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Examining the Impact of Online Education on Iranian Engineering Students during COVID-19: MCDM and Machine Learning Approach

Zahra Ghorbani[1], Abtin Boostani[2*], Ali Ghorbanian[2]

[1]*PhD Student, Edinburgh Business School, Heriot-Watt University, Edinburgh, Scotland (UK)*

[2]*Assistant Professor, Department of Industrial Engineering, Esfarayen University of Technology, Esfarayen, Iran*

Abstract

In this research, we introduce a comprehensive framework designed to assess the influence of remote learning during the COVID-19 pandemic on the sleep habits, interpersonal competencies, mental health, digital technology, and academic performance of engineering students. Additionally, we examine how these factors relate to the student's Grade Point Average (GPA). To achieve this, we conducted a web-based questionnaire survey involving 500 participants. The collected responses were subjected to various statistical analyses, including the Best-Worst Method, One-Sample Wilcoxon Signed Ranked Test, Spearman's Rank Correlation, Multilayer Perceptron, and K-nearest neighbors. The study outcomes revealed statistically significant impacts of online classes during the COVID-19 pandemic on several aspects, including delayed sleep time, sleep quality, emotional intelligence, critical thinking, stress levels, social isolation, distraction, social life, theoretical understanding, practical understanding, and course grades among students. Interestingly, no statistically significant differences were observed in irregular sleep schedules, communication, depression, and entertainment within the surveyed sample. Furthermore, the results indicated a significant gender-based difference in delayed sleep time and stress levels, with notable variations between male and female participants. Additionally, we leveraged machine learning algorithms to establish a quantitative framework for predicting students' GPAs in online classes. Since the situation of COVID-19 is still unstable in Iran and online education is still used in the education system, the insights from this research can aid educational leaders in devising effective strategies to maintain a positive learning experience for students.

Keywords: Online Education; Engineering Students; Grade Point Average; Best-Worst Method; Machine Learning; COVID-19 Pandemic

* Corresponding Author

1. Introduction

Due to COVID-19's high transmission and mortality rates, governments swiftly implemented lockdowns and stay-at-home measures to curb the spread of the disease (WHO, 2020). One sector significantly affected by the pandemic on a global scale is education, with the widespread closure of educational institutions (Basilaia, 2020). Although online learning offers advantages such as flexibility regarding time and location, it also presents numerous challenges. These challenges encompass technical issues, learners' proficiency and confidence levels, distractions, frustration, and anxiety. Shifting from traditional face-to-face instruction to online learning represents a substantial adjustment for students and educators, impacting academic performance, mental health, and social skills (Atlam et al., 2022).

While extensive research has explored the effects of online learning during the COVID-19 pandemic on university students' performance and achievement (Pokhrel & Chhetri, 2021; Iqbal et al., 2021; Limniou, 2021; Movahed et al., 2023), there remains a scarcity of studies in specific disciplines and developing countries, such as Iran (Chabook, 2020). To the best of our knowledge, this study represents the first in-depth examination of the repercussions of online education during the COVID-19 pandemic on engineering students in Iran, encompassing aspects like sleep habits, interpersonal skills, mental well-being, digital technology usage, and academic performance. The insights from this research can aid educational leaders and policymakers in devising effective strategies to maintain a positive learning experience for students.

Compared with previous research, the core novelties of this research are as follows: (1) conducting an in-depth literature review, we identified factors and sub-factors that could affect university students' performance taking online classes. (2) using the Best-Worst Method (BWM), one of the recently proposed multi-criteria decision-making (MCDM) methods, we prioritize the identified sub-factors. (3) we designed a questionnaire based on the critical sub-factors derived in the second step and then analyzed data using statistical analysis techniques. (4) machine learning techniques are deployed to forecast students' Grade Point Averages (GPAs) in the context of online classes.

The subsequent sections of this paper are structured as follows: Section 2 outlines the literature review and hypotheses formulated for this study. Section 3 discusses the materials and methods employed, while Section 4 presents and analyzes the survey findings. In Section 5, we delve into the results achieved in this research and draw comparisons with findings from prior studies. In Section 6 we provide specific recommendations for educational leaders based on the research findings. Finally, Section 7 offers the research's concluding remarks.

2. Literature review

2.1. Impact of COVID-19 and online classes on university students' sleep habits

Sleep plays a vital role in maintaining overall health, emotions, and stress levels (Brown et al., 2018; Ordway et al., 2021). Conversely, sleep-related issues can adversely affect these aspects and are likely to influence cognitive functions, physical health, and academic accomplishments (Moore, 2012). Recent research indicates that the COVID-19 pandemic has changed adults' sleep habits, particularly in regions where lockdown measures were enforced. Investigations conducted on college students before and after the pandemic's onset and the shift to online learning have revealed decreased sleep quality, increased sleep duration, delayed sleep time, irregular sleep schedules, elevated daytime napping, and higher rates of insomnia. Furthermore, some studies have linked these sleep-related challenges to concurrent heightened stress levels and diminished academic performance (Robillard et al., 2021; Zhuo et al., 2020; Wright et al., 2020; Benham, 2021; Nozari et al., 2025).

2.2. Impact of COVID-19 and online classes on university students' interpersonal skills

Numerous researchers have highlighted the benefits of collaborative learning, such as increased participation, enhanced student confidence, and a deeper comprehension of course materials. For instance, Olakanmi (2017) conducted a study assessing the impact of the flipped classroom instructional model on the performance and attitudes of senior secondary students in a Nigerian school. The results demonstrated that students taught using the flipped classroom approach outperformed those in traditional instruction methods.

Research has revealed that students often exhibit limited critical thinking and participation in online discussions, resulting in unproductive and superficial discourse lacking collaboration (Hew et al., 2010; Stegmann et al., 2012; Nozari et al., 2025). However, Driscoll and Carliner (2005) conducted a study suggesting that deliberate online instructional strategies can stimulate critical thinking, encourage active participation, and foster the creation of innovative concepts.

Promoting creativity as well as innovation as fundamental elements of student learning and development remains a critical priority in higher education (Songkram, 2017). Online learning allows students to explore fresh concepts within their fields, refine their social presence, and enhance presentation skills. Teachers can stimulate creativity and idea-sharing among students through various platforms and media applications, which may be challenging in traditional classroom settings (Lee & Recker, 2021). When integrated effectively into the learning system, online instructional tools contribute to a profound understanding of concepts and improved subject performance (Henriksen, 2021).

Chen and Jones (2007) found that distance learners demonstrated excellent proficiency in asking questions compared to their peers attending face-to-face classes. Remote learners also reported higher satisfaction with group work and perceived communication and decision-making processes as more effective. Engaging in group discussions through dedicated online forums, where students exchange and debate ideas, positively impacts collaboration, fosters student engagement, and enhances academic performance on projects (Zarzycka et al., 2021). Emotional intelligence holds significant importance in educational psychology and serves as a predictor of academic achievement. Studies have shown that emotional intelligence directly and indirectly improves student performance in online classes (Iqbal et al., 2021; Ali & Mohammed, 2020; Norboevich, 2020).

2.3. Impact of COVID-19 and online classes on university students' mental health

While research indicates that online learning can enhance students' ability to comprehend and retain information more quickly, specific studies, such as the one by Grubic et al. (2020), argue that the restricted learning environment associated with online education may result in heightened stress levels and subsequent adverse academic outcomes. Wang et al. (2020) have documented a prevalence of self-reported moderate to severe depression. This upward trend has been linked to the overall impact of uncertainty, fears, and anxiety stemming from the health consequences of the pandemic (Brooks et al., 2020). Furthermore, following the onset of the pandemic, US college students notably identified the transition to distance learning, social isolation, and depression as sources of anxiety (Fruehwirth et al., 2021).

