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A MULTIFACETED SENTIMENT ANALYSIS APPROACH TO THE ESTIMATION OF THE STRENGTH OF ONLINE SUPPORT FOR POLITICAL CANDIDATES IN NIGERIA'S ELECTIONS

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ABSTRACT

The strength of online support for political candidates in an election is crucial to their victory at the polls, particularly in countries with advanced digital infrastructure and culture. In modern times, social media is one free space where residents express, and are persuaded to, support or show disdain for political candidates prior to an election. This has resulted in the opinion mining of political tweets to predict electoral victories at the polls. However, this is usually done by adopting a single sentiment analysis model and scraping tool. Ordinarily, no sentiment analysis model or scraping tool is a silver bullet – each has strengths and weaknesses. Thus, this study employed two contemporary scraping tools and adopted three contemporary sentiment analysis models. The models were then exposed to the scrapped political tweets of the top contestants for the Nigeria 2023 presidential election, validated with another set of political tweets of the top contestants for the 2024 Edo State governorship election, and, after that, used to predict the online support strength of the top contestants for the 2024 Ondo State governorship election. Only tweets from within the geopolitical space of elections were scrapped. A notable finding of this study is that no two sentiment analysis models estimate the same online support strength for selected candidates, even with the same set of tweets. Overall, the study holds that online support strength is necessary but insufficient to guarantee victory at the polls in Nigeria's elections.

Keywords: Election poll prediction, Nigeria election, Sentiment analysis, Sentiment analysis model, Text data analytics

INTRODUCTION

Traditional election polling methods, while valuable, can be limited in their ability to capture the rapidly evolving political landscape, especially in the age of social media (Boulianne, 2019). The role of social media platforms in shaping political landscapes has become increasingly significant. Social media platforms such as X (formerly Twitter), Facebook, Reddit, and Instagram have helped to overcome the systematically inappropriate sampling procedure in pre-poll surveys and have become prominent tools for political campaigns and activisms (Asokereb, 2023). In Nigeria, three out of five residents are active in the cyber-space (NCC, 2023) and, thus, exposed to social media platforms such as Facebook and X. X, in particular, has become a crucial platform for political discourse, where voters express their opinions, concerns, and support for various candidates (Batrinca and Treleaven, 2015). Thus, data from X can be relied upon to determine the political support strength – the politically supportive vis-à-vis dissenting residents of political candidates in Nigerian elections.

Sentiment analysis or opinion mining models are notable Natural Language Processing (NLP) and Artificial Intelligence components that help analyze and categorize social media users' sentiments towards various brands, including political candidates (Liu, 2012; Ajik et al., 2023; Attai et al., 2024). However, existing works that have used sentiment analysis models (SAMs) for election poll prediction usually rely on a single SAM. Also, researchers often rely on single scraping tools to extracttweets from X as in Kolajo and Kolajo (2018). This approach is bound to expose the prediction to possible biases or limitations of the individual SAM or scraping tools. Therefore, the sensitive nature of election-related prediction demands multiple SAM and scrapping for a reassuring prediction which is a gap, this study intends to fill.

Four notable SAMs exist in the literature, namely: (i) Bidirectional Encoder Representations from Transformers (BERT), (ii) RoBERTa, (iii) Vader, and (iv) TextBlob. The features, strengths, and weaknesses of these SAMs are summarized in Table 1. Although BERT is notoriously tweakable, it is most commonly used for political sentiment analysis. Also, two contemporary scraping tools: (i) Nitter Application Programming Interface (API) (You et al., 2024) and, (ii0 the Apify Console (KD Code, 2024) complementarily to take advantage of their various strengths and attenuate their weaknesses.

Table 1: Contemporary Sentiment Analysis Models

Model	Features	Strengths	Weaknesses
BERT (Bidirectional encoder representations from transformers) (Devin et al, 2018; 2019)	(i) BERT Uses a transformer architecture that processes text bi-directionally, allowing it to understand the context from both directions. (ii) BERT is pre-trained on a large corpus and can be fine-tuned for specific tasks, such	(i) BERT can be fine-tuned on specific tasks with relatively small datasets, making it versatile for various NLP applications (ii) BERT reads textual data bi-directionally, allowing it to capture context from both sides	(i) Complexity of implementation: The BERT model can make it very tiring and challenging for users unfamiliar with deep learning frameworks and techniques. (ii) Longer input limitations: The maximum input length is limited (typically 512 tokens), which can

