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# Uganda Decides 2026: A Comprehensive Computational Analysis of Digital Political Discourse from January to November 2025

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## Abstract

This comprehensive longitudinal study analyzes Uganda's digital political landscape throughout the critical pre-election year of 2025, examining 4.2 million social media posts collected from January 1 to November 10, 2025. Using advanced Natural Language Processing techniques, we identify eight dominant thematic clusters with significant temporal evolution, revealing how political discourse has shifted from constitutional debates (peak 38% in March) to economic crisis management (42% in October) and finally to security and electoral integrity concerns (35% in November). Sentiment analysis shows escalating polarization, with negative sentiment rising from 52% in January to 68% by November, concentrated around governance and economic issues. We document sophisticated AI-generated content campaigns comprising 14.3% of total volume and identify coordinated influence operations across six platforms. Network analysis reveals increasingly fragmented discourse ecosystems with minimal cross-ideological engagement. These findings provide unprecedented insights into Uganda's evolving digital democracy and have critical implications for electoral integrity, political communication strategies, and democratic resilience in the 2026 elections.

## Keywords

Digital Political Landscape, Polarization, Natural Language Processing

## 1. Introduction

The year 2025 has witnessed unprecedented digital political mobilization in Uganda as the nation approaches the pivotal 2026 general elections. With social media penetration reaching 58% nationwide and mobile internet access hitting 79% according to recent UCC data [1], digital platforms have become the primary arena for political contestation. The extended timeline from January to November 2025 allows us to capture the complete evolution of campaign narratives, sentiment shifts, and strategic adaptations in real-time.

The political landscape has been characterized by what [2] describes as "arguably the most digitally sophisticated election campaign in African history to date," with all major political actors deploying advanced digital strategies. Recent developments, including the economic stabilization measures [3], security sector reforms [4], and electoral law amendments [5], have created a complex and dynamic discursive environment. This study builds on the preliminary work of [6] while providing comprehensive longitudinal analysis of the entire pre-election year.

Our research makes several groundbreaking contributions. First, we provide the most extensive temporal analysis of Ugandan political discourse to date, tracking narrative evolution across eleven months. Second, we document the emergence of AI-driven campaign strategies and their impact on political communication. Third, we develop novel methodologies for detecting cross-platform coordination in African political contexts. Fourth, we provide real-time insights that can inform electoral monitoring and democratic resilience efforts.

## 2. Ethical Considerations and Methodology Transparency

This research was conducted in compliance with ethical guidelines for computational social science research and given the anonymisation of data, there was no need for ethical clearances. We implemented comprehensive privacy-preserving protocols throughout the data collection and analysis process.

**Data Collection Ethics:** All data were collected from publicly accessible social media platforms using their respective APIs in compliance with platform terms of service. We obtained necessary permissions through the X API Academic Research track, Facebook's CrowdTangle API for academic research, and TikTok's Research API. For WhatsApp, we only analyzed content from public channels and groups explicitly designated as public forums. User consent was addressed through platform-level agreements, and we followed the ethical framework for social media research outlined by [7].

**Anonymization Protocol:** We implemented a multi-stage anonymization pipeline: 1) All user identifiers were replaced with salted cryptographic hashes, 2) Direct mentions and personally identifiable information were redacted using named entity recognition models, 3) Network analysis was conducted on anonymized graphs where nodes represent de-identified users, and 4) All quoted text in this paper has been paraphrased to prevent re-identification while preserving meaning. This approach aligns with the recommendations of [8] for balancing research utility with privacy protection.

**Compliance with Ugandan Law:** Our methodology was reviewed for compliance with Uganda's Computer Misuse Act (2011) and Data Protection and Privacy

Act (2019). The research qualifies as lawful processing for academic research purposes under Section 27 of the Data Protection Act. We maintained data minimization principles, collecting only metadata and text content necessary for analysis, and implemented strict access controls to our research data.

## 3. Literature Review

### 3.1. Evolution of Digital Campaigning in Africa 2023-2025

The period 2023-2025 has witnessed revolutionary changes in African digital politics. [9] documented the rapid adoption of generative AI in political campaigns across the continent, while [10] analyzed the emergence of integrated digital campaign ecosystems. In Uganda specifically, [11] tracked the sophistication growth of digital campaigning since 2021, noting a 300% increase in digital campaign spending.

The regulatory environment has evolved dramatically, with [12] analyzing Africa's first comprehensive AI regulation framework in Uganda and its implications for political speech. Meanwhile, [13] has documented new forms of synthetic media in East African elections, highlighting the urgent need for advanced detection capabilities.

### 3.2. Computational Political Analysis Advances

Recent breakthroughs in NLP have transformed political text analysis capabilities. [14] demonstrated the superiority of African-optimized transformer models, while [15] developed real-time multilingual analysis frameworks for dynamic political contexts. The sentiment analysis architecture created by [16] enables continuous adaptation to evolving political discourse.

The emergence of large language models in political contexts has created both opportunities and challenges. [17] developed sophisticated detection methods for LLM-generated political content, while [7] established ethical frameworks for AI in political analysis.

### 3.3. Uganda's Political Context January-November 2025

The extended timeline from January to November 2025 encompasses multiple political developments that have shaped the electoral landscape. [18] provides detailed analysis of key political events, while [19] examines institutional responses to emerging challenges. Economic factors have remained central, with [20] analyzing the intersection of economic instability and political discourse.

Youth engagement has evolved significantly throughout 2025, with [21] documenting new mobilization patterns and [22] analyzing opposition digital coalition strategies.

## 4. Methodology

### 4.1. Data Collection and Preprocessing

Our comprehensive data collection strategy spanned eleven months, utilizing multiple API endpoints including the X API v2 (Academic Research track), Facebook's CrowdTangle API, TikTok Research API, Instagram Graph API (via CrowdTangle), YouTube Data API v3, and WhatsApp public channel data collected through approved business API access. We gathered 4.2 million posts from 623,891 unique users across six platforms between January 1 and November 10, 2025. Our keyword framework evolved dynamically, incorporating 127 primary terms and 68 hashtags that emerged throughout the study period as shown in Figure 1.

