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SENTIMENT ANALYSIS ON THE IMPLEMENTATION OF LIMITED FACE-TO-FACE CLASSES USING NAÏVE BAYES ALGORITHM: A STUDENT'S POST-PANDEMIC PERSPECTIVE

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Abstract

With the drop in COVID-19 cases, hybrid learning modality has been the solution by the Philippine government to address the concern of higher education institutions (HEIs) on delivering virtual and onsite classes simultaneously. Bulacan State University, an HEI in the City of Malolos, Bulacan, started implementing limited face-to-face classes, following the provisions and guidelines of the Philippine government. The study utilised a sentiment analysis approach to determine the students' thoughts and feelings toward limited face-to-face classes enrolled in the College of Information and Communications Technology (CICT). The polarity of the student responses was grouped accordingly, whether positive, negative, or neutral. The Naïve Bayes algorithm was utilised to train a model to analyse the annotated data. The accuracy for the students' online learning conditions is 88.74%, and 91.59% for implementing limited face-to-face classes. It has been found that during online learning, students' conditions were more on the negative polarity with a predicted negative class precision of 99.43%, which reduces their engagement and motivation in learning due to surroundings and technical problems. However, it has been highlighted that students found that the implementation of limited face-to-face learning is more on the positive polarity with a predicted positive class precision of 96.40%, which presents that limited face-to-face learning has a positive outcome for the students. With such positive results for the students, universities, specifically Bulacan State University, should continue developing guidelines on the continuity of face-to-face classes aligned with the mandates of the Philippine government.

Keywords: Face-to-face learning, Higher education, Machine learning, Naïve Bayes algorithm, Post-pandemic, Sentiment analysis.

1. Introduction

Starting in 2021, countries have begun shifting from online classes to hybrid learning modalities as the Coronavirus Disease 2019 (COVID-19) threats have been reduced on a global scale, allowing countries to shift to their known traditional, face-to-face classes slowly. Universities around the globe have started implementing the hybrid learning modality, a learning modality that enables the combination of two worlds, online learning, and in-person learning [1, 2]. The hybrid learning modality allows students to be present online and present in person to learn the same lesson conducted by their professors through information and communication technology (ICT). ICT enables the conduct of hybrid learning where faculty members discuss in person and are also joined in a video conferencing to share the discussion with students present online [3, 4]. This learning modality opens new doors to higher education as a possible modern approach and a silver lining from what the COVID-19 pandemic has brought.

The Republic of the Philippines, through the initiative of the Commission on Higher Education (CHED), together with the Department of Health (DOH), crafted a guideline about implementing limited face-to-face learning as the threat of COVID-19 reduces in the country [5]. In addition to such a guideline, CHED provided additional guidelines on implementing limited face-to-face learning in higher education institutions (HEIs) in the alert level 1 system [6].

As the Province of Bulacan is one of the provinces situated under the alert level 1 system, Bulacan State University (BulSU) started reviewing its current learning modalities. It provided guidelines for implementing limited face-to-face learning (F2FL) starting in 2021 [7]. After that, BulSU started implementing a hybrid flexible (HyFlex) learning modality during the first semester of the academic year 2022-2023. HyFlex learning modality allows the students to have a cyclical shifting schedule where half of the class is present in person, and half will be online. The shift will be reversed in the succeeding week to allow each student to experience the limited face-to-face classes. Faculty members use web cameras to be seen online by the students while discussing, utilising the video conferencing platform used within the university [8]. One of its colleges, the College of Information and Communications Technology (CICT) is actively implementing the HyFlex learning modality the university requires. With the lack of classrooms available in the college due to repairs and renovations, only selected courses have implemented the limited face-to-face classes from the Bachelor of Science in Information Technology (BSIT) and Bachelor of Library and Information Science (BLIS) programs. Since BSIT and BLIS students have grasped online learning already, transitioning from purely online learning to a hybrid learning modality will raise different opinions, thoughts, and feelings among the students of BulSU-CICT.

Having that said, the study aimed to analyse the opinions, thoughts, and feelings of BSIT and BLIS students on the limited face-to-face learning implementation. To deliver the sentiment analysis, natural language processing (NLP) and machine learning (ML) techniques were employed to determine the polarity of responses [9, 10].