	as question answering and sentiment analysis. (iii) It is beneficial for text classification and other NLP task	of a word, which enhances its understanding of meaning	be restrictive for tasks requiring more extended context (iii) BERT requires significant computational resources for training and fine-tuning
Vader (Valance Aware Dictionary and Sentiment reasoned) (Hutto, 2014)	(i) Specifically designed for sentiment analysis, especially for social media texts. (ii) Real-time Performance: fast and efficient for real-time sentiment analysis. (iii) Vader gives Polarity and also intensity.	(i) Domain-specific: Vader is particularly effective for social media text, handling Slang. (ii) Lexicon-based: Vader uses a Prebuilt lexicon that captures sentiment in details, making it very good for polarity detection.	(i) Vader has difficulty with context and may misinterpret sarcasm or irony. (ii) The effectiveness of Vader is limited to the words in its lexicon, which may not cover all contemporary Slang or jargon.
RoBERTa (Robustly optimized BERT Pretraining Approach) (Liu et al., 2019)	(i) Generally outperforms BERT on various NLP benchmarks due to its robust training methodology. (ii) RoBERTa modified BERT by training on more data, removing the objectivity of the next sentence prediction, and using dynamic masking.	(i) RoBERTa uses dynamic masking during training, which helps the model learn and identify better text representations. (ii) RoBERTa consistently outperforms many models on NLP tasks due to its extensive training on a large corpus.	((i) Data Hungry: RoBERTa consistently requires a large amount of data to perform optimally, which will limit certain applications. (ii) Computationally intensive: RoBERTa requires significant computational resources for training and fine tuning. (iii) It is very complex.
TextBlob (Loria, 2018; Ajik et al., 2023)	(i) It provides simple APIs for everyday NLP tasks, including speech tagging, noun phrase extraction, and sentiment analysis. (ii) Ease to use: A user-friendly library for processing textual data, built on NLTK and pattern.	((i) User-friendly: TextBlob is an excellent help to People new to NLP, offering simple APIs for everyday tasks. (ii) It provides excellent functionalities for text analysis, parts of speech tagging, and noun Phrase extraction, making it easy for beginners in NLP (iii) TextBlob uses two excellent properties for his sentiment analysis: polarity and subjectivity.	(i) Performance Limitations: TextBlob may not perform as well on complex sentiment analysis tasks as more advanced models like RoBERTa. (ii) TextBlob has Limitations in terms of words and number of input tweets.

Related Works

The use of SAM on political tweets in Nigeria's elections-related exploration or prediction only began recently and is scanty. Olabanjo et al. (2023) applied the Bidirectional Encoder Representations from Transformers (BERT) model to explore the post-election support trend of Nigerians for the 2023 presidential election based on political tweets. The results revealed that Atiku has the most followers, Tinubu has the largest network of active friends, and Peter Obi has the most total impressions and positive feelings. They concluded that opinion mining on Twitter can serve as a generic foundation for projecting election outcomes and producing insights. However, BERT is susceptible to tweaking and, thus, subject to researcher bias. Besides, other SAMs may have performed differently.

Wusu et al. (2023) used the BERT model to predict the winner of the Lagos State 2023 governorship election based on political tweets. Using about 800,000 extracted tweets, they predicted that the People Democratic Party (PDP) candidate would win the election, with the All Progressive Candidate (APC) coming second. Again, BERT is susceptible to tweaking and hence subject to researcher bias, and the other SAM may have estimated a different outcome.

Attai et al. (2024) applied the TextBlob model to explore the post-election support trend of the Nigerian 2023 presidential election based on political tweets. They reported that only one of three electorates was satisfied with the election result. Again, the use of other SAM may have produced a different outcome. Unlike previous studies on the use of political tweets for election related prediction, this study employs multiple non-tweakable SAMs on political tweets to estimate the online support strengths of political candidates in Nigeria's elections based on political tweets.

MATERIALS AND METHODS

This study adopted the three contemporary non-tweakable SAMs – TextBlob, RoBERTa, and Vader – to estimate the political support of residents for political candidates in elections in Nigeria. Non-tweakable SAM helps rule out researcher-biased influence on the study, a crucial reliability concern. In particular, this study focused on the top three candidates and their political parties for the 2023 presidential and 2024 Edo State Governorship election as well as the top two 2024 Ondo State governorship elections. The use of the top three candidates and their parties for the 2023 presidential elections, the 2024 Edo State Governorship election and the top two for the 2024 Ondo State election was incident on the sensitivity of TextBlob to candidates' tweet traffic strength, usually indicated by a minimum of 500 tweets (Loria, 2018). The top parties considered were the All Progressive Congress (APC), the People's Democratic Party (PDP), and the Labour

Party (LP) due to their coverage and antecedents in recent elections and geopolitical spaces under consideration.

Only seven to 100 days old tweets to the individual election polls were extracted for sentiment analysis. The Nitter API and the Apify Console are popular contemporary tools for tweet extraction in X. While the Nitter API is Python programming language-driven, the Apify Console is an independent online scraping tool. It does not require any programming language implementation to be used. Only tweets emanating from the political space for an election were extracted for analysis and estimation of the online support strength of the candidates for the election. Tweets with political content usually contain neutral, positive or negative sentiments about a political party or candidate. The tweet extraction criteria are captured in Table 2.

The selected SAM pipelines in Jupyter Notebook – an Integrated Development Environment (IDE) for the Python programming language – were then served the tweets for each election after preprocessing to automatically perform sentiment analysis on the tweets for insights related to the elections. The Python programming language's strong support for the selected SAM (TextBlob, RoBERTa, and Vader) and the Nitter API necessitates its use. The choice of Jupyter IDE among rival Python IDE such as IDLE, PyCham, Atom, and Spyder is based on user-friendliness and familiarity.

