International Journal of Distance Education Technologies
Volume 19 • Issue 1 • January-March 2021

The Challenges Faced in Technology-Driven Classes During COVID-19

Sangeeta Sharma, Birla Institute of Technology and Science, Pilani, India
Arpan Bumb, Birla Institute of Technology and Science, Pilani, India

ABSTRACT

In the wake of coronavirus pandemic, social distancing became a mandate that led to the transition from traditional classroom-based lectures to computer-based learning. This paper extensively deals with the ranking of the challenges faced by instructors and students. Primary data from 624 participants (399 students and 225 instructors) is collected through a questionnaire. To assign the ranking to the challenges, Technique of Order Preference Similarity to Ideal Solution (TOPSIS) is deployed. A contextual model is developed by using Interpretive Structural Model (ISM) technique that further provides recommendations for prioritizing the challenges that need to be addressed to mitigate the problems faced in online lectures in coronavirus situation. The number of variables is reduced to simplify the interpretation by exploratory factor analysis. The study also provides the basis to formulate the strategies for policymakers and administration after identifying which challenges need to be addressed first for mitigating all the other challenges.

KEYWORDS

Classroom-Based Lectures, Computer-Based Learning, Coronavirus, Exploratory Factor Analysis, ISM, Lectures, Social Distancing, TOPSIS

INTRODUCTION

Education can be imparted through multiple platforms such as traditional face to face delivery, E-education and mixed methods. Today, universities are banking on online media completely for their distance learning programs that are completely executed through computers, laptops or mobile phones on platforms like Zoom, Google Meet, Cisco Webex etc. However, in traditional classroom which involves face to face delivery, the instructors sometimes would switch to online resources to illustrate the concepts graphically. However, this coronavirus pandemic propelled the instructors to switchover completely to the online mode of teaching as social distancing became a norm.

In India, the decision for lockdown which started from March 25th 2020 was sudden. As a result of coronavirus pandemic, the academic calendar could not be followed as planned and students and teachers were both left in uncertainties and tribulations for the future. The course content was not completed and it required immediate measures to complete the content and continue the classes amidst lockdown. In this scenario, online classes were considered as the best possible alternative for

DOI: 10.4018/IJDET.20210101.oa2

the traditional classes as many of the past studies by Bernard et al. (2004), Jahng et al. (2007) have concluded that learning outcomes of traditional and online classes are similar. This platform was also the most feasible to launch, keeping in mind the constraints of social distancing presented by COVID-19 situation, while following the same time schedule as of traditional classes as the time to prepare and gather resources for online classes was negligible for both students and instructors. The students and instructors were present in different geographical locations, which also led to difficulties in conducting traditional classes. All these aspects contributed to a decision of organizing online classes.

Online classes encouraged students to attend the lectures as the content in video lectures incorporates interesting features such as the integration of audio and visual media that make the lectures interactive. Although online classes provided a lucrative alternative for traditional classes, they were ridden with many challenges. The immediate problems were lack of access to resources and infrastructure to conduct online classes, increased workload at home, mental stress and uncertainties due to Corona pandemic. Other problems were related to inadequate training and responsiveness of administrative authorities which limited the use of online platforms. Further, the lack of response by authorities led to anxiety in students especially who were about to receive their degree or certification. Some of the students and faculty members did not have access to the internet because of remote locations and incessant power failures. Motivation level of students was at a low ebb due to disconnect from friends, instructors and forced departure to their homes. This presented a unique challenge for the instructors as they had to improve the motivation levels of students as in the past studies by Deimann and Bastiaens (2010), high level of motivation in students is needed in order to make online classes successful.

It is necessary to understand these challenges as it would allow the government, administration and policy makers to provide solutions and facilities to instructors and students to make online classes successful and maximize the learning outcome. This paper aims to present a ranking for the challenges to the technology aided classes for students and instructors by using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. As the number of challenges identified are large, Exploratory Factor Analysis (EFA) is used in order to combine some of the challenges under latent variables facilitating easy interpretations and analysis. The paper also presents recommendations on how to mitigate the challenges by using an Interpretive Structural Model (ISM) based approach. The recommendations were further validated by students and instructors in order to select most effective one.

The interpretations of the study will allow to understand the various challenges faced during online classes from the perspective of students and instructors and enable effective strategy formulation in order to maximize the learning outcome. This can be accomplished by understanding the ranking of the challenges which identifies the impact created by the individual challenges. Further, by analyzing the contextual relationships between the challenges, the challenges having a higher influence or driving ability can be identified. The stakeholders involved in pedagogy can make efforts to mitigate the challenges which have a higher impact and have a greater power to drive other challenges.

BACKGROUND

Traditional vs Online Classes

Online classrooms are inevitably blended with the education system and are considered as an alternative to traditional classrooms. The past studies by Picciano and Seaman (2009), Kim et al. (2011), and Nacu et al. (2016) have supported the claim that the number of students enrolled in online classes is continuously increasing. Online classrooms gain leverage over traditional classrooms by providing several benefits such as flexibility over time, convenience, path, the pace of learning, and cost-effectiveness (Carnevale, 2000). The content in online classes is delivered through audio as well as visual media that allows the use of various forms of videos, animations, illustrations in online classrooms (Mayer, 2014), which positively influences student engagement (Junco et al., 2011). The combined use of media elements provides enhanced processing, visualization, and delivery of content and concepts, effective use of which can improve the attention level of students (Costley & Lange, 2020). However, there is a lower retention rate associated with online classes (Stover, 2005) which is attributed to the multiple features offered by online platforms such as screen sharing, audio settings, video display, aspect ratio of the screen etc. which can overwhelm the learners leading to distractions.

Past studies on online classes are focused more on the factors that are in tune with traditional lecture-based instructional models, identifying the reasons for lower grades and absence in the classes (Ho et al., 2014). In other studies, the attention is on technology adoption, continuation of use of technology, and learning outcomes (Panigrahi et al., 2018). Along with the use of technology the importance of feedback on students' performance has not been reduced. Feedback allows students to rectify their mistakes for a better understanding of the concepts and improve the learning outcomes. It also allows students to communicate effectively with peers and instructors encouraging social interaction. The role of feedback by the instructor is also considered highly important in the study by Gašević et al. (2015). The opportunities for receiving immediate feedback from the instructor is less in online classes (Faux & Black-Hughes, 2000).

Due to the deluge of material delivered at a fast pace, student tend to drop the courses taken online (Frankola, 2001; Oblender, 2002). As online classes have different nature compared to traditional, many students who are successful in traditional classroom model in terms of receiving higher grades, improved feedback, better retention etc. are not comfortable in online classes (Cheung & Kan, 2002) and it is a little tricky to understand the factors that can act as a predictor for success in online classes. This makes students more comfortable in attending the classes in the traditional format. Traditional classes allow the students to clarify their doubts immediately, however, in online classes due to lack of physical presence the assessment of non-verbal cues is missed, leading to postponement of doubt clarification. Further, the responsibility of self-assessment and autonomy fall on student's shoulder to expedite and improve the learning abilities.

Instructor's Competences in Online Classes

In order to make online classes successful, the role of instructor cannot be ignored. The instructor plays a key role in the delivery of online lectures, which involves balancing the pace, quality, and context of the lecture (Lange & Costley, 2020). According to their study, the various media factors to be taken care of are: pace of lectures, intelligibility of the learner, quality of classes, use of diverse forms of media, and congruency between lectures. Instructors can significantly influence the learning outcomes, interest, and involvement of students. The instructor should also aim to provide an experience in a class which student would not want to miss (Bender, 2003). The role of the instructor in online classes is considered as that of a *planner* providing clear instructions, *model* acting as an inspirational figure, *coach* encouraging students to learn, *facilitator* acting as a guide, and *communicator* to provide feedback and deliver lectures effectively (Heuer & King, 2004). Similarly, study by Hung and Chou (2015) has also described the role of instructor as course designer and organizer, discussion facilitator, social supporter, technological facilitator, and assessment designer. Shea and Bidjerano (2009) concluded that teacher's involvement in a class is an important factor in developing cognitive and social presence of students. A study by Asarta and Schmidt (2013) has identified that method of presentation is more important than content in online classes. Therefore, instructors should put an effort in making the online classes interactive and improve on the method rather than the content.

Several models about digital competences required by instructors to improve learning from online classes have been proposed. These models provide a framework of how digital technologies can be used to improve education and training. They also help to align the instructor's profile to the digital competencies required for online and distance learning programs. One of the popular frameworks is the European Framework for the Digital Competence of Educators (DigCompEdu), which organizes

22 competences in six areas which include professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learner's digital competence. This model is directed to instructors at all levels of education including general and vocational learning.

Challenges Faced in Online Classes

From the viewpoint of students, the biggest challenge is lack of motivation and procrastination in attending the online classes. This is because of lack of push factor in online classes, which implies that students should be highly motivated to achieve the desired learning outcomes. Self-regulation is also required as there is a high chance to cheat in online classes (Lanier, 2006) and there are a limited number of opportunities for assessment through an online medium (Williams et al., 2012). Students should be able to self-regulate themselves as participation in online classes requires initiation by students themselves for clarifying the doubts and understanding the profound concepts for maximizing the learning output. Even in the past studies, the learning outcomes of the online classes are highly dependent on self-regulation (You & Kang, 2014; Henrie et al., 2015). Online classes require students to work and gather resources on their own to gain benefit from online classes. This is validated in the study of Diaz (2002) and Bell and Akroyd (2006) who concluded that students who perceive their academic accomplishments as their own work are more likely to succeed in online classes. The massive pre-requisites such as previous courses, academic or GPA cutoff etc. also make attending online classes challenging for the students.

