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# A machine learning dissection of Nigeria's 'Renewed Hope Agenda': Sentiment Dynamics and Thematic Salience in Public Discourse (2023–2025)

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## Abstract

This research offers a computational assessment of Nigeria's "Renewed Hope Agenda" under President Tinubu (May 2023–April 2025), probing whether its narrative framing has shifted public sentiment and policy-issue salience in national newspapers. A corpus of 24,450 articles from the two major newspapers were collected and filtered for relevant keywords and minimum length. Lexicon-based sentiment analysis (VADER) quantified monthly mean compound scores, revealing an overall positive tone (0.62–0.78), with notable dips following subsidy removal and inflationary events, and rebounds linked to communication recalibrations. Similarly, topic modelling using BERTopic with "paraphrase-MiniLM-L6-v2" embeddings identified 318 thematic clusters. Prominent topics included fuel subsidy removal, VAT reform, palliative measures, and digital transformation, while structural concerns like inflation, poverty, and insecurity persisted. Integration of NRC emotion lexicon via NRCLex enriched these themes with affective profiles, uncovering elevated anger and fear around economic policies and trust associated with governance transparency initiatives. Findings suggest that while "Renewed Hope" rhetoric maintains discursive traction, its legitimacy is contingent upon tangible socioeconomic outcomes. Methodologically, this research demonstrates the utility of combining sentiment analysis and embedding-based topic modelling for longitudinal policy discourse monitoring.

**Keywords:** Sentiment; VADER; BERT; Embedding; NRCLex

## 1. Introduction

Political narratives play important role in shaping public sentiment and influencing policy priorities while they drive governance outcomes. The capacity of political administrations to formulate and propagate effective narratives sometime determines their perceived legitimacy and efficacy among citizens (Lewis and Kling, 2024; Price, 2012). In Nigeria, the inception of Bola Ahmed Tinubu's presidency in May 2023 marked the launch of the "Renewed Hope Agenda," envisioned as a transformative blueprint which was coined to address the socio-economic challenges and rekindle citizens' trust in governance. While the administration continue to progress day by day, the administration's strategy has been the consistent projection of "renewed hope" as an overarching motif for policy discourse with emphasis on themes of economic revitalization, improved governance transparency, and enhanced public welfare (Orintunsin, 2025; Olusegun, 2024; Eze and Nwasogwa, 2023). This research seeks to critically examine whether this deliberate and strategic narrative has measurably shifted public sentiment and heightened the salience of specific policy issues within public discourse, leveraging advanced machine-learning techniques for robust and detailed analysis.

The contemporary Nigerian socio-political context provides a compelling motivation for this inquiry. Over the years, Nigeria grappled with widespread public dissatisfaction attributed to persistent economic instability, rising insecurity, and governance deficits that severely eroded public trust in political institutions (Ogbu and Chukwuemeka, 2024; Adofu and Alhassan, 2018). The Buhari administration (2015-2023), despite initial optimism and its "Change" mantra, faced substantial criticism for perceived inefficiencies and policy failures, leading to deepening cynicism and disenchantment

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among the populace (Olasupo, Patrik and Abioro, 2024; Adekunle and Alokpa, 2023). Hence, the "Renewed Hope Agenda" emerged not only as a corrective narrative but also as a critical rhetorical device fabricated to rebuild public confidence, shift existing sentiments positively, and reveal policy initiatives as priorities in public and media discourses.

Nevertheless, political narratives, even when they are well-articulated, they do not automatically translate into improved public trust or a perceptible shift in policy salience. Researchers like Capano, Galanti and Barbato (2023), McConnell (2010) and Powell (2004) mentioned that successful political narratives must be consistently reinforced by tangible policy outcomes and responsive governance practices. The Nigerian context, historically characterized by deep-seated skepticism towards political rhetoric, presents unique challenges for the "Renewed Hope Agenda." Considering thus, mere propagation of a compelling narrative does not guarantee its resonance or acceptance by citizens, particularly given historical disillusionments and entrenched skepticism.

Against this backdrop, the core research question emerges: *Has the "Renewed Hope Agenda" effectively shifted public sentiment and enhanced policy salience within Nigerian public discourse?* To address this question broadly, a critical and methodologically sophisticated approach is required. This research employed advanced machine-learning techniques, notably sentiment analysis and topic modelling, to rigorously analyze textual data extracted from Nigeria leading newspaper, covering the period from the inception of Tinubu's government to the present. These methodological choices are strategically motivated by the need to quantify and systematically assess qualitative shifts in public discourse while allowing for a detailed examination beyond traditional qualitative analyses.

