DP301P-Interactive Socio Technical Practicum

Perceptions and preferences of students towards online teaching during the COVID-19 pandemic

ENDTERM REPORT

submitted by Group-12

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Contents

List of Figures

List of Tables

Executive summary

COVID-19 was first discovered in the Wuhan region in China which soon became a global pandemic as declared by WHO (Cucinotta, D. and Vanelli, M., 2020). India received its first case in January and saw a rapid increase in the cases within a short span of time. As a result, lockdowns and multiple restrictions were imposed, which affected the lives of many people in terms of economy, education, mental and physical well being. One of the areas which has suffered significantly is the education sector, where students and teachers were compelled to attend classes online as a result of imposed lockdown. Existing literature has extensively investigated the variables such as learning loss, mental health and perception and decision making in the context of COVID-19. For example, an analysis done by T. Muthuprasad et. al., (2021) has shown that the students in the agricultural field prefer online classes, while a study conducted by Dost et. al., (2020) has shown that medical students prefer offline mode of teaching. However, to the best of our knowledge, no study has focused on how forced choice of online class conduction during COVID-19 lockdown might have affected teachers and students perception of online and offline mode of teaching-learning more specifically with respect to engineering students and faculty in India. Therefore, the present study investigated students' and faculty's perceptions towards online classes during COVID-19 and their perception of online and offline classes post COVID-19 when normalcy was achieved to see whether there is some change in their perception about online and offline mode of teaching-learning due to the learning experienced during COVID-19. Questions pertaining to positive and negative perception about online classes and positive and negative perception about offline classes along with some questions pertaining to their preferences were administered using an online survey form. Data was collected for undergraduates, masters and doctoral students, and faculty of IIT Mandi. The questionnaire contained 80 questions

which were measured on the likert scale.

The survey conducted in IIT Mandi was part of a pilot for validation of our constructs and the items. The main data collection will continue thereafter. For the available data, an item analysis followed with factor analysis was done.

Acknowledgment

We would like to earnestly acknowledge the sincere efforts and valuable time given by our mentors (Dr Purnima Bajre and Dr Neha Kaushik) whose valuable guidance and feedback have helped us a lot in completing the project successfully.

Also, we would like to thank our Institute for providing us with the a stage to combine our ideas from which our society can benefit. We are also grateful to Dr Saumya Dixit and Dr Parmod Kumar for coordinating the Inter Socio Technical Practicum so that it puts less burden on the students, and also providing valuable suggestions which helped us improve our project significantly. We would also like to thank our faculty and students for spending their time in filling up our survey and helping us sucessfully complete our project.

Thanks a lot.

Chapter 1

Introduction

The World Health Organization received many cases of a rare pneumonia-like disease that came up as flu in Wuhan, Hubei state, China on December 31st, 2019, and thus COVID-19 was proclaimed as a worldwide pandemic after a month since its first appearance (WHO, 2022). COVID-19 has impacted many elements of human life, including the economy, society, and most prominently, the educational sector. This has led to the closure of educational institutions at almost all levels and students being confined to their homes. Even before COVID-19, online education was prevalent in some of the advanced countries (Adeyeye, B et. al., 2022)., while many others had not employed this technique before the pandemic and are now compelled to do so to stave off the ill effects of the discontinuity in students' learning. In India, almost every school and government college, including the central institutes like IIT, NIT, etc., has resorted to online teaching and learning as a result of COVID-19 related restrictions. Students and the teaching community who were forced to adapt to a complete transition from physical classrooms to an online mode of teaching faced several constraints like low internet bandwidth, unfamiliarity with online teaching platforms (Sumitra, P et. al., 2021). These entire situational adjustments must have been perceived by people differently.

In the present project, we focus on the cohort of Btech students who have experienced a transition from offline to an online teaching mode and again back to the same old physical mode of teaching-learning. This transition definitely was much beyond a smooth transition

and demanded a lot of adjustment mechanisms from the stakeholders. We also presume that this forced transition must have been a learning experience for all the stakeholders and thus we try to ascertain how this learning might have contributed towards change in their perception with regard to the academic practices, online and offline class management, mental state, advantages and disadvantages of pre and post-COVID scenarios. We also want to find the preference of students between online and offline teaching by analyzing the answers to specific questions. We have circulated a Google questionnaire with four sections. The first portion gathers demographic data on the participants, such as their educational and work status, income, and infrastructure. The next section deals with the scenario during COVID-19 where we try to understand how the participants perceive themselves, that is their attitude towards academics, malpractices, results, fitness, family care and state of mind. The following section attempts to gauge the perception of students towards the current situation in terms of similar factors which we considered during COVID-19. The last section is meant to know the preference of students i.e. whether they are comfortable with the traditional method of teaching or they would prefer online mode or both i.e. hybrid mode. We have also extended our study to faculty to know their perception of offline and remote education and find their preference between the both. In this way, we can analyze both the faculty's and students' view of the two modes of learning and provide necessary suggestions to either to help improve the overall educational system.

This analysis is crucial because we need to be well prepared if pandemics like COVID-19 happen again in the future. Our study will be a huge contribution to educational policy makers in understanding the actual effects and causes of disruption of education and will help them formulate robust and insightful reforms. It will also highlight the areas of improvement in the current infrastructure, mental well being of students and access to remote education in India.

A very closer study has been conducted in the educational institutions of Nigeria (Peter, E et. al., 2020). This study intends to investigate perceptions of students of Nigerian higher education institutions using the new digital culture spawned by the COVID-19 pandemic,

online learning , which has become prevalent globally and especially in Nigeria. Based on the place of residence of the student, the study employed quantitative survey methodology and a sample of 1134 Nigerian students from universities, higher educational institutions, and polytechnics in Nigeria. Respondents completed a Google Form questionnaire in June-July 2020. They have found that students were not happy with online learning initiated by their colleges and would not wish to continue them after the pandemic because of lack of electricity and poor internet connectivity. Their study deduced that students of higher education preferred traditional offline learning instead of online classes which pushed them to the "Laggards adopter categorization" elucidated by the diffusion of innovations theory, meaning, the group that is very slow to adopt new technological innovations and is very conservative.

The survey revealed that free online learning tools were very widely used during the outbreak of COVID-19 with Zoom, WhatsApp and Google Classroom comprising a major chunk of the options. According to the data, 3 out of every 5 students (61%) spent around 2 hours every day on their online lectures. If there were physical classrooms, students would spend about a quarter of their time on academic activities as there were around 4 lectures a day each of two hours. In comparison to their counterparts in colleges of higher education (25%) and polytechnics (27%), university students (45%) were more contended with online mode. On the contrary, students in higher education were the most unhappy with online learning, with 50% expressing their dissatisfaction. This demonstrates that, while students in higher education institutions were the least likely to engage in online learning during the pandemic, university students were more likely to do so. Their survey responses show that a vast majority (75.8%) of Nigerian students do not want to have classes in hybrid mode where online teaching will run in parallel with offline lectures. The study identified 4 major hurdles to virtual learning. Poor infrastructural facilities constituted a majority (42%) of the issues followed by personal factors such as laziness, lack of attention and motivation which constituted 24% of the reasons. Environmental factors such as family distractions and excessive noise accounted for 15% of the problems, while poor economic background accounted for 18%. The study suggests that universities should promote camera demon-

strations along with the traditional book learning so that students become more interactive in online lectures. They should also increase their virtual learning to avoid lagging in academics and invest more time in virtual learning until regular offline classes resume to get the optimum level of instruction. It also recommends higher education administrators in Nigeria to get back to traditional instructional formats as soon as the situation improves, as well as a statewide reconstruction of the electricity and internet system.

