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# THE GOOD, THE BAD, AND THE NEUTRAL: TWITTER USERS' OPINION ON THE ASUU STRIKE

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## ABSTRACT

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| Aim/Purpose | Nigeria's university education goes through incessant strikes by the Academic Staff Union of Universities (ASUU). This strike has led to shared emotion on micro-blogging sites like Twitter. This study analyzed selected historical tweets from the "ASUU" to understand citizens' opinions. |
| Background | The researchers conducted sentiment analysis and topic modelling to understand Twitter users' opinions on the strike. |
| Methodology | The researchers used the Valence Aware Dictionary for Sentiment Reasoning (VADER) technique for sentiment analysis, and the Latent Dirichlet allocation (LDA) was used for topic modelling. A total of 10,000 tweets were first extracted for the study. After data cleaning, 1323 tweets were left. |
| Contribution | To the researchers' best knowledge, no published study has presented a sentiment analysis on the topic of the ASUU strike using the Twitter dataset. This research will fill this gap by providing a sentiment analysis and drawing out subjects by exploring the tweets on the phrase "ASUU." |
| Findings | The sentiment analysis result using VADER returned 567 tweets as 'Negative,' with the remaining 544 and 212 categorized as Positive and Neutral. The result of the LDA returned six topics, all comprising seven keywords. The topics were the solution to the strike, ASUU strike effect, strike Call-off, appeal to ASUU, student protest and student appeal. |
| Recommendations for Practitioners | Practitioners may also use the research to understand better the attitudes of their staff and students about the strikes to create actionable solutions before the suspension of the strike. |

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|---|---|
| Recommendations for Researchers | Researchers can use this study's findings to compare with other contexts of opinion mining. |
| Impact on Society | The findings of this study may be utilized by policymakers to better understand the viewpoints of citizens on the ASUU strike to propose feasible solutions. |
| Future Research | Future studies can collect information from other social networking and blogging sites. |
| Keywords | social media, ASUU, strike, opinion mining, sentiment analysis, topic modeling, Twitter |

# INTRODUCTION

The proliferation of information and communication technologies (ICTs) and social media (SM) platforms has made it possible for people hailing from a variety of socioeconomic backgrounds and cultural traditions to participate in productive contact and conversation with one another (Ahmed et al., 2017; Hu, 2019; Huda, 2021). Twitter is a venue for discussing recent occurrences (Drus & Khalid, 2019). Twitter users tend to exaggerate or condense the substance or opinions they provide to fit within a specific character limit (Hu, 2019). Sharing personal experiences and feelings with others is made easy with microblogging (Tyagi et al., 2019). People can debate various new trends on this channel (Ahmed et al., 2017).

The Academic Staff Union of Universities (ASUU) has been on strike indefinitely because Nigeria's higher education system has been plagued by persistent issues (Monogbe & Monogbe, 2019; Stephen & Oluwaseun, 2021). The problems include a lack of funding and infrastructural facilities, poor and incoherent remuneration, non-compliance to agreements by the government, delay in reimbursements of university staff salaries, and political meddling in education. (Amadi & Urho, 2015; Anyika et al., 2021; Monogbe & Monogbe, 2019; Oxford Analytica, 2022).

On February 14, 2022, ASUU initiated a nationwide strike at federal colleges scheduled for one month to implement the 2009 deal with the government. People's thoughts and feelings about the ongoing strikes have been flowing freely into social media platforms as a direct consequence of the proliferation of these events. These feelings have prompted users of Twitter to debate them with one another and express their perspectives. Twitter users have significantly benefited from adopting hashtags, such as #ASUU and #ASUUStrike, for communicating their viewpoints. Information is sent digitally from user to user in today's fast-paced environment, which might affect how other users interpret a specific occurrence (McGregor, 2019). According to Ramírez-Tinoco et al. (2018), sentiment analysis is a natural language processing method that may be used to evaluate and grasp sentiments and emotions. Opinions, both positive and negative, and neutral, are discussed (Medhat et al., 2014). To the researchers' best knowledge, no published study has given the people's wide-ranging attitudes and worries on this subject. On the other hand, this study will cover this vacuum by offering a sentiment analysis and pulling out topics by analyzing the tweets centered on the term "ASUU." Based on the research aim, the following research questions (RQ) will be investigated as part of this study.

