# A Post COVID-19 Analytics of African Users Perception of Online Learning

Zainab Olorunbukademi Abdulkareem[1], Yetunde Folajimi[2], Sulyman Age Abdulkareem[1]

[1]University of Ilorin

[2]Wentworth Institute of Technology

Corresponding author's email: zo.abdulkareem@unilorin.edu.ng

doi: https://doi.org/10.21467/proceedings.157.9

**ABSTRACT**

This study explores the potentials of user-generated text on twitter to offer insights into the pre- and post-COVID'19 attitude on e-learning users in Africa. First, we manually assigned positive, negative or neutral sentiment to each of the 1193 tweets collected based on their content. From the sentiment tagging, we found that half of the tweets posted about e-learning are neutral, 27% are negative and 23% are positive sentiments. Furthermore, we evaluated the tested the predictive accuracy of VADER and TextBlob automatic sentiment assigning Phython Libraries. By comparing the VANDER and TextBlob results to the manually assigned sentiments, we found the accuracy to be low at 51% and 45% respectively. This calls for more research to improve sentiments prediction of African tweets. Thus, we report our findings, including data analytics of the extracted tweets, and our future plans to create a model that would take African slangs and expressions into consideration for better sentiments prediction of African tweets.

**Keywords:** Sentiments Prediction, Slangs and Expressions, Online Learning

## 1 Introduction

Novel coronavirus (COVID-19), a severe acute respiratory syndrome, was first reported on December 31 2019, in the region of Wuhan, the central Hubei Province of China. Due to the virus's rapid transmission in humans, it soon spread worldwide. On March 11, 2020, The World Health Organization (WHO) declared COVID-19 a pandemic (Cucinotta and Vanelli 2020). Therefore, to ensure reduced infection and transmission rate of the virus, it became vital to isolate the virus' hosts. Consequently, many world economies were forced to shut down. The effects of this shutdown are felt across all sectors, from aviation to manufacturing, tourism, education, and others. Hence, the pandemic led to emergency changes in several sectors of the economy throughout the world, most especially the education sector.

Educational institutions in countries around the world, including those in Africa, were closed to stop the spread of the virus and ensure the safety of their citizens and residents. The school shut down meant students could no longer attend schools via traditional face-to-face learning. Universities were encouraged to transition to e-learning to ensure education continuance for their students during this period. Asides from the epidemiological benefits, the adoption of e-learning meant increased learning convenience, access to learning resources regardless of location and time, and reduction of $CO_2$ emissions (Michał *et al.* 2020). Despite the widespread adoption of e-learning worldwide, the use of this novel technology for the learning process has some limitations. Firstly, the success of using this approach for learning depends on numerous factors such as accessibility, assessment criteria, course content, and the usage of appropriate methods (Olokor 2020). On the other hand, poor digital skills of the handler and/or respondent can render the learning process ineffective. Additionally, the usage and efficiency of e-learning are dependent on internet accessibility and connection quality. Therefore, students in African countries that are often challenged with grossly uneven digital literacy and economic amenities may have peculiar challenges during this period.



Proceedings DOI: 10.21467/proceedings.157; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-970666-0-3

Thus, it is crucial to investigate people's perspectives of e-learning in Africa. Thus far, fewer studies have considered students' perspectives from third-world countries on switching from physical learning to e-learning e.g (Chisadza *et al.* 2021;Eze *et al.* 2020), and none of these studies have used user-generated social media content to investigate African students' perspectives about e-learning. To fill this gap, this study explores the content of social media postings made by students before and after covid-19 in the top ten African countries with the highest gross domestic profit (GDP) (Zandt 2021). These countries include Nigeria, Egypt, South Africa, Algeria, Morocco, Kenya, Ethiopia, Ghana, Angola, and Tanzania. The aim of this study is to understand students' sentiments about online learning before and after covid. Furthermore, the tweets were be used to evaluate the accuracy of the predictive capabilities of TextBlob and VADER Python libraries to predict sentiments associated with the tweets related to e-learning in the ten countries.

