COVID-19 Impact on Technical Institutions in India

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Abstract:

The COVID-19 pandemic has changed work-life balance across the world since 2019. Globally, social life has changed a lot. All the countries are following the strategy of social distance among humans to protect themselves from the novel coronavirus. Most technical educational institutions have converted to virtual mode to control the spread of infection. However, the supervised learning process is required for technical education. Various experimental and real-time project innovations need close contact among team members. The primary objective of this study is to the problems and difficulties experienced by Indian technical educational institutions' stakeholders with regard to the results of technical education. Data is collected from students, faculty, and parents related to technical institutions. According to the data, the impact has been analyzed by using Machine Learning (ML) algorithms. The findings indicated that a large number of stakeholders at technical institutions had been impacted by COVID-19.

1. Introduction:

The pandemic of COVID-19 has drastically changed the global human working environment since February 2020 in India. To control the spread of the virus, the government has announced a lockdown, due to which many people lost their jobs and were affected financially. Though many precautions were taken, many people suffered from infections, lack of food, transportation, etc. Even the distance between various countries became very small for spreading this coronavirus, and the maintenance of social distance has been increased to protect themselves from the infections.

Moreover, technical educational institutions have been locked down due to this pandemic. Almost all the learning processes have been shifted to the virtual learning mode to maintain the continuous learning progress. Virtual mode technical education follows three main parts. The first is theoretical lectures, flexible to switch to virtual mode. There are various Information and Communications Technology (ICT) tools to conduct virtual classes, such as Microsoft Teams, ZOOM meetings, Google meet, Skype, Google classroom, etc. It is very easy to maintain social distance for this type of learning process. The next one is experimental lectures, which is delivered by teachers practically; the pupil also can follow to do simulations on their own. Modern equipment of simulation tools is required to learn the laboratory part. However, the facilities are insufficient, and the teachers must evaluate the final result. Hence, the experimental lectures need direct interaction between students and teachers. The final part is placement and internship training, which are essential for technical education. This part of learning is challenging in this pandemic situation. Moreover, the research is also most important for teachers and students, in which direct interaction may give qualitative results.

In this pandemic, the significant issues in technical education are to impart graduate engineering attributes and take care of stakeholders' health and well-being. Almost all educational institutions have been turned to virtual education mode, and people's lifestyles have changed drastically due to this pandemic. This paper's main goal is to examine data gathered from stakeholder experiences at Indian technical schools in order to increase the effectiveness of the online delivery of technical education.(Challa Madhavi latha &Lamesgin Addis, 2019; Soujanya et al., 2020)

The remainder of this study is structured as follows. The literature is discussed in Section 2. The approach is the main topic of Section 3. The statistics are examined in Section 4. Section 5 comes to an end.

2. Literature review:

COVID-19 pandemic affects the world's education system and impacts students, teachers, and parents worldwide (Tadesse et al., 2020). Most countries closed their educational institutions to restrict the spread of the COVID-19(*The Impact and Implications of the COVID 19-Crisis on Educational Systems and Households - TUAC*, n.d.). According to the UNESCO report, 87% of the world's student population was affected by the closures of educational institutions during COVID-19(*UNESCO Rallies International Organizations, Civil Society and Private Sector Partners in a Broad Coalition to Ensure #LearningNeverStops*, n.d.). Many works of literature studied the importance of educational institutes across the globe during COVID-19(Niyi Jacob et al., 2021)(Babbar& Gupta, n.d.)(Goplani, n.d.)(Rashid & Yadav, 2020). COVID-19 challenged the worldwide education system and forced it to shift to e-learning modes(Dhawan, n.d.). However, this transformation in teaching methodology leads to many problems experienced by students, teachers, and parents. Some parents are not techno-friendly, which creates issues in understanding the new teaching methodology and, alternatively, lack in guiding their child to take classes online.