**RQ1:** *What sentiments can we get from the tweets on "ASUU"?*

**RQ2:** *What topics can be drawn based on the Twitter conversations on "ASUU"?*

# LITERATURE REVIEW

## *TWITTER AND OPINION MINING*

The phrase "social media" may apply to various technologies, such as blogs, networks, picture sharing, communities, microblogs, corporate social networking sites, video hosting networks, and social networks. Microblogs are a newer kind of social media technology. People may utilize numerous online social networking platforms to communicate and share their ideas and views on various life circumstances (Pak & Paroubek, 2010). Facebook, YouTube, and Twitter are a few examples of these platforms. The spread of social networking sites has aided the surge in the appeal of these services. Consumers of these platforms may converse with people from all over the world and post content in the form of actual text, still images, and motion visuals.

Furthermore, firms may use social media platforms to monitor public mood and conduct polls regarding the products they make. These channels are essential knowledge sources for companies. Microblogging applications have evolved into the most popular and extensively used platforms. Furthermore, they have transformed over time to become crucial providers of many types of information. Twitter is a well-known microblogging service that allows users to exchange, communicate, and comprehend real-time messages, known as tweets (Alajmi et al., 2016). These communications may be brief and straightforward (Das et al., 2014).

Consequently, opinion mining and sentiment analysis may benefit from the massive volumes of data accessible on Twitter (Pak & Paroubek, 2010). In recent years, there has been an upsurge in the interest that experts in these fields have exhibited in sentiment analysis of Twitter data. However, most cutting-edge research has focused on sentiment analysis to extract and classify data about Twitter users' views on several problems, such as predictions, critiques, politics, and marketing (Singh & Dubey, 2014).

Due to enormous improvements in information and communication technology, data analytics has become a necessary tool for improving company operations and an influential and successful tool in designing corporate goals to target client expectations. Opinion mining, on the other hand, is relevant to domains other than business, such as government and politics (Messaoudi et al., 2022). Opinion mining has recently gained significant momentum and interest among researchers because it may be applied in various fields.

Twitter is a kind of digital environment that helps to shape a new social structure. This communication network has over a billion logins and millions of active users who post 500 million tweets daily (Messaoudi et al., 2022). Twitter users may transmit information known as "tweets," with each tweet having a character restriction of 140 characters until October 2018 and 280 characters presently (Santos et al., 2021). Tweets are publicly visible unless the author decides to make them confidential. Twitter users may reply to and interact with a tweet in various ways, such as by pressing the "like" button, commenting on the tweet's original author, tagging another account, or retweeting the initial post. Twitter has also made Application Programming Interfaces, or APIs, accessible to simplify data collection (Singh & Dubey, 2014).

## *RELATED STUDIES*

This section explores sentiment classification and opinion mining using Twitter data. Consideration is made of trends in Nigeria. The literary works offer related methodologies, which will be reviewed for advances and future suggestions.

Kim et al. (2016) evaluated the topic coverage and sentiment dynamics of the Ebola virus in two different media: Twitter and news outlets. According to the tests, issue coverage on Twitter is less and more unclear than in the traditional media. Regarding sentiment dynamics, the longevity and variability of emotion on Twitter are less and lower, respectively. The LDA technique was used for topic modelling based on social media comments in Naiaraland. Nairaland is a Nigerian English-language internet forum. Oyebode and Orji (2019) identified and studied public emotions toward two prominent aspirants to evaluate their prospects of getting voted into the top position of leadership in Nigeria. VADER, VADER-EXT, and TextBlob were used in the study. Adamu et al. (2021) used Twitter API to gauge public opinion on disaster response, including the deployment of COVID-19 palliatives and assistance supplies. The Nigerian Local English Slang-Pidgin (NLES-P) dataset was used to train machine learning techniques like Support vector machines to classify public sentiments (Adamu et al., 2021). Guha and Pande (2021) conducted a dictionary-based sentiment analysis in R using 16,928 tweets with the Twitter hashtags #phdlife and #phdchat to find the concerns of PhD students.

