Research Article

Preference of Teaching-learning Mode of the Under-graduate Students of India in the Dawn of Adoption of the New Education Policy 2022: A Predictive Analysis

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Abstract

The blended mode of education has been given due importance in the New Education Policy 2022 to provide an adaptive and world-class education system to the new-generation learners of post-pandemic India. However, there is a question of infrastructural preparedness of the educational institutions as well as the mind-set of the students to adapt to this new opportunity as well as challenge. In this connection, the present study is an attempt to identify the probable decisive factors that contribute towards the preference of an under-graduate student among offline/traditional mode, online mode, and blended mode of teaching-learning, through the application of the Multinomial Logistic Regression (MLR) Model. Findings suggest that the choice of the students primarily depend upon their stream of education and their inclination towards technological awareness. The academic institutions can set up their infrastructure on a priority basis and design their respective curricula accordingly.

Keywords: Preference of teaching-learning mode, blended mode of lecture delivery, undergraduate students, Multinomial Logistic Regression (MLR), technological awareness, curriculum design

Introduction

Due to the onset of COVID-19 pandemic and the consequent lockdown, educational institutions across the globe came to a standstill during the second quarter of 2020. This situation created an enormous disruption in the education system affecting 94 per cent learners in more than 190 countries across all the continents (United Nations, 2020). The pandemic affected more than 90 per cent of total student population of the world during April 2020 and nearly 67 per cent during June 2020. Occurrence of COVID-19 affected more than 120 crores of students and youths worldwide (UNESCO, 2022).

In India, more than 32 crores of students were impacted by the various restrictions and the countrywide lockdown for COVID-19 (UNESCO, 2022). The pandemic created many challenges and also various opportunities for countering the challenges in a developing country like India. The Government of India and the diverse stakeholders of education initiated the process of Open and Distance learning (ODL) by adopting different digital technologies to tide over the crisis of COVID-19. Teaching establishments started opting for alternative teaching learning methods. Most of the educational institutes across India initiated online classroom teaching using various video

conferencing platforms for imparting knowledge to the students both in the urban and the rural areas. Software and applications were developed to tide over the crisis while imparting online education parallel to the mainstream teaching-learning. The Study Webs of Active-Learning for Young Aspiring Minds (SWAYAM) portal developed by the Ministry of Human Resource Development (MHRD), Government of India to ensure access, equity and quality of education among aspiring individuals, gained more prominence and popularity during this period. The online teaching-learning industry was valued at $750 million in 2020 and was predicted to reach $4 billion by 2025 (Sharma, 2022).

The online teaching-learning methods, using technologically advanced electronic equipment, internet and information technology posed to be both beneficial as well as challenging for the students as well as the teachers of the undergraduate colleges in India. It was observed that the urban undergraduates were coping with this new mode of education, though a major section of them were dissatisfied due to the high cost involved in making internet facilities, smartphones or similar technologies inaccessible to them (Chakraborty and Banerjee, 2022). However, with the offline classes resuming in full swing after the third wave of COVID-19 since early 2022, the education sector in India faced difficulties, with some institutes opting for hybrid model and some coaching institutes at national level considering mass lay-offs of employees (Sharma, 2022). While basic teaching and learning shifted offline across India since February, 2022, there remained plenty of scope for test preparations, coding, web development , digital marketing, cybersecurity and other specialised courses online. Many online tutorial platforms developed in regional languages as well. Sectors identified to have online growth potential include test preparation, skill development, soft-skills training and English-language classes for adults.

The National Education Policy (NEP) 2022 approved on 29 July 2020 by the union cabinet of India (replacing the existing educational policy of India made in 1986), is being considered as a milestone in the education system of India. This policy has been framed to include elementary education up to higher education encompassing vocational training in both urban and rural areas. Positive changes brought about by NEP 2022 includes increased accessibility to digital form of books online by the students (via Digital Library), setting up of virtual labs benefitting students of science and technology to gather experimental knowledge at undergraduate level and the adoption of Pre-Primary Holistic Education to strengthen the structure of online education in India (Sony, 2022).

Literature Review

The outbreak of novel coronavirus and subsequent lockdown forced educational institutions across the globe to move from offline to online mode of teaching learning. The concern at the initial phase of lockdown was not whether online teaching–learning methods can provide quality education; it was rather how academic institutions will be able to adopt online teaching-learning in such a massive manner (Carey, 2020). Tools and techniques for online learning safeguarding the continuity of learning, the merits and demerits of online learning platform and the perceptions of learners and educators about online learning system during lockdown, together helped in framing the necessary measures and modalities at the governmental and institutional level (Jena P. K., 2020).