Table 2: Scraping Criteria for Selected Elections

Criteria	2023 Presidential Election	2024 Edo State Election	2024 Ondo State Election
Start Date	November 22, 2022	July 18, 2024	September 30, 2024
Stop Date	January 21, 2023	August 21, 2024	November 7, 2024
Political State	Nigeria	Edo State	Ondo State
Words	Obi, Obedient, yousful, Atiku, BatShet, Batified, Atikulated, Bat	Okpe, okpebelo, Moden, Asue, Ai, Igho, Igholodolo, Akpata	Ondo 2024, lucky, luckyAiyedatiwa, Agboola

The extracted tweets were preprocessed using UTF-8 (Ivan, 2016) to eliminate noisy, inconsistent, and irregular patterns to properly prepare them for processing and attenuate sentiment bias (Hemalatha et al., 2012). Preprocessing involves separating extracted tweets (texts) into discrete tokens or words, lemmatizing or stemming the tokens to simplify them, removing stopwords devoid of sentiment semantics, and removing special characters like @, #, $, *, ", unwanted blanks, punctuations, and hypertext markup language (HTML) tags (Mielke, 2021).

As analyzed and presented by the selected SAM, the sentiment results of residents' tweets for the candidates were further processed for sentiment precision, recall, and F-measure as appropriate using Equations 1 to 3, respectively.

$$Precision = \frac{Positive\ (Pos)}{Positive\ (Pos) + Negative\ (Neg)} \quad (1)$$

$$Recall = \frac{Positive\ (Pos)}{Positive\ (Pos) + Nuetral\ (Nue)} \quad (2)$$

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall} \quad (3)$$

Equations 1 to 3 are adaptations of precision, recall, and f-measure equations (Attai et al., 2024) in the context of support strength for political candidates by residents in an election. Furthermore, to get an aggregate estimation influenced by the three SAMs adopted in this study, the harmonic mean of the precision results – online support strength (OSS) – was computed using Equation 4 for each selected candidate. Harmonic mean instead of arithmetic mean is most appropriate for this aggregation to mitigate the outliers' effect (Ebietomere and Ekuobase, 2019; Guobadia and Ekuobase, 2024).

$$OSS = \frac{3 * P_v * P_r * P_t}{P_v * P_r + P_v * P_t + P_r * P_t} \quad (4)$$

Pv is the precision of online support strength computed by the Vader model. Similarly, Pr and Pt are the precision of online support strength computed by the RoBERTa and TextBlob models.

RESULTS AND DISCUSSION

For the 2023 presidential election, a total of one million tweets were extracted; 1.5 million tweets were extracted for the 2024 Edo State Governorship election 2024, while 950,000 tweets were extracted for the Ondo State Governorship election. Figures 1 to 3 hold residents' sentiments in bar charts, as displayed in the output console for the various SAM implementations in Python for the selected candidates in the 2023 presidential election, and analyzed by Vader, RoBERTa, and TextBlob models, respectively. Similarly, Figures 4 to 6 and Figures 7 to 9 hold those of the 2024 Edo State and Ondo State Governorship elections. These results for the top candidates and political party for each election considered are summarized in its numeric equivalent and presented as shown in Table 3. Table 3 also holds the computed precision, recall, and F-measure of the residents' sentiments toward individual election candidates using Equations 1 to 3 for each selected SAM. The aggregate online support strength of individual candidates in the various elections is also presented in Table 3.

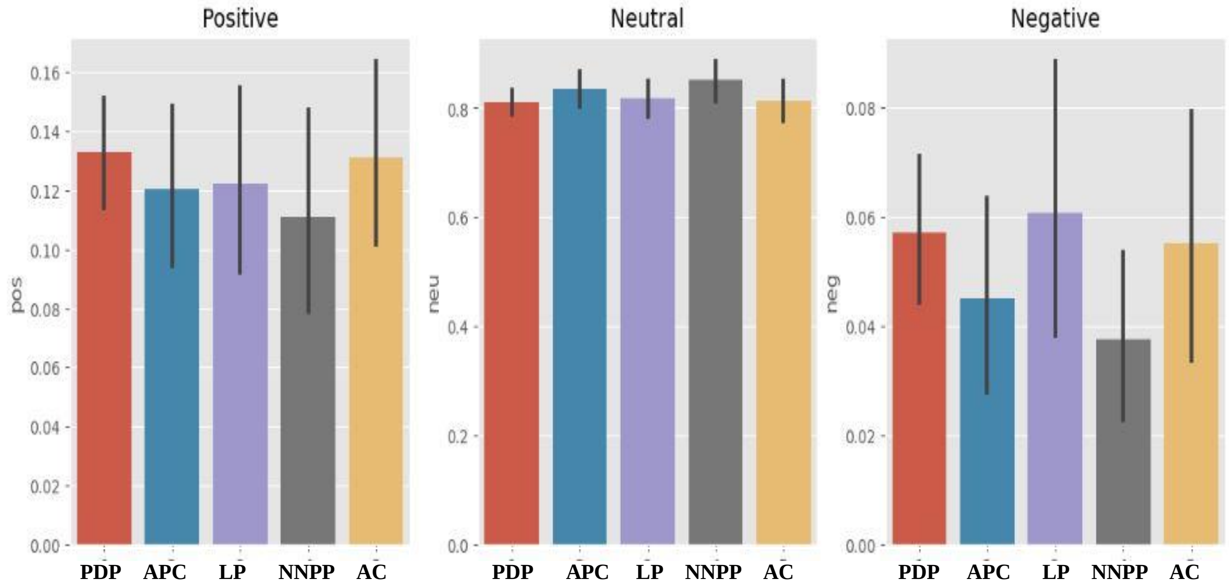

Figure 1: SentimentBar-charts of Residents in the 2023 Presidential Election by Vader

