Impact of ICT in Enhancing Learning Experience among Rural Students in India: An Empirical Analysis

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ABSTRACT
In modern world, technology plays a very important role in enhancing learning outcome among students. Many research studies undertaken in the developed world have outlined the importance of technology in enhancing learning outcomes. Noting the same, Indian states like Karnataka, Uttar Pradesh etc. have resorted to provide digital devices to their students with the hope of enhancing their learning outcomes. In this context, it becomes all the more relevant to analyze the socio economic and academic factors influencing use of technology among students. This study analyses the factors affecting use of digital devices and their effectiveness in enhancing their learning outcomes among rural students. The study covered 4 districts, comprising a sample size of 465 respondents to assist in optimum policy formulation for rural students in developing world.

Keywords: Technology in Learning, Learning Outcomes, Digital Devices, Rural Students, Socio-economic factors

INTRODUCTION
At global level, efficiency and mode of learning is revolutionized by Information Communication Technology (Buchanan, 1999, Peters, O., 2000, Selwyn 2016, Milligan, 2010). Several research studies have reported that supplementing contemporary teaching methods with digital devices enhances the efficacy of learning among students (Internet Society, 2016, Kumar, B. A et al., 2020, Malik, Manju., 2001, Singh, H.,2003, Haryani, H et al., 2012). In recent years Indian Government has realized the importance of integrating ICT in education curriculum to enhance the effectiveness of learning outcomes (Light, Daniel., 2009). Many of the states in India like Karnataka, Uttar Pradesh etc are providing digital devices like laptop and tablet to students at graduate level to enhance their learning outcomes (Nadaf, Dr-Zaffar, 2017). Given, around 65 percent of Indian population belongs to rural area, a study analyzing the usefulness of technology across different streams of students in rural areas shall be relevant to analyze the effectiveness of present policy and help in optimization of scarce resources.

LITERATURE REVIEW
Education not only leads to empowerment of masses (Saxena, N., 2017), but also results in reduction of income inequality (Jeng, R et al., 2019) and assures prosperity and stability for the nation. India has a population of about 1.2 billion (Census, 2011), of which majority are young. For a nation like India, to effectively utilize its demographic dividend providing quality education is of utmost importance (Rentería, E., 2016). There is also a great demand for education in India, as education is regarded as an effective medium for socio-economic mobility (Amutabi & Oketch, 2003). However, there are many socio-economic, infrastructural and regional barriers which inhibit Indians from accessing quality education (Bhattacharya & Sharma., 2007). Out of many factors which can enhance the effectiveness of education, Information Communication Technology has a potential to play a prominent role (Stosic, Lazar.,2015,

Sutapa Bose, 2008, Ravi Mahajan, 2011,). Information Communication technology in the field of education may include any application, service or communication device which could be used to enhance learning outcomes among students (Saxena, N., 2017). Using ICT in an optimum manner can bring paradigm shift in Teaching Learning Pedagogy (Anu Sharma et al., 2011, Kearney et al., 2012).

There are studies (Gulbahar and Guven 2008, Fuglestad 2009, Kumar, B. A et al., 2020) which support positive influence of ICT on Education and enhancing learning outcome among students. In this context, Indian Central Government has taken major initiatives like Gyan Darshan, Gyan Vani, E-Gyankosh (Pegu, U.K., 2014) and most recently Swayam Learning portal to leverage Information Communication technology for the purpose of effective content delivery and to enhance learning outcomes among students. Although, it is a step in right direction, without access to digital gadgets like laptop, smartphone, personal computer, or tablet accessing digital content from learning portals or otherwise becomes highly difficult (Yakin et al.,2020). Some of the states in India like Uttar Pradesh (Nadaf, Dr-Zaffar, 2017) and Karnataka have sought to bridge the gap between haves and have nots by distributing Laptops and Tablets for students at free of cost. There are many studies undertaken in developed world which substantiate, in the long run laptops are more useful for students in learning endeavor, such studies haven't been undertaken in India. Moreover, although there are studies which try to evaluate use of technology among particular stream of students, there is scarcity of studies which have been undertaken to comparatively evaluate use and effectiveness of technology across different streams of students.

The present study tries to bridge the gap left in the following dimensions and tries to give a comparative analysis of usefulness of technology among different streams of students, particularly in rural area, for which data has been collected spanning 4 districts, 6 colleges. 465 valid responses were taken into consideration for the purpose of data analysis and interpretation. Presently Karnataka State Government has taken the initiative of replacing laptops with tablets. In this context this study aims to analyze the usefulness of different digital devices across different faculties among rural students.

OBJECTIVES

- To analyze the significance of association between technological Usage Perceptions, accessibility to digital devices, and learning outcomes among different streams of students in rural areas.
- To identify the socio-economic factors affecting effective use of technology to enhance learning outcomes among rural students.

HYPOTHESIS

- The student's stream of study influences their accessibility to devices and technological usage perceptions.
- Socio Economic factors influence effective use of technology to enhance learning outcomes among rural students.