Themed as NaijaSenti, Muhammad et al. (2022) presented the first enormous Tweets sentiment dataset for the four major languages in Nigeria: Hausa, Igbo, Nigerian-Pidgin, and Yorùbá. The dataset consisted of approximately 30,000 annotated tweets per dialect (and 14,000 for Nigerian-Pidgin), and it included a substantial portion of code-mixed tweets (Muhammad et al., 2022). Finally, Abayomi-Alli et al. (2022) analyzed 5500 "yahoo-yahoo" tweets using VADER, Liu Hu technique, LDA, and MDS. According to the findings, VADER outshines the other sentiment models, but LDA and LSI create comparable topic models. Due to this reason, this study uses the VADER technique for sentiment analysis and LDA for topic modelling.

To the researchers' best knowledge, no published study has presented a sentiment analysis on the topic of the ASUU strike using the Twitter dataset. This research will fill this gap by providing a sentiment analysis and drawing out subjects by exploring the tweets on the phrase "ASUU". The study utilizes RapidMiner (RM) studio to extract data from Twitter and conduct the analysis. RM is a data science software suite that includes data pretreatment methods, machine - learning, and modelling operators (Nandal et al., 2022). Case transformations, text categorization, stemming, stop word deletion, and other natural language processing (NLP) methods are accessible in RM. These pre-process texts to discover meaningful links amongst words and identify what the phrase suggests (Verma et al., 2014).

## RESEARCH METHOD

This section describes the study's methodology. Tweets and other data are evaluated, while duplicate tweets are filtered to evaluate unique ones. VADER was used to analyze sentiment, and LDA to model topics. Figure 1 provides a visual representation of the five stages that make up this study: problem identification, data collection, data preparation, sentiment analysis, and topic modelling.