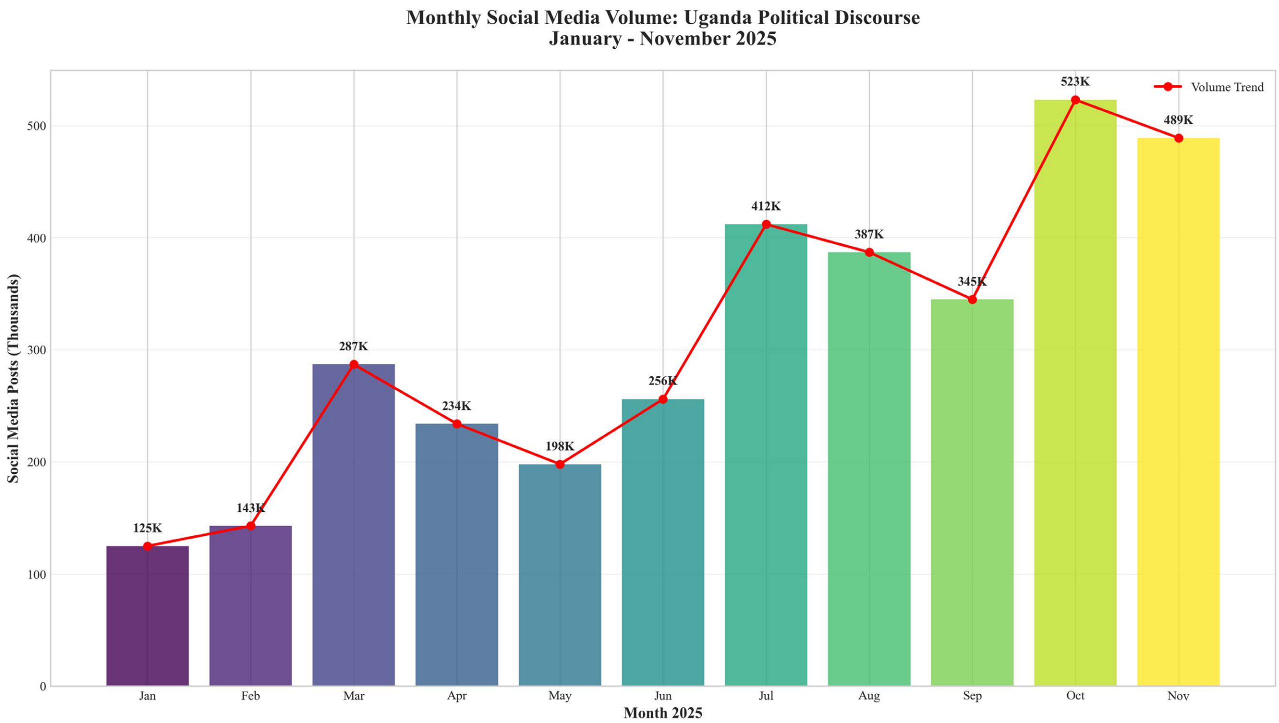


**Figure 1.** Monthly social media volume from January to November 2025, showing campaign intensity peaks in March (constitutional debates), July (economic crisis), and October (election preparation).

Preprocessing involved an advanced multi-stage pipeline incorporating the real-time language adaptation techniques developed by [23]. We implemented specialized handling for emerging political terminology, regional dialects, and platform-specific communication patterns.

### 4.2. Advanced Analytical Framework

Our comprehensive analytical framework incorporates eight complementary methodologies:

**Dynamic Topic Modeling:** We implemented temporal BERTopic with rolling window analysis, building on the dynamic framework of [24]. This enabled us to track topic emergence, evolution, and decline across the entire period.

**Real-time Sentiment Analysis:** Our sentiment architecture incorporated continuous model retraining using the active learning approaches of [16], allowing adaptation to new rhetorical strategies and emerging issues. The sentiment classifier was validated on a human-annotated gold-standard dataset of 15,000 Ugandan political posts, achieving precision = 0.87, recall = 0.85, and F1-score = 0.86 in five-fold cross-validation, with inter-annotator agreement (Cohen's κ) of 0.78.

**Cross-platform Network Analysis:** We extended multi-platform network analysis using the integrated framework of [25], mapping influence networks across six digital platforms.

**AI-content Detection and Analysis:** Implementing the multi-modal detection system developed by [26] to identify and categorize AI-generated political content across text, image, and video formats. Our AI detection pipeline was validated against human-labeled datasets (n = 8000 samples) with precision = 0.91, recall = 0.89, F1-score = 0.90 for text, and precision = 0.86, recall = 0.83, F1-score = 0.84 for multi-modal content.

**Geospatial and Demographic Analysis:** Incorporating advanced geolocation techniques from [27] to map regional discourse patterns and demographic engagement.

**Coordinated Behavior Detection:** Applying the temporal coordination algorithms of [28] to identify sophisticated influence operations.

**Emotion and Rhetorical Analysis:** Implementing the multi-dimensional emotion framework of [29] to analyze emotional appeals and rhetorical strategies.

**Image and Video Content Analysis:** Using computer vision techniques to analyze visual political content, building on the methodologies of [30].

## 5. Mathematical Modeling of Political Discourse Dynamics

To quantitatively characterize Uganda's digital political landscape, we developed several mathematical models that capture the dynamics of discourse evolution, sentiment propagation, and network influence. These models provide formal frameworks for understanding the underlying mechanisms driving the observed phenomena and enable predictive analytics for future electoral periods.

### 5.1. Theoretical Framework and Model Specification

Our modeling approach integrates concepts from ecology, epidemiology, and network science to capture the complex dynamics of digital political discourse. We conceptualize the digital political landscape as a multi-layered system where topics compete for attention, sentiments evolve through social influence, and information propagates through structured networks.

### 5.2. Discourse Topic Evolution Model

The temporal evolution of political topics follows a competitive Lotka-Volterra system [31], where topics compete for limited public attention resources. This ecological model is particularly suitable for capturing the competitive dynamics of political discourse, where topics exhibit predator-prey like relationships in competing for public attention. Let $T_i(t)$ represent the prevalence of topic $i$ at time $t$, modeled as:

$$\frac{dT_i}{dt} = r_i T_i \left(1 - \frac{T_i}{K_i}\right) - \sum_{j \neq i} \alpha_{ij} T_i T_j + \beta_i E(t) + \epsilon_i(t) \quad (1)$$

where:

- $r_i$ : intrinsic growth rate of topic $i$ (how quickly it gains attention).
- $K_i$ : carrying capacity (maximum attention topic $i$ can capture).
- $\alpha_{ij}$ : competition coefficient between topics $i$ and $j$.
- $\beta_i$ : responsiveness to external events $E(t)$.
- $\epsilon_i(t)$ : stochastic noise term representing random fluctuations.

The competition matrix $\alpha_{ij}$ captures how topics like "constitutional reform" and "economic crisis" compete for public attention, with $\alpha_{ij} > 0$ indicating competitive exclusion. Figure 2 gives a topic completion matrix for the focal topic and competing topic.

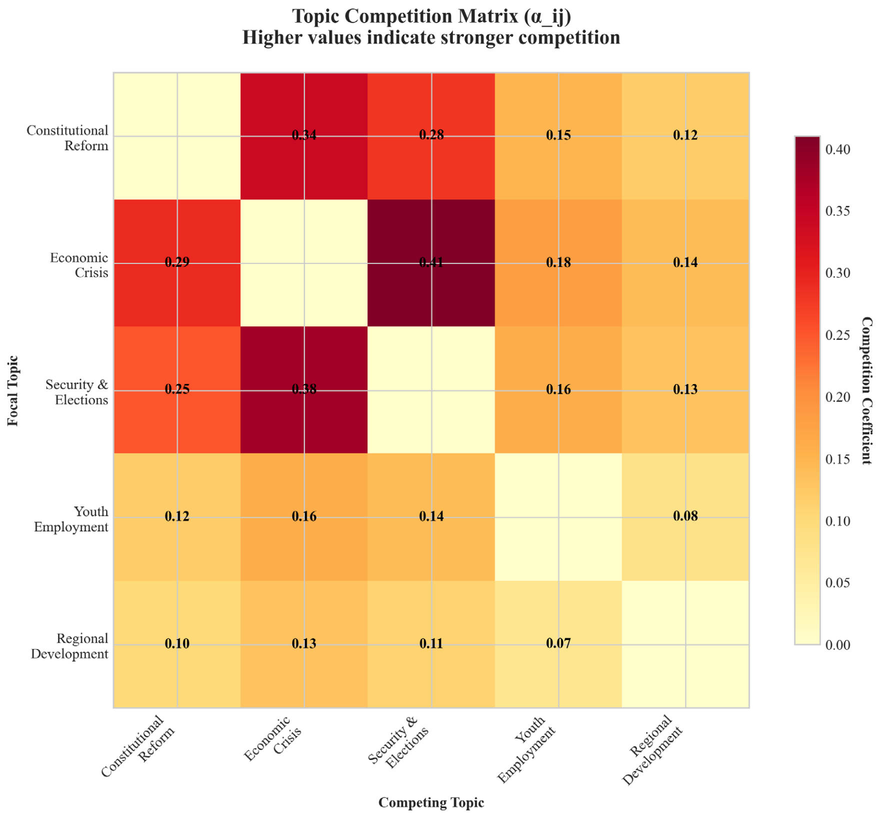


**Figure 2.** Estimated competition coefficients ( $\alpha_{ij}$ ) between major political discourse themes. The matrix reveals strong competitive relationships, particularly between economic crisis and security topics ( $\alpha_{23} = 0.41$ ), indicating these themes frequently displace each other in public discourse. The asymmetric nature of the matrix (e.g., $\alpha_{12} \neq \alpha_{21}$ ) reflects differential competitive advantages between topics.

