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A new approach in identifying the psychological impact of COVID-19 on university student’s academic performance

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Abstract  COVID-19 was first discovered in Wuhan, China on December 2019. It is one of the worst pandemics in human history. The education sector is one of the sectors most affected by the COVID-19 pandemic. Educators and students worldwide were forced to shift to online learning. Students, in particular, have suffered from the psychological impacts and learning difficulties caused by the lockdowns imposed by governments to control the pandemic. In this study, we used statistics and machine learning approaches to study the impact of COVID-19 pandemic on education systems especially on university students’ psychological health. For this purpose, a questionnaire was created, which consisted of two primary parts. The first part collects the participant’s demographic and educational characteristics, while the second part gathers information about five primary dimensions: the use of digital devices, sleep habits, social communication, emotional mental state, and academic performance. The questionnaire was distributed to university students in three Arab countries: Egypt, Jordan, and Saudi Arabia. A total of 1766 responses were returned and analyzed using statistical and machine learning approaches. The results showed an evident correlation between student’s psychological health and the use of online education during the time COVID-19. The results also showed that there is a positive relationship between digital tools used for online education and the academic performance of students during the time of COVID-19. Finally, the results highlighted the harmful impacts of COVID-19 on the education systems. The study ends by presenting suggestions and recommendations needed to improve the current online education system.
1. Introduction

COVID-19 was first discovered in Wuhan, China on December 2019. The World Health Organization (WHO) later declared the new emerging disease as a pandemic [1]. COVID-19 is one of the worst pandemics in human history due to its high rates of transmission and its comorbidity with other serious illnesses and high mortality rates (WHO, 2020). The virus spread to most countries during its first seven months and it even started a second wave in many countries even before a year has passed [2]. COVID-19 exhibits a wide range of infection-related symptoms, including inflammation and pain modulation. In fact, many researchers have examined the impact of various types of chronic inflammation on local tissues, such as the one that affects patients with COVID-19, as well as the function of the secretome and the intercellular communication between cells in these individuals [3,4].

The COVID-19 pandemic’s effect on human life has almost no boundaries. It has changed the lifestyles of billions of people as they are forced to lose work, stay at home, and learn from home. The main negative effects of the pandemic in many countries are actually caused by total lockdowns and millions of deaths. Recent reports from various continents continue to indicate a daily increase in the number of new cases and mortality due to COVID-19. A total of 90,771,208 confirmed cases of COVID-19 were reported and its death toll reached about 1,944,768 by the beginning of 2021 [1,2,5,6]. The COVID-19 pandemic influenced all areas of human life; education, research, sports, amusement, transportation, entertainment, worship, social gathering/interactions, economy, businesses, and legislative issues [7].

Globally, the education sector is one of the areas that were greatly affected by the COVID-19 pandemic. The COVID-19 pandemic caused a massive disruption of educational systems. Because of the highly sensitive situation that the virus created, colleges had to shift to online learning environments [8]. However, this may have negatively affected students’ mental and psychological health. Moreover, strengths, weaknesses, opportunities, and challenges of online learning during the pandemic needs to be studied. Currently, Machine Learning (ML) approaches are commonly used to help solving real life problems based on statistical data [5,9]. In this paper, an ML approach was adopted to examine the mental and psychosomatic impacts of online learning on students in the time of COVID-19 pandemic. Finally, the main analysis has two parts performed using machine learning algorithms and descriptive statistics, chi-square, Analysis of Variance (ANOVA) and linear logistics regression, at $\alpha = 0.05$.

This study has the following major contributions:

- It verifies the importance of online learning and studies the impact of COVID-19 pandemic on the education system especially for university students’ psychological health.
- It emphasizes the importance of enforcing the public health advice of social distancing as well as applying infection control measures to combat COVID-19.
- It raises awareness about the fruitful side of online learning technologies and digital developments.
- It examines the impact of quarantine, closures, social distancing and isolation on college students’ mental health and psychological well-being.
- It helps educational leaders and policymakers by identifying university students’ emotional needs and providing them with practical solutions to maintain a healthy educational experience among students.
- It offers proposals, suggestions and recommendations for achieving an optimal online model of learning during the post-COVID-19 era.

