Factors affecting digital education during COVID-19: A statistical modeling approach

Madhu Arora
Department of Management Studies
Rukmini Devi Institute of Advanced Studies
Rohini, Delhi, India.
aroramadhu86@gmail.com

Lalit Mohan Goyal
Department of Computer Engineering
J. C. Bose University of Science and Technology
YMCA, Faridabad, India
lalitgoyal78@gmail.com

Nalini Chintalapudi*
Department of Computer Engineering and mathematics
University of Camerino
Camerino, Italy
nalni.chintalpudi@unicam.it

Mamta Mittal
Department of Computer Science and Engineering
G. B. Pant Government Engineering College
Okhla, New Delhi, India.
Mittalmamta79@gmail.com

Correspondence*: nalini.chintalapudi@unicam.it; +39-3533776704.

Abstract— ***Worldwide governments have decided to temporarily closures of educational institutions in an attempt to minimize the spread of the COVID-19 Pandemic, which has forged significant challenges for the education community. The present study is from the digital education scenario during the COVID-19 lockdown to find out the factors affecting online learning. This study is exploratory from 1218 students who have been collected based on a structured questionnaire having a 5-point linear scale. Jamovi software has been used for data analysis and results demonstrate that there are three major factors like affordability, infrastructural, and training that affect online learning during the COVID-19. Besides, correlation analysis between these factors highlights the relationship among them. Linear regression has applied to know the impact of affordability and infrastructure on the training factor. Outcomes suggested that infrastructure has a negative impact but affordability has a positive impact on the training factor. In the present scenario, this study highlighted the importance of social distancing and digital education tools that should be adopted by schools and colleges.***

Keywords— COVID-19, Digital education, Exploratory analysis, Correlation, online learning tools.

I. INTRODUCTION

COVID-19 has affected the daily life routine in such a manner that no one even dreamed out that everything in the world would come to halt [1], [2]. Because of this novel infection, online education it becoming difficult to work on live projects, so employability would be affected [3]. Attendance in universities, colleges, and schools is a most imperative and necessary condition but now, as all global organizations have shut down for a few months, thus shifting to online classes is the only viable solution that persists in this situation. The United Nations Educational Scientific and Cultural Organization (UNESCO) released the first report which highlighted that about 290 Million students across 130 countries are impacted severely in term of education, but as per the latest report on 23rd May 2020 this figure has reached to 1.2 Billion affected learners, across 153 countries [4]. In developing countries like India, it is getting even worst that education was continuously interrupted because of the current pandemic, and 300 Million students are enforced to adopt digital education [5]. Therefore, to mitigate this effect distance learning and various online platforms have been recommended [6].

The administrators in universities, colleges, and schools ponder better approaches for dealing with this abrupt progress of online teaching. On the off chance that the lockdowns will proceed for more than six months then the education system could be largely affected. Some deeper profound issues require introspection like e-learning is not a replacement for live teaching and barrier in online learning has been discussed [7], [8]. But during this novel pandemic, online learning has been proved to be beneficial [9]–[11].

Education in online mode has been conveyed in two different ways such as recorded and live online classes. The recorded sessions can publicly visualize for the general public and are referred to as Massive Open Online Course (MOOCs) [12]. Besides, online live classes are can be conducted by webinars, google meet, or zoom meetings. However, adopting these virtual learning is not easy because these methods are included with fast internet connections along with mobile or PC. Also, the tutor or student must be an expert to handle such a transition of conventional to virtual teaching. It is always arguable about transparency, reliability, and security issues of online examination and assessment [13]. From all these mentioned factors, it is evident that students and teachers are in high pressure including stress and anxiety during this pandemic.

In this paper, we presented an extensive survey to evaluate the factors that affect digital education. Besides, an explanatory analysis was conducted to identify obvious reasons for improving the awareness of student digital education.

II. RESEARCH BACKGROUND

The COVID-19 pandemic is a global public health issue that has never been faced before. Because of its immediate spreading, almost every country has (properly) chose to close all educational institutions like primary schools, colleges, and colleges [14]. Before COVID-19, there has been a limited scope in the area of the online education system in developed nations, as generally, institutions running in distance mode of education has to provide such classes. But now, the massive lockdown has necessitated every education organization to look into this to cover the curriculum of the students. Digital technology has provided new opportunities to conduct live sessions or online classes for the students, so this is a new exploratory study area for the researchers.