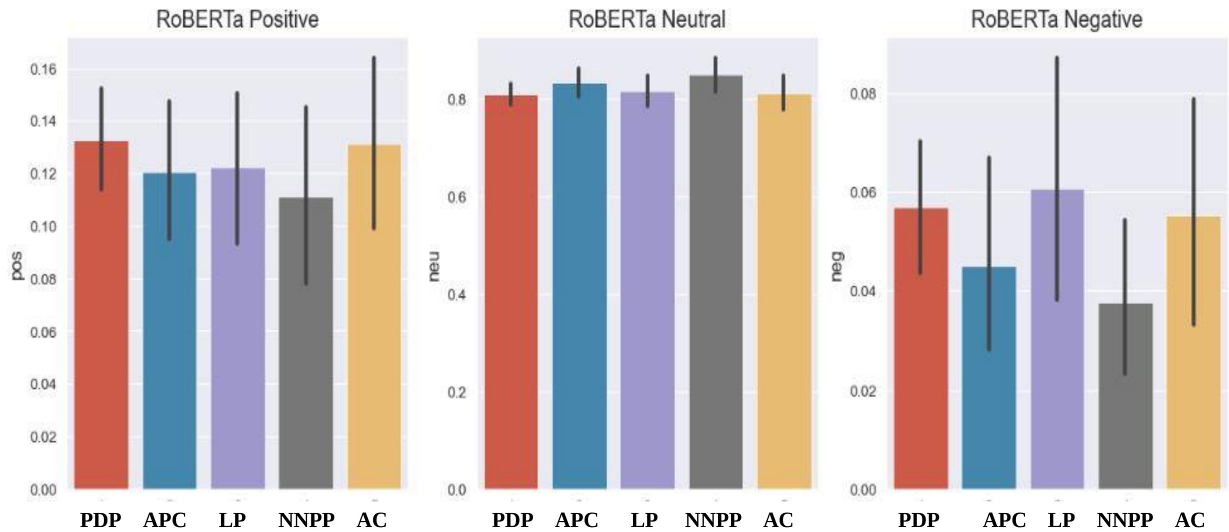

Figure 2: Sentiment Bar-charts of Residents in the 2023 Presidential Election by RoBERTa

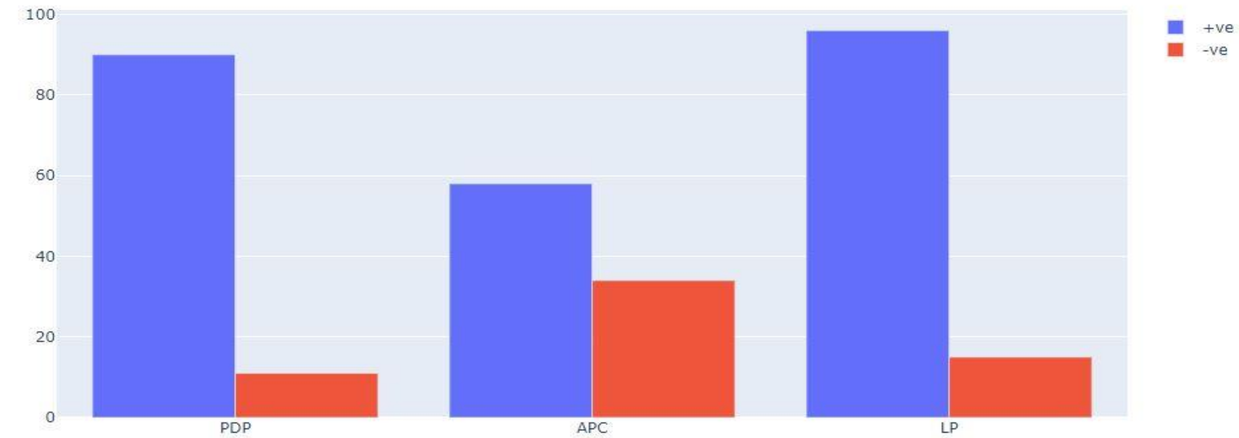

Figure 3: Sentiment Bar-charts of Residents in the 2023 Presidential Election by TextBlob

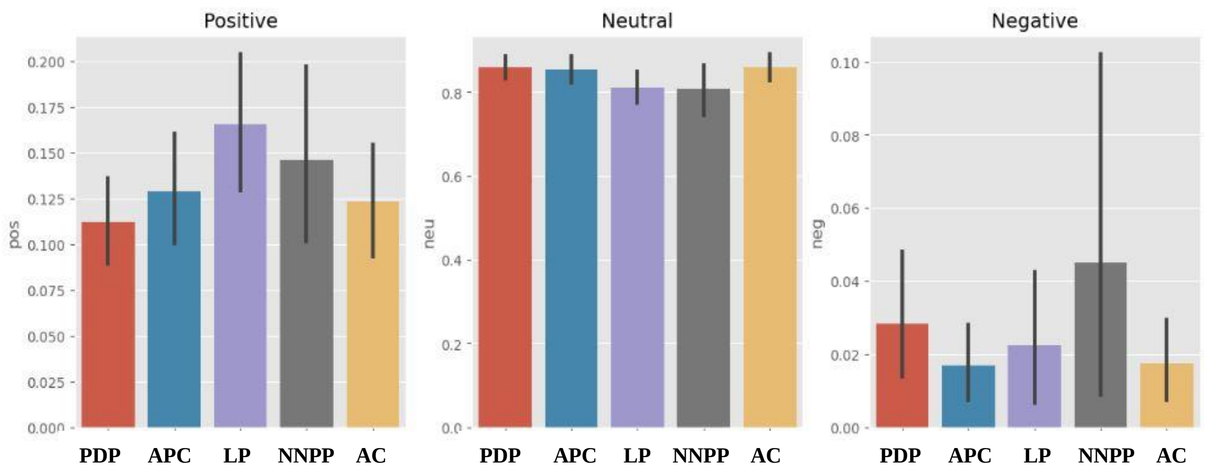

Figure 4: Sentiment Bar-charts of Residents in 2024 Edo State Governorship Election by Vader