2. Related work

Machine learning and Artificial Intelligence (AI) models are essentially used to improve the prediction accuracy of diagnosis and the screening of non-infectious diseases [10,11]. Moreover, machine learning approaches are also widely used in the analysis and prediction of COVID-19 survival rate, the discharge time of patients on clinical data and prediction of having a second wave of the COVID-19 pandemic [2,12,13].

Mishra et al. [14] utilized both quantitative and qualitative data to recognize the perceptions of instructors and students on online learning modes and web-based learning models. They investigated the use of advanced web-based learning devices including smart phone, and tablets, and found out that they have an influence on the emotional well-being of instructors and students. To extend this effort, researchers explore whether there is a correlation between the students’ prolonged use of online learning devices, due to the COVID-19 pandemic, and their psychological and mental well-being [15,16].

Shivangi [17] puts some light on the development of educational technology start-ups during the time of the COVID-19 pandemic and natural disasters and incorporates proposals for academic institutions on how to manage difficulties related with online learning. The authors [18,19] analyzed the level of academic stress experienced by students during online education and the coping strategies they use during the time of the COVID-19 pandemic.

Onyema et al. [7] analyzed the collected data using statistical (Regression) model and showed that COVID-19 has harmful effects on education such as learning disturbances, students lose their jobs and expanded student obligations. The findings showed that a large number of educators and students used technology to continue online learning. However, online learning was impeded due to many factors such as poor network, power, and infrastructure issues.
Zohair et al. [2, 20] proposed different regressor machine learning models for COVID-19 pandemic and its second rebound. Moreover, the models are utilized to estimate the effect of climate on the transmission of COVID-19 by extracting the connection between the number of asserted cases and atmospheric factors on explicit areas.

Previous researchers focused on the use of data to identify university students' mental and psychological needs as well as the perception of academic stress experienced by students during current online education and proposed effective solutions to improve educational processes. However, these studies lack some promising features that could enable us to survey the vital difficulties of online learning particularly when it is the only available option. These features can be helpful to understand the academic pressure experienced by students and how cultural and educational modification can be executed during pandemics like the COVID-19.

3. Impact of COVID-19 pandemic on online education

3.1. The concept of online education

At present, the notion of an online education system has become an essential part of education. The use of appropriate educational technologies increases accessibility to learning resources such as online learning, mobile learning, distance learning, virtual learning, and collaborative learning approaches to meet the need of diverse learners [21]. Therefore, the rapid development of technology in the field of education has transformed the traditional teacher-based education system into a more flexible venue where students participate and learn [22]. Meanwhile, students are faced with the challenge of transitioning from traditional methods to online learning. The main factors that affect the success of online education are the high speed of internet connections, high-quality learning software, and the cost and availability of technology [7, 23].

After schools closed, the quality of teaching and learning decreased, particularly for students with special needs because they need more physical attention [24]. The new technology cannot have the same effect of in-person interactions between students and teachers. Many students can not cover the cost of buying the necessary learning technology during school closures [22, 25].

3.2. SWOT analysis of online learning

During natural disasters like floods, hurricanes, and earthquakes, the learning process becomes challenging to many students in schools and colleges. During these situations, schools are forced to close in order to protect human lives. While being away from school, many students may face psychological issues, such as stress, anxiety, depression, and sleeplessness. At these times, the education system should utilize new ways of teaching and facilitating learning activities to address the psychological issues that students face [17].

To help prevent the spread of COVID-19, most schools and universities are currently closed. These are currently using online learning and remote teaching to continue amid the challenges of the COVID-19 pandemic. Many software companies have supported the universities during this pandemic by designing software. But these software were already available even before the COVID-19 pandemic. Their was not prompted by the pandemic. The SWOT Analysis of Online Learning During COVID-19 is shown in Fig. 1.

