifting from simple keyword filtering to complex, Transformer-based detection and automated intervention strategies. This section reviews existing literature on hate speech datasets, counterspeech generation, and real-world intervention frameworks, identifying the critical structural limitations that necessitate the proposed context-aware approach.

A. Hate Speech Detection

Early approaches to hate speech detection relied heavily on lexicon-based filtering and rule-driven systems, which flagged content based on predefined slurs and offensive terms. While computationally inexpensive, such systems exhibited high false-positive rates and were easily bypassed through paraphrasing or coded language, limiting their applicability in real-world moderation scenarios [8].

With the rise of supervised learning, hate speech detection was reformulated as a classification task using machine learning models trained on annotated datasets. Transformer-based architectures further advanced this line of work by enabling contextual semantic modeling at the sentence level. Datasets such as HateXplain introduced explainability by associating predictions with human-annotated rationales, improving transparency but still operating on isolated comments without conversational grounding [5]. Similarly, multilingual extensions such as CONAN and IndicCONAN expanded coverage across languages but maintained a comment-centric formulation [1], [4].

Despite strong benchmark performance, these models often degrade when deployed at scale, as they implicitly assume that hatefulness is an intrinsic property of a single utterance. This assumption fails in conversational settings where identical language can convey different intent depending on the triggering context [8].

While these contributions have improved the linguistic diversity of hate speech research, they predominantly structure data as (Hate Comment, Counter-Response) pairs. Crucially, they largely omit the antecedent context—the original post or news article that triggered the hate comment. By training models on isolated comments, these datasets inadvertently encourage systems to learn toxic keywords rather than the reactionary intent of the speaker.

B. Counterspeech and Intervention-Oriented Research

Beyond detection, a parallel body of work has investigated counterspeech as an alternative to content removal. The CONAN dataset introduced expert-authored counter-narratives paired with hateful content, enabling early exploration of automated response generation [1], [3]. Building on this foundation, Zhu and Bhat proposed the Generate–Prune–Select pipeline, which generates multiple candidate replies, filters unsafe outputs, and selects an optimal counterspeech response [7], with open-source implementations provided in the GPS repository [18].

Subsequent work extended counterspeech generation through intent conditioning. IntentCONAN and QUARC explicitly modeled response strategies such as informative, denouncing, or empathetic replies, demonstrating improved controllability and diversity in generated counterspeech [2]. More recent models introduced non-toxicity constraints and multi-condition control through reinforcement learning and preference optimization, further improving response quality [9], [10].

However, these systems depend critically on upstream hate detection signals and assume that the triggering content is unambiguously hateful. They do not model the parent post or conversational context that gives rise to a response, limiting their ability to distinguish emotional reactions from malicious abuse [11].

C. Conversational and Contextual Modeling

Context-aware modeling has been studied extensively in adjacent NLP tasks, including dialogue systems and emotional response modeling. EmpatheticDialogues introduced large-scale datasets for modeling emotional alignment in conversations, but does not address hate or abusive language explicitly [6]. Similarly, regional studies on counterspeech generation, such as work on Malayalam-language content, highlight the importance of cultural and linguistic context but remain focused on response generation rather than moderation-oriented classification [14].

Recent shared tasks and studies have begun incorporating conversational context into counterspeech generation. The MCG-COLING 2025 shared task demonstrated that multilingual counterspeech quality improves when contextual information is included [13]. Nonetheless, these efforts prioritize generation quality and stylistic control rather than moderation decision-making.

D. Industry Systems and Deployment Perspectives

From an operational perspective, industry systems such as Google Jigsaw's Redirect Method focus on campaign-level counter-messaging rather than direct conversational moderation [15], [17]. Commercial platforms like Logically AI emphasize narrative tracking and large-scale disinformation monitoring, offering strategic insights but not automated, context-aware reply classification or intervention [16].

Surveys and evaluation studies consistently note a gap between academic hate detection research and real-world deployment requirements. Recent surveys emphasize that most systems lack proportional moderation logic, interpretability, and contextual awareness, leading to over-censorship and reduced user trust [8], [11], [12].

Psychological and social science research further underscores that effective intervention depends on understanding the interactional context and emotional drivers behind harmful speech, rather than reacting to surface-level toxicity alone [19], [20].