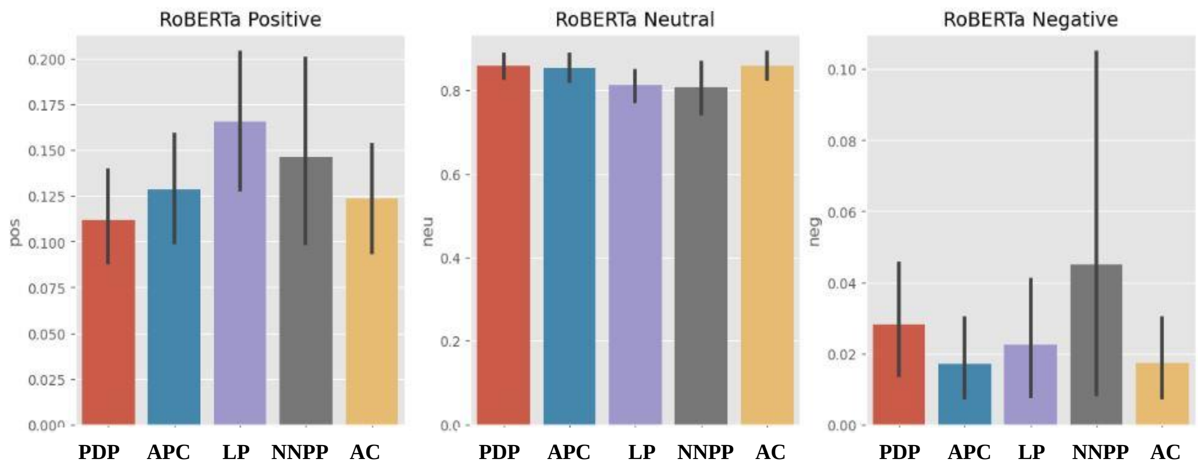

Figure 5: Sentiment Bar-charts of Residents in 2024 Edo State Governorship Election by RoBERTa

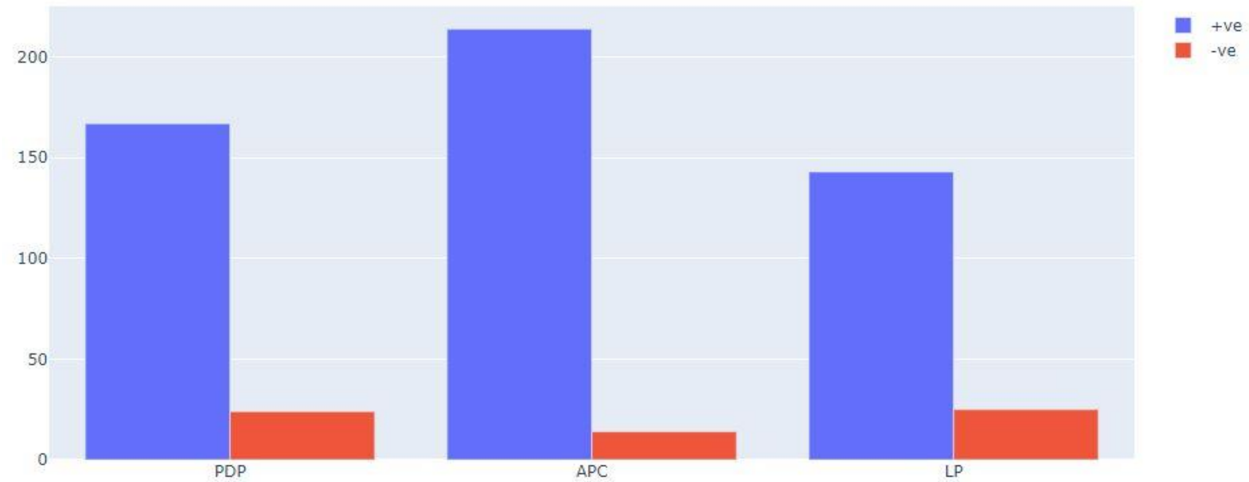

Figure 6: Sentiment Bar-charts of Residents in 2024 Edo State Governorship Election by TextBlob

