International Journal of Computing Sciences Research (ISSN print: 2546-0552; ISSN online: 2546-115X)
Vol. 5, No. 1, pp. 568-583
doi: 10.25147/ijcsr.2017.001.1.60
https://stepacademic.net

Short Paper*

Mining Students' Feedback in a General Education Course: Basis for Improving Blended Learning Implementation

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Date received: September 11, 2020
Date received in revised form: November 2, 2020; November 25, 2020
Date accepted: November 29, 2020

Recommended citation:

> Valderama, A. M. C., Vinluan, A. A., & Moraga, S. D. (2021). Mining students' feedback in a general education course: Basis for improving blended learning implementation. *International Journal of Computing Sciences Research*, 5(1), 568-583. doi: 10.25147/ijcsr.2017.001.1.60

Abstract

Purpose – The role of student feedback is paramount in the continuous improvement cycle in teaching and learning. The same applies to academic institutions implementing traditional face-to-face, blended, and fully online learning who leverage feedback analysis as an underlying and powerful approach in its construction of design in quality, efficiency, and effectiveness. In this paper, the acquisitions of feedback from students quantifiably and qualitatively such as mining of actual comments are the primary source of data. The study unravels the research question of how unstructured students' feedback be mined to prescribe course improvements in a blended learning course.

Method – An analysis of the students' responses who have mostly "strongly disagreed" from their Learning Management System experience survey is achieved statistically via bottom box scoring. These courses stem from a roster of blended learning programs offered at Jose Rizal University. From this exacting general education course, a qualitative text mining approach comprising of text pre-processing, topic extraction, sentiment analysis, and data visualization using actual student comments are probed.

Results – The Canvas LMS experience survey ensued HIS C101, a general education course identified with the most responses of students' strong disagreement. The study prescribes the employment of a feedback mining process which presents the results of the text mining approach from the qualitative comments from HIS C101 learners that seemingly resolves in the formation of recommendatory action plans aiming the improvement of the blended learning implementation.

Conclusion – With the feedback mining process in place, it serves as a channel and basis for improving the blended learning experience of the students.

Recommendations – More so to gather a more profound indulgence to expedite the university stakeholders in course improvement cycles in the other courses offered and included in the blended learning programs of the university.

Research Implications – Learner criticism is invariably considered vital if an institution has constant methods in the improvement cycle on how they implement the teaching and learning process. Any improvement in the cycle must take the client's feedback as input and thus converted it into definite action plans. This research is timely and immutable as diverse modes have come across the practices of teaching and learning in the world at large.

Keywords – students' feedback, text mining, blended learning, general education course, feedback mining

INTRODUCTION

The role of students' feedback is paramount in the continuous improvement cycle in teaching and learning. The same applies to academic institutions implementing traditional face-to-face, blended, and fully online learning as underlying approaches. In this paper, the acquisition of students' feedback through mining their comments that come directly from student views will be acquired, mined, and translated to action plans. Gottipati, et al. (2017) illustrated the teaching and learning continuous improvement cycle as follows. Step 1, the students experience the course when the instructor delivers the course. Step 2 details when the students give feedback about their experience. This feedback can include both quantitative and qualitative data. In step 3, the instructor analyzes the feedback, and lastly, in step 4, the instructor re-designs the teaching approach and the curriculum content based on the insights gained from the analysis. One of the significant objectives of this research is to develop a blended learning feedback mining process that empowers the HEI's administration to inspect the reproaches of their clients' learning experience in the blended learning course and thus upgrade them accordingly. As many educational institutions pay a ton of consideration to quantitative input, measurable correlations are processed and presented to school administrators. In any case, the subjective remarks given by students are not completely intercepted. In this paper, the conceptual framework of the study centers on catching and investigating criticism information from students' perceptions basing on their qualitative comments using text mining. In turn, the framework will give the fundamental structure in the implementation of a course feedback mining process that the university may utilize for addressing the results of the learning management system survey.

