Rodrigo, M. M. T. et al. (Eds.) (2021). Proceedings of the 29th International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Prelude to Full Online Learning: Educational Interventions from the Voice of the Customers

Arlene Mae CELESTIAL-VALDERAMA[a*], Albert A. VINLUAN[b] & Joel B. MANGABA[c]
[a]*Jose Rizal University, Mandaluyong City, Philippines*
[b]*New Era University, Quezon City, Philippines*
[c]*University of Makati, Makati City, Philippines*
*arlene.valderama@jru.edu

Abstract: Learning institutions and universities have made a huge and forced transition to full online learning modality in the school year 2020-2021. Specifically, before this, blended learning environments have taken its place in most educational setup and it is customary to allow students, pertaining to as the voice of the customer to provide immediate feedback through surveys to collect views covering their satisfaction in the entire course as the semester concludes. In Jose Rizal University, student feedback is gathered in several survey instruments. One is the Canvas Experience Survey, which allows students to submit feedback on the effectiveness of the blended learning course implementation. It seeks student feedback on areas where the teaching and learning process could be improved. This paper creates a venue for educational interventions directly from the students, as the voice of the customer. It creates a course feedback mining system that will allow the administrators to examine the shortcomings of their clients' blended learning experiences and, as a result, intervene to improve them. An analysis of the student responses from Canvas experience survey is presented quantitatively and a qualitative text mining approach comprising of text pre-processing using lemmatization and n-gram, aspect extraction, sentiment analysis employing VADER, and recommendatory statement action plan intervention shall be accessed by institution's respective groups supporting them to the continuous improvement of the teaching and learning cycle implementation of blended learning courses. A mean of the numerical value of the selected course totals to 3.71 interpreted as Strongly Agree and an overall sentiment polarity score of 0.14 resulting in a positive sentiment. The correlation r value is -0.43 which results in a moderate relationship. As aspects were extracted from responses from each question, educational interventions through statement action plans are accessed by the respective office to address these concerns. Therefore, prelude to full online learning modality, the students' voice was heard, and it expedites the University stakeholders in the improvement cycle to courses offered under the blended learning programs of the University.

Keywords: Feedback mining system, student feedback, text mining, blended learning experience, action plans, educational interventions, voice of the customer

1. Introduction

Student feedback is the most important in the cycle of continual improvement in learning and teaching. Same is true for schools and universities which use traditional, multi-faceted, blended and full-online learning as their main advances. Student feedback holds useful statistics about their intellectual experiences in gaining appropriate knowledge. It can include facts about teaching methodologies, evaluation design of student assessment, utilization of institution resources, and other elements of teaching. This can shape a key factor for educators and school owners aiding them in advancing their internal policies and systems, thus educational interventions. In this article, student feedback will be collected, mined, and transformed into action plans by mining their remarks, which originate directly from the students' voices.

A growing body of survey analysis has been implemented in the university and has investigated on customer's satisfaction, specifically on laboratory, library, and services. In the academic side, there are classroom learning experience surveys and the Canvas experience survey. However, little attention has been given to students' written feedback as resolutions for this were maintained and perceived to address based on the quantitative results of the survey. There are group discussions focusing in addressing the low results of the survey instrument's criterion. This study investigates and addresses the disparity in the students' slants of written feedback with emphasis on their emotional responses and sentiments as their written comments are analyzed and will serve as the basis for the improvement of their blended learning experience.

As this work best exemplifies the art on mining student experiences and feedback in a blended learning course using text analytics approach, the succeeding papers attest that this line of studies best compliment the thorough analysis of universities and institutions in implementing their new strategies in facing student feedback and how their existing and future methodologies shall create great impact on their clients, the students. Sivakumar and Reddy (2016) analyzed the collected online student feedback from the Twitter API and used clustering and classification techniques to measure the semantic relevance between screen words and student opinion sentences and share student opinions.