![Fig. 1 The SWOT Analysis of Online Learning During COVID-19.](image)
● Strengths: An online learning system is a necessary solution to help us cope with this challenging time. Among the many benefits of an online learning system are flexibility of time and location as well as customizability to suit the needs of particular learners. The available online tools are more efficient in creating an effective, interactive, collaborative, and fruitful learning environment. This environment can contain many learning resources such as audio, videos, lectures, queries, books, and online exams that are accessible to most students at any time.

● Weaknesses: In online learning, there are no direct person-to-person interaction between students and teachers. Also, students can face many technical problems such technical difficulties when using online platforms and the slow internet. Some psychological problems, such as frustration and confusion, occur while learning online.

● Opportunities: The online learning system is developing rapidly and many opportunities are available in recent years. The new technologies behind digital learning platforms created new opportunities for educational institutions to take advantage of. Thus, almost all academic institutions have shifted to this system during the COVID-19 pandemic [26]. These platforms can help students to enhance problem-solving skills, better understanding, critical thinking abilities, and adaptability.

● Threats: Online learning faces numerous challenges going from students’ issues, lecturers’ issues, and substance issues. These challenges are a threat to institutions in engaging students to participate in the learning process [27]. Problems encountered in online learning systems include a lack of standards for development of e-resources, quality control, and e-content delivery. Moreover, a huge amount of investment is necessary to train human resources, maintain equipment, and develop online content. Therefore, an effective and efficient educational system needs to be developed to grant education online. Instructors can introduce the educational plan in different formats. They can use videos, audios and documents. It is advantageous if instructors supplement their talks with video visits, virtual gatherings, and so on to get prompt feedback and establish personal connections with the students.

4. Methodology

The study design involved 1766 students from various Arab countries. An online questionnaire was used to collect various types of information including demographic information, digital tools, sleeping habits, social interaction, academic performance, psychological state, anxiety and depression scale. The main analysis has two parts performed using machine learning algorithms and descriptive statistics, chi-square, Analysis of Variance (ANOVA) and linear logistics regression, at $\alpha = 0.05$.

A Chi-Square test for independence compares two variables in a contingency table to see whether they are related. Generally, it tests to see whether distributions of categorical variables differ from each other. A small Chi-Square test statistic means that the observed data fit the expected data, or there is a strong relationship. A large Chi-Square test statistic implies that the data does not have a relationship. The p-value is used to test if results are significant or not. The degree of freedom is the number of categories minus 1. The alpha level(\(\alpha\)) is 0.05 (5%), but it could have other values such as 0.01 or 0.10. If Statistic $>=\text{Critical Value}:\text{significant result, reject the null hypotheses (H0), dependent.}$ If Statistic $<\text{Critical Value}:\text{not significant effect, fail to reject the null hypotheses (H0), independent.}$

For this work, the hypotheses are:

- H0: The features digital tools and academic performance are independent.
- H1: Digital tools and academic performance are not independent.

The one-way ANOVA tests are conducted to determine the mean of some numeric variable differs across the levels of one categorical variable. It essentially answers the question: do any of the group means differ from one another? ANOVA involves more calculations than the t-test, but the process is similar: calculate the F-statistic value and then compare the test statistic to a critical value based on a probability distribution.

Fig. 2 presents the steps of the proposed model for classifying the answers of students regarding COVID-19 effects. This architecture’s basic idea is to use the collected dataset of university students for analysis by ensemble machine learning algorithms.

