Factors Affecting Internet Data Consumption amongst College Students during the Pandemic

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Abstract

This paper seeks to evaluate the factors affecting Internet data consumption amongst undergraduate and postgraduate students during the COVID-19 Pandemic and the subsequent lockdown in India. The paper uses data obtained from a primary survey of Internet users to determine the effect of various factors on the consumption of Internet data. The changes are evaluated through the lens of six major socio-economic indicators that are age, gender, income level, occupation, area of residence, and social category. We find that there has been a significant increase in Internet data consumption in the post-Pandemic period and there are several changes in the patterns of consumption. We also find that family income, expenditure on the Internet and time spent on the Internet significantly affect Internet data consumption.

JEL Classification: C51, D12, J15, J16, L86, O33
Keywords: Least Squares Estimation, Consumer Sentiment, Expenditure, Taste, Inequality, Gender Discrimination, Digital Divide, Internet, Internet Services, Technological Impact, Technology Adoption

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1 Introduction

The COVID-19 pandemic and the subsequent shift to online functioning for work, leisure, and other activities initiated massive changes in Internet services and consumption. Prior to the pandemic, India had been experiencing a rapid rise in Internet users, reaching 420 million by June 2017 (Agarwal 2017). By 2020, the estimated number of active internet users reached around 620 million. 58% were male, and most of them were from urban areas.Millions of users, especially in rural India were coming online for the first time. The pandemic, despite the massive economic crisis it has induced, has also resulted in an explosion in internet usage, both in terms of volume and subscribers.

As per telecom regulator TRAI, India had a total of 688 million broadband subscribers in September 2020 out of which just 22.26 million were fixed broadband subscribers. The top broadband players (wired and wireless) were Reliance Jio (355.93 million), Bharti Airtel (127.83 million), Vodafone Idea Ltd (112.19 million), and BSNL (21.52 million) (TRAI 2020). India's fixed broadband penetration at 6 per cent is much lower than other countries.

India's internet consumption rose by 13% since the lockdown was put in, according to telecom ministry data. The price of accessing data in fixed and mobile broadband is almost similar. The daily average consumption in this period was 9% higher than data used on March 21, the day the nationwide lockdown was announced, and 13% more than on March 19.

Speed Test, a site that analyses internet access performance across the globe, showed a 6% decline in fixed line speeds and 18% in mobile speeds when compared to the week of March 2 in its latest report on tracking COVID-19's impact on speeds around the world which was updated on April 15. As per the report, India's current broadband speed is an average of 36.17 megabits per second (Mbps) and mobile download speed is 9.67 Mbps (Rizzato 2020). OpenSignal, a mobile analytics company, analysed the download speed experience of smartphone users in India from late January until early July to understand their experience before and during the pandemic lockdown.

The Internet data speeds as well as levels and amount of usage vary by social categories such as caste and gender, as well as economic indicators such as income and occupation. Numerous reports have been conducted to evaluate these relationships. Internet use has increased considerably in recent years across the world. A report by the Pew Research Center (Jacob, Bishop and Chwe 2018) found that there has been a steady increase in internet use among developing and emerging economies. However, the digital divide persists with per capita income, age, education and in some cases, gender differentiating use of the internet. The report observes that young people are far more likely than old people to use the internet.

Internet use also increases with an increase in education. Furthermore, males are more likely to use the internet than females in developing economies.

Students especially have been affected by these inequalities. The lockdown has led to a dramatic shift in the educational sector as schools and universities across the world have shifted their classes to video conferencing platforms like Zoom and Google Meet (Pandey and Pal 2020). In India, the access to these platforms is a lot more unequal and the transition has not been the same for everyone, mediated by demographic and class factors.

This paper explores the factors affecting Internet data consumption using a multiple regression model. It uses socio-economic variables such as gender, caste, place of residence, household income, spending on Internet and Internet speed to determine a relationship. In the following section, we look at existing literature that evaluates the effect of some of these factors on Internet data consumption. After the literature review, we look at the survey data used in the research and the research methodology and then discuss the results from the regression model.

2 Literature Review

The pandemic and the subsequent lockdown have had a profound impact on the way the internet is used. Among students, this has meant an increase in consumption, although this has not been uniform. Fernandes et al. (2020) look at the impact of lockdown on internet use among adolescents in several countries including India. The paper finds that adolescents increased their use of social media sites and streaming services during the course of the lockdown. The paper also looks at the impact of internet use on well-being and finds a strong relationship between compulsive online behaviours and symptoms of depression and loneliness. Kapasia et al. (2020) assess the impact of the lockdown on university students in West Bengal. The paper finds that during the lockdown, around 70% of the students were engaged in online learning. They faced various problems including depression, anxiety, poor Internet connectivity and an unfavourable study environment. These problems were found to be acute, especially for students from remote areas and marginalised sections.