This survey helped improve student learning and instructor leadership skills. Ibrahim et al. (2019) focused on textual feedback from students about their learning experiences, methods of teaching, design in the assessment, services, and other aspects of training. They used a framework for data mining to analyze end-of-unit common textual feedback, which included four (4) machine learning algorithms: decision trees, support vector machines, random forests, and naive bayes. According to their findings, the accuracy of the closed-loop common dataset models was higher than the accuracy of the models related to the estimation and almost the same as the accuracy of the models not related to the estimation. The accuracy of the scoring models was assessed to be close to that of the scoring examples in the full dataset models. Yu et al. (2018) showed how sentimental sentiments (positive or negative) and text mining of open-ended answers from student surveys might provide useful information for bettering student experience management (SEM). They deployed artificial intelligence and machine learning-based text mining skill. Data derived from text that was previously underutilized has been discovered to be significant in CEM. They have demonstrated that a campus-wide survey can help administrators make data-driven decisions about instructional technology implementation by better understanding student experiences with it. Furthermore, Ibrahim et al. (2018) published a paper on developing a data mining-based context for inspecting students' assessment feedback gained from social media sites and/or text feedback. The research is divided into three stages: The first step is to create a model that uses sentiment analysis to automatically distinguish the polarity of student feedback. The second stage is to create a model that can certainly classify assessment issues. Third, examine the relationship between the issue(s) and student performance. This study employs various popular text classification algorithms to evaluate students' assessment feedback to improve the learning practices. Finally, Gottipati and Jiang (2012) conducted an alternative study on the growing popularity of opinion-rich web resources. They extracted user sentiments on products, social, political, and economic topics using an opinion mining approach. Such data is useful for subject specialists and is referred to as actionable content because individuals not only articulate their views, but also add their ideas, appeals, and recommendations through comments.

2. Blended Learning

2.1 Course Redesign Program

José Rizal University has long ago opted for blended learning in 2007. The university has introduced the term "Course Redesign Program" (CRP) for selected subjects within the general education program. The Course Redesign Program (CRP) reduced face-to-face meetings in the classroom, and an collaborating set of learning activities anticipated the enrolled students from various general education courses. Students enjoy the independence of carrying out their online classes and their spare time assignments on or off campus. The university currently has a separate body called the Institute for Technology-Based Learning (ITBL), which is responsible for administering blended learning courses. The Institute for Technology-Based Learning (ITBL) is run by the university's vice president for quality, linkages and technology-based learning. ITBL supports 33 courses from various universities. JRU students have long used blended learning to their advantage, and thanks to this implementation, scientists improved their learning outcomes.

3. Research Objective

With the purpose to reckon several remark comments from college students in a blended mode style, as there is little to zero concentration is given to qualitative student voice and opinions, this paper intends to principally mine student feedback using text mining approach. More so to support administrators of the programs in the ITBL and prescribe course improvements action plans making the system adaptive to the student learning experience. The main intention of the study is to embody a feedback mining system that exemplifies the mining of the student voice as feedback leading to the prescription of recommendatory action plans that equals to interventions and lead them to the corresponding administrative division. The main research objective individualizes on: 1) how can key topics be extracted from students' qualitative feedback about their blended learning experiences? 2) how would sentiment analysis gage in the key aspects of the feedback leading to the proposition of recommendatory plan intervention? And 3) how would the feedback mining system embody its recommendations to the administrators and key players of the blended learning program?

4. Research Design

The tool that will be used to collect data for this study is the University Canvas Experience Survey. The Canvas Experience Survey completes to 27 questions, 3 of which contain course information, 21 Likert, and 3 questions which are qualitative in nature as they are about learning, accessibility, assessment, and collaboration. The last 3 questions which are for qualitative inputs lead to the comment section of the best and least characteristics of the students' canvas use and as well as their suggestions for improvements. Students will respond to the survey through an anonymous online survey. Students' input will come from one blended study course in university courses run by the ITBL. To carry out this study, the students will have to answer the survey using the 21 Likert questions and the 3 qualitative questions from which they will be inquired to transcribe their thoughts and ideas concerning the relation to their real experience with Canvas. During this time, course details are deleted to ensure the concealment of responses.