The application of machine-learning methods, specifically sentiment analysis, provides the opportunity to empirically determine shifts in public mood, capturing extensive emotional tones conveyed in media reporting and public reaction. This analytical approach is particularly advantageous in capturing subtle yet significant variations in public opinion that conventional methods might overlook (Edeh et al., 2023; Ramesh et al., 2023). Similarly, topic modelling techniques enable the identification of shifts in policy salience, highlighting how effectively the administration's key policy areas are embedded and foregrounded within media coverage. Combining these techniques, the research aims to achieve a deeper understanding of the "Renewed Hope Agenda's" discursive influence, offering insights into both the perceived authenticity of governmental narratives and their substantive alignment with public concerns.

## 2. Literature Review

Since Nigeria's return to democracy in 1999, successive administrations have relied heavily on political and policy narratives to trigger public perception and assert control over national discourse. These narratives often serve dual purposes: establishing legitimacy and outlining aspirational visions for socio-economic development. From Olusegun Obasanjo's "Reform Agenda" to Umaru Musa Yar'Adua's "Seven-Point Agenda," Goodluck Jonathan's "Transformation Agenda," and Muhammadu Buhari's "Change" and "Next Level" slogans, these narratives have functioned as both governance blueprints and rhetorical devices (Eze and Nwasogwa, 2023; Dan Asabe, 2017; Gyong, 2012). While all these narratives uphold strategic intent, the efficacy of these narratives with mobilization of public trust or policy acceptance has been mixed, with growing public skepticism regarding their sincerity and impact.

Obasanjo's Reform Agenda (1999–2007) aimed at economic liberalization, anti-corruption, and civil service reform, gaining initial optimism but eventually encountering criticism due to allegations of selective anti-corruption enforcement and entrenched political patronage (Okoli, 2017; Ake and Olowojolu, 2016). Yar'Adua's Seven-Point Agenda (2007–2010) was more structurally ambitious with target to address critical sectors like energy, transportation, and security. However, it was hampered by poor implementation and his failing health (Alfred, 2022; Oke, Oluwasuji and Simon0Oke, 2011). Goodluck Jonathan's Transformation Agenda (2011–2015) focused on infrastructure and human capital development but faced credibility challenges, particularly in the wake of the Boko Haram insurgency and widespread corruption allegations (Gyong, 2012). In usual pattern, Buhari's twin narratives "Change" (2015) and "Next Level" (2019) capitalized on public disillusionment with the previous administration but later faced backlash over worsening insecurity, inflation, and rising poverty levels (Adekunle and Alokpa, 2023; Arum and Marcus, 2023; Yusuf and Mohd, 2022).

The use of sentiment analysis has particularly revolutionized the understanding of public emotion and opinion dynamics. For instance, Gudankwar et al. (2024) and Chakraborty (2023) demonstrate how opinion mining is used to categorize texts by emotional valence like positive, negative, or neutral, thus enabling more granular analysis of masses responses to certain situations. Cambria et al. (2017) extend this by introducing affective computing models that detect subtler dimensions like anger, hope, or fear, which are important in the assessment of the emotional resonance of certain narratives.

Topic modelling has also proven valuable for detecting themes and shifts with time (Krauss, Aschauer and Stockl, 2022). Chen (2023), Karaosmanoglu and Guran (2022) and Liu, Geng and Liu (2022) all demonstrate how LDA can identify dominant policy issues in media narratives, allowing researchers to map alignment (or misalignment) between government priorities and public discourse. This is particularly relevant in contexts like Nigeria, where informal and online media has served as alternative arenas for political contestation.

Despite these advancements, there remains a significant gap in the Nigerian environment and policymaking domains regarding the systematic use of Machine Learning (ML) techniques to assess the real-time effectiveness of political narratives. Most existing works are either purely qualitative or rely on small datasets that limit generalizability. Furthermore, little attention has been paid to how political narratives like Tinubu's "Renewed Hope Agenda" are received in the public sphere over time, particularly using empirical computational methods. This represents a critical gap, especially given the increasing digitalization of political discourse. Moreover, most ML-based studies in Africa have concentrated on electoral forecasting, misinformation detection, or social media sentiment around isolated events (Attai et al., 2024; Olabanjo et al., 2023; Oyebode and Orji, 2019). Thus, most research have ignored systematic analysis of long-term public sentiment in response to governance narratives or to quantify the salience of policy issues over time. Thus, while the tools exist, their application in a coherent, longitudinal, and context-specific manner remains underexplored.