Jahan et al. (2021) investigate the changes in Internet use behaviours and addiction rates among Bangladeshi students during the pandemic using a cross-sectional study. 71.6% of the participants reported experiencing internet addiction. Risk factors for internet addiction were found to be smartphone addiction, depression and anxiety. Subudhi and Palai (2020) study the degree, importance and impact of consumption of the Internet during the COVID lockdown. Anand et al. (2018) investigate internet addiction amongst engineering university students in Mangaluru, Karnataka. Gender, duration of use, time spent per day, frequency of internet use, and psychological distress all predicted internet addiction, similar to factors predicting normal internet use.

Besides the general increase in consumption, the 'digital divide' has also come to the fore during the pandemic. According to Dasgupta, Lall and Wheeler (2001), the digital divide is more due to a lack of telecommunications rather than a lack of access to Information Technology. Kamssu et al. (2004) investigate the impact of information technology (IT) infrastructure, Internet Service Providers (ISPs), and socio-economic factors on Information and Communications Technology (ICT) access and use. The paper finds a significant relationship between these factors and the adoption of the internet.

Previous studies show that age, occupation, gender, place of residence, caste and income all considerably affect internet use. While a lot of literature focuses on the demographic factors affecting the adoption of the internet, Buselle et al. (1999) look at the demographic factors that predict internet use. It was found that gender and age were significant demographic predictors of use, younger males being heavier users. Ahamed and Siddiqui (2020) analyse data from National Sample Survey (NSS) conducted in 2017-18, on 'Household Social Consumption on Education in India'. The survey finds that only one out of 10 households own a computer. There is also a stark rural-urban disparity.

Rajam, Reddy and Banerjee (2021) analyse the digital divide between disadvantaged caste groups and others. It finds that more than half of the caste-based digital gap is attributable to differences in educational attainment and income between the disadvantaged caste groups and others. Kumar and Kumara (2018) find a significant rural-urban gap in access to ICT (Information and Communications Technology).

Tewathia, Kamath and Ilavarasan (2020) similarly find that higher education, caste, occupation and ownership of assets significantly affect internet use. Less educated, lower-income groups, and marginalised caste groups neither have (Information and Communications Technology) ICT assets nor the skills to use them. Also, the highest adult education in a household, caste, and the primary source of income of the household differentiate ICT ownership and use. Overall, ICT ownership and usage are significantly different for different socio-economic groups in India. Thus, these are all critical factors in looking at the effect on Internet consumption.

3 Data and Methodology

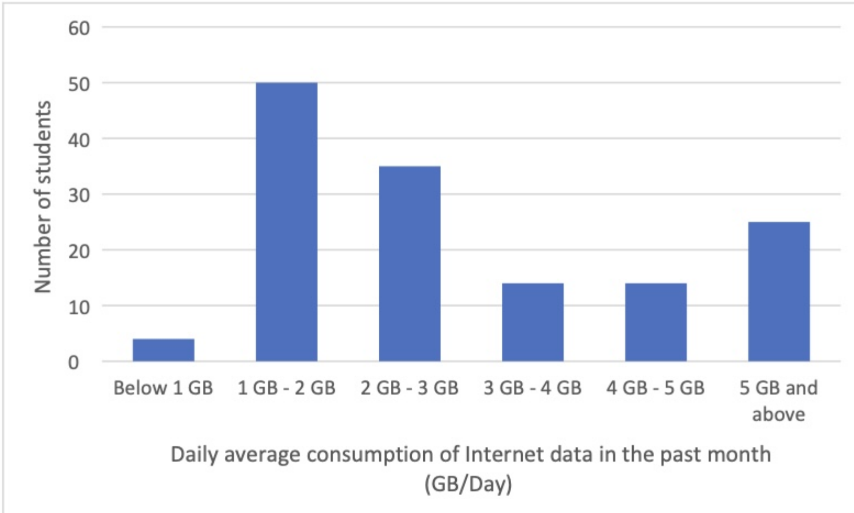
3.1 Data Description

We use primary survey data to evaluate the impact of the pandemic on Internet data consumption. A cross-sectional study was conducted between October 26 and November 28, 2020 through a survey form administered online to gauge information about each of the aforementioned variables. The online survey conducted through Google Forms was circulated to get responses from a diverse array of respondents. A sample survey was also administered prior to administering it at large to account for errors and corrections. Participation in the survey was voluntary and informed consent was taken prior to administering the survey. Only aggregated responses were evaluated, such that confidentiality and anonymity were maintained. The questionnaire for the survey is attached in the appendix in section 9e. In the main survey, a total of 192 responses were received. To control for education and occupation, we select a subset of 142 responses consisting of respondents identifying themselves as students between the ages of 17-23, i.e., undergraduate and postgraduate students in India. We present in this section the significant observations we find from the data.