Jose Rizal University has long ventured into the practice of blended learning since 2007. The institution has coined the name Course Redesign Program (CRP) to chosen courses underneath the General Education curriculum. In the CRP, face-to-face classroom meetings have been reduced to once weekly from 2 to 3 times a week, and an online interactive set of learning module sets were prepared for the students. Learners revel in the independence of partaking in their online deliverables such as assignments, interactive quizzes, and forum participation in the comfort of their own time on and off-campus. Presently, the university has been overseeing courses under the blended learning approach through the Institute of Technology-Based Learning (ITBL), which is under the umbrella of Office of the Vice President for Quality, Linkages, and Technology-Enabled Learning. As the university has started with the utilization of Moodle in the early years of its operation, university students have been owning advantage of blended learning as the institution jumps to diverse learning management systems software which at present uses the Canvas learning management system.

OBJECTIVES

To reckon numerous comments from students in a blended learning course, administrators and faculty must act upon students' responses to open-ended survey questions from experience surveys to improve the student learning experience.

The general objective of this research is to develop a blended learning feedback mining process that empowers the HEI's administration to inspect at the reproaches of their clients' learning experiences in the blended learning course and thus upgrade them accordingly. This study seeks to identify resolutions on 1) how can blended learning experience convalesce from its implementation based on a course stemming from the feedback of the students, 2) how can numerous unstructured student comments produce topic clusters to address recommendatory action plans, 3) how can the clustered feedback sentiment be aligned to course improvement with a recommended action plan?, and 4) devise a structure on how can student comments result to extracted topical themes in a feedback mining process to exemplify its value to learners, faculty, and administrators? This paper shall present elucidations on how to move in the expedition of a feedback mining process concerning the improvement of the blended learning implementation experience of students.

MOTIVATIONAL CURVE

Blended Learning

According to Thorne et al. (2003), as mentioned by Irawan et al. (2017), blended learning provides an opportunity to assimilate the groundbreaking and technological advances in online learning with the interaction and involvement toward traditional learning. Blended Learning is learning that combines the technology and customary instructor-led training in the room (Bersin, 2004, p. 56). Blended Learning has four individualities, namely: (1) learning which combines technology; (2) combination of face-to-face learning, independent, and online; (3) the mixture of effective learning, and (4) teachers and parents as facilitators and supporters (Husamah, 2014, p. 16). In the blended approach, Alontaga et al. (2013) have cited the community of inquiry framework (CoI) as applied in the university's course redesign program. The CoI framework served as the evaluation framework for the paper to determine the blended learning experience of the students and improve the blended learning programs accordingly. The CoI substantiates to three presence, social, teaching, and cognitive. Social presence is the notch to which learners experience socially and emotionally connected with others in an online atmosphere. Teaching presence embraces the design, facilitation, and course of cognitive and social processes for the realization of personally meaningful and educationally worthwhile learning outcomes; and Cognitive presence describes is the scope to which learners can construct and ratify meaning through sustained reflection and discourse (Garrison et al., 2001). The growth of online delivery has altered how it is obtained and shared. Educators interested in improving online learning can benefit from understanding formal and informal feedback flows existing in face-to-face environments and how this transfer online (Meikleham, 2018).

Learning Management System

The advent of LMS has been traced by some researchers to rudimentary training management systems, which thereafter became platforms for e-learning (Kats, 2010). LMSs bond the students with the learning gist and content in a normalized way through software and programs explicitly created for their learning. They oversee learning points, substance, and learners and control and manage the learning forms and the presentation of the students by methods for recording the activities on computers and showing statistics and plans (Alenezi, 2018). As ITBL utilizes the Canvas Learning Management System as a medium in catering the blended approach for the courses, it is correspondingly one of its ingenuities to conduct the Canvas Experience survey which aims to gauge the consummation of the students in its use. Since the infancy years of the course redesign programs of the university, feedback in its use is of primal importance. The university utilizes floating online commercial surveys to extract student views. Every school year in two semesters, the Institute of Technology-Based Learning (ITBL) conducts the Canvas Experience Survey twice, in the prelim term and the final term.