METHODOLOGY

The research paper relies on primary data for the purpose of empirical verification of hypothesis set for the study. Primary data has been collected from 465 students selected through multistage random sampling procedure. In the first stage two universities, namely University of Mysore and Davangere University, were randomly selected from Karnataka state. In the second stage, six colleges which offer graduation and / or post-graduation courses were selected randomly from these universities. Faculty-wise list of students who were commuting from rural area and pursuing either graduate or post graduate courses, during the survey year, were prepared with the help of college administration. From these lists about 20 percent of the students were selected randomly using lottery method.

Primary data has been collected from these students through well designed pre-tested schedule. The schedule was designed to illicit information concerning socio economic status of the respondents and to identify the various factors which influence the use of technology in Learning Experience among different streams of students in rural area. The reliability of the questionnaire was validated by testing the same with Cronbach's Alpha, the value of which was found to be 0.60 for 40 items in the schedule which does reflect acceptable level of reliability (>=0.60). The primary data has been analyzed through appropriate statistical techniques.

Income is an important indicator of the economic status. But collection of data pertaining to the income is very difficult whereas information about assets could be easily collected. Wealth index is a better alternative for the income level. Filmer and Pritchett (2001) popularized the use of Principal Components Analysis (PCA) for estimating wealth levels using asset indicators to replace income or consumption data. Further he noted that asset-based measures depict an individual or a household's long-run economic status. Thus, in this context having a reliable Wealth Asset Index (WAI) to analyze the significance of association between the variables becomes relevant. WAI has been computed by using the data on wealth assets like type of residential house, ownership of digital devices like Tablet, PC, Laptop, Number of Smartphones, type of cooking fuel, and Vehicles present in the house. Based on the WAI, respondents have been categorized into three groups: Rich, Poor and respondents belonging to Middle class.

Multinomial Logistic Regression Model

Multinomial logistic regression model is an extension of Binary Logistic Regression. Binary Logistic Regression provides a framework to analyze dependent variable with two categorical outcomes, which cannot be explained with the tools provided by Linear Regression model. The framework of Logistic Regression Model for a dichotomous categorical variable 'Y' with multiple explanatory variables (x_1, x_2, x_3 …. x_k) can be represented with the help of the following equation, Erkan (2016):

$$\text{Logit}\,[P(Y=1)] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \ldots + \beta_k x_k$$

Which can be represented by directly specifying $\pi(x)$ as:

$$\pi(x) = \frac{n\exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}{1 + \exp(\alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}$$

In the above equation β_i refers to the effect of x_i on the log odds that Y=1, controlling other x_j..

The framework of binomial logistic regression can be extended to multinomial logistic regression model with n independent observations with p explanatory variables and a dependent variable with k categorical outcomes. For the said model, assuming π_j to be a multinomial probability of falling in j^{th} category, if we have to construct a model showing the relationship between n independent variables, x_1, x_2, x_3 …. x_n , it can be represented with the help of the following equation, , Erkan (2016):

$$\log(\pi_j(x_i)) = \frac{\exp(\alpha_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \cdots + \beta_{nj}x_{ni})}{1 + \sum_{j=1}^{k-1} exp(\alpha_{0i} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \cdots + \beta_{nj}x_{ni})}$$

The parameters (j=1,2…. (k-1)) for the above equation are calculated with the help of multinomial logistic regression model.

Baseline Category Logit Model:

For estimating the parameters in Multinomial logistic regression model, from the given J categorical outcomes, one of them is identified as baseline category. In other words, if $\pi_j(x) = p(Y= j|x)$ for x independent variables with $\sum_j \pi_j(x) = 1$. For dependent variable Y with j multinomial categorical outcomes, $\{\pi_1(x), \pi_2(x) \ldots \pi_J(x)\}$, multinomial logistic regression model compares each categorical outcome with baseline outcome. It can be represented with the help of the following equation, Erkan (2016):

$$\log\frac{\pi_j(x)}{\pi_J(x)} = \alpha_j + \beta_j' x,$$

In the above equation, j=1, 2..., (J-1) helps us to understand the effect of x on (J-1) categorical outcomes. The above (J-1) equations help us to calculate parameters for other categorical outcomes as $\log\frac{\pi_a(x)}{\pi_b(x)} = \log\frac{\pi_a(x)}{\pi_J(x)} - \log\frac{\pi_b(x)}{\pi_J(x)}$.

