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Applying Sentiment Analytics in Mining Student Opinions for Quality Assurance

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ABSTRACT

The evaluation of higher educational institutions is important to both the Management and regulatory agencies of the institutions for growth and national development. The quality assurance departments of these institutions are continuously faced with the challenge of collecting feedbacks from the various stakeholders in order to assess the impact of their programmes and recommend improvements. The analysis of these feedbacks especially where they are textual in nature pose another challenge for the decision makers. The mining of the opinions in these feedbacks requires the use of sentiment analytic approaches. In this work, we demonstrate the application of sentiment analytics to quality assurance in a higher education institution. We designed a framework with three analytic centers that shows the processes of mining students opinions on three areas: learning experiences, teacher quality and facility assessment. The framework was implemented using R/RStudio Programming with the NRC lexicon approach using datasets from a Department in a Federal University in Nigeria. The results presented the emotional valence and distributions of the feedbacks and show that the students were generally satisfied with the quality of their lecturers and the facilities but not with the learning experiences.

Keywords: Sentiment Analytics, Mining, Students Opinions, Quality Assurance, Universities

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1. INTRODUCTION

Teaching and learning are the art of imparting knowledge, sharing ideas, and ensuring that both the teachers and learners can have a quality experience. This can take place in the classrooms, offices, conferences, seminars, symposiums, workshops, etc.

A quality learning experience involves the art of paying attention and removing all forms of distractions so that learners can comprehend all the information, instructions, directions, and advice shared by the teacher. As the primary roles of educational institutions, teaching and learning should be evaluated from time to time. There are four (4) key areas that need to be considered in the evaluation. Firstly, there is a need to x-ray how efficient is the process of imparting knowledge to available learners? Secondly, what are available teaching and learning facilities such as adequate classrooms, conducive library, adequate furniture, conducive learning environment, uninterrupted power supply, and other social amenities? Thirdly, what is the number of students that are expected to use a particular classroom for proper learning to take place? Finally, what is the quality and quantity of lecturers available for the various courses in all the faculties, departments, remedial courses, and other professional courses offered in the universities?

Adequate solutions in these key areas entails the assurance of quality in the education sector. Hayward (2006) defined quality assurance as that aspect of ensuring that teaching and learning set standards are being met and exceeded at all times to show remarkable progress in the teaching and learning experiences. Usually, there are both the internal and external standards for ensuring quality in education. It is in line with this that external bodies like the National Universities Commission (NUC), and National Board for Technical Education (NBTE) expect the over 170 Higher Educational Institutions (HEIs) to set up quality assurance directorates/units to monitor, appraise, carry out self-assessment reviews, monitor and ensure compliance, and participate in the review of academic programs to meet global standards. The quality assurance directorates in modern times achieve this mandate through the collection of feedbacks from various stakeholders in the HEIs.

However, some of the internal methods deployed by the quality assurance directorates to get necessary feedback are not automated and as such cannot meet the present-day universities' challenges. The use of suggestion boxes and complaint boxes in universities has not yielded the required improvement in the quality of teaching and learning. It makes it tedious to read and analyze comments/reviews/opinions from students using traditional human reading. It also takes a lot of painstaking efforts to collate those expressions from suggestion boxes and understudy them in record time. This ancient method of soliciting feedback has become outdated, obsolete, and not worth relying on it (Mamoon, 2016). To improve on the quality of teaching and learning there is a dire need to rejig a more modern and tested feedback mechanism (Ferguson, 2011).

There is a need to get these feedbacks from all stakeholders, lecturers, students, teaching and non-teaching staff, guardians, parent, and management. These feedbacks expressing the opinions of the stakeholders need to be analyzed to aid in decision making. In computer science, a tool that helps in carrying out this analysis is known as sentiment analysis. Sentiment analysis is a method used in grouping private and public opinions or comments into positive, neutral, and negative (Mohammed and Babatunde, 2019). It is an excellent tool in text analysis, computational linguistics and natural language processing (Kamisli, Erzurum, and Ergul, 2017). It is being conducted using various algorithms in machine learning, and a hybrid of lexicon/rule-based models to analyze comments and opinions of stakeholders (Obinna, Yusuf, and Steve, 2020). The results of the analysis have a lot of applications in improving the quality of teaching and learning in the HEIs (Garrard, 2017).

This work focuses on the provision of a sentiment analytic framework for quality assurance in the HEIs. The aim is to develop a teaching and learning quality assurance model for the HEIs using the opinions of stakeholders. The objectives are to (i). design a framework that accepts and analyses students' opinions on their learning experiences, and (ii). build a model that classifies the sentiments of various stakeholders in the HEIs and provide a quality assurance recommendation for the Management. The implementation was done using a Federal University in Nigeria as a case study where textual feedbacks were collected from students on three areas: learning experiences, teacher quality, and facility assessment. The importance of having such a good feedback management system cannot be overemphasized because of the invaluable role it would play in the process of decision making.