Various studies are being undertaken across Kashmir to Kerala, across different social and economic strata, age groups and subjects to understand the possibilities and challenges of digital education (Mathrani et al., 2021; Mandal, 2023; Sarkar 2023; Varsha and Sunitha, 2023). Bhat and Ali (2024) undertook a study on college teachers across both the genders and various academic streams. No significant difference could be found in their attitudes towards virtual classrooms which was more or less positive during the COVID-19 pandemic period. Though majority of the faculty members believe that technology-enabled digital learning promotes student engagement (Nayak and Hegde, 2024), there are many instances where it could not be followed in reality due to a number of practical problems like digital divide and lack of infrastructure and initiative from faculty, learner and administrative perspectives (Chakraborty and Banerjee, 2024). In the post-pandemic era, Thomas and Thiyagu (2024) observed the presence of a moderate level of technological anxiety among most of the high school students. According to Malla et al. (2024), in India there is lack of digital equity as a consequence of which the tribal students face academic hardships and marginalisation in virtual learning.

The undergraduate students in the urban areas of India are observed to have almost accommodated themselves with the new concept of online mode of education during the pandemic. The preference and perception of the students regarding the online classes in the field of agricultural (practical, field-oriented) education indicated that majority of the students evinced a positive attitude towards online classes in the wake of Corona (Muthuprasad, et al. 2021). However, a major section of these students is not satisfied with it. The most critical challenge appears to be the high cost involved in making internet facilities, smartphones or similar technologies inaccessible to many of them due to their financial status. Another significant setback is the high data cost, making technology beyond the reach of many of them (Chakraborty and Banerjee, 2022). Students are also found to be poorly prepared for several e-learning competencies and academic-type competencies due to low-level preparedness regarding the usage of Learning Management Systems (Parkes et al., 2015). Dhawan (2020) in her study undertook a thorough SWOC analysis of e-learning during COVID-19 pandemic and focused her study on the growth of Ed-Tech start-ups during the same period. Her study suggested that robust and resilient technological infrastructure had historically provided and has the potential to provide necessary support in the future also, to tide over any academic crisis of similar nature (Dhawan, 2020). Distance, scale, and lack of personalised teaching-learning were the three major impediments of online teaching. Meeting these challenges called for innovative solutions at the governmental as well as institutional level (Liguori and Winkler, 2020).

Keeping in mind the positive and negative impacts of COVID 19 on education, Govt. of India framed and published some measures for carrying out uninterrupted education (Jena P. , 2020). At the global level, the World Bank working with the Ministry of Education of different countries issued guidance notes offering principles to maximise countries' effectiveness in designing and executing remote learning (Barron Rodriguez, et al. 2021). The World Bank's Ed-tech team also published a Resource List encompassing remote learning, distance education and online learning during the pandemic (Muñoz-Najar, et al., 2021). They prescribed that online teaching-learning methods should be made creative, interactive, relevant, student-centric, and group-

based (Partlow & Gibbs, 2003). A study conducted by Kapasia, et al. (2020) suggested a targeted intervention for creating a vibrant space for the students belonging to the vulnerable sections of the society.

Objective of the study

To facilitate decision-making and infrastructural development of the educational institutions on the wake of the adoption of NEP 2022, the present study attempts to find out the decisive factors which contribute towards the choice of an under-graduate student among offline/traditional mode, online mode and combined/blended mode of teaching-learning (where lectures are delivered in physical classrooms using audio-visual technology).

Data

A structured questionnaire using a Google Form was framed and circulated among the undergraduate students for primary data collection. 377 responses could be collected for the study by the application of non-probabilistic snowball sampling technique. The respondents are the college-students of urban and sub-urban areas of different colleges in and around Kolkata, India in the age group of 17-21. They had access to internet and at least, had basic understanding of mobile technology.

Methodology

The study initially presents multiple cross-tabular formats for scrutinising the relationship between the selected variables. To find out the existence of any association between the chosen variables, and the strength of such association, if any, Chi-square test and Cramer's V test were applied consecutively thereafter.

Multinomial Logistic Regression (MLR) Model is generally used in cases where the dependent variable is a categorical variable with more than two categories. So finally, an MLR test has been conducted to predict the preference of college-goer students of Kolkata among:

(a) offline/ traditional teaching-learning method vis-à-vis

(b) online teaching-learning method and

(c) combined/ blended teaching-learning method.

