

Prediction Model for Depression Associated with Online Learning during Pandemic using K-means Clustering and Particle Swarm Optimization

**Hex Allain J. Guirigay, Archelle D. Lumayag, Roseclaremath A. Caroro,
Von Phillip F. Cabando, May Caroline J. Canggag, Markdy Y. Orong,
Hidear Talirongan, Rolysest K. Paredes**

College of Computer Studies, Misamis University, Ozamiz City, Philippines

Corresponding author: Roseclaremath A. Caroro, email: claire130705@gmail.com

Abstract

Most prediction models for depression do not focus on online learning as a primary area of concern. Hence, the study utilized data mining techniques and machine learning to design a prediction model that could forecast the factors related to depression in online learning. Moreover, the model used dataset normalization, attribute selection, clustering, and optimization techniques such as K-means and particle swarm optimization to extract the predictors from the data. The model identified 18 predictors out of the 55 predictors listed in the following instruments used in the study: the Patient Health Questionnaire-9, the University Student Depression Inventory, and the Quality of Student Life since Transition from a dataset of 305 respondents for the simulation. As a result, the model identified at least 28 respondents (9%) indicating depressive symptoms based on the data used to simulate the model's performance.

Keywords: depression, clustering, COVID-19, prediction model, e-learning, optimization

Introduction

Online learning, particularly in higher education, is favorable as a learning medium because of its flexibility and accessibility, quick update of educational materials, transparency in the educational process, and rapid availability of statistics in analyzing results (Wells et al., 2022). Many people opt to learn comfortably based on their availability and comfort. This approach enables the learners to access updated educational materials at their convenience, providing numerous benefits to students and reflecting its impact on their interests in using the resources and their performance (Radha et al., 2020; Wells et al., 2022). However, during the emergence and spread of COVID-19, which caused governments worldwide to close public and private establishments to limit its spread, educational institutions are among the severely impacted. The swift decisions and actions imposed by the Philippine government against the pandemic have been effective at best. Amidst the growing concerns regarding the pandemic, the educational sector postponed or canceled various activities at the beginning of March 2020. Universities acted rapidly to transfer various face-to-face courses and programs online (Sahu, 2020; Erarslan & Seker, 2021; Moreno et al., 2022). Many teachers in schools, colleges, or universities are already relying on different technological advancements and changing their pedagogical practices and teaching methods, applying the concepts of Open Educational Resources (OER), the Flipped Classroom (FC), blended learning, and Massive Open Online Courses (MOOCs), among others (Gupta & Gupta, 2020; Elshareif & Mohamed, 2021; Erarslan & Seker, 2021). Hence, e-learning has become quite popular among students worldwide, even in rural localities. Yet, online learning may affect the mental health of college students as it affects their social relationships with peers while coping with social and academic pressures (Sahu, 2020; Son et al., 2020; Hansen-Brown et al., 2022), although there is no well-established causal link between online learning and depression.

Findings show that students and the general population may be experiencing psychological effects from the outbreak of COVID-19, such as anxiety, fear, depression, and worry, among others, due to online learning (Kedracka & Kaltsidis, 2020; Hansen-Brown et al., 2022). With these experiences, depression is one of the many mental health challenges college students face as it affects their psychological well-being (Pelucio et al., 2022; Manuaba et al., 2023). Like their motivation and concentration in learning, they begin doubting their self-worth and competence. In addition, the learning conditions in online learning affect their mood and sprout self-doubt, self-isolation, and overthinking. Pressures, worries, and difficulties overwhelm students, creating a negative outlook and impeding their learning capacities. As a result, students are more likely to experience the effects of mental health, especially depression (Ahmed et al., 2020).

Several assessment tools help in assessing certain depressive factors. For instance, the Fear of COVID-19 Scale (FCV-19S) measures the fear brought by COVID-19 (Ahorsu et al., 2020; Pang et al., 2020; Perz et al., 2020) which detects a link associated with fear of COVID-19, anxiety, and depression (Alyami et al., 2020; Bitan et al., 2020). Another tool, the University Student Depression Inventory (USDI), measures depressive symptoms among university students with three interrelated subscales, namely, cognitive/emotional, lethargy, and academic motivation (Khawaja & Bryden, 2006; Balbuena et al., 2021). In addition, the Patient Health Questionnaire-9 (PHQ-9) is another screening tool for depressive symptoms such as depressed mood, sleep disturbance, fatigue, appetite changes, low self-esteem, concentration problems, psychomotor disturbance, and suicide ideation (Lamela et al., 2020; Constantini et al., 2021; Jyoti et al., 2021). On the other hand, the tool for assessing the Quality of Student Life (QoSL) since the transition to online learning focuses on the issues related to technology, online learning experience, mental and emotional issues, financial hardships, and food security (Froman et al., 2020).

Considering that online learning became even more popular during the lockdown, its adaptation and implementation exposed challenges of digitalization among many countries (El Andaloussi et al., 2022). Even in first-world countries, students encountered barriers that challenged their social presence and self-efficacy (Garner et al., 2022). However, most of these predictors do not only focus on depression but on the association of different factors, including stress, anxiety, and depression, in measuring students' mental health in their online studies. Hence, with the sudden shift in educational learning and these alarming cases of university students' coping mechanisms, predictive modeling for depression associated with online learning can help to enable the academe to identify and seek help with the different challenges the students face in an online learning environment.

