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TEXT ANALYTICS OF OPINION-POLL ON ADOPTION OF DIGITAL COLLABORATIVE TOOLS FOR ACADEMIC PLANNING USING VADER-BASED LEXICON SENTIMENT ANALYSIS

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ABSTRACT
The fast growing community of digital collaborative users across the globe continued to witness breaking of new frontiers in hitherto industries where deployment of traditional methods of computing had continued to hold sway. Notwithstanding the widespread deployment computing tools in educational institutions in Nigeria, the use of online collaborative tools is limited and seldom a commonplace in tertiary educational institutions for academic planning. This study therefore aims at extracting emotions from opinions expressed by stakeholders in the academic research industry regarding the utilitarian possibilities of collaborative tools for academic planning purposes through text mining. A VADER-based approach to Sentiment Analysis is modeled in the opinion mining study of the natural language processing use case. Assigning negative, positive, neutral and compound values to the uni-gram and bi-gram tokenized dictionary-of-known-words, experimental result shows a -0.10 mean sentiment negative score constituting a 17.27% clusters of respondents not favorably disposed to the idea while a 22.7% cluster of highly convinced respondents expressed positive sentiments about the use of collaborative tools with a mean sentiment score of 0.49. A 60.01% cluster of average respondents who expressed neutral sentiments actually tilts towards a positive emotion with a 0.39 mean score

Keywords: Collaborative tools, Academic planning, Sentiment analysis, Tertiary Educational Institutions, VADER-based Lexicon.

INTRODUCTION
In this generation, Information and Communication Technology (ICT) supports, promotes and provides the infrastructure that aids access to a wide range of digital tools with divers utilitarian values including online collaborative tools (OCT), which supports real-time teamwork in different fields, and especially in educational institutions of learning and teaching (Luca, Figlia & Scamporrino, 2021; Evwiekpaefe, & Muhammad, 2021). Services, including cloud computing (CC), mobile technology, productivity applications, social media, and online meetings and online learning environments are services supporting online collaborative tools useful for educational institutions including various digital tools for academic writings (Peel, 2017). The aforementioned have contributed in no small ways to enhance productivity and work throughput, which would be of immense benefits to the education industry for teaching, learning, research and discovery (Adeoye, 2012). Likewise, the fast evolving trend of distributed learning, distance learning and open studies have further increased the need to adopt online collaborative tools for educational activities coupled with the advent of social and physical distancing occasioned by the outbreak of the lingering COVID-19 pandemic (Nureni,et al. 2021; Bashir et al. 2021).
The un-encouraging extent of internet penetration in Nigeria notwithstanding, the utilization of digital tools for personal use and in workplace has been widespread; an impressive promise for the complete integration of cloud computing into academic planning and management with large scale benefits in the future. While discuss on integration is secondary, the all-important subject of awareness in academic communities is commonplace as both Internet of Things (IoTs) and CC are familiar phrases amongst academics and administrators alike. Indeed, borders between the artificial and virtual environments of computing is being reduced rapidly on daily basis through dynamic digitization of physical systems for delivering values for users of mobile technologies including mobile phones which is a rampant handheld device (Abdulkareem, et al. 2021).
The opportunities and values being offered by cloud computing should be a series of connected objects linking the ever-growing interconnected world for a seamless educational system at the fingertips of school regulators, operators, educators and students alike where academic planning, teaching and learning, result processing are executed with the instrumentality of CC and OCT. Key characteristics of OCT including multiple users, real time, global reach, concurrent access are central to the objectives of seamless academic planning and teaching in the 21st century with benefits comprising of shared files and calendars, reduced travel expenses, ease of communication, enhanced teamwork, global access. With easy and simple setup features and equipment which includes webcam, microphone, speaker; the implementation is easy and integration into tertiary educational institutions for academic planning purposes. Some other supporting software including Voice over Internet Protocol (VoIP), Instant messaging (IM), and document sharing software that allows users to create, edit, and maintain documents collaboratively are all commonplace amongst students and administrators alike hence the possibility of logical integration and execution in educational institutions. All aforementioned heralds the advantages and ease of adoption, however, the level of adoption of collaborative tools for academic function in tertiary educational institutions is not encouraging owing to different factors that include the

sentiment of major stakeholders who are critical in its deployment by school administrators and regulators.