Students' Feedback

Jose Rizal University employs the utilization of surveys as successful customer experience management (CEM) programs require the collection, synthesis, analysis, and dissemination of customer metrics. In summarizing survey responses, it applies the calculation of metrics using the Top Box Score. This represents the percentage of respondents who gave their best responses on the scale. Two examples of these surveys in the institution's college division are the Classroom Learning Experience survey and the Customer Satisfaction Survey. The responses of the top box score, the "strongly agree" is obtained due to the following advantages: a) it simplifies the analysis, reviewing only 1 item instead of 5 or more, b) the comparisons are quick and easy, comparing results across variables, Top 2 Box scores allow the comparison of results side-by-side more efficiently, and c) trends become easier to spot, as the survey is conducted every end of term, tracking metrics over this time, the Top 2 Box scores help identify trends in the data. This study employs the Canvas Experience Survey devised by experts who are composed of the University Vice President for QLT, the Director of the Institute of Technology-Based Learning, and an ITBL consultant. The questions of the Canvas Experience Survey contain 22 Likert-scale, 3 student information, and 3 open-ended questions that total to 28.

Text Mining

Analyzing students' feedback of assessment can lead to ascertaining issues that students struggle with and allow decision-makers to propose a suitable solution to tackle them to enhance the learning process (Ibrahim et.al., 2018). Chen et al (2014) and Pagare (2015) have collected student posts from Twitter, their objectives were to recognize the issues of engineering students concerning their academic learning per se. The qualitative feedback of students shall come from the 3 open-ended questions in the last part of the Canvas Experience Survey. The feedback process shall aid the administrators in making decisions in the aspects of teaching and learning course improvement to shove the continuance of providing the student stakeholders in caring about good education.

As the text mining approach proportions to the model solution for this study, it aims to produce topical themes from an extraction process. This stage widely utilizes content mining and machine learning methods to find valuable topics from the comments of the students. The topic is the subject of the students' comments (Nitin, et al., 2015). The initial step is to cluster the comments using a clustering algorithm. After data cleaning, the top frequency words will be clustered to extract actual topics. K-means is one of the widest used partitioning clustering methods which can divide all the observations from a dataset into k (a randomly selected number) subsets, so these subsets are used as k clusters (Nisha et al, 2015). Once the central points are computed, all the other observations will be assigned to the nearest k-clusters based on the distance between each observation and clusters. The last step of this approach is that after assigning all the observations to k-clusters, new central points and assignments will be repeated until the best similarities of all the observations in the dataset are acquired (Chouhan and Chauhan, 2014). Once clusters are generated, the next job is to extract topics for the clusters. The study intends to utilize keyword extraction to quickly identify the main points of the student comments. In this way, the identification of the topics of the comments shall allow the results of this study to label which are being discussed by the students as their main concerns. TF-IDF (term frequency-inverse document frequency) is a statistical measure of keyword extraction that evaluates how relevant a word is to a document in a collection of documents. This is computed by multiplying two metrics: how many times a word appears in a document (tf), and the inverse document frequency (IDF) which is how rare or common is the word across a set of documents or the entire data set. TF-IDF score of a word in a document is the product of tf and IDF. . The higher the score, the more relevant that word is in that document (Stecanella, 2001).

CONCEPTUAL FRAMEWORK

In the goal of fulfilling the first 3 research objectives of the study, the conceptual framework is depicted in Figure 1. The comments of the students serve as input to the structural concept of the framework. The comments will be grouped based on a common topic, using the K-means clustering algorithm. The sentiment of the topic shall then be obtained. The topics along with the sentiment polarity score will then be amassed to be reported visually. The summative report will include a demonstration of the significant clusters of the comments and words for the topic extraction task. The topics along with their sentiment polarity scores will be depicted. The negative topic result will be paralleled to an aligned business rule presented through key result areas with regards to course improvement.