Such predictions were based on their streams of education, categories (honours/ general), perceived benefits and problems experienced during online teaching-learning process post outbreak of COVID-19 pandemic.

An MLR model is a modification of the logistic regression model where the response variables are explained in terms of odds ratio, measuring the association between response and explanatory variables. Suppose in this study, we have n independent observations of p independent variables, and there are k categories for the qualitative dependent variable. One of these k categories has to be considered as the base category relative to which the multinomial logits would be constructed. Now if we intend to find the relationship between the probabilities of p independent variables and an observation falling in the j^{th} (k-1) category, the multinomial logit model would be as:

$$log\ log\left[\frac{\pi_j(x_i)}{\pi_k(x_i)}\right] = \propto_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{pj}x_{pi} \ldots\ldots\ldots (1)$$

Where, j = 1, 2, ….. , (k-1) and

i = 1, 2, …… , n

$\pi(x) = p(Y = 1|\, X = x) = 1 - p(Y = 0|\, X = x)$, or

$\pi(x) = \frac{expexp\,(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}{1 + expexp\,(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}$ and

β_i = The effect of x_i the log odds that the dependent variable (Y) is equal to 1, other x_j remaining constant, alternatively stated,

exp (β_i) = the multiplicative effect on the odds of a unit increase in other remaining constant

Since, $_j$ $_j(x)$ = 1 the equation can be represented and the model estimated as follows:

$$log\ log\ (\pi_j\ (x_i)) = \frac{expexp\ (\propto_{0i} + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \ldots + \beta_{pj} x_{pi})}{1 + \sum_{j=1}^{k-1} exp\ (\propto_{0i} + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \ldots + \beta_{pj} x_{pi})} \quad \ldots\ldots\ldots\ldots (2)$$

(El-Habil, 2012)

Findings and Analysis

To begin with, Table 1 summarises the number of responses along with their frequency distributions against each of the questions asked. It reveals that a majority of the students prefer either offline (35.5%) or blended (36.1%) mode of teaching-learning. When asked about their preferred mode of examination, each of the modes earned almost equal weightage.

Characteristics	Frequency (n)	Percentage (%)
Stream		
BA	67	18
BCom	227	60.3
BSc	83	21.7
Category		
Honours	281	74.8
General	96	25.2
Preferred mode of teaching-learning		
Offline/ Traditional	134	35.5
Online	107	28.4
Blended	136	36.1
Perceived benefits derived from Online Teaching- Learning Process		
Availability of study materials	28	7.4
Facilitation of understanding the subject using audio-visual aids (Power-point presentations, Google Docs, Jamboard, Google forms etc)	42	11.2
Getting accustomed with video conferencing technologies (like Google Meet, Zoom etc)	263	69.8

Scope for getting recorded versions of the class lectures for future reference	44	11.6
Perceived problems faced during Online Teaching- Learning Process		
Easy distraction	53	14
Expensive network connectivity (financial constraints related to data recharging)	126	33.4
Lack of motivation due to absence of formal classroom atmosphere	58	15.4
Lack of online infrastructure (Like smartphones, desktop, laptop etc)	t140	37.2
Preferred mode of examination		
Offline	190	50.4
Online	187	49.6

Chi-square test is then conducted to find out whether there is any association between the choices of the teaching-learning mode with the other selected response variables. The results of the test are captured in Table 2 which suggest that the choices of the mode of teaching-learning are associated with:

(i) the stream to which the student belongs,

(ii) his or her category, i.e., whether the student is an Honours student or not, and

(iii) the benefits derived from online teaching-learning.

Table-2: Association between Choice of Teaching-Learning Mode and Selected independent Variables

Preference of Learning Mode dependent on ↓	Pearson's Chi-Square Value**	df	p	Contingency Coefficient	Cramer's V
Stream	13.421	4	0.009*	0.185	0.133
Category	9.069	2	0.011*	0.153	0.155
Advantages of Online Learning	18.369	6	0.005*	0.216	0.156
Problems of Online Learning	4.216	6	0.651	-	-

*Significant at 1 per cent level

**All the cells have expected value more than 5.

As the values of both the Contingency Coefficient and Cramer's V are quite low for all the cases, it is implied that the strength of association between the choice of teaching-learning mode and the selected response variables are not very high. However, the null hypothesis of the Chi-Square test of the existence of no association between the choice of teaching-learning mode and the problems of online teaching-learning has failed to be rejected, and hence no association between them can be claimed. Therefore, the response variable 'the problems of online teaching-learning' has not been considered for further analysis in the modelling.