The logit transformation in multinomial logit regression model is obtained by taking the logarithms of the odds ratios after selecting the baseline category. For the three-category multinomial model, with 2 selected as the baseline category, the logarithms of odds ratios can be obtained could be written as under (Kienbaum and Klein, 2010).

$$In\left[\frac{p(y=1|x_1)}{p(y=0|x_1)}\right] = \beta_1 + \beta_{11}x_1$$

$$ln\left[\frac{p(y=1|x_2)}{p(y=0|x_1)}\right] = \beta_2 + \beta_{21}x_1$$

In the above equations, the reference baseline category is taken as "y=1" for analyzing the 2 outcomes. The generalized notation of the model can be written as (Liao,1994)

$$ln\left[\frac{\pi_j}{\pi_J}\right] = ln\left[\frac{P(y=j)}{P(y=J)}\right] = \left(\sum_{k=1}^{k}\beta_{jK}x_k\right) j = 1,\ldots\ldots..J-1$$

The above multinomial logistic regression model can be generalized to binomial logistic regression model for J=2, Erkan (2016). The results of Multinomial Logistic Regression have been interpreted with the help of Relative Risk Ratio (RRR) estimated through STATA statistical package. In Relative Risk Ratio, a comparison is made between 2 groups with a given reference outcome in terms of likelihood. In this interpretation, we calculate the risk (probability) of a case falling into comparison group to the risk (probability) of the case falling into baseline group, based on estimate values of predictors, Osborne, (2015).

Identification of Variables

Dependent Variable: In India, some of the states like Karnataka, Uttar Pradesh have been distributing Laptops, Tablets and other such digital gadgets to students. In this context, we did substantial review of literature. Studies concerning this dimension are scarce in India. Majority of the populace of Karnataka reside in rural area. We wanted to find out the usefulness of technology among rural students across different streams, hence we chose our dependent variable to be Usefulness of technology. The aim of this analysis was to find out the usefulness of technology among students across different streams as well as across different digital devices. In this backdrop, the response variable had 3 categorical outcomes. The frequencies of dependent variable across tested categories is summarized in the table below:

Table 1: Frequencies across tested categories of Dependent Variable

Outcomes related to usefulness of Technology	Frequency	Percentage
Dissatisfied in enhancing learning	57	12.3%
Moderately Satisfied in enhancing learning	207	44.5%
Highly Satisfied in enhancing learning	201	43.2%

Independent of the choice of baseline category, the model shall produce same likelihood and same fitted values, only interpretations and values of parameters will change Schafer (2006). In our analysis we have chosen second categorical outcome as baseline category.

The Independent Variables: Based on review of literature and our experience, independent variables were chosen to analyze the effect of socio-economic factors which were influencing use of technology among rural students in enhancing their learning outcomes. The explanatory variables are as under:

X_1 = Dummy for Education Stream; if Arts, 1; if Commerce, 2; if Science, 3.
X_2 = Dummy for Gender; if Female, 0; if Male, 1.
X_3 = Dummy for City Level; if Tier 2, 2; if Tier 3, 3.
X_4 = Dummy for Caste; if Scheduled Caste, 1; if Scheduled Tribe, 2; if Other Backward Caste, 3; if General (Economically Weaker Section), 4; if General ,5.
X_5 = Dummy for Mobile; if using, 1; if not using, 0.
X_6 = Dummy for Tablet; if using, 1; if not using, 0.
X_7 = Dummy for PC; if using, 1; if not using, 0.
X_8 = Dummy for Laptop; if using, 1; if not using, 0.

X_9 = Dummy for Device Owner; if Internet Cafe, 1; if belongs to neighbors, 2; if belongs to family, 3; if belongs to oneself, 4.

X_{10} = Dummy for Network Coverage; if bad, 1; if satisfactory, 2; if good,3.

X_{11} = Dummy for Availability of Electricity; if bad, 1; if satisfactory, 2; if good,3.

X_{12} = Dummy for time spent on internet for studies; 1 for 0-3 hours; 2 for 3 to 6 hours; and 3 for more than 6 hours.

X_{13} = Dummy for usage of YouTube for studies; 1 for rarely ; 2 for sometimes; 3 for most of the times; and 4 for regularly.

X_{14} = Dummy for usage of Educational websites for studies; 1 for rarely ; 2 for sometimes; 3 for most of the times; and 4 for regularly.

X_{15} = Dummy for usage of Educational apps for studies; 1 for rarely ; 2 for sometimes; 3 for most of the times; and 4 for regularly.

X_{16} = Dummy for usage of Video Conferencing Apps for studies; 1 for rarely ; 2 for sometimes; 3 for most of the times; and 4 for regularly.

X_{17} = Dummy for Medium of reading; if reading directly, 1; if taking print out, 2.

X_{18} = Dummy for Remembering things which have been read from digital devices; if bad, 1; if satisfactory, 2; if good,3.

X_{19} = Dummy for the effectiveness of Digital Devices in enhancing learning outcome; if less than satisfactory, 1; if satisfactory, 2; if more than satisfactory,3.

X_{20} = Dummy for concentration during online classes; if less than satisfactory, 1; if satisfactory, 2; if more than satisfactory,3.

X_{21} = Dummy for Technical Problems during online classes; if less than satisfactory, 1; if s satisfactory, 2; if more than satisfactory,3.

X_{22}= Composite wealth Index (The variables taken are summarised in Table 1)

Reliability of the Model

To check the reliability of the model, we have conducted computing proportion by chance accuracy, multicollinearity test, pseudo R square test and generalized Hosmer-Lemeshow test.