Wojciechowski and Palmer (2005) have identified several factors as predictors for success in online classes, including student's academic capabilities, motivation, and gender. Particularly the students having a higher grade point average (GPA) and academic acumen are more likely to succeed in online classes (Dupin-Bryant, 2004). Some of the studies also place demographic variables such as age (Murtaugh et al., 1999), gender (Willging & Johnson, 2009) and ethnicity (Stratton et al., 2007) for success in online classes. However, there are several variations obtained in the results of these studies, some conclude that older students don't perform well (Park & Choi, 2009) while others (Wojciechowski & Palmer, 2005) conclude they do. In some studies, better performance is by men (Kramarae, 2001) and in others by women (Willging & Johnson, 2009). However, there are variations in the predictors also as Lin et al. (2017) have identified that online learning outcomes from the class are not predicted by intrinsic or extrinsic motivation but the learning strategy, which includes pedagogy and learning ability.

There are innumerable hindrances in conducting online classes. Maguire (2005) reviewed thirteen studies and concluded that instructors faced numerous barriers. Muilenberg and Berge (2005) have identified several barriers to students' learning in online classes and classified them through factor analysis into eight categories- administrative issues, social interaction, academic skills, technical skills, learner motivation, time and support for studies, cost and access to the Internet, and technical problems. Haber and Mills (2008) have examined the barriers associated with the effectiveness of online classes with respect to Florida Community college faculty and concluded that several instructors face a lot of problems while conducting online classes. Gillette-Swan (2017) has identified several other problems such as inhibition in using technology, difficulty in peer interaction, and anxiety being out of comfort zone. Due to the involvement of several features and different interface in the platform, the use of various commands, procedures, and methods to execute the online classes make it necessary to train the participants to use the platform. Studies by Schmidt et al. (2016) and Rucker and Downey (2016) identified this challenge and also gave the specifications of how the training can be conducted.

Research Gap

Although, there is an abundance of the past studies in which reference to certain challenges in executing the online classes is mentioned, less is known about the ranking of these challenges and how they are related to each other. The difference in perceived ranking of the major stakeholders in online classes- instructor and student has also not been discussed in the previous studies. This aspect is necessary to understand in order to provide effective solutions by understanding which challenge presents a bigger problem to the instructors and students so that efforts can be made to mitigate it. Another necessary step is to identify which challenge leads others, it will allow to analyze their perceived impact and identify which one to address first to generate maximum benefits. The spread of COVID-19 has also presented a number of challenges as it significantly affects the mental health creating problems such as anxiety, depression, stress, uncertainties, etc. (Galea et al., 2020). These issues should also be incorporated while analyzing the challenges faced in online classes. All of these facts present a need for a study that specifically deals with the challenges and provides recommendations for mitigating them.

METHOD

The challenges faced by the students and instructors in switching over to traditional to online platform during COVID-19 were determined by consulting them through semi-structured personal interviews. The participants were asked about the challenges faced during the online classes, who were contacted by using stratified random sampling from the list of total students and instructors in the universities. The universities chosen for the study were from India and were distributed evenly in the NIRF rankings provided by Government of India. Rigorous interview of 40 minutes was conducted in which participants were asked to elaborate the challenges they faced during the online classes and determined contextual relationships of the challenges i.e. which challenge influenced others or by which it was driven. The interviews were discontinued when the challenges observed began to get repeated. In total, the sample for this step consisted of 50 students and 25 instructors. Table 1 shows the list of challenges identified by taking the union of challenges reported in the interview.

Measures

In order to identify the ranking, the challenges faced in online classes were considered as present in Table 1. A questionnaire consisting of two sections was developed in which participants had to rate the impact of each challenge faced during the online classes on a Likert scale of 1-5; 1 having the least impact and 5 having the most. In order to gauge the views of participants on the ways of mitigating the challenges in Table 1, the recommendations were mentioned in the questionnaire to be filled by the respondents. Some of the recommendations were identified while conducting the interviews, others were identified through an open-ended question. The additional responses obtained through this field was included in the analysis.

Procedure

After identifying the challenges, a questionnaire was developed and tested on a pilot sample for its reliability by using Cronbach alpha criteria yielding a value of 0.869, which is more than the recommended value of 0.7 (Taber, 2018). To measure the content validity, the method prescribed by Lynn (1986) and Waltz and Bausell (2005) is used where a group of four experts was to rate two item sections present in the questionnaire- impact of challenges and identifying recommendations, on the scale of 1-4. The following ratings were mentioned for the purpose of testing the validity of the sections: 1-not relevant, 2-somewhat relevant, 3-quite relevant, 4-highly relevant. Each expert rated the questionnaire section in the relevant zone (3 and 4). These results indicate that the questionnaire is valid as well as reliable, therefore it can be used in the main study where participants were asked to fill the questionnaire in a quiet environment in order to minimize the distractions.

Table 1. Challenges faced in online classes

S.No.	Description
1.	Delay in timing of lectures
2.	Inhibition in using technology
3.	Lack of instructions/information
4.	Directly connecting with teacher
5.	Lack of immediate feedback
6.	Lower quality of material delivered online
7.	Insufficient training to use the system
8.	Lack of interaction with peers
9.	Lack of technical skills associated for execution in platform
10.	Less confidence for online classes
11.	Procrastination
12.	Lack of personal motivation
13.	Interruptions in online classroom (by family, breaches etc.)
14.	Lack of internet access or connectivity issues
15.	Lack of understanding of operations of platform
16.	Lack of access to resources
17.	Mental stress due to corona pandemic
18.	Uncertainties leading to loss in motivation
19.	Use of mobile or other technologies during online classes
20.	Lack/problem of infrastructure to participate in online classes
21.	Distractions/disturbances in voice or presentation
22.	Teachers ignoring/delaying the doubts asked
23.	Increased workload due to home and other activities
24.	Power failure
25.	Time lag in speaking

For the study, the following data analysis methods are used:

- Interpretive Structural Modeling (ISM)

The ISM technique is used to determine structural relationships amongst the variables and provides an explanation of how the variables are related to each other. ISM has been used in researches to transform poorly developed models to well defined models (Sage, 1977). This technique provides a structure to the variables by presenting them in a graphical model with upper level variables having dependence on lower level variables. For the study, after the data collection, ISM and MICMAC analysis were used in order to analyze the contextual relationship between challenges (Sage, 1977) and to provide realistic picture of variables involved (Attri et al., 2013).

- Exploratory Factor Analysis (EFA)

When a large number of variables are encountered in a research design, it is necessary to identify the underlying constructs. This identification allows to investigate few variables combined in a form of a latent construct compared to the original variables. EFA is used in the study by using principal component analysis to make interpretations easier to understand by combining several challenges under latent variables. These latent variables are classified in accordance to the composition of the challenges within these latent parameters.

- Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is one of the most used multi-criteria decision making technique i.e. identifying the best alternative within the possible constraints. TOPSIS has been considered as a simple, intuitive and logical way of ordering objects. The classical TOPSIS method aims to assign priority to the challenges and contributes to research by providing a method to define the ranking of challenges. TOPSIS method was proposed by Huang and Yun (1981), and it has been adopted in several past studies in order to rank the challenges or barriers (Ahmadi et al., 2013; Wanke et al., 2016; Singh et al., 2017). This method is suitable in the current study because of the involvement of quantitative data. TOPSIS is a seven-step process:

Step 1: Establish a decision matrix consisting of the alternatives and criteria on which alternative are evaluated. In this study, the criteria are the ratings on the Likert scale (from 1 to 5) and the alternatives are the 25 challenges listed in Table 1.
Step 2: Calculate the normalized decision matrix.
Step 3: Calculate the weighted normalized decision matrix i.e. multiply the weights associated to each alternative in the normalized matrix.
Step 4: Determine positive and negative ideal solution.
Step 5: Calculate the separation distance i.e. deviation of each alternative from ideal positive and negative solution.
Step 6: Calculate the Closeness Coefficient i.e. relative closeness of each alternative to ideal solution.
Step 7: Rank the alternatives on basis of value of Closeness Coefficient (CC), the alternative having CC close to 1 is ranked higher.