The researchers listed several research attempts regarding sentiment analysis to address similar concerns, which served as the reference for this study. Table 1 shows the list of related research studies, including the title, machine learning used, and accuracy obtained.

Table 1. Existing sentiment analysis research studies.

Reference	Title	Machine Learning Used	Accuracy Obtained
Villavicencio et al., 2021 [11]	Twitter Sentiment Analysis towards COVID-19 Vaccines in the Philippines Using Naïve Bayes	Naïve Bayes	81.77
Delizo et al., 2020 [12]	Philippine Twitter Sentiments during Covid-19 Pandemic using Multinomial Naïve-Bayes	Multinomial Naïve Bayes	72.00
Abbas et al., 2019 [13]	Multinomial Naive Bayes Classification Model for Sentiment Analysis	Multinomial Naïve Bayes	91.00
Malik and Kumar, 2018 [14]	Sentiment Analysis of Twitter Data Using Naive Bayes Algorithm	Naïve Bayes	81.64
Samonte et al., 2017 [15]	Sentiment and opinion analysis on Twitter about local airlines	Naïve Bayesian, Support Vector Machine and Random Forest	66.67
Proposed Method	Sentiment Analysis on the Implementation of Limited Face-To-Face Classes Using Naïve Bayes Algorithm: A Student's Post-Pandemic Perspective	Naïve Bayes	91.59

In a sentiment analysis study conducted by Villavicencio et al. [11] titled "Twitter Sentiment Analysis towards COVID-19 Vaccines in the Philippines Using Naïve Bayes", the Naïve Bayes classifier was employed, achieving an accuracy of 81.77%. A reference to the previously mentioned study was also listed, which is Delizo et al.'s study [12], "Philippine Twitter Sentiments during COVID-19 Pandemic using Multinomial Naïve-Bayes", which also utilised a Naïve Bayes approach, yielding an accuracy of 72.00%. Additionally, Abbas et al.'s research [13], "Multinomial Naïve Bayes Classification Model for Sentiment Analysis", reported a higher accuracy of 91.00% with the Multinomial Naïve Bayes method. Malik and Kumar's study [14], "Sentiment Analysis of Twitter Data Using Naïve Bayes Algorithm", achieved an accuracy of 81.64% using the Naïve Bayes classifier.

Samonte et al. [15] also published another study entitled, "Sentiment and Opinion Analysis on Twitter about Local Airlines", which compared Naïve Bayes, Support Vector Machine, and Random Forest, finding Naïve Bayes to be the most accurate among the three with an accuracy of 66.67%.

The proposed method in this study using the Naïve Bayes algorithm regarding the Implementation of Limited Face-To-Face Classes in the BulSU-CICT achieved the highest accuracy of 91.59% using the Naïve Bayes classifier. As seen in Table 1, the researchers attempted to develop sentiment analysis in their chosen topics utilising the Naïve Bayes classification method and successfully attained competitive accuracy. Some key points noted in choosing Naïve Bayes in performing sentiment analysis were its simplicity and efficiency, relatively high performance or accuracy in dealing with high dimensional text data, scalability, and ease of training and updating, which are indispensable for sentiment analysis problems.

Problem statement

This study answered the following research questions explicitly:

- What are the students' conditions during online learning?
- What are the students' thoughts and feelings on the limited face-to-face learning implementation?

2. Related Work

2.1. Online learning

Online learning has been explored by universities and colleges even before the outbreak of the Coronavirus Disease (COVID-19) [16, 17]. During the pandemic, to continue education delivery, universities shifted to online learning, a pedagogical approach that enables the delivery of instruction using an online medium [18, 19]. Rosa [20] and Mukhtar et al. [19] have explored the advantages students can get from online learning. They have found out that students are likely to finish online courses when engaged and motivated, compared to a self-paced approach which lessens the motivation of students to complete the enrolled course. However, Adnan and Anwar [18] have highlighted that online learning is not advantageous to all, specifically to students who have intermittent internet connectivity, and to those who barely even have internet connectivity at all.