4.1 Course Selection

JRU uses surveys because an effective Customer Experience Management (CEM) program necessitates the compendium, synthesis, exploration, and dissemination of customer metrics. When summarizing the responses to the survey, the indicators are calculated using the Top Box Score. This is the proportion of the student responses who gave the highest rate on the scale. Two of the surveys in the academic colleges are the JRU Classroom Learning Experience (CLE) Survey and the JRU Customer Satisfaction Survey (CSS). Responses to the top box score, which received the grade "strongly agree", are due to the subsequent returns: a) the analysis is simplified, only 1 item is taken into account instead of 5 or more, b) contrasts are made quickly and easily, compare the results by variables, Top 2 Box scores permit for more effective comparisons of scores and c) trends become more visible as the survey is steered at the end of the semester, tracking the measurement during this time, Top 2 Box scores benefit in recognizing trends in the data.

The researcher crafted an analysis of the four (4) surveys run in the school year 2019-2020. Under the blended learning courses of the university in the same school year, there are 18 courses enrolled in the 1st semester and 15 in the 2nd semester. There are 11 courses under the College of Arts, Criminology, and Education (CACE), 5 under the College of Hospitality and Tourism Management (CHTM), 2 from the College of Computer Studies and Engineering (CCSE), and none from the College of Nursing (CNUR) and College of Business Administration and Accountancy (CBAA). In the 2nd semester, there are 10 from the College of ACE, 3 from the College of HTM, 1 each from the College of CSE and the College of BAA, and none from the College of Nursing.

When looking for a quantitative course rating among students who are most dissatisfied with Canvas LMS, in order to aggregate negative responses to questions on the Likert scale, the bottom box (strongly disagree) is used instead of the top box (strongly agree). Thus, in citing the fifteenth question in the survey: "I notice that course materials on Canvas have connection with the face to face (classroom) lesson content." The bottom box quantifies the most dissatisfied students as seen in Table 1.

Table 1. *Likert Scale - Bottom and Top Box*

Bottom Box				Top Box
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

Here are the steps on how the course was identified with the most categorical answers, thus, the Strongly Disagree:

1. The overall number of responses of the Strongly Disagree choice was recorded for each of the Likert-scale question in the survey.
2. Summing up all the Strongly Disagree answers in each question item, the course-subject with the highest of this bottom-box response has been resulted.
3. Then the aggregate count of all courses with the highest number of bottom box score, thus Strongly Disagree response is stemmed.

According to survey data conducted in the first semester of the 1st semester of SY 19-20, the course Readings in Philippine History coded as HIS C101 surfaced 26 times as the highest number of strongly disagree choices from students. A total of 506 responses from the bottom box were recorded. In the same semester but in the Final term, the same course, coded as HIS C101, surfaced again 23 times as the highest number of students who responded "strongly disagree" in the questions as well. This sums up to 768 bottom box responses. In the 2nd semester of the SY 19-20 on the Prelim term run of the survey, the course Art Appreciation coded as HUM C102 has 14 times appearance and was recorded as the highest number of students who chose "strongly disagree" in the scale. A total of 204 bottom box responses were recorded. In the Final term of the 2nd semester in the SY 19-20, the course National Service Training Program 2 which is coded as NST C102 has appeared 22 times as the highest number of students who responded "strongly disagree" in the scale of answers. This result sums up to 683 bottom box responses.

From these data, it is remarkable that the highest bottom-box responses belong to the course HIS C101 - Readings in Philippine History as it appeared in the 1st semester results two times. Table 2 represents a summarized view of the results.

Table 2. *Summary of Strongly Disagree Responses*

Canvas Experience Survey Run	Course	# of Appearance with SD Responses in Each Question	Total SD Responses	# of Respondents	%
Prelim Term 1st Semester SY 19-20	HIS C101 - Readings in Philippine History	26	506	2914	17.4
Final Term 1st Semester SY 19-20	HIS C101 - Readings in Philippine History	23	768	3935	19.5
Prelim Term 2nd Semester SY 19-20	HUM C102 - Art Appreciation	14	204	6679	3.1
Final Term 2nd Semester SY 19-20	NST C102 - National Service Training Program 2	22	683	1520	44.9
			2161	15048	14.4

HIS C101- Readings in Philippine History is overseen by the History department under the College of Arts, Criminology, and Education (ACE). It is a course offering across all programs of the university every 1st semester and by petition of 17 or more students in the 2nd semester or if a request from graduating students.