Fig. 2 shows the three main steps: data pre-processing, the learning process, and the best model. The available dataset is gathered from different Arabic universities, merged, and then pushed on to the proposed model. The commonly known data pre-processing techniques were applied to the dataset at the first block, such as missing data, normalization, and feature selection. In the learning process, the dataset was split randomly into two main subsets: Training set (70%) and Testing set (30%). Generally, the dataset size is not enough to train the models, where a part of it is used for validation tasks. Thus, reducing the size of training data leads to losing essential patterns in the dataset, which increases the error produced by bias. Therefore, to validate the machine learning model's stability, K-Fold Cross Validation was used to divide the data into k subsets [28]. The hyper parameters optimization technique was also applied to improve the performance of the selected algorithms. The machine learning algorithms were developed using built-in python libraries such as Keras and scikit-learn [29,30]. Finally, the predictions of the students’ responses were made in the third stage.

In the following subsections, we describe the datasets used to validate the proposed method in subSection 4.1 and the detail description of the proposed method incorporated in subSection 4.2.

4.1. Dataset description

The spread of COVID-19 has affected many sectors in society, such as the economy, education, and health. In all Arab countries, the governments declared a state of emergency to minimize the high spread of the virus. These governments followed many measures to protect people, such as suspending schools and universities, closing borders, halting flights, and
quarantine. Students are affected by this new situation. Students shifted to learning online, which led to the longer use of digital tools such as laptops, smartphones, and i-pad tablets.

The dataset was used to examine the psychosomatic impact of COVID-19’s online learning digital tools on students’ academic performance in Arab world universities. The questionnaire used in this study consists of two main parts: The first part collected demographic information for each student, such as gender, level/year, age, and cumulative average/Grade Point Average (GPA). The second part gathers data on the psychosomatic impact of online learning digital tools before and after COVID-19 and contains five main elements: (1) the digital tools such as (laptop, mobile phone, I-pad)- (2) sleeping habits, (3) social interaction, (4) psychological state, and (5) academic performance.

The research group communicated with many professors from different Arab countries teaching main courses at public and private universities to share the online questionnaire. Therefore, the devised questionnaire for the purposes of this statistical study was delivered to the students at the selected universities. The selected institutions are public and private universities from Jordan, Egypt and Saudi Arabia. The total number of received responses was 1766. The frequencies and percentages were calculated for the collected data based on Likert’s five-point scale [31].

The online questionnaire was written and launched on an online cloud platform (Google Forms), and the final responses were saved as a .csv file. A Likert-type questionnaire was designed and written in Arabic being the official language in Arab countries. The online copy of the proposed questionnaire can be accessed from the following links: Arabic Link: https://forms.gle/2hohNtVwPcFu546k8 and English Translation: https://forms.gle/DPDmhuod6qh14Yzw9
4.2. The proposed models

In this study, the ensemble machine learning algorithms were used to investigate the real effect of the use of digital tools before and after COVID-19 on the academic performance of the students [32,33]. The following machine learning models such as Logistic Regression model [34] and ensemble learning-based models such as Random Forest, AdaBoost classifier [35], Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM) [28,36], and Decision Tree [37] were used to predict academic performance.

These algorithms are selected because they are commonly used to solve many real life problems. Moreover, these models were trained with the selected features such as digital tools before and after COVID-19, sleeping hours, social interaction, psychological state, and academic performance.

5. Experimental results and analysis

This section discusses the experimental results of the proposed framework. The main results are split into two subsections: descriptive statistics and machine learning algorithms. The results are presented in tables and figures for a better visual view. SubSection 5.1 presents a detailed description of the survey questions analysis, while the descriptive statistics results are described in subSection 5.2. Finally, subSection 5.3 shows the performance results for machine learning models.

5.1. Analyzing multi-answer survey questions

A correlation matrix is simply a table that displays the correlation coefficients between variables. Each cell in this table shows the correlation between two variables. A correlation matrix is used to summarize data and demonstrate a linear relationship between variables. The line of 1’s going from the top left to the bottom right is the main diagonal, which shows that each variable always perfectly correlates with itself. This matrix is symmetrical and the same correlation is shown above the main diagonal being a mirror image of those below the main diagonal. Fig. 3 shows the correlations between digital tools and sleeping variables’ and their importance to taking quizzes and exams online. In Fig. 3, the observable pattern is that all the variables have low correlation with each other. For example, with linear regression, many correlations suggest that the linear regression estimates will be unreliable.