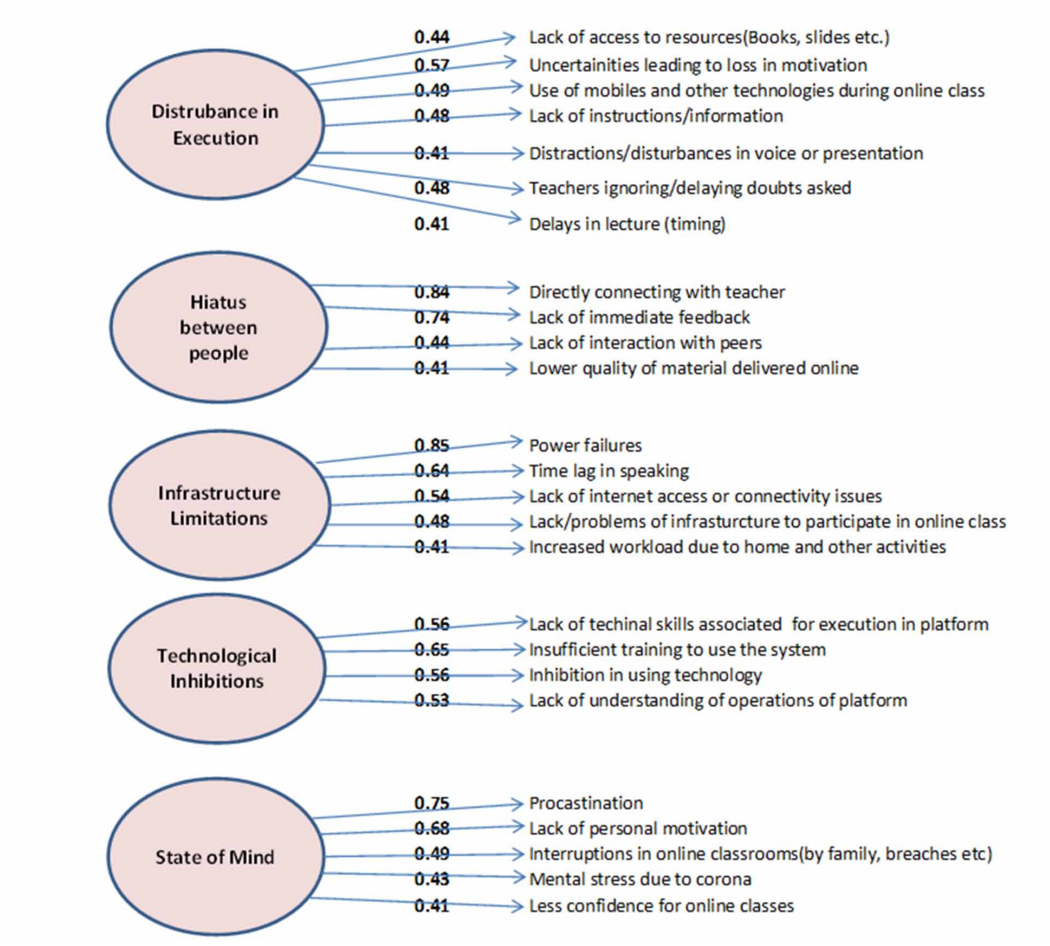
Participants

For the pilot study, the number of participants was 25 (15 students; 10 instructors). In the main study, a total of 624 participants were present. The number of students participated was 399(Age:15 to 28 years; Gender:270 males, 129 females) and number of instructors was 225(Age:26 to 58 years; Gender:60 males, 165 females). The participants were chosen randomly from 14 different academic institutes in the same manner as mentioned in Method section. The participants were from different departments such as Humanities, Economics, Management, Social Sciences, Computer science, Electrical and Mechanical engineering, etc. pursuing/teaching different degree programs such as PhD, BTech, BA, MA, BBA, MBA, MBBS, Secondary School Education, etc. The participants had already completed a part of the registered courses before the lockdown in a traditional face to face classroom and completed the rest of the course through online mode with the same time schedule, instructor and course content.

RESULTS

Before the exploratory factor analysis, outliers were removed and KMO test was conducted. KMO test confirms whether the sample collected for the study was adequate to run factor analysis or not. The minimum KMO index for the individual items was 0.87 for directly connecting with teacher. The overall KMO index obtained was 0.93 which is classified as good (Hutcheson & Sofroniou, 1999) and is more than the sufficient value of 0.5. Therefore, factor analysis could be used to group the challenges under latent variables. The number of latent variables was chosen on the basis of eigenvalue criteria. Using principal component analysis with varimax rotation, the number of variables having an eigenvalue greater than 1 was chosen. The number of latent variables that satisfies this criterion was five. The following Figure 1 depicts the grouping of challenges under latent variables and results of exploratory factor analysis.

Figure 1. Model diagram using EFA



The results are valid as Root Mean Square Error of Approximation (RMSEA) value is 0.046 which is close to 0 (MacCallum et al., 1996), Tucker-Lewis Index is 0.952, which is greater than or equal to 0.95 as specified by Hu and Bentler (1999). The latent variables observed were reported in the Table 2.

To generate the interpretive structural model, contextual relationships were identified among the challenges as described in the method section. The following Figure 2 shows the structural self-interaction matrix, where the symbols mean:

Table 2. Latent variables observed

Number of Latent Variable	Variable Name
1.	Disturbance in Execution
2.	Hiatus between People
3.	Infrastructure Limitations
4.	Technological Inhibitions
5.	State of Mind

Figure 2. Structural Self-Interaction Matrix (SSIM)

sno		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	Delays in lecture (timing)	1	A	V	V	V	V	A	V	A	A	A	A	A	A	A	A	A	A	A	A	A	V	A	A	A
2	Inhibition in using technology		1	V	V	V	V	A	A	X	X	V	X	V	A	X	A	A	O	O	A	V	V	A	O	V
3	Lack of instructions/information			1	V	X	A	V	O	V	V	V	V	V	A	V	A	A	A	V	A	A	V	A	A	A
4	Lack of connecting with teacher				1	X	X	X	O	A	X	V	V	A	A	A	O	A	A	A	A	A	X	A	A	A
5	Lack of feedback from instructor					1	O	O	A	A	A	V	V	A	A	A	V	A	A	A	A	A	O	A	A	A
6	Lower quality of material delivered online						1	A	A	X	X	V	X	A	A	A	A	A	A	A	A	A	V	A	A	A
7	Insufficient training to use the system							1	A	X	V	V	V	V	O	V	V	A	A	O	A	V	V	A	A	O
8	Lack of interaction with peers								1	V	V	V	V	O	A	V	V	X	X	V	O	O	V	A	O	O
9	Lack of techinal skills associated for execution in platform									1	V	V	V	V	O	X	X	A	A	O	A	V	V	A	O	V
10	Less confidence for online classes										1	V	V	A	A	V	A	A	A	O	A	A	V	A	A	A
11	Procastination											1	X	O	A	A	A	A	A	X	A	V	V	A	A	O
12	Lack of personal motivation												1	A	A	A	A	X	X	A	A	A	A	A	A	A
13	Interruptions in online classrooms(by family, breaches etc)													1	O	V	V	A	A	A	A	A	V	A	A	A
14	Lack of internet access or connectivity issues														1	V	V	O	O	A	A	V	V	O	A	V
15	Lack of understanding of operations of platform															1	V	A	A	A	A	V	V	A	A	A
16	Lack of access to academic resources(Books, slides etc.)																1	A	A	A	A	A	V	A	A	A
17	Mental stress due to corona																	1	X	V	O	V	V	O	O	O
18	Uncertainities leading to loss in motivation																		1	V	O	V	V	O	O	O
19	Use of mobiles and other technologies during online class																			1	O	V	V	O	O	V
20	Lack/problems of infrasturcture to participate in online class																				1	V	V	O	A	V
21	Distractions/disturbances in voice or presentation																					1	V	A	A	X
22	Teachers ignoring/delaying doubts asked																						1	X	A	A
23	Increased workload due to home and other activities																							1	O	A
24	Power failures																								1	V
25	Time lag in speaking																									1

V- Challenge i will lead to challenge j
A-Challenge j will lead to challenge i
X- Challenge i and j will lead each other
O-Challenge i and j are not linked

i and j refer to serial numbers of challenges
The final reachability matrix, shown in Figure 3 is computed by using the following rules:

If V is present in any cell (i,j)- the value in cell (i,j) is 1 and the value in cell (j,i) is 0.
If A is present in any cell (i,j)- the value in cell (i,j) is 0 and the value in cell (j,i) is 1.
If X is present in any cell (i,j)- the value in cell (i,j) is 1 and the value in cell (j,i) is 1.
If O is present in any cell (i,j)- the value in cell (i,j) is 0 and the value in cell (j,i) is 0.

Figure 3. Reachability Matrix

	01:01	02:02	03:03	04:04	05:05	06:06	07:07	08:08	09:09	10:10	11:11	12:12	13:13	14:14	15:15	16:16	17:17	18:18	19:19	20:20	21:21	22:22	23:23	24:24:00	25:25:00	influence
01:01	1	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	7
02:02	1	1	1	1	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	1	1	0	0	1	15
03:03	0	0	1	1	1	0	1	0	1	1	1	1	1	0	1	0	0	0	1	0	0	1	0	0	0	12
04:04	0	0	0	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	8
05:05	0	0	1	1	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	6
06:06	0	0	1	1	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	8
07:07	1	1	0	1	0	1	1	0	1	1	1	1	1	0	1	1	0	0	0	0	1	1	1	1	0	16
08:08	0	1	0	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	0	0	0	15
09:09	1	1	0	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	0	1	1	0	0	1	16
10:10	1	1	0	1	1	1	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	10
11:11	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	1	0	0	0	6
12:12	1	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	7
13:13	1	0	0	1	1	1	0	0	0	1	0	1	1	0	1	1	0	0	0	0	0	1	0	0	0	10
14:14	1	1	1	1	1	1	0	1	0	1	1	1	0	1	1	1	0	0	0	0	1	1	0	0	1	16
15:15	1	1	0	1	1	1	0	0	1	0	1	1	0	0	1	1	0	0	0	0	1	1	0	0	0	12
16:16	1	1	1	0	0	1	0	0	1	1	1	1	0	0	0	1	0	0	0	0	0	1	0	0	0	10
17:17	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	20
18:18	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	19
19:19	1	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	0	1	0	1	1	0	0	1	14
20:20	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	1	19
21:21	1	0	1	1	1	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	1	1	0	0	1	11
22:22	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	6
23:23	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	1	1	1	0	0	17
24:24:00	1	0	1	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0	1	1	1	0	1	1	17
25:25:00	1	0	1	1	1	1	0	0	0	1	0	1	1	0	1	1	0	0	0	0	1	1	1	0	1	14
Dependence	19	12	14	21	19	21	10	6	12	18	20	24	13	4	16	15	4	4	6	2	14	23	4	2	8	

For diagonal entries i.e. for cell where i=j, value is 1.