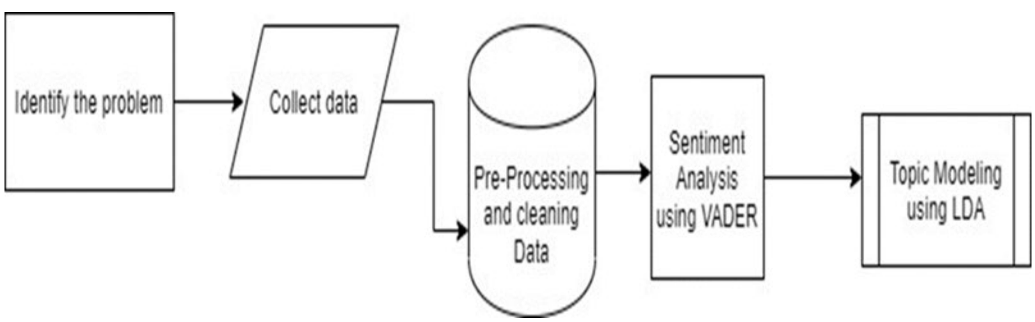


**Figure 1. Stages of the Study**

### *DATA COLLECTION*

The RM Search Twitter operator utilized English while searching for tweets, particularly those in Nigeria. This procedure took place for three days, beginning on May 14 and ending on May 16, 2022. The term "ASUU" was used to locate tweets pertinent to the search. The total number of tweets that were compiled was 10,000. Using the Remove Duplicates and Filtering actions, the researchers got rid of unnecessary data, such as retweets and duplicate tweets, by filtering out tweets with the word "RT" in the body of the post. These processes were utilized to clean up the data collection process and lessen the amount of redundant data. A total of 1,323 tweets were left, all stored in an Excel file. During the data collection process, three operators were utilized. These operators were the Search Twitter and Write Excel operators. The example of extracted data that has been stored in Excel is shown in Figure 2. During the data collection process, tweets on the ASUU strike were captured after performing data cleaning, such as removing retweets and duplicates, among other things. Next, the researchers invested significant time and effort into data preparation and pre-processing using various NLP techniques (Hasan et al., 2019). This process played an essential role in preparing the data for the subsequent step, which consisted of doing a sentiment analysis using the VADER methodology. In the end, LDA topic modelling was utilized to classify the data.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Created-A | From-Use | From-Use | To-User | To-User-Ic | Language | Source | Text | Geo-Locat | Geo-Locat | Retweet-C | Id | | |
| 2 | ######## | Peter Obi | 10507794 | PeterObi | 10507794 | en | <a href="h | I also noted that education rem | | | 615.0 | 1526273451618607106 | | |
| 3 | ######## | Dami' Ade | 156563457 | | -1 | en | <a href="h | Congratulations to the youngin | | | 158.0 | 1525802772272238592 | | |
| 4 | ######## | Channels | 125346858 | | -1 | en | <a href="h | ASUU Strike: FG Working On A F | | | 88.0 | 1525934793204158464 | | |
| 5 | ######## | Alhaji_Da | 4663353514 | | -1 | en | <a href="h | RT @Naija_PR: Students have p | | | 30.0 | 1526306876228509698 | | |
| 6 | ######## | ÅLEÊYÕU^ | 12255775573928386 | | -1 | en | <a href="h | RT @ankaboy: Make him do Tr | | | 5.0 | 1526306875582599169 | | |
| 7 | ######## | Solomon | 14872247504684441 | | -1 | en | <a href="h | RT @Mbahdeyforyou: By the ti | | | 367.0 | 1526306868041240577 | | |
| 8 | ######## | mubarak_ | 15161119302677340 | | -1 | en | <a href="h | RT @Cizzar_x: If only ASUU knw | | | 34.0 | 1526306836751720457 | | |
| 9 | ######## | ObiEze?? | 13471840541652418 | | -1 | en | <a href="h | RT @renoomokri: Dear ASUU,If | | | 124.0 | 1526306808008253440 | | |
| 10 | ######## | pLáYbØy | 12217596363716608 | | -1 | en | <a href="h | RT @SolomonDey4You: When | | | 26.0 | 1526306784369065984 | | |
| 11 | ######## | Baffa | 709114141 | | -1 | en | <a href="h | RT @AM_Saleeem: Just In: EFC | | | 65.0 | 1526306776378920967 | | |
| 12 | ######## | Onward N | 163594070 | | -1 | en | <a href="h | RT @renoomokri: Dear ASUU,If | | | 124.0 | 1526306768141160450 | | |
| 13 | ######## | no one | 12898376 | rhitaa_e | 11178304 | en | <a href="h | @rhitaa_e U have been on and | | | .0 | 1526306768036544515 | | |
| 14 | ######## | Alhaji_Da | 4663353514 | | -1 | en | <a href="h | RT @renoomokri: Dear ASUU,If | | | 124.0 | 1526306766954315776 | | |
| 15 | ######## | Yusuf Dau | 144937036 | | -1 | en | <a href="h | RT @DrMooh_: One person is s | | | 15.0 | 1526306750974025731 | | |
| 16 | ######## | seyi ajayi | 275737425 | | -1 | en | <a href="h | 80billion alleged stolen by an in | | | .0 | 1526306749023756288 | | |
| 17 | ######## | DONNIE. | 27224642 | | -1 | en | <a href="h | RT @renoomokri: Dear ASUU,If | | | 124.0 | 1526306748428083202 | | |
| 18 | ######## | Tunny | 35581022 | renoomok | 26424857 | en | <a href="h | @renoomokri ASUU is asking fc | | | .0 | 1526306705239318529 | | |
| 19 | ######## | iLa | 246691346 | | -1 | en | <a href="h | RT @DrMooh_: One person is s | | | 15.0 | 1526306698188754945 | | |
| 20 | ######## | Loyalist?? | 1910521280 | | -1 | en | <a href="h | RT @AM_Saleeem: Just In: EFC | | | 65.0 | 1526306696355885060 | | |
| 21 | ######## | V10 | 14925061 | renoomok | 26424857 | en | <a href="h | @renoomokri Both ASUU and t | | | .0 | 1526306691859496963 | | |
| 22 | ######## | Lushtreats | 15226638172384870 | | -1 | en | <a href="h | RT @jaymainxx: How I missed t | | | 23.0 | 1526306689611444224 | | |
| 23 | ######## | Scumbag? | 1231726424 | | -1 | en | <a href="h | Waiting for ASUU is like waiting | | | .0 | 1526306686977425409 | | |

**Figure 2. Screenshot of some Extracted tweets**

## *Data Pre-Processing*

The Twitter dataset was pre-processed by dividing the tweets into smaller parts called tokens, words, phrases, or bi-grams. Tweets were normalized to yield n-grams and incomplete language marks (Kathuria et al., 2021). Other operations performed on the tweets encompass:

- Transforming all elements in the collection into small letters
- Eliminating links, articles, and punctuation.
- Filter stop-lists, lexicons, and rational expressions
- Filter tokens by length from 4 to 25