## 2 Related Work

The abrupt switch from physical learning to e-learning has numerous implications for students and lecturers alike. (Aguilera-Hermida 2020) investigated the perception of college students to the use and acceptance of online learning in the United States of America (USA). The opinions of the students were sampled quantitatively and qualitatively. The study revealed that the transition to online learning brought unpleasant experiences for students. Besides, the students reported that they find online learning to be more complex and pointed out that the lack of supporting resources was a significant challenge.

Furthermore, (Adnan 2020) explored 126 students' perspectives on online learning during the COVID-19 pandemic in Pakistan. A large cross-section of the students examined have reservations about digital learning. They highlighted inadequate internet facilities and ineffective technology as the major challenges that hindered the efficiency of online learning in Pakistan. Pakistan is a developing country like most African countries; hence, similar challenges experienced by students using e-learning in the country might be shared with students in developing African countries.

Additionally, (Hussein *et al.*, 2020) performed a qualitative study to examine the attitude of undergraduate students to emergency online learning in the United Arab Emirates (UAE). The study's findings show that safety, convenience and cost-effectiveness are the positives of online learning. Besides, they identified insufficient support from staff, heavy workload, distraction and problems with the internet as the limitations of online learning in UAE. Moreover, (Kapasia *et al.*, 2020) investigated the impact of social lock-down on the learning of undergraduate and graduate students in India. The opinions of 232 students were sampled via Google form, WhatsApp and electronic mail. Students in remote areas reported marginalization, depression, anxiety and poor internet connectivity as the significant issues they encountered due to the abrupt switch to e-learning. Contrariwise, (Michał *et al.*, 2020) sampled medical students' opinions about online learning during COVID-19 in Poland and reported that e-learning is a valuable tool for teaching medical students and is highly accepted.

## 3 Data Collection and Description

Twitter is one of the most popular social media networks globally, and data on the platform is accessible to the public. After users create an account, they can follow other accounts of interest and post tweets (contents and text limited to 280 words at a time). Twitter is commonly used in academic re-search and has significantly represented social, political, and scientific opinions (Massaro *et al.* 2021). We searched for e-learning related posts in the 10 African countries mentioned above, using selected keywords: online learning, e-learning and online class. Tweets retrieved were posted from June 7, 2011 to February 3 2020. Only 1193 unique tweets that were in English were used in this study (the distribution of the tweets across countries is shown in Table 1 below). As part of the pre-processing steps before data analysis, we went through stop word removal by removing words like “a”, “an”, “and” “this”. Furthermore, each word is tokenized, and lemmatization of words is conducted to group words to their root word.

The retrieved tweets were categorized into pre-pandemic tweets, which include posts related to e-learning before 2020 (233 tweets) and post-pandemic tweets, which includes tweets related to e-learning after 2020 (960 tweets). Figure 1 shows the rise of tweets related to e-learning post-pandemic across the 10 countries. For pre-covid data, Morocco, Tanzania, and Egypt are the countries with the highest number of tweets with 48 (20.6%) and 45 (19.3%) tweets, respectively. However, for data collected during the period of covid, Nigeria and Egypt have the highest frequency of tweets with 458 (47.7%) and 85 (8.9%), respectively. Interestingly, tweets from Nigeria make up almost half of the post-covid data, even with the national Twitter ban of Nigeria’s federal government from June 5 2021, to January 13 2022 (Nimi and Busari 2022). This suggests Nigerian students are more active on Twitter in comparison to other students in the other 9 countries.