We have undertaken a similar and a more comprehensive evaluation of the perception of students as well as faculty towards online and offline teaching methods and further analyzed their preference among both.

1.1 Problem Statement

We have undertaken a similar and a more comprehensive evaluation of the perception of students towards online and offline teaching methods and further analyzed their preference among both.

1.2 Objectives

We will contribute to the pool of knowledge by accomplishing two objectives that are as follows :

1. We have analyzed the factors in terms of positives and negatives of online and offline modes of teaching and studying that has led to preference they opted for both the modes.

Chapter 2

Literature Review

2.1 Existing literature

COVID-19 was first discovered in the city of Wuhan in China and spread to various countries across the globe within a very short span of time. The major cause of this disease is Severe Acute Respiratory Syndrome CoronaVirus-2 (SARS-CoV-2) and has led to a high mortality; thousands have contracted the virus worldwide (Li et. al., 2020). In order to bring down the active cases in the country, the state imposed quarantines and lockdown measures, wherein movement was curtailed, and people were confined to their homes which hampered the progress of academic institutes, enterprises, research work, and tourism, public places, malls, cinema theaters, libraries, and almost entire social activities that required physical interactions were shut down, which disturbed everyday life (Hafeez et. al., 2020). The situation worsened as these restrictions were extended due to the spread of the disease with its increasing strength and reproduction number (R0), and a lack of vaccinations by continuous COVID-19 mutations, such as Alpha-coronavirus (alpha-CoV), Beta-coronavirus (beta-CoV), Gamma-coronavirus (gamma-CoV) and Delta-coronavirus (delta-CoV) (Cucinotta et. al., 2020; Hafeez et. al., 2020; Li et. al., 2020). Drastic effect of the disease and its capability to mutate itself marked a disruption of day-to-day activities of society, which led to various health implications, the most common of which was mental stress (Xiong et. al., 2020).

Educational institutes (colleges, universities, and schools) were also shut down. That led to an immediate halt in academic work. Subsequently, many educational institutions have resorted to online mode of teaching so as to continue the academic activities. Initially, it was hard for both faculty and students to adapt to this, as this was a new way of teaching. In India, people associated with academic practices faced added difficulties due to technical and network inaccessibility.In online education, the quality of learning depends on the way a lecture is delivered to the learner, learners' motivation and satisfaction with the environment created by the online mode of teaching (Bignoux Sund, 2018). Considering the constraints of teaching-learning in an online mode, extensive research has been conducted in order to measure the perception and preference of students towards online and traditional ways of learning. These works can be broadly divided into two sets; the first set deals with preference of learners and the other set involves assessing the perception of learners towards online learning. Preference for a particular mode of teaching is measured by the readiness or willingness of the learners to engage, collaborate, and learn in the environment that is created by the teaching mode. One research by Adam et al., (2012) suggested that in terms of satisfaction, both online and offline modes of teaching do not have any significant difference if they are designed properly. Warner et. al., (1998) introduced the concept of "readiness" for online teaching, which was further refined by numerous studies (Bandura, 1977, 1986, 1997; Compeau and Higgins, 1995; Deci and Ryan, 1985; Eastin and LaRose, 2000; Evans et. al., 2000; Guglielmino, 1977; Garrison, 1997; Fairchild et al., 2005; Hannafin, 1984; Hung et al., 2010; Lin and Hsieh, 2001; McVay, 2000, 2001; Palloff and Pratt, 1999; Reeves, 1993; Ryan and Deci, 2000; Roper, 2007; Smith et. al., 2003; Smith, 2005; Shyu and Brown, 1992; Tsai and Tsai, 2003; Tsai and Lin, 2004). They concluded that factors responsible for influencing readiness towards online learning are motivation for learning, self-learning, effectiveness of computer and internet, learner control, and the effectiveness of online communication. Studies were also conducted to improve the efficacy of online learning by analyzing the perceptions of students. Hence, a number of studies were done and documented both favorable and unfavorable perceptions towards online learning. They have concluded that the ability to make an effective online class depends on factors such as properly structured course content, well-prepared instructors, technology accessibility,

prompt feedback, and efficient collaboration with co-learners. However, studies like (Hara and Kling, 1999; Nguyen, 2015; Smart and Cappel, 2006) had shown that if these factors are well addressed, then significant difference in satisfaction and academic learning between online and traditional modes of teaching does not exist.

With the rise of COVID-19 cases around the globe, the mode of learning has changed from offline to online. Studies were conducted to measure the perception and preference of students towards online learning during the pandemic. Perception and preference were evaluated using offline or online surveys of students. T. Muthuprasad et al., (2021) conducted a survey of "307 agricultural graduates from different universities of National Agricultural Research System (NARS). The graduates comprised 136 undergraduates, 84 postgraduates and 87 doctoral students. They collected data on their demographic features, followed by learners' preferences, perception, advantages, constraints and suggestions, using objective questions having a 5 point likert scale and subjective questions". The study found that the proficiency of teachers and learners in using technologies such as a computer, smartphone or internet is an important factor in terms of the efficacy of online mode of delivering lectures. Another important factor is the interactivity between students and the faculty. Overall, the online mode of teaching was preferred by the students over the traditional way due to the availability of recorded videos along with proper follow up in the former. Another study by Dost et. al., (2020) assessed the perception of around 3700 medical students across the UK, using a 20-item national level online survey, based on a 5-point likert scale. Some questions were open-ended. By this, they collected the data on demographics, experience, possible barriers and benefits of online teaching. They suggested that the online mode should be made more interactive by incorporating polls, quizzes or breakout rooms etc. Students preferred traditional mode of teaching over online mode due to more face-to-face interaction in the former. The perceived benefit of online mode was found to be related to greater flexibility provided by teaching platforms (3D simulation labs, video conferencing applications etc.). This includes recorded lectures, online notes, pre-recorded tutorials and online flashcards. And the perceived barriers were found out to be family distractions, poor internet connectivity and lack of interaction between faculty and students.

A study by Akuratiya et. al., (2020) aims to examine the perception of 130 IT students' regarding online learning that happened during the COVID-19 pandemic period in Sri Lanka. It concluded that although there were challenges (such as less interaction, social isolation, technical problems etc.) in online teaching, 79.7% of the respondents perceived an online mode of teaching better than its traditional counterpart, and 82.9% of students preferred the integration of the two. A similar study by Sarkar et. al., (2021), examined the Public University Students in Bangladesh and found that they preferred the conventional way of teaching over the online, because of the problems associated with the latter mode such as difficulty in understanding, network inaccessibility, isolation etc. (Baber, 2020) performed a cross-country study between undergraduate students of India and South Korea. Data was collected using a survey of 100 students in these two countries sampled using convenience sampling, and the responses were administered using a 5-point likert scale. The study concluded that certain factors such as interaction in online classes, students' motivation, engagement, course structure, and instructors' technical knowledge play an important role in students' learning and satisfaction. It was also found that across countries, the difference in their learning outcomes and satisfaction levels is insignificant. As a conclusion, claims made by the recent studies on the perception and the preference of students towards the online mode of teaching are in line with the theories developed in early 2000s. The field of study is an important factor in determining the perception and preference of students towards online learning. Medical fields are more practice oriented, hence it requires proper interaction between the faculty and the students, which was not being provided efficiently by online education, hence students preferred the offline mode. Similarly, the IT field requires less interaction as compared to fields, hence students prefer online mode as it is more flexible than offline mode.