Many teachers and students face challenges due to poor internet connectivity(Tarkar, 2020). Most educators strongly believe that e-learningcould never compete in the classroom teaching environment, even though many have been vocal about technology-friendly education forecasts for years(Xiao et al., 2021). Educators' significant challenges were also in the part of training and awareness. Along with a lack of interest in the subjects and confusion about the value of online classes, lack of awareness is the most important factor in why students did not adopt e-learning. The main negatives of e-learning modalities were lower attendance, the lack of a human touch, and the lack of engagement because of connection problems.(Arora & Srinivasan, 2020). During the COVID-19 lockdown, most of the students experienced symptoms of anxiety, tension,

despair, wrath, and post-traumatic stress. Students' psychological behaviour is also impacted by breaking rules, peer pressure, and technological difficulties during self-learning activities. The inability to adapt the e-learning platform to academic activities during COVID-19 was the primary cause of the students' stress.(Chhetri et al., 2021). The impact of COVID-19 on Indian technical institutes' stakeholders was covered in this study.

3. Methodology:

During this COVID-19 pandemic, technical education stakeholders from various institutions in India were invited to collect data about their experience of virtual learning mode. The questionnaire is based on skills engineering graduates acquire by following a virtual learning mode. Primary data has been collected from students, faculty, and parents who have gave back on technical education experience during the pandemic. The data collected from students are related to their skills attainment. The students' data represents personal, economical, psychological, and demographical perceptions and identifies whether the students are reaching the technical education skills.

Faculty information includes personal, economic, technological, psychological, and demographic perceptions. Further, whether the faculty is satisfied with virtual teaching is identified. Moreover, parents' data shows the economic, technological, and monitoring perceptions and identify whether their ward is monitored effectively learning process is efficient or not(Sharma et al., 2021). Finally, the collected data has been analyzed by using machine learning algorithms(Yadav et al., 2021).

Objectives:

The paper's primary goal is to examine

- Whether the students are acquiring skills through virtual learning
- Whether the faculty can teach effectively by using the virtual teaching process.
- Whether the parents are satisfied with the virtual teaching and learning process.

4. Data Analysis:

This paper analyzes the information collected from technical education stakeholders such as students (362), faculty (115), and parents (84). The information gathered is split into two main categories: Common data represented as PP1 to PP9, and graduate attributes represented as QQ1 to QQ10.

Common data

Table 1 shows the various attributes used for common data collection concerning students, faculty, and parents.

 Table 1: Common Information from the Respondents

PP1	Gender	Gender	Gender
PPP2	Is online learning a burden economically	Is online teaching a burden economically	Is online education a burden economically
PP3	Area	Area	Area
PP4	Internet connectivity	Internet connectivity	Internet connectivity
PP5	Is your location supporting your network	Is your location supporting your network	Is your location supporting your network
PP6	Are you able to concentrate on virtual learning	Are you able to teach on the virtual platform	whether your ward is concentrating on virtual learning
PP7	Are you able to express your doubts	Are you able to clear student's doubts	Does your home environment support online learning
PP8	Does your home environment support online learning	Does your home environment support online teaching	Is your ward maintaining discipline during online classes
PP9			Are you able to monitor your ward

246 members do not feel economically burdened in student responses; the remaining 119 pupils feel economically burdened. From the teacher's point of view, 89 faculty do not feel burdened, but the remaining 26 people face an economic burden to bear. 250 students, 92 faculties, and 60 parents are from urban, and 112 students, 23 faculties, and 24 parents are from rural areas. 58 parents are not feeling burdened economically, but 26 members face an economic burden.

Figure1 shows the mean, minimum and maximum possibilities of virtual learning based on the properties of PP3, PP4, and PP5.