2. LITERATURE REVIEW

Ogbuju *et al*. (2020) demonstrated that sentiment analysis can be applied in a national scale to analyze the opinion of citizens. They applied it on the Nigerian nationwide lockdown due to the covid19 outbreak using tweets extracted from Twitter in a period of three months. Their findings showed that Nigerians accepted the lockdown measures in good fate and were willing to fight against COVID19.. Dalipi et al. (2021) showed the effort of researchers in evaluating freely expressed feedback from massive open online courses undertaken by student from 2015 to 2021. Aydin *et al.* (2021) carried out opinion mining on student feedback which were freely expressed on their teaching and learning experiences concerning an Open Distance Education in the Turkish education system. The dataset used were 4652 tweets with a unique hashtag from student concerning their examination experiences between interval of one week before examination were conducted and one week after the examination was finalized. The dataset underwent various stages of cleaning, normalization, tokenization, and stopword removal. The result showed 232 positive, 1075 negative, and 3345 neutral Tweets.

Achmadi *et al.* (2020) analyzed opinion of Twitter users on 501 universities brand in Indonesia in 2020 using textblob library in Python programming and expressing the results in positive, negative and neutral segments. The result was presented for use by the Directorate of Higher Education. Baddam *et al*. (2019) used the same approach to determine the polarity of students' opinions based on their comments about their learning experiences. A total of 939 student feedback were collected on 110 business related courses over an academic session. This was done to aid the evaluation of the Midwestern University in the USA. The university believed that in order to improve on teaching and learning, it is imperative to use machine learning algorithms to evaluate course performance indexes by gathering freely and anonymous feedback from student. Their results were presented on five (5) sentiment scale: "Very Negative", "Moderately Negative", "Neutral", "Moderately Positive", and "Very Positive".

Likewise, Alexa (2021) unveiled the public's opinion on three state universities in the city of Iowa in the USA, which gives an insight on all the parameters concerning school life and what transpired within and outside the campuses to help the general public to form an opinion on where they want their wards to study. It gives a scorecard for students willing to transfer their studies from one institution to another to make the right decisions.

Jiménez *et al.* (2020) used students' feedbacks to analyzed the impact of online and offline teaching and learning models in a private University between 2019 to 2020 as follows: (i) normal student-lecturer interactive classes taught in 2019 (pre-COVID); (ii) a sudden shift to online classes, early part of 2020 (early-COVID); and (iii) fully engaging online classes with later introduction of make shift offline classes, later part of 2020 (late-COVID). Cummins *et al*. (2021) carried out sentiment analysis of feedbacks expressed by student and examiners over Programming. While they work to have an automatic opinion mining application that will have reusable codes, source materials and other collaborative tools, their findings were presented in three categories Positive, Neutral and Negative with results of 10%, 58%, and 32% for students and 9%, 67%, 24% for examiners respectively.

Mary *et al*. (2016) designed and tested a framework using Naive Bayes and Semantics Analysis to support curriculum and programme development, course content creation and facilities overhaul from analyzing all the stakeholders' comments. This showed a significant improvement on teaching and learning. Samuel, Mahsa, and Wageeh (2016) observed that evaluations of teaching and learning styles on different courses and programmes can be analyzed systematically using student feedback mechanism in various educational institutions. These feedbacks generated by anonymous respondents about student learning experiences are expressed in 5 or 7 point Likert scales. Using an SVM machine learning classification method, 57% of free-text responses were found to be correctly classified to their corresponding satisfaction score. Established connections between quantitative scores and their comments can be an excellent source of identifying unique actions that addressed specific problem areas, and further highlights those views that encourages student learning experiences.

Omran et al. (2020) described methods of improving teaching and learning techniques in attaining global set academic standards by using 2000 positive and 2000 negative comments collected from the RateMyProfessors.com. The classification process was based on supervised machine learning Multinomial Naive Bayes (MNB) with 86% accuracy, Maximum Entropy (MaxEnt) with 86% accuracy and Support Vector Machine (SVM) with 85% accuracy. The works reviewed showed that Machine Learning algorithms like Naive Bayes, SVM, etc. had been mostly used in the determination of the sentiments. The lexicon approach has not been commonly in use. This show that there is a gap in literature concerning the limited utilization of lexicon based approach in carrying out sentiment analysis in the domain of educational quality assurance. This work seeks to explore this approach.