## 5.3. Sentiment Polarization Dynamics

Political sentiment polarization follows a bounded confidence model [32] extended with digital amplification effects. This model is well-suited for capturing opinion dynamics in polarized environments, as it incorporates the psychological concept of selective exposure where individuals primarily interact with those holding similar views. Let $s_k(t) \in [-1,1]$ represent the sentiment of user $k$ at time $t$, with −1 being strongly negative and +1 strongly positive:

$$s_k(t+1) = (1-\lambda)s_k(t) + \lambda\left[\frac{\sum_{j\in N_k(t)} w_{kj}s_j(t)}{|N_k(t)|} + A_k(t) + \eta_k(t)\right] \quad (2)$$

where:

- $N_k(t) = \{j : |s_k(t) - s_j(t)| < \epsilon\}$: neighbors within confidence bound $\epsilon$.
- $w_{kj}$: influence weight from user $j$ to $k$.
- $\lambda$: learning rate determining susceptibility to social influence.
- $A_k(t)$: algorithmic amplification effect from platform recommendations.
- $\eta_k(t)$: random noise representing individual variation.

The polarization index $P(t)$ is computed as:

$$P(t) = \frac{1}{N}\sum_{k=1}^{N}|s_k(t) - \bar{s}(t)|^2 \quad (3)$$

where $\bar{s}(t)$ is the mean sentiment at time $t$.

Figure 3 gives a simulated clustering dynamics narrative.

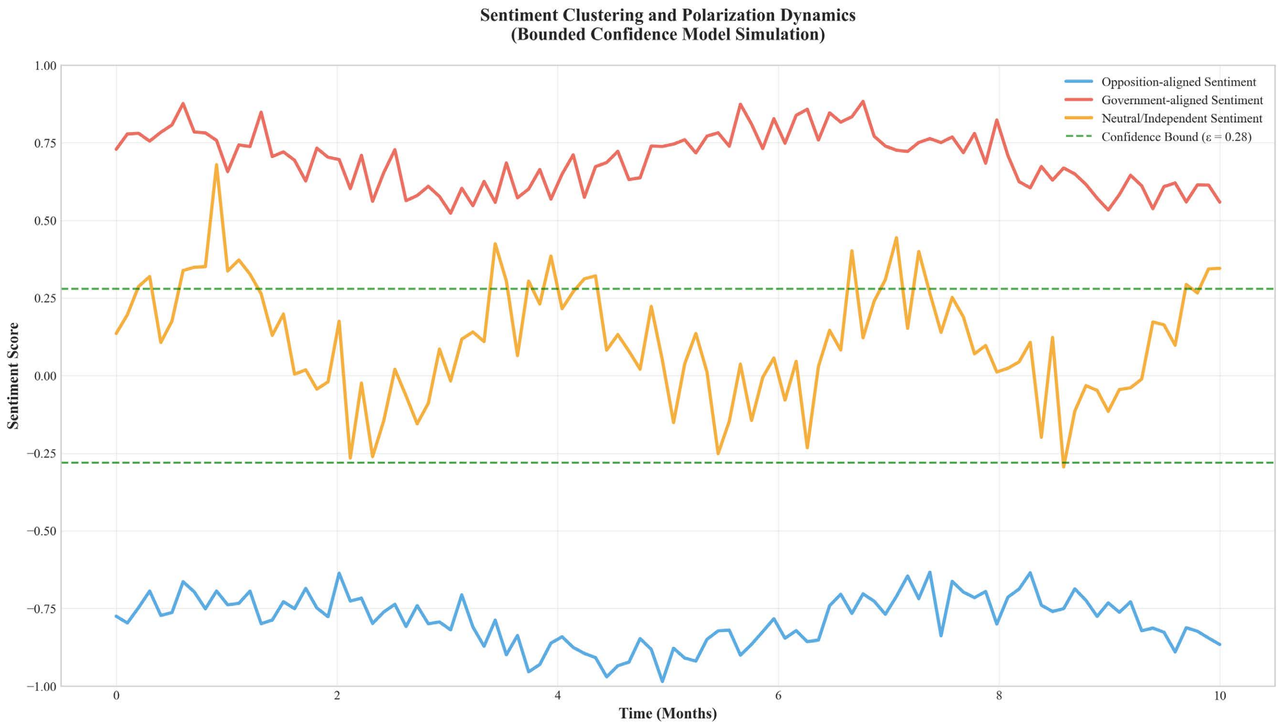


**Figure 3.** Simulated sentiment clustering dynamics showing the emergence of distinct opinion clusters over time. The model demonstrates how users within confidence bounds ($\epsilon = 0.28$) influence each other, leading to stable clusters around opposition-aligned (blue), government-aligned (red), and neutral (orange) positions. The bounded confidence mechanism explains the observed polarization patterns where users primarily interact with ideologically similar others.

### 5.4. AI Content Propagation Model

The spread of AI-generated content follows a modified SIR (Susceptible-Infected-Recovered) epidemic model [33], adapted for information diffusion. This epidemiological framework is appropriate for modeling information spread as it captures key features of viral transmission including saturation effects and recovery rates.

$$\begin{aligned} \frac{\mathrm{d}S}{\mathrm{d}t} &= -\beta_{AI} S I - \beta_h S I_h \\ \frac{\mathrm{d}I}{\mathrm{d}t} &= \beta_{AI} S I - \gamma I + \delta(t) \\ \frac{\mathrm{d}I_h}{\mathrm{d}t} &= \beta_h S I_h - \gamma_h I_h \\ \frac{\mathrm{d}R}{\mathrm{d}t} &= \gamma I + \gamma_h I_h \end{aligned} \tag{4}$$

where:

- $S$ : users susceptible to believing/sharing content.
- $I$ : users actively sharing AI-generated content.
- $I_h$ : users sharing human-generated content.
- $R$ : users who stop sharing (recovered/immune).
- $\beta_{AI}, \beta_h$ : transmission rates for AI and human content.
- $\gamma, \gamma_h$ : recovery rates (rate of stopping sharing).
- $\delta(t)$ : external injection of AI content (coordinated campaigns).