Academic staff and administrators are central to the full implementation and integration of the software platform in schools hence the critical nature of their opinion and sentiments about cloud computing. With their favorable disposition to its full implementation as part of university culture, operations of the collaborative tools for teaching, learning and administration will be easy and fruitful. Consequent upon the foregoing, this paper seek to conduct a sentiment analysis on shades of personal opinions shared by the major stakeholders in tertiary educational institutions including lecturers, academic planners, administrators over the subject of cloud computing and its collaborative tools for efficient and effective delivery of academic activities and policies. The study would discover semblance of positive, negative and neutral sentiments expressed in their opinions through the instrumentality of text mining.

This paper's impact is to extend existing literature by unraveling the sentiments surrounding the adoption or otherwise of online collaborative tools in teaching, learning and administration of tertiary educational institutions by stakeholders for academic planning purposes.

LITERATURE REVIEW

It is noteworthy that from software development life cycle, to end users in its use case and further to its future research amongst academia, the subject matter of software, software applications and especially software engineering are collaborative task hence characterized with the inclusion of different people and indeed, research has shown the relevance of social aspects in the development team (Obaidi & Klünder, 2021), deployment phase, marketing period, utilization preference and possible upgrade of same software. Hence, interest is high in the research community on the sentiment analysis of issues associated with software and its application tools as well as studies bothering on the deployment and utilization of online collaborative digital tools for academic planning and teaching (Abubakar, Sufyanu & Abubakar, 2020). In this section, a review on existing SA paradigms is presented while alongside discussing reviews on the deployment digital tools; online collaborative tools for cloud computing in educational institutions.

While analyzing the impact of Cloud Computing (CC) on online education, (Al-Malah, et al. 2021) opines that crisis in the education industry could be overcome by resorting to the deployment of electronic cloud in distance education with an overview of unique specifications of the cloud environment and the possibilities inherent in their application in colleges and tertiary educational institutions. The work reiterates the importance of CC while enjoining decision-makers of the feasibility of migrating to the digital era of academic planning maintaining that CC promises large storage, opportunity for security and the confidentiality of students' data, comprehensive coverage for fast internet access etc.

In Arvajaa & Hämäläinenb (2021), study mirrors a pedagogical view to discuss their theoretical and experimental study in the investigation of online collaborative interaction in the education industry with the sole aim to re-conceptualize the notion of productive interaction. While focusing on the need to turn attention to the dialogic notions of alterity, dialogic approach, and dialogic positioning, data from an online university course was deployed to clarify and explore their framework. The study asserts that instructional support is applicable to generate collaborative interaction, which guides students through collaborative activities and ultimately inspire learning potentials.

In its study, (Wang, et al. 2020) proposes an aspect-level SA based on Gradual Machine Learning (GML), which enables accurate automated class labeling contrary to the manual labeling effort. The iterative factor graph inference inherent in the novel GML, with high labeling accuracy, enhanced the study outcome on the benchmark datasets with higher performance over the unsupervised options and state-of-the-art supervised DNN models in literature. The polarity classification approach adopted in the study, a characteristic approach of GML based on iterative factor graph inference, which reduces human intervention in class labeling, validates the efficacy of proposed solution through the benchmark data.

Appel, et al. (2017) covers an overview of the intricacies of deploying a hybrid approach to SA in their work which is centered around sentiment lexicon, rules, negation handling, language variables and uncertainty management on two datasets via sentiment twitter and movie review corpus. Result is compared with state-of-the-art with Naïve Bayes and maximum entropy supervised learning methods of same corpus. Experimental result returns hybrid version with better outcome on precision and accuracy scores when applied to SA problems at sentence levels. Major components of the proposed framework include the linguistic variable, negation handling process, semantic rules, sentiment lexicon, and the ambiguity management process components.