3. SYSTEM ANALYSIS AND METHODOLGY

3.1 Description of the Existing System

There are five (5) major areas of the quality assurance system in HEIs. According to Mahfoodh (2013), there includes internal quality assurance (self-analysis, quality plan, monitoring, and evaluation), external quality assurance (carries out necessary benchmarking, audit, assessment and review), accreditation (courses, programs and institutions), accountability, and continuous improvement. The system under the auspices of this research, deals with the internal quality assurance whereby the university itself evaluates his people and programmes, to ensure quality. This evaluation is usually done through assessment of various lecturers as it concerns the quality of teaching and learning in the university.

This is achieved by providing feedback boxes or suggestion boxes for student unanimously provide review of their learning experiences on this various courses/lectures. After the student have provided these feedbacks, the quality assurance unit of the university, collects them and reads through them to identify the various areas that needs improvements and those areas that needs commendations. The existing model is manually based and it is very cumbersome to individually read through those feedbacks and analyze them for effectiveness/efficiency. The existing system in assessing quality assurance in the domain of teaching and learning is the internal quality assurance facet of the quality assurance model. This internal quality assurance facet deals with four areas as seen above. The evaluation area is the main part of this work as it affects the teaching and learning activities directly. The major internal stakeholders who are involved in this are the student, who provide feedbacks on their learning experiences.

The disadvantages of the existing system outweigh the advantages; they are as follows:

(i) It is purely manual and time consuming.
(ii) It is very tedious to collate, analyze and produce a recommendation.
(iii) The bureaucracy of getting the recommendations to the Management is sometimes very cumbersome
(iv) The recommendations produced cannot be visualized.

3.2 Description of the Proposed/New System

The proposed system is designed to take care of the evaluation area of the internal quality assessment facet. Having the aim to develop a teaching and learning quality assurance model for HEIs in Nigeria, using the opinion of stakeholder, we designed a framework that accepts and analyses student' opinions on teaching or their learning experiences. The description of the framework as it concerns the internal quality assurance facet is shown in Figure 1

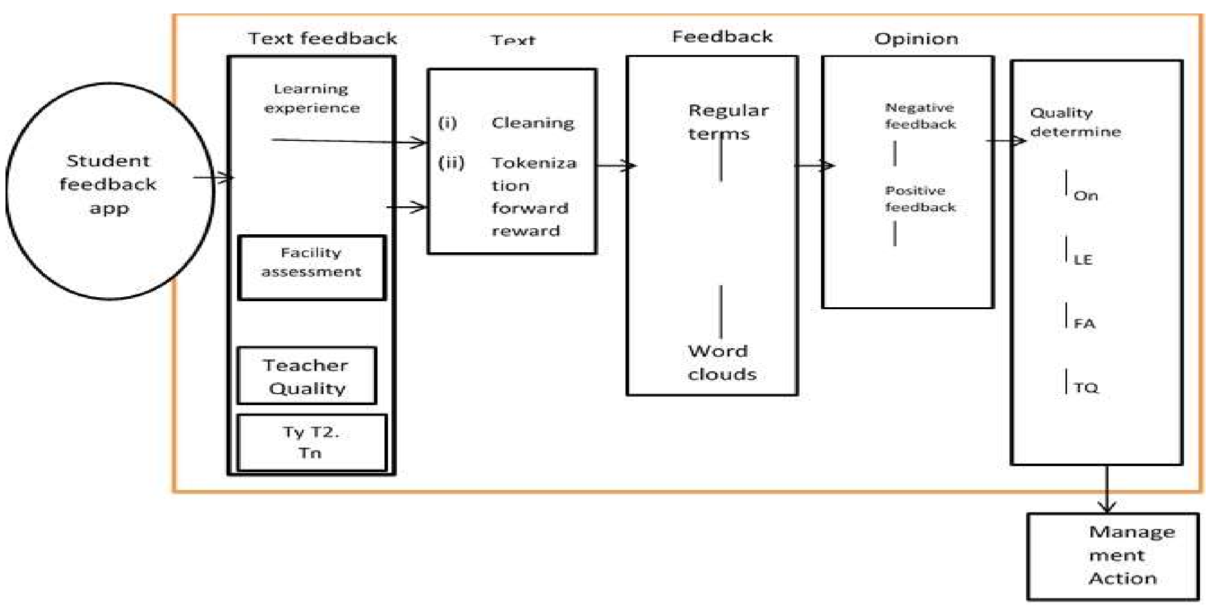


Figure 1 Analytic Framework for Internal Quality Assurance

The new system uses a feedback app to collect textural datasets from stakeholders (student) on their learning experiences, facility assessment and teachers'/lectures' quality. These datasets are passed on for text preprocessing and subsequently feedback analysis to develop an opinion model that shows the sentiment of each feedback on the different area presented. The output is passed on to the management of the HEIs for implementation/action. Furthermore, the analytic framework in Figure 1 is extended for application across different universities for application of the external quality assurance facet by the commission and board