The existing literature, however, has focused mainly on the perception of students during COVID-19. To the best of our knowledge, there is no work which has analyzed the factors across different timestamps i.e. before and after COVID-19. In our study, we will be evaluating and comparing the perception and preference of students in India during these two

timelines.

Chapter 3

Proposed Methodology

3.1 Participants

We selected students from IIT Mandi as the respondents for this study because IIT Mandi has a diverse population from different social and economic backgrounds. Total number of students who participated were 131.

3.2 Procedure

We designed a structured and unstructured preliminary questionnaire so as to capture the perception and preference of the students.

3.3 Domain of the study

We shared the link to the Google form that was having the questions of the survey via the institute email. Participation in the survey was completely voluntary. We have disabled the link for circulating the Google forms after 21 days for students and 14 days for faculty. We received responses from a total of 131 students and 12 faculty from IIT Mandi.

3.4 Data collection

Data was collected on demographic features, followed by students' and faculty's preferences, perception of offline and online classes. The statements were prepared based on an extensive review of literature and discussion with mentors to minimize researchers' bias. To analyze and summarize the perception, statements were rated on a five-point Likert scale. To summarize the data, five-point summary, frequency, and percentage were calculated for most of the questions.

3.5 Descriptive statistical analysis

For descriptive statistical analysis, we calculated the basic parameters of each of the factors. We looked at parameters such as mean, variance, median, standard deviation, skewness, kurtosis, range and interquartile range.

3.6 Item and factor analysis

Item analysis was used in order to assess the quality of items (questions) within a factor and of the test as a whole. Assuming that our data was influenced by five factors (preference, online benefits, online demerits, offline benefits and offline demerits), we first separated out the survey questions belonging to each category, and then for each of these categories a correlation analysis was performed. A correlation matrix is calculated for each of the categories. We considered a correlation value above 0.4 as "descent", and questions having very few "descent" correlation with other questions were simply discarded. We also conducted factor analysis to identify the relationship between all the variables that are included in a given dataset and to statistically prove the underlying factors in the test. Ordinal regression analysis was used to predict the behavior of preferences (ordinal level dependent variables) with the set of perceptions (independent variables).

3.7 Ordinal regression analysis

First a normality test was conducted to see if our data belongs to the normal distribution or not. We found that the significance level for each of the factors was less than our alpha threshold which was 0.05. So ordinal regression was performed. The next section discusses the results of each of the analyses presented above.

Chapter 4

Results

4.1 Student responses

4.1.1 Descriptive statistical analysis

4.1.1.1 Missing values in the data

We first checked if there were any missing values in the dataset, and we found none.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
F1	131	100.0%	0	0.0%	131	100.0%
F2	131	100.0%	0	0.0%	131	100.0%
F3	131	100.0%	0	0.0%	131	100.0%
F4	131	100.0%	0	0.0%	131	100.0%
F5	131	100.0%	0	0.0%	131	100.0%

Fig. 4.1: This table shows the number and percent of missing values in our data. One can clearly see that there are no missing values.

4.1.1.2 Basic statistics

Then we checked the first order and second order statistics of the factors. The following table illustrates that -

			Statistic	Std. Error
F1	Mean		3.7252	.08448
	95% Confidence Interval for Mean	Lower Bound	3.5581	
		Upper Bound	3.8923	
	5% Trimmed Mean		3.7751	
	Median		3.8571	
	Variance		.935	
	Std. Deviation		.96690	
	Minimum		1.29	
	Maximum		5.00	
	Range		3.71	
	Interquartile Range		1.43	
	Skewness		-.562	.212
	Kurtosis		-.446	.420

Fig. 4.2: The table shows the statistics for factor 1

F2	Mean		3.9027	.08162
	95% Confidence Interval for Mean	Lower Bound	3.7412	
		Upper Bound	4.0641	
	5% Trimmed Mean		3.9750	
	Median		4.0000	
	Variance		.873	
	Std. Deviation		.93417	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.50	
	Skewness		-.956	.212
	Kurtosis		.587	.420

Fig. 4.3: The table shows the statistics for factor 2

F3	Mean		3.3206	.10559
	95% Confidence Interval for Mean	Lower Bound	3.1117	
		Upper Bound	3.5295	
	5% Trimmed Mean		3.3562	
	Median		3.3333	
	Variance		1.461	
	Std. Deviation		1.20852	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		2.00	
	Skewness		-.351	.212
	Kurtosis		-.839	.420

Fig. 4.4: The table shows the statistics for factor 3

F4	Mean		3.9580	.07735
	95% Confidence Interval for Mean	Lower Bound	3.8050	
		Upper Bound	4.1110	
	5% Trimmed Mean		4.0407	
	Median		4.2500	
	Variance		.784	
	Std. Deviation		.88533	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.00	
	Skewness		-1.346	.212
	Kurtosis		1.864	.420

Fig. 4.5: The table shows the statistics for factor 4

F5	Mean		3.9186	.09046
	95% Confidence Interval for Mean	Lower Bound	3.7396	
		Upper Bound	4.0975	
	5% Trimmed Mean		3.9934	
	Median		4.0000	
	Variance		1.072	
	Std. Deviation		1.03535	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.67	
	Skewness		-.791	.212
	Kurtosis		-.193	.420

Fig. 4.6: The table shows the statistics for factor 5

4.1.1.3 Distribution of data

We also checked their distribution of the 5 factors using histograms. One can clearly see that the distributions are not normally distributed and are skewed.

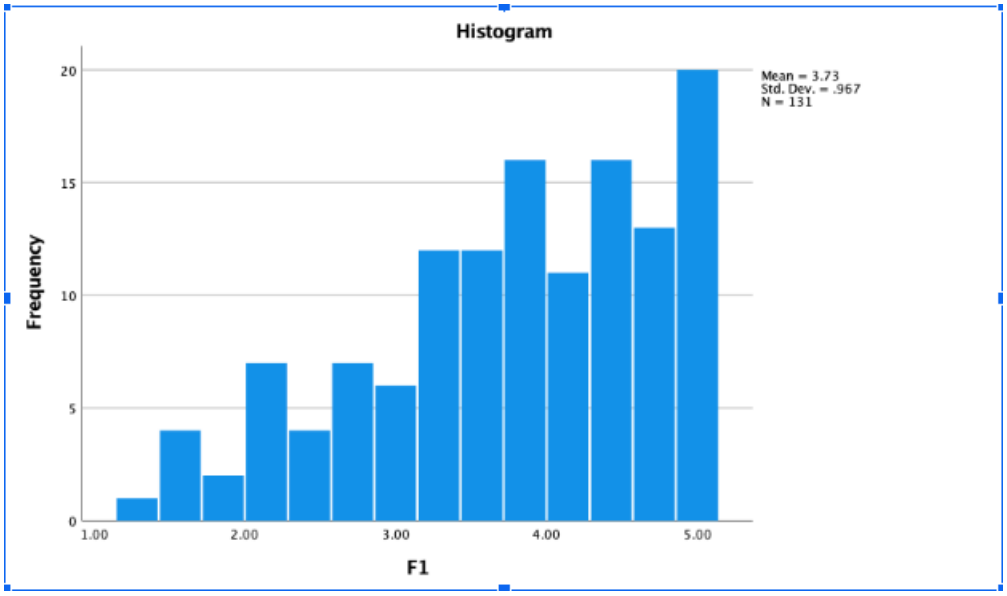

Fig. 4.7: Histogram showing the distribution of responses of items present in factor 1