Looking at this data, the researcher has turned its focus on this course. HIS C101 is a code for Readings in Philippine History. It is a part of the General Education curriculum in the university in the late 2000s. As it is categorized as a General Education course, it focuses on the meaning and significance of history and the important role that historians play in society. It introduces the students to the disciplines and major schools of thought that affect the hermeneutics and writing of history. The students are trained to collect, organize, and examine information and write sequential narratives in various styles of academic history through understanding the primary activities of the historians, their assumptions and limitations, and their social responsibility. HIS C101 is tagged by the university as one of the blended learning-style of courses run through a weekly 1.5-hour face-to-face meeting with their faculty. Their remaining learning pursuits for the students are done online for the comfort of both learners and teachers. Feedback on the learning experience of students officially enrolled in this course is central to this study, as this feedback will be extracted using text analysis.

4.2 Text Mining Phases

As text mining approach is employed, extracting the students' comments and opinions from the survey instrument as its source is initiated. Their input serves as central to continued implementation of the blended learning program. It serves as key decision-making influencers of university administrators. The text extraction steps mentioned in the study focus on opinion mining as it involves the extraction of feelings and thoughts are central to almost all personal activity. It has been a well-researched topic of research over the past decade, focusing primarily on opinion mining, sentiment classification, opinion synthesis, and real-world applications. Opinion source or the holder is the person as the origin who presents the opinion (Liu, 2010). The natural language processing (NLP) model is highly utilized in the study as this research field is committed to automatic processing of human language. This processing of the students' comments aids in the succeeding phases of sentiment classification, clustering, and mining the opinions of the students. Preprocessing comments using common natural language processing (NLP) techniques includes stop word removal, part-of-speech (POS) tagging, lemmatization, and bigrams that clearly help improve the accuracy of the pitch classification.

Sentiment classification targets on how the data will be classified into positive or negative polarities (Pang et al. 2002). Like opinion extraction, close-grained analysis of sentiment is needed in opinion mining studies, and it is extremely effective to recognize the throbs of the student who raised their comments.

4.3 Aspect Extraction

Aspect extraction is the most essential segment of the system. This stage extensively utilizes the content digging and machine learning methods to find invaluable topics from the statements of the students. The topic is the subject matter of the students' comment (Nitin, et. al. 2015). In the pursuit of elucidating research question 2 of the study, the cleansed text shall be subjected for topic extraction to target the student's central point.

In this section, the aspect extraction stages employed in the study are chosen which were as well as frequently used classification techniques that can inevitably classify the topics from the students' comments. To prepare the data, the data set for the selected course HIS C101 was used. To compare the models, the use of text assessment measures: recall, precision, and F-score as seen on Manning et al. (2008).

4.4 Sentiment Analysis

At this phase, the aim is to identify the overall positive or negative remarks to a particular comment. Comments are subject to the sentiment polarity calculation algorithm. Polarity has a float value in the range of [-1.0, 1.0] and subjectivity has also a float value in the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective (Loria, 2018). Every single word is scored and the aggregate score of the whole sentence will imply whether the sentiment has a positive score, that is [if >= to zero] or has a negative score, that is [if < zero]. The idea of mining the sentiment of the students' written statements justify the machine learning algorithm that generates a score between 0 and 1. Scores which are nearer to 1 indicates positive sentiment, and scores adjacent to 0 imply negative sentiment. Values near to a score of 0.5 are neutral or indeterminate. A score of 0.5 signifies neutrality. When a text string could not be investigated for sentiment or has no sentiment, the score is always 0.5 exactly as stated in the documentation of Microsoft Azure (2019). The VADER sentiment analysis is also prevalent in this study. VADER which stands for Valence Aware Dictionary and sEntiment Reasoner is based on a word list and rule-based tool for sentiment analysis that is explicitly accustomed to sentiments conveyed in social media. It uses a combination of a lexicon sentiment which is a list of features of words. They are usually marked positive or negative depending on the semantic orientation. The Vader compound metric follows specific values for a negative, positive, and neutral sentiment for the compound score.