Computing Proportion by Chance Accuracy Rate: Proportion Chance by accuracy is used to check the reliability of the accuracy of predictions made by the model. To get the result, calculation of proportion of cases for each group is done based on the number of cases in each group of the dependent variable. By squaring and totaling the proportion of cases in each group ($0.123^2 + 0.445^2 + 0.432^2$) we get 0.3997 = 39.97%. 25% is the benchmark that is used to improve the rate of accuracy of Multinomial Logistic Regression Model over the accuracy achievable by chance alone. Thus, the benchmark set by proportion by chance criterion for our model is: 1.25 * 0.399778 =0.4997, which is approximately 50 percent.

Table 2: Classification of the Selected Model

Categorical Outcomes	Predicted			
	Dissatisfied	Satisfied	Highly Satisfied	Percent correct
Dissatisfied	37	16	4	64.9%
Satisfied	9	144	54	69.6%
Highly Satisfied	3	60	138	68.7%
Overall Percentage	10.5%	47.3%	42.2%	68.6%

From the above table we can see that the overall accuracy of the model is 68.6 percent, which is higher than the benchmark set by proportion by chance accuracy rate. This reflects the predictions made by our model is reliable to the extent of 68.6%.

Test for Multicollinearity: Occurrence of Multicollinearity in the model reduces the accuracy of estimated coefficients, which shall reduce statistical power of model. Presence of multicollinearity can make p- values used to verify statistical significance of independent variables unreliable, Garson (2009). To test the presence of multicollinearity, we checked the asymptomatic correlation matrix. In the matrix, the value of the majority of correlation coefficients were less than 0.10 reflecting there is no serious issue of multicollinearity in the model.

Generalized Hosmer-Lemeshow Goodness of fit test for Multinomial Regression Model: Goodness of fit test for multinomial logistic regression model can be tested with the help of generalised Hosmer-Lemeshow Goodness of fit test through STATA software. The test is based on sorting the observations to $1 - \hat{\pi}_{i0}$ which is the complement of estimated probability. Then 'g' groups are formed, containing n/g observations. Then for each categorical outcome, sums of estimated and observed frequencies are calculated for each categorical outcome,

$$O_{kj} = \sum_{1 \in \Omega k} \hat{\pi} lj$$

$$E_{kj} = \sum_{1 \in \Omega k} \hat{\pi} ij$$

In the above equations, k=1,…….g; j=0,……..,c-1; and Ωk represents indices of the n/g observations in group k. The goodness of fit for the model can be obtained by tabulating the values of O_{kj} and E_{kj} . From the observed and estimated frequencies of the table, multinomial goodness of fit test statistic is calculated, which is Pearson's chi-squared statistic:

$$\chi^2_{HL} = \sum_{g=1}^{G} \frac{\left(O_g - E_g\right)^2}{E_g\left(1 - \frac{E_g}{n_g}\right)}$$

In the above equation, O_g represents observed events, E_g represents expected events and n_g represents number of observations for the g^{th} risk decile group; G represents number of groups. Hosmer Lemeshow test statistic follows χ^2 distribution with G-2 degrees of freedom. If the p-value < 0.05 it indicates the model is poor fit.We ran Hosmer Lemeshow test in STATA, the results of which are summarized in the following table:

Table 3: Generalized Hosmer Lemeshow Goodness of fit test

Observations	No. Outcome Values	Base outcome value	Number of groups	χ^2 Statistic	Degrees of Freedom	Prob > χ^2
465	03	02	10	19.856	16	0.227

From the above table, we can see that we do not have enough evidence to reject null hypothesis, thus, our model appears to be stable.

McFadden's Pseudo R Square: According to McFadden (1977, p.35), if the value of Mcfadden's Pseudo R square lies between 0.2 to 0.4, it means that the model is an excellent fit. The McFadden's Psuedo R square value for our model was 0.211 as calculated by STATA indicating that our model is a good fit.

RESULTS AND DISCUSSION

According to the reviewed literature, it was expected that, the science students are more at ease in utilizing the technology compared to other streams of students like arts and commerce. Thus, when Government is formulating any policy with the objective of enhancing the learning outcome of using technology, understanding the differences would result in formulating an effective policy. The results pertaining to the significance of relationship between technology induced learning and learning outcomes among different streams of students has been consolidated in Table 4.

Table 4: Significance of Association between Technological Usage Perceptions and Learning outcomes among different streams