As mentioned in Wiles (2020), students engaged in online classes face a significant increase in screen time, which disrupts their daily routines and can have a holistic impact on their mental well-being. Students encounter five key challenges during online classes. Firstly, they experience fatigue that arises without specific symptoms and can lead to mental health issues. Secondly, they may suffer from headaches or other physical discomfort. Thirdly, they may become demotivated when faced with assignments from their teachers. Fourthly, feelings of isolation may arise due to a lack of interaction with peers and others. Finally, they may struggle to understand the content presented by lecturers or peers during online classes, as online learning significantly differs from in-person dialogue.

2.4. Impact of COVID-19 and online classes on university students' digital technology

Jones (2008) introduced a framework categorizing college students' Internet usage into three groups: 1) early adoption and heavy usage behavior; 2) increased motivation and educational benefits; and 3) alterations in social life. The utilization of the Internet for academic purposes, such as conducting online research, accessing educational resources, communicating with instructors and peers, and exploring a wide range of academic subjects, has played a pivotal role in enhancing educational achievements. However, the Internet is also a significant source of entertainment for college students, involving activities like online gaming and movie-watching, which consume a substantial amount of their time. This diversion into entertainment on the Internet can lead to academic distraction, impacting students' ability to perform academic tasks accurately and effectively (Limniou, 2021). Numerous studies have investigated the phenomena of multitasking and distraction within lecture theater environments and their influence on student performance (May & Elder, 2018; Jamet et al., 2020).

2.5. Impact of COVID-19 and online classes on university students' academic performance

As outlined by Mandasari (2020), there are several challenges associated with the implementation of E-Learning within the classroom, which include the following: (1) Insufficient interaction among lecturers and students, as well as among students themselves, can impede the development of values within the teaching and learning process. (2) Using online learning methods may diminish students' practical skills in medical and engineering disciplines. (3) There is a shift in the role of lecturers, who must transition from their prior expertise in conventional teaching methods to mastering instructional techniques utilizing ICT (Information Communication Technology). (4) Students lacking high motivation for learning tend to face difficulties and may experience academic setbacks. (5) Access to internet facilities is not universally available, often linked to issues concerning electricity, telecommunications, and computer accessibility in certain regions.

2.6. Impact of sleep habits, interpersonal skills, mental health, digital technology, and academic performance on GPA

Research has shown that a student's Grade Point Average (GPA) does not directly indicate their learning or memory abilities. Instead, a student's GPA is influenced by a complex interplay of various factors within their environment. These factors encompass intelligence, motivation, interpersonal skills, personality, socioeconomic status, health issues, sleep patterns, digital proficiency, historical and current educational systems, academic workload, program of study, and aptitude in test-taking (Rodríguez-Planas, 2022; Hershner, 2020; Feng et al., 2019; Adams & Blair, 2019).

This study adopts a comprehensive approach that considers multiple significant factors and their constituent elements, including sleep patterns, interpersonal skills, mental well-being, digital technology usage, and academic performance. It seeks to explore the impact of these factors on the academic achievements of engineering students in Iran. A four-step research methodology combines MCDM, statistical analysis, and machine learning techniques to achieve this. Figure 1 provides an overview of the theoretical framework of this study.

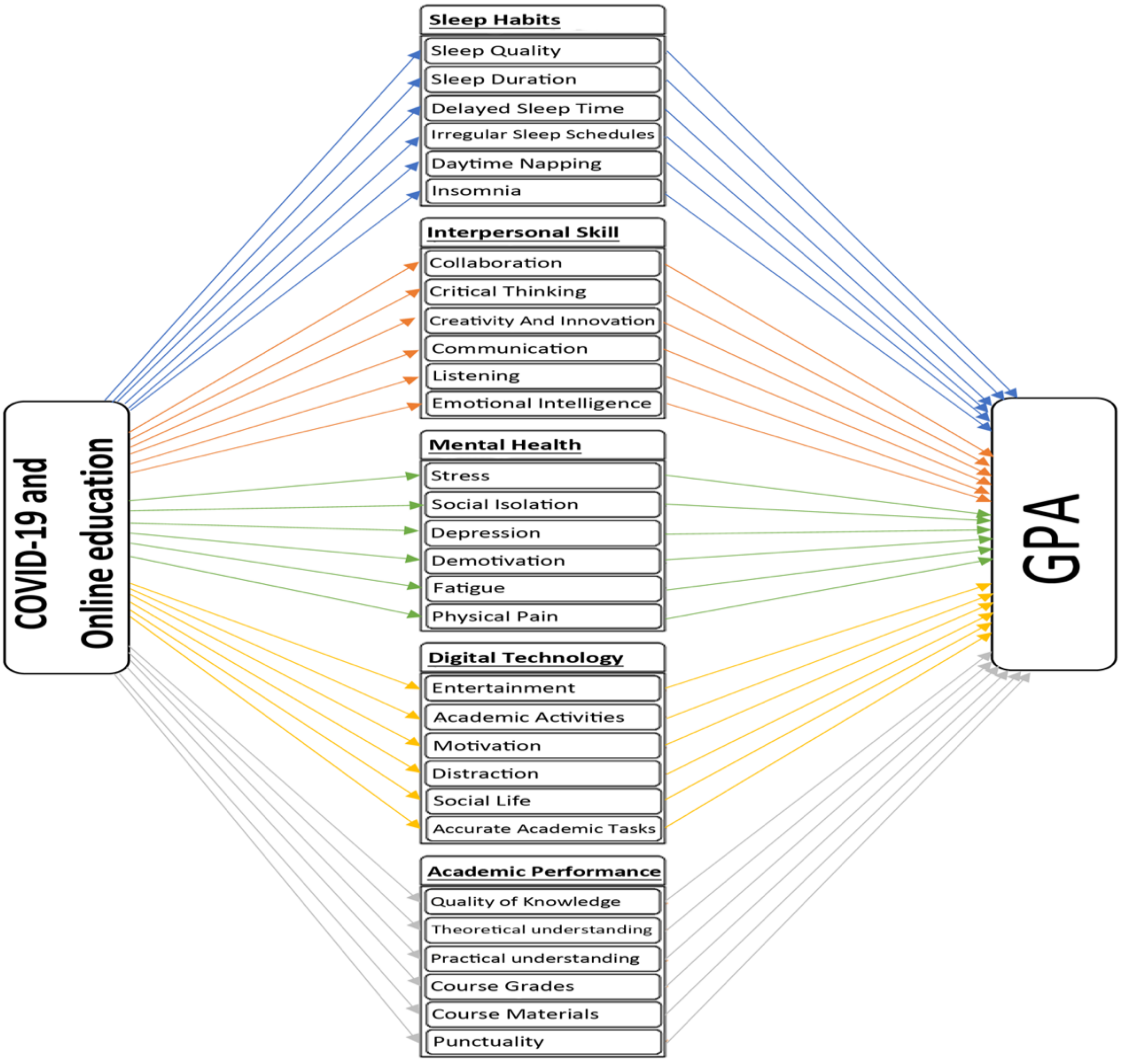

Figure 1. The theoretical framework of the impact of COVID-19 and online classes on sleep habits, interpersonal skills, mental health, digital technology, and academic performance

3. Research methodology

This study employed the best-worst method, involving university pedagogical experts in face-to-face discussions to rank the significance of research components. Subsequently, a questionnaire was devised based on the three most critical components identified within each domain. Data collected through the questionnaire underwent rigorous analysis employing statistical tools and qualitative and quantitative methodologies. Additionally, machine learning algorithms were utilized to predict students' GPAs in the context of online classes. Figure 2 demonstrates the research methodology diagram.