After analyzing the antecedent and precedent set from the matrix represented in Figure 3, the following map (shown in Figure 4) for the influence (marked on y axis) which provides a measure of driving power of challenge and dependence (marked on x axis) which provides an estimate of dependence on other challenges is obtained by calculating the sum of individual rows and columns respectively. The serial number of challenges as present in Table 1 is marked on the map by plotting the values obtained for influence and dependence as mentioned in Figure 3. The results indicate a good fit as the challenges are aligned equally with the dependence and influence axis. From this step, the challenges are classified in six levels by combining the challenges present as clusters. The final model is depicted in Figure 5.

Figure 4. Influence and dependence map

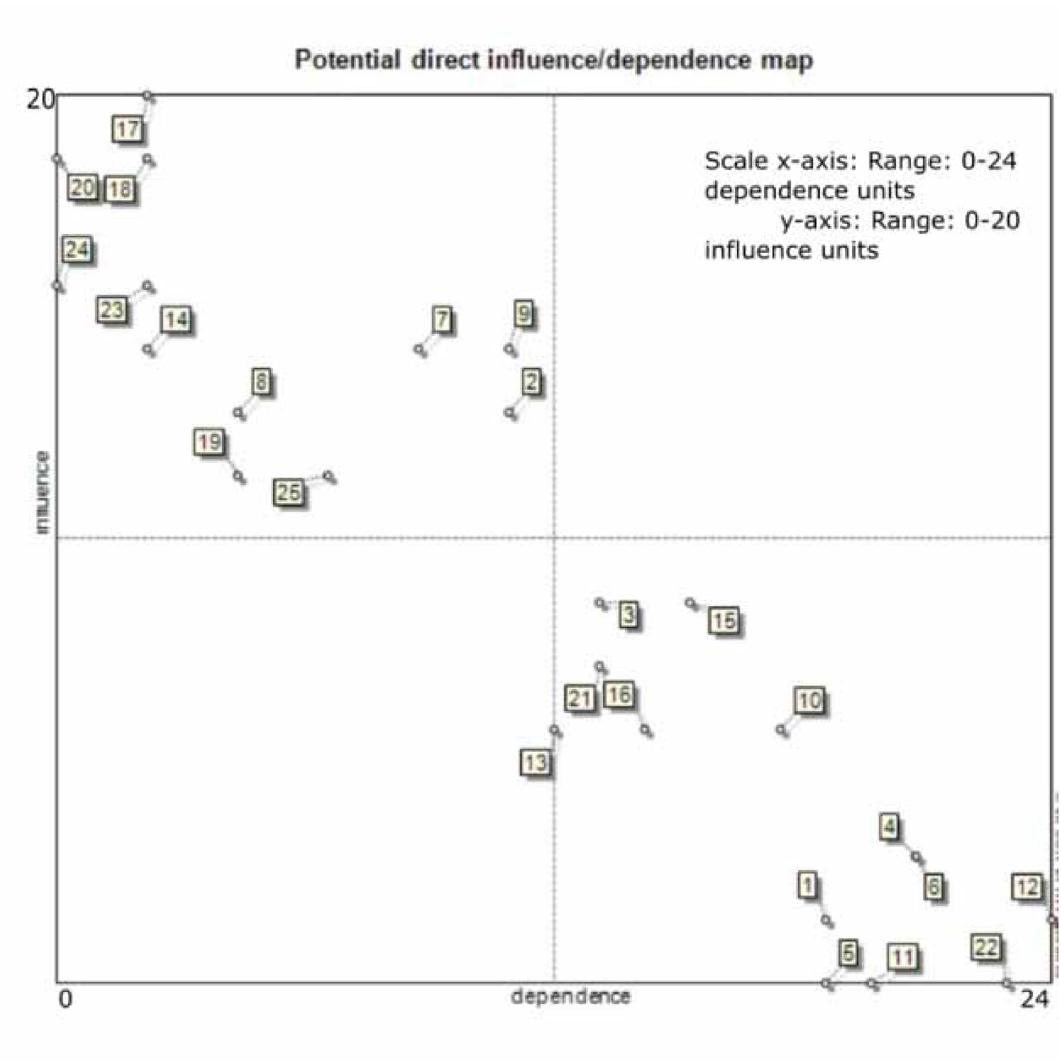
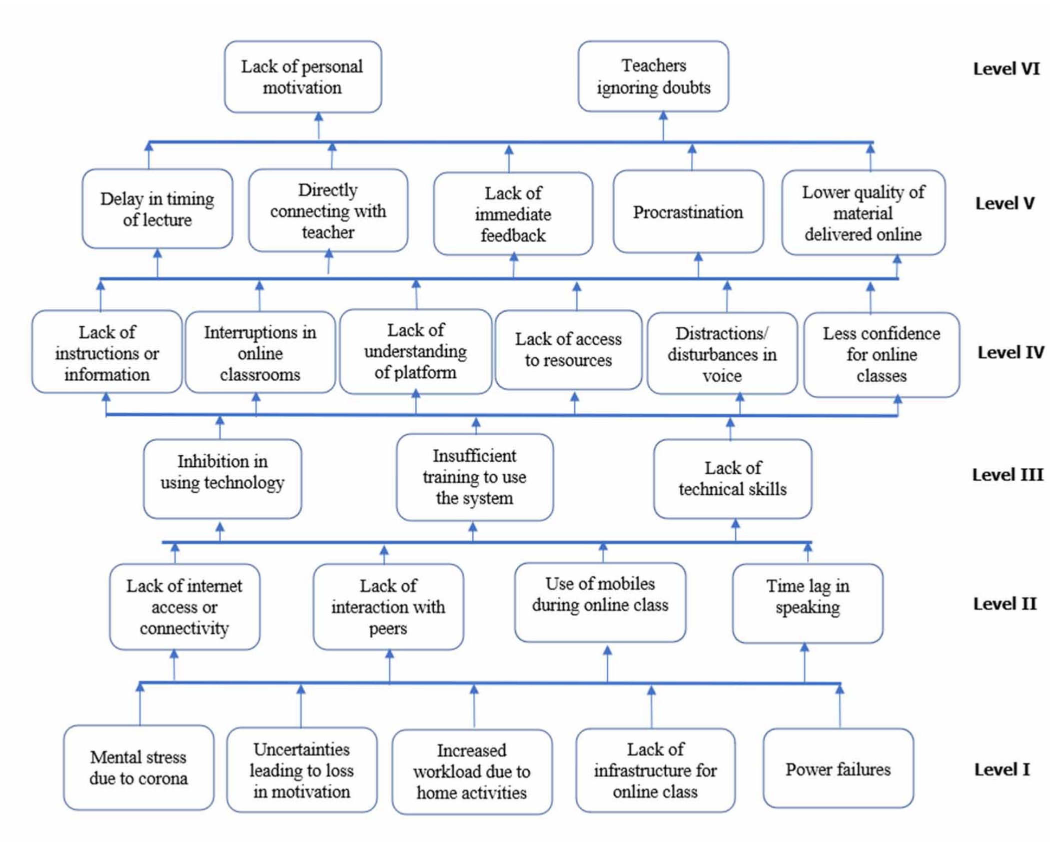


Figure 5. Final Graph Interpretive Structural Model (ISM)



To generate the ranking of the challenges in three categories- students, instructor and overall, TOPSIS technique was used, consisting of seven methods as prescribed by Huang and Yun (1981). The initial decision matrix consists of 25 identified challenges (as rows) and number of people (as columns) who rated the particular scale item on 1-5 on Likert scale. The following Figure 6

Figure 6. Initial decision matrix

	Number of total respondents					Number of students					Number of faculty				
Challenges	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Delays in lecture (timing)	89	52	37	19	11	52	29	29	15	8	37	23	8	4	3
Inhibition in using technology	69	53	32	32	22	39	30	22	26	16	30	23	10	6	6
Lack of instructions/information	68	63	34	28	15	38	40	22	19	14	30	23	12	9	1
Directly connecting with teacher	32	40	44	46	46	20	19	36	23	35	12	21	8	23	11
Lack of immediate feedback	44	45	49	41	29	27	25	36	23	22	17	20	13	18	7
Lower quality of material delivered online	62	40	40	32	34	28	23	30	28	24	34	17	10	4	10
Insufficient training to use the system	72	40	30	40	26	43	27	19	24	20	29	13	11	16	6
Lack of interaction with peers	45	29	51	40	43	26	15	31	27	34	19	14	20	13	9
Lack of techinal skills associated for execution in platform	68	52	38	28	22	43	33	22	17	18	25	19	16	11	4
Less confidence for online classes	90	40	34	23	21	50	26	22	15	20	40	14	12	8	1
Procastination	58	38	41	36	35	29	17	30	29	28	29	21	11	7	7
Lack of personal motivation	61	28	35	38	46	28	18	23	27	37	33	10	12	11	9
Interruptions in online classrooms(by family, breaches etc)	60	36	35	43	34	31	21	22	31	28	29	15	13	12	6
Lack of internet access or connectivity issues	41	34	33	45	55	21	22	22	22	46	20	12	11	23	9
Lack of understanding of operations of platform	73	46	33	40	16	52	28	17	26	10	21	18	16	14	6
Lack of access to resources(Books, slides etc.)	49	44	29	47	39	21	30	14	31	37	28	14	15	16	2
Mental stress due to corona	58	59	32	37	22	32	40	17	25	19	26	19	15	12	3
Uncertainities leading to loss in motivation	49	36	48	39	36	24	20	26	31	32	25	16	22	8	4
Use of mobiles and other technologies during online class	44	42	35	45	42	17	25	28	25	38	27	17	7	20	4
Lack/problems of infrasturcture to participate in online class	60	39	47	35	27	33	26	31	20	23	27	13	16	15	4
Distractions/disturbances in voice or presentation	34	41	42	61	30	18	21	26	41	27	16	20	16	20	3
Teachers ignoring/delaying doubts asked	78	35	41	38	16	46	23	18	31	15	32	12	23	7	1
Increased workload due to home and other activities	43	34	33	50	48	20	20	19	34	40	23	14	14	16	8
Power failures	67	39	38	34	30	38	25	23	22	25	29	14	15	12	5
Time lag in speaking	57	38	46	38	29	32	29	23	27	22	25	9	23	11	7

shows the initial decision matrix obtained by collecting the number of responses corresponding to a particular rating mentioned on the Likert scale in the questionnaire. A total of three tables are constructed considering responses from students, instructors, and overall category consisting of both students and instructors.