The study also employed the dependency rule-based approach using Spacy model in Python for dependency parsing which in turn is crucial in aspect extraction. In the dependency rule approach, treating topics or words as a potential aspect or presentation word relies on a dependency type relationship, the word part of speech (POS) tag in this regard, and the extraction rule. (Salwa, et. al, 2018).

5. Results and Discussions

5.1 How can key topics be extracted from students' qualitative feedback about their blended learning experiences?

Employing the text mining and analytics process, the student comments underwent the text pre-processing stage. Twenty-one (21) questions asked for student views relating to the Likert scale questions. The dataset used were the comments of the students who attended the courses under the blended learning program for the school year 2019-2020. The comments were collected at 1 of the 2 feedback cycles, on the 2nd semester of the academic year. There was a total of 140 student comments utilized as responses evaluated in this study. As their comments went through pre-processing, student responses have undergone stop words removal, lemmatization, n-grams, and POS tagging were employed in the program. Table shows 3 random student feedback responses from question no. 1 in the Canvas Experience Survey and the text pre-processing results.

Table 3. *Question 1-Student Responses and the Text Pre-Processing Stages*

I can easily log-in and log-out my Canvas account.	**CLEANSED TEXT**	**TOKENIZED TEXT**	**POS TAGS**	**ASPECT TERMS**
I can easily log-in and log-out my canvas account because of faster internet	easily log log canvas account faster internet	['easily', 'log', 'log', 'canvas', 'account', 'faster', 'internet']	[('easily', 'RB'), ('log', 'VBZ'), ('log', 'JJ'), ('canvas', 'NN'), ('account', 'NN'), ('faster', 'RBR'), ('internet', 'NN')]	['faster internet', 'easily log']
It was easy for me to log-in and log-out my account because I don't encounter any problem so far.	easy log log account encounter problem far	['easy', 'log', 'log', 'account', 'encounter', 'problem', 'far']	[('easy', 'JJ'), ('log', 'NN'), ('log', 'NN'), ('account', 'VBP'), ('encounter', 'NN'), ('problem', 'NN'), ('far', 'RB')]	['account', 'problem']
Sometimes it's hard to log-in and log-out my canvas account inside the campus because of the internet connection.	sometimes hard log log canvas account inside campus internet connection	['sometimes', 'hard', 'log', 'log', 'canvas', 'account', 'inside', 'campus', 'internet', 'connection']	[('sometimes', 'RB'), ('hard', 'JJ'), ('log', 'NN'), ('log', 'NN'), ('canvas', 'NN'), ('account', 'NN'), ('inside', 'RB'), ('campus', 'JJ'), ('internet', 'NN'), ('connection', 'NN')]	['account', 'internet connection']
I can easily log-in and log-out because of this PC especially at home is canvas is alright to use.	easily log log pc especially home canvas alright use	['easily', 'log', 'log', 'pc', 'especially', 'home', 'canvas', 'alright', 'use']	[('easily', 'RB'), ('log', 'VBZ'), ('log', 'JJ'), ('pc', 'NN'), ('especially', 'RB'), ('home', 'RB'), ('canvas', 'NN'), ('alright', 'NN'), ('use', 'NN')]	['easily log']
I Strongly Agree because there was no problem that I	strongly agree problem encountered log log account	['strongly', 'agree', 'problem', 'encountered', 'log', 'log', 'account']	[('strongly', 'RB'), ('agree', 'JJ'), ('problem', 'NN'), ('encountered',	['Strongly Agree']

encountered in log-in and log-out of my account.			'VBD'), ('log', 'JJ'), ('log', 'NN'), ('account', 'NN')]	

5.2 How would sentiment analysis gage in the key aspects of the feedback leading to the proposition of recommendatory plan intervention?