This research addresses these gaps by leveraging machine learning to implement sentiment analysis and topic modelling on a rich corpus of newspaper articles from two of Nigeria's most influential dailies—Punch and Guardian. By focusing on the period from the inception of the Tinubu administration to the present, the research captures both the temporal dimension and evolving nature of public response. Furthermore, newspapers as a data source provide a hybrid of elite discourse and public reaction, particularly in a context where social media data are often distorted by bots, echo chambers, or censorship (Jiang et al., 2021, Liu, 2019).

## 3. Data Collection

Data collection using web scraping involves systematic extraction of content from websites through automated scripts (Prashanth, Tejaswini and Sindhu, 2024; Wahed et al., 2024). First, a list of target websites (in this case, WordPress-based news outlets) is defined, along with relevant keywords describing the Renewed Hope agenda within a specified date range. The scraper sends HTTP GET requests to the website's API endpoints (such as /wp-json/wp/v2/posts) to retrieve articles in JSON format. Each article's title, excerpt, and full content are cleaned by removing HTML tags and unnecessary formatting. The combined text is then tokenized to determine word count and assessed against a list of predefined keywords. Only articles that contain the keywords and exceed a minimum word count threshold are stored. The relevant metadata (like date, title, URL, and word count) is then saved into a structured format in DataFrame. Finally, the dataset is exported as a CSV file for further analysis (Table 1).

**Table 1** Web scrapping Pseudocode for Data Collection

| **Pseudocode for Web Scraping Algorithm Implemented** |
|---|
| **Given:**<br>S = $\{s_1, s_2, \ldots, s_n\}$ K = $\{k_1, k_2, \ldots, k_m\}$ $D = [d_{\text{start}}, d_{\text{end}}]$ $T_{\min}$<br>S: set of WordPress-based site URLs<br>K: set of primary keywords<br>$D$: user-defined date interval<br>$T_{\min}$: minimum word-count threshold<br>**Initialize:** A ← ∅<br><br>**for** each site $s_i \in$ S **do**<br>$p \leftarrow 1$<br>**repeat**<br>response ← GET $s_i$+"*/wp-json/wp/v2/posts*", params<br>**if** response.status ≠ 200 **then break**<br>**end if** |

$P_p \leftarrow$ response.json()
**if** $P_p = \emptyset$ **then break**
**end if**
**for** each post $a \in P_p$ **do**
title ← HTMLStrip $a$ [" title"] [" rendered"]
excerpt ← HTMLStrip $a$ [" excerpt"] [" rendered"]
content ← HTMLStrip $a$ [" content"] [" rendered"]
text ← title + excerpt + content
$text_{clean} \leftarrow$ Join text.split()
$W \leftarrow text_{clean}$.split()
*matched* $\leftarrow \exists\, k_j \in K$ such that $k_j \in text_{clean}$
**if** *matched* $\wedge\, W \geq T_{\min}$ **then**
$A \leftarrow A \cup$ {site : $s_i$, date : $a$["date"][: 10],
title : title, url : $a$[" link"], text : $text_{clean}$, word count : $W$}
**end if**
**end for**
$p \leftarrow p + 1$
**until** no more pages
**end for**
**Postprocess:** convert A to DataFrame and export as CSV

After web scrapping, a total of 24,450 articles were collected from 29th May 2023 to 30th April 2025 around the key words defined based on the Renewed Hope Agenda.

## 4. Analysis and Modelling

The main exploratory analysis implemented is word cloud plot to recognize the recurring words around the Renewed Hope Agenda (Figure 2). While word clouds have been criticized for oversimplifying discourse in some quarters (Hicke, Goenka and Alexander, 2022; Atenstaedt, 2017), yet they remain a powerful exploratory tool. Researchers like Lourdusamy, Thangavel and Johnbosco (2021) and Bashri and Kusumaningrum (2017) affirmed that the immediate salience of large tokens in word cloud help non-technical audiences to grasp topical emphases before deeper modelling like the dynamic topic models or sentiment analysis is presented. In the policy-communication context of Nigeria's "Renewed Hope" agenda, word cloud instantly reveals whether economic-development language dominates over social-welfare or security terms, thus offering a visual hypothesis generator for subsequent quantitative analysis. The word cloud was generated using the WordCloud class from the wordcloud Python library. The WordCloud class is subsequently instantiated to tokenize input string (all text), counts word frequency and visually represents the words by assigning font sizes based on their frequencies.