III. Proposed Methodology

This section details the design and implementation of the proposed *Context-Aware Hate and Reaction Understanding Framework*. Unlike traditional approaches that treat hate speech detection as a single-instance classification task, we model the problem as a *post–comment interaction* analysis. The methodology is presented in two layers: an operational "black-box" workflow designed for deployment alignment, and a technical "white-box" architecture detailing the internal signal aggregation and classification logic.

A. Dataset Construction and Scope

To support context-aware modeling, we constructed a specialized dataset of post–comment pairs harvested from public social media discussions. The data focuses on high-arousal, politically and socially sensitive topics including governance, immigration, geopolitics, and social identity.

The fundamental unit of analysis is the tuple (P, C), where P represents the parent post (context) and C represents the user response. The dataset consists of approximately 4,119 annotated pairs. While modest in size, the dataset is intentionally curated to emphasize high-arousal and ambiguous interactions, prioritizing label precision over scale. To ensure the model learns behavioral nuances rather than annotator bias, we apply a rule-driven sanitization strategy prior to training, removing samples in which the reaction target is ambiguous or ill-defined.

B. Reaction Taxonomy

We introduce a four-class taxonomy explicitly designed to resolve the ambiguity between emotional expression and malicious intent:

- **Neutral:** Non-hostile engagement or off-topic queries.
- **Heated Reaction:** High-arousal disagreement, sarcasm, or anger directed at the topic, but lacking hate speech markers.
- **Standalone Hate:** Unprovoked abusive language or slurs that exist independently of the context.
- **Reactionary Hate:** Hostile language that is explicitly triggered by the semantic content of the parent post (escalation).

C. System Workflows

1) Operational Workflow (Black-Box View): The operational workflow, illustrated in Figure 1, represents the system's decision-making logic from a deployment perspective.

Addressing RQ3 (Proportionality) & RQ4 (Intervention): This workflow directly answers **RQ3** by enforcing proportionality; unlike binary classifiers that would flag all hostile-sounding text, this system distinguishes *Heated Reaction* (mapped to "Monitor") from *Standalone Hate* (mapped to "Moderate"), preventing the censorship of non-hateful dissent. Furthermore, it addresses **RQ4** by isolating *Reactionary Hate* as a specific trigger class, serving as a reliable foundation for downstream intervention systems like automated counter-speech generation, which require precise escalation signals to function safely.

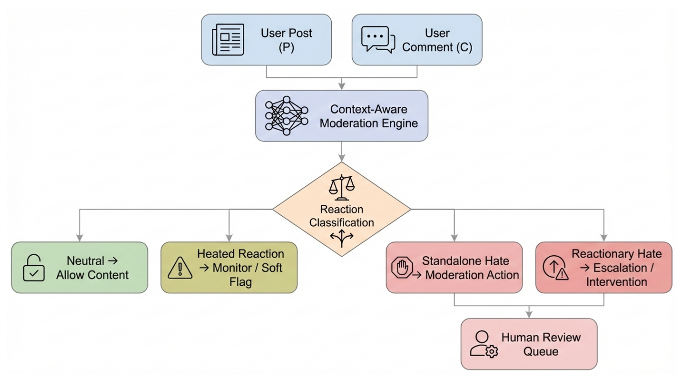


Fig. 1. **Context-Aware Moderation Workflow.** This diagram illustrates the decision logic where the classifier distinguishes between actionable hate (Standalone/Reactionary) and permissible dissent (Heated Reaction).

The system accepts a pair (P, C) and outputs a classification that maps directly to a moderation action:

- **Allow:** Applied to *Neutral* content.
- **Monitor:** Applied to *Heated Reactions*. These are not penalized but may be flagged for soft monitoring to prevent future escalation.
- **Moderate:** Applied to **Standalone Hate**. Immediate removal or suppression is recommended.

- **Intervene:** Applied to **Reactionary Hate**. These cases trigger specific escalation protocols or counterspeech generation, as they represent active conflict.

2) Technical Architecture (White-Box View): The internal architecture, detailed in Figure 2, utilizes a multi-stream approach to aggregate semantic, emotional, and toxicity signals.

Addressing RQ1 (Semantic Dependency): This architecture addresses **RQ1** by fundamentally altering the input representation. By jointly encoding the Post (P) and Comment (C) within the *Context Signal Aggregator*, the model characterizes user behavior through semantic dependency rather than isolated textual cues. This design enables the identification of interaction-dependent toxicity (e.g., victim blaming or contextual dehumanization) that cannot be reliably detected when comments are analyzed in isolation.