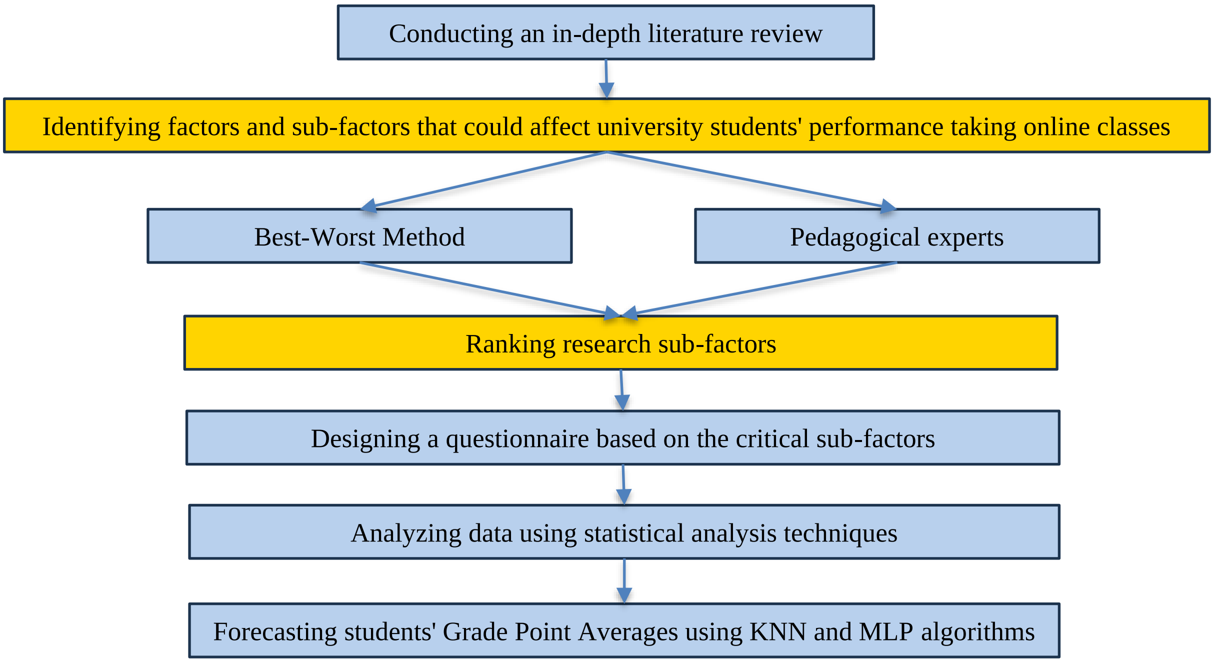

Figure 2. The research methodology diagram

3.1. Best-Worst Method (BWM)

This study utilizes a recently developed MCDM technique known as the "best-worst method" (Rezaei, 2015). This method assesses various alternatives based on a set of decision criteria through a systematic pairwise comparison process. First, the decision criteria are identified, and among them, the best (typically the most desirable or significant) and the worst (usually the least desirable or important) criteria are selected. Subsequently, the decision-maker provides their preferences by comparing the best criterion against all other criteria and by comparing all criteria against the worst criterion, using a predefined numerical scale (e.g., 1 to 9). These two sets of pairwise comparisons serve as input for an optimization problem, from which the criteria weights are determined. Table 1 displays the research factors and their respective components.

Table 1. Research factors and their components

Factors	Components	References
Sleep Habits (F_1)	Sleep Quality (C_{11})	Robillard et al., 2021; Zhuo et al., 2020; Wright et al., 2020; Benham, 2021
	Sleep Duration (C_{12})	
	Delayed Sleep Time (C_{13})	
	Irregular Sleep Schueles (C_{14})	
	Daytime Napping (C_{15})	
	Insomnia (C_{16})	
Interpersonal Skills (F_2)	Collaboration (C_{21})	Olakanmi, 2017; Hew et al., 2010; Stegmann et al., 2012; Lee & Recker, 2021; Henriksen, 2021; Chen et al., 2007; Zarzycka et al., 2021; Iqbal et al., 2021; Ali & Mohammed, 2020; Norboevich, 2020
	Critical Thinking (C_{22})	
	Creativity and Innovation (C_{23})	
	Communication (C_{24})	
	Listening (C_{25})	
	Emotional Intelligence (C_{26})	
Mental Health (F_3)	Stress (C_{31})	Grubic et al., 2020; Wang et al., 2020; Brooks et al., 2020; Fruehwirth et al., 2021; Wiles, 2020
	Social Isolation (C_{32})	
	Depression (C_{33})	
	Demotivation (C_{34})	

Factors	Components	References
	Fatigue (C_{35})	
	Physical Pain (C_{36})	
Digital Technology (F_4)	Entertainment (C_{41})	Jones, 2008; Limniou, 2021; May & Elder, 2018; Jamet et al., 2020
	Academic Activities (C_{42})	
	Motivation (C_{43})	
	Distraction (C_{44})	
	Social Life (C_{45})	
	Accurate Academic Tasks (C_{46})	
Academic Performance (F_5)	Quality of Knowledge (C_{51})	Mandasari, 2020
	Theoretical Understanding (C_{52})	
	Practical Understanding (C_{53})	
	Course Grades (C_{54})	
	Course Materials (C_{55})	
	Punctuality (C_{56})	

3.2. Data collection

Upon identifying the three fundamental components within each factor, a questionnaire was crafted to explore the research inquiries. To ensure the questionnaire's validity, it underwent a validation process involving feedback and comments from three experts who assessed its relevance, consistency, and clarity. A pilot study was conducted by administering the questionnaire to a randomly chosen sample of participants (N = 30). The initial reliability of the questionnaire was assessed separately for each factor using Cronbach's alpha, producing the following results: sleep habits (Cronbach's alpha = 0.75), interpersonal skills (Cronbach's alpha = 0.89), mental health (Cronbach's alpha = 0.82), digital technology (Cronbach's alpha = 0.84), and academic performance (Cronbach's alpha = 0.76). All reliability coefficients exceeded the generally accepted threshold of 0.6 (Cohen et al., 2007).

We asked professors from various public and private universities across Iranian cities to distribute the online questionnaire to their students during the 2021–2022 academic year, resulting in 500 responses. The final version of the questionnaire encompassed sections for demographic information (e.g., age, gender, and year), featuring 43 multiple-choice items, statements rated on a five-point Likert scale (ranging from 1 = strongly disagree to 5 = strongly agree), and a question concerning GPA. The online questionnaire was created and hosted on a cloud-based platform (survey.porsline.ir), with the collected responses stored in an Excel file.

3.3. Data analysis

The gathered data underwent comprehensive analysis utilizing IBM Statistical Analysis (IBM SPSS 27) and the Python programming language. The researchers initiated the analysis by employing nonparametric assessments, specifically the Shapiro-Wilk and Kolmogorov-Smirnov tests, to evaluate the normality of the research variables. Subsequently, a One-Sample Wilcoxon Signed Ranked Test and Mann-Whitney U test were used. Furthermore, advanced machine learning techniques were harnessed to predict students' Grade Point Average (GPA). Specifically, this predictive modeling process utilized the multilayer perceptron and the k-nearest neighbors algorithms.

4. Results

In this section, we delve into the outcomes of the devised framework.

4.1. BWM for prioritizing research factors' components

This research employed the BWM to identify each factor's top three crucial components. We considered the top three extracted components during the questionnaire design phase to enhance its precision. These determinations were made with input from a panel of five pedagogical experts and faculty members during an in-person meeting. Additionally, we calculated a consistency ratio to assess the reliability of the outcomes (as illustrated in Table 2).