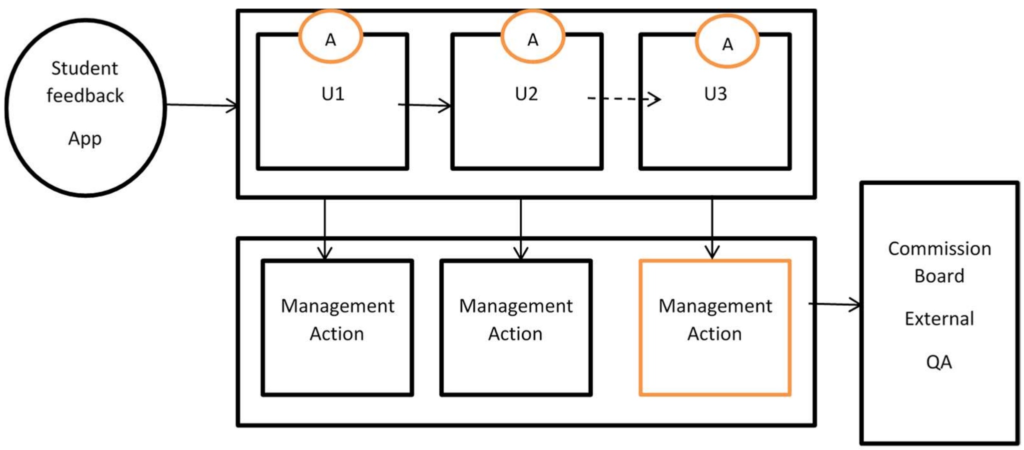


Figure 2: The Framework Extended for Application Across Different Universities

The high-level model show that each aspect of the analytics is presented to the HEI's management for implementation purposes. The HEIs also may open up the result to the Commission/Board for the evaluation of their institution as it concerns the quality of teaching/learning experiences of their stakeholders (student).

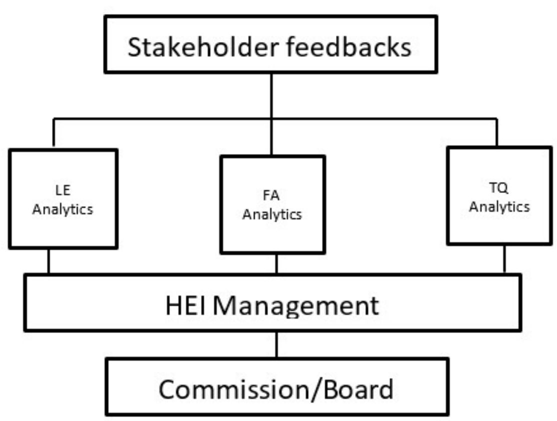


Figure 3: High level model for the new system

It can be seen that the new system has the following control centers:

1. The Learning Experience Analytics: The feedback of students on their learning experiences as regards to how examination results are being graded, the way test and examination are being conducted, how they feel in pursuit of their study and how they understand their lecturers. This center handles all the feedbacks that concerns the student learning experience. The results of the analyses of the feedbacks would be forwarded to the Management for necessary actions.
2. Facility Assessment Analytics: This has to do with different facilities such as classrooms, hostels, laboratories, toilets, etc. and how student feel concerning them. This Centre handles all facilities related problems and escalate to Management, so that necessary maintenance, upgrade, renovation and reconstruction can be carried out accordingly.
3. Teacher Quality Analytics: This deals with the quality of the teachers or lecturers, and their level of professionalism in teaching, innovations in their teaching styles, level of student performance in the courses taught and value of their contribution to entire learning cycle.