Literature Review

Fear of COVID-19 Scale (FCV-19S)

The Fear of COVID-19 Scale (FCV-19S) measures the fear brought by COVID-19 (Ahorsu et al., 2020; Pang et al., 2020; Perz et al., 2020), which detects a link with fear of COVID-19 virus, anxiety, and depression (Alyami et al., 2020; Bitan et al., 2020). In addition, the fear of COVID-19 correlates mostly with worry and stress and, to a lesser extent, with depression. Even though there was a lower correlation between fear and depression, the increased number of daily new cases and deaths aired in the media influenced the mood disorders of the person (Duan & Zhu, 2020; Klomek, 2020; Liu et al., 2020). Besides, during the early phases of the COVID-19 pandemic, studies detected moderate to severe anxiety, stress, and depression symptoms in the population of China (Huang & Zhao, 2020). In addition, the pandemic challenges the psychological responses and instances of insomnia among adults who are experiencing mental health disorders (Sun et al., 2021). Furthermore, younger populations are more vulnerable to anxiety and depressive symptoms (Huang & Zhao, 2021).

University Student Depression Inventory (USDI)

The University Student Depression Inventory (USDI) measures depressive symptoms among university students with three interrelated subscales, namely, cognitive/emotional, lethargy, and academic motivation (Khawaja & Bryden, 2006; Balbuena et al., 2021). This instrument includes thirty items from the Student Depression Inventory with categories on academic motivation, lethargy, and cognitive/emotional. In addition, the inventory generated results on the prevalence of depression, symptoms, and support among Australian undergraduate students (Loosemore et al., 2020). In addition, a study using USDI shows that gender and rural/urban educational background greatly contribute to depressive symptoms (Thwala & Pillay, 2023).

Patient Health Questionnaire-9 (PHQ-9)

The Patient Health Questionnaire-9 (PHQ-9) is another screening tool for depressive symptoms such as depressed mood, sleep disturbance, fatigue, appetite changes, low self-esteem, concentration problems, psychomotor disturbance, and suicide ideation (Lamela et al., 2020; Constantini et al., 2021; Jyoti et al., 2021). With its ease of use and accurate results, the primary care and clinics used PHQ-9 as a depression screening measure (Lamela et al., 2020). Moreover, the 9-item version of the tool is the most reliable (Constantini et al., 2021). During the height of the pandemic, the researchers and experts used the tool to assess the severity of the depressive symptoms of the respondents who experienced personal and professional hardship, fear, depression, anxiety, and somatic symptoms (Jyoti et al., 2021).

Quality of Student Life (QoSL)

The tool for assessing the Quality of Student Life (QoSL) since the transition to online learning focuses on issues related to technology, online learning experiences, mental and emotional issues, financial hardships, and food security (Froman et al., 2020). During the pandemic, students have difficulty communicating with instructors and classmates, performing coursework, and balancing priorities (Froman et al., 2020; Garner et al., 2022). The QoSL tool contains 42 items that draw insights that despite having technology at hand for the students, there is a problem in balancing their learning experiences and social interactions while having troubles with financial, housing, and mental health issues (Froman et al., 2020).

Data Modeling

Data modeling for prediction, for instance, exploits the vast data on the mental health status of students and processes them to generate useful information that helps in decision-making. Modeling data includes several steps, including preprocessing, data treatment and analysis, interpretation, and evaluation. Data preprocessing aims to reduce or eliminate disturbances such as experimental error, missing data, noisy data, and inconsistent data to provide a more appropriate result. For instance, the attribute selection methods reduce the dimensionality of the features, increase the accuracy of classification, and prevent overfitting (Naheed et al., 2020; Dikshit-Ratnaparkhi et al., 2021) with three types: filter, wrapper, and embedded methods (Bashir et al., 2022; ElDahshan et al., 2023). According to the different metrics, the filter type evaluates the relationship between a single feature variable and a categorical variable, selecting a feature whose evaluation value is higher than the threshold value (Bashir et al., 2022; ElDahshan et al., 2023). As a result, the technique removes noisy features quickly and with minimal processing.

Clustering, on the other hand, performs unsupervised classification that generates cluster labels for an object by dividing the data into useful and meaningful groups, generating cluster labels for the objects (Mostafa, 2020) to produce better clustering results on the difference between the clusters and the similarity within those clusters. Popular and commonly used clustering algorithms include K-means, which is valuable for undirected knowledge discovery and is simple (Ahmed et al., 2020; Ikotun et al., 2023). This clustering algorithm divides the dataset into a constant number (k), where k is the number of clusters, randomly choosing k number of centroids, wherein the centroid is the data point at the center of a cluster where its data-driven nature is an advantage and does not require any prior labels and adapts to unlabeled datasets (Yang et al., 2020).

Regarding data optimization, the approach reduces or maximizes the objective of a function or problem and determines the best choice of variables for that function or problem. Real-world and optimization problems have non-linear restrictions, complexity, high computational time, non-convex, and wide search spaces, which make them challenging to solve (Abualigah et al., 2021). For instance, population-based optimization algorithms solve the multiple traveling officers' problem (MTOP) by evaluating the real-parking sensor data with other metrics (Qin et al., 2020). Also, the population-based algorithm evolves optimized function goals through cooperative and competitive interactions among individuals where massive information exists during the search process (Fung et al., 2020; Cheng et al., 2021).

Methods

The Prediction Model for Depression

The study followed a series of steps in coming up with indicators of depression based on the four depression screening tools, as presented in Figure 1. The model preprocessed the students' mental health data obtained from the consolidated statements as specified in the depression screening tools. The model then groups the data into clusters using the

K-means clustering algorithm. The significant cluster underwent further optimization using the particle swarm optimization algorithm, an approach used to extract the most evident indicators of depression associated with online learning during the pandemic.