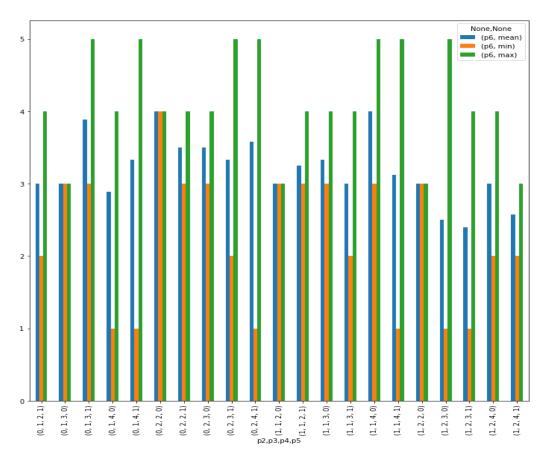


Figure 1: Virtual learning mean, minimum and maximum possibilities for students

Figure 1 and Figure 2 show the fulfillment of virtual learning/teaching based on PP2, PPP3, PP4, and PP5 attributes.

According to the graph, each group has various frequencies of possibilities for the facilities required to learn virtually. 33% are fully equipped with the facilities required for virtual learning. 47% are just sufficient facilities for online education. 20% do not have the facilities for online mode of education. Figure 2 reveals the 62.5% probability for high-equipped facilities for faculty. Medium or sufficient facilities are available for 25%, and low facilities probability is 12.5%.

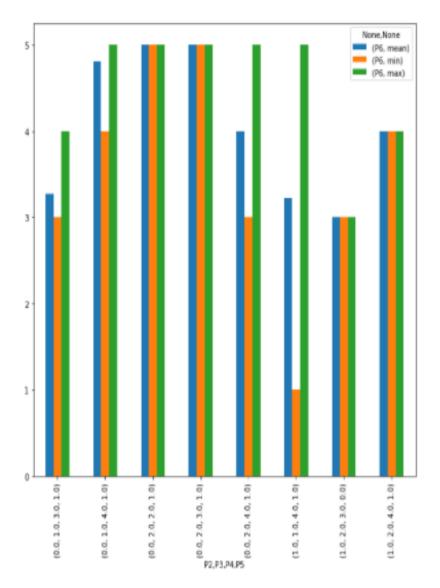


Figure 2: Virtual learning mean, minimum and maximum possibilities for faculty

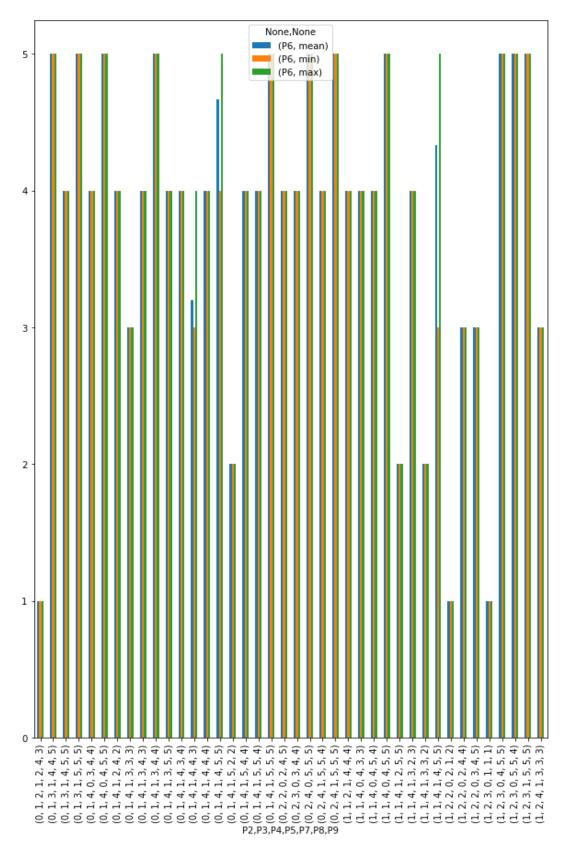


Figure 3: Virtual learning mean, minimum and maximum possibilities for faculty

Figure 4 represents the supporting possibilities of students, faculties, and parents' home environment for virtual learning. According to the personal opinion of students and faculty, virtual learning/teaching is more prone to get knowledge.