TOPSIS requires input weights for each criterion, which in this case are responses 1 to 5 obtained through section 1 of the questionnaire. The weights for all of the three cases were generated by using entropy method as used in past studies such as Zou et al. (2006). To generate the weights, the matrix in Figure 6 was first normalized, i.e. dividing each entry of matrix with the sum of particular column as prescribed in the study of Zou et al. (2006). Then the following equations were used:

$$E_j = -K \sum R_{ij} \ln(R_{ij})$$

where Rij is the entry in the matrix and i, j ranges from the first entry of the table to the last entry.

K is the natural logarithm of normalized entry of the particular matrix element being considered as per the values of i and j:

$$d_j = 1 - E_j$$

$$W_j = \frac{d_j}{\sum d_j}$$

For the overall case, the weights for response observed were 1-0.20795, 2-0.12165, 3-0.08014, 4-0.16186, 5-0.42838; for students- 1-0.25221, 2-0.13783, 3-0.12995, 4-0.12656, 5-0.35343; for faculty- 1-0.08786, 2-0.08638, 3-0.13554, 4-0.26301, 5-0.42718. The sum of weights in each of the categories is 1. Although the weights are in similar ranges for all three categories; slight difference is observed due to normalization of the variation in data points.

In step 2 of TOPSIS, table in Figure 6 is normalized by dividing the square root of the sum of squares in each column for three categories. The normalized matrix is then multiplied with the associated weights. For example, in the overall category data, for item scale 1, 0.20795 is multiplied with each entry in that column. The following Figure 7 show the results after multiplying the weights.

Figure 7. Weighted normalized matrix

	Weighted matrix for overall category					Weighted matrix for students					Weighted matrix for instructors				
Challenges	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Delays in lecture (timing)	0.292999	0.24439	0.190831	0.097046	0.066739	0.305808	0.222853	0.232171	0.114384	0.058621	0.271188	0.271795	0.109404	0.058284	0.097745
Inhibition in using technology	0.227157	0.24909	0.165043	0.163446	0.133478	0.229356	0.230537	0.17613	0.198265	0.117242	0.219882	0.271795	0.136756	0.087426	0.195491
Lack of instructions/information	0.223865	0.296088	0.175358	0.143015	0.091008	0.223475	0.307383	0.17613	0.144886	0.102587	0.219882	0.271795	0.164107	0.131139	0.032582
Directly connecting with teacher	0.105348	0.187992	0.226934	0.234954	0.27909	0.117619	0.146007	0.288212	0.175389	0.256467	0.087953	0.24816	0.109404	0.335133	0.358399
Lack of immediate feedback	0.144854	0.211491	0.252722	0.209415	0.175948	0.158785	0.192115	0.288212	0.175389	0.161208	0.1246	0.236343	0.177782	0.262278	0.228072
Lower quality of material delivered online	0.204112	0.187992	0.206303	0.163446	0.206284	0.164666	0.176745	0.240177	0.213517	0.175863	0.2492	0.200892	0.136756	0.058284	0.325818
Insufficient training to use the system	0.237033	0.187992	0.154728	0.204308	0.157747	0.25288	0.207484	0.152112	0.183014	0.146553	0.212553	0.153623	0.150431	0.233136	0.195491
Lack of interaction with peers	0.148146	0.136295	0.263037	0.204308	0.260889	0.152904	0.115269	0.248183	0.205891	0.249139	0.139259	0.16544	0.273511	0.189423	0.293236
Lack of techinal skills associated for execution in platform	0.223865	0.24439	0.195988	0.143015	0.133478	0.25288	0.253591	0.17613	0.129635	0.131897	0.183235	0.224526	0.218809	0.160281	0.130327
Less confidence for online classes	0.296292	0.187992	0.175358	0.117477	0.127411	0.294046	0.199799	0.17613	0.114384	0.146553	0.293176	0.16544	0.164107	0.116568	0.032582
Procastination	0.190943	0.178593	0.211461	0.183877	0.212351	0.170547	0.130638	0.240177	0.221142	0.205174	0.212553	0.24816	0.150431	0.101997	0.228072
Lack of personal motivation	0.20082	0.131595	0.180516	0.194092	0.27909	0.164666	0.138322	0.184136	0.205891	0.271122	0.24187	0.118172	0.164107	0.160281	0.293236
Interruptions in online classrooms(by family, breaches etc)	0.197528	0.169193	0.180516	0.219631	0.206284	0.182309	0.161376	0.17613	0.236393	0.205174	0.212553	0.177257	0.177782	0.174852	0.195491
Lack of internet access or connectivity issues	0.134977	0.159794	0.1702	0.229846	0.333695	0.1235	0.169061	0.17613	0.167763	0.337071	0.146588	0.141806	0.150431	0.335133	0.293236
Lack of understanding of operations of platform	0.240325	0.216191	0.1702	0.204308	0.097075	0.305808	0.215168	0.1361	0.198265	0.073276	0.153917	0.212709	0.218809	0.203994	0.195491
Lack of access to resources(Books, slides etc.)	0.161314	0.206792	0.14957	0.240062	0.23662	0.1235	0.230537	0.112083	0.236393	0.271122	0.205223	0.16544	0.205133	0.233136	0.065164
Mental stress due to corona	0.190943	0.277289	0.165043	0.188985	0.133478	0.18819	0.307383	0.1361	0.19064	0.139225	0.190564	0.224526	0.205133	0.174852	0.097745
Uncertainities leading to loss in motivation	0.161314	0.169193	0.247564	0.1992	0.218419	0.141142	0.153692	0.208153	0.236393	0.234484	0.183235	0.189075	0.300862	0.116568	0.130327
Use of mobiles and other technologies during online class	0.144854	0.197392	0.180516	0.229846	0.254822	0.099976	0.192115	0.224165	0.19064	0.27845	0.197894	0.200892	0.095729	0.29142	0.130327
Lack/problems of infrasturcture to participate in online class	0.197528	0.183293	0.242407	0.178769	0.163814	0.194071	0.199799	0.248183	0.152512	0.168535	0.197894	0.153623	0.218809	0.218565	0.130327
Distractions/disturbances in voice or presentation	0.111932	0.192692	0.216619	0.311569	0.182016	0.105857	0.161376	0.208153	0.312649	0.197846	0.11727	0.236343	0.218809	0.29142	0.097745
Teachers ignoring/delaying doubts asked	0.256786	0.164493	0.211461	0.194092	0.097075	0.270523	0.176745	0.144106	0.236393	0.109914	0.234541	0.141806	0.314538	0.101997	0.032582
Increased workload due to home and other activities	0.141562	0.159794	0.1702	0.255385	0.291225	0.117619	0.153692	0.152112	0.25927	0.293105	0.168576	0.16544	0.191458	0.233136	0.260654
Power failures	0.220573	0.183293	0.195988	0.173662	0.182016	0.223475	0.192115	0.184136	0.167763	0.183191	0.212553	0.16544	0.205133	0.174852	0.162909
Time lag in speaking	0.187651	0.178593	0.237249	0.194092	0.175948	0.18819	0.222853	0.184136	0.205891	0.161208	0.183235	0.106354	0.314538	0.160281	0.228072

After computing weighted normalized matrix, the maximum and minimum ideal solutions are identified and distance from each of these alternatives is calculated by the following equations:

Positive Ideal = $A_{+} = \{(\max R_{ij}), (\max R_{ij}), i = 1,2,3.....m\} = \{R_{1+}, R_{2+}, ...R_{n+}\}$

Negative Ideal = $A_{-} = \{(\min R_{ij}), (\min R_{ij}), i = 1,2,3,....m\} = R_{1-}, R_{2-}, ...R_{n-}\}$

The normalized distances d+ and d- are calculated by taking the square root of the sum of squares of these values by using:

Distance from positive Ideal $(d+) = \{ \sum_{j=1}^{5} (A_{j+} - R_{ij})^2 \}^{0.5}$

Distance from negative Ideal $(d-) = \{ \sum_{j=1}^{5} (R_{ij} - A_{j-})^2 \}^{0.5}$

Finally, the closeness coefficient (CC) is calculated by using the value d-/(d+ + d-). When the closeness coefficient (CC) is close to 1, it is more comparable to the ideal solution and is ranked higher. The following Tables 3, 4 and, 5 depict the ranking of the challenges in different categories.

Figure 8 shows the closeness coefficient for the challenges. The value of closeness coefficient is represented on the x-axis and challenges are presented on the y-axis. The values are shown for three categories-students, instructors, and overall. The difference in perception of the challenges can be easily gauged by comparing the observed value of closeness coefficient among the categories.