To simulate the performance of the prediction model, the researchers distributed survey instruments containing consolidated statements from the PHQ-9, FCV-19S, USDI, and QoSL tools to undergraduate respondents from a university in the southern Philippines. Data collection strictly observed confidentiality and anonymity following the Data Privacy Act of 2012 of the Republic of the Philippines.

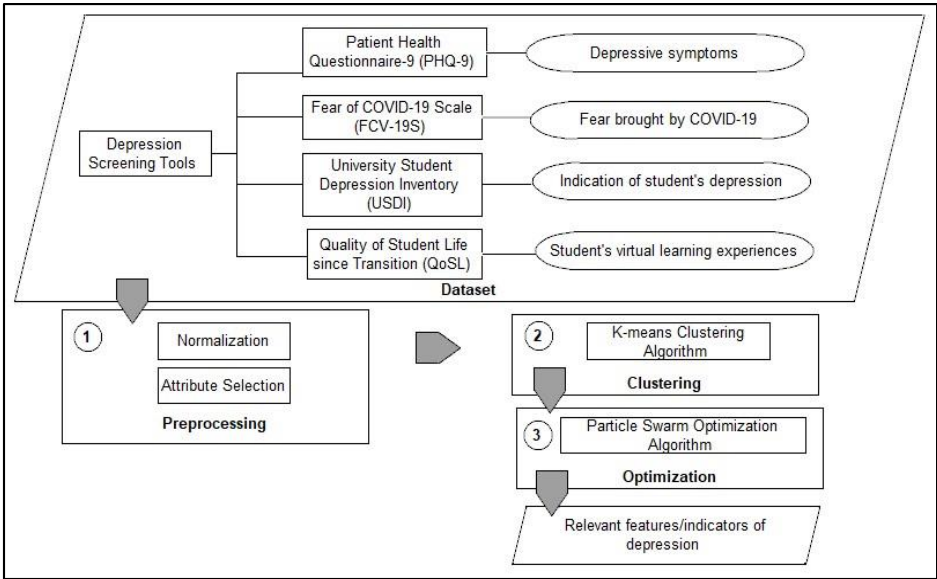


Figure 1. Prediction Model on Depression Associated with Online Learning

Preprocessing

The obtained dataset underwent a series of preprocessing, as presented in Figure 2. Hence, the 302 entries underwent normalization needed for the next preprocessing step. Normalizing the data ensures a balanced scale of attributes between 0 and 1, considering the unknown data distribution. The normalization of the data was done using the WEKA application, which used unsupervised filters for attributes and the default range for the resulting values between 0 and 1 for the normalization intervals. After the normalization, feature or attribute selection extracts the more meaningful attributes from the general attributes. Attribute selection techniques in data mining select effective feature subsets for the dataset. The researchers used the information gain to identify more meaningful attributes. The attribute selection used the information gain and ranker options to determine the informative features of the dataset after obtaining the entropy.

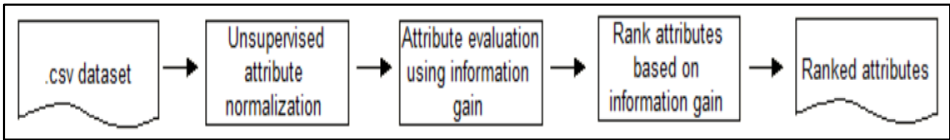


Figure 2. Preprocessing stages for the prediction model

Clustering and Optimization

After obtaining the ranked attributes based on the InfoGain values, the data belonging to the significant ranking underwent clustering. The researchers used the K-means clustering algorithm to determine groups or clusters of attributes. The study used the particle swarm optimization algorithm to identify the attributes from the resulting clusters. This approach further identifies the attributes that determine the predictors of depression associated with online learning. The clustering process utilized the WEKA application with the following steps presented in Figure 3.

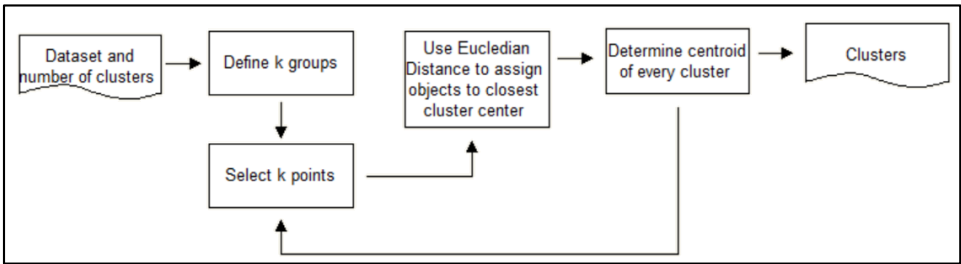


Figure 3. Data clustering for the prediction model

The selected predictors of depression underwent further optimization to improve the selection of the predictors since some data do not fully determine the correct predictors. The process of clustering and optimization utilized the WEKA application with the steps presented in Figure 4.