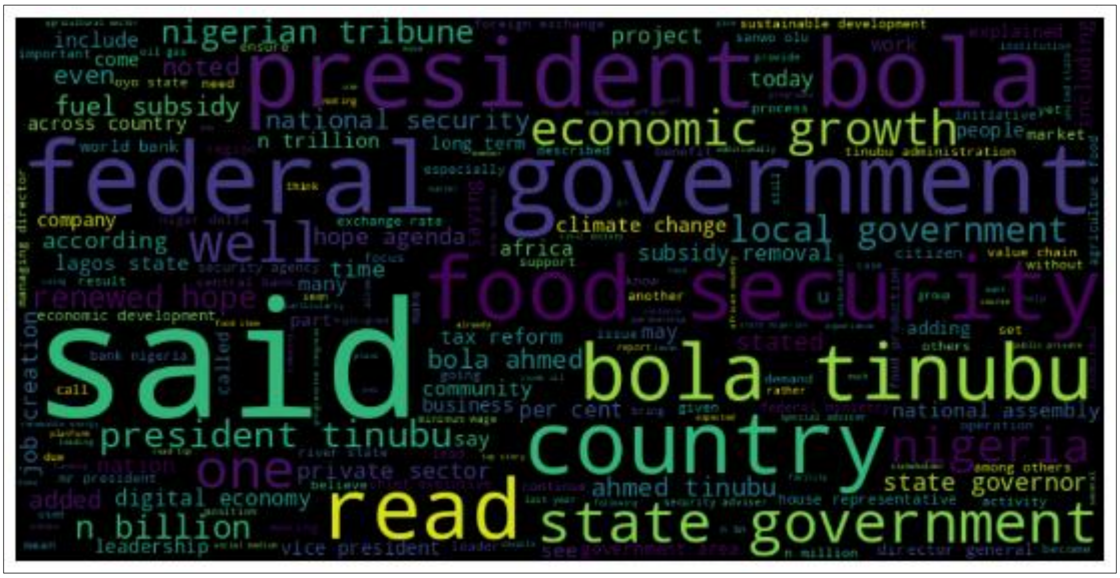


**Figure 1** Word Cloud Map to represent media coverage based on the Renewed Hope Agenda

The cloud in Figure (1) is dominated by references to "president," "Bola Tinubu," and "federal government," signaling that many coverage by the Nigeria media is heavily centered on the new administration's statements and initiatives. Recurrent appearance of the verb "said" indicates most articles are reportorial, quoting official pronouncements rather than analyzing them. Large tokens like "food security," "economic growth," and "fuel subsidy" highlight the policy triad which includes agriculture, macro-economy, and subsidy removal. The phrase "renewed hope" is visible in the plot which confirms that the administration's own branding has successfully penetrated media space. Recurrent mentions of "national security" and "climate change" show secondary but persistent concerns alongside around the economy. The coexistence of "private sector," "business," and "n billion" points to a narrative that frames government policy in investment and monetary terms.

### 4.1. Sentiment Analysis

Lexicon-based sentiment polarity was plotted from May 2023 to April 2025 using VADER. VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool optimized for short-form text to quantify sentiment polarity through the compound score, which ranges from –1 (most negative) to +1 (most positive) (Hoti and Ajdani, 2023). The VADER script groups text sentiment data by month, using df["date"].dt.to_period("M").dt.to_timestamp() to normalize and align each article's sentiment to its corresponding month. It then applies groupby() and computes the mean compound score for each month. This yields temporal trend of sentiment polarity (Figure 2).

The sentiment trend in Figure (2) shows that overall public reaction, as measured by VADER's compound score, has remained largely positive throughout the observed period (May 2023 to April 2025). Sentiment begins strongly close to 0.7, reflecting an optimistic tone, possibly linked to policy announcements. A sharp decline follows in June 2023, dipping to around 0.62, this corresponds to controversial events around the policy feedback. However, sentiment rebounds quickly, reaching a peak around October and November 2023, indicating successful government messaging and improved public perception. The beginning of 2024 sees another decline, with January and February dropping below 0.64, this suggests renewed skepticism and some negative press coverage.

This period is followed by a substantial recovery from March through May 2024, where the average sentiment stabilizes around 0.74, highlighting renewed confidence. In July 2024, a steep drop to below 0.57 marks the lowest sentiment in the entire series, possibly due to economic disruptions and high level of criticism. Remarkably, the sentiment rebounds again in the second half of 2024, returning to a stable range above 0.73 from September onwards. The peak is observed in November 2024, at approximately 0.78, indicating a period of strong public approval. Early 2025 sustains this positivity, although a slight dip in March and April 2025 brings the average down to around 0.71. Despite fluctuations, the sentiment trend demonstrates resilience, with most months remaining in the upper positive range. The overall pattern suggests a responsive public mood that improves or worsens based on policy actions, media framing, and government communication.