DISCUSSION

As the first latent variable in the EFA model consists of the challenges related to disturbance in execution, it is named as *Executional barriers*. The second latent variable comprises of the challenges which have an effect on social contact, hence called *Hiatus between people*. The third latent variable is named *Infrastructure Limitations*, as it is related to problems associated with infrastructure. The fourth latent variable comprises of technology and platform-based challenges, therefore are listed as *Technological Inhibitions*. The fifth latent variable constituted various challenges relating to *State of mind*, hence named so.

From Figure 4, the challenges which have a high influence and low dependence (present in the top left corner) are called driver variables which constitute of mental stress due to Corona, uncertainties leading to loss in motivation, increased workload due to home activities, lack of infrastructure, power failure, time lag in speaking, use of mobiles during classes, lack of interaction with peers, lack of internet access, inhibition in using technology, insufficient training and lack of technical skills. If we compare these driver variables with EFA model, these challenges form a part of the latent variables constituting of technological inhibition and infrastructure barrier.

The challenges which have a low influence and high dependence (present in the lower right corner of Figure 4) are termed as dependent variables and they comprise of lack of instruction, interruptions in online classrooms, lack of understanding of platform, lack of access to resources, distractions/ disturbances in voice presentation, less confidence for online classes, lower quality of material delivered online, procrastination, lack of immediate feedback, directly connecting with teacher, delay in timing of lecture, teachers ignoring doubts and lack of personal motivation. If we compare these

Table 3. Overall ranking for the challenges

Challenges	d+	d-	CC (Overall)	Rank
Lack of internet access or connectivity issues	0.04038	0.11658	0.74273	1
Increased workload due to home and other activities	0.04218	0.09987	0.70305	2
Lack of personal motivation	0.04178	0.09445	0.69321	3
Directly connecting with teacher	0.04959	0.09411	0.65492	4
Use of mobiles during online class	0.04996	0.08420	0.62760	5
Lack of interaction with peers	0.05100	0.08590	0.62746	6
Lack of access to resources	0.05340	0.07778	0.59291	7
Uncertainties leading to loss in motivation	0.06162	0.06864	0.52696	8
Procrastination	0.06189	0.06679	0.51904	9
Interruptions in online classrooms	0.06248	0.06603	0.51381	10
Lower quality of material delivered online	0.06415	0.06463	0.50188	11
Distractions/disturbances in voice	0.07657	0.06107	0.44367	12
Power failures	0.07201	0.05674	0.44068	13
Time lag in speaking	0.07514	0.05300	0.41361	14
Lack of immediate feedback	0.07706	0.05243	0.40489	15
Insufficient training to use the system	0.07989	0.05116	0.39039	16
Lack/problems of infrastructure	0.07982	0.04864	0.37864	17
Less confidence for online classes	0.09496	0.04810	0.33623	18
Inhibition in using technology	0.09073	0.04219	0.31739	19
Mental stress due to corona	0.09109	0.04087	0.30975	20
Lack of technical skills associated	0.09163	0.04101	0.30918	21
Teachers ignoring/delaying doubts asked	0.10477	0.03805	0.26641	22
Lack of understanding of operations of platform	0.10422	0.03697	0.26183	23
Delays in lecture	0.11982	0.04145	0.25723	24
Lack of instructions/information	0.10876	0.03428	0.23967	25

dependent variables with EFA model, these challenges form a part of the latent variables constituting of hiatus between people and state of mind.

The variables having low dependence and low influence are called autonomous variables and those having high dependence and high influence are linkage variables. The model doesn't contain any of these variables which is evident from Figure 4 as there are no entries in the lower left and upper right corner. From these details, a contextual model is obtained by combining specific clusters. The six clusters identified are arranged in six levels, lower levels formed by driver variables and upper levels formed by dependent variables.

In Figure 5; the challenges in the lower levels of the model drive the challenges in the upper level as these challenges have more influence and less dependence. The challenges present in Level 1 have cumulative effect on all the upper levels i.e. Level 2, 3, 4, 5, and 6, similarly, all the lower levels challenges have an effect on upper level challenges. Hence, while addressing the challenges, priority should be given to the lower levels including Level 1 that consist of the challenges- Mental stress due to corona, Uncertainties leading to loss in motivation, Increased workload due to home

Table 4. Student's ranking of the challenges

Challenge	d+	d-	CC (Students)	Rank
Lack of internet access or connectivity issues	0.05501	0.09945	0.64385	1
Lack of personal motivation	0.05214	0.07835	0.60041	2
Increased workload due to home and other activities	0.05746	0.08532	0.59756	3
Lack of access to resources	0.05819	0.07853	0.57436	4
Use of mobiles during online class	0.06070	0.08034	0.56962	5
Lack of interaction with peers	0.05799	0.07183	0.55326	6
Directly connecting with teacher	0.06214	0.07423	0.54435	7
Uncertainties leading to loss in motivation	0.06074	0.06628	0.52181	8
Interruptions in online classrooms	0.06208	0.05884	0.48661	9
Procrastination	0.06406	0.05885	0.47883	10
Power failures	0.06450	0.05616	0.46543	11
Less confidence for online classes	0.07486	0.05972	0.44375	12
Distractions/disturbances in voice	0.07401	0.05701	0.43509	13
Lack/problems of infrastructure	0.07071	0.05044	0.41634	14
Insufficient training to use the system	0.07405	0.05213	0.41311	15
Lower quality of material delivered online	0.07095	0.04989	0.41288	16
Time lag in speaking	0.07242	0.04745	0.39584	17
Lack of technical skills	0.07899	0.05093	0.39202	18
Lack of immediate feedback	0.07611	0.04723	0.38291	19
Teachers ignoring/delaying doubts asked	0.08539	0.05006	0.36958	20
Mental stress due to corona	0.07999	0.04594	0.36481	21
Lack of understanding of operations of platform	0.09723	0.05508	0.36163	22
Delays in lecture	0.10249	0.05620	0.35415	23
Inhibition in using technology	0.08332	0.04391	0.34515	24
Lack of instructions/information	0.08923	0.04469	0.33369	25

and other activities, Lack/problems of infrastructure to participate in online class, and Power failures, Level 2 consisting of Lack of internet access or connectivity issues, Time lag in speaking, Use of mobiles and other technologies during online class, and Lack of interaction with peers, and Level 3 having the challenges Inhibition in using technology, Insufficient training to use the system, and Lack of immediate feedback. The challenges in Level 1 are related to effect on mental health and availability of infrastructure which have direct influence on the challenges present is all levels. For example, mental stress can lead a person to use mobile phones during class to release the anxiety. Similarly, power failure can lead to lack of internet access, time lag in speaking and lack of interaction. Hence, policymakers should focus on challenges located in lowest level first, to effectively abate all the challenges. The upper levels of the model can be dealt at a later stage. In all, the first three levels can be considered as drivers and last three levels can be considered as driven challenges and if the challenges present in driver levels are effectively countered the problems can be resolved quickly.

It was predicted that the recommendations which affect the lower level would be perceived as the most useful in dealing with the challenges, which is observed in the recommendation section of

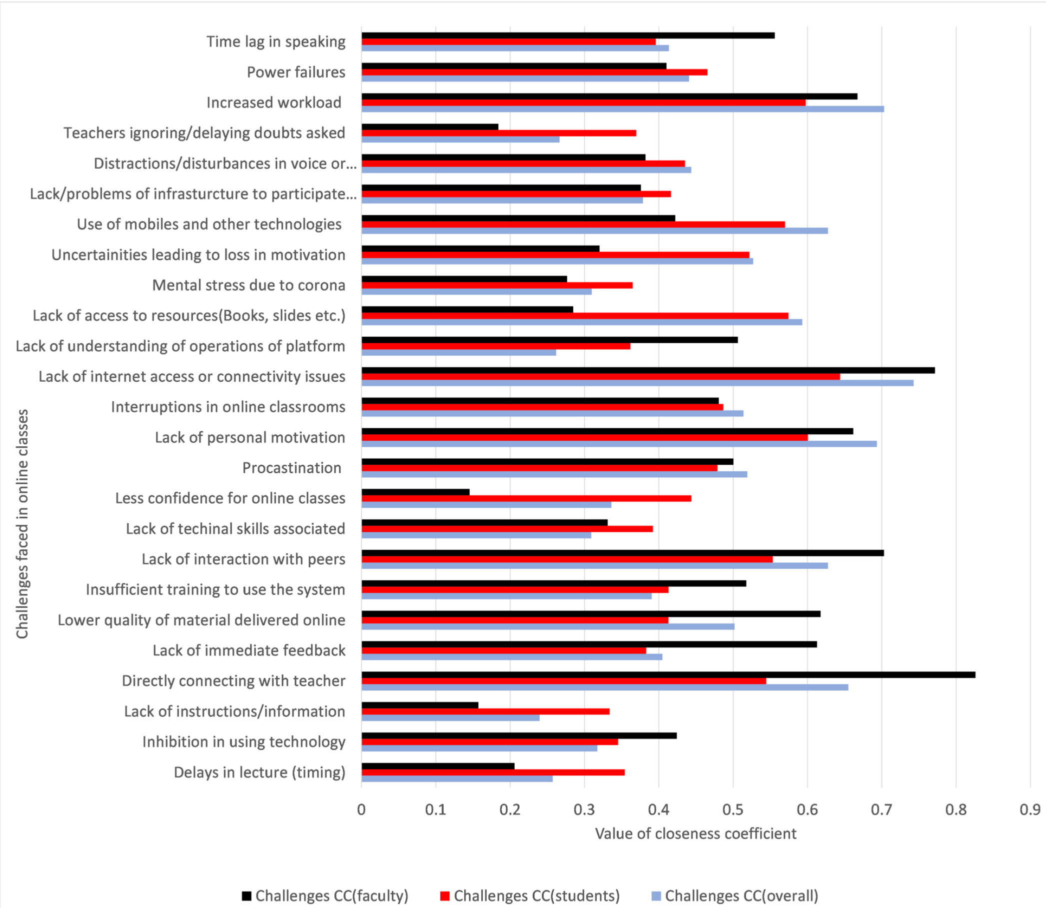
Table 5. Instructor ranking of the challenges