## *Sentiment Analysis*

Sentiment analysis extracts emotions from sentences, documents, or aspects/features (Botchway et al., 2019). It classifies tweets as positive, negative, or neutral. Lexicon-based machine learning uses a dictionary or lexicon list (Villavicencio et al., 2021). Each lexicon has a positive or negative sentiment. VADER, an emotion modelling approach for SM, was developed (Hutto & Gilbert, 2014). VADER evaluates a document's lexical properties to establish a preliminary sentiment polarity and then applies five morphological and syntax-based rules to adjust it (Elbagir & Yang, 2019). VADER gives tweets positive, negative, neutral, and compound ratings (Hutto & Gilbert, 2014). Positive, negative, and neutral ratings are text proportions. The compound score aggregates all lexical evaluations between -1 (most negative) and +1. (most positive) (Vyas & Uma, 2018). This study used RM to analyze VADER sentiment.

- Compute each tweet's VADER score
- Tweets with VADER compound scores above 0.05 are considered positive. Tweets with VADER compound scores between -0.05 and 0.05 are deemed neutral or otherwise negative. This categorization utilizes RM's generate attribute.

### *TOPIC MODELING*

Topic modelling uses word clusters and their occurrence in each text or tweet to find abstract subjects in a corpus or data set (Vayansky & Kumar, 2020). NLP uses it to find themes and extract semantics from unsorted materials, notably in SM, text mining, and knowledge discovery (Barde & Bainwad, 2017). This study uses the subject to assess the respondents' emotions and dialogues in the corpus. LDA is a Hierarchical Bayesian method in which each element is described as a discrete composite over subtexts(Jelodar et al., 2019). LDA papers have several themes. Using the bag-of-words assumption, the subjects are limited to a fixed lexical distribution (Jelodar et al., 2019).

## RESULT AND DISCUSSION

This section presents the results of the analysis carried out on RM, and the conclusions and themes are addressed. The outcomes of the pre-processing stage, sentiment analysis, and topic modelling are presented.

### *PRE-PROCESSING AND CLEANING RESULTS*

After cleaning the text, removing duplicates, and preliminary processing, the corpus comprised 1323 collected tweets, Table 1 illustrates the top 10 phrases that occurred the most frequently. This list was produced before the technique that detects duplicates was carried out. There were 11,231 instances of the phrase "ASUU" in the table and a total of 5548 occurrences of the term "strike." The word "strike" was the second most often used term after "ASUU." Figure 3 shows the word cloud that was generated. Once duplicates have been removed, the word cloud reveals the top 30 phrases mentioned in the tweets.

**Table 1. Top 10 occurring words.**

| Word | Appearance in Document | Total Appearance |
|---|---|---|
| asuu | 9151 | 11231 |
| strike | 5273 | 5548 |
| university | 1676 | 1685 |
| appeal | 1605 | 1643 |
| Nigeria | 1560 | 1575 |
| consider | 1487 | 1509 |
| resume | 1504 | 1508 |
| president | 1477 | 1482 |
| religious | 1460 | 1473 |
| body | 1438 | 1448 |


**Figure 3. Word Cloud of Top 30 words.**

## *Sentiment Analysis Results*

This study analyzed VADER sentiment ratings on tweets written entirely in English. After completing the calculations necessary to determine the sentiment of each tweet, the researcher divided the results into three unique classes: positive, negative, and neutral. The investigation comprised a total of 1323 English tweets; 567 of those tweets were categorized as "negative," while the remaining 544 and 212 were, respectively, defined as "positive" and "neutral." Figure 4 illustrates the distribution of the different sentiment categories. The results of the study are presented in Table 2, along with example tweets and their respective sentiments. Based on the first tweet in Table 2, the writers feel that the students should not let the strike impact them and should instead focus on acquiring new skills. Based on the fourth tweet in Table 2, the writers feel that students continue to be present at the university despite the strike. As can be observed in tweet number five, the negative emotion is caused by ASUU disregarding the president's (Buhari's) request. In response to **RQ1**, the study reveals that most respondents held negative opinions. This is because students wish to continue attending their studies.