This study aimed at identifying students' learning conditions during their online learning, before transitioning to limited face-to-face classes, as mandated by the Philippine government. The researchers explored the polarity and subjectivity of the student's thoughts and feelings toward their learning conditions on online learning.

2.2. Face-to-face learning during the pandemic

With the silver lining presented by the drop in COVID-19 cases in the country, the Philippine government, starting mid-2021, has provided guidelines that will aid online learning and start implementing limited face-to-face learning [5, 6]. Limited face-to-face learning will enable students to attend virtual and onsite classes at a time, to slowly bring back the traditional, face-to-face courses, which was found to be one of the major issues during online learning [18].

The researchers, with the implementation of limited face-to-face learning at Bulacan State University, aimed at determining students' thoughts and feelings toward implementing such a learning modality amid the pandemic. The study aimed to highlight students' experiences and their polarity, be it positive, negative, or neutral, to understand students' sentiments toward implementing limited face-to-face learning. Additionally, students' thoughts and feelings will be visualised to easily determine the most frequent words used to express their feelings and thoughts on the implementation of limited face-to-face classes.

2.3. Sentiment analysis using machine learning

Machine learning (ML), a subset of artificial intelligence (AI), is a technique that aims to provide computer programs (machines) that learn [21-23]. Machine learning aims to learn from past events to predict what could happen in the future [24, 25]. Several studies have already used machine learning techniques to analyse sentiment. Agarwal and Mittal [26], Ahmad et al. [27], Rosa and Abad [28], Hasan et al. [29], and Jain and Dandannavar [30] have used machine learning techniques in their studies to deliver sentiment analysis. Historical data has been collected and gathered, undergone cleaning, training, and testing, visualised, and interpreted the results.

Additionally, several studies have utilised the Naïve Bayes algorithm to conduct a sentiment analysis. Abbas et al. [13], Delizo et al. [12], Malik and Kumar [14], Samonte et al. [15], and Villavicencio et al. [11] have utilised the Naïve Bayes algorithm in conducting their sentiment analysis in their studies. The results of their studies showed an accuracy range from 70% to 90%, highlighting the use of Naïve Bayes as a quality algorithm when dealing with sentiment analysis.

This study aims to utilise the same technique, the Naïve Bayes algorithm, in delivering a sentiment analysis approach to the student's thoughts and feelings on the students' conditions on online learning and implementation of limited face-to-face classes. The researchers' target is to understand students' sentiments on their conditions of online learning and the implementation of limited face-to-face learning if they are positive, neutral, or negative sentiments

3. Methods and Design

3.1. Participants demographic profiles

Upon the conclusion of the first semester of the academic year 2022-2023, students from the College of Information and Communications Technology (CICT) of Bulacan State University (BulSU), specifically those under the Bachelor of Science in Information Technology (BSIT) and Bachelor of Library and Information Science (BLIS) programs have been identified as the respondents of the study. CICT's total population during the data collection is 2,973 students from BSIT and BLIS programs. To select sample data from the population, the researchers intend to use a simple random sampling technique. Table 2 presents the demographics of the student participants.

Table 2. Respondents' demographic profiles.

Program	Frequency (*N*=903)	Percentage (%)
BSIT	***n*=885**	**98.01**
1st-Year	207	22.92
2nd-Year	67	7.42
3rd-Year	288	31.89
4th-Year	323	35.78
BLIS	***n*=18**	**1.99**
2nd-Year	15	1.66
3rd-Year	3	0.33

Respondents who participated in the survey are 98.01% (885 out of 903) BSIT students and 1.99% (18 out of 361) BLIS students. The number of student respondents came from the majority of the BSIT program as this is the largest program in the College of Information and Communications Technology, with at least 10 sections per year level.

3.2. Data collection

This study utilised a survey questionnaire sent to the faculty advisers of the students for distribution at the end of the first semester of the academic year 2022-2023. The questionnaire was developed using Google Forms, which contained questions regarding the student's degree program, year level, and section. Then, students were asked two open-ended questions: 1) "What are your learning conditions during the pandemic?" and 2) "What are your thoughts and feelings on the implementation of limited face-to-face classes this 1st Semester, A.Y. 2022-2023?" The students were informed of the purpose of the data gathering through informed consent. Students were also assured that their data would be treated with confidentiality. The survey questionnaire was open until before the beginning of the second semester of the academic year 2022-2023.