1. Consumption of Internet Data

Most students consume between 1 GB to 3 GB of data on average every day, although a significant number (17.6%) consume more than 5 GB per day. This reflects the necessity of internet data for students.

Figure 1: Daily Average Consumption of Internet Data in the Past Month by Students

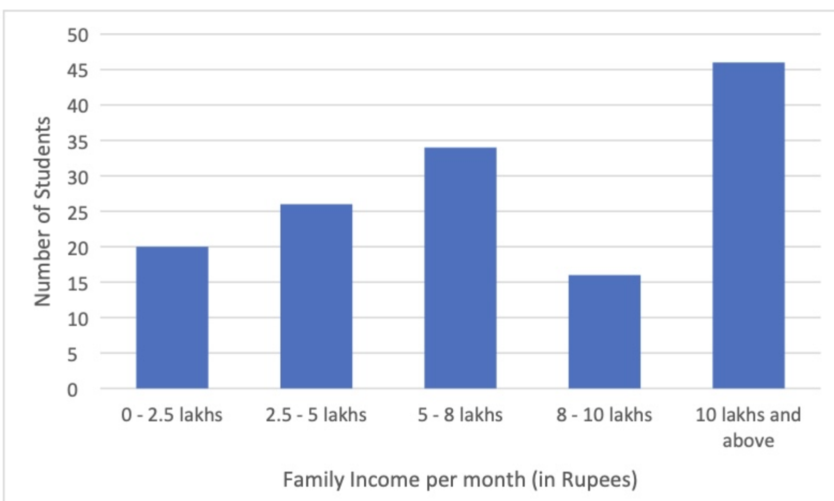


Source: Authors' Visualisation from survey responses.

2. Family Income

Family Income is distributed across the different categories, although there is a significant number, 32.4% of students, who have family income above 10 lakhs per month. Thus, the survey sample is economically well-off relative to the overall population.

Figure 2: Family Income Per Month of the Students

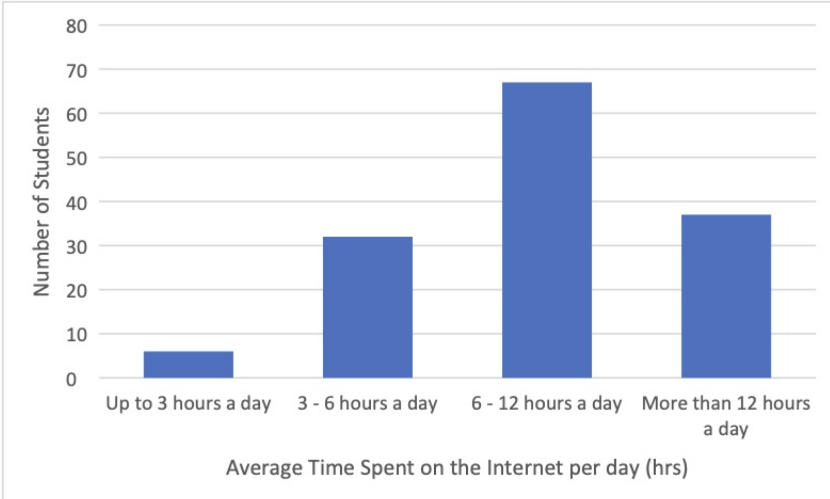


Source: Authors' Visualisation from survey responses.

3. Time Spent on the Internet

Most students in the survey sample spend more than 6 hours per day on the Internet. This also reflects the importance internet holds over students' lives.

Figure 3: Average Time Spent on the Internet by Students

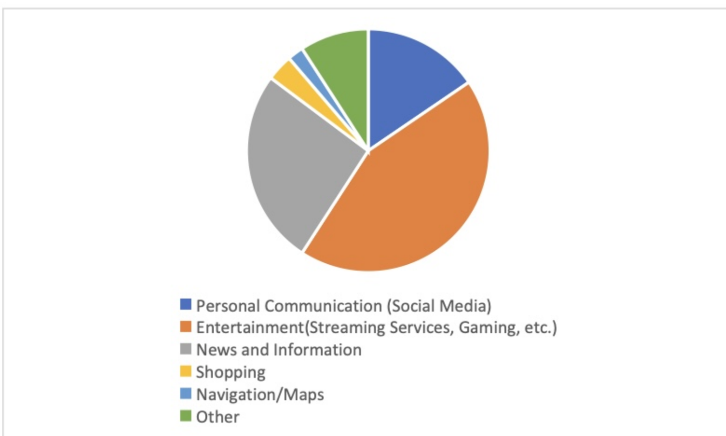


Source: Authors' Visualisation from survey responses.