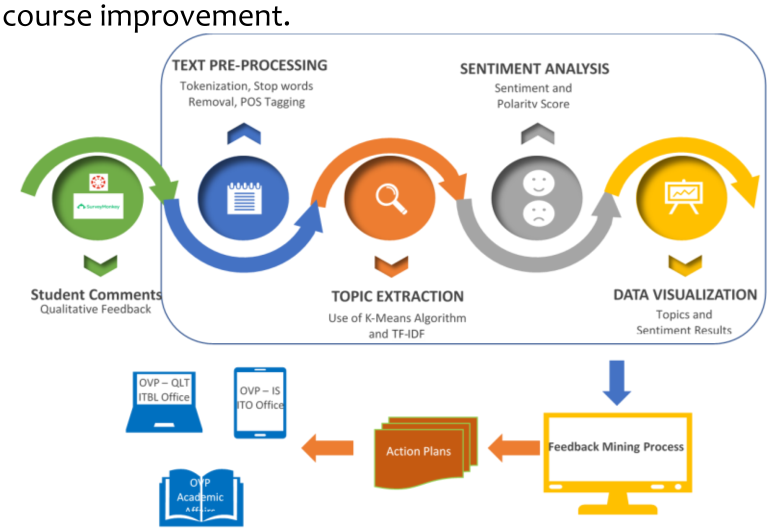

Figure 1. Conceptual Framework of the Study

In data visualization, the study aims to exhibit a graphic report of the results of the feedback alongside the sentiment and polarity of the topics extracted from the qualitative comments of the students. The text mining processes targets to be embedded into the feedback mining process which in turn allows the users to exploit on the menus from Canvas experience survey managed by the Institute of Technology-Based Learning (ITBL) to the analysis of survey results, and to the generation of action plans that would be directed to the offices of concern, i.e., VP for Academics, VP for IS for the Information Technology Office, and the ITBL.

RESEARCH DESIGN AND METHODOLOGY

Course Selection

The course selection in this quantitative approach discusses how the course was identified. In the conduct of the selection of which course to mine qualitative comments from, a responses summary was obtained in a quantitative approach. The researchers used the Canvas Experience Survey to determine the course in which responses have achieved strong disagreement. The Canvas Experience Survey for the school year 2019-2020 was utilized. During the first semester, there was a total of 2914 respondents enrolled in the blended learning courses who participated in the survey for the Prelim term. Another survey was conducted in the Final term and there were 3935 respondents. In the second semester, there were 6679 respondents in the Prelim term and 1520 in the Final term. These respondents are from the 18 courses signed up in the blended learning program. Specifically, there are 11 respondents from the College of Arts, Criminology, and Education (ACE). These are mostly identified as General Education courses as they are mostly offered across all programs in the university. From the College of Hotel and Tourism Management (HTM), there are 11 courses, and from the College of Computer Studies and Engineering (CSE), there are 2. During the second semester, a total of 15 courses were enrolled. Explicitly, 10 from the College of ACE, 3 from the College of HTM, and 1 each from the College of CSE and the College of Business Administration and Accountancy (BAA).

Text Pre-Processing

The source of the qualitative feedback from the students shall be obtained from the last 3 questions in the Canvas Experience Survey. The comments of the students will undergo data cleaning. This involves text pre-processing which pertains to the practice of preparing and cleaning the text data, thus qualitative comments of the students. First, they will be tokenized. Tokenization manages the parting of the text content into units during the pre-handling of text information. The removal of needless punctuation, exclamation, question marks, any additional unnecessary symbols, and special marks shall also be used, and modify words that contain uppercase letters or special marks. The removal of the stop words from the comments will be employed to reduce noise. Parts of Speech tagging, by tagging the components of speech to a paragraph of text, we can identify the relevant set of words that form up the entities inside a paragraph of text.