3.3. Data preparation and preprocessing

Upon the conclusion of data collection using a Google Form, the number of student responses was 903, 885 from BSIT students and 18 from BLIS students. Students were advised to answer in English as these are the only words to be processed for analysis. The two (2) questions asked to the students were annotated with their polarity, either positive, negative, or neutral polarity. Only 666 responses were included upon data preparation and preprocessing for the students' online learning conditions. On the other hand, for the student's thoughts and feelings toward implementing limited face-to-face classes, only 714 responses were included after they went through data preparation and preprocessing. The following processes are applied to the dataset in preparation for natural language processing (NLP).

3.3.1. Data cleaning

This process involves the removal of numbers and special characters from the student responses. This process also includes the transformation of all letters into lowercase letters.

3.3.2. Tokenization

This process involves the removal of white spaces and punctuation marks on the student responses. This process also splits the responses into individual words.

3.3.3. Stopword removal

This process involves the removal of stopwords. During this process, common stopwords such as "a," "an," "the," "of," "at," and the like were removed. The operator Filter Stopwords English was used to process the removal of the stopwords.

3.3.4. Stemming

This process involves returning the base form of the words from the student responses, e.g., happy, happier, and happiest, which can be stemmed to its base form, “happy.”

3.4. Training and testing models

Several models can be used to analyse students' sentiments on their online learning conditions and the implementation of limited face-to-face learning. The three common machine learning algorithms used in sentiment analysis are Logistic Regression, Naïve Bayes, and Support Vector Machine (SVM) algorithms. The RapidMiner Studio was used to train and test the models in doing sentiment analysis.

Regarding accuracy in predicting sentiment analysis on students’ online learning conditions, Logistic Regression resulted in 76.85% accuracy, Naïve Bayes resulted in 88.74% accuracy, and SVM with 60.36% accuracy. In terms of the sentiments of students on the implementation of limited face-to-face learning, Logistic Regression resulted in 87.76% accuracy, Naïve Bayes resulted in 91.59% accuracy, and SVM resulted in 75.68% accuracy.

Comparing the performances of the three algorithms mentioned above, the researchers decided to use the Naïve Bayes algorithm since it presented the highest accuracy in determining the sentiments of students on both online learning conditions and on the implementation of face-to-face learning. In contrast, Naïve Bayes resulted in 88.74% and 91.59% accuracies, respectively.

4. Results and Discussion

4.1. What are the students’ conditions during online learning?

Regarding the students’ online learning conditions, students who found that online learning is advantageous on their end were annotated as positive. Students who felt difficulties in the delivery of online learning were marked as negative. Lastly, students who either have a good or difficult condition during the delivery of online learning were marked as neutral. Figure 1 presents the polarity of the student responses as annotated.

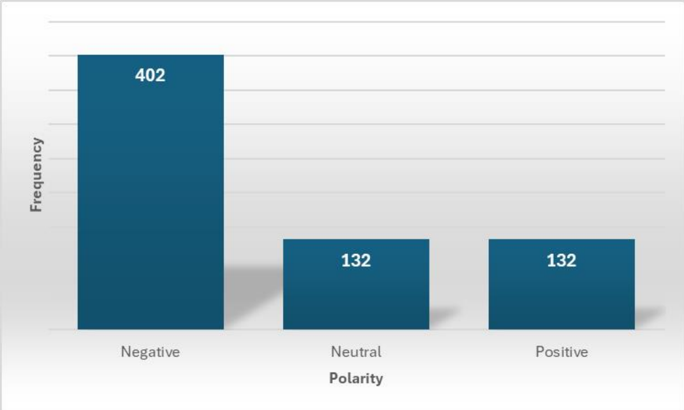

Fig. 1. Frequency of online learning conditions polarity.