Challenges	d+	d-	CC (Faculty)	Rank
Directly connecting with teacher	0.03320	0.15757	0.82595	1
Lack of internet access or connectivity issues	0.03952	0.13338	0.77144	2
Lack of interaction with peers	0.05042	0.11923	0.70280	3
Increased workload due to home and other activities	0.05427	0.10887	0.66732	4
Lack of personal motivation	0.05918	0.11571	0.66161	5
Lower quality of material delivered online	0.07829	0.12645	0.61762	6
Lack of immediate feedback	0.06355	0.10056	0.61275	7
Time lag in speaking	0.07424	0.09297	0.55599	8
Insufficient training to use the system	0.07881	0.08455	0.51757	9
Lack of understanding of operations of platform	0.07985	0.08190	0.50633	10
Procrastination	0.08607	0.08620	0.50038	11
Interruptions in online classrooms	0.08415	0.07787	0.48064	12
Inhibition in using technology	0.09854	0.07260	0.42423	13
Use of mobiles during online class	0.10301	0.07526	0.42215	14
Power failures	0.09542	0.06637	0.41022	15
Distractions/disturbances in voice	0.11378	0.07033	0.38198	16
Lack/problems of infrastructure	0.10380	0.06252	0.37590	17
Lack of technical skills	0.10902	0.05399	0.33124	18
Uncertainties leading to loss in motivation	0.11377	0.05359	0.32023	19
Lack of access to resources	0.12952	0.05158	0.28483	20
Mental stress due to corona	0.12038	0.04604	0.27667	21
Delays in lecture	0.13593	0.03524	0.20587	22
Teachers ignoring/delaying doubts asked	0.15259	0.03445	0.18420	23
Lack of instructions/information	0.15069	0.02814	0.15734	24
Less confidence for online classes	0.15224	0.02592	0.14551	25

the questionnaire as, if the challenges present in lower levels are altered the effect is transmitted to the upper levels as well. 360(57.7%) of the participants chose the recommendation ‘conscious effort should be made to focus in online classes’. This recommendation mitigates majority of the challenges present in levels 1, 2 and 3. It was followed by the recommendation ‘think all is going to be well’ which was selected by 300(48.1%) participants. ‘Administration should provide backup infrastructure’ was chosen by 267(42.7%) participants. Other recommendations were: ‘maintain cordial environment’ selected by 234(37.5%) participants, ‘formal training should be provided’ by 83(39.9%), ‘believe you can handle multi-facet tasks’ by 225(36.1%), ‘teachers should provide correct instructions’ by 219(35.1%), ‘time should be spent in exercising’ by 213(34.1%), ‘family members should not be allowed to interrupt in classes’ by 168(26.9%) etc.

Regarding the ranking of the challenges, the highest overall challenge is presented by lack of internet access, increased workload and the least is by delays in lecture and lack of information. For students, the highest perceived challenge was lack of internet access and lack of personal motivation,

Figure 8. Closeness coefficients and rankings



whereas for instructor it was direct connect with teachers and interaction with peers. The lowest-ranked challenges for students were inhibition using technology and lack of instruction as students are more comfortable using technology as compared to instructors. Further lack of instructions can be easily countered by contacting the resource person or peers; for the instructor it was less confidence and lack of instructions as instructors are taking the course for a long time and don't feel much of a difference when the medium of delivery changes. Major differences are explained further.

Direct connect with teacher and peers are the challenges which affect the instructor more than the students, because instructors are habituated to deliver the classes in traditional format, interacting with students and peers in order to make the course content better, online classes limit this interaction. Instructors are heavily conscious about the quality of lecture delivered in online classes and they are not ready to compromise with the quality of material delivered whereas most students are not familiar with the subject at the time it is taught, hence lower quality of material is not much of a challenge for them. Hence, lower quality content is perceived as a bigger challenge by the instructor than students. When everyone is at home, there is an increased workload of managing lectures as well as doing daily chores of home, this presents a big challenge to the instructor as they have to manage home chores along with professional tasks. Instructors do not use technology frequently, hence explaining the inhibition to use technology, insufficient training, and lack of understanding of operations is perceived as a greater challenge by the instructor.

Lack of resources and instructions affect students more, as instructors have access to resource material and have good command over the subjects they teach and don't need resources as much as students need. Mental stress and uncertainties have more effect on students as they are immature as compared to instructors. Moreover, students' lives are at a progressive stage and every decision can impact their career. There is a tendency of students to use mobile phones during class which distracts them and is a big challenge from the student's viewpoint as compared to the instructor. Lack of infrastructure and power failures are perceived as a bigger challenge for students as uncertainties are more from student's perspective due to situations at their home and instructors with administration's support can reduce these challenges for them by backup facilities. Delays in lecture also affect students more than instructors as they are anxious about the content, delivery style and learning outcomes of the online lectures, especially in COVID-19 situation.

Some of the challenges are equally rated by students and instructors. Procrastination has been equally ranked by both students and instructors as it is based on personal behavior not category. Interruptions in classes are also ranked equal as interruptions break the pace of lecture and instructor and students both are affected alike.

CONCLUSION

The sudden shift from traditional classes to the online mode of instructions caught the instructors and students unaware. They did not get sufficient time for preparation and were not able to gather the appropriate resources amidst the lockdown. Online classes pose multiple challenges such as overwhelming features provided by platforms, lack of internet access, inhibitions while using technology, lack of social interaction, etc. Combined with these challenges were the problems associated with coronavirus pandemic such as mental stress and anxiety resulting from the uncertainties. Hence, there were a number of challenges for both students and instructors while participating in online classes.

The ranking of the challenges by TOPSIS method presents the viewpoint of students and instructor for problems in executing the online classes. These rankings allow to understand which of the challenge has greater impact. Meticulous efforts can be made to assuage the challenge.

To interpret how the challenges affect each other and which challenges have a greater role to play in the given scenario, an ISM model is generated. This model provides an approach to help in deciding which challenges need to be addressed first to mitigate all the challenges effectively. The challenges which are present in Level I of the ISM significantly influence the other challenges, hence they should be mitigated first. Lack of access to internet ranked as the most significant challenge affecting all the other challenges as it is present in Level 1 of ISM model, should be addressed first. Although lack of personal motivation is considered a big challenge in the overall ranking, its effect is due to other challenges, which is evident as it lies in the top level of ISM. Hence, it should not be the prime challenge to mitigate. It is of utmost importance for the universities to make the online classes successful, in order to do so they must provide proper infrastructure, backup power and internet facilities.

The main focus for any policymaker should be to rectify the strategy so it reduces the impact of challenges in the first three level of ISM. This can be accomplished by the recommendations: conscious effort should be made to focus in the class, administration should provide backup services, cordial environment must be maintained and formal training should be provided.

LIMITATIONS

Although, the study has considered the impact of 25 challenges, more challenges can be encountered at later stages. The study does not deal with open learning systems as COVID-19 has not affected this particular style of study as compared to instructor based traditional style of teaching. Further, this study does not consider the personal competences of instructors and students as during the COVID-19 the students registered in particular course continued to learn under the same instructor for the remaining part of the course, only the medium of delivery of lectures changed. The effect of personal competences and learning abilities will have a role if either the students or instructors changed during the course execution or the mode of course offering was different.

REFERENCES

Ahmadi, H., Rad, M.S., Nilashi, M., Ibrahim, O. & Almaee, A. (2013). Ranking the Micro level critical factors of electronic medical records adoption using TOPSIS method. *Health Informatics*, *4*(2).

Asarta, C. J., & Schmidt, J. R. (2013). Access patterns of online materials in a blended course. *Decision Sciences Journal of Innovative Education*, *11*(1), 107–123. doi:10.1111/j.1540-4609.2012.00366.x

Attri, R., Dev, N., & Sharma, V. (2013). Interpretive structural modelling (ISM) approach: An overview. *Research Journal of Management Sciences*, *2319*, 1171.

Bell, P. D., & Akroyd, D. (2006). Can factors related to self-regulated learning predict learning achievement in undergraduate asynchronous Web-based courses. *International Journal of Instructional Technology and Distance Learning*, *3*(10), 5–16. PMID:18066365

Bender, T. (2012). *Discussion-based online teaching to enhance student learning: Theory, practice and assessment*. Stylus Publishing, LLC.

Bernard, R. M., Abrami, P. C., Lou, Y., Borokhovski, E., Wade, A., Wozney, L., Wallet, P. A., Fiset, M., & Huang, B. (2004). How does distance education compare with classroom instruction? A meta-analysis of the empirical literature. *Review of Educational Research*, *74*(3), 379–439. doi:10.3102/00346543074003379

Carnevale, D. (2000). Study Assesses What Participants Look for in High-Quality Online Courses. *The Chronicle of Higher Education*, *47*(9), A46–A46.