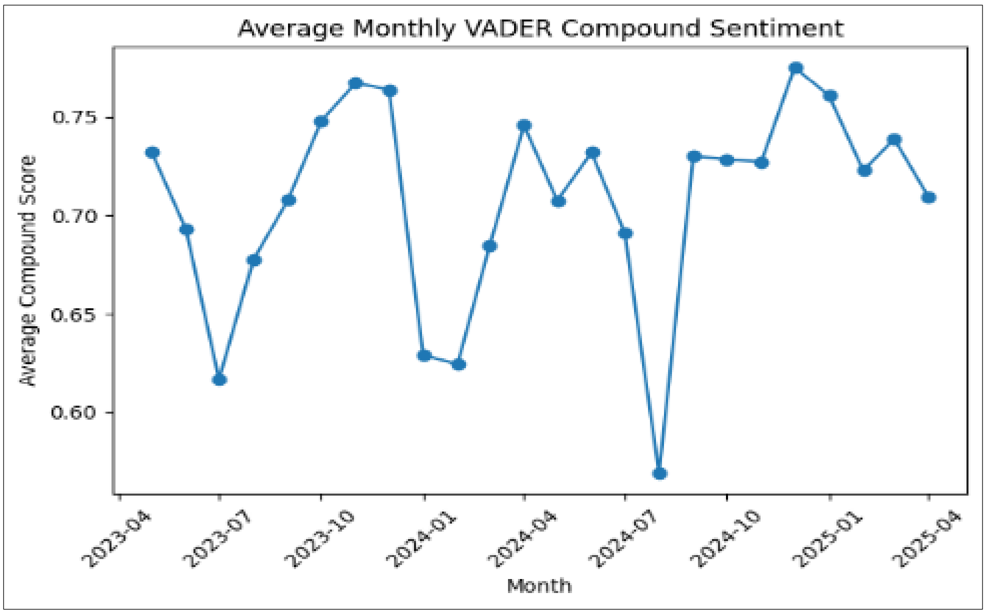


**Figure 2** VADER Sentiment Polarity Month Trend

### 4.2. Topic Modelling

Topic modelling was implemented using BERTopic with NRCLex (Table). For this method, semantic embeddings were generated for each article using the "paraphrase-MiniLM-L6-v2" SentenceTransformer model, and topics were inferred via the BERTopic framework, which couples UMAP dimensionality reduction with HDBSCAN clustering to identify cohesive thematic clusters. Each document was then analysed with the NRC Emotion Lexicon (via NRCLex) to extract raw counts for basic affective categories like trust, joy, anger, and fear. Emotion vectors were expanded into separate DataFrame columns and aggregated by topic, computing mean emotion scores to quantify the affective profile of each theme. Heatmap was plotted to visually emphasize topics with particularly strong emotional signatures while masking negligible values to reduce clutter.

**Table 2** Pseudocode for BERTopic

| **Pseudocode: Topic Modelling** |
|---|
| *// STEP 1: Load and prepare data*<br>*LOAD CSV file "/content/renewed_hope_articles_processed.csv" INTO DataFrame df*<br>*EXTRACT the "text" column from df, dropping any missing values, INTO list docs*<br><br>*// STEP 2: Topic modelling with BERTopic*<br>*INITIALIZE embedding_model as SentenceTransformer("paraphrase-MiniLM-L6-v2")*<br>*INITIALIZE topic_model as BERTopic(using embedding_model, verbose = TRUE)*<br>*FIT topic_model on docs, producing:*<br>*topics ← array of topic assignments for each document*<br>*probs ← array of topic probabilities*<br>*ADD topics array to df as new column "topic"*<br><br>*// STEP 3: Emotion detection on each document*<br>*DEFINE FUNCTION extract_emotions(text):*<br>*CREATE NRCLex instance on text*<br>*RETURN raw_emotion_scores dictionary* |

```
APPLY extract_emotions to each row in df["text"],
STORE results in df["emotions"] (each row is a dict of emotion counts)

// STEP 4: Expand emotion dictionaries into columns
CONVERT df["emotions"] series of dicts INTO a new DataFrame emotion_df
(each emotion label becomes its own column; missing values → 0)
CONCATENATE df["topic"] and emotion_df horizontally INTO combined_df

// STEP 5: Aggregate emotion scores by topic
GROUP combined_df BY "topic"
CALCULATE mean of each emotion column per topic INTO topic_emotions
REMOVE the "noise" topic (index = –1) from topic_emotions, if present

// STEP 6: Visualize with heatmap
// STEP 7: Export aggregated results
WRITE topic_emotions to CSV file "topic_emotion_aggregates.csv"
END
```

Heatmap in Figure (3) was generated by grouping each article's NRC-Lex emotion scores according to the BERTopic assignment and computed mean score for each emotion within each topic.