In Paruchuri, et al. (2021), a systematic literature review on product reviews sentiments using machine learning was studied with a germane research question on identifying best learner algorithms for SA studies. Three different levels of sentiment classification including the document level, aspect level and sentence is reviewed in the primary studies of the survey. Learner algorithms of the Naïve Bayes, support vector machine (SVM), Decision tree, K-nearest neighbor (KNN), neural network and random forest is used to classify into the positive, negative and neutral reviews of SA. (Aljuaid, et al. 2020) used SA on In-text citations to identify important citations on the premise that quantitative and qualitative of citations is a precursor to fair assessment of a research work. Sentiments and cosine similarity scores were deployed as features in the binary classification carried out in the study on SVM, Random forest and KLR learner algorithms. Proposed approach achieved a 0.83 f-measure improvement over state-of-the-art.

In the work of (Al-Radaideh & Al-Qudah, 2017), a mathematical tool of rough set theory analyzes doubt, inadequate information and data reduction is used for SA to classify 4800 tweets corpus posted in Arabic language. Result shows the proposed framework is an appealing option with an enhanced overall accuracy and a reduced number of used terms in classification with a corresponding faster process on large dataset.

For a large-scale sentiment extraction from Yahoo! Answers, (Kucuktunc & Cambazoglu, 2012) assigns a quantitative positive or negative mood to 1.5M corpus of answers while taking cognizance of the interplay between sentiments and other factors such as gender, level of education, age, subject of discuss plus the time of the day on the question answering web site. This enhances the possibility of finding the nexus between properties of the question asker: answer pair influences the sentiment present in the post. Study shows that dynamics influencing the disposition of the users is not only stimulating from a sociological point of view, but likewise has possibilities in marketing, recommender systems and search engines.

In the work of (Liu & Cocea, 2017), a fuzzy granulation towards an interpretable SA model is described on a public movie data corpus while addressing limitations noticed with

Bag-of-Words. Such limitations are with respect to interpretability and computational complication, which is addressed by the fuzzy method while preserving the classification performance with prominent algorithms used for sentiment analysis including Naïve Bayes and SVM. A model described as deep Multi-task for mockery detection and SA in Arabic language is the thrust of (Mahdaouy, et al. 2021) by introducing an end-to-end deep multi-task learning which avails knowledge interface between two tasks. The model encapsulates a dual-directional encoder demonstration from transformers; a multi-task attention relationship module with two task classifiers.

A comparative analysis of deep learning models deployed for SA was the aim of the work of (Zahidi, Younoussi, & Al-Amrani, 2021) targeting Python and Java programming languages driven-models for their large set of deep learning libraries useful for SA. Keras Python, Theamo, and TensorFlow frameworks are discovered to be popular models in the research domain as discovered by the survey. In (Abdulkareem, Zeebaree & M.Sadeeq, 2021), a review of potentials, inhibitions and issues associated with CC and IoT tools are carried out. The study observed that academia have drawn the interest of IoT as an important component of academic planning with the potential to link almost every unit of the academic environment with the global world

. **Table 1: Related Work**

Authors	Methods	Results	Weakness(es)
Liu et al. (2016)	Latent Dirichlet Allocation (LDA)	This study showed that emotion recognition and topic mining of Massive Open Online Courses (MOOCs) text feedbacks had positive impact in improving user experience for teachers and students	Sequential procedures cucumbersome
Aljuaid et al. (2020)	Support Vector Machine, Random Forest and Kernel Logistic Regression	This research offered an in-text citation sentiment analysis-based approach for binary classification which effectively enhanced the results of the researchers' citations.	Extensive list of content-based features. limited to binary classification of training data
Nikolic et al. (2020)	Naïve-based classifier, Online sentiment analyzers	This research provides insights into the impact of aspects (extracted from student's comments) based sentiment analysis for improving teaching–learning process	Low details and accuracy as large quantities of labeled training data were required
Wang et al. (2020)	Gradual Machine Learning (GML)	This authors provided a technical solution for accurate machine labeling of training data without the requirement for manual labeling training data in aspect-based sentiment analysis	Less effective for detailed level of analysis
Al-Shabi (2020)	VADER, SentiwordNet, Sentistrength, Liu and Hu opinion Lexicon and AFINN-III	The research provides an assessment on five of the most important and well-known lexicons used in the field of sentiment analysis. The results identify that the accuracy of classification using Vader lexicon were higher for positive and negative sentiments.	Original tweets were used without data pre-processing
Nureni, Ogunlusi & Uloko (2021)	Support Vector Machine, Random Forest , Naives Bayes and Kernel Nearest Neighbor	The study examined real-time COVID-19 Twitter discussions and concerns using tweets posted by Twitter users for public health awareness, patient destigmatization and containing the spread of the COVID-19 pandemic	Extensive list of content-based features limited to binary classification of training data
Ahmad et al. (2021)	Content Analysis	The paper showed the positive level of participation and involvement of academic staff to their WhatsApp group discussions; with emojis being the most preferred form of communication	Limited in scope