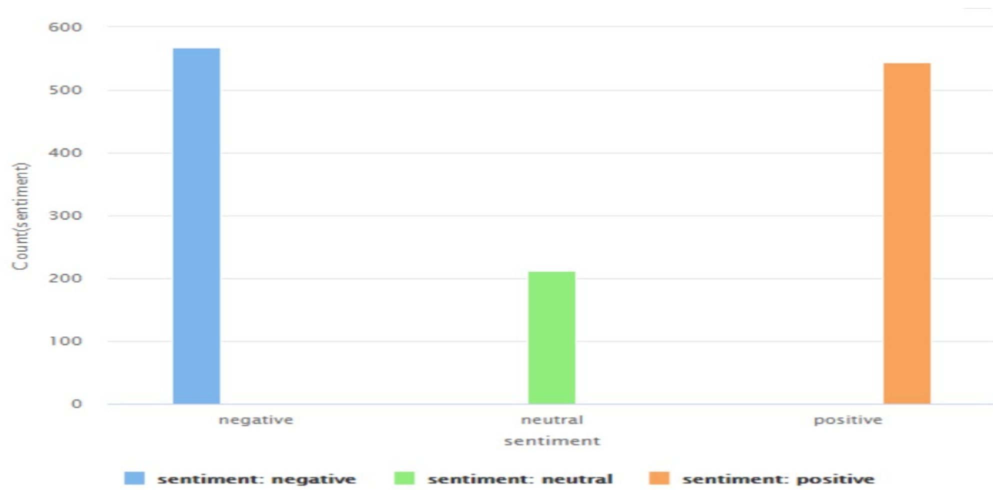


**Figure 4. Result of Sentiment Analysis.**

**Table 2. Featured Tweets and Sentiments**

| FEATURED TEXT(Tweets) | SENTIMENT |
|---|---|
| 1. *"One good thing about this ASUU strike...A lot of students financial status will change for the better. Happened in 2020 during the lockdown and ASUU strike. It's happening again now. If you're a student, it's annoying to hear but learn a skill or start a business now."*<br>2. *"I have made peace with the additional 3 months of the strike, ASUU and FG stop messing with my head!"* | **Positive** |
| 3. *"A degree is not the equivalent of being educated. ASUU"*<br>4. *"Why Many Students Remain On Campus Despite ASUU Strike"* | **Neutral** |
| 5. "*ASUU ignores Buhari's plea, insists strike is in students' interest*"<br>6. "*ASUU strike: Education is becoming a mere side hustle"* | **Negative** |

## *TOPIC MODELING RESULTS*

This fundamental analysis shows a brief understanding of the collected data. LDA topic modelling is applied to analyze the topics hidden in these tweets. Six topics and seven keywords were set out using Rapid Miner. To reply to the **RQ2**, the topics and their keywords are shown in Table 3.

**Table 3. LDA Topics and Keywords.**

| Key-words | Topic 1: Solution to Strike | Topic 2: ASUU Strike Effect | Topic 3: Strike Call-off | Topic 4: Appeal to ASUU | Topic 5: Students Protest | Topic 6: Student Appeal |
|---|---|---|---|---|---|---|
| **1** | ASUU | ASUU | ASUU | ASUU | Protest | ASUU |
| **2** | Need | Strike | Strike | Government | ASUU | Strike |
| **3** | People | Students | Call | Strike | Schools | Appeal |
| **4** | Problem | universities | Students | Like | Students | Would |
| **5** | Solution | Nigeria | Know | Help | Strike | students |
| **6** | someone | effect | Time | consider | Nigeria | Consider |
| **7** | marketing | Union | School | Appeal | North | Education |

### Solution to strike

For the sake of this study, Topic 1, labelled "**Solution to Strike**", consists of the keywords *ASUU, need, problem, solution, someone*, and *marketing*. This topic shows that the citizens ensure the strike is not drawing them back. Tweets with a solution to the strike included various methods to find unique solutions, like learning new skills, finding part-time jobs, travelling abroad to study, starting businesses, and holding incompetent leaders into account. For example, a user tweeted how important it is to learn new skills and wisely use free time due to the strike. Another user tweeted how students made use of the COVID-19 lockdown and started online businesses, emphasizing the same efforts needed during the ASUU strike.

Many users also marketed on-demand skills like online marketing, affiliate marketing, and social commerce. For example, a user tweeted how affiliated marketing can earn individuals thousands of Naira monthly. Some users marketed their products on social media for sale. Many users emphasized how they have started learning new skills. For example, a user has been learning photo-shop but having difficulties with data and internet connection.