Students' responses regarding their conditions during online learning were annotated with the majority of negative polarity (402 out of 666). On the other hand, students' responses were annotated as positive (132 out of 666) and neutral polarity (132 out of 666). The Naïve Bayes algorithm was used for training and testing [31], and the results displayed that the model achieved 88.74% accuracy. The conditions of the students throughout online learning are depicted in Table 3 with the confusion matrix, which contains the true positives, neutrals, and negatives as well as the number of predicted items. Percentages for precision and recall were also calculated.

Table 3. Confusion matrix on the students' online learning conditions.

Label	True Negative	True Neutral	True Positive	Class Precision
Predicted Negative	**348**	0	2	99.43%
Predicted Neutral	34	**129**	16	72.07%
Predicted Positive	20	3	**114**	83.21%
Class Recall	86.57%	97.73%	86.36%	

The last column shows the class precision percentage, while the rest of the columns reflect the predicted neutral, predicted positive, and predicted negative polarities according to the developed model. In contrast, the rows show the dataset's true positive, neutral, and negative sentiments, while the last row shows the class recall percentage. Based on the findings, the developed model accurately predicted 348 negative feelings out of the 350 true negative sentiments that were classified, giving the negative polarity a class precision of 99.43% and a class recall of 86.57%. For negative, neutral, and positive polarities, 348, 129, and 114 were correctly predicted sentiments.

To evaluate the performance of the proposed method, the researchers documented other statistical measures such as kappa values, precision, and recall. The developed model has achieved .810 kappa, which signifies that the predicted values have almost perfect agreement with the actual values in the dataset. Having high kappa values means that the model's prediction is highly reliable.

Moreover, two additional statistical measures used were precision and recall, the developed model attained 85.88% precision and 90.29% recall. Precision tells the researchers how well the model performs in predicting true positives over all the predicted positives by dividing the true positive by the sum of true positives and false positives, it can be calculated using this formula:

$$Precision = TP \ / \ TP+FP \tag{1}$$

Recall measures how well the model performs in predicting true positives compared with the actual positive instances in the dataset. In our case, recall answers the question of how many of the positive polarities were correctly predicted by the model. Recall percentage can be obtained by dividing the true positives by the sum of true positives and false negatives [32].

$$Recall = TP/ \ TP+FN \tag{2}$$

Based on the results, it can be drawn that the model has successfully attained high percentages in precision and recall measures, having 85.88% and 90.29%, respectively. To visualise students' sentiments regarding their online learning conditions on each polarity, a word cloud was presented. Figure 2 presents the word cloud on students' sentiments on their online learning conditions separated as positive, neutral, and negative.

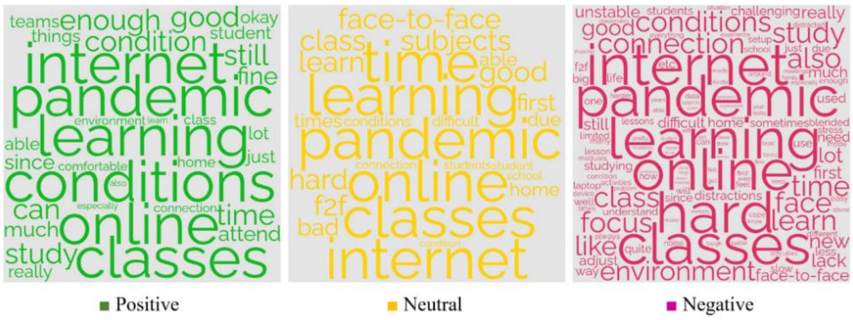

Fig. 2. Word clouds on students' positive, neutral, and negative sentiments regarding their online learning conditions.

Figure 2 presents, the largest words are the most mentioned from each polarity. The most highlighted words from the word clouds are "pandemic," "online," "learning," and "internet". Regarding the students' positive sentiments on their online learning conditions, a student mentioned, "Honestly, the learning modality is convenient because we have time to do our activities based on our convenience and available time". Another student stated, "Because the lessons and sessions are recorded, I can go back and review whatever I don't understand, which improves my learning conditions during the pandemic." These sentiments have highlighted the advantages students have during the pandemic.