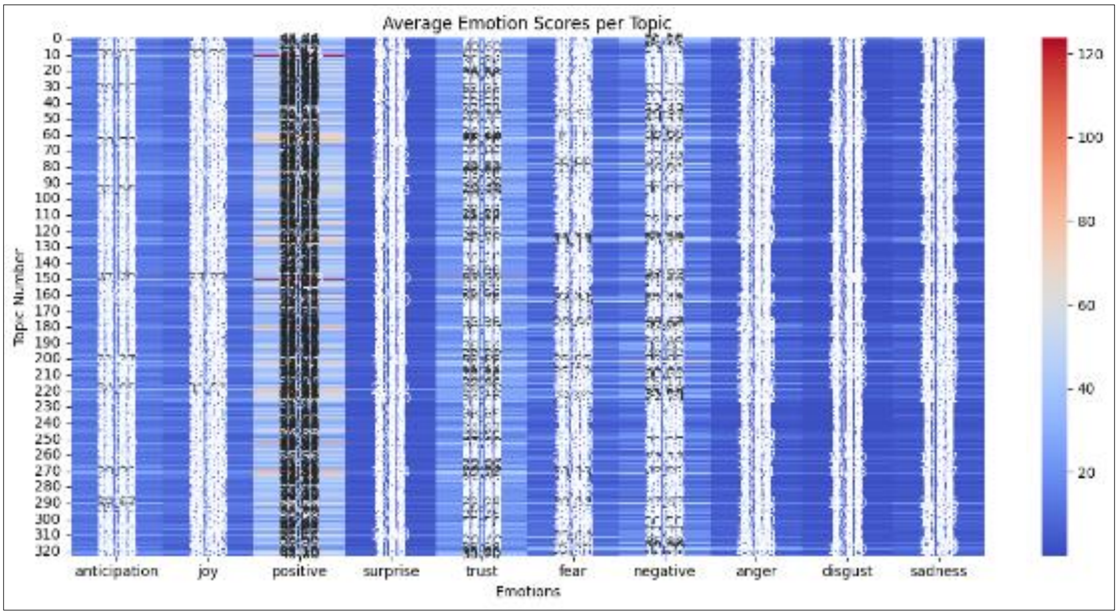


**Figure 3** Heatmap displaying Average Emotion Scores Per Topic

```
Topic 0: tax, bills, taxes, reform, vat
Topic 1: subsidy, fuel, removal, petrol, price
Topic 2: customs, ncs, comptroller, command, adeniyi
Topic 3: bill, senate, bills, house, legislative
Topic 4: award, awards, recognition, africa, contributions
Topic 5: arrested, court, emefiele, troops, dss
Topic 6: appointment, approved, ngelale, tinubu, ajuri
Topic 7: palliatives, palliative, removal, subsidy, distribution
Topic 8: mou, signed, agreement, memorandum, signing
Topic 9: tinubu, president, bola, his, victory
Topic 10: lady, wife, oluremi, first, women
Topic 11: strike, nlc, labour, tuc, congress
Topic 12: my, you, she, what, her
Topic 13: abducted, rescued, kidnapped, kidnapping, police
Topic 14: internet, telecom, mtn, broadband, ncc
Topic 15: china, chinese, cooperation, trade, nigeria
Topic 16: ai, artificial, intelligence, data, technology
Topic 17: climate, change, waste, plastic, environmental
Topic 18: women, gender, womenâ, she, equality
Topic 19: farmers, inputs, tractors, wheat, farm
Topic 20: maritime, marine, port, blue, ports
Topic 21: naval, admiral, rear, headquarters, appointed
Topic 22: education, teachers, schools, school, learning
Topic 23: steel, minister, federal, fg, health
Topic 24: nddc, delta, niger, region, ogbuku
Topic 25: conference, summit, event, host, africa
Topic 26: justice, court, judiciary, judicial, legal
Topic 27: fct, wike, territory, nyesom, minister
Topic 28: livestock, fodder, animal, feed, veterinary
Topic 29: budget, expenditure, billion, appropriation, 2025
Topic 30: skills, digital, youth, youths, training
Topic 31: tinubu, security, president, forces, bola
Topic 32: akpabio, senate, his, congratulated, governor
Topic 33: dangote, refinery, cement, petroleum, products
Topic 34: road, umahi, contractors, roads, works
Topic 35: farmers, training, nirsal, extension, oyo
```