NN, NNS and NNP are the most important POS for identifying keywords. These words can be used in different senses and their positive and negative scores may be different in other senses. It is equally important to calculate the sum of positive and negative score from all sense of the tags (Saqib, et. al, 2020). Figure 1 shows a snippet in extracting the aspects using the noun groups or noun phrases. The study employed the spacy model in the Python programming language.

```
#Extracting Aspects

for word,tag in flattened_tagged:
    if(tag=='NN' or tag=='NNP'):
        if(prevTag=='NN' or prevTag=='NNP'):
            currWord= prevWord + ' ' + word
        else:
            aspectList.append(prevWord.upper())
            currWord= word

    prevWord=currWord
    prevTag=tag
#Eliminating aspect which has 1 or less count
for aspect in aspectList:
        if(aspectList.count(aspect)>1):
                if(outputDict.keys()!=aspect):
                        outputDict[aspect]=aspectList.count(aspect)
outputAspect=sorted(outputDict.items(), key=lambda x: x[1],reverse = True)
aspect_list.append(outputAspect)
#print(outputAspect)
```

Figure 1. Algorithm for Extracting Aspects.

To maximize the presentation of results, a correlation between the student responses in the Likert scale acquiring their numerical value alongside their qualitative comment with its sentiment score were retrieved and Pearson correlation value is $r = -0.426445$ which denotes a moderate relationship. Table 4 shows the result for question number 4.

Table 4. *Question #4 Results of Aspect, Numerical Value, Sentiment Score, and Sentiment*

Question 4: I have no issues accessing my Canvas account using the wired internet connection in the computer laboratories.	ASPECT TERMS	Numerical Value	SENTIMENT SCORE	SENTIMENT
Yes because it is reliable and faster	['reliable']	3.8	0.4019	Positive
It's fine most of the time but sometimes during examination the connectivity to the internet was so slow.	['connectivity', 'examination']	3.4	0.1027	Positive
Yes, I don't have any issues accessing my canvas account using wired internet connection.	['account', 'wired internet']	4	0.4019	Positive
Sometimes I can not access my account because sometimes in	['Sometimes access']	3.4	-0.05	Negative

JRU the internet connection is very slow even in laboratory.				
I Strongly Agree because I have no issues to access my canvas account using wired connections in any available computers here.	['using here', 'Strongly Agree', 'available computers']	3.4	0.34	Positive

These results shall set forth the sentiment of each student feedback and from which the sentiment of the student responses is generated. To extend these results, Pearson correlation analysis with p-value was employed to present the relationship of the numerical value of the Likert responses and the opinions of the students to each question. This correlation measures the linear association between these two variables and their strength of relationship. The mean of the numerical value of the responses for the selected course totals to 3.71 interpreted as Strongly Agree and an overall sentiment polarity score of 0.14 resulting to a positive sentiment. The correlation value of r is -0.426445.5 and it has a moderate relationship. These results show only a restrained link as they correlate their agreement to the Likert responses vis a vis the sentiment of their comment.

5.3 How would the feedback mining system embody its recommendations to the administrators and key players of the blended learning program?

On the intent of this study to utilize a feedback mining system that extracts student responses to gain their sentiments, alongside this goal is the provision of recommendatory action plans to progress the cycle of teaching and learning the courses in an environment running under blended learning.

To the faculty and administrators, as the result of topic modelling and aspect extraction, the aspects shall then be integrated to generic action plans accessible to the specific division of the university that can handle the overall aspect of the student feedback as shown in Figure 2 a question item from the survey that displays a result for a negative sentiment. It shows a word cloud of the aspects, the aspects, student feedback, the sentiment score, and the sentiment interpretation. The word cloud shown allows the administrative users of the system the most frequent aspects from the student responses as how they feel about the related question.