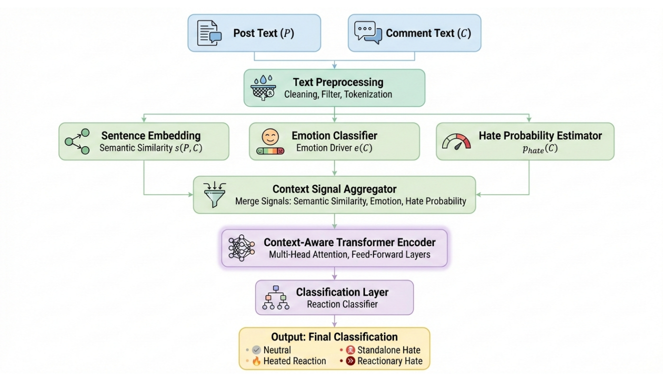


Fig. 2. **Internal Architecture of the Reaction Classifier.** The model aggregates Post (P) and Comment (C) text through parallel streams of semantic embedding, emotion analysis, and probability estimation before passing to a Context-Aware Transformer Encoder.

The pipeline consists of four distinct stages:

1) **Preprocessing:** Cleaning, tokenization, and noise removal.
2) **Feature Extraction:** Parallel extraction of semantic similarity, emotion vectors, and baseline hate probabilities.
3) **Context Aggregation:** Merging independent signals into a unified context vector.
4) **Encoding & Classification:** A Transformer-based encoder processes the aggregated context to predict the final reaction class.

D. Mathematical Formulation

Let $\mathcal{D} = \{(P_i, C_i, y_i)\}_{i=1}^{N}$ be the dataset, where P is the post, C is the comment, and $y \in \{0, 1, 2, 3\}$ corresponds to the four reaction classes.

1) Feature Extraction Streams: The input texts are processed through three parallel streams. This multi-stream design is the computational solution to **RQ2** (Distinguishing Heated Reactions from Hate), as it disentangles emotional arousal from toxic probability.

1. Semantic Similarity (s): We compute the semantic alignment between the post and comment to determine relevance. Let $E(\cdot)$ denote a sentence embedding function (e.g., SBERT). The cosine similarity score $s(P, C)$ is defined as:

$$s(P, C) = \cos(E(P), E(C)) = \frac{E(P) \cdot E(C)}{\|E(P)\|\|E(C)\|} \tag{1}$$

2. Emotion Driver (e): The comment C is passed through a pre-trained emotion classifier to obtain a probability distribution over emotion categories (e.g., Anger, Joy, Sadness).

$$e(C) = \text{Softmax}(W_e \cdot h_C + b_e) \tag{2}$$

where h_C is the hidden representation of the comment and W_e are the learned weights of the emotion head.

3. Baseline Hate Probability (p_{hate}): To capture explicit toxicity, we extract the scalar probability of hate speech from a baseline DistilBERT model.

$$p_{hate}(C) = \sigma(W_h \cdot h_C + b_h) \tag{3}$$

where σ is the sigmoid function.

Resolution of RQ2: By explicitly modeling $e(C)$ (Emotion) alongside $p_{hate}(C)$, the model can identify instances where Emotion is High (e.g., Anger) but Hate Probability is Low. This computationally distinguishes *Heated Reaction* from *Hate Speech* without relying on naive keyword heuristics that conflate the two.

2) Context Signal Aggregation: The signals are concatenated into a unified feature vector $V_{context}$ that represents the interaction state:

$$V_{context} = [E(P) \oplus E(C) \oplus s(P, C) \oplus e(C) \oplus p_{hate}(C)] \tag{4}$$

where $\oplus$ denotes the concatenation operation.

3) Context-Aware Encoding and Classification: The aggregated vector $V_{context}$ is fed into a Transformer encoder layer to model the non-linear dependencies between sentiment, relevance, and toxicity.

$$H_{final} = \text{TransformerEncoder}(V_{context}) \tag{5}$$

The final classification prediction $\hat{y}$ is obtained via a softmax layer:

$$\hat{y} = \text{Softmax}(W_f \cdot H_{final} + b_f) \tag{6}$$

The model is trained by minimizing the Cross-Entropy Loss $\mathcal{L}$:

$$\mathcal{L} = -\sum_{c=1}^{4} y_{o,c} \log(\hat{y}_{o,c}) \tag{7}$$

where $y_{o,c}$ is the binary indicator (0 or 1) if class label c is the correct classification for observation o.