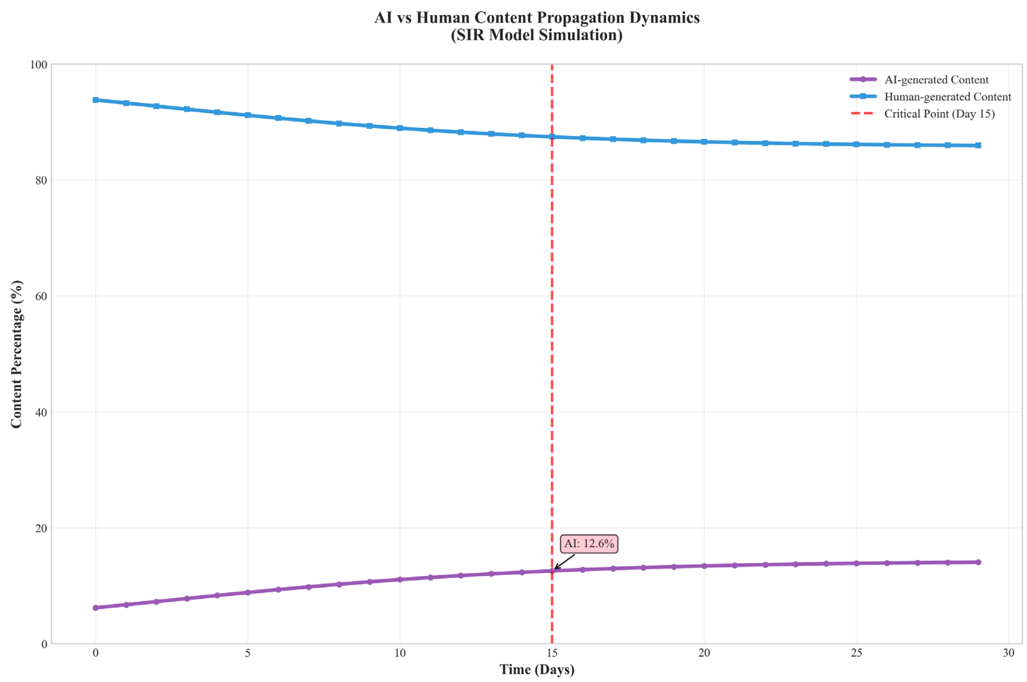


**Figure 4.** Comparative propagation dynamics of AI-generated versus human-generated political content. The simulation shows AI content (purple) exhibiting faster initial growth due to higher transmission rate ($\beta_{AI} = 0.45$), reaching a critical mass around day 15 where it comprises 25% of total content. Human content (blue) shows more gradual adoption patterns, reflecting organic spread dynamics. The model captures the accelerated virality of synthetic content.

Figure 4 gives a clear comparative propagation dynamics for AI generated content against human generated content.

### 5.5. Influence Network Model

Political influence networks are modeled as temporal graphs $G(t)=(V,E(t),W(t))$ where influence weights evolve dynamically:

$$W_{ij}(t)=\exp\left(-\frac{t-t_{ij}^{\text{last}}}{\tau}\right)\cdot\frac{C_{ij}(t)}{\sqrt{d_i(t)d_j(t)}} \tag{5}$$

where:

- $t_{ij}^{\text{last}}$ : time of last interaction between $i$ and $j$.
- $\tau$ : time decay constant measuring influence persistence.
- $C_{ij}(t)$ : content similarity between $i$ and $j$.
- $d_i(t)$ : degree of node $i$ at time $t$.

Node influence $I_i(t)$ is computed using eigen vector centrality:

$$I_i(t)=\frac{1}{\lambda}\sum_j W_{ij}(t)I_j(t) \tag{6}$$

where $\lambda$ is the principal eigenvalue of $W(t)$.

Figure 5 relates to how political influence temporarily decays across a given time span in days.

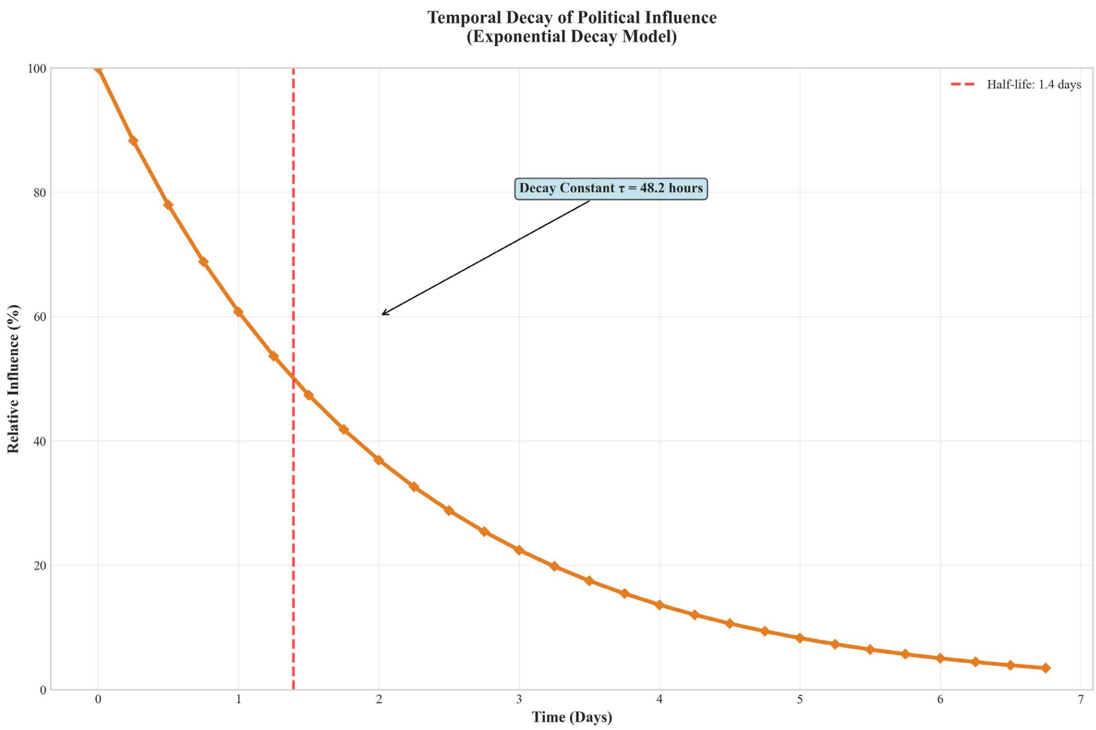


Figure 5. Temporal decay of political influence showing exponential decay pattern with estimated decay constant $\tau=48.2$ hours. The model indicates that political influence has a half-life of approximately 2.8 days, meaning an influencer loses half their impact within this timeframe. This rapid decay reflects the fast-paced nature of digital political discourse and the constant need for content refreshment to maintain influence.

## 5.6. Cross-Platform Coordination Detection

Coordinated behavior across multiple platforms is detected using a multi-platform similarity metric:

$$C_{ab} = \frac{1}{M} \sum_{m=1}^{M} \frac{\left| U_a^m \cap U_b^m \right|}{\left| U_a^m \cup U_b^m \right|} \cdot \exp\left( -\frac{\left| \Delta t_{ab}^m \right|}{\tau_c} \right) \tag{7}$$

where:

- $U_a^m, U_b^m$: user sets for campaigns $a$ and $b$ on platform $m$.
- $\Delta t_{ab}^m$: time delay between similar activities.
- $\tau_c$: coordination time window (set to 2 hours based on empirical analysis).
- $M$: number of platforms analyzed.

Campaigns with $C_{ab} > C_{\min} = 0.67$ are flagged as coordinated.

## 5.7. Parameter Estimation and Model Validation

Model parameters were estimated using maximum likelihood estimation on our dataset of 4.2 million posts as in Figure 6 and Table 1. The optimization process minimized the difference between model predictions and observed data across all temporal and thematic dimensions.