**Table 1:** *Distribution of e-learning Related Tweets across Countries*

| Country | Period After Covid | | Period before covid | | | | % of Negative Tweets | % of Positive Tweets | % of Neutral Tweets |
|---|---|---|---|---|---|---|---|---|---|
| | Tweet Frequency | % | Tweet Frequency | % | Total Tweet Frequency | % | | | |
| **Algeria** | 22 | 2.3% | 12 | 5.2% | 34 | 2.8% | 5.9 | 79.4 | 14.7 |
| **Angola** | 9 | 0.9% | 15 | 6.4% | 24 | 2.0% | 4.2 | 87.5 | 8.3 |
| **Egypt** | 85 | 8.9% | 27 | 11.6% | 112 | 9.4% | 10.7 | 67.0 | 22.3 |
| **Ethiopia** | 55 | 5.7% | 29 | 12.4% | 84 | 7.0% | 6.0 | 58.3 | 35.7 |
| **Ghana** | 75 | 7.8% | 13 | 5.6% | 88 | 7.4% | 34.1 | 45.5 | 20.5 |
| **Kenya** | 78 | 8.1% | 7 | 3.0% | 85 | 7.1% | 23.5 | 45.9 | 30.6 |
| **Morocco** | 57 | 5.9% | 48 | 20.6% | 105 | 8.8% | 8.6 | 52.4 | 39.0 |
| **Nigeria** | 458 | 47.7% | 29 | 12.4% | 487 | 40.8% | 47.8 | 41.9 | 10.3 |
| **South Africa** | 73 | 7.6% | 8 | 3.4% | 81 | 6.8% | 17.3 | 49.4 | 33.3 |
| **Tanzania** | 48 | 5.0% | 45 | 19.3% | 93 | 7.8% | 2.2 | 48.4 | 49.5 |
| **Grand Total** | 960 | 100% | 233 | 100% | 1193 | 100% | | | |

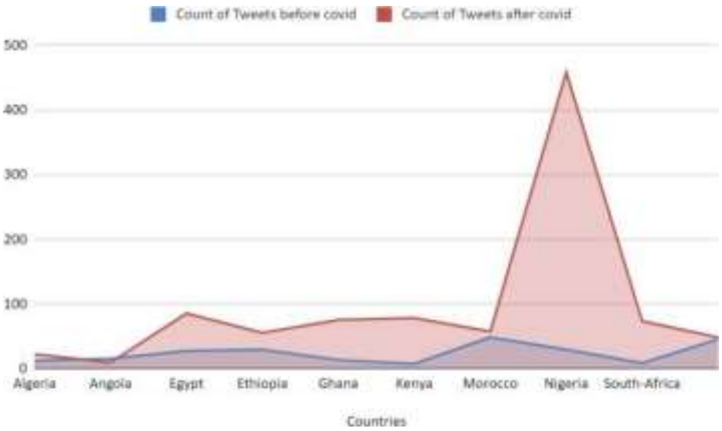


**Figure 1:** *Increment of Tweets related to e-learning post-pandemic*

## 4 Analysis and Results

### 4.1 Sentiment Analysis

To understand people’s attitudes to e-learning, we conducted a qualitative analysis of all tweets to assign sentiments manually. This process was carried out and cross-validated by the research team. A tweet with positive sentiment is tagged “positive”, a tweet with negative sentiment is tagged “negative” while a tweet

Proceedings DOI: 10.21467/proceedings.157
ISBN: 978-81-970666-0-3

Series: AIJR Proceedings
ISSN: 2582-3922

with neutral sentiment is tagged “neutral”. Figure 2 shows the distribution of tweets based on sentiment associated with them: 50% of the tweets were neutral, 27% were negative and the remaining 23% were positive. Therefore, half of the tweets are neutral and does not contain any emotional expression (e.g “DVC representing VC at opening ceremony of the Training Work- shop for E-Learning Tutors at UNIMAID”). Table 2 shows the distribution of positive tweets in the 10 countries used in the study. Nigeria and Ghana has the highest percentage of negative tweets at 47.8% and 34.1%, respectively. Angola and Algeria have the highest percentage of positive tweets at 87.5% and 79.4%, respectively.