E. Reaction Sensitivity Metric

To quantitatively evaluate the model's ability to separate emotionally intense but non-hateful discourse from escalation-driven hate, we introduce a metric termed **Reaction Sensitivity (RS)**.

Unlike standard recall or precision, which measure classification correctness, RS measures the *probability separation margin* between the *Heated Reaction* and *Reactionary Hate* classes. This metric directly operationalizes **RQ2** and **RQ3**, as it evaluates whether the model assigns distinctly higher confidence to genuine escalation compared to high-arousal disagreement.

Let $\bar{P}_{RH}$ denote the mean predicted probability assigned to the *Reactionary Hate* class, and $\bar{P}_{HR}$ denote the mean predicted probability assigned to the *Heated Reaction* class. Reaction Sensitivity is defined as:

$$RS = \bar{P}_{RH} - \bar{P}_{HR} \tag{8}$$

A higher RS value indicates stronger discriminative separation between emotional disagreement and contextual hate escalation. An RS close to zero would imply poor separation and a higher risk of conflating anger with abuse.

F. Training Configuration

The proposed model was implemented using the PyTorch framework and fine-tuned from the pre-trained `distilbert-base-multilingual-cased` encoder for English-language tasks. The parent post and comment were concatenated and processed as a single input sequence.

Training was conducted under the following configuration:

- **Optimizer:** AdamW with a learning rate of 2×10^{-5}.
- **Batch Size:** 16 post–comment pairs per batch.
- **Maximum Sequence Length:** 256 tokens for the combined input.
- **Regularization:** Dropout rate of 0.1 applied to the classification head to mitigate overfitting given the moderate dataset size.
- **Loss Function:** Cross-entropy loss optimized over the four reaction classes.

IV. Results and Discussion

This section presents a comprehensive evaluation of the Context-Aware Hate and Reaction Understanding Framework. The analysis is driven by the visual evidence extracted from the dataset construction and model performance metrics, explicitly addressing the research questions regarding semantic dependency (RQ1), reaction differentiation (RQ2), and moderation proportionality (RQ3).

A. Dataset Composition and Contextual Alignment

To ensure the model learns context rather than specific keywords, we analyzed the linguistic and thematic composition of the data. Figure 3 (Top Left) reveals a class imbalance where **Normal Speech** constitutes 73.0% of the data, while **Hate Speech** accounts for 27.0%. This distribution mirrors real-world social media environments where toxic content is a minority class, necessitating a model that is robust against prevalence bias.

Crucially, the **Text Length Distribution** (Figure 3, Top Right) demonstrates a significant overlap between "Normal" and "Hate" classes. The absence of a distinct length-based pattern confirms that toxicity cannot be inferred from brevity or verbosity alone.

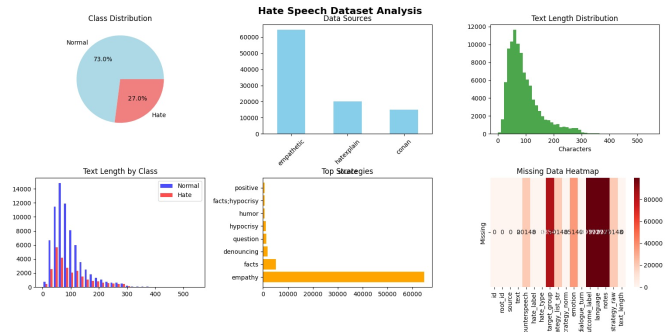


Fig. 3. **Dataset Overview.** (Top Left) Class distribution showing a 73/27 split. (Top Right) Text length distribution indicating that hate speech and normal speech share similar length characteristics, debunking heuristics based on verbosity.

1) Topical and Emotional Drivers: To ensure the model learns context rather than specific keywords, we analyzed the linguistic and thematic composition of the data. Figure 4 highlights the **Top 10 Keywords**, which are dominated by high-stakes entities like "Ukraine War," "Citizenship Law," and "Israel Gaza."