4. Type of Internet activity consuming most data

43.7% of students spend most of their internet data on consuming entertainment, while 26.1% spend most data on news and information. Furthermore, 15.5% of students spend most of their data on news and information. A very small section spends it on shopping, navigation or other activities. Thus, entertainment and news and information are the most data-consuming activities for students.

Figure 4: Type of Internet consuming most data per day among students

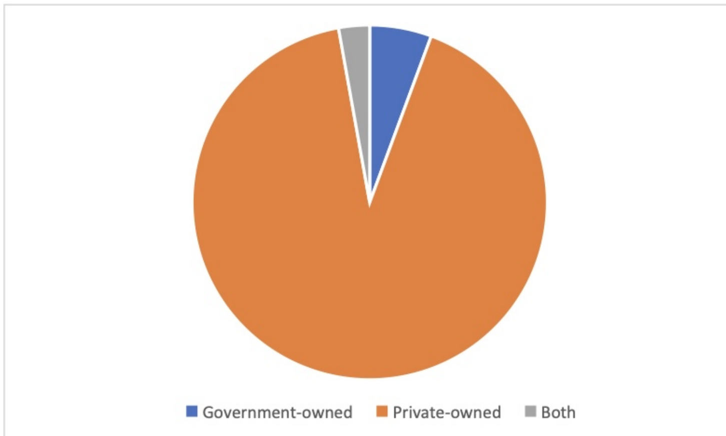


Source: Authors' Visualisation from survey responses.

5. ISP Type

91.5% of students in the survey use a private Internet Service Provider, whereas 5.6% use a government-owned service provider. This reflects the reliance on private companies for internet services.

Figure 5: Internet Service Provider Type of the Students

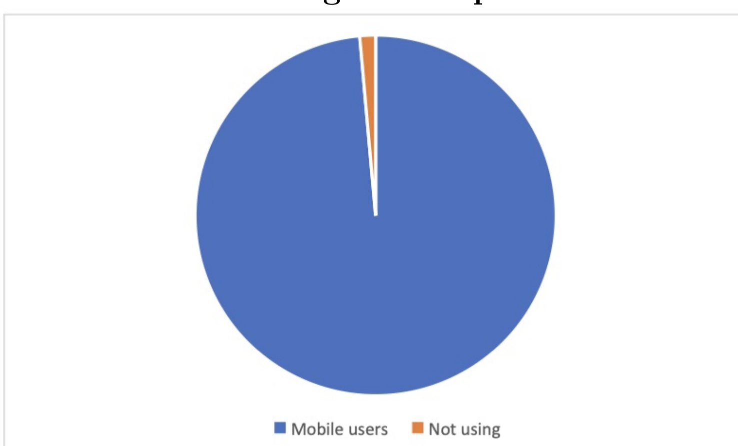


Source: Authors' Visualisation from survey responses.

6. Mobile users

98.6% of the students in the sample use Mobile Data regularly, thus reflecting the importance of phones in internet use.

Figure 6: Share of students using Mobile phones to access the Internet

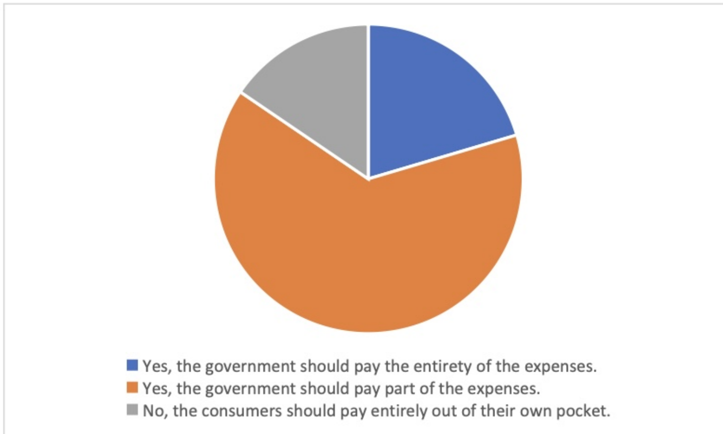


Source: Authors' Visualisation from survey responses.