Table 1 shows the results of the Chi-squared test for the selected features and the target column "Taking quizzes and exams online". In Table 1, for the feature "Before:time do you spend using digital tools”, the Significance value is 5.671340e-09 (i.e. p = 5.671340e-09), which is below 0.05. Therefore, the use of digital tools is statistically significant for online education. Fig. 4 shows the results of Robust Linear Models (RLM) and ordinary least squares (OLS) regression. From Fig. 4, it is clear that there is a positive relationship between the digital tools and academic performance during COVID-19.

The test output yields an F-statistic of 0.801 and a p-value of 0.524, indicating that there is no significant difference between the means of each group as shown in Table 2. The test result suggests that the groups don’t have the same sample means since the p-value is significant at a 99% confidence level. From Table 2, the p-value is 0.524 (i.e. \( p = 0.524 \)), which is more than 0.05, this means that the use of technology for online education has no statistical significance. As p is more than 0.05, we can accept the null hypothesis that there is a difference between the means of the weights of "digital tools” and "Taking quizzes and exams online from home was not comfortable and made me nervous”.

Table 1 Summary for the Chi-squared test and p-value.

| Features                                      | \( \chi^2 \)   | p-value         |
|------------------------------------------------|---------------|-----------------|
| Before: digital tools                          | 0.701991      | 9.510832e-01    |
| After: digital tools                           | 0.308145      | 9.892824e-01    |
| Before: time you spend using digital tools     | 44.257849     | 5.671340e-09    |
| After: time you spend using digital tools      | 2.360133      | 6.698435e-01    |

Fig. 3 A heatmap are typically used to visualize correlation matrix.
Table 2  Summary for the ANOVA test.

|          | Sum_sq | Df | F    | PR(>F) |
|----------|--------|----|------|--------|
| F32      | 2.048  | 4.0| 0.801| 0.524  |
| Residual | 994.618| 1556.0| NaN  | NaN    |

Table 3  Conduct t-test on each pair.

| Col1         | Col2         | t-statistic | p-value |
|--------------|--------------|-------------|---------|
| Strongly Agree| Disagree     | 1.264628    | 0.206364|
| Strongly Agree| Uncertain    | 1.482647    | 0.138521|
| Strongly Agree| Agree        | 0.035165    | 0.971955|
| Strongly Agree| Strongly Disagree | 0.218497    | 0.827101|
| Disagree     | Uncertain    | 0.067536    | 0.946184|
| Disagree     | Agree        | −1.059130   | 0.290014|
| Disagree     | Strongly Disagree | −0.627922   | 0.530509|
| Uncertain    | Agree        | −1.220489   | 0.227530|
| Uncertain    | Strongly Disagree | −0.707326   | 0.479788|
| Agree        | Strongly Disagree | 0.167128   | 0.867341|

Table 3 provides the results of a separate t-test for each pair of groups and the statistic and p-values. The statistic value represents the t-test statistic and the P-values indicates the alpha level or significance level. The p-values for each pairwise t-test suggest that the mean of "Strongly Agree" is likely similar with the other groups since the p-values for each t-test involving the "Strongly Agree" group is more than 0.05.

Table 4 shows the Tukey test’s output, the average difference, a confidence interval, and reject column to reject the null hypothesis for each pair of groups at the given significance level. In this case, the test suggests accepting the null hypothesis for all pairs, which means that all groups are not different from each other.