Table 2. The optimal values of the weight coefficients of the components in each factor

Factors/Components	Code	ξ^*	Local Weights	Rank
Sleep Habits	**F_1**	**0.0787**	**-**	**-**
Sleep Quality	C_{11}	-	0.1575	**3**
Sleep Duration (the worst)	C_{12}	-	0.0394	6
Delayed Sleep Time (the best)	C_{13}	-	0.3937	**1**
Irregular Sleep Schedules	C_{14}	-	0.2362	**2**
Daytime Napping	C_{15}	-	0.0945	4
Insomnia	C_{16}	-	0.0787	5
Interpersonal Skills	**F_2**	**0.0567**	**-**	**-**
Collaboration	C_{21}	-	0.0832	5
Critical Thinking	C_{22}	-	0.2079	**3**
Creativity and Innovation	C_{23}	-	0.1040	4
Communication (the best)	C_{24}	-	0.3592	**1**
Listening (the worst)	C_{25}	-	0.0378	6
Emotional Intelligence	C_{26}	-	0.2079	**2**
Mental Health	**F_3**	**0.1034**	**-**	**-**
Stress	C_{31}	-	0.2585	**2**
Social Isolation	C_{32}	-	0.1292	**3**
Depression (the best)	C_{33}	-	0.4135	**1**
Demotivation	C_{34}	-	0.0862	4
Fatigue	C_{35}	-	0.0738	5
Physical Pain (the worst)	C_{36}	-	0.0388	6
Digital Technology	**F_4**	**0.1004**	**-**	**-**
Entertainment (the best)	C_{41}	-	0.4017	**1**
Academic Activities	C_{42}	-	0.1004	4
Motivation	C_{43}	-	0.0837	5
Distraction	C_{44}	-	0.2510	**2**
Social Life	C_{45}	-	0.1255	**3**
Accurate Academic Tasks (the worst)	C_{46}	-	0.0377	6
Academic Performance	**F_5**	**0.0757**	**-**	**-**
Quality of Knowledge	C_{51}	-	0.1136	4
Theoretical understanding (the best)	C_{52}	-	0.3787	**1**
Practical understanding	C_{53}	-	0.2272	**2**
Course Grades	C_{54}	-	0.1515	**3**
Course Materials (the worst)	C_{55}	-	0.0379	6
Punctuality	C_{56}	-	0.0909	5

4.2. Demographic statistics

The demographic profile of the participants is presented in Table 3. The table illustrates that 53.4% of the respondents were male, while 46.6% were female. Furthermore, a significant portion of the participants came from public universities.

Table 3. The participant's demographic information

Variable	Categories	Frequency	Percent (%)
Gender	Male	267	53.4
	Female	233	46.6
Age	18-22	285	57
	23-25	79	15.8
	26-30	70	14
	30 and above	66	13.2
Level/Year	Bachelor's	372	74.4
	Master's	113	22.6
	PhD	15	3
Institution	Public	435	87
	Private	65	13
GPA before COVID-19 (out of 20)	0-10	0	0
	11-14	62	12.4
	15-17	247	49.4
	18-20	191	38.2

4.3. Normality test of the variables

The distribution of variables was examined using nonparametric tests, namely the Kolmogorov–Smirnov and Shapiro-Wilk tests. The results of these tests indicated that the variables did not follow a normal distribution (p-value < 0.05), as shown in Table 4.

Table 4. Normality test of the variables

Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Delayed Sleep Time	0.220	500	<0.001	0.892	500	<0.001
Irregular Sleep Schedules	0.165	500	<0.001	0.922	500	<0.001
Sleep Quality	0.156	500	<0.001	0.893	500	<0.001
Communication	0.106	500	<0.001	0.966	500	<0.001
Emotional Intelligence	0.097	500	<0.001	0.964	500	<0.001
Critical Thinking	0.099	500	<0.001	0.947	500	<0.001
Depression	0.87	500	<0.001	0.960	500	<0.001
Stress	0.114	500	<0.001	0.949	500	<0.001
Social Isolation	0.128	500	<0.001	0.950	500	<0.001
Entertainment	0.101	500	<0.001	0.953	500	<0.001
Distraction	0.136	500	<0.001	0.946	500	<0.001
Social Life	0.122	500	<0.001	0.940	500	<0.001
Theoretical understanding	0.114	500	<0.001	0.931	500	<0.001
Practical understanding	0.175	500	<0.001	0.902	500	<0.001
Course Grades	0.114	500	<0.001	0.940	500	<0.001

Figures 3-7 show histograms illustrating the results of normality tests conducted on research variables. As can be seen in the figures, the variables did not follow a normal distribution.

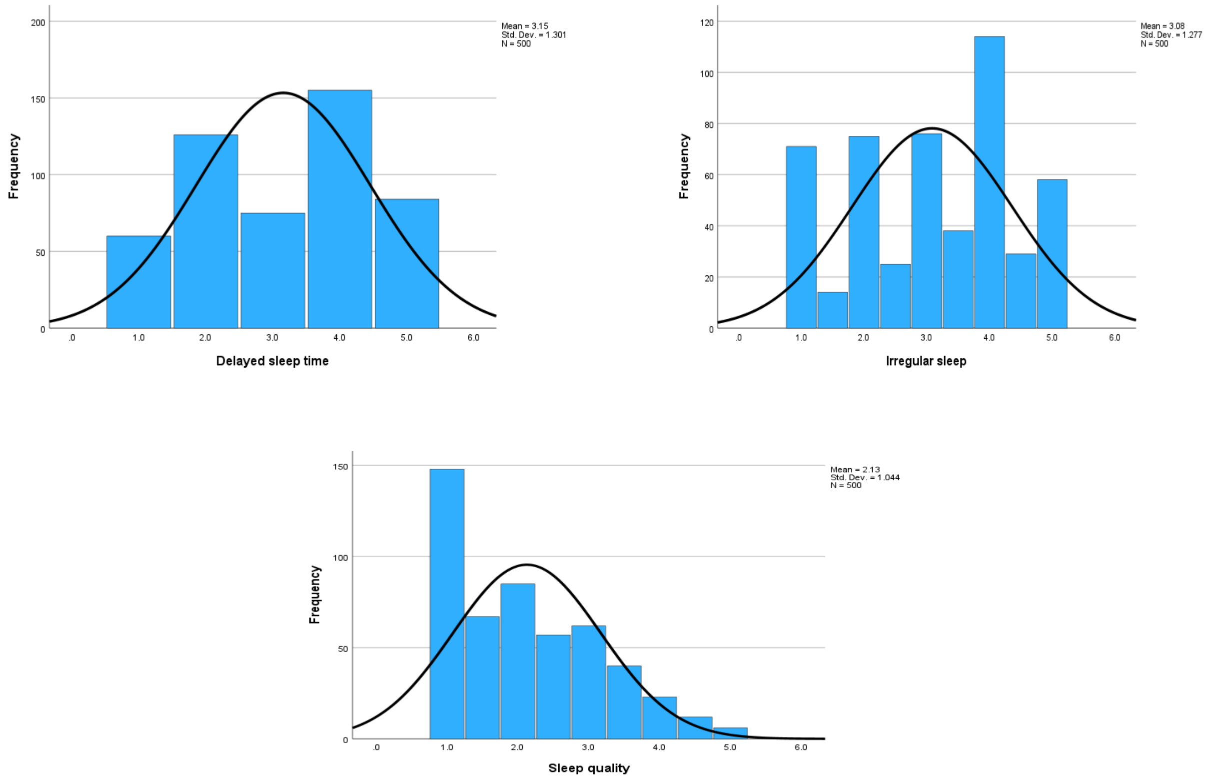

Figure 3. Normality assessment for Delayed Sleep Time, Irregular Sleep Schedules, and Sleep Quality