Topic Extraction Stages

Extraction is an essential segment. This stage widely utilizes content mining and machine learning methods to find valuable topics from the comments of the students. Clustering is an initial step to cluster the comments using a clustering algorithm. After data cleaning, the top frequency words will be clustered to extract actual topics. Clustering is a technique for grouping objects based on similarity. Clustering is executed dependent on examining the likeness or the disparity of every perception. Similitude and difference can be computed by a few distance measurements which are executed dependent on a subjective assurance by clients, as interpreted by (Li, 2019). The partitioning clustering approach refers to the process that "partitions the data points into k clusters such that the data points within a cluster are more similar to each other than data points in different clusters" (Zhao, Han & Pan, 2010). From the students' feedback to the extracted topic, the K-means clustering is employed using the formula of Li (2019) as conducted by performing the following steps: Set up K (arbitrary) number of clusters based on the requirement, finding central points of each cluster, assigning observations to their nearest clusters, and repeat 1st and 2nd steps.

Additionally, in the topic extraction stage, keyword extraction is utilized. It is known as a text analysis technique which is process-identified as automatically extracting the most important words and expressions in a text. It aids in summarizing the content of a text and recognize the main topics. In this way, the identification of the topics of the comments shall allow the results of this study to label which are being discussed by the students as their main concerns.

Sentiment Analysis

Finding the sentiment of each comment gives the academic council of the institution an investigation of aggregate conclusions against each topic or each cluster in the whole data collection. Estimation alludes to the inspiration or antagonism of a given remark. For instance, given the remark, "sometimes I cannot understand my instructor", the assumption is "negative". In this stage, the goal is to locate the general positive or negative sentiment for a given remark. The comments are subjected to a sentiment polarity computing algorithm. To achieve accuracy, in cases of incorrect classification, i.e., a positive polarity generates a negative polarity score, the study means to apply the use of n-grams particularly bigrams to further increase the precision of the approach (Rajput et al., 2016). To further analyze the performance of the proposed sentiment classification approach, recall, precision, and F-score shall be presented for all three classes (positive, negative, neutral). In this stage, the goal is to locate the general positive or negative sentiment for a given remark. The comments are subjected to a sentiment polarity computing algorithm. Polarity is a numerical value within the range [-1.0, 1.0] and subjectivity is within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective (Loria, 2018). Each word is scored and the cumulative score of the sentence will indicate whether the sentiment is positive (if greater than or equal to zero) or negative (if less than zero). The concept of mining the sentiment of the students' comments justifies the machine learning algorithm that generates a score between 0 and 1. Scores that are nearer to 1 signifies positive sentiment, and scores adjacent to 0 indicate negative sentiment. Values near to a score of 0.5 are neutral or indeterminate. A score of 0.5 signifies neutrality. When a string could not be analyzed for sentiment or has no sentiment, the score is always 0.5 exactly (Microsoft Azure, 2019).

Data Visualization

Data visualization provides user-friendly summaries of the quantitative results obtained from the previous phases. Once the comments have been clustered into topics and the sentiment for each cluster is known, the comments shall be categorized and will be presented in graphical form. To produce interactive dashboards, the results from sentiment analysis stages are combined. Through graphs and tables, the compiled results will be shown. The graphs are interactive in nature so that in each cluster of comments the faculty can carry out a deeper analysis of the topic or sentiment.

RESULTS AND DISCUSSION

Course Selection

The first objective of this study implies how the blended learning experience can be convalesced from its implementation based on a course stemming from the feedback of the students. The course selection in this quantitative approach discusses how the course was identified. In the conduct of the selection of which course to mine qualitative comments from, a responses summary was obtained in a quantitative approach. The researchers crafted analysis of the four (4) surveys conducted in the School Year 2019-2020. In the search of quantifying the course with the students most unsatisfied with the Canvas LMS, looking to aggregate the negative responses from the 22 Likert scale questions, the use of the Bottom Box (Strongly Disagree) is applied instead of the Top Box (Strongly Agree). Thus, citing the fifteenth question in the survey: "*I notice that course materials on Canvas have a connection with the face to face (classroom) lesson content,*" this and all the Likert scale questions were answered by the students "agreeing to disagree." The bottom box quantifies the most unsatisfied students as seen in Table 1.