Table 4  Tukey test with the P-value at 95% confidence interval.

| Group1 | Group2 | Mean diff | P-adj | Lower | Upper | Reject |
|--------|--------|-----------|-------|-------|-------|--------|
| 0      | 1      | −0.0765   | 0.7989| −0.2722 | 0.1191 | False  |
| 0      | 2      | 0.0018    | 0.9   | −0.144 | 0.1477 | False  |
| 0      | 3      | −0.0151   | 0.9   | −0.2435 | 0.2132 | False  |
| 0      | 4      | −0.0816   | 0.694 | −0.2595 | 0.0962 | False  |
| 1      | 2      | 0.0784    | 0.7279| −0.1009 | 0.2577 | False  |
| 1      | 3      | 0.0614    | 0.9   | −0.1896 | 0.3125 | False  |
| 1      | 4      | −0.0051   | 0.9   | −0.2112 | 0.2011 | False  |
| 2      | 3      | −0.0169   | 0.9   | −0.2315 | 0.1976 | False  |
| 2      | 4      | −0.0835   | 0.5955| −0.2431 | 0.0762 | False  |
| 3      | 4      | −0.0665   | 0.9   | −0.3039 | 0.1709 | False  |

Fig. 4  Comparing OLS and RLM regression.
5.2. Descriptive statistics results

The Questionnaire’s main objective is to collect students’ responses on questions about the impact of long-time use of digital online learning tools on their psychological health. The proposed questionnaire questions were designed based on related questionnaires implemented for similar purposes [31,38]. The questions were distributed using online Google Forms.

The questionnaire based on a Likert-type design contained 20 questions where the first part allowed students to select the type of digital tools and how long they used these tools before and after COVID-19. For the rest of the questions, the students had the choice to choose answers ranging from “strongly agree” to “strongly disagree”. The data was collected during the first term of the academic year 2020–2021 for Egypt and Saudi Arabia and the second semester of 2019–2020 for Jordan. During these semesters, the universities started using the online learning platforms due to the COVID-19 situation.

The demographic information of the participants is shown in Table 5. This table also presents the distribution of respondents among countries: 43.9% of the respondents were from Jordan, 47.6 % were from Egypt, while 8.6% were from Saudi Arabia. It also shows that 61% of the respondents were females, while 39% were males.

Table 6 shows the participants’ responses about using smart tools before and after COVID-19. This table shows whether long time use of digital tools for academic purposes leads to distraction or not. The data infers that 31.2% have already been using digital devices for a long time but this percentage hit 50.5% after the COVID-19 pandemic started.

Table 7 shows the distribution of students’ sleeping habits as affected by their daily use of digital tools. Table 7 shows that the sleep time of 50.7% of the participants has been affected during the time of COVID-19 due to the heavy use of digital devices.

Table 8 presents the participants’ responses on their social behaviour and whether the lockdowns, curfews, and use of e-learning tools, have impacted their life activities. This table also shows the psychological challenges that students face during the COVID-19 pandemic, such as stress, frustration, tension, and depression. Finally, the last part of this table investigates the consequences of social and psychological impact on the students’ academic performance.

Table 9 presents a country-wise distribution of the participants’ responses regarding the effect of online learning tools on their academic performance, quizzes and exams, and most of the respondents strongly agreed in each country. Therefore, it implies that there is a strong relationship between academic performance and online learning tools.

### Table 5 The participants’ demographic information

| Variable       | Categories | Frequency | Percent |
|----------------|------------|-----------|---------|
| Country        | Egypt      | 840       | 47.6    |
|                | Jordan     | 775       | 43.9    |
|                | Saudi Arabia | 151     | 8.6     |
| Gender         | Female     | 1077      | 61.0    |
|                | Male       | 689       | 39.0    |
| Age            | 18–24      | 1660      | 94.0    |
|                | 25–29      | 74        | 4.2     |
|                | 30 and above | 32     | 1.8     |
| Level/Year     | first      | 375       | 21.2    |
|                | second     | 564       | 31.9    |
|                | third      | 400       | 22.7    |
|                | fourth     | 287       | 16.3    |
|                | other      | 140       | 7.9     |
| GPA            | 0–60/ 0–0.2 | 41        | 2.3     |
|                | 60–69/ 2.0–2.49 | 138   | 7.8    |
|                | 70–79/ 2.5–2.99 | 423  | 24.0   |
|                | 80–89/ 3.0–3.49 | 524  | 29.7   |
|                | 90–100/ 3.5–5 | 640  | 36.2   |