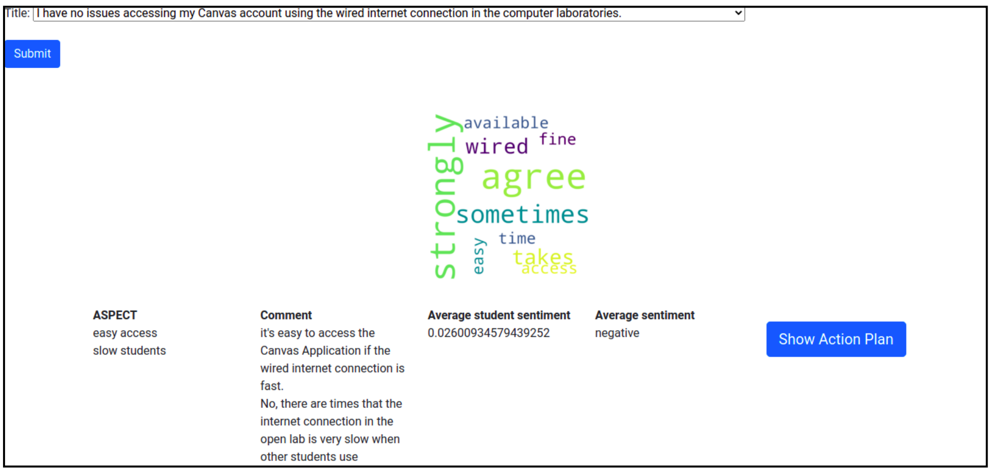

Figure 2. Visuals for a Negative Sentiment

For further performance analysis of the identified approach in arriving at the results of the sentiment classification method, the computation of precision, recall, and F1 score is obtained and as reported in Table 5. Precision computes and shows the number of positive results which thus fit in to the positive classification. Recall determines and calculates the number of positive class results out of all positive outcomes in the dataset. The F-measure presents and computes a single score that assesses both the concerns of precision and recall in one number. Table 5 reports the performance measure of the sentiment results. These values indicate good performance as it had high recall and precision results.

Table 5. *Performance Measure of Sentiment Results.*

Measurement	*Values*
Precision	1.00
Recall	0.89
F1 Score	0.89

Table 6 presents a confusion matrix of the identification sentiment results as identified by the sentiment polarity scores contrary to the actual sentiments generated. The confusion matrix reveals the pertinency of the presented approach.

Table 6. *Confusion Matrix*

	Identified by the Presented Approach		
	Predicted Negative	*Predicted Positive*	*Total*
Actual Negative	1	15	*16*
Actual Positive	0	124	*124*
Total	*1*	*139*	*140*

The table shows that there were 124 positive feedbacks in the data set and 124 were classified correctly. Similarly, in the case of the negative feedback, 1 out of the negative comments were identified correctly. Thus, the proposed approach was able to achieve an accuracy of 89.3%.

The action plans will serve as educational interventions and the output of this analysis shall serve as supporting attributes for the administrators of the Academic Division, Information Technology Office, and the Institute of Technology Based Learning (ITBL) enabling them to improve the implementation of the blended learning program. The study takes the action plan interventions based on the following elements:

- Clearly defined aspects from student feedback analysis.
- The timescales are real-time as the results generated are from the Canvas Learning Experience survey as they are conducted within the term and semester.
- The plan is derived from actual past student responses and is focused on the future.
- The tasks in the plan contribute to the improvement of the teaching and learning cycle of the courses under the blended learning program.
- The plan is detailed for its aims and the responsibility on the action takers and implementers are direct.

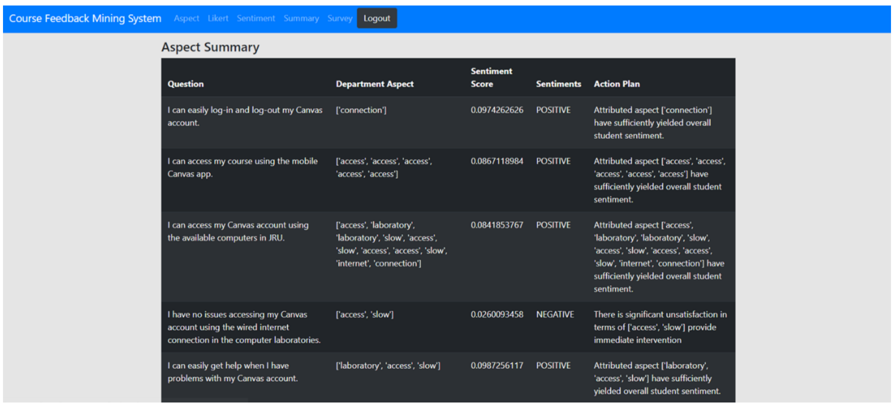

Figure 3. Aspect Summary for the Information Technology Office.