Table-3: Case Processing Summary for the calculation of By Chance Accuracy Rate

Preference	N	Marginal Percentage (%)
1 Offline/ Traditional	134	35.54
2 Online	107	28.38
3 Blended	136	36.07
Valid	377	100
Missing	0	
Total	377	
Subpopulation	22[a]	

a. The dependent variable has only one value observed in 3 (13.6%) subpopulations.

Table 3 is an excerpt of a larger table comprising of all the response as well as explanatory variables. Each sub-population involves a unique combination of explanatory variables specified in the model. Out of the 22 combinations in this case, only 3 (13.6%) subpopulations have one observed value of the dependent variable. Therefore, the proportional by chance accuracy rate (the sum of squares of proportions) can be calculated to be $(0.3554^2 + 0.2838^2 + 0.3607^2) = 0.336956 = 33.7\%$. Hence, the benchmark criteria for the proportional by chance accuracy rate would be 1.25 * 0.336954 = 42.12%. Moreover, as the value of standard errors is not more than 2 in the parameter estimates (Table 4), the model would not produce any spurious outcome (El-Habil, 2012).

In the next stage we looked for the value of standard errors of more than 2 in the parameter estimates table, as portrayed in Table 4. But to our satisfaction no such value could be obtained, signifying that the model would not produce any spurious outcomes (El-Habil, 2012).

Table-4: Parameter Estimates Table

Preference[a]		B	Std. Error	Wald	df	Sig.	Exp(B)
Offline	Intercept	.768	.521	2.176	1	.140	
	[Stream=1]	-.029	.409	.005	1	.943	.971
	[Stream=2]	-.284	.305	.867	1	.352	.753
	[Stream=3]	0[b]	.	.	0	.	.
	[Category=1]	.270	.318	.724	1	.395	1.310
	[Category=2]	0[b]	.	.	0	.	.
	[Advantages=1]	.004	.588	.000	1	.995	1.004
	[Advantages=2]	-.947	.517	3.352	1	.067	.388
	[Advantages=3]	-1.062	.393	7.300	1	.007	.346
	[Advantages=4]	0[b]	.	.	0	.	.

Online	Intercept	-.843	.650	1.682	1	.195	
	[Stream=1]	1.141	.467	5.962	1	.015	3.130
	[Stream=2]	.662	.388	2.912	1	.088	1.940
	[Stream=3]	0[b]	.	.	0	.	.
	[Category=1]	-.363	.297	1.494	1	.222	.696
	[Category=2]	0[b]	.	.	0	.	.
	[Advantages=1]	.219	.746	.086	1	.769	1.245
	[Advantages=2]	.185	.625	.088	1	.767	1.203
	[Advantages=3]	.245	.514	.227	1	.633	1.278
	[Advantages=4]	0[b]	.	.	0	.	.

a. The reference category is combination/ blended.
b. This parameter is set to zero as it is redundant.

For the response variable "Stream", 1 stands for BA, 2 for BCom and 3, i.e., the baseline, stands for BSc. For the response variable "Category", 1 stands for Honours and 2 stands for General category students. Response variable "Advantages" have four classes. Here 1 stands for Study Materials, 2 for Audio-visual Aids, 3 stands for Technology and 4 stands for Recorded Lectures. As the parameter estimates of the independent variable "Category" was not statistically significant (Table 4) the model was recalculated after eliminating the stated variable.

Table-5: Remodelled Parameter Estimates Table

Preference[a]		B	Std. Error	Wald	df	Sig.	Exp(B)
Offline	Intercept	1.039	.413	6.340	1	.012	
	[Stream=1]	-.098	.400	.060	1	.807	.907
	[Stream=2]	-.353	.294	1.439	1	.230	.703
	[Stream=3]	0[b]	.	.	0	.	.
	[Advantages=1]	-.020	.587	.001	1	.973	.980
	[Advantages=2]	-.937	.516	3.296	1	.069	.392
	[Advantages=3]	-1.073	.393	7.458	1	.006	.342
	[Advantages=4]	0[b]	.	.	0	.	.
Online	Intercept	-1.225	.576	4.516	1	.034	
	[Stream=1]	1.266	.456	7.706	1	.006	3.547
	[Stream=2]	.780	.376	4.302	1	.038	2.181
	[Stream=3]	0[b]	.	.	0	.	.
	[Advantages=1]	.274	.744	.135	1	.713	1.315
	[Advantages=2]	.184	.624	.087	1	.769	1.202
	[Advantages=3]	.278	.513	.293	1	.588	1.320
	[Advantages=4]	0[b]	.	.	0	.	.

a. The reference category is combination/ blended.
b. This parameter is set to zero as it is redundant.