The accomplishment of any digital system is depending on its usage by users [15]. Therefore, in students' points of view adopting digital education is the key criterion for the success of the online learning system. At the same time, it is important to address the problems that are facing while e-learning adoption. Many studies in the literature were spoken about digital education problems across the world. In [16], UAE student acceptance for adopting e-learning technology was quantified. The research was conducted on 435 students from five different universities. The outcomes mention that the self-ability of computer operation, system quality, and computer playfulness are the factors that have a large impact on adopting digital education methods. Another study on 697 Malaysian students has confirmed the demand for mobile learning apps to enhance modern education systems [17]. Scholars incorporated the Unified Theory of Acceptance and Use Technology (UTAUT) model to explore the literature facts in the acceptance of mobile learning apps for higher education. The results identified that compatibility, trust, perceived awareness, self-efficacy, resource availability, and security are key parameters for acceptance of e leaning and success of mobile learning projects.

A quantitative study on 286 students highlighted the connection between student's behavioral decisions and the integration of digital education in academics [18]. The framework work was developed by adopting the TAM3 (Technology Acceptance Model-3) model and student data was investigated by structural equation modeling for understanding the factors that influence student decision to adopt e-learning systems. The decision outcomes like administrative involvement and controlling in institutional e-learning management can tend to large acceptance of TAM3 models. In [19], the TAM model was extended and updated by De Lone and McLean (DL&ML) information systems to evaluate the results of quality features in the acceptance of mobile learning. The results revealed that factors like quality in learning content and design, interactivity, User Interface (UI) design, functionality, customization, accessibility, and response have large effects on student's perspective of adopting mobile learning methods. In [19], it is also mentioned that mobile learning is unavoidable solution during Covid-19, in spite of its health consequences.

However, the difficulties of implementing new regulations in education with short pandemic time is not an easy task [20]. With this new pandemic, it is clear that the academic system is vulnerable to external risks [21]. It is also well noted that this transformation into digital academic delivery comes across many attitudinal modifications and logistic challenges [22]. In a technological view, e-learning is entirely depending on the accessibility of PCs or mobiles and internets, students or teachers with low internet connections possibly affects the access to online learning. It is a big challenge for learners, faculty, and institutions for providing technical equipment in order to create virtual sessions [23]. Feldman J introduced some challenges for addressing student evaluation while handling digital education during this pandemic [24].

Firstly, student academic performance can largely affect by differences between economic, racial, and resource provision and stress and anxiety associated with pandemic can have negative effects on learner ability. In addition, not all teachers or instructors are ready for remotely delivering high-quality education. Therefore, the challenges for the adoption of digital education from the student point of view were well discussed in the current study. To the best of our knowledge, it is the primary study on high participant (students) number for addressing all limitations involved with socio-economic, technology, digital competence, compatibility, and supervision factors.

III. Methods

This section presents the data collection and software tools that we used for simulation purposes.

A. Study type

Factor analysis is to scale down the large data into meaningful variables to understand the problem statement. It is of two types: one is Exploratory Factor Analysis (EFA) and the other is Confirmatory Factor Analysis (CFA). EFA has applied where there is no supporting literature and researchers explore it to find out new factors related to the topic. In CFA, researchers have some theory base supported by earlier literature.

Currently, there is no such type of study exists, where the need for online education is mandatory in all aspects to mitigate the effect of a pandemic like COVID-19. So, the need for online education for a massive scale never felt earlier, it was prevailing only in distance mode of education. Thus, in this situation, an exploratory study is found more appropriate for this research.

B. Participants

The online questionnaire had delivered to 3,500 students, and 1218 (35%) have actively participated in this study. Before initiating the survey, each student has been properly read the informed consent which portrays their interest in participation. After tapping the button 'next', participants are considered for agreeing to the online questionnaire. The survey included closed-ended questions and students can provide a rating of scale 1-5 for each question. No student personal information was collected during this study.

C. Hypothesis and definations

Null Hypothesis (H_0): The null hypothesis is considered as the present study is exploratory and no earlier literature review is available to support an alternative hypothesis. Here, if a no significant correlation between digital education and factors like affordability, infrastructural, and training for online learning has been denoted by H_0.

Alternative Hypothesis (H_1): The hypothesis will be tested at 1 and 5 percent level of significance. Its null hypothesis is rejected, then the alternative hypothesis will be considered for acceptance. Here, if a significant correlation between digital education and the mentioned factors has denoted by H_1.