### ASUU strike effect

Topic 2 is labelled as the "**ASUU strike effect**" and consists of *ASUU, strike, students, universities, Nigeria, affect,* and *union*. The topic shows the effect of the ASUU strike on the citizens. For example, a user tweeted how it is essential to see the negative and positive impacts of the strike after some months. Another user tweeted how some lecturers and students were interviewed on the effects of the ASUU strike.

### Strike call-off

Topic 3 is labelled "**Strike call-off** "and consists of the keywords *ASUU, strike, call, Students, know, time,* and *School.* Twitter users spread rumors about when the strike will be called off. For example, a user shared a rumor that the strike would be suspended in one week. Another user tweeted that the strike would end only during the election period.

Other users expressed eagerness for the strike to be called off, meaning they are eager to return to school. For example, a user tweeted about wasted time and the importance of returning to classes. One of the reasons for the anticipation is that some users believe their colleagues from private institutions are attending classes when they are not. For example, one user tweeted how frustrating it is to witness other students attending lessons. Another factor is that some students are nearing graduation, having already spent much time at university due to prior strikes. Many users asked when the strike would be suspended and schools' resumption time. For example, a user tweeted asking for school resumption time.

### Appeal to ASUU

Topic 4 is labelled as "**Appeal to ASUU**," consisting of the keywords *ASUU, government, Strike, Like, Help, consider,* and *appeal.* This topic involves requests by the government and other concerned individuals for ASUU to end the strike. Through the president and several governing bodies, the government appealed to ASUU for the strike to end. For example, a user tweeted that President Buhari appealed for ASUU to end the strike. The topic also involves ASUU appealing to the government to meet their demands.

The topic involves appeals from religious groups. For example, a user tweeted how ASUU might consider the appeals made by religious bodies like Nigeria's inter-religious council (NIREC) to end the strike.

Celebrities and parents also made several appeals through Twitter. A user shared how parents appealed to ASUU over the long-lasting strike. Finally, a Nigerian celebrity Teni with the handle @TeniEntertainer, voiced her concerns on Twitter and appealed to ASUU to end the strike. This appeal triggered several users to request financial help from her; for example, a user tweeted demanding funds to learn to program.

### Students protest

Topic 5 is labelled as "**Students protest**," which consists of the keywords *protest, ASUU, Schools, students, strike, Nigeria*, and *North*. This topic shows that citizens are engaging in protests to end the strike. This topic involves protest plans, protest venues, protests from students of different schools, and peaceful protests. For example, a user tweeted that some female students threatened to carry a nude protest. Another user tweeted how students are doing the right thing by engaging in peaceful demonstrations.

### Student appeal

Topic 6 is labelled as "**Student appeal**," consisting of the keywords *ASUU, strike, appeal, would, students, consider*, and *education*. This topic shows students' appeals to ASUU and Government to end the strike. The students cry out their voices on Twitter to the Government and ASUU to make swift decisions to end the ongoing strike. A user tweeted how ASUU might consider religious bodies' appeals but not the students. Another user tweeted how the strike has affected their academics and asked ASUU to consider the appeal so they can return to school.

Finally, another user remarked that government authorities are unwilling to make reforms because their children attend international schools.

## *Discussion*

The analysis results show that most users show negative sentiments about the ASUU strike on Twitter. However, the researchers were shocked by the high account of positive sentiments on the topic because educational strikes are generally seen as negative trends (Amadi & Urho, 2015; Anyika et al., 2021; Monogbe & Monogbe, 2019). The positive sentiments are due to students utilizing the period to learn new skills, start online businesses, and use their free time to develop themselves.

Analyzing the critical topics of the study, the researchers observed that students were finding a solution to the problem; the same scenario occurred during the COVID-19 lockdown, and students could persist in not being in their classes and use the period to improve their skills. This insight paves the way for future studies on how university strikes can be viewed on a positive account by students. Also, the strike impacted students negatively and positively, hence the topic 2 "ASUU effect".

Also, another key topic is the strike call-off; it is observed that users shared their opinions but at the advent of sharing rumours. For example, rumors like strike call-off dates and fake news regarding the matters concerning the ASUU strike. These rumors can be alarming and psychologically affect other users who come across this news. For example, some users will have high hopes based on the rumors that the strike will be called off on a particular date, only to be disappointed if it is not. Policymakers should find strategies to tackle fake news on social media, especially Twitter, as the rate is alarming. Stegmair and Prybutok (2022) state how easy it can be to share rumors or spread hate on Twitter because of the anonymity it offers. Another issue is re-sharing. Twitter provides an option to Retweet(re-share); Twitter users should be careful with what information they re-share. Koohikamali and Sidorova (2017) highlight the need to consider the outcomes of re-sharing and spreading fake news to the public.