7. Internet as a public utility

20.4% of the students support the idea of the government providing Internet as a public utility and paying expenses entirely, while 64.1% feel that the government should only pay a part of the expenses. 15.5% of respondents oppose the idea and feel that consumers should pay for the Internet entirely out of their own pocket. Thus, we see significant support for government intervention in providing internet access.

Figure 7: Opinion of Students on government paying for Internet expenses

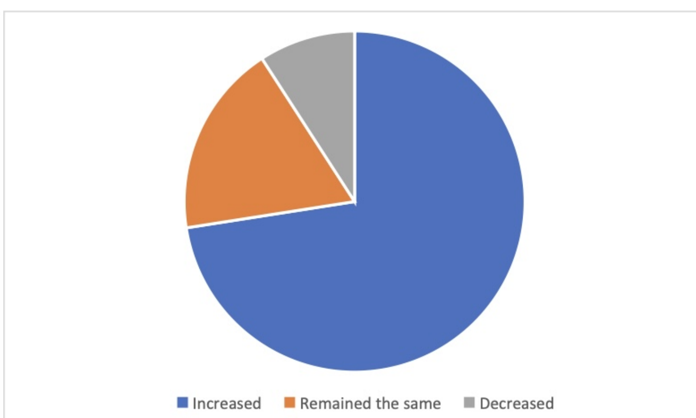


Source: Authors' Visualisation from survey responses.

8. Change in data usage

72.5% of surveyed students found an increase in data usage after the pandemic as compared to before, whereas 18.3% found their data usage to have remained more or less the same. Only 9% of respondents experienced a decline in data usage. This reflects the increased reliance on internet for education and other essential activities.

Figure 8: Change in Data Usage of the Students after the Pandemic as compared to before

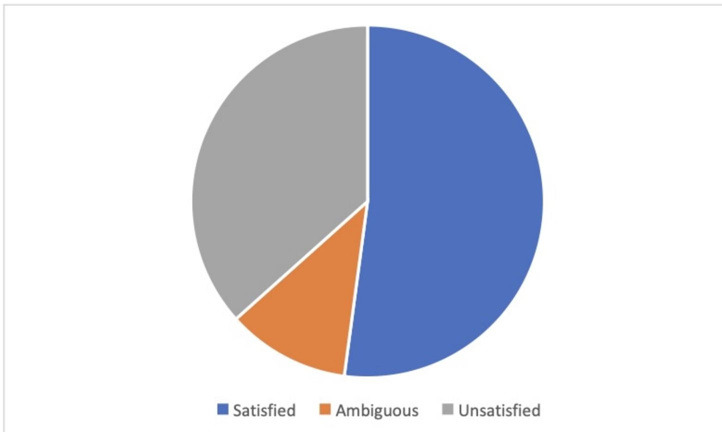


Source: Authors' Visualisation from survey responses.

9. Satisfaction with Internet Speed

52.1% of students reported being satisfied with their internet speed whereas 11.3% were ambiguous about their satisfaction level. A significant number, 36.6% of respondents, were unsatisfied with the speed of their internet connection. This indicates that internet speed remains an issue for many students.

Figure 9: Student Satisfaction with Internet Speed



Source: Authors' Visualisation from survey responses.

3.2 Econometric Model

The survey data provided options grouped into intervals for questions, due to the lack of accurate exact information on specific variables from the participants. Long (1997), Stewart (1983) and Tobin (1958) provide the method to be used for estimating the parameters of a linear model when the dependent variables fall in a certain interval on a continuous scale. A hybrid of probit analysis and multiple regression is recommended. However, as probit is beyond the scope of this paper, we use Ordinary Least Squares (OLS) method for multiple linear regression. Cross-sectional data for 142 students in the age group of 17-23 is used. The effect of gender, place of residence, caste, family income, expenditure on internet and internet speed on usage of internet data is analysed. Following is the model used for estimation:

$$\begin{aligned} dataus e = \beta_0 + \beta_1 \text{ gender }_i + \beta_2 \text{ residence }_i + \beta_3 \text{ categ }_i + \beta_4 \ln(\text{faminc})_i + \beta_s \ln(\text{intspend})_i \\ + \beta_6 \text{ inttime }_i + \beta_7 \text{ intspeed }_i + u_i \end{aligned} \tag{1}$$

The descriptive statistics of the variables used in the model are mentioned in the Appendix in Section 9a. The description of these variables is as follows –

Table 1: Description of Data

Conceptual Variable	Observable Variable	Description
Usage of Internet data	datause	Daily average consumption of Internet data in the past month (GB/Day)
Gender	gender	0: Male; 1: Female
Place of residence	residence	0: Urban area; 1: Rural Area
Caste	categ	0: General, 1: Category (OBC/SC/ST)
Family Income	ln(faminc)	Log of Family Income per month
Expenditure on Internet	ln(intspend)	Log of sum of family expenditure on WiFi and Individual Expenditure on Mobile Data per month
Time spent on Internet	inttime	Average time spent on Internet per day (hours/day)
Internet Speed	intspeed	Internet download speed in Mbps

Source: Authors' descriptions.