In terms of the neutral sentiments of the students, a student mentioned, "At first, it was difficult to **learn,** but as time went by and I got used to an **online** setting, I **learned** to manage things correctly." Another student has the same sentiment and mentions, "Good and **learn** a lot during **online** class but sometimes bad due to **internet** connection".

Lastly, regarding the students' negative sentiments, a student complained, "Hard to be honest. I struggle to learn because it's noisy here, and you have responsibilities at home that overlap with my **learning** time". Another student complains mostly about their internet connection and mentions, "I have experienced difficulty in **learning** our courses. There are also times that I lost my **internet**, and I couldn't attend my class". Another student had the same complaint on their internet and said, "I'm having a hard time focusing on my studies because of my **internet**."

4.2. What are the students' thoughts and feelings on the limited face-to-face learning implementation?

Figure 3 displays a graphic representation of the polarity of the students' opinions and sentiments toward introducing limited in-person learning. Positive polarity was assigned to respondents who support using limited in-person instruction, whereas negative polarity was assigned to respondents who do not. Respondents who weren't sure about the restricted face-to-face deployment were assigned a neutral polarity.

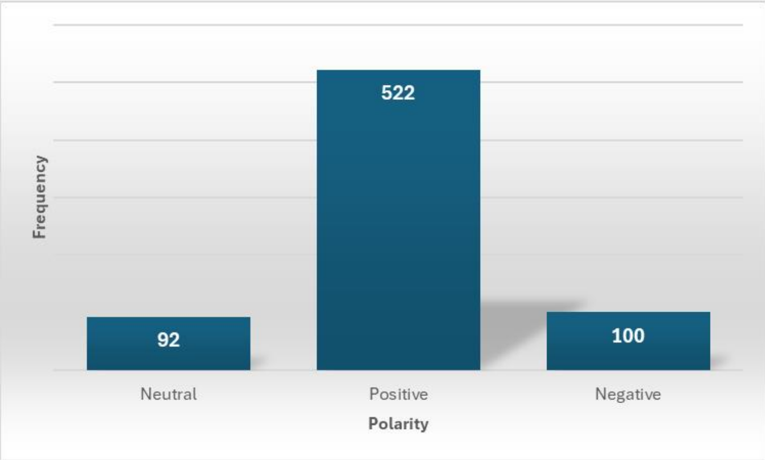

Fig. 3. Frequency of students' thoughts and feelings on the limited face-to-face learning implementation.

The Naïve Bayes algorithm was used for training and testing [31], and the results showed that the model had a 91.59% accuracy rate. Regarding their opinions on implementing the limited face-to-face learning at Bulacan State University, the confusion matrix, which contained the true positive, neutral, and negatives as well as the number of predicted items, is displayed in Table 4. Additionally, percentages for recall and precision were calculated.

Table 4. Confusion matrix on the implementation of limited face-to-face learning.

Label	True Neutral	True Positive	True Negative	Class Precision
Predicted Neutral	**74**	34	0	68.52%
Predicted Positive	16	**482**	2	96.40%
Predicted Negative	2	6	**98**	92.45%
Class Recall	80.43%	92.34%	98.00%	

Based on the results, the developed model predicted 482 positive sentiments among the 522 labelled true positive responses, which equates to a class precision of 96.40% and class recall of 92.34% for the positive polarity. The numbers in bold format indicate the number of accurately predicted polarities. Thus, 74, 482, and 98 accurately predicted sentiments for neutral, positive, and negative responses, respectively.

Other measures used for the sentiments of students on limited face-to-face learning implementation, same with their online learning conditions, were kappa, precision, and recall. The Naïve Bayes algorithm calculated a .953 kappa, which shows that there is an almost perfect agreement with the actual values from the dataset on students' sentiments on limited face-to-face implementation.

In terms of precision and recall, the model received a 96.40% precision and a 98.37% recall. Based on these results, the model attained correct prediction and was able to recognise all necessary and pertinent instances which presented that using the Naïve Bayes algorithm in classifying sentiments of students on limited face-to-face learning was the best model.