The recalibrated model, as depicted in Table 5, produced mixed outcomes. In case the preferred mode is online, the parameter estimates are not found to be significant for the response variable "Advantages"; nonetheless, it produced significant results for the offline mode. Similarly, the response variable "Stream" appeared to provide statistically significant values for online mode but not for offline mode. Further diagnostic tests revealed the that the only difference in the Case Processing Summary of the new model is that in this new model the number of subpopulations has been reduced to 12 from 22. Moreover, now only 1 (8.3%) subpopulation has one observed value of the dependent variable.

Table-6: Classification Table of the Selected Model

Observed	Predicted			
	Offline	Online	Combination	Percent Correct
Offline	44	13	77	32.8%
Online	16	22	69	20.6%
Combination	20	15	101	74.3%
Overall Percentage	21.2%	13.3%	65.5%	44.3%

The Classification Table 6 of the new model shows that the computed overall percentage of 44.3% is greater than the proportional by chance accuracy rate of 42.12% as calculated earlier from Table 3. Hence, the classification accuracy criterion has been satisfied.

Table-7: Pseudo R-Square

Cox and Snell	.081
Nagelkerke	.091
McFadden	.039

The Pseudo R-Square statistic has been reported in the Table 7. Moreover, the computed asymptotic correlation matrix substantiated that the correlation between the choice of teaching-learning mode and stream, as well as, the choice of teaching-learning mode and advantages of online teaching-learning are very low, reducing the likelihood of occurrence of multi-collinearity problem in this model.

Table-8: Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	118.854			
Final	87.033	31.821	10	0.001

Table-9: Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	87.033[a]	.000	0	.
Stream	101.093	14.060	4	.007
Advantages	104.525	17.492	6	.008

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Table 8 proves that the model is a well fitted one, as the Chi-Square value is significant at 1% level, rejecting the null hypothesis of no difference between the model with independent variables and the model without independent variables. Thus, the existence of a relationship among the dependent and independent variables is sustained. Table 9 also validates the existence of a relationship among the dependent and independent variables. Moreover, it also portrays that there is a relationship between the dependent variable and each of the independent variables individually. Hence, in the next Table 10 we are encapsulating the significant results only from Table 5, for further analysis.

Table-10: Parameter Estimates Table

Preference[a]		B	Std. Error	Wald	Df	Sig.	Exp(B)
Offline	Intercept	1.039	.413	6.340	1	.012	
	[Advantages=3]	-1.073	.393	7.458	1	.006	.342
	[Advantages=4]	0[b]	.	.	0	.	.
Online	Intercept	-1.225	.576	4.516	1	.034	
	[Stream=1]	1.266	.456	7.706	1	.006	3.547
	[Stream=2]	.780	.376	4.302	1	.038	2.181
	[Stream=3]	0[b]	.	.	0	.	.

a. The reference category is combination/ blended.

b. This parameter is set to zero as it is redundant.

Table-11: Estimated Probabilities of Six Possible Outcomes of the Model

Teaching-Learning Mode	BA		BCOM		BSC	
	Technology	-	Technology	-	Technology	-
Offline $(\hat{\pi}_1)$	0.3213	0.5806	0.2740	0.5247	0.4276	0.6860
Online $(\pi\square_2)$	0.3463	0.2140	0.4424	0.2897	0.2938	0.0713
Blended $(\pi\square_0)$	0.3324	0.2054	0.2835	0.1856	0.4424	0.2427

The column "Exp(B)" of Table 10 shows the odds ratio of the independent variables with the dependent variable. An odds ratio greater than 1 indicates an increase in the dependent variable, as is evident in case of 'Online' mode, from Table 10; and an odds ratio less than 1 indicates a decrease in the dependent variable, as in case of 'Offline' mode; while an odds ratio close to 1 indicate non-responsiveness, i.e. a unit change in the independent variable would not result in any change in the dependent variable.