Learning Outcome	Usage Perceptions	Stream				Fishers Exact Value (Probability)
		Arts	Commerce	Science	Total	
Ability to Recall	Hardly Remember	45 (23.32)	48 (21.72)	03 (05.88)	96 (20.65)	Fisher's exact
	Can Manage	43 (22.28)	94 (42.53)	26 (50.98)	163 (35.05)	
	Good	105 (54.40)	79 (35.75)	22 (43.14)	206 (44.30)	Significant at 1%
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	
Focus on Online Class	Less than Satisfactory	58 (30.05)	43 (19.46)	02 (3.92)	103 (22.15)	Fisher's exact
	Satisfactory	64 (33.16)	86 (38.91)	22 (43.14)	172 (36.99)	
	Good	71 (36.78)	92 (41.62)	27 (52.94)	190 (40.86)	Significant at 1%
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	
Device Enhanced Learning	Less than Satisfactory	50 (25.91)	46 (20.81)	00 (00.00)	96 (20.65)	Fisher's exact
	Satisfactory	143 (74.09)	175 (79.19)	16 (31.37)	334 (71.83)	
	Good	00 (00.00)	00 (0.00)	35 (68.63)	35 (7.53)	Significant at 1%
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	
Utility of Tech in Exam	Less than Satisfactory	36 (18.65)	21 (9.50)	00 (00.00)	57 (12.26)	Fisher's exact
	Satisfactory	85 (44.04)	91 (41.18)	31 (60.78)	207 (44.52)	Significant at 1%
	Good	72 (37.31)	109 (49.32)	20 (39.22)	201 (43.23)	
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	

In the above table, it is interesting to note that, among the three streams of students, science students had least trouble (5.88%) in recalling what they had studied from digital gadgets and arts students had significant trouble in recalling what they had studied (23.32%) from the same. To test the statistical significance of association between different streams of students Fishers Exact Value has been calculated which was found to be statistically significant at 1 percent probability level.

Focus on online class is another variable which plays a significant role in the determination of learning outcome. It was expected that, the focus would vary among different streams of students when using technological gadgets and it was expected that students of science stream would be more technologically inclined. To test the statistical significance Fisher's Exact test was used, which was siginificant at 1 percent. Among the different streams of students, students belonging to science stream exhibited a greater focus (52.94%) and least difficulty (03.92%) in focusing on online classes. Conversely, arts students were faced with more distractions (30.05%) among the three streams when it came to focusing on online class and they were least satisfied (36.78%) among the three streams, when it came to focus on the same.

Among different streams, science students hold the perception that technological devices have highly enhanced their learning outcomes (68.63%) and students belonging to arts stream hold least favourable view (25.91%) with regards to same. The statistical significance of this relationship is validated through Fisher's Exact Value whose probability value is found to be highly significant. When it comes to comparison between science and arts students, majority of the commerce students (79.19%) feel they are just about satisfied with the use of technological devices. With respect to utility of technology in exam, it was observed that, students belonging to science stream have no negative perception of technology and interestingly commerce students feel it is more useful than science students. However, when we analyse the total number of students who have positive perception of usefulness of technology in exam, nearly all science students (100 %) have positive perception. The statistical significance is upheld by relevant statistical test.

Usefulness of technology in the learning process is dependent on the use of digital devices. As to better understand the relationship between the same, we have analysed the significance of association between device usage patterns and learning outcomes among different streams of students, the results of which have been consolidated in Table 5.

When it came to usage of devices, we expected science students to have greater duration of usage. However as per our survey, students belonging to arts stream seem to have greater duration of usage, compared to commerce and science which requires further investigation as this seems to be an anomaly. However, the results are validated by Fisher's Exact Value.

Table 5: Significance of Association between Device Usage Patterns and Learning outcomes among different streams of students

Learning Outcome	Usage Perceptions	Stream				Fishers Exact / Chi-Square
		Arts	Commerce	Science	Total	
Accessing Device	0-3 Hours	129 (66.84)	146 (66.06)	44 (86.27)	319 (68.60)	Fisher's exact
	3-6 Hours	57 (29.53)	64 (28.96)	07 (13.73)	128 (27.53)	
	6 Hours & Above	07 (3.63)	11 (04.08)	00 (00.00)	18 (03.87)	0.050
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	Significant at 1%
Device Ownership	Internet Cafe	04 (2.07)	005 (02.26)	0 (0.00)	09 (01.94)	Fisher's exact
	Your neighbor	06 (3.11)	010 (04.52)	0 (0.00)	16 (03.44)	
	Your family	87 (45.08)	080 (36.20)	10 (19.61)	177 (38.06)	0.007
	You	96 (49.74)	126 (57.01)	41 (80.39)	263 (56.56)	Significant at 1%
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	
Access	Reading Directly	102 (52.85)	118 (53.29)	45 (88.24)	265 (056.99)	Chi-Square
	Print Out	91 (47.15)	103 (46.61)	06 (11.76)	200 (043.01)	22.82
	Total	193 (100.00)	221 (100.00)	51(100.0)	465 (100.00)	(Pr = 0.0001)

From the study it was observed that, students belonging to science stream (80.39%) largely owned their own devices and the least amount of device ownership was found among students belonging to arts stream (49.74%) which was on expected lines.

Probability Value (significant at 1 percent) of Fishers Exact test further reflects that we have enough evidence to reject null hypothesis and infer that there is significant relationship between the aforementioned variables.

As far as medium of interface was concerned, students belonging to science stream (88.24%) seemed more proficient in directly reading from the digital devices as opposed to other streams like and commerce (53.29%) and arts (52.85%), which was on expected lines. Chi Square test was conducted to validate the inference which was found to be statistically significant at 1 percent probability level.