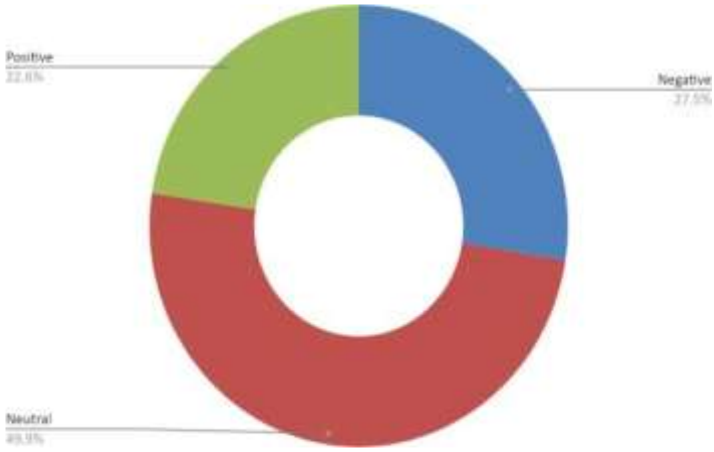


**Figure 2:** *Distribution of Tweet Sentiments*

## 4.2 Word Frequency

Word frequency count was performed to find the most frequently used tweets related to e-learning in the pre-covid and post-covid tweets. This is to identify the theme of the textual data. The results are presented using bar-graphs. Figure 3 - Figure 6 represents the most frequent words and their counts in the pre-covid and post-covid tweets, respectively, using bar chats and word cloud representations. The negative tweets show that internet, data, fair, work, and access appear among the most frequent words: this suggests that people are concerned about internet availability, e-learning ability to “work”, its fairness, and general accessibility to everyone. Contrariwise, positive tweets contain words like support, advance, help, first, leading, new, great, among the most frequent words: this suggests some expression of hope, signifying the optimism about e-learning as a way of getting adequate education since the onset of the pandemic.