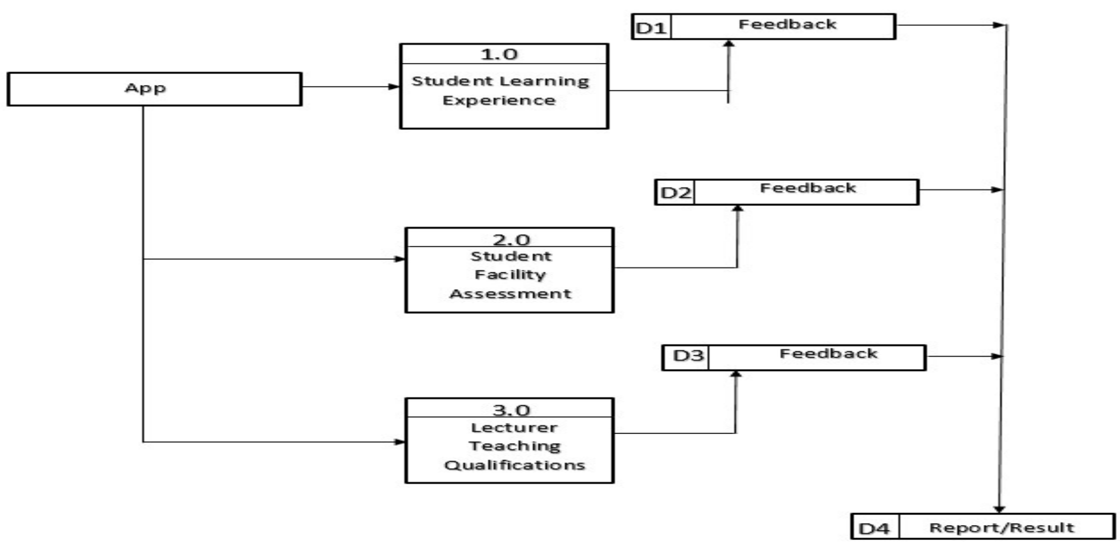
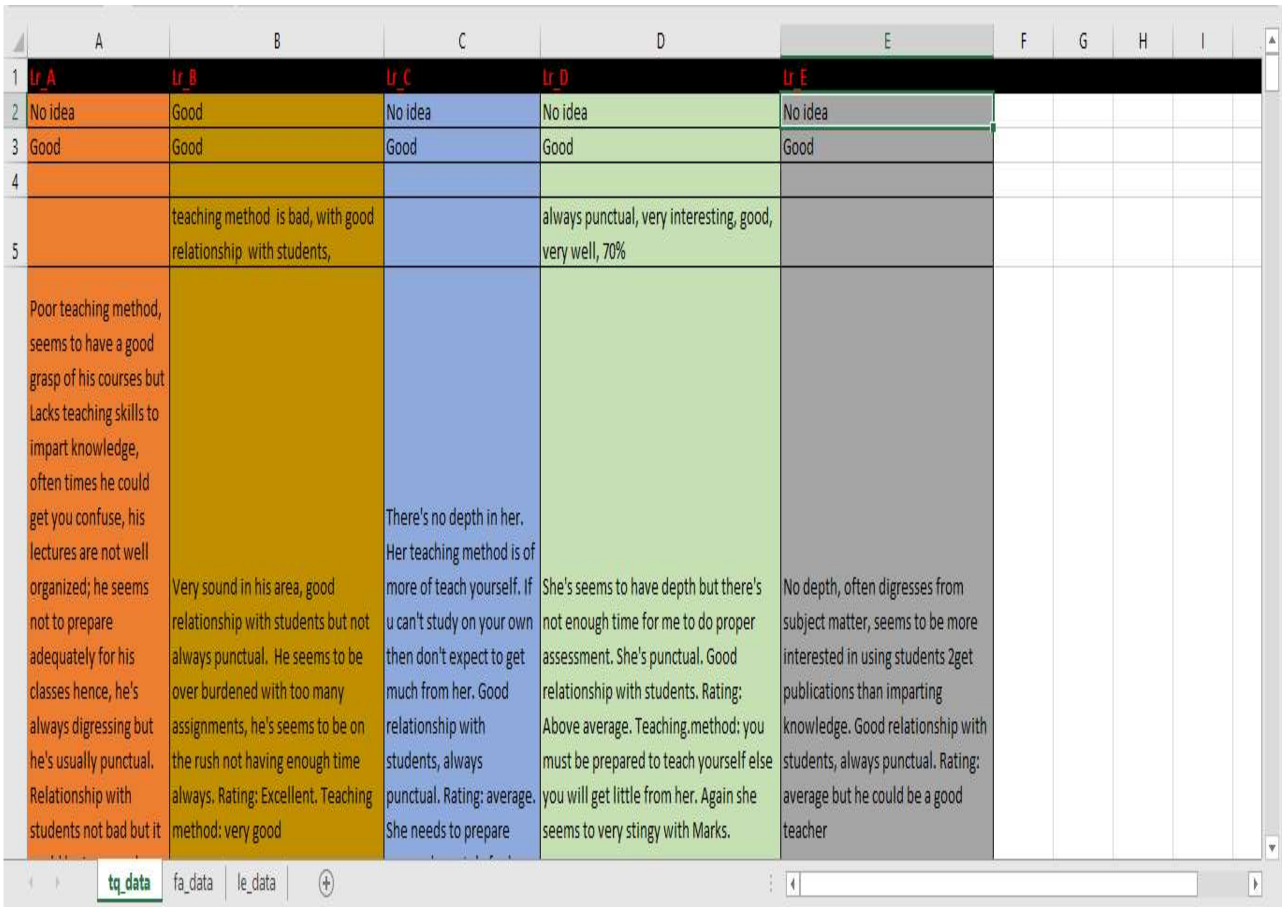


Figure 5: Data Flow Diagram of the Teaching and Learning Quality Assurance Model

In the Figure above the feedbacks from students on the three areas are collected and pass on to the appropriate control centre where the required analytics would be carried out. The results would be presented to the Management and the Commission/Board as the case be may.