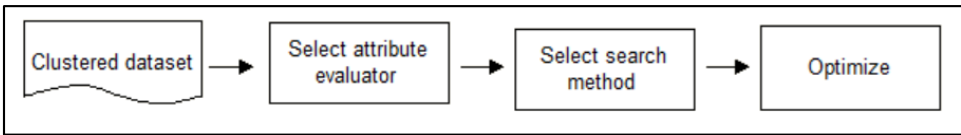


Figure 4. Cluster optimization for the prediction model

Results

Attribute Selection

For model simulation, the dataset has 302 instances with 55 attributes under the categories QoSL, PHQ-9, FCV-19S, and USDI. This dataset underwent unsupervised attribute normalization, checking the missing values for every instance and the characteristics of the data dispersal. Figure 5 presents the normalized data for each category.

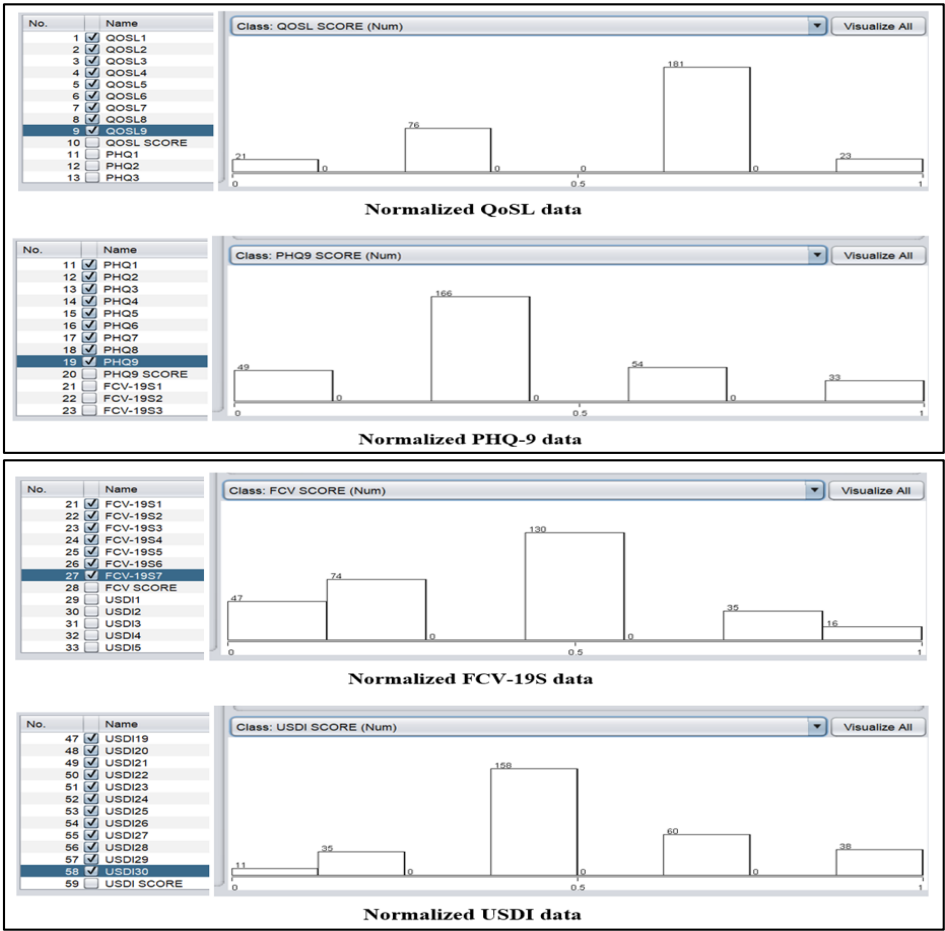


Figure 5. Normalized data for each category

After normalizing the attribute data of the four categories, the results underwent further selection by obtaining its information gain values by ranking. Using the WEKA application, the model used the 'InfoGainAttributeEval' option as the attribute evaluation with 'Ranker' as the search option. Table 1 presents the ranked attributes and their corresponding information gain values.

Table 1. Ranked attributes and their corresponding information gain values.

Information Gain	Attributes	
FCV-19S		
0.2488	FCV-19S1:	I am most afraid of coronavirus-19
0.2267	FCV-19S4:	I am afraid of losing my life because of coronavirus-19
0.2209	FCV-19S3:	My hands become clammy when I think about coronavirus-19
0.2204	FCV-19S2:	It makes me uncomfortable to think about coronavirus-19
0.2087	FCV-19S5:	When watching news and stories about coronavirus-19 on social media, I become nervous or anxious
PHQ-9		
0.1648	PHQ2:	Feeling down, depressed, or hopeless
0.1431	PHQ6:	Feeling bad about yourself — or that you are a failure or have let yourself or your family down
0.0737	PHQ8:	Moving or speaking so slowly that other people could have noticed or so fidgety or restless that you have been moving a lot more than usual
0.0733	PHQ7:	Trouble concentrating on things, such as reading the newspaper or watching television
0.0685	PHQ1:	Little interest or pleasure in doing things
USDI		
0.4268	USDI22:	I feel disappointed in myself
0.4219	USDI18:	The challenges I encountered in my studies overwhelmed me
0.4188	USDI21:	My mood affects my ability to carry out assigned tasks
0.4109	USDI130:	I have trouble completing study tasks
0.3922	USDI14:	I feel sad
QoSL		
0.1451	QoSL2:	I have been in situations where it has affected my mental health
0.1431	QoSL3:	Finding it hard to balance work and school life
0.1313	QoSL9:	Grading seems to be stricter
0.1312	QoSL5:	Lack of personal motivation
0.1073	QoSL6:	There is an increase in the workload

Cluster Analysis

With the 20 top predictors of depression associated with online learning based on the obtained data stated above, the model further processes these data accordingly to determine the groups or clusters of attributes that greatly define the depressive symptoms of the respondents. Table 2 presents the cluster distribution, while Table 3 presents the final cluster centroids of the 20 selected attributes. On the other hand, Figure 6 shows the scatterplot of the three clusters.