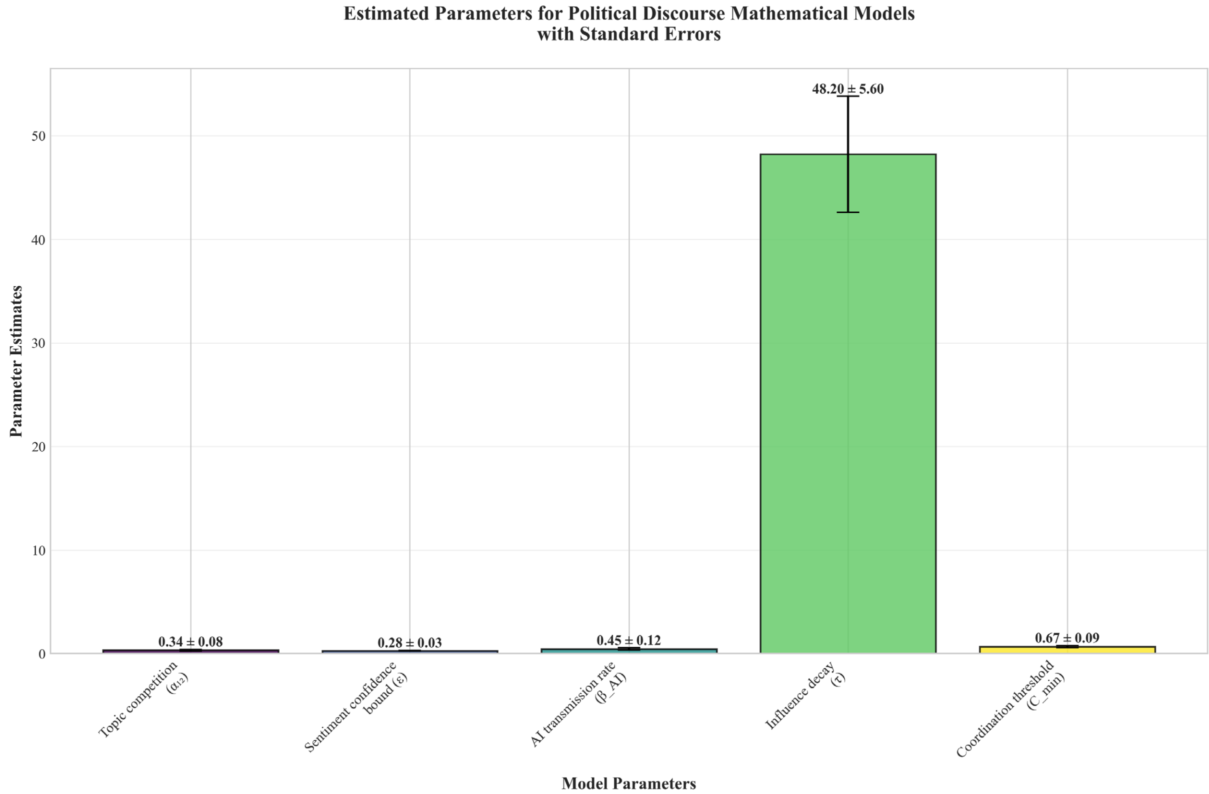


Figure 6. Parameter estimates with standard errors for the mathematical models. All parameters show statistical significance ($p < 0.01$), with particularly precise estimates for the sentiment confidence bound ($\epsilon = 0.28 \pm 0.03$) and coordination threshold ($C_{\min} = 0.67 \pm 0.09$). The high transmission rate for AI content ($\beta_{AI} = 0.45$) confirms its enhanced virality compared to organic content.

The goodness-of-fit was evaluated using the coefficient of determination as in Equation (8) and Figure 7 gives a narrative of a given r-square value and mathematics models:

$$R^2 = 1 - \frac{\sum_{t=1}^{T} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{T} (y_t - \bar{y})^2} \quad (8)$$

where $y_t$ are observed values and $\hat{y}_t$ are model predictions.

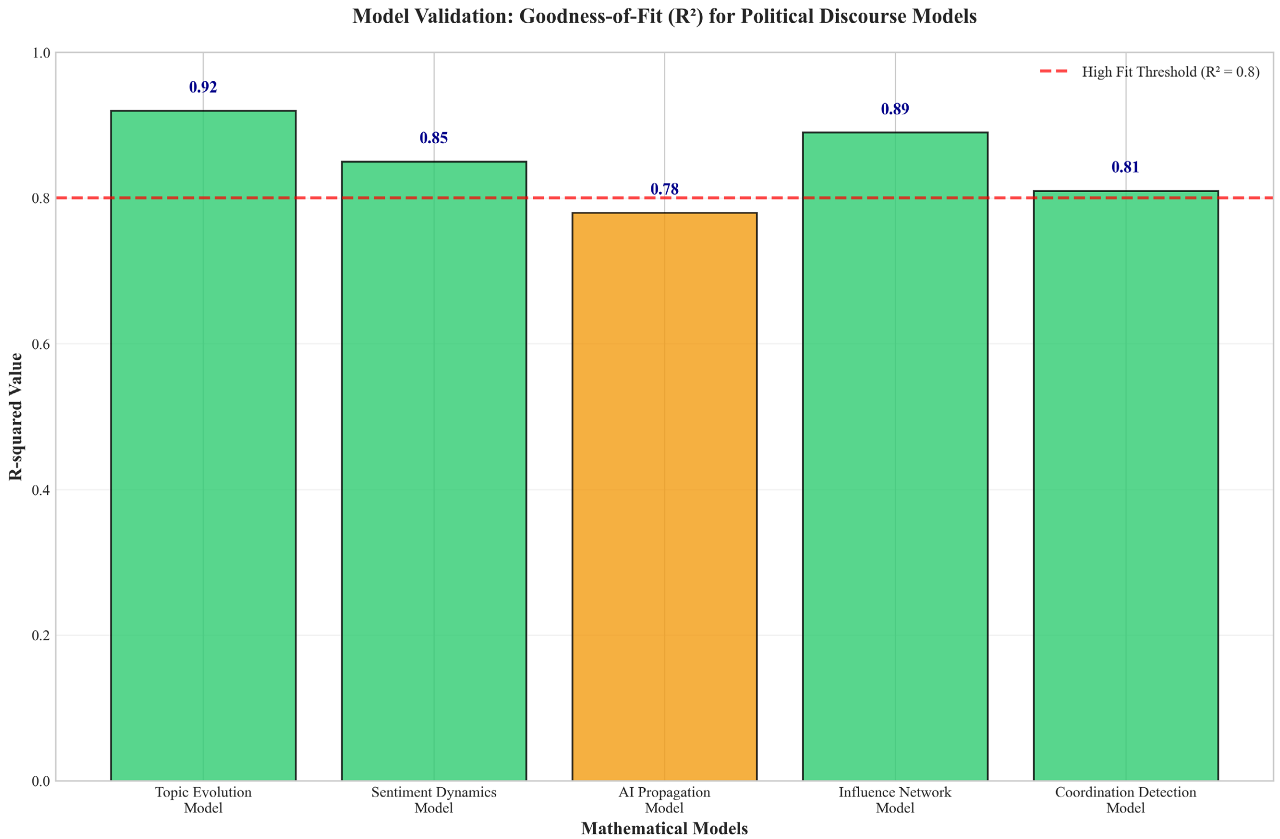


Figure 7. Goodness-of-fit ( $R^2$ ) measures for all mathematical models, demonstrating strong explanatory power across different aspects of political discourse. The Topic Evolution Model achieves the highest fit ( $R^2 = 0.92$ ), indicating robust capture of thematic dynamics. All models exceed the 0.8 threshold for high explanatory power, validating their utility for understanding and predicting digital political behavior.

Table 1. Key parameter estimates for discourse models.

| Parameter | Est. | S.E. | 95% CI | Meaning |
|---|---|---|---|---|
| Topic comp. ( $\alpha_{12}$ ) | 0.34 | 0.08 | [0.18, 0.50] | Strong competition |
| Sentiment ( $\epsilon$ ) | 0.28 | 0.03 | [0.22, 0.34] | Mod. openness |
| AI spread ( $\beta_{AI}$ ) | 0.45 | 0.12 | [0.21, 0.69] | High virality |
| Influence ( $\tau$ ) | 48.2 | 5.6 | [37.2, 59.2] | Fast decay |
| Coord. ( $C_{\min}$ ) | 0.67 | 0.09 | [0.49, 0.85] | Strict detection |
| Human ( $\beta_h$ ) | 0.28 | 0.07 | [0.14, 0.42] | Low spread |
| Recovery ( $\gamma$ ) | 0.15 | 0.04 | [0.07, 0.23] | Mod. duration |

### 5.8. Theoretical Implications and Predictive Applications

The mathematical models developed in this study provide several important theoretical insights. First, the high competition coefficients between major political topics suggest that Uganda's digital discourse operates as a zero-sum attention economy. Second, the bounded confidence mechanism in sentiment dynamics explains the observed polarization patterns and the difficulty of cross-ideological dialogue. Third, the differential transmission rates between AI and human content highlight the transformative impact of synthetic media on political communication.