Table 1. Likert Scale - Bottom and Top Box

Bottom Box				**Top Box**
Strongly Disagree	Disagree	N/A	Agree	Strongly Agree
1	2	3	4	5

Here are the stages of how the course was identified:

- For each Likert-scale question in this survey, the total number of responses of the bottom-box (Strongly Disagree) was retrieved.
- Per total Strongly Disagree responses in each question, the course with the highest bottom-box response is derived.

- From this result, an aggregate count of all courses with the highest number of "Strongly Disagree" responses is stemmed.

From the data of the survey conducted in the first 6 weeks of the semester, thus called the Prelim term of the 1st semester of SY 19-20, the course HIS C101-Readings in Philippine History appeared 26 times as the highest number of students who responded Strongly Disagree in the questions. A total of 506 bottom box responses were recorded. In the Final term of the same semester, the same course, HIS C101- Readings in Philippine History appeared 24 times as the highest number of students who responded Strongly Disagree with the questions. A total of 823 bottom box responses were recorded. In the 2nd semester of the same school year, the Prelim term run of the survey recorded the course, HUM C102 Art Appreciation with 14 times appearance as the highest number of students who responded Strongly Disagree in the questions. A total of 204 bottom box responses were recorded. For the Final term of the 2nd semester in the same school year, the course NST C102 National Service Training Program 2 has appeared 23 times as the highest number of students who responded Strongly Disagree in the questions. A total of 738 bottom box responses were recorded. From these, it is notable that the highest bottom-box responses belong to HIS C101-Readings in Philippine History, a general education course, as it appeared in the 1st-semester results twice. Table 2 presents a summary.

Table 2. Summary of Bottom Box (SD) Responses

Canvas Experience Survey Run	Course	# of SD Responses per Question	Total SD Responses	# of Respondents
Prelim Term 1st Semester	HIS C101	26	506	2914
Final Term 1st Semester	HIS C101	24	823	3935
Prelim Term 2nd Semester	HUM C102	14	204	6679
Final Term 2nd Semester	NST C102	23	738	1520

The university's Canvas Experience Survey is the tool to be used in the data collection of this study. The Canvas Experience survey contains a total of 28 questions identifiably 3 for course information, 22 Likert-scale questions, and 3 qualitative questions on accessibility, instruction, and assessment and collaboration. The last 3 qualitative input inquiries result in the commentary part of students' least and best features of Canvas and their suggestions for improvements. The manner from which students will answer the survey is through an anonymized online survey. The students' input data will come from one blended learning course in the university's ITBL managed courses. In the conduct of this study, all 28 questions excluding course information doubles into qualitative questions as the students will be asked to type down their opinions and ideas that concern them relating to the Likert scale question stated. In this interval, the course information is removed to secure the anonymity of the responses. The survey will be floated online, and the link shall be provided to the students.

The goal of text analytics also referred to as text data mining or text mining is to derive high-quality information from text. Typical text mining tasks include text categorization, text clustering, concept or entity extraction, production of granular taxonomies, sentiment analysis, document summarization, correlations, and entity relation modeling (Gottipati et al., 2017). Throughout this study, the following phases model the text analytics approach.