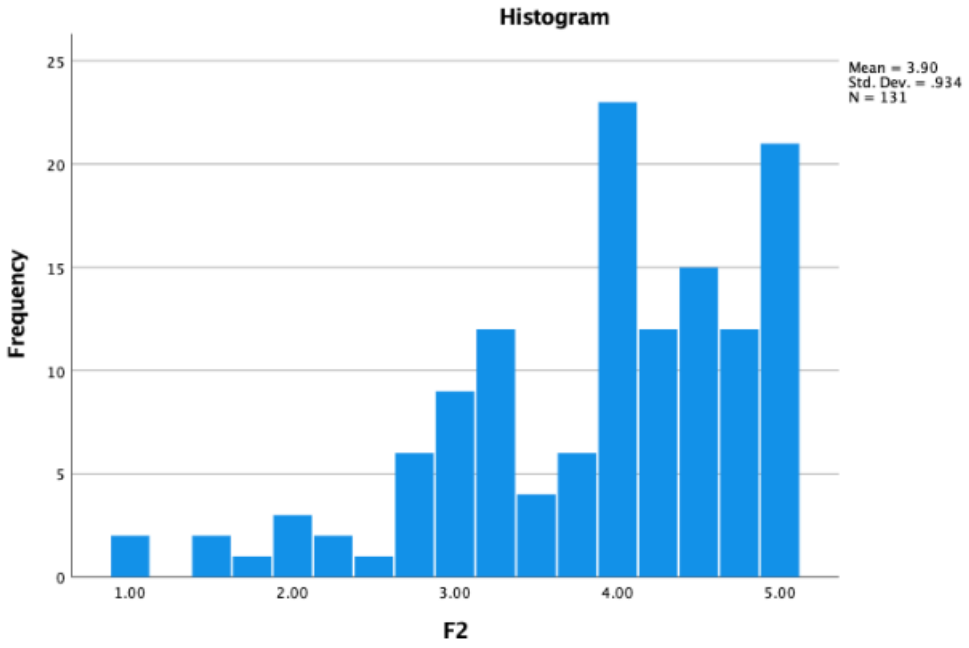

Fig. 4.8: Histogram showing the distribution of responses of items present in factor 2

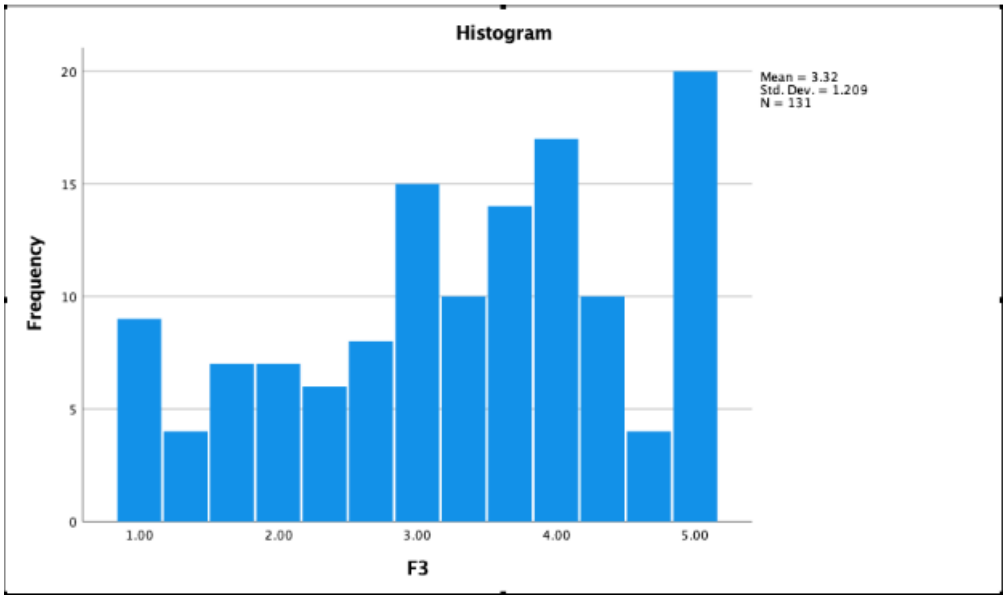

Fig. 4.9: Histogram showing the distribution of responses of items present in factor 3

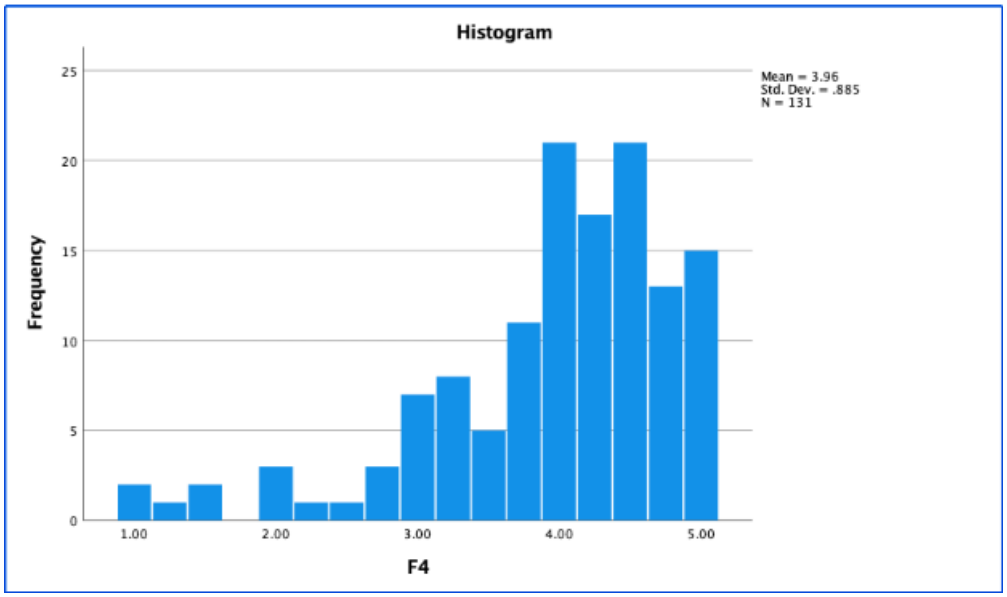

Fig. 4.10: Histogram showing the distribution of responses of items present in factor 4