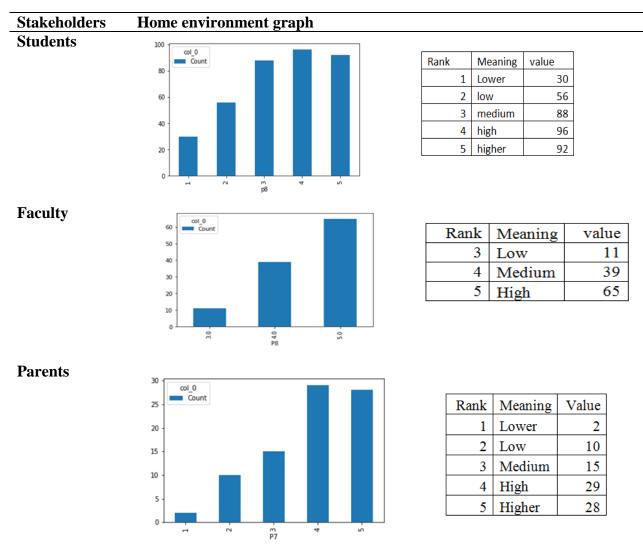


Figure 4: Supporting home environment grades.

The different physical locations, contexts, and cultures in which students learn are referred to as the learning environment. Because learners must do the learning, the goal is to establish a comprehensive learning environment that maximizes students' ability to learn. To check the learning environment, PP8 is analyzed, and the observed results are shown in Figure 4. 24% of the students and 10% of faculty are unable to learn/teach from home due to various disturbances. 25% of pupils and 34% of instructors can adjust to the home environment. The remaining 51% and 56% are flexible for virtual education from home. As per the parent's responses, the home environment supports 68%, the adjustable home environment is 18%, and the remaining 14% of respondents do not have a suitable home environment for virtual learning.

	PP1	PP2	PP3	PPP4	PP5	PP6	PP7	PP8
count	362	362	362	362	362	362	362	362
	1.51933	0.32044	1.30939	3.64088	0.77900	3.23204	3.32596	3.45303
mean	7	2	2	4	6	4	7	9
	0.50031	0.46729	0.46288	0.60312	0.41549	0.96548	1.04674	1.25181
std	7	2	3	0	1	2	1	5
	1.00000	0.00000	1.00000	2.00000	0.00000	1.00000	1.00000	1.00000
min	0	0	0	0	0	0	0	0
	1.00000	0.00000	1.00000	3.00000	1.00000	3.00000	3.00000	3.00000
25%	0	0	0	0	0	0	0	0
	2.00000	0.00000	1.00000	4.00000	1.00000	3.00000	3.00000	4.00000
50%	0	0	0	0	0	0	0	0
	2.00000	1.00000	2.00000	4.00000	1.00000	4.00000	4.00000	5.00000
75%	0	0	0	0	0	0	0	0
	2.00000	1.00000	2.00000	4.00000	1.00000	5.00000	5.00000	5.00000
max	0	0	0	0	0	0	0	0

Table2: Descriptive statistics for common data of Students

Table3: Descriptive statistics for common data of faculty

	PP1	PP2	PP3	PP4	PP5	PP6	PP7	PPP8
count	115	115	115	115	115	115	115	115
mean	0.530	0.226	1.200	3.800	0.974	4.278	4.261	4.470
std	0.501	0.420	0.402	0.463	0.160	1.013	0.879	0.667
min	0.000	0.000	1.000	2.000	0.000	1.000	1.000	3.000
25%	0.000	0.000	1.000	4.000	1.000	4.000	4.000	4.000
50%	1.000	0.000	1.000	4.000	1.000	5.000	4.000	5.000
75%	1.000	0.000	1.000	4.000	1.000	5.000	5.000	5.000
max	1.000	1.000	2.000	4.000	1.000	5.000	5.000	5.000