3.3 Description of the Approach

The methodology adopted in this work is the Natural Language Processing Techniques. The dataset was collected using a student feedback application implemented with the Google Form services. A physical collection was also carried out by meeting up the students in the classrooms to freely write on their learning experiences, school facilities and lecturers' quality. The data were collated onto a codebook on MS Excel (Figure 6). On the teacher quality, data were collected on 5 lecturers but 3 were chosen for the analysis; they were anonymized as Lr_A (or T_A) on the codebook.



	A	B	C	D	E	F	G	H	I
1	Lr A	Lr B	Lr C	Lr D	Lr E				
2	No idea	Good	No idea	No idea	No idea				
3	Good	Good	Good	Good	Good				
4									
5		teaching method is bad, with good relationship with students,		always punctual, very interesting, good, very well, 70%					
6	Poor teaching method, seems to have a good grasp of his courses but Lacks teaching skills to impart knowledge, often times he could get you confuse, his lectures are not well organized; he seems not to prepare adequately for his classes hence, he's always digressing but he's usually punctual. Relationship with students not bad but it	Very sound in his area, good relationship with students but not always punctual. He seems to be over burdened with too many assignments, he's seems to be on the rush not having enough time always. Rating: Excellent. Teaching method: very good	There's no depth in her. Her teaching method is of more of teach yourself. If u can't study on your own then don't expect to get much from her. Good relationship with students, always punctual. Rating: average. She needs to prepare	She's seems to have depth but there's not enough time for me to do proper assessment. She's punctual. Good relationship with students. Rating: Above average. Teaching.method: you must be prepared to teach yourself else you will get little from her. Again she seems to very stingy with Marks.	No depth, often digresses from subject matter, seems to be more interested in using students 2get publications than imparting knowledge. Good relationship with students, always punctual. Rating: average but he could be a good teacher				

tq_data | fa_data | le_data

Figure 6: Dataset

Using the R/Rstudio programming tool, the dataset was preprocessed by removing noise, stop word, tokenization, lemmatization, and conversion to lower cases. The sentimentr (Rinker, 2021) and syuzhet (Jockers, 2015) libraries for text polarity extraction and calculations, and ggplot2 (Wickham, 2016) for visualizations were used. The sentiments on each feedback were extracted and the NRC lexicon (Mohammad & Turney, 2013) were used for the categorization of the emotions on the three areas.

4. RESULTS AND DISCUSSION

The result presents the emotional valence, sentiment distribution and word cloud of the feedbacks in Figure 10 showing the keywords that generated the insights. First, the emotional valence shows a general positive throughout the narration time for all the Teachers. Specifically, as displayed in Figure 7, while T_B and T_C show an overall positive narration, T_A shows a minor negative narration amidst its mostly positive feedbacks.