D. Statistical analysis

To analysis the data Jamovi software [25] has been used, as statements are in a five-point Likert scale and not confirmed variables, factor analysis is suitable and specifically EFA. Jamovi is open-source software and is specially designed to provide recent developments in statistical methods. It is integrated with different statistical packages like ANOVA, t-test, reliability and factor analysis, regression, and correlation analysis.

IV. Results and discussion

A. EFA Assesment

Table 1 presents the four key factors with 10-item questionaries' that justifies challenges for e-learning adoption during the present pandemic. The minimum residual extraction method in combination with a varimax rotation method was used for factor labeling. For instance, the challenges for the training factor included four items labeling such as priority for offline learning (0.810), difficulty in understanding (0.770), no user friendly (0.582), and more time consuming (0.575). Whereas affordability factors included lack of smartphone (0.924) and PC or Tablet (0.620) and Infrastructure factors associated with no power supply (0.585), not able recharge data package (0.578), and no internet access (0.514). Some students personally mentioned that they do not have enough knowledge on how to operate e-learning with a factor loading of 0.684. However, we ignored this item as an individual or single opinion that cannot be possible to labeled as a separate factor in the EFA approach.

TABLE 1. Factors that present challenges of online learning during the lockdown period.

Factor	**Item**	**Scale**					**Uniqueness**
		1	2	3	4	5	
Training	Hard to follow	0.810					0.321
	Not understandable	0.770					0.345
	No user friendly				0.582		0.406
	Time consuming	0.575					0.533
Affordability	No smartphone		0.924				0.074
	No PC/ Tablet					0.620	0.441
Infrastructure	Lack of Electricity /regular power supply			0.585			0.545
	Can't afford a data package				0.578		0.499
	No access to internet			0.514			0.505
Personal	Do not know how to use			0.684			0.366

B. Model fitting tests

Table 2 present the model fitting parameters for online education during COVID-19. Root Mean Square Error of Approximation (RMSEA) ranging from 0 to 1 and the low RMSEA value present better model fitting. The outcome model presents RMSEA of 0.0203 (2%, 90% CI), and ranging from 0-5.72% represents the generated model is accurately fitted. According to Newsom J (2015), if model parameters like Tucker-Lewis Index (TLI) are greater than 0.95 and Bayesian Information Criterion (BIC) is low or negative value then the model is well defined [26]. Therefore, the TLI value of 0.995, negative BIC value (-53.6) also proves that the developed model has perfectly matched with study requirements.

TABLE 2. Model fit measures for online learning in the lockdown period.

RMSEA	RMSEA 90% CI		TLI	BIC	Model Test		
	Lower	Upper			χ^2	df	p
0.0203	0.00	0.0572	0.995	-53.6	12.7	11	0.317

Another test that tests the model fitting is Bartlett's test of sphericity. This test is worked on the null hypothesis (H_0) which assumes that all variables are not correlated, and if the H_0 value near to zero then the model fitting is considered as perfectly valid [27]. From Table 3, it is evident that $p<0.001$ presents high model significance. In addition, Kaiser-Meyer-Olkin (KMO) tests are the Measure of Sampling Adequacy (MSA) to check whether the sample is enough to represent the factor items [28]. In this test, if MSA>0.50 then the model said properly fitted. From Table 4, all item values are satisfied with this rule including an overall value of 0.836.

TABLE 3. Bartlett's test of sphericity

χ^2	df	P
1544	45	< 0.001

* df: degrees of freedom.

TABLE 4. The MSA values of each questionnaire item

N	Item	MSA
1.	Hard to follow when compared to traditional offline learning	0.817
2.	Difficulties in understanding	0.788
3.	No user friendly	0.810
4.	Time-consuming	0.790
5.	I do not have a smartphone	0.892
6.	I do not PC/ Tablet	0.895
7.	Lack of Electricity/regular power supply	0.904
8.	Can't afford a data package	0.785
9.	No access to internet	0.879
10.	Do not know how to use	0.825
	Overall	**0.836**

In multivariate statistical analysis, the scree plots decide the number of factors that can retain in EFA [29]. Figure 1 depicts the scree plot that presents Eigenvalues on Y-axis and factors on X-axis. The first three factors are above the zero lines and the rest of them below a line. Therefore, the factors above the line are easily retained, also these three factors were passed all the above tests of model fitting.