Table 4: Descriptive statistics for common data of Parents

	PP1	PP2	PP3	PP4	PP5	PP6	PP7	PP8	PPP9
count	84	84	84	84	84	84	84	84	84
mean	1.274	0.310	1.286	3.631	0.750	3.964	3.845	4.190	4.083
std	0.449	0.465	0.454	0.673	0.436	1.135	1.092	1.047	1.067
min	1.000	0.000	1.000	2.000	0.000	1.000	1.000	1.000	1.000
25%	1.000	0.000	1.000	3.000	0.750	3.000	3.000	4.000	3.000
50%	1.000	0.000	1.000	4.000	1.000	4.000	4.000	4.000	4.000
75%	2.000	1.000	2.000	4.000	1.000	5.000	5.000	5.000	5.000
max	2.000	1.000	2.000	4.000	1.000	5.000	5.000	5.000	5.000

Table 2, Table 3, and Table 4 show the descriptive statistics of common data of students, faculty, and parents, which reveals that the maximum number of students, faculty, and parents support virtual learning. Moreover, virtual learning and virtual teaching are very flexible in this pandemic and provide more insights into subject learning techniques and teaching methodologies, which will save money and time. According to the parents, virtual education is better because of this pandemic, but they wanted more interaction between teachers and students. Moreover, parents are suggested that of conducting more quizzes, exams, and experimental activities than theory classes. Furthermore, due to this pandemic, they expect more technologically innovative teaching methods from the faculty.

OLS	Regression I	Results	
	Faculty	Students	Parents
Dep. Variable:	PP6	PP6	PP6
Model:	OLS	OLS	OLS
Method:	Least	Least	Least
	Squares	Squares	Squares
No. Observations:	115	362	84
Df Residuals:	111	358	77
Df Model:	4	4	7
Covariance Type:	nonrobust	nonrobust	nonrobust
R-squared (uncentered):	0.961	0.904	0.979
Adj. R-squared	0.96	0.903	0.978
(uncentered):			
F-statistic:	687.5	838.8	523.3
Prob (F-statistic):	2.60E-77	2.34E-180	3.48E-62
Log-Likelihood:	-146.61	-530.37	-75.068
AIC:	301.2	1069	164.1
BIC:	312.2	1084	181.2
Omnibus:	22.899	3.405	5.238
Prob (Omnibus):	0.00	0.182	0.073
Skew:	-1.044	-0.212	-0.199
Kurtosis:	4.411	2.78	4.315
Durbin-Watson:	2.242	1.926	2.224
Jarque-Bera (JB):	30.43	3.451	6.609
Prob (JB):	2.47E-07	0.178	0.0367
Cond. No.	27.2	10.9	26.6

 Table 5: OLS Regression results

Table 6: Pearson coefficient correlation of Common attributes for Students' data

	PP1	PP2	PP3	PP4	PP5	PP6	PP7	PP8
PP1	1.000							
	-							
PP2	0.050	1.000						
PP3	0.094	0.283	1.000					

PP4	0.216	- 0.239	- 0.295	1.000				
PP5	0.021	0.291	0.335	0.257	1.000			
PP6	- 0.090	0.214	0.112	0.020	0.101	1.000		
PP7	- 0.070	- 0.361	- 0.094	0.125	0.179	0.632	1.000	
PP8	0.074	- 0.363	0.223	0.165	0.321	0.481	0.492	1.000

Table 7: Pearson coefficient correlation of Common attributes for faculty data

	PP1	PP2	PP3	PP4	PP5	PP6	PP7	PP8
PP1	1.000							
PP2	0.175	1.000						
PP3	0.078	0.146	1.000					
	-							
PP4	0.068	0.099	-0.349	1.000				
PP5	0.174	-0.303	-0.327	0.284	1.000			
	-							
PP6	0.397	-0.499	-0.073	0.157	0.207	1.000		
	-							
PP7	0.297	-0.541	0.000	0.000	0.236	0.774	1.000	
	-							
PP8	0.069	-0.351	-0.059	0.137	0.362	0.350	0.253	1.000