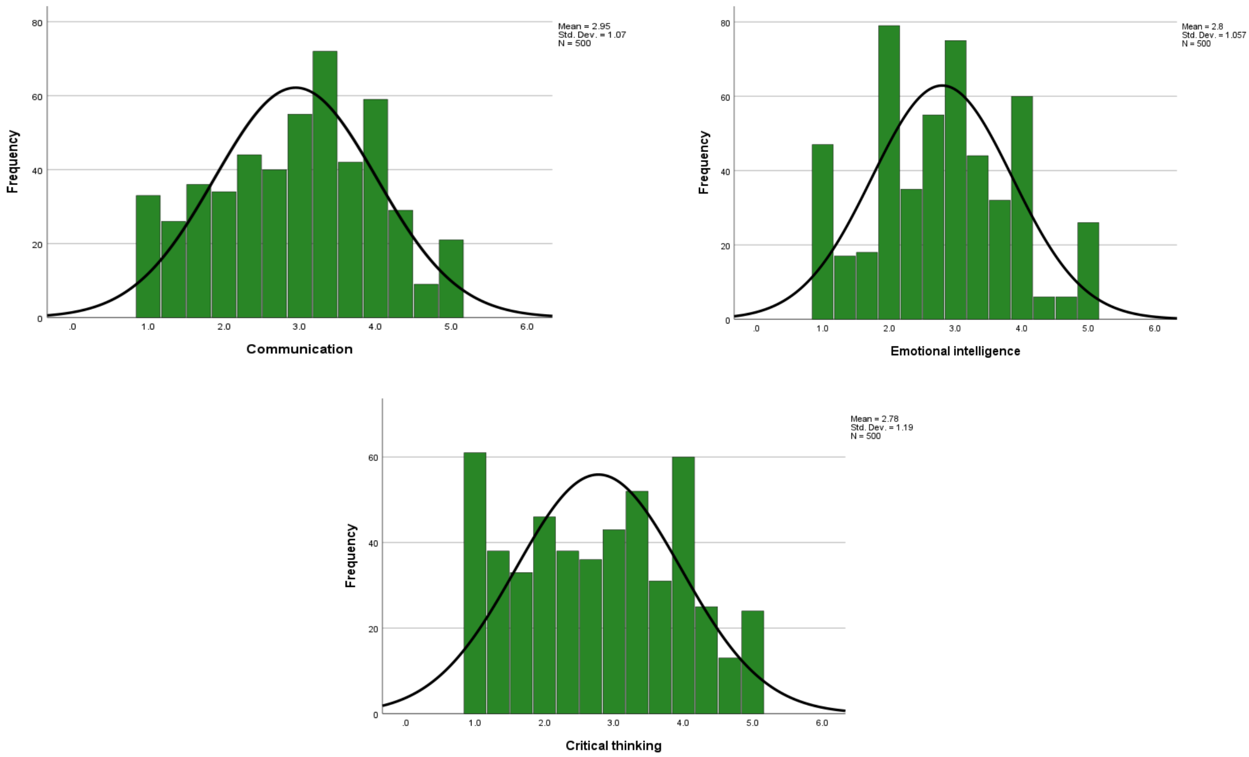

Figure 4. Normality assessment for Communication, Emotional Intelligence, and Critical Thinking