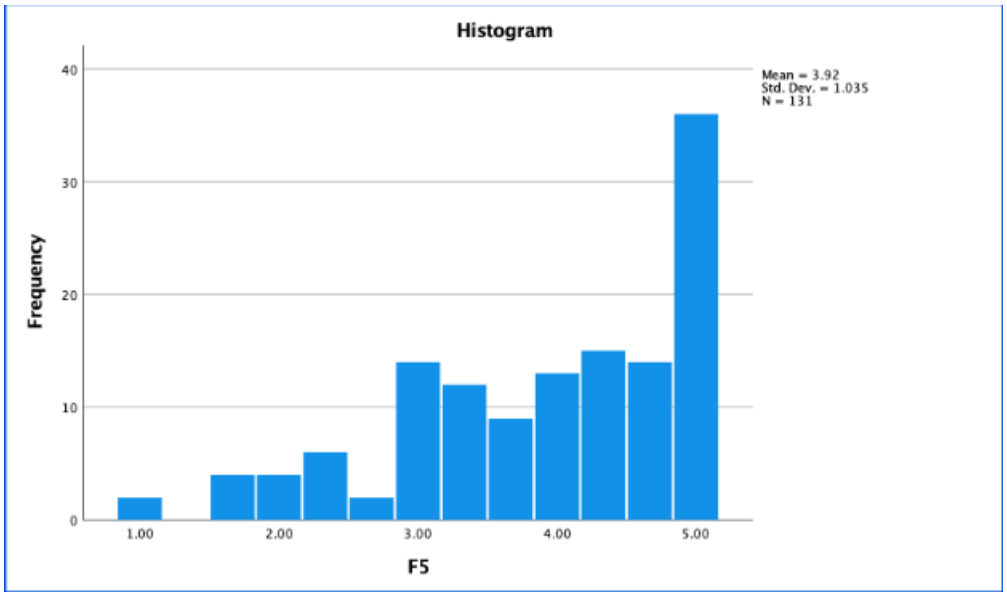

Fig. 4.11: Histogram showing the distribution of responses of items present in factor 5

4.1.2 Item analysis

We assume that our data is influenced by five factors, namely preference, online benefits, online demerits, offline benefits and offline demerits. Based on that we first separate out the survey questions belonging to each category.

Table 4.1: SELECTED QUESTIONS FOR DIFFERENT CATEGORIES

Category	**Questions**
Online benefits	Q3,Q4,Q5,Q6,Q7,Q8,Q11,Q12, Q15,Q16,Q17,Q18,Q20,Q45
Online demerits	Q13,Q25,Q26,Q32,Q33,Q40,Q42,Q43,Q44
Offline benefits	Q49,Q50,Q60,Q66,Q68,Q69,Q70,Q71,Q73
Offline demerits	Q53,Q54,Q55,Q62,Q63,Q65,Q75
Preference	Q76,Q79,Q80,Q81

Then for each of these categories a correlation analysis is performed which will help us retain questions with high correlation. A correlation matrix is calculated for each of the categories. Correlation value above 0.4 is considered "descent". Questions having very few "descent" correlation with other questions are discarded. This leaves us with the following questions.

Table 4.2: QUESTIONS REMAINING AFTER APPLYING ITEM ANALYSIS

Category	**Questions**
Online benefits	Q4, Q5, Q6, Q7, Q8, Q11, Q45
Online demerits	Q26, Q32, Q33, Q43
Offline benefits	Q50, Q60, Q66, Q69
Offline demerits	Q54, Q55, Q65
Preference	Q79, Q80, Q81

Table 4.3: Correlation matrix of online benefits

	Q4	**Q5**	**Q6**	**Q7**	**Q8**	**Q11**	**Q45**
Q4	1	0.5	0.47	0.45	0.5	0.45	0.42
Q5	0.5	1	0.52	0.59	0.43	0.42	0.47
Q6	0.47	0.52	1	0.49	0.44	0.3	0.41
Q7	0.45	0.59	0.49	1	0.45	0.42	0.54
Q8	0.5	0.43	0.44	0.45	1	0.43	0.4
Q11	0.45	0.42	0.3	0.42	0.43	1	0.49
Q45	0.42	0.47	0.41	0.54	0.4	0.49	1

Table 4.4: Correlation matrix of online demerits

	Q26	**Q32**	**Q33**	**Q43**
Q26	1	0.52	0.5	0.42
Q32	0.52	1	0.48	0.39
Q33	0.5	0.48	1	0.44
Q43	0.42	0.39	0.44	1

Table 4.5: Correlation matrix of offline benefits

	Q50	**Q60**	**Q66**	**Q69**
Q50	1	0.36	0.55	0.44
Q60	0.36	1	0.51	0.53
Q66	0.55	0.51	1	0.7
Q69	0.44	0.53	0.7	1

Table 4.6: Correlation matrix of offline demerits

	Q54	**Q55**	**Q65**
Q54	1	0.68	0.66
Q55	0.68	1	0.57
Q65	0.66	0.57	1

Table 4.7: Correlation matrix of preferences

	Q79	**Q80**	**Q81**
Q79	1	0.42	0.47
Q80	0.42	1	0.46
Q81	0.47	0.46	1

This concluded our item analysis but in order for us to be sure that these were indeed the underlying factors we needed to perform the factor analysis.

4.1.3 Factor analysis

Correlation matrix for all the selected questions is calculated and then eigenvalues and eigenvectors for this correlation matrix are obtained. The entire data is projected on the top 5 eigenvectors and correlation of this projected data is calculated with initially selected questions. This gives us the component matrix with each correlation as the factor loading.

Table 4.8: COMPONENT MATRIX

	1	**2**	**3**	**4**	**5**
Q4	0.67	0.06	-0.19	-0.3	0.29
Q5	0.67	0.3	-0.06	-0.24	0.29
Q6	0.61	0.26	0.27	-0.27	0.25
Q7	0.67	0.39	0.08	-0.23	-0.06
Q8	0.66	0.02	0	-0.34	-0.01
Q11	0.67	-0.16	-0.06	-0.23	-0.13
Q45	0.72	0.09	-0.08	-0.13	-0.22
Q26	-0.21	0.64	0.36	0.13	-0.14
Q32	0.07	0.57	0.59	-0.1	0
Q33	-0.15	0.64	0.39	0.28	-0.04
Q43	-0.23	0.68	0.18	0.04	0.22
Q54	0.77	0.08	-0.01	0.18	-0.31
Q55	0.74	-0.04	0.07	0.13	-0.29
Q65	0.75	0.17	0.1	0.26	-0.33
Q50	-0.16	0.77	-0.13	0.04	0.09
Q60	-0.42	0.46	-0.43	-0.12	-0.07
Q66	-0.17	0.67	-0.49	-0.11	-0.29
Q69	-0.31	0.56	-0.57	-0.12	-0.13
Q79	0.55	-0.07	-0.2	0.56	0.07
Q80	0.49	0.18	-0.22	0.44	0.34
Q81	0.57	0.22	-0.3	0.34	0.28

We then perform varimax rotation on the component matrix to obtain the rotated component matrix.