Use of technology among students, among other factors is also influenced by the economic status of their family. In this context it becomes relevant for us to test the nature of significance between the wealth asset index of the respondent's family and accessibility to relevant infrastructure and gadgets among the respondents. The relevant results are summarised in Table 6. In the survey results it was interesting to find out that majority of the people with high wealth assets (60%) were residing in Reinforced Concrete Cement (RCC) houses and majority of the poor people (24.51%) were residing in hut as compared to the other two categories. The significance of association between the two variables is validated by Fisher's Exact Value which was significant at 1 %. Moreover, we also observed that students belonging to families having high wealth asset index had the highest access to privacy (78.46%) as compared to other students belonging to families having lower wealth assets, which was validated by chi square test.

From the survey results, we observe that families with high wealth index own the highest percentage of computers (09.23%) and as per expectations, none of the families in low wealth index category have access to personal computer.

Significance of association among the variables was validated through Fisher's exact test. Similar to the ownership of personal computers, we also observed that, none of families belonging to lower economic tier have access to tablet and only students belonging to rich families had access to tablet.

Table 6: Significance of Association between Wealth Asset Index and Accessibility to Technology and Infrastructure

Accessibility / Ownership	Infrastructure and Devices	Wealth Asset Index				Fishers Exact Value (Probability) / Chi Square
		Low	Medium	High	Total	
Type of House	Hut	63 (24.51)	21 (14.69)	01 (1.54)	85 (18.28)	Fisher's exact Significant at 1%
	Tiles	177 (68.87)	65 (45.45)	22 (33.85)	264 (56.77)	
	Sheets	05 (1.95)	08 (5.59)	03 (04.62)	16 (3.44)	
	RCC	12 (4.67)	49 (34.27)	39 (60.00)	100 (21.51)	
	Total	257 (100.00)	143 (100.00)	65 (100.00)	465 (100.00)	
Privacy for Studying	Absent	116 (45.14)	48 (33.57)	14 (21.54)	178 (38.28)	Chi-Square 14.16 (Pr = 0.001)
	Present	141 (54.86)	95 (66.43)	51 (78.46)	287 (61.72)	
	Total	257(100.00)	143 (100.00)	65 (100.00)	465 (100.00)	
Personal Computer	Not Owned	257(100.00)	142 (99.30)	59 (90.77)	458 (90.77)	Fisher's exact Significant at 1%
	Owned	00 (00.00)	01 (00.70)	06 (09.23)	07 (1.51)	
	Total	257 (100.00)	143 (100.00)	65 (100.00)	465 (100.00)	
Tablet	Not Owned	257 (100.00)	141 (98.60)	64 (98.46)	462 (99.35)	Fisher's exact 0.044
	Owned	00 (00.00)	02 (01.40)	01 (01.54)	03 (00.64)	
	Total	257 (100.00)	141 (100)	65 (100.00)	465 (100.00)	
Laptop	Not Owned	213 (90.66)	131 (91.61)	50 (76.92)	414 (89.03)	Chi- Square 11.43 (Pr = 0.003)
	Owned	24 (9.34)	12 (8.39)	15 (23.08)	51 (10.97)	
	Total	257 (100.00)	143 (100.00)	65 (100.00)	465 (100.00)	
Device Ownership	Internet Cafe	04 (2.07)	05 (2.26)	00 (0.00)	09 (1.94)	Fisher's Exact Significant at 1%
	Your neighbor	06 (3.11)	10 (4.52)	00 (0.00)	16 (3.44)	
	Your family	87 (45.08)	80 (36.20)	10 (19.61)	177 (38.06)	
	you	96 (49.74)	126 (57.01)	41 (80.39)	263 (56.56)	
	Total	193 (100.00)	221 (100.00)	51 (100.00)	465 (100.00)	
Access of Electricity	Less than satisfactory	10 (3.89)	09 (06.29)	05 (07.69)	24 (5.16)	Chi-Square 04.98 (Pr = 0.289)
	Satisfactory	103 (40.08)	60 (41.86)	19 (29.23)	182 (39.14)	
	More than Satisfactory	144 (56.03)	74 (51.75)	41 (63.08)	259 (55.70)	
	Total	257 (100.00)	143 (100.00)	65(100.00)	465 (100.00)	

Significance of association between the said variables is validated through Fisher's Exact Value. Similar trend is observed even in context of Laptop. Around 23.08 percent of students belonging to rich families own laptop as opposed to only 9.34 % of poor families owning laptop.

Chi- Square test significant at 1 percent probability validates the association between the said variables. Hence, it comes as no surprise that around 80 percent of the students belonging to families with high wealth assets have their own digital devices whereas hardly 49% of the students belonging to poor families have access to their own devices. Association is validated through Fisher's Exact.The most interesting inference from table 6, is one which is not significant. According to Chi-Square test there is no significant association between the wealth asset index of families and access to electricity. This does seem to be meaningful as electricity has become necessary good in India.