Figure 4 presents the word clouds of the students' sentiments toward implementing limited face-to-face learning. On limited face-to-face learning, several classes of students from selected courses were conducted on campus. The rest of their classes were conducted online. Students have mixed emotions regarding this, having positive, neutral, and negative sentiments.

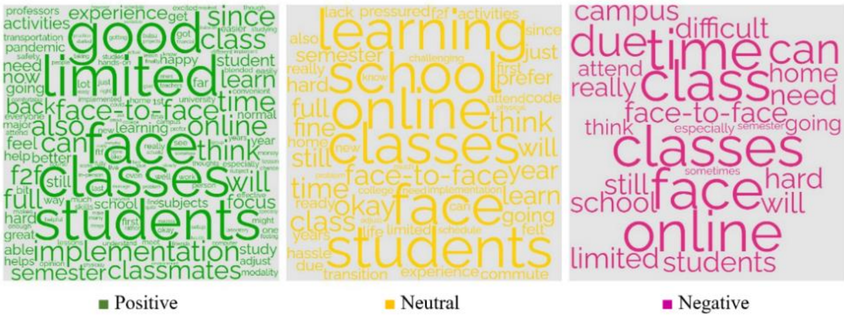

Fig. 4. Word clouds on students' positive, neutral, and negative sentiments regarding limited face-to-face implementation.

Highlighting what students have experienced, some words that stood out among their sentiments were "classes," "face," "good," and "online". In the students' negative sentiments, their adjustments were their concerns, as one of the students said "I was hesitant and nervous because we came from **online classes** therefore, we really need to adjust and adapt to the new modalities. It is really hard, and you need a lot of motivation to continue." Some wanted full implementation of face-to-face classes rather than a limited setup. A student mentioned, "I am not in favour of the limited **face**-to-**face** and much like it to be in full **face**-to-**face classes** because years have passed, and I want some in-person interactions with my classmates and peers".

On students' neutral sentiments, a student mentioned, "For me, I'm not in favour of face-to-face, but I'm not against it either. I want blended learning because we know we have limited facilities in our dear school." Some students were favourable of the setup but still encountered several such as their travel from their homes to the campus. A student said, "Having limited **face**-to-**face classes** gives us students an ability to ask directly to our professors on some of our concerns in some matters but it's a bit hard for us students to commute 2-3 times a week."

Highlighting the students' positive sentiments, some have mentioned what they have gained from this setup. A student said, "As a daughter of a solo parent the implementation of limited **face**-to-**face classes** this 1st Semester, A.Y. 2022-2023 is best for me because it saves more money." Since they do not have to commute to attend some of their classes, their parents were able to save more money on the limited face-to-face setup. Another student also mentioned, "During my first weeks of implementation of limited face-to-face, my learning cognitive skills is very improved, and I discovered new things." This highlighted the beauty of conducting face-to-face classes, where students have actual interaction with their professors. Lastly, another student said, "**Face**-to-**face classes** will help me to focus on certain tasks and schoolwork." This proves that such a setup served the students well in their learning conditions.

5. Conclusions and Recommendations

Upon analysing the students' thoughts and feelings regarding their online learning conditions, it has been concluded that using the Naïve Bayes algorithm to train and test students' sentiments, the accuracy for the students' online learning conditions is 88.74% and 91.59% for the implementation of limited face-to-face learning. Students have a negative polarity with a class precision of 99.43% and class recall of 86.57% regarding their online learning conditions since they are losing focus, engagement, and motivation in learning and having technical problems such as poor internet connection and no available device. However, students' thoughts and feelings regarding the implementation of limited face-to-face learning were a positive polarity with a class precision of 96.40% and class recall of 92.34%, which presents that the students appreciated the return of the traditional, face-to-face classes, even in a limited scale of attending onsite courses, combined with virtual classes through hybrid learning modality implementation.

With the study's conclusions, the following are the highlighted recommendations: (1) Further studies should explore the thoughts and feelings of a larger population, targeting students across other disciplines as well; (2) Universities should consider developing policies that will guide students in their studies while implementing traditional, face-to-face classes; and (3) HEIs should explore options for students more than face-to-face classes as hybrid learning presented advantages as well in the learning of the students.

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