Table 8: Pearson coefficient correlation of Common attributes for Parents' data

	PP1	PP2	PP3	PP4	PP5	PP6	PP7	PP8	PP9
PP1	1.00								
PP2	-0.06	1.00							
PP3	0.03	0.37	1.00						
PP4	-0.18	-0.44	-0.48	1.00					
PP5	0.05	-0.39	-0.55	0.46	1.00				
PP6	-0.10	-0.34	-0.14	0.33	0.18	1.00			
PP7	-0.06	-0.38	-0.18	0.40	0.37	0.73	1.00		
PP8	-0.09	-0.27	-0.17	0.27	0.24	0.75	0.63	1.00	

PP9	-0.17	-0.17	-0.07	0.11	0.12	0.75	0.60	0.85	1.00

Graduate Attributes

However, whether the virtual learning and virtual teaching support the outcome-based education is one of the major issues in making qualitative education. The following (Table 9) parameters are used in this study to find quality-based education.

Code	Student	Faculty
QQ1	Are you able to develop teamwork,	Are you able to supervise student
	managerial, and leadership skills?	learning?
QQ2	Do you acquire knowledge and skills in modern tools and technology?	Are you able to impart knowledge and skills on modern tools and technology?
QQ3	Are you able to function on multidisciplinary teams	Are you able to communicate effectively
QQ4	Are you able to communicate effectively	Are you able to inspire the student to lifelong learning in virtual mode?
QQ5	Are you able to understand contemporary issues	Are you able to impart depth knowledge in technical subjects?
QQ6	Are you able to recognize the need for life- long learning?	
QQ7	Are you able to understand the impact of engineering solutions in a global and societal context?	
QQ8	Are you able to apply techniques, skills, and modern engineering tools?	
QQ9	Are you able to acquire depth knowledge in technical subjects?	
QQ10	Do you acquire the ability to apply the depth	
	of knowledge to solve real-time problems?	

Descriptive statistics:

A person analyzes the frequency of each data point in the distribution and describes it using the mean, median, or mode, which measures the most common patterns of the analyzed data set.

	QQ1	QQ2	QQ3	QQ4	QQ5	QQ6	QQ7	QQ8	QQ9	QQ10	Performance
count	362	362	362	362	362	362	362	362	362	362	362
mean	3.000	3.320	3.243	3.442	3.287	3.492	3.536	3.337	3.271	3.271	3.320
std	1.104	1.087	1.066	1.070	1.018	1.102	0.962	1.059	1.025	1.036	0.854
min	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.300
25%	2.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	2.800
50%	3.000	3.000	3.000	3.000	3.000	4.000	4.000	3.000	3.000	3.000	3.200
75%	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000
max	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

Table 10: Descriptive statistics for graduate attributes of Students

Table 10 and 11 shows the measures of the central tendency of descriptive statistics, which focus on average values of data sets and analyze the data. Each data point's analysis is described by mean, standard deviation, and minimum and maximum values.

Table 11: Descriptive statistics for graduate attributes of Faculty

QQ1	QQ2	QQ3	QQ4	QQ5
115	115	115	115	115
3.878	4.217	4.313	3.565	4.243
1.027	0.723	0.680	1.052	0.708
1	3	3	1	1
3.5	4	4	3	4
4	4	4	3	4
5	5	5	4	5
5	5	5	5	5
	115 3.878 1.027 1 3.5 4 5	$\begin{array}{ccccc} 115 & 115 \\ 3.878 & 4.217 \\ 1.027 & 0.723 \\ 1 & 3 \\ 3.5 & 4 \\ 4 & 4 \\ 5 & 5 \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Pearson coefficient correlation:

The correlation coefficient is a statistical measure that expresses how closely two variables are related. The coefficient's value ranges from -1.0 to 1.0, with a calculated number greater than 1.0 indicating a function error. A perfect negative correlation is represented by a coefficient of -1.0, whereas a perfect positive correlation is represented by a coefficient of 1.0. A coefficient of 0.0, on the other hand, indicates that the two variables have no relationship.