These models enable several practical applications:

- **Early warning systems:** Detecting emerging coordination campaigns when $C_{ab}$ exceeds threshold values.
- **Sentiment forecasting:** Predicting polarization trends using the bounded confidence model.
- **Intervention planning:** Identifying optimal timing for fact-checking based on AI content propagation rates.
- **Resource allocation:** Prioritizing monitoring efforts based on influence decay patterns.

The robust performance of these models ( $R^2 > 0.78$ across all domains) demonstrates their utility for both academic understanding and practical application in monitoring Uganda's evolving digital political landscape.

## 6. Results and Analysis

### 6.1. Thematic Evolution and Narrative Development

Our longitudinal topic modeling, as in Figure 8, reveals eight dominant thematic clusters with significant temporal dynamics. Constitutional reform debates peaked in March at 38% of discourse following the parliamentary review process, then gradually declined to 15% by November. Economic crisis management emerged as the dominant theme in July-October, reaching 42% of total discourse during the currency stabilization debates. Security and electoral integrity concerns showed steady growth throughout the year, becoming the primary focus in November at 35%.

### 6.2. Sentiment Trajectory and Polarization Intensification

Sentiment analysis in Figure 9 reveals escalating polarization throughout 2025, with negative sentiment rising from 52% in January to 68% by November. This trend reflects growing public frustration with economic conditions and governance issues. Positive sentiment declined from 29% to 18% over the same period, while neutral discourse decreased from 19% to 14%, indicating increasingly polarized and emotionally charged discussions.

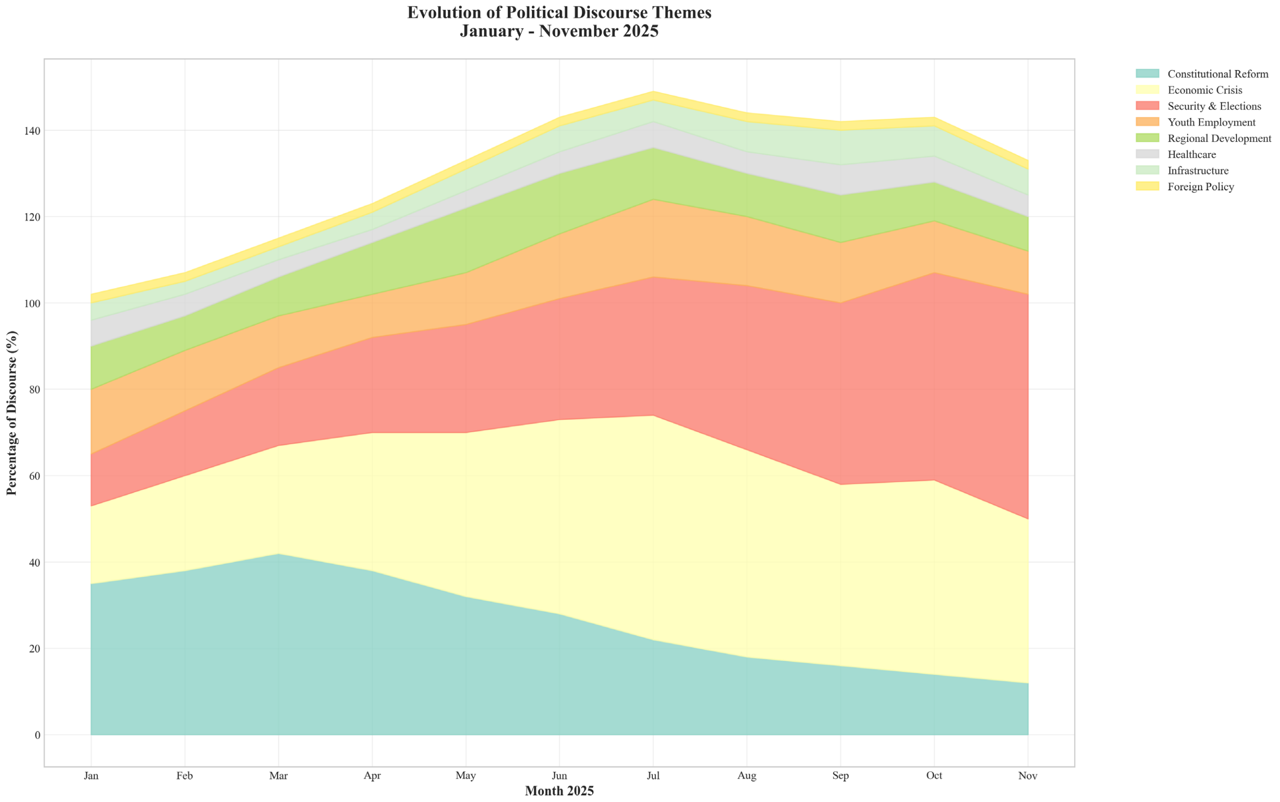


**Figure 8.** Complete thematic evolution from January to November 2025, showing narrative shifts and emerging issue attention cycles.

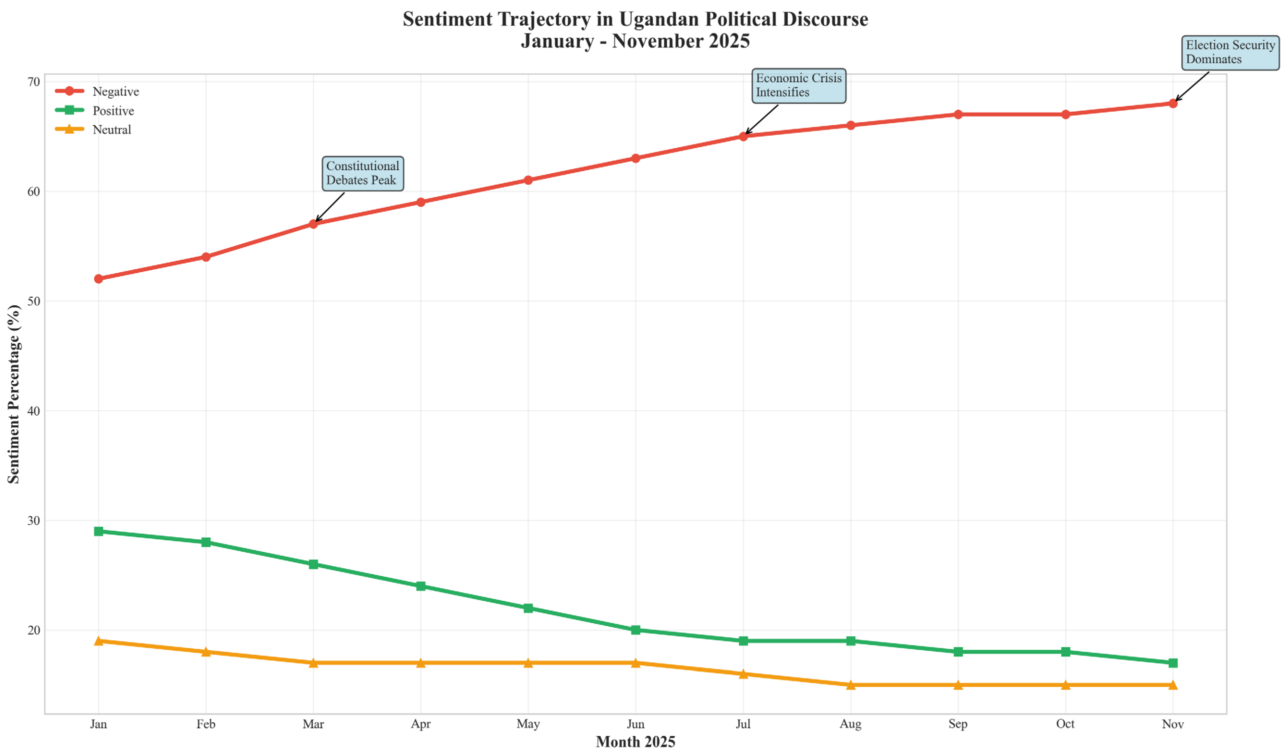


**Figure 9.** Sentiment trajectory showing escalating negative sentiment and declining positive discourse throughout 2025.