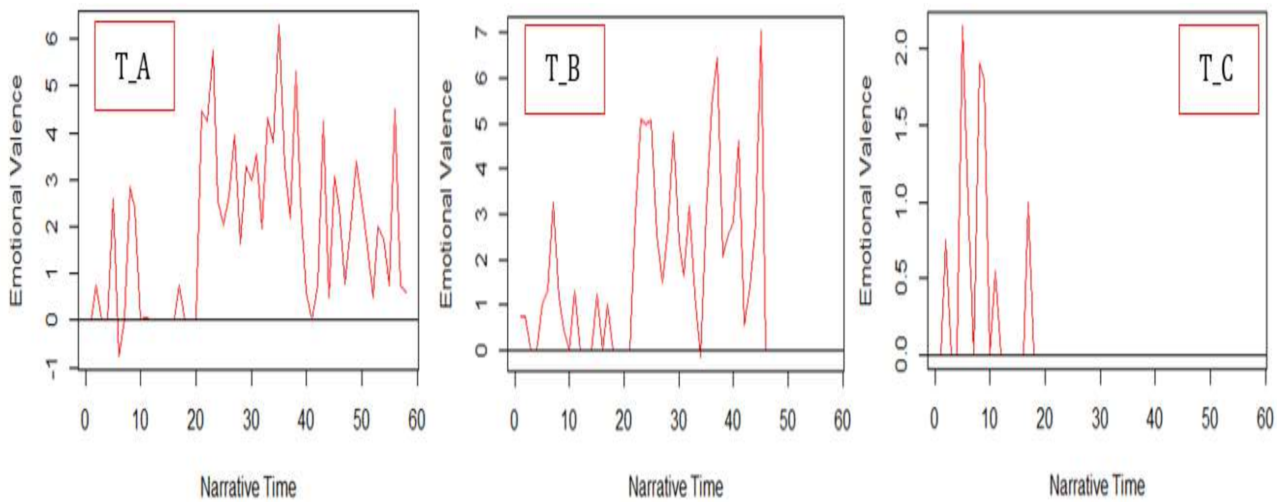
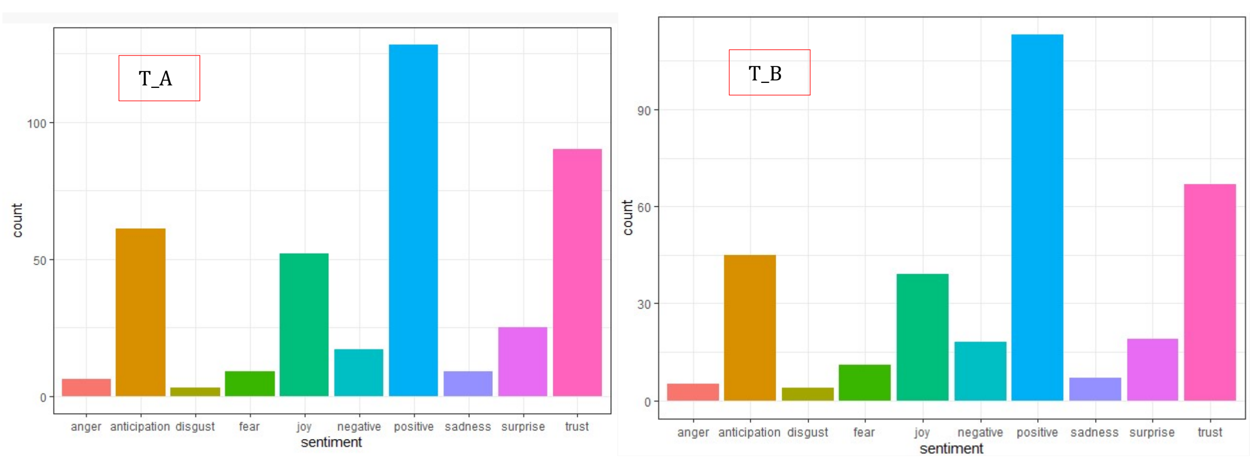


Figure 7: Emotional Valence of feedbacks on Teachers A, B, and C.

Secondly, in Figure 8, the sentiment distribution confirms the overall positive result shown by the emotional valence as there are more positive counts of the feedbacks for all the lecturers. The distribution of the eight basic emotions were shown. High anticipation, joy and trust as well as low anger, fear and sadness were expressed by the students about their Lecturers. The disgust emotion was very low for T_A and T_B while T_C had no disgust emotion – although it has the lowest data points (counts). The Combined_A,B,C presents the total feedback analysis for all the lecturers in the department and it shows high positive emotions also. In essence, the sentiment distribution shows that the students are happy with the quality of their lecturers/teachers.



T_C

Combined_A,B,C

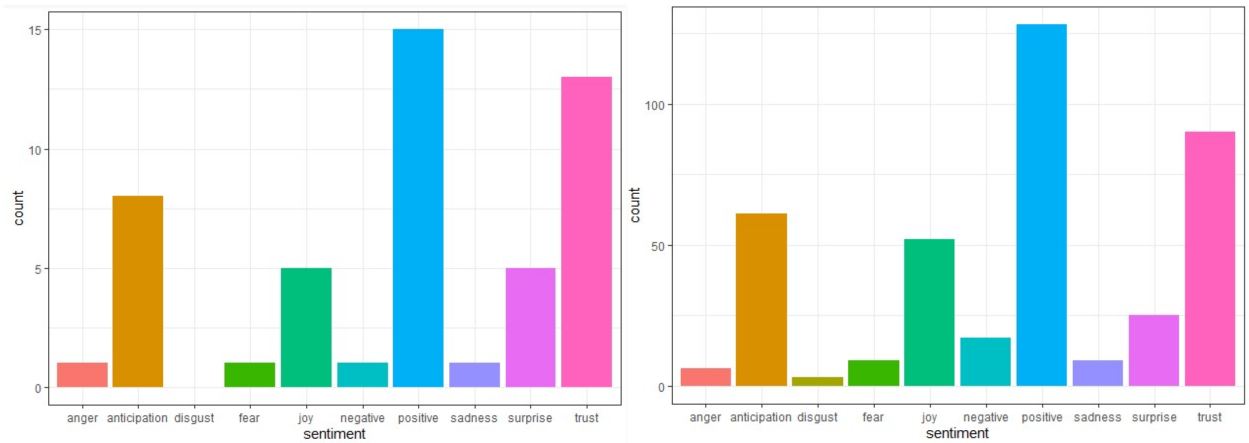


Figure 8: Sentiment Distribution of Feedbacks on the Lecturers

Thirdly, the sentiment distribution of the feedbacks on the university facilities (Figure 9) show no disgust and anger emotions, very low fear and sadness emotions and a high anticipation, trust and joy emotions. That means that the students are satisfied with the university facilities and give a positive feedback on them. However, the presence of the surprise emotion across the entire distributions indicates that there may be certain expectations which were not met.