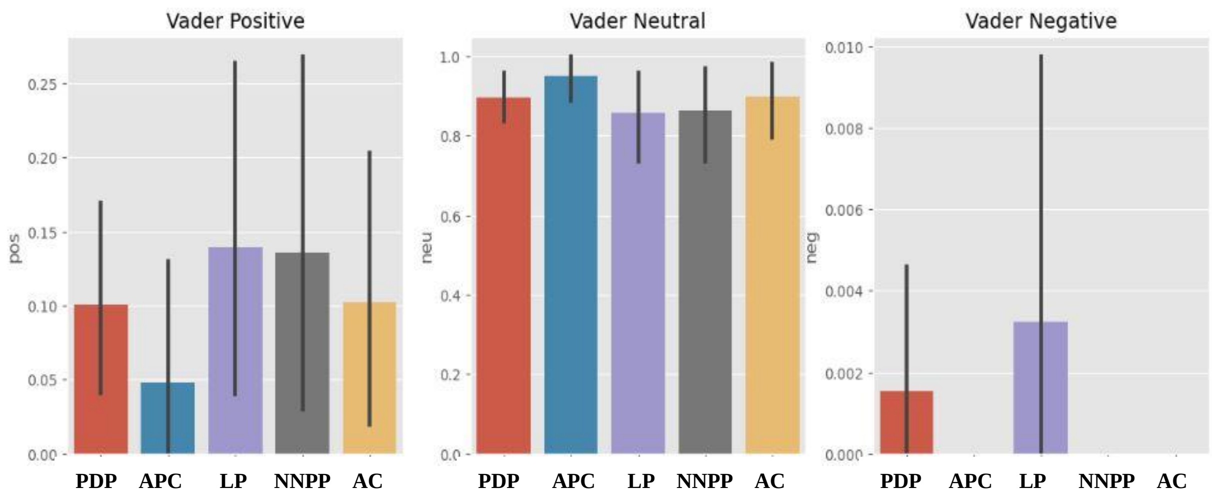

Figure 7: Sentiment Bar-charts of Residents in 2024 Ondo State Governorship Election by Vader

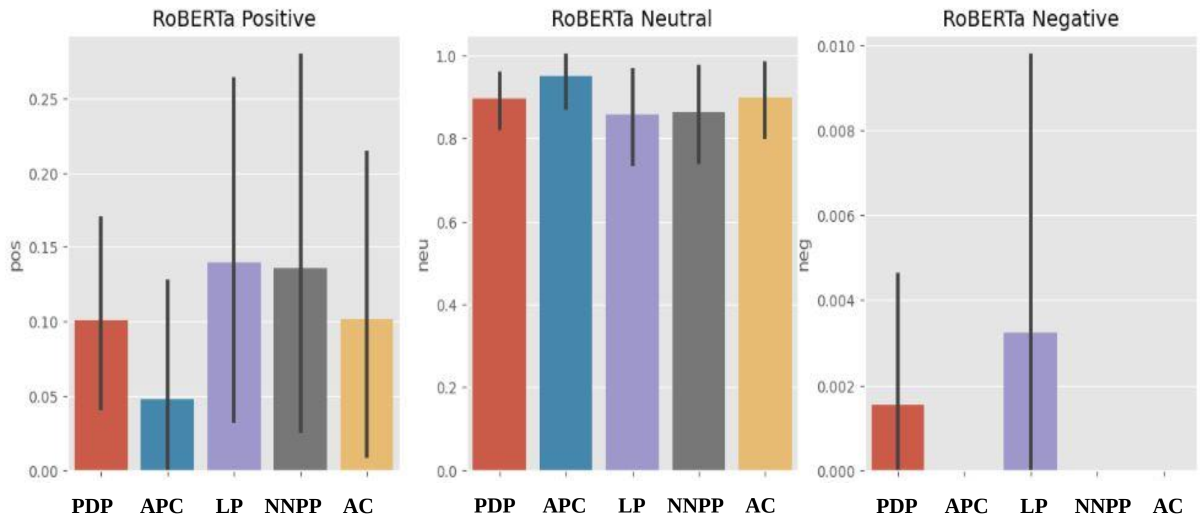

Figure 8: Sentiment Bar-charts of Residents in 2024 Ondo State Governorship Election by RoBERTa

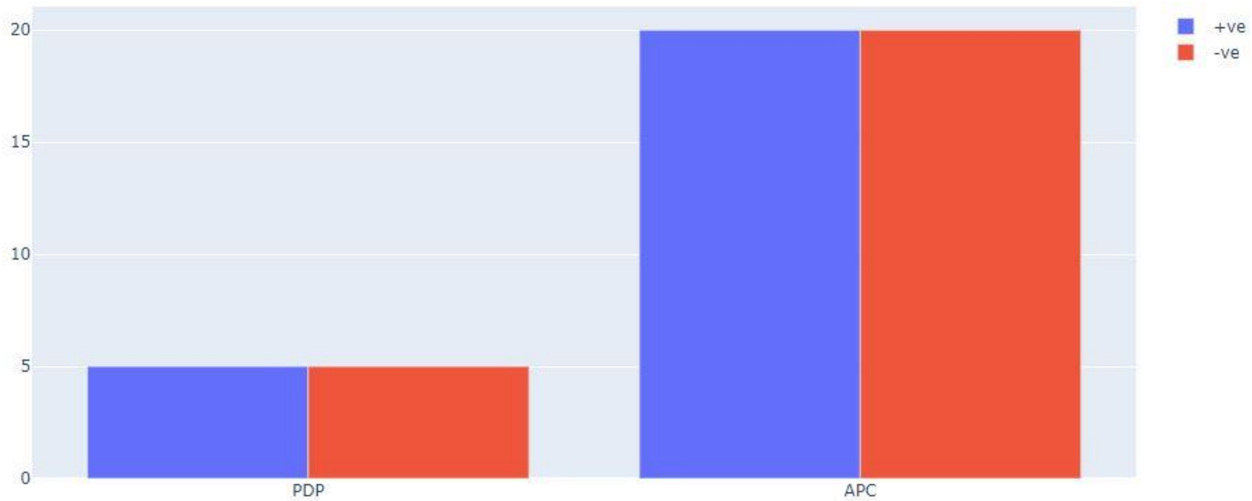

Figure 9: Sentiment Bar-charts of Residents in 2024 Ondo State Governorship Election by TextBlob