Figure 3 exhibits a view of the ITO login which are filtered aspects for the division to address. This interface shows a summary report of the Canvas question, the aspect extracted specifically for the department (ITO), the overall sentiment score for the responses of the students, its actual verbal remark sentiment, and the action plan.

6. Conclusions

This study aimed to embody broaden a blended learning feedback mining process that permits the university administration to examine the voice of their customers' learning capabilities under the blended learning style of courses under such program and provide interventions appropriately. The article provides an explanation of the progress made in the feedback mining process to improve a student's blended learning experience. The system is a resolute of text mining where the comments of the students from their LMS experience survey was used as the dataset. Text analytics processing was employed as the raw comments were lemmatized and analyzed and key topics were derived from them to serve as aspects. The aspects were the voice of the students as aliases that operated and motivated the study to generate recommendations on the improvements of the students' blended learning experience.

The study also aimed to produce the feedback mining system that embedded and customized the entire processes of the goals and objectives of this paper. An interface was developed from where students shall enter their comments and the text mining of their feedback takes place as their aspects breeds into recommendatory actions. These results categorically aid the blended learning programs of the university as they have transitioned to full online learning modality over the period of virtual classes at present times.

References

Sivakumar, M. and Reddy, U. S. (2016). Aspect based sentiment analysis of students' opinion using machine learning techniques. 2017 International Conference on Inventive Computing and Informatics (ICICI), Coimbatore, 2017, pp. 726-731. doi: 10.1109/ICICI.2017.8365231

Ibrahim Z.M., Bader-El-Den M., Cocea M. (2019) Mining Unit Feedback to Explore Students' Learning Experiences. In: Lotfi A., Bouchachia H., Gegov A., Langensiepen C., McGinnity M. (eds) Advances in Computational Intelligence Systems. UKCI 2018. Advances in Intelligent Systems and Computing, vol 840. Springer, Cham

Yu, C., Jannasch-Pennell, A. & DiGangi, S. (2018). Enhancement of Student Experience Management in Higher Education by Sentiment Analysis and Text Mining. International Journal of Technology and Educational Marketing, 8(1), 16-33. IGI Global. Retrieved October 7, 2019 from https://www.learntechlib.org/p/186633/

Ibrahim, Z., Bader-El-Den, M., & Cocea, M. (2018). A data mining framework for analyzing students' feedback of assessment. In C. Glahn, & L. Dirckinck-Holmfeld (Eds.), Proceedings of the 13th EC-TEL Doctoral Consortium co-located with 13th European Conference on Technology Enhanced Learning (EC-TEL 2018) [13] (CEUR Workshop Proceedings; Vol. 2294). CEUR Workshop Proceedings.

Gottipati, S. & Jiang, J. (2012). Extracting and Normalizing Entity-actions from Users' Comments. (2012). Proceedings of COLING 2012, December 8-15, Mumbai. 995-1010. Research Collection School of Information Systems.

Liu, B (2010). Sentiment analysis and subjectivity. In N Indurkhya, FJ Damerau (Eds.), Handbook of natural language processing, (2nd ed.).

Pang, B, Lee, L, Vaithyanathan, S (2002). Thumbs up? Sentiment classification using machine learning techniques. In EMNLP '02: Proceedings of the 2002 pages 79–86, July 2002.

Nitin, G. I., Gottipati, S. and Shankararaman, V. (2015). Analyzing educational comments for topics and sentiments: A text analytics approach. IEEE Frontiers in Education Conference (FIE), El Paso, TX, 2015, pp. 1-9. doi: 10.1109/FIE.2015.7344296

Manning, CD, Raghavan, P, Schütze, H (2008). Introduction to information retrieval. New York: Cambridge University Press.

Loria, S. (2018), Textblob: Simplified Text Processing. http://textblob.readthedocs.org/en/dev

Salwa, A. & Sharef, N., Murad, M. & Azman, A. (2018). Aspect Extraction Performance with POS Tag Pattern of Dependency Relation in Aspect-based Sentiment Analysis. 1-6. 10.1109/INFRKM.2018.8464692.

Saqib, M., Naeem, T. & Mahmood, K. (2020). Extraction of key/title/aspect words from document using wordnet. 2455-7196.