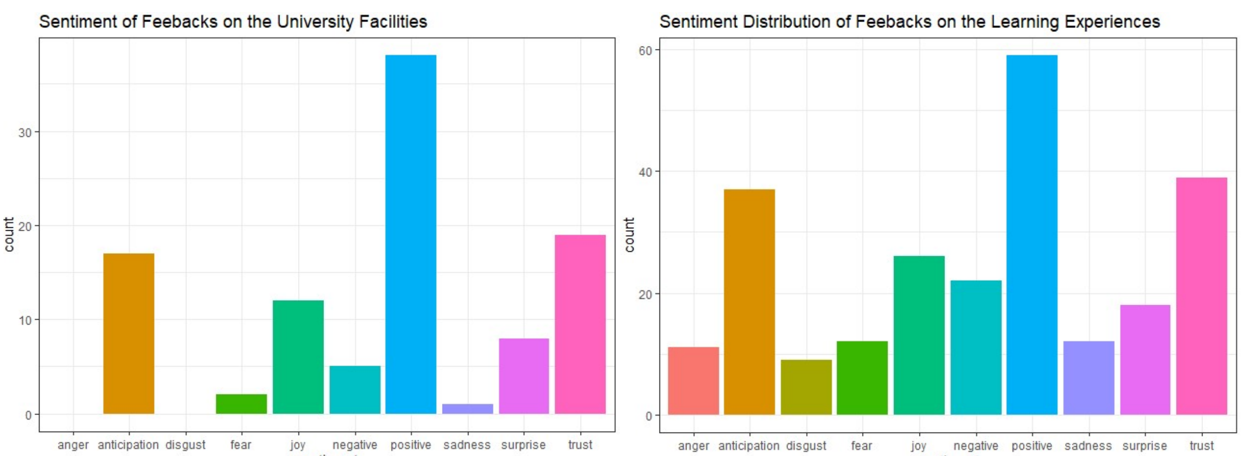


Figure 9: Sentiment Distribution of Feedbacks on the University Facilities and learning Experiences

On the other hand, the sentiment distribution of feedbacks on the learning experiences show that though a high positive emotion was recorded, considerable negative emotions like anger, disgust, and sadness were prevalent. This shows that the students were not totally satisfied with the learning experiences in the Department.

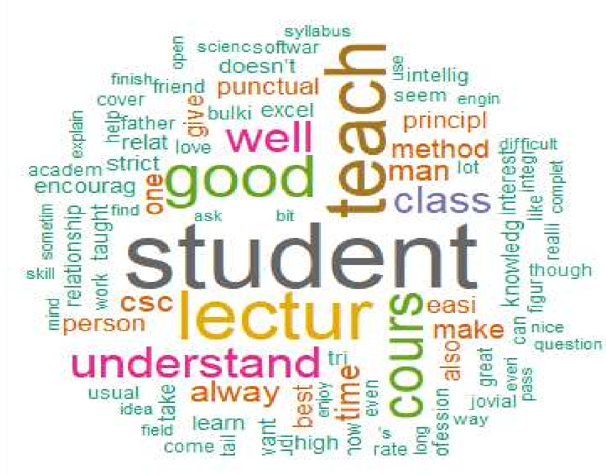


Figure 10: Word Cloud to measure Quality Teaching

While the results of Baddam et al. (2019) and Cummings et al. (2021) were presented on a 5-sentiment scale expressing percentages of the positivity, negativity and neutrality, this work presented an elaborate result that shows the emotional distribution of the students' feedbacks in 8-basic emotions as well as in the positive and negative bars. This is in accordance with the NRC lexicon which involves categorization of words into eight (8) basic emotions (Mohammad & Turney, 2013). In Amran et al. (2020), machine learning algorithms were employed as a common practice, however, this work had used the NRC lexicon approach to analyze the textual feedbacks and express the results in simple visualizations ready for the Management's or Board's decisions. Most of the works in this domain uses tweets (Achmadi et al., 2020; Aydin et al., 2021) which are publicly available, but the framework designed and used in this work allows an app to collect and collate the datasets directly from the concerned stakeholders thus making the result more useful.

5. CONCLUSION

This work had designed three (3) analytic control centers that accesses students' feedbacks on their learning experiences, quality of lecturers and the condition of the school facilities using sentiment analysis. The framework employed has the capacity to send the result of the analysis to the school management/regulatory agencies/boards for quality assurance in the concerned areas. The result of the implementation done with a Federal University in Nigeria shows that the feedbacks were generally positive on all the centers and highlights the negative areas where attentions may be paid to for improvement.

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