In the model, we have placed the blended mode of teaching-learning as the baseline category denoted π_0 by and its estimate by $\pi\square_0$; offline mode denoted by $\pi\square_1$ and its estimate by π_2 and online mode by and its estimate by $\pi\square_2$. Therefore, from the parameter estimates of Table 7 we can compute the respective probabilities as follows:

Firstly, as we have three categories (J = 3) of the dependent variable, we would be having the following two equations:

$y_1 = log(\frac{\pi_1}{\pi_0})^0$..... (3)

and

$y_2 = log(\frac{\pi\square_2}{\pi\square_0})^0$..... (4)

Therefore, $y_1 = log(\frac{\hat{\pi}_1}{\hat{\pi}_0})^0$ = 1.039 – 1.073 (Advantages=3)

And $y_2 = log(\frac{\pi\square_2}{\pi\square_0})^0$= -1.225 + 1.266 (Stream=1) + 0.780 (Stream=2)

The rest of the categories of the independent variables cannot be included in the equations as they were not found to be statistically significant at 5% level of significance. Secondly, $\pi\square_0, \pi\square_1$ *and* $\pi\square_2$ are computed where e or exp = 2.71828 is the base of the natural logarithmic system.

$$\pi\square_0 = \frac{1}{1+expexp\,(y_1)+\,expexp\,(y_2)} \text{ ..... (5)}$$

$$\pi\square_1 = \frac{expexp\,(y_1)}{1+expexp\,(y_1)+\,expexp\,(y_2)} \text{ ..... (6)}$$

$$\pi\square_2 = \frac{expexp\,(y_2)}{1+expexp\,(y_1)+\,expexp\,(y_2)} \text{ ..... (7)}$$

There were 12 sub-populations in this model and the prediction is based upon classifying the combination in one of the three groups of the dependent variables. No corresponding statements about most of the categories of the independent variables can be made as the odds ratios of those independent variables were not found to be statistically significant. The model comprises of two equations to estimate the three response probabilities (π_0, π_1, π_2):

$y_1 = log(\frac{\hat{\pi}_1}{\hat{\pi}_0})^0$ = 1.039 – 1.073 (1) = - 0.034 or

$y_1 = log(\frac{\hat{\pi}_1}{\hat{\pi}_0})^0 = 1.039 - 1.073$ (0) = 1.039

And $y_2 = log(\frac{\pi\square_2}{\pi\square_0})^0$= -1.225 + 1.266 (1) = 0.041

$y_2 = log(\frac{\pi\square_2}{\pi\square_0})^0$= -1.225 + 0.780 (1) = - 0.445

Suppose, a student is interested in becoming technically aware, then

y_1 = 1.039 -1.073- (1) = -0.034

Otherwise, y_1 = 1.073 (0) = 1.039

Secondly, suppose, a student is in Arts stream, then

y_2 = -1.225 + 1.266 (1) = 0.041

Or if a student is in Commerce stream, then

y_2 = -1.225 + 0.780 (1) = - 0.445

Had he/she been in Science stream (baseline category), the value would have been

y_2 = -1.225

Hence, by using the above equations, the estimated probability of occurrence of each of the six possibilities can be estimated to be:

Case 1: Where an undergraduate student of Arts stream to whom technological awareness is the biggest advantage of online class:

$$\pi\square_0 = \frac{1}{1 + exp\ exp\ (-0.034) + exp\ exp\ (0.041)_0} = 0.3324$$

$$\hat{\pi}_1 = \frac{exp\ exp\ (-0.034)_0}{1 + exp\ exp\ (-0.034) + exp\ exp\ (0.041)_0} = 0.3213$$

$$\pi\square_2 = \frac{exp\ exp\ (0.041)}{1 + exp\ exp\ (-0.034) + exp\ exp\ (0.041)} = 0.3463$$

Similarly, the calculated probabilities of the rest of the five possibilities have been encapsulated in Table (11) which can be explained in a Case-by-Case basis as follows:

Case 2: An undergraduate student of Arts stream to whom technological awareness is the biggest advantage of online class is likely to give almost equal preference to all the three teaching-learning modes. There is almost equal probability of him/ her choosing any mode of teaching-learning,

Case 3: An undergraduate student of Arts stream to whom technological awareness is not something of concern has the probability of 0.5806 to occur that (s)he would choose offline teaching-learning mode over other modes of teaching-learning.

Case 4: An undergraduate student of Commerce stream to whom technological awareness is the biggest advantage of online class has a probability of 0.4424 to occur that (s)he would choose online teaching-learning mode of training.

Case 5: An undergraduate student of Commerce stream to whom technological awareness is not something of concern has the probability of 0.5247 to occur that (s)he would choose offline teaching-learning mode over other modes of teaching-learning.