Table 2. Cluster distribution.

Cluster	Cluster Instances	
0	68	(23%)
1	168	(56%)
2	66	(22%)

Table 3. Final cluster centroids of 20 selected attributes.

Attribute	Full Data (302)	Cluster 0 (68)	Cluster 1 (168)	Cluster 2 (66)
USDI22	3.1225	3.2647	2.6607	4.1515
USDI18	3.1457	3.1765	2.7381	4.1515
USDI21	3.2384	3.4412	2.7619	4.2424
USDI30	3.2616	3.4265	2.8095	4.2424
USDI14	3.1258	3.2059	2.6964	3.3636
PHQ2	2.4901	2.7353	2.0476	3.3636
PHQ6	2.5596	2.8529	2.0893	3.4545
PHQ8	2.4172	2.7206	2.0119	3.1364
PHQ7	2.4702	2.6765	2.0595	3.3030
PHQ1	2.3940	2.6324	2.0536	3.0152
FCV-19S1	2.8907	2.0882	2.7738	4.0152
FCV-19S4	3.0033	2.1471	2.8869	4.1818
FCV-19S3	2.7715	1.8971	2.6964	3.8636
FCV-19S2	2.9007	2.0000	2.8214	4.0303
FCV-19S5	2.7881	1.8235	2.7798	3.8030
QOSL2	2.4867	2.1761	2.9167	1.7121
QOSL3	2.5000	2.1471	2.9464	1.7273
QOSL9	2.6844	2.7794	2.9148	2.0000
QOSL5	2.4515	2.0949	2.9148	2.0000
QOSL6	2.4817	2.3894	2.8095	1.7424

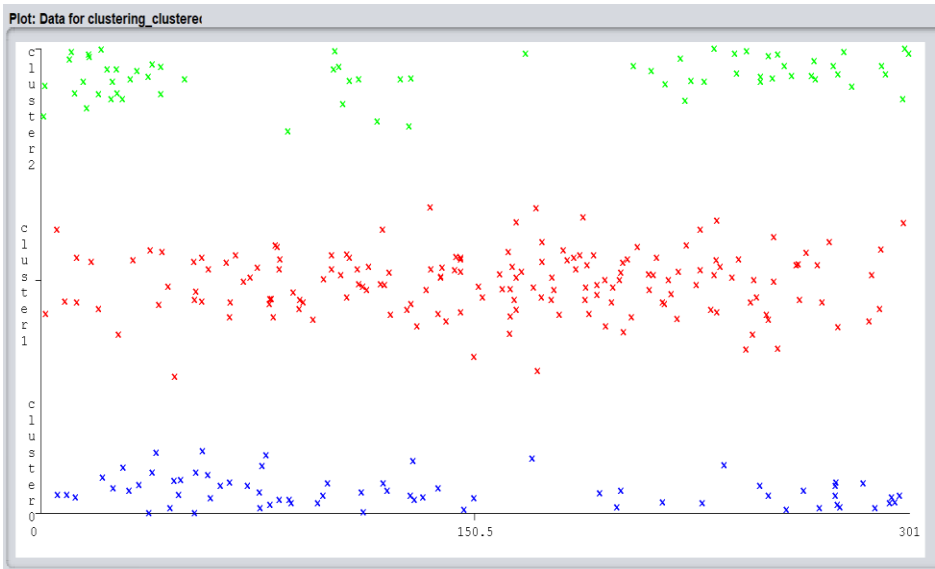


Figure 6. Final clusters of the 20 selected attributes

Determining Causes of Depression Associated with Online Learning

Using the simulated data, the model determined the significant cluster among the three clusters. However, some data belonging to the clusters do not fully contribute to the expected predictors. Hence, the final phase of the model's step is to determine the causes of depression associated with online learning through optimization. Figure 7 shows the optimized values of the clustered data, while Table 4 shows the final list of causes of depression related to online learning as generated by the model using the simulated data.

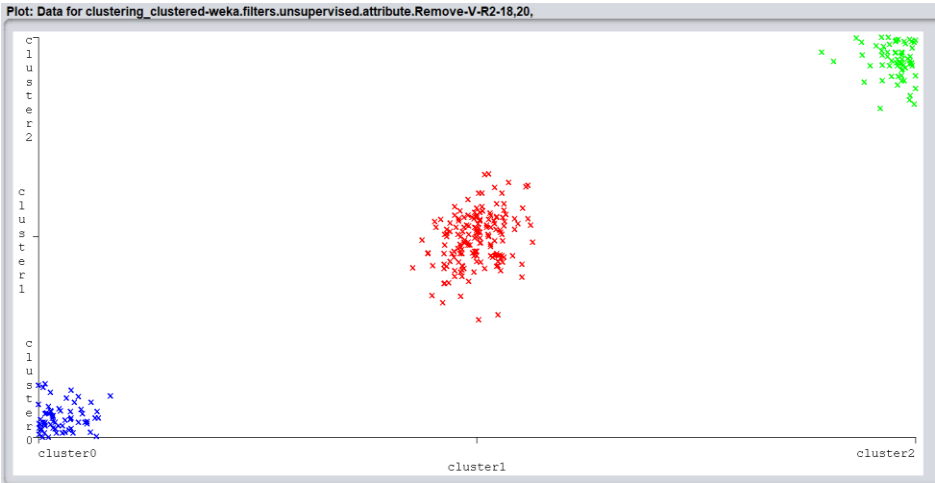


Figure 7. Optimized attributes from clustered data

Table 4. Causes of depression associated with online learning.