The results of multinomial logistic regression model has been analyszed with Relative Risk Ratios estimated through STATA statistical software package. Among the three categorical outcomes, namely , Dissatisfied students, Moderately satisfied students and Highly satisfied students, regarding use of technology,Moderately satisfied students was taken as baseline refrence category. Table 7 summarizes the estimates of categorical outcomes of dissatisfied students vis-a-vis moderately satisfied students with use of technology in enhancing their learning outcomes.

In the above comparison, we find that Education stream is significant at 1 percent and having relative risk ratio (rrr) of less than 1. This implies that for each one unit increase in this variable that there is a greater risk of the case falling to base reference category which is predicted to change by a factor of 0.363. Thus in other words, given, dummy for Education stream was: 1 for arts, 2 for commerce and 3 for science, science students are more comfortable in use of technology as compared to commerce and arts.It is also observed that Mobile significant at 10 percent probability has relative risk ratio of 0.109. Given, the dummy for Mobile represents 0 for absence and 1 for presence, it implies that, Students who use mobile are likely to be 0.109 times more comfortable in finding technology to be useful as opposed to students who are not using mobile.The next variable having significant relationship with dissatisfaction among students in use of technology is Educational Apps (0.002), with a relative risk ratio of 0.821.This implies that for each unit increase in this variable, there is a greater risk of the case falling to base reference category.

Table 7: Coefficient, Standard Error and Reverse Risk Ratio Estimates and $\boldsymbol{p}$ Values of the Multinomial Logistic Regression Model (Comparison for 1:2)

Usefulness of Technology	Parameters	Estimates			
		RRR	Std. Err.	z	Probability>z
Categorical comparison of " Dissatisfied Students " vis-a-vis " Moderately Satisfied Students" with use of technology in enhancing their learning outcomes (Comparison 1:2)	xEducation Stream	0.363	0.131	-2.79	0.005
	xGender	1.299	0.507	0.67	0.502
	xCitylevel	1.117	0.457	0.27	0.786
	xCaste	0.962	0.126	-0.29	0.770
	Mobile	0.109	0.136	-1.77	0.076
	Tablet	0.000	0.007	-0.03	0.978
	PC	0.375	0.598	-0.61	0.539
	Laptop	0.697	0.508	-0.49	0.622
	xdeviceowner	0.758	0.210	-1.00	0.317
	xNetworkCoverage	1.581	0.447	1.62	0.106
	xAvailibility of Electricity	0.928	0.324	-0.21	0.831
	xTimespentoninternet4studies	1.212	0.414	0.56	0.572
	xYouTubeUseful	1.119	0.208	0.61	0.545
	xEducationalWebsitesUseful	1.197	0.229	0.94	0.348
	xEducationalApps	0.547	0.106	-3.11	0.002
	xVideoconferencingapps	0.821	0.157	-1.03	0.304
	xReadingway	0.753	0.290	-0.73	0.462
	xRemembering things	0.677	0.139	-1.90	0.058
	xDeviceEnhancedLearning	0.404	0.157	-2.32	0.020
	xconcentrationduringonlinecl	0.411	0.117	-3.11	0.002
	xTechnicalProblemsinonlinecl	0.641	0.241	-1.18	0.238
	-constant	1059.696	2277.183	3.24	0.001

Thus we can infer that students who used video conferencing apps were 0.821 times more likely to find technology more useful in enhancing learning outcome as opposed to students who were not video conferencing apps. We also find that concentration during online classes and remembering things, both significant at 1 percent have relative risk ratio of 0.41 and 0.64 respectively. This implies that students who are able to concentrate are 0.41 times more likely to feel technolonlogy to be moderately useful than the students who are not able to concentrate during online classes. Finally, the students who are able to remember things are 0.64 times more likely to feel technology to be moderately useful in enhancing their learning outcome as opposed to students who are not able to adquately remember things during online classes.

Table 8 summarizes the estimates of categorical outcomes of highly satisfied students vis-a-vis moderately satisfied students with use of technology in enhancing their learning outcomes. Here we observe that, City Level which is significant at 5 percent probability has relative risk ratio of 0.561. It implies that there is

0.561 times likelihood of risk that the case shall fall to base reference as opposed to comparison category. Given the Dummy for city level was 2 for tier 2 and 3 for tier 3, it implies that students who are belonging to tier 3 city (less developed) are more likely to find technology to be 0.561 times moderately useful than the students who belong to tier 2 city.