Table 4.9: Rotated component matrix

	1	**2**	**3**	**4**	**5**
Q4	0.74	-0.19	0	0.25	0.13
Q5	0.75	0.08	0.04	0.28	0.16
Q6	0.71	0.25	-0.18	0.1	0.16
Q7	0.64	0.22	0.08	0.08	0.45
Q8	0.64	-0.13	-0.08	0	0.36
Q11	0.48	-0.28	-0.14	0.03	0.46
Q45	0.47	-0.1	0.02	0.11	0.59
Q26	-0.12	0.75	0.2	-0.1	0.04
Q32	0.24	0.77	-0.07	-0.17	0.07
Q33	-0.14	0.79	0.11	0.07	0.04
Q43	0.06	0.66	0.28	0.07	-0.26
Q54	0.28	-0.01	-0.07	0.28	0.75
Q55	0.27	-0.05	-0.2	0.2	0.71
Q65	0.23	0.14	-0.1	0.29	0.78
Q50	0.08	0.52	0.57	0.16	-0.13
Q60	-0.12	0.1	0.71	-0.07	-0.22
Q66	0	0.19	0.88	-0.03	0.1
Q69	-0.05	0.07	0.86	0	-0.12
Q79	0	-0.13	-0.14	0.69	0.39
Q80	0.2	0.04	0	0.75	0.13
Q81	0.3	-0.01	0.09	0.72	0.2

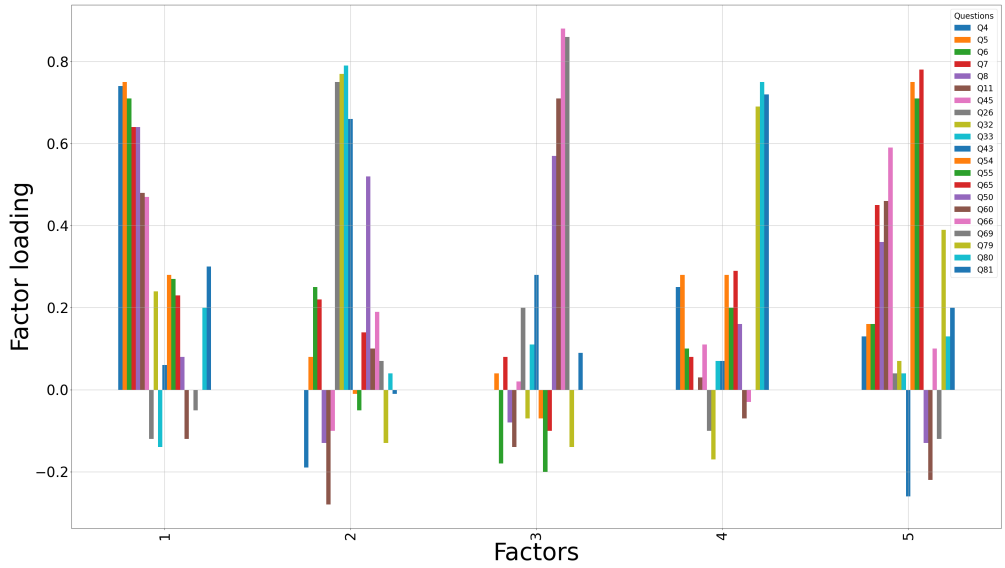

Fig. 4.12: Factor loading vs factors for student responses

Each question measures a factor such that its absolute value of factor loading is greater than 0.5.

Table 4.10: QUESTIONS MEASURING DIFFERENT FACTORS

Category	**Questions**
Factor 1	Q4, Q5, Q6, Q7, Q8
Factor 2	Q26, Q32, Q33, Q43, Q50
Factor 3	Q50, Q60, Q66, Q69
Factor 4	Q79, Q80, Q81
Factor 5	Q45, Q54, Q55, Q65

We can see that questions measuring factor 1 resemble online benefits questions, factor 2 resembles online demerits, factor 3 resembles offline benefits, factor 4 resembles preference and factor 5 resembles offline demerits.

4.1.4 Ordinal regression

First a normality test using Kolmogorov-Smirnov test was performed to check if the collected data belongs to a normal distribution or not. We found that the significance level was much smaller than the alpha threshold that we took (0.05), which clearly indicates that the data was not normally distributed.

	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
F1	.094	131	.007
F2	.175	131	<.001
F3	.109	131	<.001
F4	.183	131	<.001
F5	.152	131	<.001

Fig. 4.13: Significance value after conducting Kolmogorov-Smirnov test

Based on the normality test, we applied the ordinal regression where the dependent variable is preference and independent variables are the other factors.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	575.156			
Final	521.629	53.527	4	<.001

Link function: Logit.

Fig. 4.14: Significance value for the model used to fit the data

We can see that the significance level is less than the alpha threshold of 0.05, which means that the regression line has fitted the data well. Nagelkerke R^2 was found out to be 0.34, which means that only 34% of the data is explained by the independent variables.

4.2 Faculty responses

4.2.1 Item analysis

We assume that our data is influenced by five factors, namely preference, online benefits, online demerits, offline benefits and offline demerits. Based on that we first separate out the survey questions belonging to each category.

Table 4.11: SELECTED QUESTIONS FOR DIFFERENT CATEGORIES

Category	**Questions**
Online benefits	Q2, Q3, Q4, Q5, Q8, Q18, Q22, Q23, Q25, Q29, Q30, Q34, Q35
Online demerits	Q1, Q6, Q7, Q9, Q10, Q11, Q12, Q13, Q14, Q15, Q16, Q17, Q19 Q20, Q21, Q24, Q26, Q27, Q28, Q31, Q32, Q33, Q36, Q37, Q38
Offline benefits	Q40, Q41, Q42, Q43, Q44, Q45, Q46, Q47, Q48, Q49, Q50, Q52 Q59, Q60, Q61
Offline demerits	Q39, Q51, Q53, Q54, Q55, Q56, Q57, Q58
Preference	Q62, Q63, Q64, Q65, Q66

Then for each of these categories a correlation analysis is performed which will help us retain questions with high correlation. A correlation matrix is calculated for each of the categories. Correlation value above 0.4 is considered “descent”. Questions having very few “descent” correlation with other questions are discarded. This leaves us with the following questions.