Table 3: On-line Support Strength of Political Candidates in Selected Nigeria Elections

Aspirants (Party)	Vader Positive (Ov)	Vader Negative (Nv)	Vader Neutral (Ev)	Vader Precision (Pv)	Vader Recall (Rv)	Vader F-Measure (Fv)	RoBERTa Positive (Or)	RoBERTa Negative (Nr)	RoBERTa Neutral (Er)	RoBERTa Precision (Pr)	RoBERTa Recall (Rr)	RoBERTa F-Measure (Fr)	TextBlob Positive (Ot)	TextBlob Negative (Nt)	TextBlob Precision (Pt)	Aggregate Online Support Strength
Atiku (PDP)	0.1347	0.0570	0.8074	0.7027	0.1430	0.2376	0.1319	0.0570	0.8000	0.6983	0.7457	0.7212	88.8889	10.1852	0.8972	**0.7557**
Tinubu (APC)	0.1222	0.0452	0.8296	0.7300	0.1284	0.2184	0.1200	0.0452	0.8148	0.7264	0.7681	0.7466	57.4074	33.3333	0.6327	**0.6933**
Obi (LP)	0.1236	0.0607	0.8148	0.6706	0.1317	0.2202	0.1222	0.0607	0.8030	0.6681	0.7294	0.6974	95.3704	14.8148	0.8655	**0.7241**
Asue (PDP)	0.1125	0.0280	0.8644	0.8007	0.1152	0.2014	0.1116	0.0274	0.8036	0.8029	0.8032	0.8031	165.0000	22.5000	0.8800	**0.8263**
Okpebolo (APC)	0.1292	0.0168	0.8552	0.8849	0.1312	0.2286	0.1295	0.0171	0.8000	0.8834	0.8396	0.8609	213.7500	13.1200	0.9422	**0.9027**
Akpata (LP)	0.1625	0.0221	0.8092	0.8803	0.1672	0.2811	0.1451	0.0217	0.7636	0.8699	0.8133	0.8406	142.5000	24.3700	0.8540	**0.8679**
Ajayi (PDP)	0.1010	0.0016	0.8976	0.9844	0.1011	0.1834	0.0990	0.0015	0.9111	0.9851	0.9466	0.9655	4.8214	4.8214	0.5000	**0.7442**
Aiyedatiwa(APC)	0.0474	0.0000	0.9561	1.0000	0.0472	0.0902	0.0480	0.0000	0.9778	1.0000	0.9888	0.9944	19.6428	19.6428	0.5000	**0.7500**

Interpretation and Discussion of Result

Generally, positive sentiment for a candidate indicates the support of residents towards the candidate online; negative sentiments indicate the disdain of residents towards the candidate online, while neutral sentiments signal the indifference of residents towards the candidate online. In reality, the indifferent residents can be induced, coerced, and influenced by emotional factors such as religion, tribe, and other social affinity. This study collectively terms inducement, coercion, and emotional influences as "Reality Factors" (RF). However, residents' positive and negative sentiments online are a clear signal of support or opposition.

6.1. The 2023 Nigeria's Presidential Election

For the 2023 Presidential election, as evident in Table 3 and Figure 1, the results of Vader analytics show that the PDP candidate, Atiku, has the most substantial online support strength (Fv = 0.2376), followed by the LP candidate, Obi (Fv = 0.2202) and then the APC candidate, Tinubu (Fv = 0.2184). Tinubu, however, has the highest online support strength precision (Pv = 0.7300), the lowest negative sentiment score (Nv = 0.0452) and recall sentiment score (Rv = 0.1284), and the highest neutral score (Ev = 0.8296). The implication is that with excellent exploitation of RF, Tinubu winning the 2023 presidential election is very likely to Vader's analytics.

The RoBERTa result (see Table 3 and Figure 2) shows that Tinubu has the most substantial online support strength (Fr = 0.7466), followed by Atiku (Fr = 0.7212), and then Obi (Fr = 0.6974). Again, Tinubu has the highest online support strength precision (Pr = 0.7264), the lowest negative sentiment score (Nr = 0.0452), and the highest neutral score (Er = 0.8148). Obi, however, has the lowest recall sentiment score (Rr = 0.7294). Thus, using RoBERTa analytics, Tinubu will likely win the 2023 presidential election. The generally high neutral sentiments compared to the positive and negative sentiment scores by both the Vader and RoBERTa analytics signal high voter apathy in the 2023 Nigerian Presidential election.