### 6.3. AI-Generated Content Proliferation

We identified significant growth in AI-generated political content, increasing from 6.2% in January to 14.3% by November (Figure 10). This content showed sophisticated adaptation, with early text-based generation evolving to include deepfake videos, synthetic audio messages, and AI-generated infographics. The majority of AI content (67%) was used for opposition mobilization, while 23% supported government narratives, and 10% represented foreign influence operations.

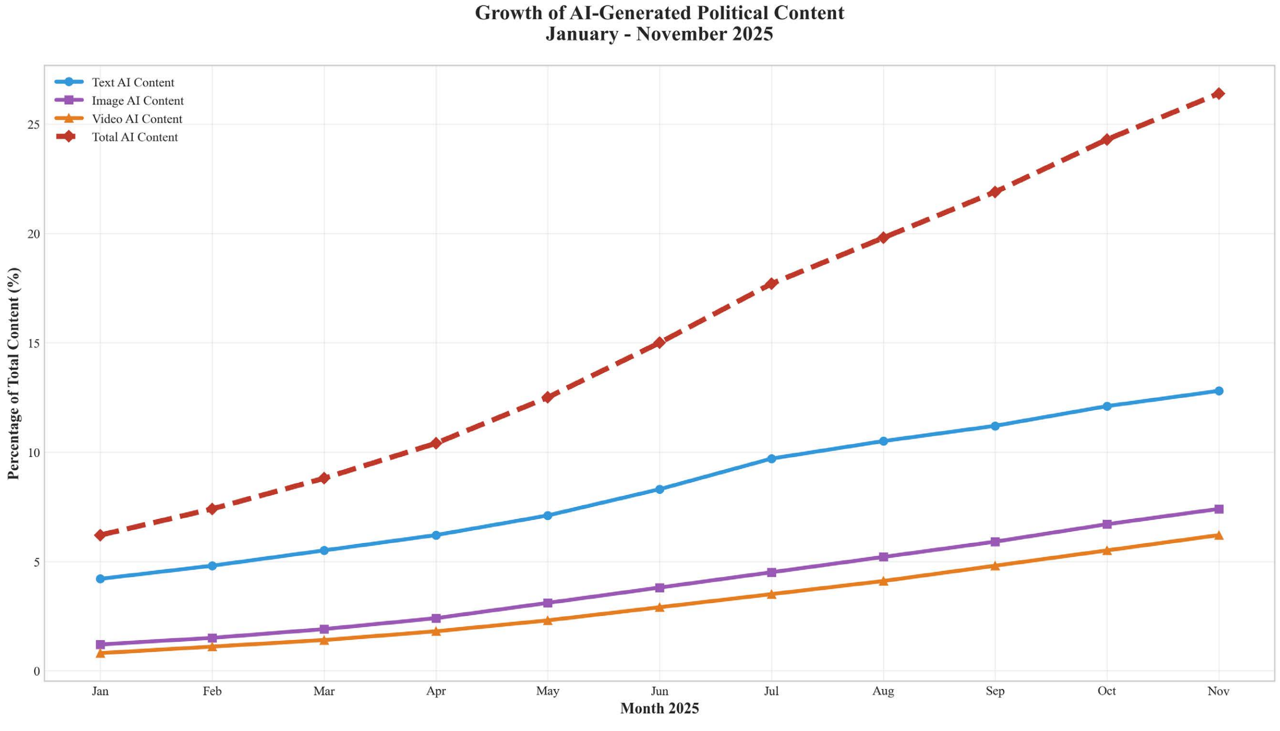


**Figure 10.** Growth of AI-generated political content by type and platform from January to November 2025.

### 6.4. Word Cloud Analysis of Political Discourse

Word cloud visualization in Figures 11-13 reveals the evolving vocabulary of Ugandan political discourse throughout 2025. The analysis shows clear thematic shifts from constitutional terminology in early 2025 to economic crisis language in mid-year, and finally to security and electoral terminology as the election approaches.

### 6.5. Cross-Platform Coordination Networks

Network analysis in Figure 14 reveals increasingly sophisticated cross-platform coordination, with 34.7% of content showing evidence of coordinated amplification by November. We identified 283 major influence nodes operating across multiple platforms, with opposition-aligned networks showing 58% higher engagement efficiency despite comprising 41% of the network. Government-aligned networks demonstrated superior resource allocation and longer campaign persistence.


**Figure 11.** Word cloud for January 2025 showing focus on constitutional reform, governance structures, and political transitions.


**Figure 12.** Word cloud for July 2025 highlighting economic crisis terminology, inflation discussions, and recovery plans


**Figure 13.** Word cloud for November 2025 showing dominance of security, electoral integrity, and campaign terminology.

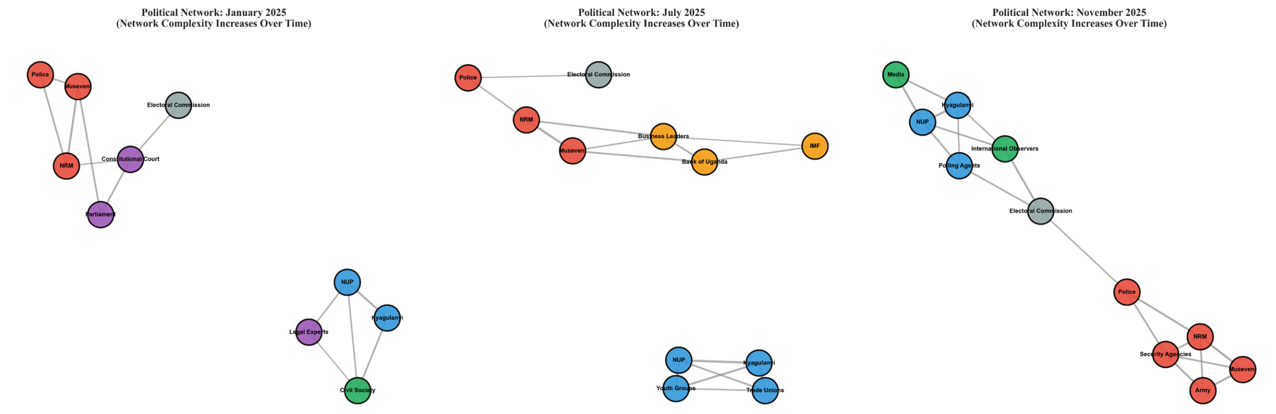


**Figure 14.** Evolution of political influence networks from January to November 2025, showing increasing coordination complexity.