MATERIALS AND METHODS

The overall process of the research work, as encapsulated in Figure 1, presents a four-phase model of the study as unraveled in this section. Opinion poll of stakeholders in academic planning unit of tertiary educational institutions in Nigeria is collected in Phase I, courting across respondents from both privately and public institutions. Next, as computed in Phase II, is data preprocessing for consequent model development, while SA is carried out in phase III with the *Valence Aware Dictionary and sEntiment Reasoner (VADER)* approach. Phase IV encompasses of Data output sampling, and result visualizations for consequent analysis. Details of the phases are as explained in what follows.

Data Capturing

An online collaborative tool, Google Form, is designed to capture data from respondents including their opinion on the subject of digital collaborative tools and their deployment for academic planning and quality control purposes in tertiary education of learning. Their opinion, expressed through text, is in response to the open-ended question; *what do you think about the adoption of online collaborative tools for academic planning and administration*? This was retrieved from the Google form designed for the purpose of this study. The Google opinion poll form was active for five weeks, after which one hundred and ten (110) responses were gotten after five weeks. The textual responses are as presented in the screenshot of Figure 2 and preprocessed as a tab-separated file format. The 110 features yield a total of 1013 text-tokens representing responses from stakeholders. Other attributes of the captured data include the age-range, professional cadre, computer literacy level, level of academic qualification, years of experience on the job, and the open-ended question upon which the sentiment analysis is carried on.

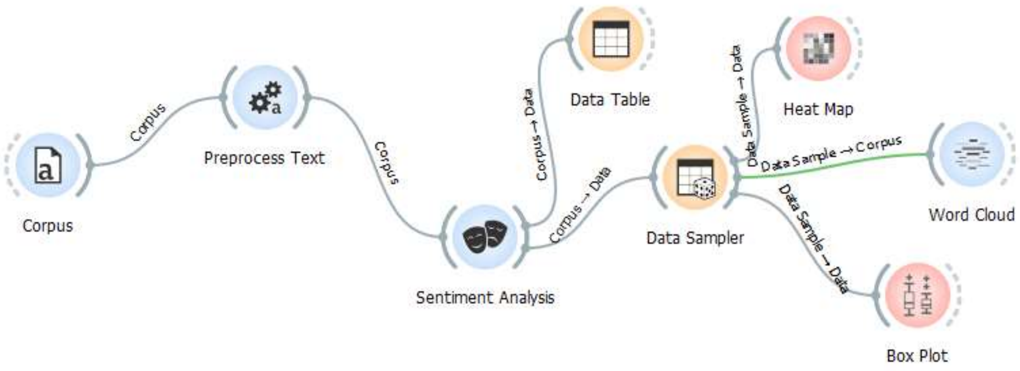

Figure 1: Four-Phase Pipeline of the Model

Data Preprocessing

The structured nature of the means of data capturing reduced responses' complexities to the barest minimum as against experiences from data sources like the social media. However, as proposed in Olaleye, et al. (2021), the following preprocessing steps are carried out on the largely structured data for better results:

- **Transformations**: steps including conversion of corpus to lower case and removal of *urls*
- **Noise removal**: removal of punctuations, white space etc.
- **Tokenization**: an important phase in natural language processing, including tokenization of text responses into word-tokenization using *Regexp* approach. A uni-gram and bi-gram approach of word-tokenization is implemented.
- **Filtering**: involves removal of stop words including articles, conjunctions, prepositions which do not carry enough discriminative content needed for the opinion-mining task.