### Table 6 The participants’ responses on using smart tools (mobile phone, laptop, i-pad).

| Variable                                         | COVID-19          |
|--------------------------------------------------|-------------------|
| I always use digital tools in studying.          |                   |
| Before                                           | 31.2              |
| After                                            | 27.5              |
| When I use smart tools in e-learning, I am distracted. |                   |
| Before                                           | 28.0              |
| After                                            | 24.2              |

### Table 7 The students’ responses regards sleeping habits.

| Variable                                 | COVID-19          |
|------------------------------------------|-------------------|
| I have specified time for wake-up and bedtime. |                   |
| Before                                   | 39.9              |
| After                                    | 23.6              |
| Long use of smart tools affected my sleeping habits. |                   |
| Before                                   | 28.2              |
| After                                    | 28.2              |
5.3. The performance results for machine learning models

Generally, to overcome biased classification, respondents’ gathered data is randomly split into training and testing sets. Table 10 describes the classification report of the selected machine learning models. The Logistic Regression, Decision Tree, SVC, XGB, and Deep learning models have achieved the best performance, which is 100%, 100%, 100%, and 100% for accuracy, precision, recall, and F1-score, respectively. On the other hand, the lowest performance was achieved by the AdaBoost method, accuracy, precision, recall, and F1-score at 93%, 79%, 100%, and 88%, respectively.

6. Discussion

The current study investigates the negative effects of COVID-19 on the higher education system and the different frustrations that prevent students from learning effectively. As a result, educational activities are negatively affected by the COVID-19 pandemic, such as limited access to laboratories, an increase in students’ debts, and loss of learning interests among learners.

The COVID-19 pandemic produced problems in all life sectors, especially in the education system, as it led to the decrease of education opportunities for many students. The significant difficulties that hurdle the student to join online education this pandemic are digital skills, lack of electricity, accessibility, network issues, and inadequate facilities. More than 70% of the respondents of the proposed questioner agreed that the previous factors restricted their engagement in online education.

The study shows that COVID-19 lockdowns have many effects, such as increasing pressure on students, parents, and educational institutions. The study results agree with the previous researchers [21–23] for the need for technology in traditional education is the right solution. Moreover, the COVID-19 pandemic will be a new phase for online learning and will allow people to look at online learning technologies’ fruitful side.

### Table 8 Students’ social interaction, Psychological state, academic performance and distance learning.

| Variable                                                                 | Strongly Agree | Agree | Uncertain | Disagree | Strongly Disagree |
|--------------------------------------------------------------------------|----------------|-------|-----------|----------|------------------|
| Long use of digital tools causes students isolation                      | 48.5           | 32.2  | 10.2      | 6.6      | 2.5              |
| Staying home for long periods of time leads to lethargy and laziness.    | 59.0           | 23.6  | 10.4      | 4.5      | 2.6              |
| Prolonged use of e-learning tools often leads to boredom, nervousness,  | 51.0           | 32.1  | 10.0      | 5.1      | 1.8              |
| and tension.                                                             |                |       |           |          |                  |
| Some students cannot afford buying all necessary digital tools, which is  | 64.7           | 26.1  | 7.0       | 1.6      | 0.6              |
| embarrassing and frustrating.                                            |                |       |           |          |                  |
| I don’t recommend continuing with the online learning model because it is | 45.0           | 23.5  | 18.3      | 9.4      | 3.9              |
| socially and psychologically unhealthy.                                  |                |       |           |          |                  |
| Measures of lockdown, closures, and quarantine, brought by COVID-19 caused| 52.3           | 27.1  | 12.9      | 5.9      | 1.7              |
| stress, frustration, and depression.                                     |                |       |           |          |                  |
| Online quizzes and exams made students nervous and uncomfortable.        | 40.3           | 22.3  | 17.1      | 12.5     | 7.9              |
| Long use of digital tools leads to low academic performance.             | 49.9           | 26.6  | 14.1      | 6.8      | 2.6              |
| Face-to-face learning increases students academic achievement.           | 56.8           | 28.5  | 10.2      | 2.8      | 1.7              |