Table 12: Pearson coefficient correlation for graduate attributes of Student data

	Per	QQ1	QQ2	QQ3	QQ4	QQ5	QQ6	QQ7	QQ8	QQ9	QQ10
Per	1.000										
QQ1	0.828	1.000									
QQ2	0.820	0.655	1.000								
QQ3	0.861	0.762	0.740	1.000							
QQ4	0.781	0.689	0.597	0.692	1.000						
QQ5	0.810	0.631	0.617	0.670	0.671	1.000					

QQ6	0.786	0.546	0.562	0.619	0.581	0.629	1.000				
QQ7	0.778	0.501	0.609	0.586	0.566	0.606	0.650	1.000			
QQ8	0.840	0.625	0.666	0.648	0.572	0.624	0.631	0.681	1.000		
QQ9	0.809	0.641	0.593	0.619	0.502	0.610	0.549	0.583	0.696	1.000	
QQ10	0.791	0.630	0.597	0.627	0.442	0.514	0.596	0.566	0.669	0.781	1.000
	_										

*note: per - refers to Performance of student

Tables 12 and 13 show that all exploratory variables positively correlate with performance attributes. In other words, if the graduate attributes are increased, the Performance of students and faculty could be increased.

Table 13: Pearson coefficient correlation for graduate attributes of Faculty data

	QQ1	QQ2	QQ3	QQ4	QQ5	Per
QQ1	1					
QQ2	0.331292	1				
QQ3	0.469369	0.502713	1			
QQ4	0.542939	0.379021	0.510473	1		
QQ5	0.583669	0.546814	0.605244	0.566951	1	
Per	0.789205	0.672703	0.764897	0.808274	0.832386	1

*note: per - refers to Performance of student

 Table 14: Multiple Regression Analysis

OLS Regression Results						
	Students	Faculty				
No. Observations:	11	6				
Df Residuals:	1	1				
Df Model:	10	5				
Covariance Type:	nonrobust	Nonrobust				
Omnibus:	2.207	Nan				
Prob (Omnibus):	0.332	Nan				
Skew:	0.61	0.24				
Kurtosis:	1.813	2.05				
R-squared (uncentered):	1	1				
Adj. R-squared	1	1				
(uncentered):	1	1				
F-statistic:	6.94E+28	1.28E+30				
Prob (F-statistic):	2.95E-15	6.72E-16				
Log-Likelihood:	364.36	205.49				
AIC:	-708.7	-401				
BIC:	-704.7	-402				
Durbin-Watson:	0.032	1.51				
Jarque-Bera (JB):	1.328	0.283				
Prob (JB):	0.515	0.868				
Cond. No.	38.9	10.3				

Table 14 shows the multiple linear regression results for the Performance of students and faculty members. The probability and F-Stat are significant at the 1 percent level. The skewness of students is 0.61, which is between 0.5 and 1, which means data are lightly skewed positively. The faculty member's skewness is 0.24, which is between -0.5 to 0.5, meaning the data are nearly symmetrical. The Durbin Watson for students and faculty is below 2 values, showing the positive autocorrelation. The Jarque-Bera values for students are 1.328 and for faculty 0.283.

5. Conclusion

Faculties and students should be trained to use technology to utilize online teaching-learning. In this paper, we discussed the issues and challenges faced by stakeholders of technical educational institutions in India. Government and educational institutions should adopt the policy to provide hassle-free internet access and necessary technical support to students to encourage e-learning. As a result, students would engage in e-classes and remain focused on their studies. Prevailing measures are required to subside the stress level of students. Many online learning platforms offer different levels of certified courses with different teaching methods and quality of learning assessments on the same subjects. To maintain the quality of online programs, technical institutions in India need quality assurance benchmarks, keeping in mind the swift growth in e-learning modes. Government should support technical educational institutes to strengthen their resources to run online educational activities. Students also need to be supported with better technological access as most students cannot afford the facilities. Indian indigenous knowledge system is widely accepted for its scientific innovations, values, and ease in support of developing sustainable technologies. This traditional knowledge system in different fields should flourish and integrate with present-day mainstream technical education.

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