**Figure 3:** *Positive Tweets Word Cloud*

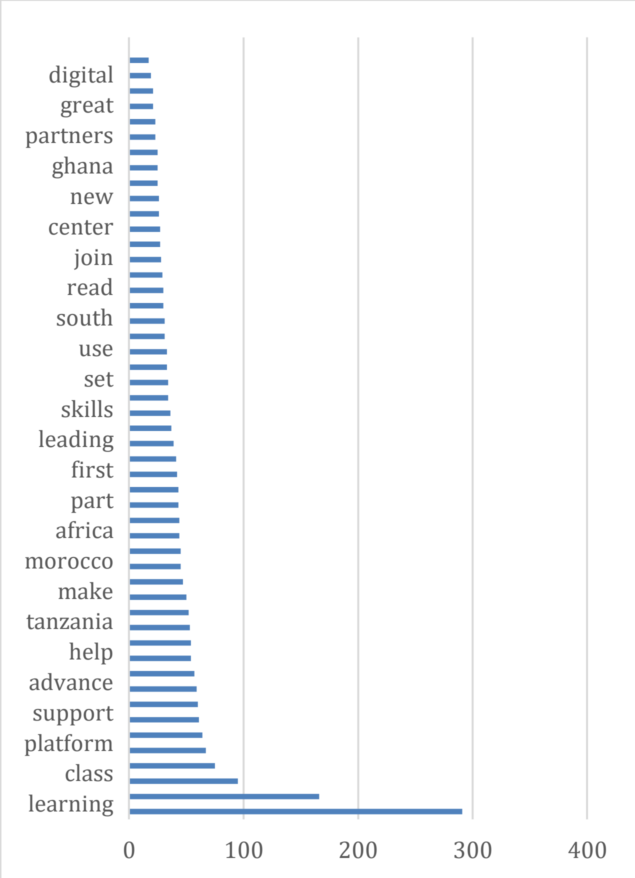


**Figure 4:** *Positive Tweets Word Count*

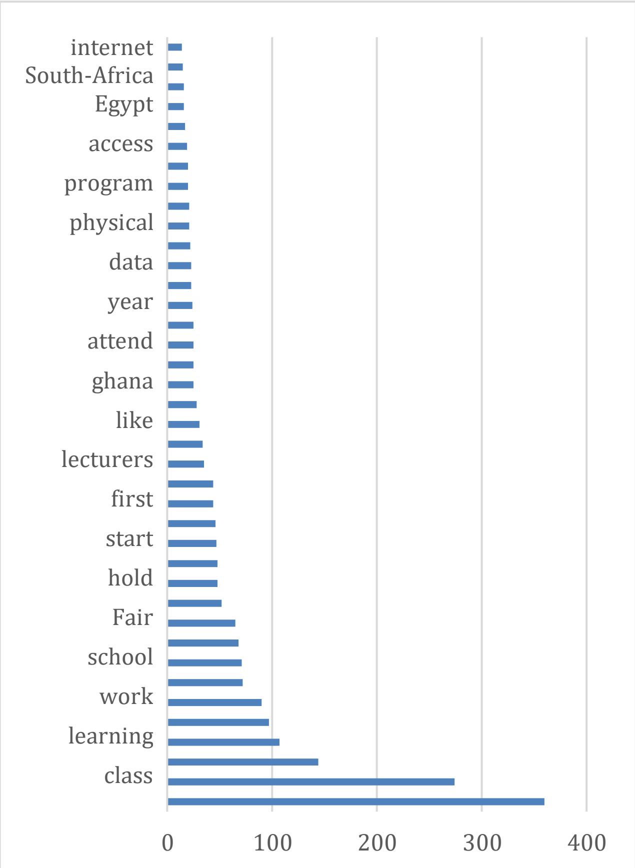


**Figure 5:** *Negative Tweets Word Cloud*

Proceedings DOI: 10.21467/proceedings.157
ISBN: 978-81-970666-0-3

Series: AIJR Proceedings
ISSN: 2582-3922


**Figure 6:** *Negative Word Cloud*

### 4.3 Testing Prediction of TextBlob and VADER Phython Libraries

TextBlob and VADER (Valence Aware Dictionary and Sentiment Reasoner) were applied to the tweets respectively to evaluate their ability to predict the sentiment of each tweet accurately. TextBlob is a Python library that can be used to process textual data is often used in Natural Language Processing (Mas Diyasa *et al.*, 2021; Suanpang *et al.*, 2021). Similarly, VADER is a Python library especially suited for social media text (Mohamed Ridhwan & Hargreaves, 2021). TextBlob and VADER can tag part-of-speech of words, extract them, and perform sentiment analysis, text translation, and other NLP tasks. TextBlob and VADER assign a sentiment score between -1 and 1. The closer a sentiment score is to -1, the more negative the text is, the closer it is to 1, the more positive it is, and a sentiment score of 0 is a neutral text.

We conducted a sentiment analysis on the tweets by using TextBlob and VADER, respectively. The results were compared to the manually assigned sentiments. The comparison shows a low prediction accuracy of both TextBlob and VADER, with only 45% and 51% matching the manually assigned sentiments.

## 5 Conclusion

In this work, we have performed a sentiment analysis on the tweets related to e-learning in ten African countries with the highest Gross Domestic Profit (GDP) to identify people's perceptions of e-learning in the countries. Furthermore, we performed word frequency query to obtain the common themes in positive and negative tweets. Furthermore, we explore the ability of automated python libraries VADER and TextBlob to predict the tweets' sentiments' accuracy. We found the accuracy of these python libraries to be low when predicting the tweets. This may be due largely to the contrast in the training model, which is basically US English, as opposed to frequent terms and slangs that are significant in African tweets, for example, Nigerian terms like "wahala" (meaning stress), "ko le work" (meaning it can't work), or "na so" (sarcastic yes) are popularly used in African tweets, and these phrases are not present in the English dictionary, thereby causing some bias in the training mode . Therefore, we are currently developing machine learning models that are sensitive to African slangs and expressions and more accurately predict the sentiments associated with African tweets. Future work is encouraged in these areas in order to minimize algorithmic bias in prediction accuracy.

## 6 Publisher's Note

AIJR remains neutral with regard to jurisdictional claims in institutional affiliations.

### How to Cite

Abdulkareem *et al.* (2024). A Post COVID-19 Analytics of African Users Perception of Online Learning. *AIJR Proceedings*, 60-66. https://doi.org/10.21467/proceedings.157.9

## References

Adnan, M. 2020. Online learning amid the COVID-19 pandemic: Students perspectives. *Journal of Pedagogical Research*, *1*(2), 45– 51.

Aguilera-Hermida, A. P. 2020. College students' use and acceptance of emergency online learning due to COVID-19. *International Journal of Educational Research Open*, *1*, 100011.