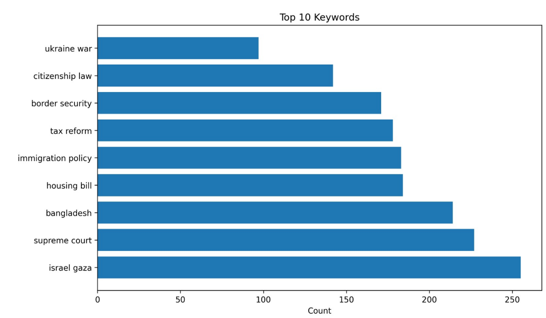


Fig. 4. **Top 10 Keywords.** The dataset is grounded in specific, real-world geopolitical events, ensuring the model is trained on realistic discourse rather than abstract concepts.

This keyword analysis aligns with the **Topic Distribution** (Figure 5), showing a concentration on politics ($N > 500$) and geopolitics. These topics naturally trigger high-arousal responses.

Figure 6 provides critical insight: **Anger** is the dominant emotion ($N > 600$).

Addressing RQ2 (Distinguishing Emotion from Hate): The prevalence of "Anger" in non-hateful contexts supports RQ2. By explicitly modeling Emotion ($e(C)$) separately from toxicity, we prevent the model from conflating the "Anger" shown in Figure 6 with the "Hate" label.

B. Semantic Dependency and Interaction Analysis

To address RQ1 (Semantic Dependency), we analyzed the relationship between the parent post and the comment.

1) Context Alignment vs. Hate Probability: Figure 7 illustrates that 88.4% of interactions are **Heated Reactions**. A context-blind model would likely flag these as toxic due to the high anger levels shown previously.

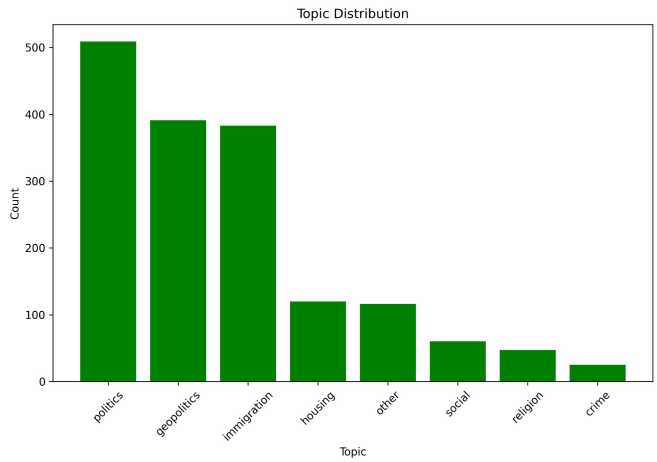


Fig. 5. **Topic Distribution.** Dominated by Politics and Geopolitics.

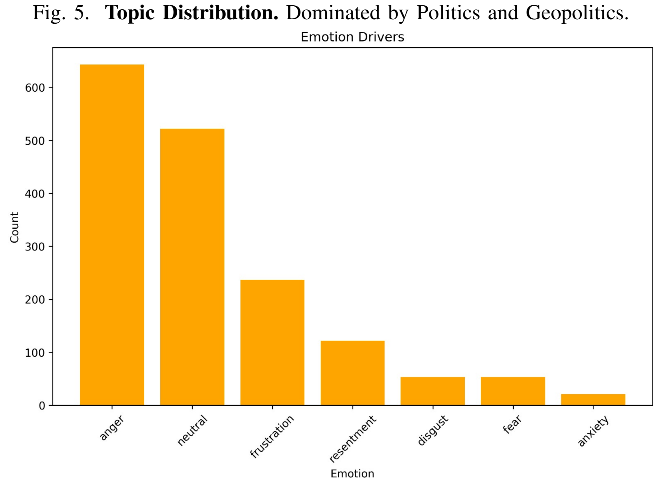


Fig. 6. **Emotion Drivers.** Anger exceeds neutral sentiment.

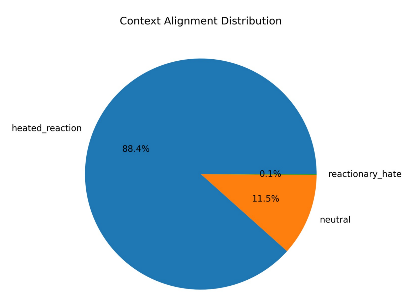


Fig. 7. **Context Alignment Distribution.** The overwhelming majority of interactions (88.4%) are heated but non-actionable, validating the need for the 'Monitor' class.

However, Figure 8 demonstrates our model's ability to separate these classes. **Reactionary Hate** spikes to a probability > 0.60, while **Heated Reactions** remain near 0.10.