VADER-based Lexicon SA Modeling

The Lexicon-based SA determines polarity to classify the opinion expressed by respondents into three categories of either *Positive, Neutral & Negative* while its Vader-approach scores each word-token, as expressed by respondents in their texts, using combination of an emotion lexicon (Hota, Sharma, & Verma, 2021). The approach assumes sentiment is related to presence of certain words or phrase (for bi-gram or more) in an opinion structurally represented. Hence, features (text responses) are assigned a certain sentiment values referred to as a lexicon. It is used as a predefined list of words noted as *dictionary of known words*, with word-synonyms associated therewith. In line with the work of (Hota, Sharma & Verma, 2021), the frequency of the occurrence of each word in the dictionary determines the computations of its positive, negative or its neutral state hence, this study plays weight on emphasis.

In this work, polarized lexicon is adopted such that the word 'i' is assigned numeric value 1, 0, or -1 for positive, neutral or negative emotion. Hence, polarity of an opinion 'I' (expressed by a respondent) is:

$$I = \{i_1, i_2, i_3, \dots, i_n\} \quad (1)$$

and equation 1 is calculated based on determining the occurrence-frequency of words 'i' from the lexicon '1' which occurs in 'y'. The pos (1,y) and neg (1,y) are positive and negative words from '1' that occurs in 'y' with the adds:

$$sum(1,y) = pos(1,y) – neg(1,y) \quad (2)$$

hence, sentiment placement $s_1(y)$ of a feature 'y' under polarized lexicon '1' is derived by:

$$s_1(y) = 1 \text{ if } sum(1,y) > 0 = 0 \text{ if } sum(1,y) = 0 = -1 \text{ if } sum(1,y) < 0 \quad (3)$$

The compound score characterized with the VADER-based approach adopted in this work is computed by adding the valence scores of each work in the lexicon, which is rejigged with the rules and normalized between -1 (extreme negative) and +1 of extreme positive. Sentiment is then calculated as:

Positive sentiment:

compound score >= 0.05; (4)

Neutral sentiment:
between compound score > -0.05 and < 0.05; (5)

while Negative sentiment assumes:
compound score <= -0.05 (6)

For the SA, this study used Orange data mining tool for the Natural Language Processing, text preprocessing and analytics, and data visualizations.

RESULTS AND DISCUSSION

VADER-based approach applied to the text corpus identified emotions in words hence calculated sentiments inherent in the most reliable way as described in Equations 4-6. For an in-depth analysis, positive, negative, neutral and a compound score is calculated for each opinion expressed by the 110 data features. Table 2 shows the above-mentioned scores of the first twenty opinions with respect to the methodology presented in Figure 1. A plot of the overall compound score, showing the total sentiment of an opinion where -1 is the most negative and 1 as the most positive, is presented in Figure 2. Consequent upon the SA, the corpus is passed to the Data sampler to retain 10% of the corpus for easy visualizations using replicable deterministic sampling. Hence, using the Merge by K-Means to combine responses with same polarity into one line, the Heat map outcome is as presented in Figure 3 while the cluster by rows to create a clustered visualization of selected similar responses is presented in Table 2 showing a total of 20-clustered instances having varying compound scores. The entire outcome constitutes a *22.7%* of respondents who are favorably disposed to the idea of digital collaborative tools for academic planning. Whereas, a cluster constituting a 17.27% of respondents, having compound scores between *-0.27* to *-0.52* (some of which are captured on Table 1) expresses negative sentiments in their opinions. An appreciable cluster of respondents constituting *60.03%* of opinions expressed a neutral sentiment towards their opinion about deployment of digital collaborative tools for academic planning purposes. The word cloud outputs the most prominent tokens in the *dictionary-of-known-words* based on the output of the Data sampler aforementioned as presented on Figure 4 as the comparison of mean compound scores is on the box plot presented in Figure 5.