Table 4.12: QUESTIONS REMAINING AFTER APPLYING ITEM ANALYSIS

Category	**Questions**
Online benefits	Q5, Q8, Q29
Online demerits	Q1, Q14, Q15, Q17, Q19
Offline benefits	Q40, Q42, Q43, Q45, Q47, Q48
Offline demerits	Q53, Q55, Q56
Preference	Q62, Q64, Q66

Table 4.13: CORRELATION MATRIX OF ONLINE BENEFITS

	Q5	**Q8**	**Q29**
Q5	1	0.65	0.79
Q8	0.65	1	0.54
Q29	0.79	0.54	1

Table 4.14: CORRELATION MATRIX OF ONLINE DEMERITS

	Q1	**Q14**	**Q15**	**Q17**	**Q19**
Q1	1	0.73	0.73	0.53	0.55
Q14	0.73	1	0.82	0.48	0.53
Q15	0.73	0.82	1	0.71	0.43
Q17	0.53	0.48	0.71	1	0.75
Q19	0.55	0.53	0.43	0.75	1

Table 4.15: Correlation matrix of offline benefits

	Q40	**Q42**	**Q43**	**Q45**	**Q47**	**Q48**
Q40	1	0.66	0.56	0.9	0.63	0.48
Q42	0.66	1	0.75	0.73	0.64	0.75
Q43	0.56	0.75	1	0.52	0.59	0.75
Q45	0.9	0.73	0.52	1	0.63	0.44
Q47	0.63	0.64	0.59	0.63	1	0.69
Q48	0.48	0.75	0.75	0.44	0.69	1

Table 4.16: Correlation matrix of offline demerits

	Q53	**Q55**	**Q56**
Q53	1	0.72	0.56
Q55	0.72	1	0.63
Q56	0.56	0.63	1

Table 4.17: Correlation matrix of preferences

	Q62	**Q64**	**Q66**
Q62	1	0.56	0.55
Q64	0.56	1	0.44
Q66	0.55	0.44	1

This concluded our item analysis but in order for us to be sure that these were indeed the underlying factors we needed to perform the factor analysis.

4.2.2 Factor analysis

Correlation matrix for all the selected questions is calculated and then eigenvalues and eigenvectors for this correlation matrix are obtained. The entire data is projected on the top 5 eigenvectors and correlation of this projected data is calculated with initially selected questions. This gives us the component matrix with each correlation as the factor loading.

Table 4.18: COMPONENT MATRIX

	1	**2**	**3**	**4**	**5**
Q5	0.41	0.69	-0.37	-0.05	0.33
Q8	0.3	0.41	-0.74	0.03	0.12
Q29	0.41	0.71	-0.18	0.34	0.26
Q1	-0.82	0.28	0	-0.13	0.43
Q14	-0.84	0.22	0.25	0.07	-0.1
Q15	-0.89	0.13	0.29	0.05	-0.05
Q17	-0.48	0.12	0.71	-0.33	0.19
Q19	-0.41	0.19	0.48	-0.64	0.22
Q40	-0.7	0.22	-0.27	-0.23	-0.41
Q42	-0.75	0.41	-0.31	0.18	-0.13
Q43	-0.77	0.26	-0.02	0.37	-0.16
Q45	-0.75	0.09	-0.42	-0.32	-0.36
Q47	-0.64	0.49	-0.3	-0.04	0.18
Q48	-0.82	0.32	0.09	0.34	0.24
Q53	0.15	0.74	0.26	0.22	-0.36
Q55	0.43	0.74	0.42	0.03	0.11
Q56	0.43	0.29	0.65	0.4	-0.1
Q62	0.46	0.54	-0.2	-0.55	-0.13
Q64	0.51	0.44	0.09	-0.47	-0.05
Q66	0.44	0.55	0.28	-0.02	-0.46

We then perform varimax rotation on the component matrix to obtain the rotated component matrix.

Table 4.19: ROTATED COMPONENT MATRIX

	1	**2**	**3**	**4**	**5**
Q5	-0.04	0.19	-0.08	0.31	0.87
Q8	0.1	-0.11	-0.46	0.29	0.71
Q29	-0.05	0.46	-0.18	-0.01	0.8
Q1	0.63	-0.27	0.61	-0.25	0.24
Q14	0.73	0.09	0.41	-0.28	-0.22
Q15	0.7	0.02	0.48	-0.33	-0.26
Q17	0.15	0.14	0.88	-0.08	-0.25
Q19	0.17	-0.04	0.88	0.25	-0.11
Q40	0.85	-0.14	0.02	0.23	-0.19
Q42	0.91	-0.02	-0.01	-0.16	0.15
Q43	0.8	0.12	0.05	-0.41	-0.06
Q45	0.86	-0.37	0	0.26	-0.19
Q47	0.74	-0.13	0.22	-0.05	0.39
Q48	0.71	0.04	0.35	-0.56	0.16
Q53	0.23	0.84	-0.04	0.16	0.18
Q55	-0.2	0.76	0.27	0.19	0.44
Q56	-0.36	0.83	0.07	-0.2	-0.02
Q62	-0.06	0.19	0	0.83	0.38
Q64	-0.25	0.31	0.15	0.66	0.26
Q66	-0.06	0.77	-0.1	0.43	0.03

Each question measures a factor for which its absolute value of factor loading is greater than 0.5.

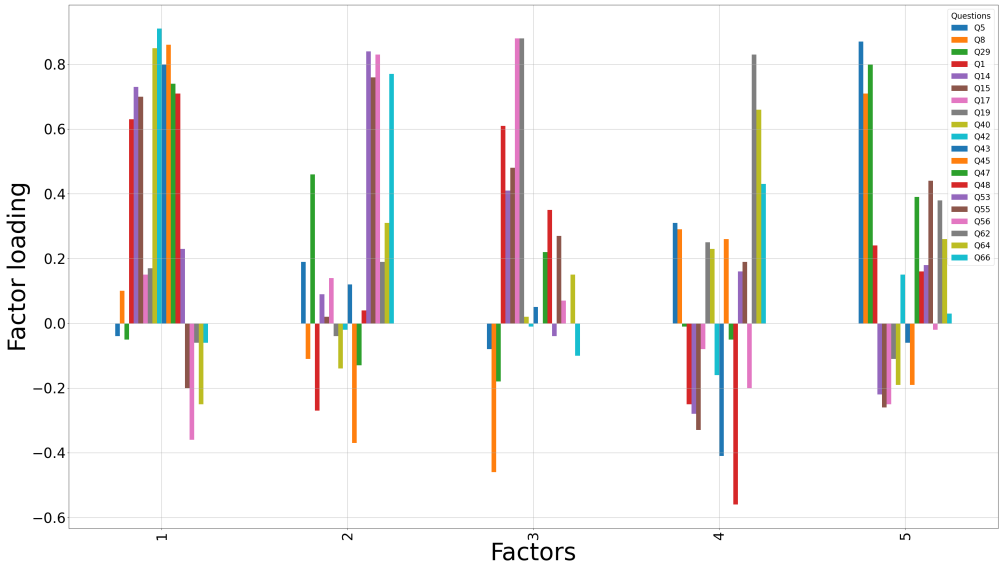

Fig. 4.15: Factor loading vs factors for faculty responses

Table 4.20: QUESTIONS MEASURING DIFFERENT FACTORS

Category	**Questions**
Factor 1	Q1, Q14, Q15, Q40, Q42, Q43, Q45, Q47, Q48
Factor 2	Q53, Q55, Q56, Q66
Factor 3	Q1, Q17, Q19
Factor 4	Q48, Q62, Q64
Factor 5	Q5, Q8, Q29

We can see that questions measuring factor 1 resemble offline benefits questions, factor 2 resembles offline demerits, factor 3 resembles online demerits, factor 4 resembles preference and factor 5 resembles online positives.