Causes	
USDI22:	I feel disappointed in myself
USDI18:	The challenges I encountered in my studies overwhelmed me
USDI21:	My mood affects my ability to carry out assigned tasks
USDI130:	I have trouble completing study tasks
USDI14:	I feel sad
PHQ2:	Feeling down, depressed, or hopeless
PHQ6:	Feeling bad about yourself — or that you are a failure or have let yourself or your family down
PHQ8:	Moving or speaking so slowly that other people could have noticed or so fidgety or restless that you have been moving a lot more than usual
PHQ7:	Trouble concentrating on things, such as reading the newspaper or watching television
PHQ1:	Little interest or pleasure in doing things
FCV-19S1:	I am most afraid of coronavirus-19
FCV-19S4:	I am afraid of losing my life because of coronavirus-19
FCV-19S3:	My hands become clammy when I think about coronavirus-19
FCV-19S2:	It makes me uncomfortable to think about coronavirus-19
FCV-19S5:	When watching news and stories about coronavirus-19 on social media, I become nervous or anxious
QoSL2:	I have been in situations where it has affected my mental health
QoSL3:	Find it hard to balance work and school life
QoSL5:	Lack of personal motivation

Discussion

With the sudden shift in educational learning in the Philippines, depression is one of the many relatively serious problems for students in their online learning environment. As a result of the educational mode shift, distance learning has become the new pedagogy for most universities, colleges, institutions, and schools in the country, especially during this pandemic. Unfortunately, it consequently affects the mental health of college students since their social life is also changing from the usual face-to-face to virtual. With these experiences, depression is one of the many mental health challenges college students face as it affects their psychological well-being of a student. Furthermore, with the rising cases of depression, prediction models for depression helped researchers assess mental health. However, most of these predictors do not solely focus on depression but on the association of different factors, like stress, anxiety, and depression, in measuring students' mental health in their online studies.

The simulation using a dataset of 302 entries enables the model to select 20 out of the 55 predictors used in the study based on the data obtained from the four depression screening tools, namely the PHQ-9, FCV-19S, USDI, and QoSL. From a diverse entry of the QoSL attributes between 1 and 4 based on the simulated data, the normalization process enables to standardize the attributes to entries between 0 and 1. With the similarity of the data distribution with the unnormalized, this result defines that the values have a fair distribution. QoSL result has an average weighted mean of 0.526 with a standard deviation of 0.038, which signifies that the data are closely similar within the distribution. In addition, from a diverse entry of the PHQ-9 attributes between 1 and 4 based on the simulated data, the normalization process enables standardizing the attributes to entries between 0 and 1. With the similarity of the data distribution with the unnormalized, this result defines that the values have a fair distribution. PHQ-9 result has an average weighted mean of 0.492 with a standard deviation of 0.039, which signifies that the data are closely similar within the distribution. Regarding the diverse

entry of the FCV-19S attributes between 1 and 5 based on the simulated data, the normalization process enables to standardize the attributes to entries between 0 and 1. With the similarity of the data distribution with the unnormalized, this result defines that the values have a fair distribution. FCV-19S result has an average weighted mean of 0.451 with a standard deviation of 0.034, which signifies that the data are closely similar within the distribution. Lastly, from a diverse entry of the USDI attributes, presented in the figure below, between 1 and 5 based on the simulated data, the normalization process enables standardizing the attributes to entries between 0 and 1. With the similarity of the data distribution with the unnormalized, this result defines that the values have a fair distribution. USDI result has an average weighted mean of 0.624 with a standard deviation of 0.499, which signifies that the data are closely similar within the distribution.

Moreover, Table 1 shows the top five attributes for each category as the identified predictors of depression. About FCV-19S, the thought of COVID-19 already creates mental stress in the respondents, whereas the PHQ-9 top predictors show that the respondents are troubled and restless. On the other hand, USDI's top predictors define the low self-esteem and declining interest of the respondents in learning, while the quality of student life of the respondents shows having challenging learning experiences.

Regarding the clustering of data, the Simple K-means clustering algorithm used in the model defined the clusters or groups of attributes specifying three clusters. Of the resulting clusters, it is Cluster 2 that has more concrete data similarities over the other two clusters, as shown in Table 2. Table 3 presents these data similarities with data ranging from >2.0 to <3.0 . This cluster of the simulated data shows that the model can identify significant clusters. As reflected in Table 3, the clusters shown in Figure 6 showed similar graphical data of the second cluster (in red color) having positions close to each other, contributing to more than 50% of the instances. Also, the other two clusters have a lower percentage of data similarities. Hence, the second cluster defines the significant cluster of attributes.

Among the 20 selected attributes with three clusters where the second cluster defines the most significant cluster of attributes, these attributes underwent optimization. Through WEKA's particle swarm optimization algorithm, the model further removed two attributes. Hence, the model finally produced 18 attributes - five from USDI, PHQ-9, and FCV-19S and three from QoSL. Using the simulated data and among the 55 attributes from four depression screening tools, QoSL, FCV-19S, PHQ-9, and USDI, the model identified the top five attributes from each screening tool as candidate attributes for depression predictors. Out of the 20 selected candidate attributes analyzed as predictors of depression associated with online learning, 18 were significant. However, the model predicts different depressive symptoms depending on the data gathered. With this result, the model can identify the most depressive symptoms experienced by the students. Moreover, based on the data used in the simulation, the model showed at least 28 respondents (9%) who manifested these depressive symptoms.