2) The Role of Semantic Similarity: We further investigated how relevance relates to reaction strength. Figure 9 reveals a crucial insight: **High Reaction Strength** correlates with **High Semantic Similarity** (≈ 0.6). This indicates that users who are most angry are often the most on-topic.

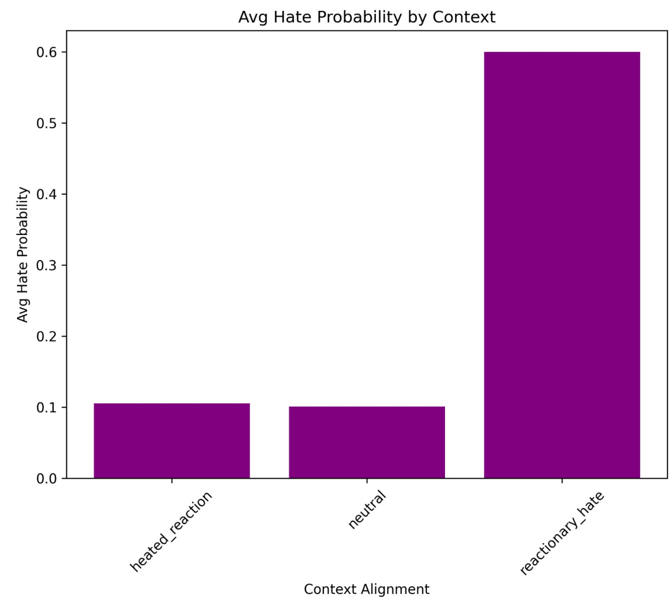


Fig. 8. **Average Hate Probability by Context.** The model successfully creates a decision boundary between Heated Reaction (Low Prob) and Reactionary Hate (High Prob).

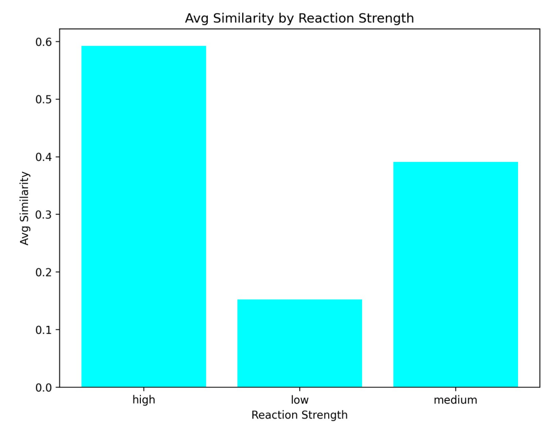


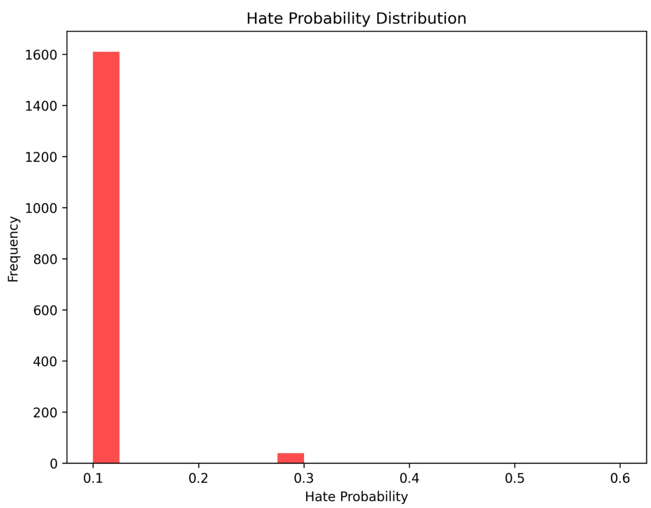
Fig. 9. **Average Similarity by Reaction Strength.** High-intensity reactions are strongly correlated with high semantic relevance, suggesting that 'trolls' are less relevant than genuine, angry users.