Text Mining Approach

The second specific objective on how numerous unstructured student comments can produce topic clusters to address recommendatory action plans is apprehended in the stages of the text mining approach discussed subsequently. In the first phase, data collection is executed. The comments function as the input as the pre-processed data. The second phase is to extract individual sentences and phrases using tokenizers. Tokenization deals with the splitting of text into units during data preprocessing. Text can be tokenized into paragraphs, sentences, phrases, and single words. The delimiters used in this process vary with data sets (Nitin et al, 2015). In the stop word removal, the most frequently used words in English are useless in text mining as they will be removed. Stop words are language-specific functional words that carry no information and are therefore removed from the documents during the data preprocessing stage (Nitin et al, 2015). POS tagging and transform cases will also be applied to the process. The third phase will be extracting the topics using clustering techniques. The last stage is the visualization. The solution model for mining the feedback of the students' qualitative data shall undergo the following processes:

Text Pre-Processing

The comments of the students will undergo data cleaning, enumerating the following pre-processing phases. This involves text pre-processing which pertains to the practice of preparing and cleaning the text data, thus qualitative comments of the students. Table 3 shows the text pre-processing stages.

Table 3. Text Pre Processing Stages

Student's Feedback in a Document	Tokenized words	After Stop Words Removal	POS Tagging
I can access the modules and I have always been notified when there are things to do or announcements.	[I, can, access, the modules, and, I, have, always, been, notified, when, there, are, things, to, do, or, announcements]	access module notified announcements	VB NN VBD NNS

Topic Extraction Stages

The third specific objective of the study on how the clustered feedback sentiment be aligned to course improvement with a recommended action plan is recognized in the stages of topic extraction and sentiment analysis. As topics and sentiments are generated, suggested action plans, and which division will address them will reflect. As the study intends to utilize keyword extraction to quickly identify the main points of the student comments, the computation of the document terms with their frequencies, document topics, and term topics was derived to result in the extracted topics in Table 4. It depicts a sample of comments and extracted topics.

Table 4. Sample Student Comments and Extracted Topics

Student Comments	Topics
The prof never disappoints us.	Faculty interaction
my prof good at teaching by using the canvas	Faculty preparation
sometimes I cannot understand my instructor	Faculty feedback
I can access the modules and I have always been notified when there are things to do or announcements.	LMS modules
I think it's fine but I would suggest another notification just in case an announcement or things to do that aren't been seen or get override by other tasks or by a slow connection.	Announcement notifications, slow connection

Sentiment Analysis

Finding the sentiment of each comment gives the academic council of the institution an investigation of aggregate conclusions against each topic or each cluster in the whole data collection. Table 5 portrays the student comments and their sample-generated and extracted topic including the sentiment label and the polarity score.

Table 5. Sample Document for Comments with Sentiment Label and Polarity Score

Student Comments	Extracted Topic	Sentiment	Polarity Score
The prof never disappoints us.	Faculty interaction	Positive	0.98570585250854492
my prof good at teaching by using the canvas	Faculty preparation	Positive	0.0785155147314072
sometimes I cannot understand my instructor	Faculty feedback	Negative	0.0141316400840878
I can access the modules and I have always been notified when there are things to do or announcements.	LMS modules	Positive	0.98570585250854492
I think it's fine but I would suggest another notification just in case an announcement or things to do that aren't been seen or get override by other tasks or by a slow connection.	Announcement notifications, slow connection	Negative	0.0046278294175863

Data Visualization

The fourth and last specific objective on how a feedback mining process exemplifies its value to learners, faculty, and administrators is addressed in data visualization and the development of a feedback mining process. In data visualization, the study intends to provide interactive graphs and user-friendly summaries of the results of the extracted topics, the sentiments, and its polarity scores. The graphs are interactive in nature so that in each cluster of comments the faculty can carry out a deeper analysis of the topic or sentiment.

Feedback Mining Process

The course feedback mining process shall have the following menus and features from its inception to application. They are Student Login, Student access to Canvas Experience Survey, and Administrator access to results which shall display the Clustered Topics (as modeled in Table 4), Visualization Report of Sentiment Analysis Scores – This shall portray an interactive dashboard that indicates actual results as students' feedback is entered and mined, and Action Plan Recommendation and Generator – based on the topics extracted and the sentiment scoring, extracted topics with negative sentiment scores shall be directed to the appropriate department but not limited to Academic Council (Dept. Chair, Dean, VP for Academics) – faculty related feedback, Institute of Technology-Based Learning – Canvas related comments about modules, assessment, etc., and Information Technology Office – in-campus related access connection issues.