4 Analysis

Table 2: Regression Results

Variable	Coefficient	Standard Error	t	Pr>|t|^2	Lower-Bound (95%)	Upper-Bound (95%)
Intercept	2.070	2.194	0.943	0.347	-2.270	6.410
Gender	0.213	0.216	0.990	0.324	-0.213	0.640
Residence	-0.128	0.806	0.158	0.874	-1.723	1.467
categ	0.134	0.299	0.449	0.654	-0.458	0.726
ln(faminc)	-0.269	0.132	2.032	**0.044****	-0.530	-0.007
ln(intspend)	0.500	0.120	4.169	**<0.0001*****	0.263	0.737
inttime	0.078	0.035	2.228	**0.028****	0.009	0.147
intspeed	0.000	0.001	0.214	0.831	-0.001	0.001

Source: Authors' calculations.

Table 3: Regression Statistics

Observations	142
Sum of Weights	142
Degree of Freedom	134
R^2	0.212
Adjusted R^2	0.170

Source: Authors' calculations.

The above table mentions the regression coefficients of the dependent variables along with the standard errors and p-values. The partial coefficient correlation matrix for the variables is listed in Appendix section 9b. Goodness of fit statistics are mentioned in Appendix section 9c whereas the multicollinearity tests are in section 9d. We find no significant multicollinearity or heteroscedasticity for the data set.

R2 is a measure of goodness of fit of the model. The value of 0.212 indicates that the model explains 21.2% of the changes in the dependent variable. The adjusted R2 gives a value of 0.17, indicating that the model explains 17% of the changes in the dependent variable.

We use t-test values to check for significance of the variables. Time spent on the Internet is found to be significant at 99% level of significance, whereas family income and time spent on Internet are significant at 95% level of significance. Gender, place of residence, caste and internet speed are not found to be significant at all. We evaluate the reasons for significance and signs of the coefficients.

1. Gender

Gender is not found to significantly predict internet data use at all three levels of significance. This could be due to similar data use patterns amongst male and female students. Studies show that women face disadvantages in using the internet due to socio-economic disadvantages that they experience. However, since this data is not representative and selects a subset of the population, it could be an anomalous result specific to this data set.

2. Place of residence

Place of residence is also not found to significantly predict internet data use at all three levels of significance. Again, the use of unrepresentative data set of college students who would be more likely to come from privileged backgrounds would change the dynamics.

3. Caste

Similar insignificant results are also observed for caste due to above mentioned reasons.

4. Family Income

Family Income is found to be significant in determining Internet data consumption at 95% level of significance. However, the coefficient of family income is surprisingly found to be negative. This can be interpreted specific to the data, as it consists largely of higher income students, increase in family income leads to fall in share of expenditure on Internet and reliance on non-personal data services. We find that if family income increases by 100% on average, Internet data use goes down by about 0.27 units.

5. Expenditure on Internet

Expenditure on Internet is found to be significant in determining Internet data consumption at 99% level of significance. The coefficient is positive, indicating that a 100% increase in Internet expenditure leads to an increase in Internet data use of about 0.5 units.

6. Time spent on Internet

Time spent on Internet is found to be significant in determining Internet data consumption at 95% level of significance, The coefficient is positive, indicating that a 100% increase in time spent on Internet leads to an increase in Internet data use of about 0.08 units.

7. Speed of Internet

Internet speed is not found to be significant in determining Internet data use at all three levels of significance. This could be due to the necessary nature of Internet use, as the responses by students indicate. Thus, regardless of the speed of internet, students need to use it on a regular basis and thus internet data consumption is not significantly affected by it.