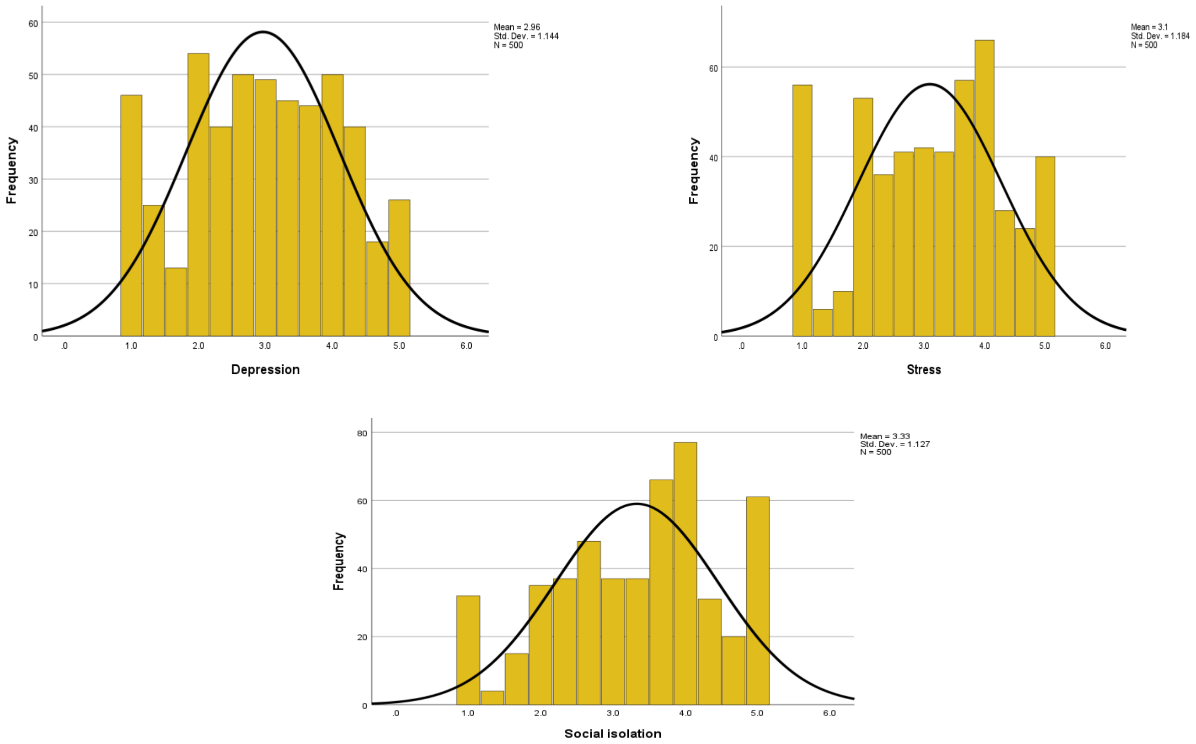

Figure 5. Normality Assessment for Depression, Stress, and Social Isolation

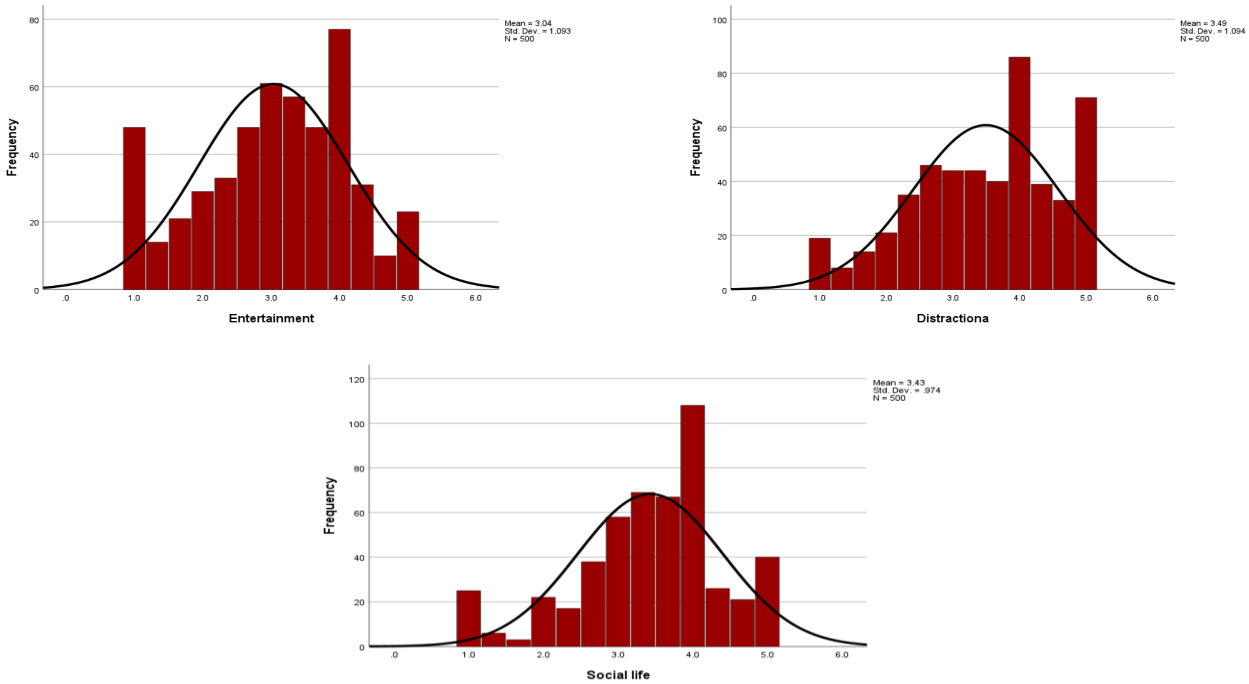

Figure 6. Normality Assessment for Entertainment, Distraction, and Social Life

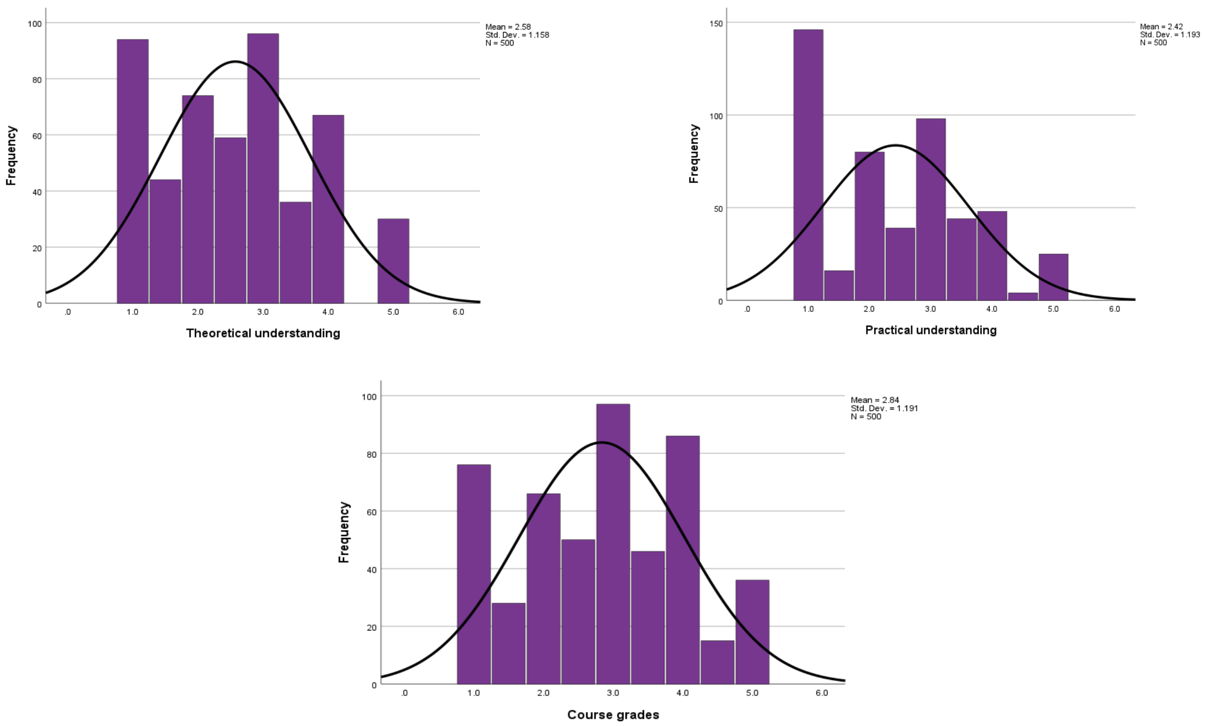

Figure 7. Normality Assessment for Theoretical understanding, Practical understanding, and Course Grades

4.4. Analysis of sleep habits components

To assess the sleep habits of engineering students during online classes, we used a one-sample Wilcoxon Signed Rank Test, as presented in Table 5. The test results indicated that students generally reported going to bed late at night most of the time during COVID-19 ($p = 0.010 < 0.05$). Additionally, they experienced fewer waking up mid-sleep and nightmares during sleep, suggesting that online classes during COVID-19 positively impacted sleep quality ($p = 0.001 < 0.05$). However, their views on irregular sleep schedules did not significantly differ from neutral views ($p > 0.05$).

Table 5. One-Sample Wilcoxon Signed Ranked Test for Sleep Habits

Components	Total N	Std. Deviation	Standard Test-Statistic (Z)	Asymptotic Sig. (2-tail)
Delayed Sleep Time	500	1.301	-2.589	0.010
Irregular Sleep Schedules	500	1.277	-1.208	0.227
Sleep Quality	500	1.044	-14.288	<0.001

4.5. Analysis of interpersonal skills components

To assess the impact of online classes on the interpersonal skills of engineering students, a one-sample Wilcoxon Signed Rank Test was conducted, and the results are presented in Table 6. The test results indicated that online classes during COVID-19 had a negative effect on engineering students' emotional intelligence, which relates to their ability to comprehend, control, and positively use emotions ($p = 0.001 < 0.05$). Furthermore, critical thinking skills, particularly in solving complex problems and understanding new engineering concepts, were also negatively impacted by online classes ($p = 0.001 < 0.05$). However, students' perceptions of whether online courses improved their relationships with classmates, facilitated idea exchange, and made it easier to present projects did not significantly differ from neutral views ($p > 0.05$).

Table 6. One-Sample Wilcoxon Signed Ranked Test for Interpersonal Skills

Components	Total N	Std. Deviation	Standard Test-Statistic (Z)	Asymptotic Sig. (2-tail)
Communication	500	1.069	-1.115	0.265
Emotional Intelligence	500	1.057	-4.206	<0.001
Critical Thinking	500	1.189	-4.189	<0.001

4.6. Analysis of mental health components

To assess the impact of online classes on the mental health of engineering students, a one-sample Wilcoxon Signed Rank Test was conducted, and the results are presented in Table 7. The test results indicated that online classes during COVID-19 had several adverse effects on engineering students' mental health. Specifically, online courses were associated with increased stress, fear regarding academic progress, higher levels of social isolation, and a feeling of disconnection ($p = 0.001 < 0.05$). However, students' perceptions of whether online classes gave them a sense of instability, negative emotions, or caused them to lose interest in the lessons did not significantly differ from neutral views ($p > 0.05$).

Table 7. One-Sample Wilcoxon Signed Ranked Test for Mental Health

Components	Total N	Std. Deviation	Standard Test-Statistic (Z)	Asymptotic Sig. (2-tail)
Depression	500	1.144	-0.555	0.579
Stress	500	1.184	-1.967	0.049
Social Isolation	500	1.127	-6.416	<0.001

4.7. Analysis of digital technology components

To assess the impact of online classes on engineering students' digital technology usage, we used a one-sample Wilcoxon Signed Rank Test, and Table 8 shows the results. The test outcomes revealed that online classes during COVID-19 had several effects on students' digital technology habits. Specifically, online classes increased students' tendency to become distracted using computers and smartphones while taking courses and positively impacted their social lives ($p = 0.001 < 0.05$). On the other hand, students' perceptions of using digital technology for entertainment were not significantly different from neutral views ($p >= 0.05$).

Table 8. One-Sample Wilcoxon Signed Ranked Test for Digital Technology

Components	Total N	Std. Deviation	Standard Test-Statistic (Z)	Asymptotic Sig. (2-tail)
Entertainment	500	1.093	-1.100	0.271
Distraction	500	1.093	-9.330	<0.001
Social Life	500	0.974	-9.465	<0.001

4.8. Analysis of academic performance components

To assess the impact of online classes on the academic performance of engineering students, a one-sample Wilcoxon Signed Rank Test was conducted, and Table 9 shows the results. The outcomes revealed several effects of online classes during COVID-19 on students' academic performance. Specifically, online classes decreased students' theoretical understanding, practical understanding, and course grades in both practical and theoretical courses ($p = 0.001 < 0.05$).