### Table 9 The distribution of the participants’ responses regarding the effect of digital tools on academic performance.

|                                                | Egypt       | Jordan     | Saudi Arabia |
|------------------------------------------------|-------------|------------|--------------|
| Strongly Disagree                             | 3.0%        | 1.9%       | 6.6%         |
| Disagree                                      | 8.9%        | 4.9%       | 15.2%        |
| Uncertain                                     | 14.2%       | 11.6%      | 21.9%        |
| Agree                                         | 20.2%       | 31.6%      | 24.5%        |
| Strongly Agree                                | 55.7%       | 49.9%      | 31.8%        |

### Table 10 The performance results for machine learning models.

|                      | Time       | Accuracy | Precision | Recall | F1 | ROC_AUC | R² | MSE |
|----------------------|------------|----------|-----------|--------|----|---------|----|-----|
| Logistic Regression  | 1.05557    | 1        | 1         | 1      | 1  | 1       | 1  | 0   |
| Decision Tree        | 1.69245    | 1        | 1         | 1      | 1  | 1       | 1  | 0   |
| SVC                  | 1.8749     | 1        | 1         | 1      | 1  | 1       | 1  | 0   |
| Random Forest        | 678.864    | 0.996109 | 1         | 1      | 1  | 0.996337| 0.997887| 0.00389105|
| XGB                  | 4.13605    | 1        | 1         | 1      | 1  | 1       | 1  | 0   |
| AdaBoost             | 1.4805     | 0.935798 | 0.792453  | 1      | 0.884211 | 0.891495 | 0.686166 | 0.577821 |
| Deep Learning        | 197.191    | 1        | 1         | 1      | 1  | 1       | 1  | 0   |
The following are the study’s limitations in a summary: there are substantial advantages to the proposed machine learning model, but it also has a number of disadvantages, the most obvious of which are that it performs similarly to a traditional one; it also takes a long time to run; and the model’s parameters must be carefully tuned. For this study, the sample size of students who answered an online questionnaire on COVID-19 was too small to create effective machine learning models, so all of the data from individual students was used. Furthermore, we were unable to provide information on particular topics, such as 1) the clinical correlation between stem cells, 2) tissue healing following inflammation-associated tissue damage, and 3) clinical issues associated with COVID-19.

7. Conclusion

Regardless of the challenges that may distress and affect our technical online learning experience during the current COVID-19 pandemic, results of this experimental study have found that online learning to be constructive and practical and the students’ interaction to be good. However, most participants agreed that it could not replace the traditional method of learning due to some issues in terms of currently available infrastructure, engagement techniques, semantic web techniques, and the need for enhanced knowledge management. Stakeholders in the education sector should create powerful systems to manage the post-COVID-19 era. Moreover, there is a positive relationship between the used digital tools for online education and academic performance during the COVID-19 pandemic. This pandemic will also be a new stage for online learning and it will make people more confident in the online learning system.

Future work could focus on applying the proposed model to other countries over the world to evaluate online learning for university students with respect to the COVID-19 pandemic. Besides, there is a critical need to carry out an investigation about the effectiveness of virtual education and students’ fears and tensions amidst such pandemics. Moreover, researchers may investigate more comprehensive deep learning models, which would be based on the feature extraction achieved by advanced optimization methods. In addition, researchers can apply this presented algorithm to solve other complicated optimization problems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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