**Figure 4** Extract of list of topics identified by BERTopic

The implemented model captured 318 topics by different media around "Renewed Hope Agenda" (Figure 4). Topic 0's focus on taxation and VAT reform suggests sustained public attention to fiscal policy, reflecting anxiety about government revenue measures that underwrite the administration's spending commitments. The prominence of Topic 1 and Topic 7 around fuel subsidy removal shows that policy as an enduring flashpoint, one that consistently triggers skepticism and anger in public discourse. Topic 2's concentration on customs and the Nigeria Customs Service highlights trade facilitation issues, suggesting that economic reform narratives extend beyond headline reforms to technical governance domains. Legislative processes appear in Topic 3 and Topic 30, indicating that both parliamentary bill-making and effective legislation are arenas where "hope" must compete with procedural opacity. The recurrent appearance of "palliatives" (Topic 7, Topic 196, Topic 306) signals persistent discourse on relief measures which is an emotional fulcrum where hope and frustration coexist. Infrastructure themes like ports in Topic 20, roads in Topic 34, and energy transition in Topic 67 mirror the administration's stated growth objectives, yet the parallel emergence of "inflation" (Topic 50, Topic 55) and "poverty" (Topic 55) topics suggests that economic gains are uneven and contested. Digital innovation topics (16, 37, 54, 94, 102, 132, 294) illustrate the "Renewed Hope" emphasis on technology. Foreign relations and diplomacy surface in topics like China cooperation (Topic 15, Topic 143), EU trade (Topic 89, Topic 198), and Russia–Ukraine war (Topic 66), illustrating that "hope" extends into Nigeria's global positioning. Agriculture and food security appear repeatedly (Topics 19, 28, 36, 77, 82, 113, 131, 206, 218, 260), indicating that rural livelihoods remain central to the social contract. Health and education well captured in Topics 22, 58, 93, 112, 122, 123 reveal continuing public interest in human capital, even as specialized clusters on vaccines (Topic 207) reflect post-COVID policy debates. The emergence of protest and labour unrest in Topic 11, 118, 128, 251 indicates that public trust is fragile, easily mobilized into collective action when narratives of "hope" fall short of material improvements. Finally, Topic 317's emphasis on tourism hints at soft-power aspects of the agenda, yet the overwhelming volume of tightly clustered governance, economic, and security topics suggests that while the "Renewed Hope Agenda" has generated new policy frames, public discourse remains preoccupied with long-standing structural challenges. Across these 318 topics, there is a media narrative ecosystem in which hope is invoked but continually measured against tangible outcomes in taxation, subsidy, security, infrastructure, and social welfare which all indicate that narrative success strongly depend not only on rhetorical framing but on demonstrable and lived improvements in citizens' daily lives.

## 5. Discussion of Results

The empirical findings from sentiment analysis and topic modelling align with, reinforce, and also advance existing works on political narratives in Nigeria, as outlined in the literature review (section 2.0). First, the observed sentiment trend in Figure (2) began with optimism in May 2023 and fluctuated according to political events which reflects the pattern noted in previous administrations like Obasanjo's "Reform Agenda" and Buhari's "Change" mantra. These narratives initially sparked optimism but eventually faced backlash (Eze and Nwasogwa, 2023; Okoli, 2017), and similarly, sentiment toward the "Renewed Hope Agenda" dropped during controversial policy episodes like subsidy removal. This validates the literature's argument that legitimacy claims through political slogans often enjoy short-term emotional buy-in, which deteriorates under poor implementation.

Second, the persistent sentiment rebound seen between March–May 2024 and again in late 2024 suggests that public mood is not merely reactive but also conditioned by government responsiveness and communication, confirming Cambria et al. (2017), who argue that affective computing possess the potential to track emotion fluctuation in response to external stimuli such as media narratives. This also highlights the resilience of hope-based narratives when communication strategies are recalibrated effectively, a detailed often underrepresented in static political analysis.

The topic modelling analysis provides granular insight into issue salience beyond mere sentiment polarity that was produced by VADER in section (4.1). The outcome of implemented BERTopic model strongly align with Krauss et al. (2022) and Chen (2023), who showed that topic models reveal alignment gaps between elite policy focus and public concern. For example, while the government emphasizes digital transformation (topics 16, 54, 94), the public discourse clusters heavily around inflation (Topics 50, 55, 105) and subsidy removal (Topics 1, 7, 187), indicating a possible dislocation between rhetorical optimism and citizens lived reality, a situation similarly levelled at Goodluck Jonathan's "Transformation Agenda" during the Boko Haram crisis (Gyong, 2012).