Case 6: An undergraduate student of Science stream to whom technological awareness is the biggest advantage of online class has a probability of 0.4424 to occur that (s)he would choose blended mode of teaching-learning.

Case 7: An undergraduate student of Science stream to whom technological awareness is not something of concern has the probability of 0.686 to occur that (s)he would choose offline teaching-learning mode over other modes of teaching-learning.

Conclusion

The study substantiates that though the undergraduate students have almost accommodated themselves with the new concept of online education during the COVID period, nevertheless, given the option to choose among offline/ traditional mode, online mode and blended mode of teaching-learning, it is highly probable that they would choose offline mode of training. Though there is scope of self-paced audio-visual learning, the importance of personal interaction, more importantly for practical lessons can never be understated. The decisive factors, in this regard, are the stream of education and their inclination towards acquisition of technological competence, depending on which the final choices of the

undergraduate students vary. Hence, during the implementation of the NEP 2020 in higher education, these factors should be given due cognizance to ensure its wholesome success.

In this age of Machine Learning (ML), Artificial Intelligence (AI) and Big Data Analysis (BDA), there is no way that we can avoid the digital platform and mode. Instead, to remain competitive, the sooner we adopt, the better it is for the upcoming generations. To bring e-learning into the mainstream, and to eliminate the digital divide, a robust and sensible policy at the governmental level to bring education-technology platforms under one umbrella is the need of the hour. At the Governmental level, new schemes can be introduced for providing instruments of communication and internet service free of cost or at a subsidised rate to the students belonging to economically backward sections both in urban and rural areas. These measures along with the modification of the education sector can bring about a new dawn in the overall education system of India making it inclusive in its true sense. Online teaching-learning might supplement the regular classroom lectures, but should not be thought as a replacement to it. Technology-enabled face to face teaching-learning should be promoted to aid and facilitate quality education in India. As proposed in NEP 2020, this journey towards digitisation should be transitional. The faculty members should be induced and trained first, and the students introduced to the digital teaching-learning mode from their primary school-level, if not from the pre-primary level. However, the greatest importance should be given on building the digital infrastructure to bridge the digital divide and make online education accessible and affordable to each and every student, failing which the overall purpose of this endeavour would fail to its core. Given the on-going shifts in educational paradigm, especially in the context of post-pandemic recovery, adoption of academic technology has become a matter of prime importance and urgency. Hence, the academic institutions should set up their infrastructure on a priority basis even if in piecemeal, and design their respective curricula accordingly.

The major drawback of this study is that the respondents are solely the college-goers of Kolkata metropolitan area and its surrounding suburbs, who have both access to internet and knowledge of smart technology. This academic gap could be bridged by the future researchers by taking a larger sample from all strata of the society. Nonetheless, the study can serve as a blueprint for auxiliary analysis to take active stance for the successful implementation of the NEP 2022 through gradual adoption of technology in the traditional academic institutions.

Declaration of Competing Interest

The authors declare that they have no known competing/ conflicting financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Barron Rodriguez, M., Cobo, C., Muñoz-Najar, A., & Sánchez Ciarrusta, I. (2021). R*emote learning during the global school lockdown: multi-country lessons***.** Washington DC: World Bank Group.

Bhat, M. A., & Ali, S. (2024, July 1). Attitude of College Teachers towards Virtual Classroom during COVID-19 Pandemic. https://journals.ncert.gov.in/IJET/article/view/269

Carey, K. (2020). Everybody Ready for the Big Migration to Online College? Actually, No. Retrieved from The Upshot: https://www.nytimes.com/2020/03/13/upshot/coronavirus-online-college-classes-unprepared.html

Chakraborty, D., & Banerjee, S. (2022). Perception about Online Teaching_ Learning Method among select Undergraduate Students of Kolkata, West Bengal. In Education in the Community: Now and Then (pp. 87-95). Kolkata: Avenel Press.

Dhawan, S. (2020). Online Learning: A Panacea in the Time of COVID-19 Crisis. Journal of Education Technology Systems, 49(1), 5-22.

El-Habil, A. M. (2012). An Application on Multinomial Logistic Regression Model. Pakistan Journal of Statistics and Operation Research, 8(2), 271-291.

Jena, P. (2020, July). Impact of Pandemic COVID-19 on Education in India. International Journal of Current Research, 12(7), 12582-12586.

Jena, P. K. (2020, May). Online Learning during Lockdown Period for COVID-19 in India. International Journal of Multidisciplinary Educational Research, 9(5(8)), 82-92.