Table 9. One-Sample Wilcoxon Signed Ranked Test for Academic Performance

Components	Total N	Std. Deviation	Standard Test-Statistic (Z)	Asymptotic Sig. (2-tail)
Theoretical understanding	500	1.158	-7.653	<0.001

Practical understanding	500	1.192	-9.912	<0.001
Course Grades	500	1.190	-3.059	0.002

4.9. Gender Differences

A Mann-Whitney U Test was conducted to explore potential gender-based differences in various research components. The results revealed significant differences between male and female students in two areas. First, there was a statistically significant difference in delayed sleep time, with females (Mean Rank = 166.88) experiencing a higher delay compared to males (Mean Rank = 139.59) ($U = 9613.50$, $Z = -2.786$, $p = 0.005 < 0.05$). Second, the difference in stress levels between females (Mean Rank = 269.33) and males (Mean Rank = 234.06) was statistically significant ($U = 26717$, $Z = -2.736$, $p = 0.006 < 0.05$). However, there were no significant differences between females and males in other research components.

4.10. Correlations between research components and GPA

Since this study's components did not follow a normal distribution pattern, Spearman's rank correlations were employed to examine the relationships between these variables and students' GPAs (at the 0.01 significance level). As shown in Figure 8~~2~~, course grades and stress exhibited the most substantial associations with GPA, with correlation coefficients of $\rho = 0.549$ ($p < 0.01$) and $\rho = 0.402$ ($p < 0.01$), respectively. However, sleep quality displayed the weakest association, with a correlation coefficient of $\rho = 0.180$ ($p < 0.01$).

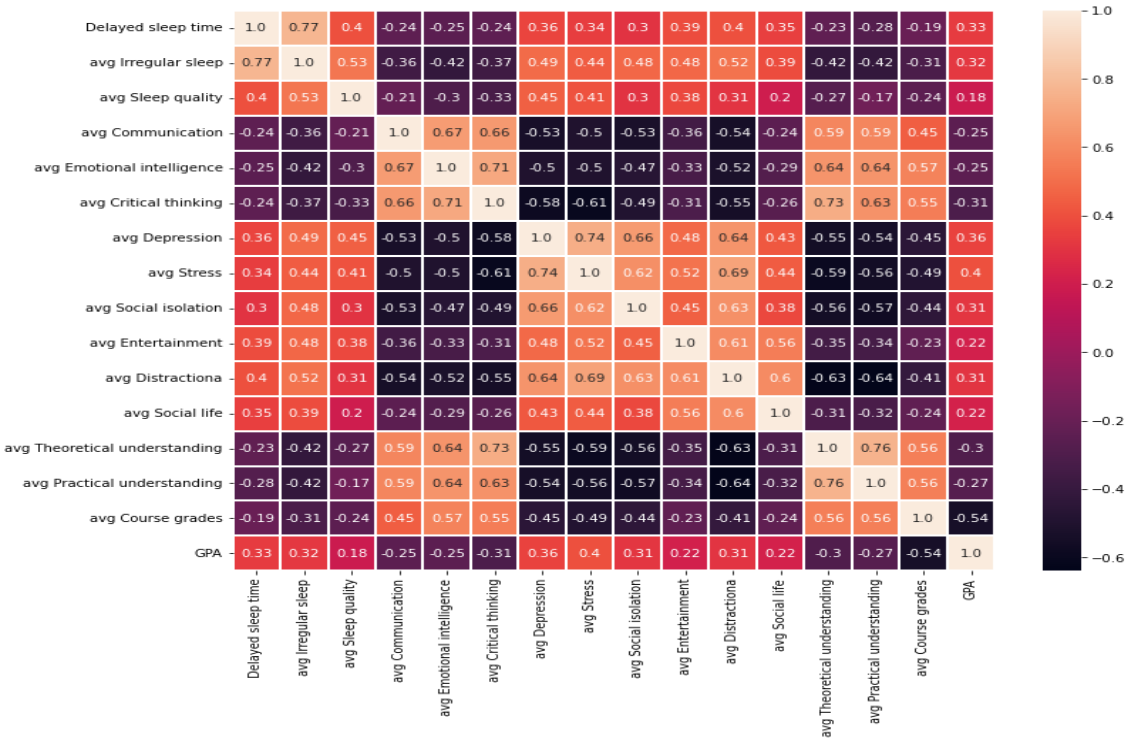

Figure 8. Spearman's rank correlation coefficients

4.11. Predicting GPA using machine learning models

We employed machine learning algorithms, namely the Multilayer Perceptron (MLP) and K-Nearest Neighbors (KNN), to forecast students' GPAs in online classes. The MLP is a powerful neural network algorithm that has shown success in handling complex patterns and non-linear relationships in data. By utilizing this method, we aim to capture the intricate relationships between various factors that contribute to students' academic performance in online classes. On the other hand, the KNN algorithm is a non-parametric method that relies on proximity-based classification.

The MLP is a feed-forward neural network comprising three layers: an input layer, a hidden layer, and an output layer. The input layer receives the input data to be processed, while the output layer handles tasks such as classification and prediction. The MLP's architecture includes a series of hidden layers between the input and output layers, facilitating complex data processing (Koosha et al., 2022). On the other hand, K-Nearest Neighbors (KNN) is a supervised learning algorithm utilized for both regression and classification tasks. KNN operates by predicting the correct class for test data by measuring the distance between the test data point and all the training data points. It then selects the K nearest data points to the test data for making predictions.

The inputs to the GPA prediction model are as follows: Delayed Sleep Time, Irregular Sleep Schedules, Sleep Quality, Communication, Emotional Intelligence, Critical Thinking, Depression, Stress, Social Isolation, Entertainment, Distraction, Social Life, Theoretical understanding, Practical understanding, Course Grades. To assess the performance of these machine learning models, we utilized four evaluation criteria: accuracy, precision, recall, and F-measure. In the preprocessing step, data were scaled between 0 and 1. To mitigate potential bias in classification, the collected data from respondents were randomly divided into training (75%) and testing (25%) sets. Table 10 provides a classification report for the selected machine learning models based on the mean results of ten runs, focusing on three GPA classes (1=better, 2=not changed, 3=worse).

Table 10. The performance results for machine learning models

ML model		Precision	Recall	F1	Accuracy
MLP	1	0.7201	0.7322	0.7215	0.7856
	2	0.7794	0.7909	0.7781	
	3	0.8586	0.8279	0.8385	
KNN	1	0.7747	0.8003	0.7845	0.8384
	2	0.8567	0.8438	0.8474	
	3	0.8785	0.8683	0.8720	

In Figure 9, we have provided a Precision-Recall curve to demonstrate the superiority of KNN over MLP in the research dataset. The chart illustrates a single iteration with two scenarios. To scrutinize the details, separate displays are presented for each class. Class one is represented in red, class two in green, and class three in blue (KNN algorithm in bold and MLP algorithm in a lighter shade). As evident from the figure, both algorithms have performed well across all three classes. Notably, as the chart extends higher towards the right, it signifies better algorithm performance. In the KNN, all three classes exhibit superior performance. Additionally, for both classifiers, the performance is observed to be the best for class three. Class two follows in the next ranking, with class one in the third position.