Table 2: Cluster of First Twenty Opinions

S/N	Response	Positive	Negative	Neutral	Compound
1.	welcome development …	0.306	0.131	0.563	0.4191
2.	educators not ready …	0	0	1	0
3.	computer literacy low …	0	0.512	0.488	-0.2732
4.	internet access …	0	0.524	0.476	-0.296
5.	costly system	0	1	0	-0.1027
6.	difficult learn …	0	0.714	0.286	-0.3612
7.	students know …	0	0	1	0
8.	only ict graduate …	0	0	1	0
9.	nigeria not ripe …	0	0	1	0
10.	could still be …	0	0.318	0.682	-0.1027
11.	good development…	0.75	0	0.25	0.4588
12.	only private university could do…	0	0	1	0
13.	bad poor internet…	0	0.423	0.577	-0.296
14.	personal computer for staff…	0	0	1	0
15.	government not serious…	0.379	0	0.621	0.0572
16.	online collaborative tool…	0	0	1	0
17.	cyber security source…	0.444	0	0.556	0.34
18.	unpopular among academics…	0	0.368	0.632	-0.3252
19.	only few understand…	0.485	0	0.515	0.5719
20.	internet fraudsters could hack…	0	0.639	0.361	-0.7947

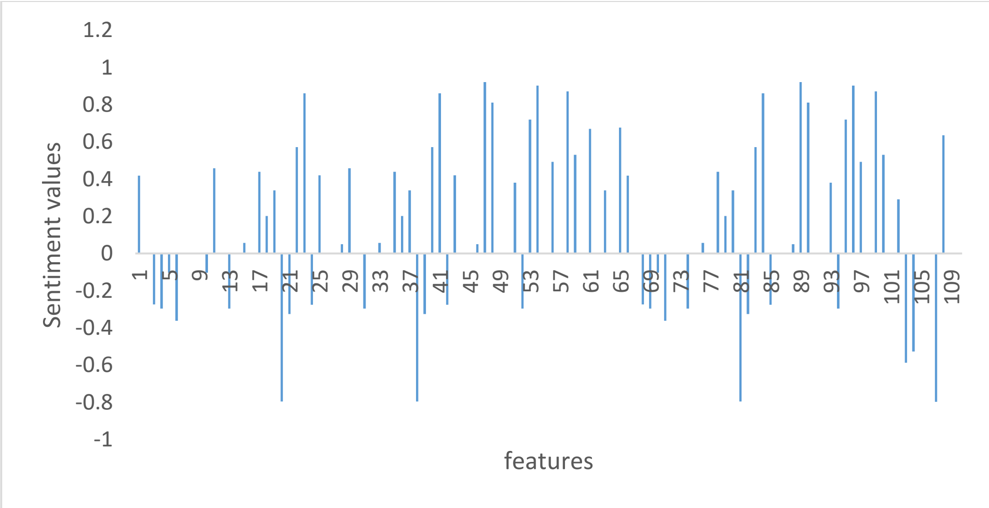

Figure 2: Compound score values for the text corpus

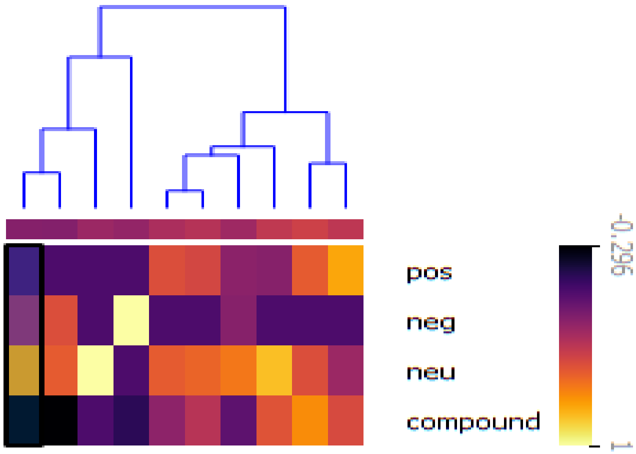

Figure 3: Heat map of responses with same polarity

Figure 4: Word cloud of prominent tokens as expressed

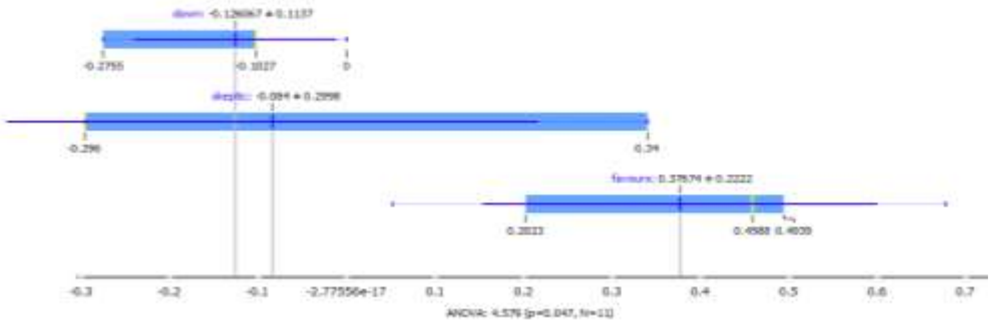

Figure 5: Box plot of the mean scores

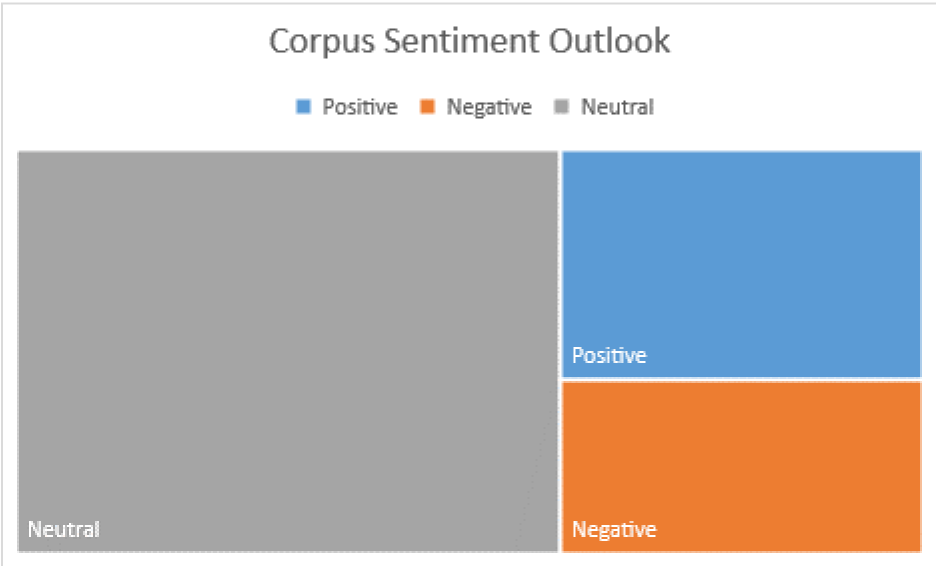

Figure 6: VADER-based sentiment outlook of the opinion poll

Consequent upon the foregoing, the sentiment outlook, with the approach of VADER presented on Figure 6, clearly shows the emotions expressed by respondents concerning their thoughts in the possible deployment of digital collaborative tools for academic planning, teaching, research and tertiary educational institution administration. Though sentiment score may vary with respect to the lexicon data used for calculating polarity hence affecting the total percentage of sentiments expressed, in the approach of this study, majority