5 Conclusion

The major finding of our paper is that family income, expenditure on internet and time spent on Internet significantly affect internet consumption. The negative relationship with family income can indicate decrease in reliance on personal data. The impact of expenditure and time spent on Internet is reflective of their impact on Internet use. However, gender, place of residence, caste and internet speed are not found to significantly affect Internet consumption. This can be due to non-representative nature of the data set as discussed in the analysis. Furthermore, we also obtain several insights on Internet consumption patterns of college students. Almost all students use mobile data and private Internet Service Providers. Entertainment and news and information are the Internet activities that consume most data for the largest number of students. For most students, Internet consumption has increased after the Pandemic, with mixed satisfaction regarding Internet speeds. Further research on this topic can be done using more representative data sets. The limitations of this paper other than the unrepresentative data set are the use of OLS method using midpoints instead of ordered probit. A more detailed analysis is required to evaluate the changes in Internet data consumption on these lines.

A Appendix

A.1 Descriptive Statistics

Table 4: Descriptive Statistics

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation
datause	142	0.500	5.000	2.827	1.402
gender	142	0.000	1.000	0.507	0.502
residence	142	0.000	1.000	0.965	0.185
categ	142	0.000	1.000	0.155	0.363
ln(faminc)	142	11.513	13.710	12.482	0.881
ln(intspend)	142	4.605	8.700	6.879	0.903
inttime	142	1.500	12.000	8.451	3.008
intspeed	142	0.000	2000.000	57.722	195.173

Source: Authors' calculations.

A.2 Partial Correlation Coefficient Matrix

Table 5: Partial Correlation Coefficient Matrix

	gender	residence	categ	ln(faminc)	ln(intspend)	inttime	intspeed	datause
gender	1							
residence	-0.036	1						
categ	-0.045	-0.024	1					
ln(faminc)	-0.067	0.182	0.05	1				
ln(intspend)	0.161	-0.013	-0.15	-0.162	1			
inttime	0.129	0.022	-0.029	-0.12	0.088	1		
intspeed	0.016	0.032	-0.062	-0.175	-0.012	-0.08	1	
datause	0.161	-0.051	-0.031	-0.25	0.371	0.223	0.027	1

Source: Authors' calculations.

A.3 Multicollinearity Statistics

Table 6: Multicollinearity Statistics

	gender	residence	catge	ln(faminc)	ln(intspend)	inttime	intspeed
Tolerance	0.958	0.958	0.972	0.892	0.928	0.955	0.949
VIF	1.044	1.044	1.029	1.122	1.078	1.047	1.054

Source: Authors' calculations.

A.4 Goodness of Fit Statistics

Table 7: Goodness of Fit Statistics

Observation	142
Sum of Weights	142
Degree of Freedom	134
R^2	0.212
Adjusted R^2	0.17
Mean	1.63
Squared Root	
Root Mean Square of the Errors	1.277
Mean Absolute Percentage Errors	51.273
Durbin-Watson Statistic	2.56
Mallows Cp Coefficient	8
Akaike Information Criterion	77.146
Schwarz's bayesian Criterion	100.792

Source: Authors' calculations.

A.5 Questionnaire

Section 1

Email, Age, Gender, Social Category, State/Union Territory, Current Area of Residence, Profession, Family Income per Annum

Section 2 - Internet Services Usage Patterns

1. Does your place of work/study provide you with Internet services?
   - Yes
   - No
2. Which of the following mediums do you use to access the Internet? (Select all that apply)
   - Cable
   - Fiber Optics
   - Digital Subscriber Line
   - Dial-Up
   - Satellite Internet
   - Mobile Broadband
   - Other
3. Which of the following do you use more often to access the Internet?
   - Mobile Broadband
   - Wi-Fi
4. What type of Internet Service Provider do you use?
   - Government-owned
   - Private-owned
   - Other
5. Please name your Internet Service Provider companies (Airtel, Jio, etc.)
6. Which devices do you use to access the Internet?

- Mobile/Smartphone
- PC
- Laptop
- Tablet
- Other

7. Are you working or studying from home since the Pandemic began?
    - Yes
    - No
8. On an average, approximately how often do you use the Internet?
    - More than 12 hours a day
    - 6 - 12 hours a day
    - 3 - 6 hours a day
    - Up to 3 hours a day
    - Few times a week
    - Few times a month
    - Rarely
9. How often does your job/line of work or study require you to access the Internet?
    - More than 12 hours a day
    - 6 - 12 hours a day
    - 3 - 6 hours a day
    - Up to 3 hours a day
    - Few times a week
    - Few times a month
    - Rarely
10. Which type of personal activity do you spend approximately the most time using the Internet on? (With 1 being the highest and 6 being the lowest)

- News and Information
- Entertainment (Streaming Services, Gaming, etc.)
- Personal Communication (social media)
- Shopping
- Navigation/Maps
- Other