The TextBlob analytics only presents results as positive and negative sentiments, thus restricting its analysis to only precision. The Textblob analytics (see Table 3 and Figure 3) made evident that Atiku has the most substantial online support strength (Pt = 0.8972), followed by Obi (Pt = 0.8655), and then Tinubu (Pt = 0.6327). Although Obi has the highest positive sentiment score (Ot = 95.3704), it, however, has a higher negative sentiment score (Nt = 14.8148) than Atiku (Nt = 10.1852). Thus, by TextBlob analytics, Tinubu had no chance of winning the 2023 presidential election.

6.2. The Edo State Governorship Election

For the 2024 Edo State Governorship election, as evident in Table 3 and Figure 4, the results of Vader analytics show that the LP candidate, Akpata, has the most substantial online support strength (Fv = 0.2811), followed by the APC candidate, Okpebolo (Fv = 0.2286) and then the PDP candidate, Asue (Fv = 0.2014). Okpebolo, however, has the highest online support strength precision (Pv = 0.8849) and the lowest negative sentiment score (Nv = 0.0168). However, Asue has the highest neutral sentiment score (Ev = 0.8644) and the lowest recall score (Rv = 0.1152). Considering the 2023 presidential election trend, these results imply that either Okpebolo or Asue winning the 2024 Edo State Governorship election highly depends on their exploitation strength of RF. Thus, according to Vader's analytics, Okpebolo winning the 2024 Edo State Governorship election is very likely.

The RoBERTa result (see Table 3 and Figure 5) shows that Okpebolo has the most substantial online support strength (Fr = 0.8609), followed by Akpata (Fr = 0.8406) and then Asue (Fr = 0.8031). Again, Okpebolo has the highest online support strength precision (Pr = 0.8834) and the lowest negative sentiment score (Nr = 0.0171). Asue, however, has the lowest recall sentiment score (Rr = 0.8032) and the highest neutral sentiment score (Er = 0.8036). These results imply that either Okpebolo or Asue winning the 2024 Edo State Governorship election highly depends on their exploitation strength of RF. Thus, by RoBERTa analytics, Okpebolo winning the 2024 Edo State Governorship election is very likely. The generally high neutral sentiments compared to the positive and negative sentiment scores by both the Vader and RoBERTa analytics signal high voter apathy in the 2024 Edo State Governorship election.

The Textblob analytics results (see Table 3 and Figure 6) made evident that Okpebolo has the most substantial online support strength (Pt = 0.9422), followed by Asue (Pt = 0.8800), and then Akpata (Pt = 0.8540). Thus, according to TextBlob analytics, Okpebolo winning the 2024 Edo State Governorship election is very likely.

6.3. The Ondo State Governorship Election

For the 2024 Ondo State Governorship election, as evident in Table 3 and Figure 7, the results of Vader analytics show that the PDP candidate, Ajayi, has the most substantial online support strength (Fv = 0.1834), and then the APC candidate, Aiyedatiwa (Fv = 0.0902). Aiyedatiwa, however, has the highest online support strength precision (Pv = 1.0000), the lowest negative sentiment score (Nv = 0.0000) and recall sentiment score (Rv = 0.0472), and the highest neutral score (Ev = 0.9561). Considering the 2023 presidential election trend, this result from Vader analytics implies that Aiyedatiwa of the APC, with excellent exploitation of RF, will win the 2024 Ondo State Governorship election.

The RoBERTa result (see Table 3 and Figure 8) shows that Aiyedatiwa has the most substantial online support strength (Fr = 0.9944) and Ajayi (Fr = 0.9655). Again, Aiyedatiwa has the highest online support strength precision (Pr = 1.0000), the lowest negative sentiment score (Nr = 0.0000), and the highest neutral sentiment score (Er = 0.9778). Ajayi, however, has the lowest recall sentiment score (Rr = 0.9466). These results imply that Aiyedatiwa winning the 2024 Ondo State Governorship election is highly possible with excellent exploitation of RF. Thus, by RoBERTa analytics, Aiyedatiwa of the APC, with excellent exploitation of RF, has a better chance of winning the 2024 Ondo State Governorship election. The generally high neutral sentiments compared to the positive and negative sentiment scores by both the Vader and RoBERTa analytics signal high voter apathy in the 2024 Ondo State Governorship election.

The Textblob analytics was undecided, as evident from Table 3 and Figure 9, on the online support strength of either candidate for the 2024 Ondo State Governorship election.

Overall, taking the harmonic mean of the online support strength precision, Atiku came top for the 2023 Nigeria presidential election; Okpebolo came top for the 2024 Edo State Governorship election, while for the upcoming 2024 Ondo State Governorship election, Aiyedatiwa is top. From the preceding analysis and discussions, it is evident that the strength of online support for political candidates is necessary but insufficient to determine their victory at the elections in Nigeria's elections.

CONCLUSION

The need to involve more than one sentiment analysis model in estimating (online) support strength of political candidates using social media data has been made evident. The online support strength of political candidates of selected elections in Nigeria has been estimated from X tweets of residents in the geopolitical space of the elections using three none tweakable sentiment analysis models (Vader, RoBERTa, and TextBlob) implemented with the Python programming language on the Jupyter notebook. These three sentiment analysis models produced different results for the same set of tweets. Further analysis of the results shows that the strength of online support for political candidates is necessary, but more is needed to determine their victory in Nigeria's elections. Political candidates in Nigeria, though encouraged to maintain strong online support strength, are strongly advised to take the RF of their geopolitical space very seriously, at least for now and until the country experiences a significantly improved digital infrastructure and culture.

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