Kapasia, N., Paul, P., Roy, A., Saha, J., Zaveri, A., Mallick, R., et al. (2020). Impact of lockdown on learning status of undergraduate and postgraduate students during COVID-19 pandemic in West Bengal, India. Children and Youth Services Review, 1-5.

Liguori, E., & Winkler, C. (2020). From Offline to Online: Challenges and Opportunities for Entrepreneurship Education Following the COVID-19 Pandemic. Entrepreneurship Education and Pedagogy, 1-6.

Malla, H. A., Noor-Ul-Amin, S., & Malla, R. A. (2024, July 1). Digital Learning and Digital Divide: Scaling the Gap of Access and Equity among Schedule Tribe Students during Covid-19 Pandemic: A Case Study Approach. https://journals.ncert.gov.in/IJET/article/view/327

Mandal, C. K. (2023). Blended Learning: A Redefined Learning Strategy in the field of Secondary Education in the light of NEP 2020. Vidhyayana, 8(Special Issue 6), 42. https://vidhyayanaejournal.org/journal/article/view/748/768

Mathrani, A., Sarvesh, T., & Umer, R. (2021). Digital divide framework: online learning in developing countries during the COVID-19 lockdown. Globalisation Societies and Education, 20(5), 625–640. https://doi.org/10.1080/14767724.2021.1981253

Muñoz-Najar, A., Gilberto, A., Hasan, A., Cobo, C., Azevedo, J., & Akmal, M. (2021). Remote Learning during COVID-19: Lessons from Today, Principles for Tomorrow. World Bank.

Muthuprasad, T., Aiswarya, S., Aditya , K., & Jha, G. (2021). Students' perception and preference for online education in India during COVID -19 pandemic. Social Sciences & Humanities Open, 3(1), 1-11.

Nayak, V., & Hegde, K. P. (2024, July 1). Exploring the use of technology and online resources in commerce and Management Education: A study of NEP Curriculum Implementation in Karnataka. https://journals.ncert.gov.in/IJET/article/view/321

Parkes, M., Stein, S., & Reading, C. (2015). Student preparedness for university e-learning environments. The Internet and Higher Education, 25, 1-10.

Partlow, K., & Gibbs, W. (2003). Indicators of constructivist principles in internet-based courses. Journal of Computing in Higher Education(14).

Sarkar, B. (2023). Online and Digital Education in the light of National Policy on Education 2020: An Interpretation. In Multidisciplinary Approach to Sustainable Development Goal (SDG) 8 (pp. 74–80). Selfypage Developers Pvt Ltd. https://www.researchgate.net/profile/Biplab-Sarkar-15/publication/372079252_Online_and_Digital_education_in_the_light_of_National_Policy_on_Education_2020An_interpretation/links/64a3fd788de7ed28ba744f7a/Online-and-Digital-education-in-the-light-of-National-Policy-on-Education-2020An-interpretation.pdf#page=81

Sharma, K. (2022). Mass layoffs, offline classes: How edtech is coping with schools, colleges reopening. Retrieved from The Print: https://theprint.in/india/education/mass-layoffs-offline-classes-how-edtech-is-coping-with-schools-colleges-reopening/958120/

Sony. (2022). National Education Policy 2022: What Is New Education Policy. Retrieved from Indian Government Schemes: https://pmkisanyojanalist.in/national-education-policy/

Srivastava, A., & Sinha, N. (2023). Online and Digital Education: Ensuring Equitable use of technology in respect to National Education Policy- 2020. Research Communications, 1(2), 68–74. https://research-communications.cmpcollege.ac.in/wp-content/uploads/2024/02/11-Akanksha-Srivastava-Online-and-Digital-Education-Ensuring-Equitable-Use-of-Technology-National-Education-Policy-2020-Modified.pdf

Thomas, M. V., & Thiyagu, K. (2024, July 1). Technological Anxiety in the Post-Pandemic Era: A Study among Higher Secondary Students of Kerala. https://journals.ncert.gov.in/IJET/article/view/315

UNESCO. (2022). Education: From disruption to recovery. Retrieved from UNESCO: https://en.unesco.org/covid19/educationresponse

United Nations. (2020). Policy Brief: Education during COVID 19 and beyond. United Nations.

Varsha, P., & Sunitha, R. (2023). Government Initiatives in Online Education System and NEP 2020. IITM Journal of Management and IT, 14(1 & 2), 76–85. https://www.indianjournals.com/ijor.aspx?target=ijor:iitmjmit&volume=14&issue=1and2&article=012