Furthermore, it can be noted that concerned individuals made several appeals for ASUU to end the strike. This finding agrees with the literature that Twitter is an excellent avenue for making appeals and sharing opinions (Pak & Paroubek, 2010; Singh & Dubey, 2014). However, more individuals need to voice their opinions for it to be a daily trend on Twitter. The power of social media cannot be underestimated. The researchers recommend that policymakers look into all the appeals made by users on Twitter, as it is generally the concern of citizens. Future studies should create more room for the content analysis of tweets to get a bigger picture.

Twitter users voiced their opinions concerning protests. However, it is worth commending that the users engage in peaceful protest due to the fear of what transpired in the #EndSars protest (Lekki Massacre) in Nigeria. Dambo et al. (2021) explained how Twitter users' activities played a vital role in the tragedy at the protest. Hence, policymakers and relevant security authorities need to monitor these activities on Twitter. Policymakers can use the information to know the citizens' plans by understanding the protests' time and venue. This information will aid them in finding preventive measures.

Finally, students have been appealing on Twitter for ASUU to end the strike. There should be more appeals from students, and they should go about their requests with due diligence without spreading hate towards the government and ASUU. This constant appeal allows government officials and ASUU staff to engage with the students. The researchers recommend that government officials reply to some of the tweets and notify the users of their plans on how to tackle the strike; this can help reduce tension caused by the strike.

The findings further add to the transdisciplinary approach of informing sciences by emphasizing the relevance of both human and technological concerns in understanding Twitter usage to share opinions on relevant matters. This study is the pioneer in providing insights into the ASUU strike using Twitter data. This research confirms the findings of previous studies that show how vital VADER and LDA are for sentiment analysis and topic modelling with Twitter data (Abayomi-Alli et al., 2022; Oyebode & Orji, 2019). Due to a large amount of slang and broken English in our dataset, the results further verified VADER's effectiveness on both English and non-English content.

The researchers stress that the findings cannot be generalized to all citizens as this is just a segment of Twitter users. The fact that the researcher opted to collect data over only three days is the study's primary limitation; it would have been preferable to collect information over a more extended period. Another limitation of this study is that the data analysis is performed solely utilizing an unsupervised lexicon-based technique. Understanding may be improved by employing several distinct approaches to machine learning. The last limitation is that the researchers did not train the algorithm to detect emoticons or slang; they only included tweets written in English. This is the only language that was considered. Including the widely spoken dialects in Nigeria will be more efficient, including Hausa, Igbo, Yoruba, and Pidgin English.

## CONCLUSION

During this study, sentiment analysis and topic modelling were carried out utilizing a sample of historical tweets containing the term "ASUU." At the beginning of the research process, 10,000 tweets were collected. Following the cleansing of the data, there were 1323 tweets remaining. The research was carried out using the 1323 tweets that were left. The VADER approach was applied to carry out sentiment analysis, while the LDA was utilized for topic modelling. The sentiment analysis results with VADER determined that 567 of the tweets had a 'Negative' sentiment, while the remaining tweets were categorized as Positive (544) and Neutral (212). The findings indicate that the respondents had majorly negative feelings. After running the LDA, the results showed six different topics containing seven different keywords. The themes tagged for discussion were the solution to strike, ASUU strike effect, strike call-off, appeal to ASUU, student protest, and student appeal. The findings of this study may be utilized by policymakers to better understand the viewpoints of citizens on the ASUU strike to propose feasible solutions. Universities may use the study to gain a better understanding of the opinions staff and students render towards the strikes in order to develop solutions that may be implemented prior to the cessation of the strike.

As part of the future research that will be carried out, the researchers aim to compare tweets from the day that the strike was proclaimed to the day that it would be called off. In addition, the researchers intend to compile data from a wide variety of additional social networking and blogging websites. The researchers intend to utilize various machine-learning methods in future studies. In addition, the researchers aim to conduct a content analysis to understand better how the strike impacted the students.

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