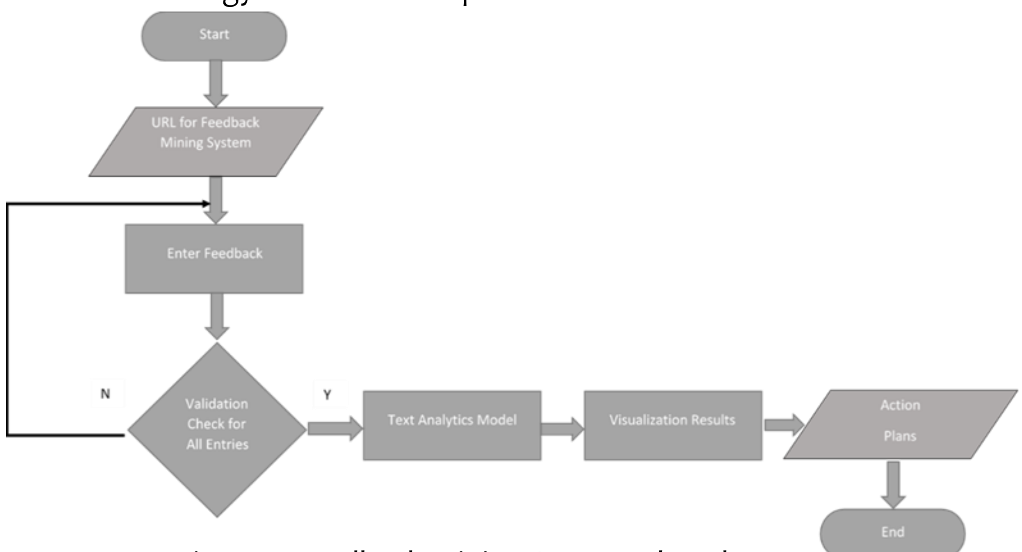

Figure 2. Feedback Mining Process Flowchart

An action plan generator interface with a timeline will be provided and the appropriate offices shall facilitate input. Positive sentiment scores shall be subjected to appropriate offices similarly and action plans may be in the forms of commendations and incentives based on performance indicators in the employee appraisal form. Figure 2 illustrates the flowchart of the system entirety. This feedback mining process will then lead to the development of a feedback mining system.

CONCLUSIONS AND RECOMMENDATIONS

This study is aimed at the development of a feedback mining process to improve the blended learning implementation of a general education course managed and offered by the College of Arts, Criminology, and Education in Jose Rizal University. An analysis has been conducted to determine the course with the most students who strongly disagreed on their Canvas Experience Survey. From Likert scale questions and results analysis, the course HIS C101-Readings in Philippine History flaunted to be the most with strong disagreement from student responses. The qualitative questions of the survey are then set to serve as textual data representing students' feedback in the teaching and learning process in the education context and are consequently analyzed through the text mining process to produce valuable topics, clusters, and sentiment scoring. The study suggests consorting with proposed action plans to assist administrators in retaining the implementation of the courses in the blended learning programs. With the feedback mining process in place, it may serve as a channel and basis for improving the blended learning experience of the students. More so to aid and expedite the university stakeholders in their process of course improvement cycles of the blended learning programs of the university.

RESEARCH IMPLICATIONS

Learner criticism is invariably considered vital if an institution has the vision of constant assessment and distinct methods in the improvement cycle on how they implement the teaching and learning process. Any improvement in the cycle must take the client's feedback as input and thus converted it into definite action plans. This research is timely and immutable as diverse modes have come across the practices of teaching and learning in the world at large. Further, the Philippine system of education is in continuous pursuit to deliver quality in any kind of abrupt change in the environment as it is thriving the educational landscape at present times due to a pandemic.

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