Cheung, L. L., & Kan, A. C. (2002). Evaluation of factors related to student performance in a distance-learning business communication course. *Journal of Education for Business*, *77*(5), 257–263. doi:10.1080/08832320209599674

Deimann, M., & Bastiaens, T. (2010). The role of volition in distance education: An exploration of its capacities. *The International Review of Research in Open and Distributed Learning*, *11*(1), 1–16. doi:10.19173/irrodl.v11i1.778

Diaz, D. P. (2002). Online drop rate revisited. *Extending the Pedagogy of Threaded-Topic Discussions., 2002*(1).

Dupin-Bryant, P. A. (2004). Pre-entry variables related to retention in online distance education. *American Journal of Distance Education*, *18*(4), 199–206. doi:10.1207/s15389286ajde1804_2

Faux, T. L., & Black-Hughes, C. (2000). A comparison of using the Internet versus lectures to teach social work history. *Research on Social Work Practice*, *10*(4), 454–466. doi:10.1177/104973150001000406

Frankola, K. (2001). Why online learners drop out. *WORKFORCE-COSTA MESA*, *80*(10), 52–61.

Galea, S., Merchant, R. M., & Lurie, N. (2020). The mental health consequences of COVID-19 and physical distancing: The need for prevention and early intervention. *JAMA Internal Medicine*, *180*(6), 817. doi:10.1001/jamainternmed.2020.1562 PMID:32275292

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71. doi:10.1007/s11528-014-0822-x

Gillett-Swan, J. (2017). The challenges of online learning: Supporting and engaging the isolated learner. *Journal of Learning Design*, *10*(1), 20–30. doi:10.5204/jld.v9i3.293

Grandon, E. E., Alshare, K., & Kwun, O. (2005). Factors influencing student intention to adopt online classes: A cross-cultural study. *Journal of Computing Sciences in Colleges*, *20*(4), 46–56.

Haber, J., & Mills, M. (2008). Perceptions of barriers concerning effective online teaching and policies: Florida community college faculty. *Community College Journal of Research and Practice*, *32*(4-6), 266–283. doi:10.1080/10668920701884505

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education*, *90*, 36–53. doi:10.1016/j.compedu.2015.09.005

Heuer, B. P., & King, K. P. (2004). Leading the band: The role of the instructor in online learning for educators. *Journal of Interactive Online Learning*, *3*(1), 1–11.

Ho, A., Reich, J., Nesterko, S., Seaton, D., Mullaney, T., Waldo, J., & Chuang, I. (2014). *HarvardX and MITx: The first year of open online courses, fall 2012-summer 2013.* HarvardX and MITx Working Paper No. 1.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. doi:10.1080/10705519909540118

Hung, M. L., & Chou, C. (2015). Students' perceptions of instructors' roles in blended and online learning environments: A comparative study. *Computers & Education*, *81*, 315–325. doi:10.1016/j.compedu.2014.10.022

Hutcheson, G. D., & Sofroniou, N. (1999). The multivariate social scientist: Introductory statistics using generalized linear models. *Sage (Atlanta, Ga.)*.

Hwang, C. L., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications*. Springer-Verlag. doi:10.1007/978-3-642-48318-9

Jahng, N., Krug, D., & Zhang, Z. (2007). Student achievement in online distance education compared to face-to-face education. *European Journal of Open, Distance and E-Learning, 10*(1).

Junco, R., Heiberger, G., & Loken, E. (2011). The effect of Twitter on college student engagement and grades. *Journal of Computer Assisted Learning*, *27*(2), 119–132. doi:10.1111/j.1365-2729.2010.00387.x

Kim, J., Kwon, Y., & Cho, D. (2011). Investigating factors that influence social presence and learning outcomes in distance higher education. *Computers & Education*, *57*(2), 1512–1520. doi:10.1016/j.compedu.2011.02.005

Kramarae, C. (2001). The Third Shift: Women Learning Online. American Association of University Women Educational Foundation.

Lange, C., & Costley, J. (2020). Improving online video lectures: Learning challenges created by media. *International Journal of Educational Technology in Higher Education*, *17*(1), 1–18. doi:10.1186/s41239-020-00190-6

Lanier, M. M. (2006). Academic integrity and distance learning. *Journal of Criminal Justice Education*, *17*(2), 244–261. doi:10.1080/10511250600866166

Lin, C. H., Zhang, Y., & Zheng, B. (2017). The roles of learning strategies and motivation in online language learning: A structural equation modeling analysis. *Computers & Education*, *113*, 75–85. doi:10.1016/j.compedu.2017.05.014

Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing Research*, *35*(6), 382–386. doi:10.1097/00006199-198611000-00017 PMID:3640358

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130–149. doi:10.1037/1082-989X.1.2.130

Maguire, L. L. (2005). Literature review–faculty participation in online distance education: Barriers and motivators. *Online Journal of Distance Learning Administration*, *8*(1), 1–16.

Mayer, R. E. (2014). Multimedia instruction. In *Handbook of research on educational communications and technology*. Springer. doi:10.1007/978-1-4614-3185-5_31

Muilenburg, L. Y., & Berge, Z. L. (2005). Student barriers to online learning: A factor analytic study. *Distance Education*, *26*(1), 29–48. doi:10.1080/01587910500081269

Murtaugh, P. A., Burns, L. D., & Schuster, J. (1999). Predicting the retention of university students. *Research in Higher Education*, *40*(3), 355–371. doi:10.1023/A:1018755201899

Nacu, D. C., Martin, C. K., Pinkard, N., & Gray, T. (2016). Analyzing educators' online interactions: A framework of online learning support roles. *Learning, Media and Technology*, *41*(2), 283–305. doi:10.1080/17439884.2015.975722

Oblender, T. E. (2002). A Hybrid Course Model-One Solution to the High Online Drop-out Rate. *Learning and Leading with Technology*, *29*(6), 42–53.

Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018). Online learning: Adoption, continuance, and learning outcome—A review of literature. *International Journal of Information Management*, *43*, 1–14. doi:10.1016/j.ijinfomgt.2018.05.005

Park, J. H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Journal of Educational Technology & Society*, *12*(4), 207–217.

Picciano, A. G., & Seaman, J. (2009). K-12 Online Learning: A 2008 Follow-Up of the Survey of US School District Administrators. Sloan Consortium.

Rucker, R., & Downey, S. (2016). Faculty technology usage resulting from institutional migration to a new learning management system. *Online Journal of Distance Learning Administration*, *19*(1).

Sage, A. (1977). *Interpretive Structural Modeling: Methodology for Large-scale Systems*. McGraw-Hill.

Schmidt, S. W., Tschida, C. M., & Hodge, E. M. (2016). How faculty learn to teach online: What administrators need to know. *Online Journal of Distance Learning Administration*, *19*(1), 1–10.

Shea, P., & Bidjerano, T. (2009). Community of inquiry as a theoretical framework to foster "epistemic engagement" and "cognitive presence" in online education. *Computers & Education*, *52*(3), 543–553. doi:10.1016/j.compedu.2008.10.007

Singh, S., Singh, R. K., & Seth, N. (2017). Ranking of critical success factors for online retailing by TOPSIS approach. *International Journal of Productivity and Quality Management*, *21*(3), 359–374. doi:10.1504/IJPQM.2017.084460

Stover, C. (2005). Measuring and understanding student retention. *Distance Education Report*, *9*(16), 1–7.

Stratton, L. S., O'Toole, D. M., & Wetzel, J. N. (2007). Are the factors affecting dropout behavior related to initial enrollment intensity for college undergraduates? *Research in Higher Education*, *48*(4), 453–485. doi:10.1007/s11162-006-9033-4

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, *48*(6), 1273–1296. doi:10.1007/s11165-016-9602-2

Tucker, S. (2001). Distance education: Better, worse, or as good as traditional education? *Online Journal of Distance Learning Administration*, *4*(4).

Waltz, C. F., & Bausell, B. R. (1981). *Nursing research: design statistics and computer analysis*. Davis FA.

Wanke, P., Azad, M. A. K., & Barros, C. P. (2016). Predicting efficiency in Malaysian Islamic banks: A two-stage TOPSIS and neural networks approach. *Research in International Business and Finance*, *36*, 485–498. doi:10.1016/j.ribaf.2015.10.002

Willging, P. A., & Johnson, S. D. (2009). Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Networks*, *13*(3), 115–127.

Williams, K. C., Cameron, B. A., & Morgan, K. (2012). Supporting online group Projects1. *NACTA Journal*, *56*(2), 15.

Wojciechowski, A., & Palmer, L. B. (2005). Individual student characteristics: Can any be predictors of success in online classes. *Online Journal of Distance Learning Administration*, *8*(2), 13.

You, J. W., & Kang, M. (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers & Education*, *77*, 125–133. doi:10.1016/j.compedu.2014.04.018

Zou, Z. H., Yi, Y., & Sun, J. N. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental Sciences (China)*, *18*(5), 1020–1023. doi:10.1016/S1001-0742(06)60032-6 PMID:17278765

Sangeeta Sharma (PhD) has been working as faculty of communication, creativity, and advertising for the last 25 years in the Department of Humanities and social sciences at BITS, Pilani, and had been head of department and coordinator of centre for women studies. She is an active and lively person who participates in sports and related activities. Dr. Sharma is an academician of par excellence for the last two and half decades. She has excelled in all aspects of academics such as classroom delivery, corporate connect and training, writing of books and research papers, paper presentation in national and international conferences, editorial work and organizing academic events, etc.

Arpan Bumb is a student at Birla Institute of Technology and Science, Pilani, and has a strong academic background. He consistently is in the top 10 percentile of the class and has topped in ten courses at the undergraduate level. He is interested in marketing mix, market research, and consumer behavior and has certification in them.