Chisadza, C.;Clance, M.; Mthembu, T.; Nicholls, N.; and Yitbarek, E. 2021. Online and face-to-face learning: Evidence from students' performance during the Covid-19 pandemic. *African Development Review*, *33*(S1), S114–S125. https://doi.org/10.1111/1467-8268.12520.

Cucinotta, D.; and Vanelli, M. 2020. WHO Declares COVID-19 a Pandemic. *Acta Bio-Medica : Atenei Parmensis*, *91*(1), 157–160. https://doi.org/10.23750/abm.v91i1.9397.

Eze, S. C.; Chinedu-Eze, V. C. A.; Okike, C. K.; and Bello, A. O. 2020. Factors influencing the use of e-learning facilities by students in a private Higher Education Institution (HEI) in a developing economy. *Humanities and Social Sciences Communications*, *7*(1), 1–16. https://doi.org/10.1057/s41599-020-00624-6 during COVID-19 pandemic in West Bengal, India. *Children and Youth Services Review*, *116*(June), 105194. https://doi.org/10.1016/j.childyouth.2020.105194.

Hussein, E.; Daoud, S.; Alrabaiah, H.; and Badawi, R. 2020. Exploring undergraduate students' attitudes towards emergency online learning during COVID-19: A case from the UAE. *Children and Youth Services Review*, *119*(November), 105699. https://doi.org/10.1016/j.childyouth.2020.105699.

Kapasia, N., Paul, P., Roy, A., Saha, J., Zaveri, A., Mallick, R., Barman, B.; Das, P.; and Chouhan, P. 2020. Impact of lockdown on learning status of undergraduate and postgraduate students.

Mas Diyasa, I. G. S.; Marini Mandenni, N. M. I.; Fachrurrozi, M. I.; Pradika, S. I.; Nur Manab, K. R.; anf Sasmita, N. R. 2021. Twitter Sentiment Analysis as an Evaluation and Service Base On Python Textblob. *IOP Conference Series: Materials Science and Engineering*, *1125*(1), 012034. https://doi.org/10.1088/1757- 899x/1125/1/012034.

Massaro, M.; Tamburro, P.; La Torre, M.; Dal Mas, F.; Thomas, R.; Cobianchi, L.; and Barach, P. 2021. Non-pharmaceutical Interventions and the Infodemic on Twitter: Lessons Learned from Italy during the Covid-19 Pandemic. *Journal of Medical Systems*, *45*(4). https://doi.org/10.1007/s10916-021-01726-7.

Michał, B.; Michalina, Z.-B.; Monika, S.; Andrzej, J.; and Beata, W.-K. 2020. Student's Perception of Online Learning during COVID Pandemic. *Indian Journal of Pediatrics*, *87*(7), 554. https://doi.org/10.1007/s12098-020-03327-7.

Mohamed Ridhwan, K.; and Hargreaves, C. A. 2021. Leveraging Twitter data to understand public sentiment for the COVID-19 outbreak in Singapore. *International Journal of Information Management Data Insights*, *1*(2), 100021.https://doi.org/10.1016/j.jjimei.2021.100021.

Nimi, P. and Busari, S. 2022. Nigeria to lift Twitter ban after six- month suspension.*EditionCNN*.https://edition.cnn.com/2022/01/12/africa/nigeria-lifts- twitter-ban-intl/index.html Accessed: 2022-02-06.

Olokor, F. 2020. E-learning can't work in Nigeria, says ASUU. *Punch News Paper*. https://punchng.com/e-learning-cant-work-in- nigeria-says-asuu/ Accessed: 2021-12-26.

Suanpang, P.; Jamjuntr, P.; and Kaewyong, P. 2021. Sentiment Analysis With a Textblob Package Implications for Tourism. *Journal of Management Information and Decision Sciences*, *24*(6), 1–9. http://ezproxy.hct.ac.ae/login?url=https://www.proquest.com/sch olarly-journals/sentiment-analysis-with-textblob- package/docview/2604574875/se-2?accountid=1215.

Zandt, F. 2021 .*Africa's Biggest Economies*. https://www.statista.com/chart/26371/african-countries-with-the-highest-gdp-over-time/ Accessed: 2021-12-26.