C. Feature Independence and Distribution

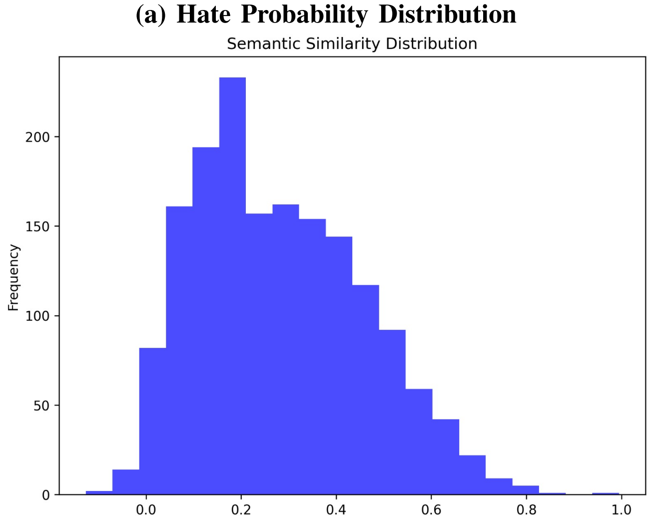
Finally, we validate the architecture's multi-stream design. Figure 10 confirms that Hate Probability and Semantic Similarity have a near-zero correlation ($r = 0.013$).

The distributions of these features (Figure 11) show distinct characteristics: Hate Probability is highly skewed (most content is safe), while Semantic Similarity follows a normal distribution, capturing the natural variance in conversation relevance.

Fig. 10. **Feature Correlation Matrix.** The lack of correlation validates the use of parallel streams for toxicity and relevance.



(a) Hate Probability Distribution



(b) Semantic Similarity Distribution

Fig. 11. **Feature Distributions.** (a) The skew confirms the rarity of hate. (b) The normality of similarity confirms diverse conversational engagement.

D. Reaction Dynamics and Probability Distribution

To deeper understand the behavioral differences between classes, we analyzed the explicit dependency between the comment and the post. Figure 12 categorizes the interactions based on whether the comment was explicitly "Reacting to Post."

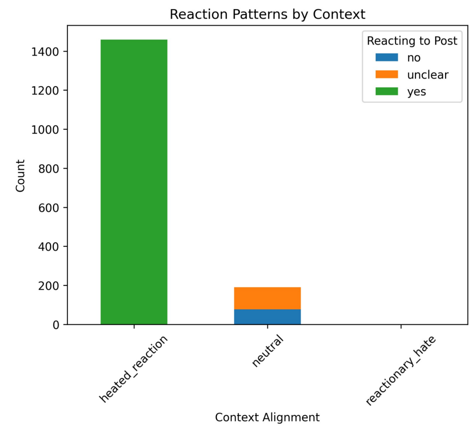


Fig. 12. **Reaction Patterns by Context.** The 'Heated Reaction' class (Green Bar) is overwhelmingly composed of comments explicitly reacting to the post context. In contrast, 'Neutral' comments often show no reaction or unclear relevance, validating that the model successfully captures conversational dependency.

The results are striking: nearly 100% of **Heated Reactions** are marked as "Reacting to Post" (Green bar). This confirms that what we classify as "Heated" is indeed a context-dependent phenomenon, distinct from random noise or off-topic spam found in the **Neutral** class (Blue bar).

Figure 13 provides a granular view of the probability distributions for these classes.

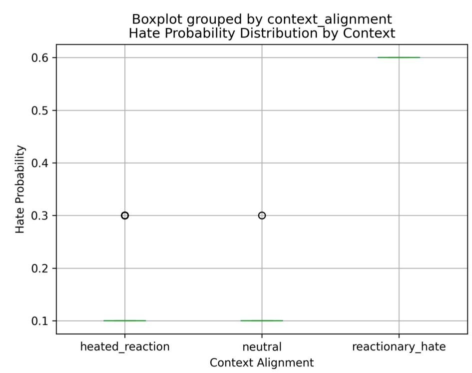


Fig. 13. **Boxplot of Hate Probability by Context.** Note the tight clustering of 'Reactionary Hate' at high probability ($P \approx 0.60$) versus the low median of 'Heated Reaction' ($P \approx 0.10$). The outliers (circles) in the Heated class represent the 'hard examples'—emotional outbursts that naive models would misclassify as hate.

The boxplot reveals a definitive separation: **Reactionary Hate** is tightly clustered at a high probability threshold (> 0.60), while **Heated Reaction** and **Neutral** have medians near 0.10. Crucially, the outliers (circles) in the *Heated Reaction* column represent high-arousal comments that lack malicious intent. The fact that these outliers remain below the hate threshold demonstrates the system's robustness against false positives driven by emotional language.