The study only used a dataset to simulate the performance of the prediction model. Although the study showed that the model can determine depressive symptoms associated with online learning, its simulation utilized only a small dataset from one specific region. Hence, future enhancement of the model will be simulated through a larger dataset comprising data from varied areas to eliminate the possibility of biases. Further, the model needs to undergo validation testing for its performance and prediction accuracy. Also, a comparative study on other models utilizing similar depression screening tools is important to identify what triggers depression aside from online learning using all these attributes used in the study.

Literature Cited

Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The arithmetic optimization algorithm. *Computer methods in applied mechanics and engineering*, 376, 113609.

Ahmed, G., Negash, A., Kerebih, H., Alemu, D., & Tesfaye, Y. (2020). Prevalence and associated factors of depression among Jimma University students. A cross-sectional study. *International journal of mental health systems*, 14(1), 1-10.

Ahmed, M., Seraj, R., & Islam, S. M. S. (2020). The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 9(8), 1295.

Ahorsu, D. K., Lin, C. Y., Imani, V., Saffari, M., Griffiths, M. D., & Pakpour, A. H. (2020). The fear of COVID-19 scale: development and initial validation. *International journal of mental health and addiction*, 1-9.

Alyami, M., Henning, M., Krägeloh, C. U., & Alyami, H. (2021). Psychometric evaluation of the Arabic version of the Fear of COVID-19 Scale. *International journal of mental health and addiction*, 19(6), 2219-2232.

Bashir, S., Khattak, I. U., Khan, A., Khan, F. H., Gani, A., & Shiraz, M. (2022). A novel feature selection method for classification of medical data using filters, wrappers, and embedded approaches. *Complexity*, 2022.

Bitan, D. T., Grossman-Giron, A., Bloch, Y., Mayer, Y., Shiffman, N., & Mendlovic, S. (2020). Fear of COVID-19 scale: Psychometric characteristics, reliability and validity in the Israeli population. *Psychiatry research*, 289, 113100.

- Cheng, S., Ma, L., Lu, H., Lei, X., & Shi, Y. (2021). Evolutionary computation for solving search-based data analytics problems. *Artificial Intelligence Review*, 54(2), 1321-1348.
- Costantini, L., Pasquarella, C., Odone, A., Colucci, M. E., Costanza, A., Serafini, G., ... & Amerio, A. (2021). Screening for depression in primary care with Patient Health Questionnaire-9 (PHQ-9): A systematic review. *Journal of affective disorders*, 279, 473-483.
- Dikshit-Ratnaparkhi, A., Bormane, D., & Ghongade, R. (2021). A novel entropy-based weighted attribute selection in enhanced multicriteria decision-making using fuzzy TOPSIS model for hesitant fuzzy rough environment. *Complex & Intelligent Systems*, 7(4), 1785-1796.
- Duan, L., & Zhu, G. (2020). Psychological interventions for people affected by the COVID-19 epidemic. *The lancet psychiatry*, 7(4), 300-302.
- El Andaloussi, Z., Benbba, B., & Kamal, S. (2022). Exploring the Encgt Business School Students' Perceptions toward E-Learning during the Covid-19 Pandemic: A Quantitative Descriptive Study. *IJTM International Journal of Trade and Management*, 1(1), 27-40.
- ElDahshan, K. A., AlHabshy, A. A., & Mohammed, L. T. (2023). Filter and Embedded Feature Selection Methods to Meet Big Data Visualization Challenges. *Computers, Materials & Continua*, 75(1).
- Elshareif, E., & Mohamed, E. A. (2021). The Effects of E-Learning on Students' Motivation to Learn in Higher Education. *Online Learning*, 25(3), 128-143.

- Erarslan, A., & Seker, M. (2021). Investigating E-Learning Motivational Strategies of Higher Education Learners against Online Distractors. *Online Learning*, 25(2), 262-279.
- Froman, V., Berumen, D., Rodriguez, J., & Stute, C. (2020). COVID-19 student survey: Online learning experiences and challenges experienced related to the COVID-19 pandemic. *Mt. SAC COVID-19 Student Survey*, 1(1), 1-44.
- Fung, R., Villar, J., Dashti, A., Ismail, L. C., Staines-Urias, E., Ohuma, E. O., ... & Miller, R. (2020). Achieving accurate estimates of fetal gestational age and personalised predictions of fetal growth based on data from an international prospective cohort study: a population-based machine learning study. *The Lancet Digital Health*, 2(7), e368-e375.
- Garner, S., Kuborn, S., & Chisum, M. (2022). Confidence in Crisis: Student Self-Efficacy and the Online Pivot. *International Journal on Innovations in Online Education*, 6(1).
- Gupta, S. B., & Gupta, M. (2020). Technology and e-learning in higher education. *International Journal of Advanced Science and Technology*, 29(4), 1320–1325.
- Hansen-Brown, A. A., Sullivan, S., Jacobson, B., Holt, B., & Donovan, S. (2022). College Students' Belonging and Loneliness in the Context of Remote Online Classes during the COVID-19 Pandemic. *Online Learning*, 26(4), 323-346.
- Huang, Y., & Zhao, N. (2020). Generalized anxiety disorder, depressive symptoms and sleep quality during COVID-19 outbreak in China: a web-based cross-sectional survey. *Psychiatry research*, 288, 112954.

- Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*, 622, 178-210.
- Jyoti, B., Kiran, M., Srivastava, R., Jaiswal, V., Kumari, S., & Sinha, A. K. (2021). Psychological consequences of lockdown on dental professionals during the early phase of the COVID-19 pandemic. *Journal of Education and Health Promotion*, 10.
- Khawaja, N. G., & Bryden, K. J. (2006). The development and psychometric investigation of the university student depression inventory. *Journal of affective disorders*, 96(1-2), 21-29.
- Kedra, K., & Kaltsidis, C. (2020). EFFECTS OF THE COVID-19 PANDEMIC ON UNIVERSITY PEDAGOGY: STUDENTS' EXPERIENCES AND CONSIDERATIONS. *European Journal of Education Studies*, 7(8).
- Klomek, A. B. (2020). Suicide prevention during the COVID-19 outbreak. *The lancet psychiatry*, 7(5), 390.
- Lamela, D., Soreira, C., Matos, P., & Morais, A. (2020). Systematic review of the factor structure and measurement invariance of the patient health questionnaire-9 (PHQ-9) and validation of the Portuguese version in community settings. *Journal of Affective Disorders*, 276, 220-233.
- Liu, S., Yang, L., Zhang, C., Xiang, Y. T., Liu, Z., Hu, S., & Zhang, B. (2020). Online mental health services in China during the COVID-19 outbreak. *The Lancet Psychiatry*, 7(4), e17-e18.

- Loosemore, M., Lim, B., & Ilievski, M. (2020). Depression in Australian Undergraduate Construction Management, Civil Engineering, and Architecture Students: Prevalence, Symptoms, and Support. *Journal of Civil Engineering Education*, 146(3), 04020003.
- Manuaba, I. B. A. P., Darmayani, I. G. A. S., Sindhughosa, D. A., Yani, M. V. W., Remitha, N. P. S. I., Sasmana, I. G. A. P., ... & Supadmanaba, I. G. P. (2023). Levels of anxiety and depression of students and responses to online learning methods during the COVID-19 pandemic. *Bali Medical Journal*, 12(1), 550-555.
- Moreno, R., Flood, L. D., Rausch, M. A., Takahashi, A., & Kluge, S. L. (2022). Making Sense of Crisis: Instructional Designers' Experiences with Emergency Remote Teaching. *Online Learning*, 26(4), 304-322.
- Mostafa, S. M. (2020). Clustering Algorithms: Taxonomy, Comparison, and Empirical Analysis in 2D Datasets. *Journal of Artificial Intelligence*, 2(4), 189.
- Naheed, N., Shaheen, M., Khan, S. A., Alawairdhi, M., & Khan, M. A. (2020). Importance of features selection, attributes selection, challenges and future directions for medical imaging data: a review. *Computer Modeling in Engineering & Sciences*, 125(1), 314-344.
- Pang, N. T. P., Kamu, A., Hambali, N. L. B., Mun, H. C., Kassim, M. A., Mohamed, N. H., ... & Jeffree, M. S. (2020). Malay version of the fear of COVID-19 scale: Validity and reliability. *International Journal of Mental Health and Addiction*, 1-10.

- Pelucio, L., Simões, P., Dourado, M. C. N., Quagliato, L. A., & Nardi, A. E. (2022). Depression and anxiety among online learning students during the COVID-19 pandemic: a cross-sectional survey in Rio de Janeiro, Brazil. *BMC psychology*, 10(1), 192.
- Perz, C. A., Lang, B. A., & Harrington, R. (2020). Validation of the Fear of COVID-19 Scale in a US College Sample. *International journal of mental health and addiction*, 1-11.
- Qin, K. K., Shao, W., Ren, Y., Chan, J., & Salim, F. D. (2020). Solving multiple travelling officers problem with population-based optimization algorithms. *Neural Computing and Applications*, 32(16), 12033-12059.
- Radha, R., Mahalakshmi, K., Kumar, V. S., & Saravanakumar, A. R. (2020). E-Learning during Lockdown of Covid-19 Pandemic: A Global Perspective. *International Journal of Control and Automation*, 13(4), 1088–1099.
- Sahu, P. (2020). Closure of universities due to coronavirus disease 2019 (COVID-19): impact on education and mental health of students and academic staff. *Cureus*, 12(4).
- Son, C., Hegde, S., Smith, A., Wang, X., & Sasangohar, F. (2020). Effects of COVID-19 on college students' mental health in the United States: Interview survey study. *Journal of medical internet research*, 22(9), e21279.
- Sun, Q., Qin, Q., Basta, M., Chen, B., & Li, Y. (2021). Psychological reactions and insomnia in adults with mental health disorders during the COVID-19 outbreak. *BMC psychiatry*, 21(1), 1-10.

- Thwala, J. D., & Pillay, I. (2023). Adult first-year students' reports of depressive symptoms at a rural South African university. *South African Journal of Psychology*, 53(1), 102-110.
- Wells, C. N., Pass, M. B., & Walsh, J. E. (2022). Face-to-Face vs. Online Asynchronous Teaching in a Conservation Biology Course. *Online Learning*, 26(2), 241-253.
- Yang, Z., Chen, C., Li, H., Yao, L., & Zhao, X. (2020). Unsupervised classifications of depression levels based on machine learning algorithms perform well as compared to traditional norm-based classifications. *Frontiers in Psychiatry*, 11, 45.