of respondents are neutral towards the subject matter. Concerns rose up, as evident from Figure 4 shows germane issues bothering on internet access especially, which bothers on issues of internet penetration and reliability in the country. The mean sentiment *-0.10* negative score (Figure 5) shows the average respondent in the negative cluster have a strong reservation against the idea of digital tools for whatever reasons. An average mean of *0.49*, however, shows a weak conviction on the average respondent who expressed positive sentiment about the idea while the cluster of average respondents on the neutral divide with a *0.39* mean score tilts towards the positive direction of the divide.

CONCLUSION

A VADER-based sentiment analysis approach is adopted in this study to extract sentiments from emotions inherent in the opinions of major stakeholders in tertiary educational institutions in Nigeria over the possibility of deploying digital collaborative tools for academic planning purposes which include amongst others the teaching, learning, research and delivery. The text analytics approach of the study assigned positive, negative and neutral values to the text corpus of respondents resulting with a compound score of emotions as expressed in their response to the open-ended question asked overt the subject matter. Experimental result shows that majority of over 60% clustered respondents were neutral in their opinions though with an average member tilting towards positive emotions while a 22.7% were of convincing positive opinion towards the idea. The rest expressed a strong negative conviction against the concept. Issues bothering on internet were of prominent information gain hence the main crux of the neutral sentiments discovered. Future work will engage a more robust corpus for deeper insights.

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