Also, the emotional layering of each topic through the NRC Lexicon pushes beyond traditional sentiment analysis by revealing the affective intensity tied to each policy area. This expands upon Gudankwar et al. (2024) and Chakraborty (2023), whose studies emphasized sentiment valence, by quantifying how specific themes (palliatives or police violence) are associated with complex emotions such as fear, trust, or anger, thereby offering a multidimensional understanding of narrative reception.

Importantly, while existing literature critiques policy narratives for their top-down structure and lack of feedback loops, this research demonstrates how sophisticated machine learning techniques can serve as real-time barometers of public trust and emotional climate. This represents a methodological advancement over prior qualitative or small-scale studies, as noted by Olabanjo et al. (2023) and Oyebode and Orji (2019), whose focus was largely on electoral events rather than longitudinal policy discourse.

The extraction of over 300 coherent topics also reinforces Chen's (2023) argument that media data can reveal a sophisticated narrative ecosystem, with co-occurring issues like subsidy reform, palliative rollout, digital economy, and education forming the policy discourse's semantic core. This finding challenges simplistic binary classifications of media coverage as either pro- or anti-government and instead supports Liu, Geng, and Liu (2022)'s notion of issue multiplexity in public discourse.

However, unlike past ML-based studies which often focus on social media posts, this research's reliance on newspaper data provides more elite-mediated sentiment, avoiding the noise and bot interference flagged in Jiang et al. (2021). As such, the results are potentially better with capturing agenda-setting dynamics, not just reactive expressions, thereby offering a strategic tool for policy monitoring.

Lastly, the affective divergence between infrastructure-related topics (roads, energy, ports) and socio-economic concerns (poverty, unemployment, food insecurity) signifies the tension between aspirational and material dimensions of the "Renewed Hope" narrative. While the administration projects modernization, the emotional undercurrent of fear and anger in many topics shows that hope is contingent upon distributional justice and economic relief, echoing Arum and Marcus (2023) who argued that rhetoric alone cannot restore trust in governance.

## 6. Conclusion

This research has demonstrated the computational capabilities of machine learning techniques in quantifying public sentiment and thematic salience surrounding Nigeria's "Renewed Hope Agenda." The use of VADER sentiment analysis revealed a generally positive but fluctuating emotional tone in media coverage between May 2023 and April 2025, suggesting an emotionally responsive public sphere. Considerably, these fluctuations aligned with major policy events like the fuel subsidy removal and inflationary spikes, confirming that public sentiment remains closely associated with economic conditions. Topic modelling using BERTopic further uncovered 318 distinct thematic clusters, which reflect the breadth and diversity of media focus around governance, economy, and social interventions. These topics highlighted structural concerns like poverty, unemployment, and subsidy as central to public discourse despite the administration's narrative emphasis on digital transformation and infrastructure.

The integration of emotion lexicons like NRCLex enriched the analysis by revealing dominant emotional dimensions such as fear, trust, and anger across specific topics. The layered analysis implemented in this work goes beyond binary sentiment classification to unveil the detailed emotional responses driving policy perception. Compared to prior administrations and academic literature, the "Renewed Hope" narrative retains rhetorical traction, but its long-term legitimacy appears conditional on visible, inclusive, and material improvements. The research contributes methodologically by validating the utility of lexicon-based and embedding-based models in analyzing elite-driven discourse within a print media ecosystem.

Despite some limitations, including the exclusion of social media noise and possible editorial bias in print sources, the research provides a template for real-time policy narrative monitoring. Overall, the findings confirm that while political narratives like “Renewed Hope” can frame discourse, their public reception is ultimately judged against real-world realities.

### 6.1. Future Work

Future work should incorporate social media data like Twitter and Facebook to complement newspaper sentiment and capture real-time, grassroots-level reactions to the Renewed Hope Agenda. Integrating deep learning models like LSTM, BERT, or RoBERTa will improve sentiment and emotion classification accuracy, especially for detecting subtle affective shifts. Also, multimodal approaches that combine text with images or videos from news and social media platforms could provide a richer context for public sentiment analysis. Further works may also apply causal inference techniques to explore whether specific government actions directly influence shifts in sentiment or emotional tone. A comparative analysis between regions or demographic groups will uncover spatial or socioeconomic variations in narrative reception. Importantly, integrating government policy timelines and socioeconomic indicators will strengthen the link between media discourse and actual policy impact.

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