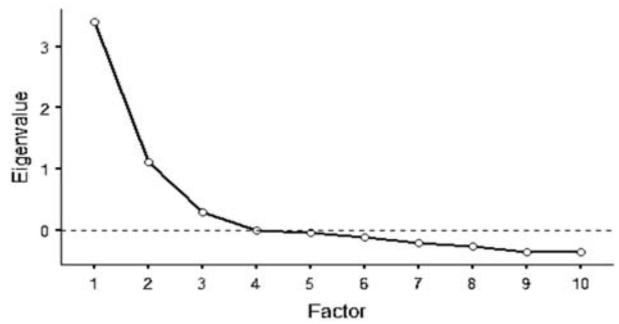

Fig 1. Scree Plot of factors identified for online learning in the lockdown period.

C. *Factor correlation*

Table 5 presents the correlation matrix three mentioned factors. The positive correlation between training and infrastructure can be observed as 0.261, between training and affordability resulted as 0.531 correlation, and between infrastructure and affordability are correlated by 0.618. Table 6 shows the preliminary relationship between the factors. The hypothesis was tested both at 1% and 5% significance levels. The null hypothesis (H_0) was rejected for all three variables and no significant association between these factors was found. Therefore, a significant correlation was found for the alternative hypothesis.

TABLE 5. Correlation Matrix of training, infrastructure, and affordability

Factor	Parameter	Training	Infrastructure	Affordability
Training	Pearson's r			
	p-value			
Infrastructure	Pearson's r	0.261^{***}		
	p-value	< 0.001		
Affordability	Pearson's r	0.531^{***}	0.618^{***}	
	p-value	< 0.001	<0 .001	

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 6. Experimental outcomes about the relation of training, infrastructure, and affordability

Variable	Relation with	Relationship	Significant@ 1% and 5%	H0	H1
Training	Affordability	Positive	Yes	Rejected	Accepted
Infrastructure	Training	Positive	Yes	Rejected	Accepted
Affordability	Infrastructure	Positive	Yes	Rejected	Accepted

Table 7 presents the results of a linear regression model with a model coefficient of training (dependent). The estimative coefficients of infrastructure and affordability are observed as -0.102 and 0.647 (i.e., every unit change of affordability represents a change in training by 0.647).

Predictor	Estimate	SE	95% Confidence Interval		T	p	Stand. Estimate
			Lower	Upper			
Intercept	2.07	0.075	1.92	2.22	27.06	< 0.001	0.67
Infrastructure (Independent)	-0.10	0.028	-0.15	-0.04	-3.55	< .0001	-0.10
Affordability (Independent)	0.64	0.033	0.58	0.71	19.48	< .0001	0.59

V. CONCLUSION

The present study has conducted to understand the main factors that affect the acceptance of digital education in academics during COVID-19. Three key factors such as training, infrastructures, and affordability were included with 10 item questionnaires that were included and the EFA method is employed to identify significance among them. Different statistical tests were conducted to test the model fitness and identify the relationship between the factors. Outcomes highlighted that for every single change of infrastructure and affordability, a similar change can be observed in training. The present study can be useful for the researchers, faculty, and government in policy-making for the conduction of digital education in the future.

REFERENCES

[1] S. Chawla, M. Mittal, M. Chawla, and L. Goyal, "Corona Virus - SARS-CoV-2: An Insight to Another way of Natural Disaster," EAI Endorsed Trans. Pervasive Heal. Technol., 2020, doi: 10.4108/eai.28-5-2020.164823.

[2] N. Chintalapudi, G. Battineni, G. G. Sagaro, and F. Amenta, "COVID-19 outbreak reproduction number estimations and forecasting in Marche, Italy," Int. J. Infect. Dis., 2020, doi: 10.1016/j.ijid.2020.05.029.

[3] M. Arora and M. Mittal, "Relation of Live Projects with Employability using Path Analysis Model," in Procedia Computer Science, 2020, vol. 167, pp. 1675–1683, doi: 10.1016/j.procs.2020.03.378.

[4] "School closures caused by Coronavirus (Covid-19)." https://en.unesco.org/COVID19/educationresponse (accessed Sep. 10, 2020).

[5] "COVID-19 in India: Education disrupted and lessons learned." https://www.brookings.edu/blog/education-plus-development/2020/05/14/COVID-19-in-india-education-disrupted-and-lessons-learned/ (accessed Sep. 10, 2020).

[6] P. Sahu, "Closure of Universities Due to Coronavirus Disease 2019 (COVID-19): Impact on Education and Mental Health of Students and Academic Staff," Cureus, 2020, doi: 10.7759/cureus.7541.