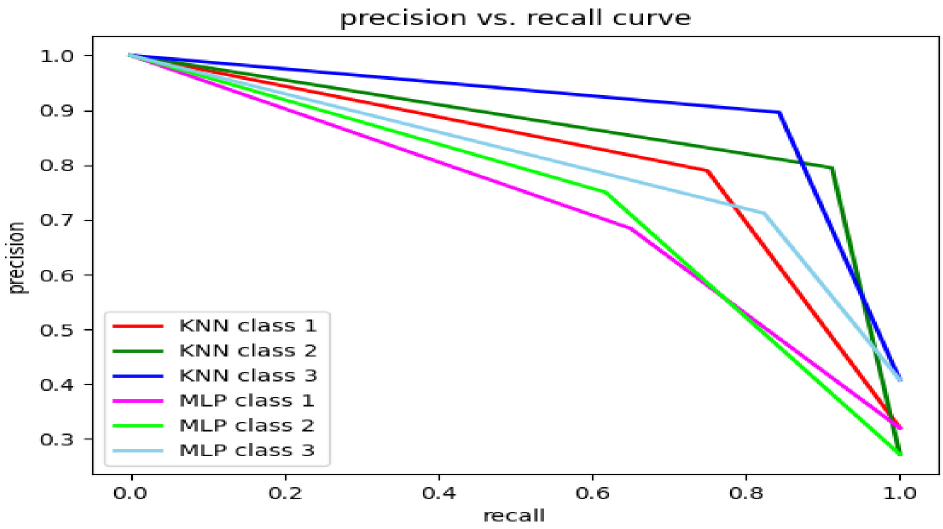

Figure 9. Precision-Recall curve for KNN and MLP algorithms

5. Discussion

The results of sleep habits components indicated that students frequently went to bed late during COVID-19. This finding aligns with prior studies by Robillard et al. (2021) and Benham (2021), which observed a significant increase in delayed sleep time among college students during the pandemic. Additionally, the data revealed that engineering students experienced fewer mid-sleep awakenings and nightmares during sleep, indicating improved sleep quality during online classes in the COVID-19 era. This contradicts the findings of Wright et al. (2020), who reported poor sleep quality in their sample during lockdown. One possible explanation could be that students in online classes may experience reduced anxiety about solving math problems teachers pose. However, our research did not find a statistically significant difference in students' irregular sleep schedules. Furthermore, Spearman's rank correlation analysis demonstrated positive correlations between delayed sleep time, irregular sleep habits, and sleep quality, with GPA.

The outcomes of interpersonal skills components revealed that online classes during COVID-19 had a detrimental impact on engineering students' emotional intelligence, diminishing their ability to understand, control, and positively utilize emotions. This observation has not been previously documented in the literature. Furthermore, the student's proficiency in solving complex problems and comprehending new engineering concepts declined during online classes. This outcome contradicts the findings of a prior study by AlMahdawi et al. (2021), which suggested a significant improvement in critical thinking skills during online classes. This discrepancy might be attributed to engineering courses' reliance on mathematical calculations, making it challenging to grasp abstract concepts in an online learning environment. However, our research did not identify a statistically significant difference in engineering students' communication skills. Additionally, emotional intelligence, critical thinking, and communication negatively correlated with GPA.

The outcomes of mental health components revealed that online classes during COVID-19 had a notable impact on engineering students. They experienced a significant increase in stress levels and harbored apprehensions about their academic progress. Moreover, these online courses contributed to heightened feelings of social isolation, leaving engineering students with a sense of disconnection. However, there were no statistically significant differences in levels of depression. These findings are consistent with a substantial body of prior research, which reported increased stress and social isolation among students participating in online classes during the COVID-19 pandemic (Grubic et al., 2020; Wiles, 2020). Stress, depression, and social isolation exhibited positive correlations with GPA.

The results of digital technology components indicated that online classes during COVID-19 significantly impacted engineering students. They became notably more distracted, often using computers and smartphones for tasks like texting and visiting websites related to entertainment (movies, TV shows, music groups, or sports stars) while attending courses (multitasking). Furthermore, online classes significantly improved the social lives of engineering students. This phenomenon may be attributed to the reduced face-to-face communication during the COVID-19 pandemic, prompting students to engage in more online social interactions during virtual classes. Interestingly, there was no statistically significant difference in entertainment levels within the sample. Additionally, entertainment, distraction, and social life positively correlated with GPA.

The results of academic performance components revealed a significant decline in engineering students' theoretical understanding, practical understanding, and course grades, both in practical and theoretical courses, during online classes amid the COVID-19 pandemic. This decline could be attributed to the challenging nature of comprehending engineering concepts and principles within limited time constraints and the online class environment. A noteworthy issue for engineering students was the inability to design and conduct research effectively in an online class setting. Furthermore, theoretical understanding, practical understanding, and course grades exhibited negative correlations with GPA.

A Mann-Whitney U Test identified significant differences between male and female students regarding delayed sleep time and stress but found no significant differences in other research components.

Machine learning algorithms, including the Multilayer Perceptron (MLP) and K-Nearest Neighbors (KNN), were employed to develop predictive models for students' GPAs in online classes. The models were evaluated based on accuracy, precision, recall, and F-measure, with KNN outperforming MLP with an accuracy measure of 0.8384 compared to MLP's 0.7856. This indicates the potential of machine learning algorithms to predict students' academic performance effectively, providing valuable insights for educators and institutions in an evolving educational landscape.

6. Recommendations for educational leaders based on the research findings

A vital issue worth mentioning is that, since the situation of COVID-19 is still unstable in Iran and online education is still used in the education system, the insights from this research can aid educational leaders in devising effective strategies to maintain a positive learning experience for students. In addition, the findings of this research mainly focus on online learning, and not only they can be used in Iran but also worldwide in designing online education. Beloved, we provided more specific recommendations for educational leaders based on the research findings.

- Sleep habits:
  - Implement awareness campaigns and educational programs to promote healthy sleep habits among students.
  - Consider adjusting course schedules and workload to accommodate students' sleep patterns.

- Interpersonal skill:
  - Offer workshops or seminars for students to enhance their emotional intelligence skills, especially in the online learning environment.
  - Provide counseling services to support students dealing with emotional challenges during online classes.

- Mental health:

- Establish mental health support services, including counseling and therapy sessions, to help students cope with increased stress levels and feelings of social isolation.
- Encourage the creation of virtual support communities to foster a sense of connection among students in online classes.

• Digital Technology:
- Implement guidelines or workshops on the effective use of digital technology during online classes, emphasizing minimizing distractions and multitasking.
- Encourage the development of digital literacy skills to help students navigate online resources more efficiently.

• Academic performance:
- Explore innovative teaching methods and technologies to enhance online learning experiences and engagement.
- Offer additional support and resources for students struggling with theoretical understanding and practical application in online courses.

7. Conclusion, Implications, and Limitations

This study aimed to investigate the potential impact of online classes during the COVID-19 pandemic on the sleep habits, interpersonal skills, mental health, digital technology usage, and academic performance of engineering students in Iran. This research used the BWM to identify each factor's top three crucial components, which were then considered during the questionnaire design phase to enhance its precision. Moreover, the study explored how these factors might influence the students' GPAs. Notably, this research is one of the first to examine engineering education in a developing country.

The findings of this study revealed statistically significant effects of online classes during the pandemic on various aspects, including delayed sleep time, sleep quality, emotional intelligence, critical thinking, stress levels, social isolation, distractions, social life, theoretical understanding, practical understanding, and course grades. However, no statistically significant differences were observed regarding irregular sleep schedules, communication, depression, and entertainment among the surveyed participants. Interestingly, the study also noted gender-based differences, particularly concerning delayed sleep time and stress levels.

Despite the valuable insights gained from this study, certain limitations should be acknowledged, including restricted access to respondents and technical challenges associated with conducting online surveys. Additionally, achieving the intended sample size, especially for effective machine learning models, proved challenging. Future research could consider expanding the study to encompass a more extensive range of universities in Iran and employing larger sample sizes through cluster or stratified random sampling methods. Furthermore, there is potential for extending this research to evaluate online learning experiences for university students in other countries affected by the COVID-19 pandemic.

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