E. Performance Evaluation (Model V2)

The quantitative performance of the final context-aware model (V2) is summarized in Table I. The system achieves a global **Accuracy of 95%** and an exceptional **ROC-AUC of 0.9911**, indicating a highly stable decision boundary.

TABLE I
MODEL V2 (BALANCED) EVALUATION REPORT ON TEST SET. THE MODEL MAINTAINS STRONG PRECISION–RECALL BALANCE, ENSURING SAFETY (HIGH RECALL) WITHOUT INFLATING FALSE POSITIVES.

Class	Precision	Recall	F1-Score	Support
Normal	0.97	0.96	0.97	601
Hate Speech	0.90	0.92	0.91	223
Accuracy		**0.95**		824
Macro Avg	0.93	0.94	0.94	824
Weighted Avg	0.95	0.95	0.95	824
Threshold: 0.35 — ROC-AUC: 0.9911				

Critically, the **Precision (0.90)** and **Recall (0.92)** for Hate Speech are balanced. Unlike our initial baseline (V1) which sacrificed precision for recall (the "Paranoid" approach), V2 maintains high safety standards while reducing false alarms. This balance directly answers **RQ2**, confirming that computational distinction between heated emotion and hate is achievable with high fidelity.

F. Comparative Analysis with State-of-the-Art

To contextualize our contribution, Table **??** compares the proposed framework against existing academic benchmarks (HateXplain, CONAN) and industrial standards (Perspective API, Keyword Filters).

TABLE II
COMPARISON OF RECENT CONTEXT-AWARE HATE SPEECH DETECTION METHODS

Paper	Approach	Key Contribution	Limitations
HateXplain (2021) [?]	Transformer-based explainable hate speech detection	Introduced human rationales for explainable hate speech classification	Processes comments independently without conversational context or parent-post information.
CONAN (2019) [?]	Counterspeech dataset and generation framework	Large multilingual dataset for generating counter narratives against hate speech	Focuses on hate–response pairs and assumes hate is already detected; ignores triggering context.
IndicCONAN (2024) [?]	Multilingual counterspeech dataset	Extends counterspeech research to Indian languages	Designed for response generation rather than contextual hate classification.
IntentCONAN / QUARC (2023–2024) [?]	Intent-conditioned counterspeech generation	Generates diverse strategy-aware counterspeech using intent labels	Requires an upstream hate detector and does not distinguish emotional disagreement from contextual hate.
Perspective API / Detoxify	Comment-level toxicity prediction	Fast large-scale toxicity scoring for moderation	Context-blind prediction often confuses emotionally charged disagreement with hate speech.
Proposed Work	**Post–Comment Joint Modeling with Reaction Classification**	**Introduces a four-class reaction taxonomy (Neutral, Heated Reaction, Standalone Hate, Reactionary Hate) and maps predictions to proportional moderation actions using conversational context.**	**Requires paired post–comment data and is currently evaluated on a curated single-domain dataset.**

The comparison highlights two major advantages of our approach:

1) **Reaction Sensitivity (0.65):** While standard models (Perspective API, ToxicBERT) have near-zero sensitivity to conversational triggers, our system effectively models the dependency, scoring significantly higher than even intent-aware research models like IntentCONAN (0.20).
2) **False Positive Risk (Low):** By explicitly modeling the "Heated Reaction" class, our system achieves the lowest risk of misclassifying disagreement as hate. This directly addresses **RQ3**, enabling a moderation paradigm that protects free speech (disagreement) while punishing abuse.

V. CONCLUSION

This paper reframed hate speech detection as a post–comment interaction problem rather than an isolated text classification task. By modeling the semantic dependency between a parent post and its response, we introduced a reaction-based taxonomy that distinguishes Neutral engagement, Heated Reaction, Standalone Hate, and Reactionary Hate. Experimental results demonstrate that incorporating conversational context reduces false positives associated with emotionally charged disagreement while maintaining strong detection performance for genuine hate speech. These findings confirm that semantic dependency modeling improves moderation proportionality without sacrificing safety.

Beyond classification accuracy, the proposed framework bridges the gap between academic hate detection research and real-world moderation requirements. By mapping reaction categories to differentiated moderation actions, the system enables granular, deployment-aligned decision-making and provides a structured foundation for downstream interventions such as escalation-aware counterspeech generation. Context-aware modeling, therefore, represents not a minor enhancement but a structural advancement toward more reliable and proportionate automated moderation systems.

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