[7] A. Emery, "E-lectures and online learning: Not a replacement for live teaching," Medical Teacher. 2017, doi: 10.1080/0142159X.2017.1367373.

[8] D. O'Doherty, M. Dromey, J. Lougheed, A. Hannigan, J. Last, and D. McGrath, "Barriers and solutions to online learning in medical education - An integrative review," BMC Medical Education. 2018, doi: 10.1186/s12909-018-1240-0.

[9] S. J. Daniel, "Education and the COVID-19 pandemic," Prospects, 2020, doi: 10.1007/s11125-020-09464-3.

[10] Z. Zayabalaradjane, "COVID-19: Strategies for Online Engagement of Remote Learners.," Online Submiss., 2020.

[11] A. K. Arora and R. Srinivasan, "Impact of pandemic covid-19 on the teaching – learning process: A study of higher education teachers," Prabandhan Indian J. Manag., 2020, doi:

10.17010/pijom/2020/v13i4/151825.
[12] M. B. Hoy, "MOOCs 101: An Introduction to Massive Open Online Courses," Med. Ref. Serv. Q., 2014, doi: 10.1080/02763869.2014.866490.
[13] G. Battineni et al., "Factors affecting the quality and reliability of online health information," Digit. Heal., vol. 6, pp. 1–11, 2020, doi: 10.1177/2055207620948996.
[14] G. Battineni, N. Chintalapudi, and F. Amenta, "SARS-CoV-2 epidemic calculation in Italy by SEIR compartmental models," doi: 10.1108/ACI-09-2020-0060.
[15] M. A. Almaiah and M. M. Alamri, "Proposing a new technical quality requiremnts framework for mobile learning applications," J. Theor. Appl. Inf. Technol., 2018.
[16] a Al-Adwan, A. A.- Adwan, and J. Smedley, "Exploring students acceptance of e-learning using technology acceptance model in jordanian universities," Int. J. Educ. Dev. Using Inf. Commun. Technol., 2013.
[17] M. A. Almaiah, M. M. Alamri, and W. Al-Rahmi, "Applying the UTAUT Model to Explain the Students' Acceptance of Mobile Learning System in Higher Education," IEEE Access, 2019, doi: 10.1109/ACCESS.2019.2957206.
[18] S. S. Al-Gahtani, "Empirical investigation of e-learning acceptance and assimilation: A structural equation model," Appl. Comput. Informatics, 2016, doi: 10.1016/j.aci.2014.09.001.
[19] M. A. Almaiah, M. A. Jalil, and M. Man, "Extending the TAM to examine the effects of quality features on mobile learning acceptance," J. Comput. Educ., 2016, doi: 10.1007/s40692-016-0074-1.
[20] S. L. Schneider and M. L. Council, "Distance learning in the era of COVID-19," Arch. Dermatol. Res., 2020, doi: 10.1007/s00403-020-02088-9.
[21] A. Bozkurt and R. C. Sharma, "Emergency remote teaching in a time of global crisis due to CoronaVirus pandemic," Asian J. Distance Educ., 2020, doi: 10.5281/zenodo.3778083.
[22] "How the shift to remote learning might affect students, instructors and colleges." https://www.insidehighered.com/digital-learning/article/2020/03/25/how-shift-remote-learning-might-affect-students-instructors-and (accessed Sep. 14, 2020).
[23] S. Palvia et al., "Online Education: Worldwide Status, Challenges, Trends, and Implications," Journal of Global Information Technology Management. 2018, doi: 10.1080/1097198X.2018.1542262.
[24] Joe Feldman, "To Grade or Not to Grade? - Educational Leadership." http://www.ascd.org/publications/educational-leadership/summer20/vol77/num10/To-Grade-or-Not-to-Grade¢.aspx (accessed Sep. 14, 2020).
[25] "jamovi - Stats. Open. Now." https://www.jamovi.org/ (accessed Sep. 10, 2020).
[26] J. T. Newsom, "Some Clarifications and Recommendations on Fit Indices," in Testing Structural Equation Models, 2015.
[27] J. Mallat, "Understanding the null hypothesis (H0) in non-inferiority trials," Critical Care. 2017, doi: 10.1186/s13054-017-1685-2.
[28] A. Field, Discovering statistics using IBM SPSS statistics. 2013.
[29] R. D. Ledesma, P. Valero-Mora, and G. Macbeth, "The Scree Test and the Number of Factors: a Dynamic Graphics Approach," Span. J. Psychol., 2015, doi: 10.1017/sjp.2015.13.