Table 8: Coefficient, Standard Error and Reverse Risk Ratio Estimates and
$\boldsymbol{p}$Values of the Multinomial Logistic Regression Model (Comparison for 3:2)

Usefulness of Technology	Parameters	Estimates			
		RRR	Std. Err.	z	Probability>z
Categorical comparison of " Highly Satisfied Students" vis-a-vis " Moderately Satisfied Students" with use of technology in enhancing their learning outcomes (Comparison 3:2)	xEducation Stream	1.262	0.250	1.18	0.240
	xGender	1.088	0.264	0.35	0.728
	xCitylevel	0.561	0.138	-2.33	0.020
	xCaste	0.941	0.075	-0.75	0.452
	Mobile	0.797	0.676	-0.27	0.789
	Tablet	1.341	0.519	0.76	0.449
	PC	1.828	1.971	0.56	0.576
	Laptop	1.836	0.672	1.66	0.097
	xdeviceowner	1.094	0.204	0.48	0.630
	xNetworkCoverage	0.783	0.129	-1.48	0.138
	xAvailibility of Electricity	1.431	0.299	1.71	0.086
	xTimespentoninternet4studies	0.818	0.166	-0.98	0.325
	xYouTubeUseful	0.832	0.095	-1.60	0.111
	xEducationalWebsitesUseful	0.842	0.101	-1.43	0.153
	xEducationalApps	0.952	0.106	-0.44	0.663
	xVideoconferencingapps	1.312	0.155	2.29	0.022
	xReadingway	0.987	0.234	-0.05	0.958
	xRemembering things	1.725	0.236	3.98	0.000
	xDeviceEnhancedLearning	1.013	0.280	0.05	0.961
	xconcentrationduringonlinecl	1.655	0.243	3.42	0.001
	xTechnicalProblemsinonlinecl	1.380	0.338	1.32	0.188
	-constant	0.184	0.282	-1.11	0.269

In other words, it means that students belonging to tier 2 city which has better socio-economic infrastructure are more likely to feel technology is highly useful in enhancing their learning outcome as opposed students belonging to tier 3 city.

Further we observe that, Laptop, being significant at 10% probability level has a relative risk ratio of 1.836. This means for every 1 unit increase on that variable, there is 1.836 times likelihood that the case shall fall to comparison category. It implies that the student who uses laptop is to technology to be highly useful in enhancing his or her learning outcome as opposed to the student who is not using laptop, which is supported by previous literature as well. Then we observe, availability of electricity which is significant at 10 percent to have RRR of 1.431.

Given the dummy for availability of electricity to be 1 for bad, 2 for satisfactory and 3 for more than satisfactory, it means that higher the availability of electricity increases the likelihood of higher satisfaction among students in using technology to enhance their learning outcomes.This is rational as there is a positive relationship between availability of electricity and usefulness of digital devices. We also observe that, Video Conferencing Apps significant at 5% probability level has a RRR of 1.312. It means that, students who use Video Conferencing apps more frequently are more 1.312 times more likely to be highly satisfied with effectiveness of technology in enhancing their learning outcome as opposed to the students who don't frequently use learning apps. Finally, we observe that, remembering things and concentration during online class, both of which are significant at 1 percent have relative risk ratio of 1.65 and 1.38 respectively. This implies that greater the ability to recall and concentrate on the digital content among the students, greater shall be the likelihood that the students will be highly satisfied with usefulness of technology in enhancing their learning outcomes.

POLICY IMPLICATIONS

The study reinforces previous studies which support effectiveness of technology in enhancing learning outcomes. However, the other relationships which have been analysed in the study brings out three important policy implications, which needs to be taken into consideration by the government while distributing digital gadgets for students in Rural Areas.

- Income inequality is a veritable fact in India. Rich families can afford and do provide digital gadgets for their children; However, poor families struggle with the same. In this context, Government providing free digital devices is certainly a step in right direction.
- While distributing digital gadgets among students, some state governments are distributing Laptops, some are distributing Tablets. In this context it becomes more pertinent to analyse which of the two devices are more useful for students in enhancing their learning outcome; From our study, particularly in rural areas, we found out that, students find Laptop to enhance their learning outcome as opposed to mobile and we did not find any significant relationship between usefulness of technology and tablet. So, distributing Laptops for students in rural area would be optimum use of resources.
- From the study we also found out that, students belonging to arts stream were most dissatisfied with use of technology. This may be because of their lack of exposure to the same. State Governments must focus on training arts students in use of basic ICT. This could be done by inculcating the same in their educational curricula.

CONCLUSION

The study undertaken in rural India brings out some important aspects which is helpful in the field of policy formulation. Although the study reiterates technology is helpful in enhancing learning experience among students, it also observes that ease of using technology varies across streams, even among the students present in the same region. Thus, State Governments just resorting to distribute laptops or tablets to students is not going to enhance their learning outcomes. The State Governments must bring in short term courses to familiarize the students with use of the said gadgets before distributing the same. This is more so relevant for students belonging to arts stream. Moreover, recently Karnataka State Government unilaterally decided to distribute tablets instead of laptops for students pursuing higher education in Government Colleges across all the streams. Our study, which was conducted across 5 districts found out that, students found laptop to be more useful than tablets. Hence, while, framing policies concerning distribution of devices to leverage ICT, it is better for the Government to take the feedback of the stakeholders concerned. The study undertaken by this research acknowledges and appreciates the steps taken by some of the Indian States to enhance learning experience and outcomes of students by providing them with electronic gadgets. However at the same point of time, the study brings out the effectiveness of the same so as to ensure there is optimum utilization of resources.

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