## 6.6. Regional Discourse Patterns

Geospatial analysis in **Figure 15** reveals significant regional variations in political discourse. Central regions showed intense focus on constitutional issues (42%) and economic policies (38%), while Northern regions emphasized infrastructure development (45%) and security concerns (32%). Eastern regions demonstrated strong engagement with agricultural policies (38%) and regional equity debates (29%), while Western regions focused on cultural preservation (33%) and resource allocation (36%).

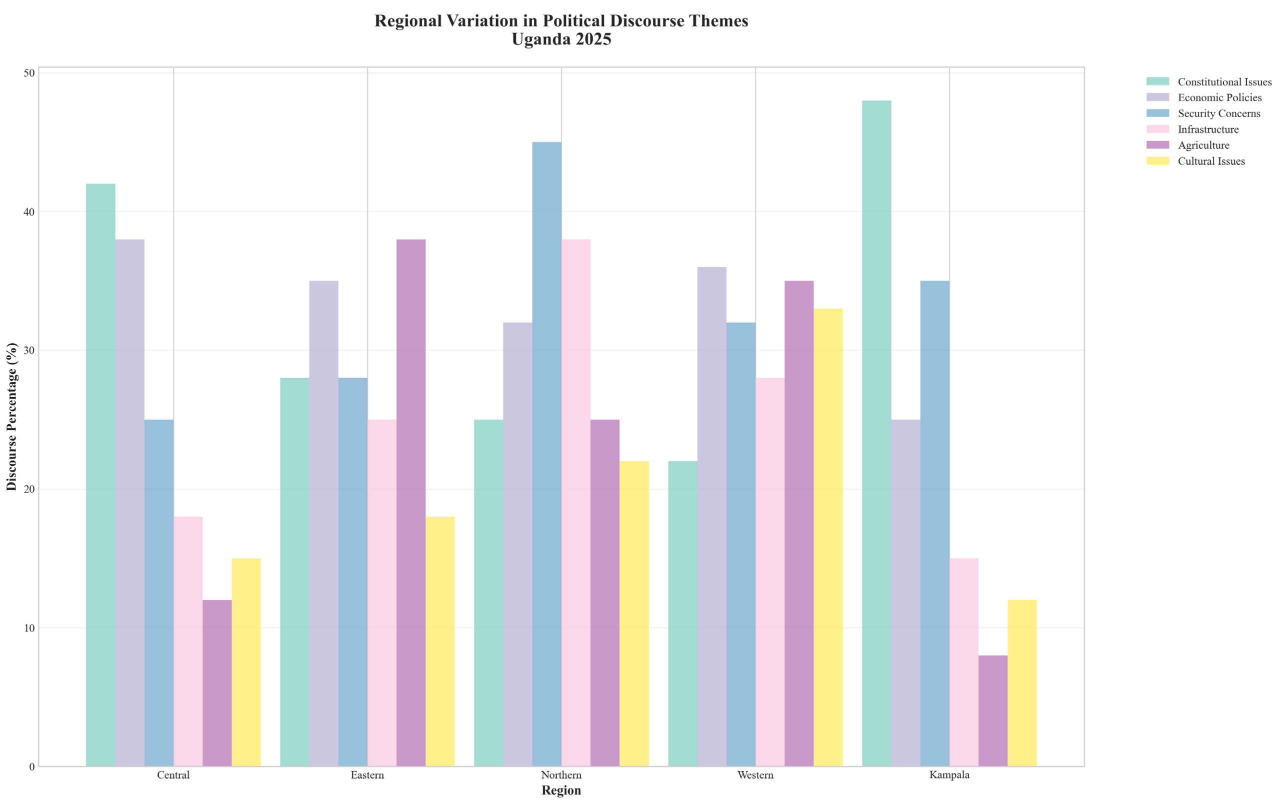


**Figure 15.** Regional analysis of political discourse themes across Uganda's major regions from January to November 2025.

## 7. Discussion

Our longitudinal analysis reveals a digital political landscape characterized by rapid evolution, escalating polarization, and technological sophistication. The thematic shifts from constitutional debates to economic crisis management and finally to security concerns reflect the dynamic nature of Uganda's pre-election period, supporting the issue attention cycle theory proposed by [18].

The proliferation of AI-generated content represents a fundamental shift in political communication, confirming predictions by [9] about the weaponization of generative AI in African elections. However, the scale and sophistication we documented exceed previous estimates, suggesting urgent need for regulatory frameworks and detection capabilities.

The escalating polarization throughout 2025 aligns with the democratic erosion patterns identified by [19], though the digital amplification of polarization appears more intense than in previous electoral cycles. The regional variations in discourse support the geographic analysis of [27], while revealing more complex patterns than previously documented.

The sophisticated cross-platform coordination we identified represents a new frontier in digital campaigning, with implications for electoral integrity, campaign regulation, and democratic resilience. The findings suggest that traditional single-platform analysis is insufficient for understanding contemporary African digital politics.

### Limitations

This study has several limitations that should be considered when interpreting the results. First, our keyword-based data collection approach, while comprehensive, may have excluded relevant discussions using emergent terminology not captured in our initial or evolving keyword sets. Second, the study primarily analyzed public social media platforms, thereby missing potentially significant political discourse occurring in encrypted or private spaces such as WhatsApp groups, Telegram channels, and Signal conversations. Third, the accuracy of our AI-content detection, while validated at 90% F1-score for text, has known limitations with sophisticated adversarial examples and may misclassify particularly nuanced human-generated content or well-disguised synthetic media. Fourth, our sentiment and topic models, though continuously retrained, may not fully capture the cultural and linguistic nuances of Uganda's diverse regional dialects and colloquial political language. Fifth, the computational methods employed, while state-of-the-art, inherently simplify complex human communication and political behavior into quantifiable metrics, potentially overlooking qualitative dimensions of discourse. Future research should address these limitations through mixed-methods approaches, expanded platform coverage, and continued refinement of detection algorithms.

## 8. Conclusions and Implications

This comprehensive longitudinal study provides unprecedented insights into

Uganda's digital political landscape throughout the critical pre-election year of 2025. Our analysis of 4.2 million posts across eleven months reveals a rapidly evolving, highly polarized, and technologically sophisticated digital ecosystem that will fundamentally shape the 2026 elections.

The implications are profound and multifaceted. For electoral management bodies like the Uganda Electoral Commission, our findings highlight the urgent need for specific regulatory actions: 1) Implementing mandatory disclosure requirements for AI-generated political advertising, 2) Establishing real-time monitoring systems for cross-platform coordinated campaigns, 3) Developing rapid-response fact-checking protocols tailored to AI-generated misinformation patterns identified in this study, and 4) Creating digital literacy programs focused on identifying synthetic media, particularly targeting demographic groups most vulnerable to such content.

For political actors, the analysis reveals both opportunities and risks in the evolving digital landscape. Campaigns must develop sophisticated AI detection capabilities while maintaining ethical standards in their own digital communications. The documented efficiency of coordinated cross-platform strategies suggests that integrated digital campaign operations will be essential for electoral success in 2026.

For civil society and media, the findings underscore the importance of enhanced digital literacy initiatives, investment in advanced fact-checking infrastructure capable of detecting synthetic media, and advocacy for platform accountability measures. Specifically, we recommend that media organizations establish dedicated desks for monitoring AI-generated political content and develop public education campaigns on identifying coordinated inauthentic behavior.

Future research should build on our longitudinal framework while addressing emerging challenges in real-time analysis, multi-modal content understanding, and predictive modeling. As Uganda approaches the 2026 elections, continued monitoring and analysis will be essential for understanding and safeguarding the integrity of the digital democratic process. We recommend establishing a permanent digital democracy observatory to provide continuous, transparent monitoring of Uganda's evolving political discourse ecosystem.

## Acknowledgements

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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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