Chapter 5

Discussion

The results primarily discussed how students and teachers perceived offline and online learning, during and after the COVID-19 outbreak on the basis of their responses to the survey we shared. The survey also encapsulates the instructor and student preferences for both instructional modalities. From the factor analysis in the results section, we observe that items 4,5, 6, 7, and 8 contribute towards the benefits of the online mode. Item 4 implies that online classes were comfortable as students did not have to get ready for class. Item 5 claims that online classes were convenient because recorded lectures were provided after the class. The 6th item conveys that online classes were enjoyable because attendance was not mandatory. The 7th and 8th items assert that a lot of time was saved because the students had the option to watch the recorded lectures at an increased speed and they didn't have to commute from one building to another after every lecture. Then coming to the second construct, which is the demerits of online mode, we observe that items 26,32,33,43,50 play a crucial role in establishing it. Item 26 and 32 indicate that students found it difficult to keep their attention focused during online classes and were easily distracted by social media notifications. Item 33 says that students often get irritated by online classes. Furthermore, students were against online mode because they couldn't freely interact and share their problems and ideas with their friends and classmates, which is evident from items 43 and 50. These were the insights related to the online mode of learning.

Next, we discuss the benefits of offline mode, which are captured by factor 3 through items

50, 60, 66, and 69. In offline mode, as items 50 and 60 indicate, students were able to discuss with their peers and professors in person, which eases communication and helps them better understand the concepts. Items 66 and 69 talk about the practical courses. They note that students are able to learn more from in-person labs and that the physical presence of TA's helps resolve doubts more efficiently. Now, moving to factor 5, which measures the demerits of offline mode, we note that it is largely influenced by items 45, 54, 55, and 65. Item 45 tells us that students enjoyed the comforts of home during online mode, which is not possible now. Items 54, 55, and 65 claim that students are not enjoying offline classes because task switching (moving from one interesting activity to the other) is not possible and they are not able to watch recorded lectures (which are anyway not available) at an increased speed.

At the end, we look into the preferences of students marked by factor 3. Items 79, 80, and 81 are the pivotal elements in determining the preference of students. Item 79 asserts that students prefer to remain on campus and attend online classes in present and future too. Item 80 claims that students should be given the option of both; an online or an offline class, and liberty to switch while on campus. And item 81 poses that students should be given the freedom to attend or not offline classes without any penalty, respectively. From the above items, the preference of students is patent. Most of them would like to have a hybrid mode of teaching. We have also analyzed the relationship between various demographics and preferences. Students belonging to the monthly income group of greater than INR 50000 (55%) prefer to be given the option between offline and online mode without any penalty. The same is the case with students having a monthly income of less than 50000 INR. This indicates that family income does not play a significant role in determining the preference. With respect to internet connection, students relying on both mobile data (83%) as well as wifi/ethernet (36%), prefer to be given freedom to attend or not attend offline classes without any penalty. Next, we compare the education level of the student with his/her preference. Undergraduate students (68%) prefer to be given freedom to attend or not attend offline classes without any penalty. Masters students (12%) equally prefer hybrid mode as well as offline classes and postgraduate students (21%) clearly prefer the offline mode of learning.

We also look at how the type of area students live in affects their preference. Students who live in cities (1,00,000 to 10,00,000 people) and metropolitans (More than 10,00,000 people) (41%) opt for a hybrid mode of teaching without any penalty. The same is the preference of students who live in towns (15000 to 1,00,000 people), small towns (3000 to 15000 people) and villages (less than 3000 people), which constitute 60% of the total respondents. Hence, we can conclude that the majority of the respondents prefer to be given freedom to attend or not attend offline classes without any penalty irrespective of their demographic details, excluding Masters and Postgraduate students who favor classes only in the offline mode.

The limitations of our study include that the questions of the research questionnaire are not standardized. A credible questionnaire measures what it claims to measure. A standardized questionnaire is one that asks precisely the same questions to all the participants, without any perceivable change in context, and ensures that all the responses are uniformly recorded (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC420179/). While we haven't administered the survey to a particular focus group for testing and then validating our questions, we have put in our best effort to make the survey questions objective, straightforward, and lucid. Our questions went through several iterations of careful scrutiny by experts in the field, and we have incorporated their valuable suggestions before administering the survey to students and faculty. We have also tried to ensure that the survey questions are comprehended by everyone in the same way as we wanted them to be by avoiding weasel words like regularly, frequently, commonly etc. We have tried to be specific and quantified the parameters wherever possible to stave off any discrepancy in understanding the questions asked. We placed ourselves in the shoes of the participants and tried to envisage all possible reasons and outcomes for each question and section. Nevertheless, we also provided an option of "any other" to capture the responses that were not mentioned in the questionnaire and analyzed them separately.

In addition, the results of our study are based on convenience sampling, which is an example of non-probability sampling, where some members of the population have no possibility of being picked and the participants are chosen because they are present at the right place at

the right time. Predominantly, students resort to convenience sampling as it is free of cost, saves time, and makes the process of research much simpler compared to other sampling techniques as you only require the availability and willingness of people to partake in the survey. For instance, it is much easier to approach family and friends than any stranger. But the major disadvantage of convenience sampling is that it is not representative of the entire population. The results of the study cannot be generalized to a wider group of people. Moreover, we have to rely on what is being said by the respondents, which in many cases can be inaccurate. For example, if a person is in a hurry to leave for sports, he/she may not answer correctly and will mark what they feel is essential to just complete the form. So, it may lead to false data.

Another major limitation is recall bias which occurs when there is a potential difference between the reported outcome and the actual or experienced outcome. This happens because subjects remember certain events depending on the nature of outcome. For instance, a student who has got very few marks in a course is more likely to remember his mental state during COVID-19, the distractions he faced etc compared to a student who has done very well in that course. When compared to a mother who has normal children, a mother who has a child with an impairment is more likely to recall the medications she took during pregnancy. Thus, the recall of an individual can vary based on the events' consequences and can thus affect the data collected.

In addition to the above limitations, we have got a lesser number of responses than expected from students despite being the first group to float the form.The cohort has been given ample time to complete the questionnaire, as well as repeated reminders. A more disheartening thing is the negligible participation from the faculty and hence we could not carry out any analysis for them. This is not only our constraint but also the institute's limitation.

Chapter 6

Conclusion

The contours of the education system changed from its traditional way to the online mode as the novel coronavirus spread across the country, and eventually became the primary means of instruction for that period. Academia shifted to online platforms to continue their instruction/teaching during the pandemic. Initially, both faculty and students were finding it hard to cope with the new mode of teaching but later they became adept at it. To document the perception and the preferences of both the parties towards the new mode of education, a survey was conducted and then a number of statistical tests were conducted. Unfortunately due to less number of samples, we failed to make any concrete inferences.

Our study indicates that the majority of the students manifested a positive attitude towards a hybrid mode of teaching after the pandemic. They found online learning to be advantageous because of the flexibility and convenience that it provides to the learners, due to availability of recorded lectures, notes, no attendance policy and easy interaction with the instructors and peers. However, for some courses which are practicum based, students preferred offline classes, firstly because of the limitations of the online classes such as technological constraints, late feedback, malpractices in online examinations and lack of knowledge about handling technologies among the course instructors, and secondly, offline classes are more interactive as compared to online classes and practicum courses need a high level of guidance. Therefore, to fully incorporate online mode of teaching in future, one must take care of these factors so as to make it more effective and productive for the learners. Hence we

hope that our study will prove useful for renovating the online mode of teaching for higher education.

Chapter 7

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