Section 3 –Data Usage Patterns

1. What is your approximate average daily consumption of data for using Internet in the past month?
   - Below 1 GB
   - 1 GB - 2 GB
   - 2 GB - 3 GB
   - 3 GB - 4 GB
   - 4 GB - 5 GB
   - 5 GB and above
2. What was your approximate average daily consumption of data for using Internet before the pandemic?
   - Below 1 GB
   - 1 GB - 2 GB
   - 2 GB - 3 GB
   - 3 GB - 4 GB
   - 4 GB - 5 GB
   - 5 GB and above
3. How has your Internet Data usage changed post the 2020 Pandemic as compared to before? (Scale of 1-5)
4. Which type of personal activity consumes most of your Internet Data? (With 1 being the highest and 6 being the lowest)
   - News and Information

- Entertainment (Streaming Services, Gaming, etc.)
- Personal Communication (social media)
- Shopping
- Navigation/Maps
- Other

5. On an average, approximately what percent of your total Internet data is used for the purpose of studying/working from home? *

- 0% - 25%
- 25% - 50%
- 50% - 75%
- 75% - 100%
- Not sure

6. What is your approximate current average monthly expenditure on Mobile Data for using the Internet? *

- ₹0 - ₹200
- ₹200 - ₹500
- ₹500 - ₹1000
- ₹1000 - ₹2000
- ₹2000- ₹3000
- ₹3000 and above
- Do not use Mobile Data

7. What was your approximate average monthly expenditure on Mobile Data for using the Internet before the Pandemic? *

- ₹0 - ₹200
- ₹200 - ₹500
- ₹500 - ₹1000
- ₹1000 - ₹2000

- ₹2000- ₹3000
- ₹3000 and above
- Did not use Mobile Data

8. What is your household's approximate current average monthly expenditure on Wi-fifor using the Internet? *

- ₹0 - ₹200
- ₹200 - ₹500
- ₹500 - ₹1000
- ₹1000 - ₹2000
- ₹2000- ₹3000
- ₹3000 and above
- Do not use Wi-Fi

9. What was your household's approximate average monthly expenditure on Wi-fi forusing the Internet before the Pandemic? *

- ₹0 - ₹200
- ₹200 - ₹500
- ₹500 - ₹1000
- ₹1000 - ₹2000
- ₹2000- ₹3000
- ₹3000 and above
- Did not use Wi-fi

Section 4 –Internet Speed

This section asks you questions about the speed of your Internet. You can use the following link to conduct an online speed test to determine the download speed of your Internet connection. The information is relevant to questions asked in this section. The site is safe and does not use your personal data.

https://www.speedtest.net/

1. From the test above, what is the download speed of your Internet connection (in Mbps)?
2. Are you satisfied with the speed of your Internet connection? (Scale of 1-10)
3. Do you support the government providing Internet as a public utility?
    - Yes, the government should pay the entirety of the expenses.
    - Yes, the government should pay part of the expenses.
    - No, the consumers should pay entirely out of their own pocket.
4. Please respond with any feedback, comments and/or questions that you have for this survey.

References

[1] Agarwal, S. (2017). Internet users to touch 420 million by june 2017: Iamai report. *The Economic Times*.

[2] Ahamed, S. and Z. M. Siddiqui (2020). Disparity in access to quality education and the digital divide. *Ideas for India*.

[3] Anand, N., P. A. Jain, S. Prabhu, C. Thomas, A. Bhat, P. Prathyusha, S. U. Bhat, K. Young, and A. V. Cherian (2018). Internet use patterns, internet addiction, and psychological distress among engineering university students: A study from india. *Indian journal of psychological medicine 40*(5), 458–467.

[4] Busselle, R., J. Reagan, B. Pinkleton, and K. Jackson (1999). Factors affecting internet use in a saturated-access population. *Telematics and Informatics 16*(1-2), 45–58.

[5] Dasgupta, S., S. Lall, and D. Wheeler (2001). *Policy reform, economic growth, and the digital divide: An econometric analysis*, Volume 2567. World Bank Publications.

[6] Fernandes, B., U. N. Biswas, R. T. Mansukhani, A. V. Casarín, and C. A. Essau (2020). The impact of covid-19 lockdown on internet use and escapism in adolescents. *Revista de psicología clínica con niños y adolescentes 7*(3), 59–65.

[7] GOWRI, S. N. and D. KESAVAN. A study on growth and development oftelecommunication service sector in india.

[8] Jahan, I., I. Hosen, F. Al Mamun, M. M. Kaggwa, M. D. Griffiths, and M. A. Mamun (2021). How has the covid-19 pandemic impacted internet use behaviors and facilitated problematic internet use? a bangladeshi study. *Psychology Research and Behavior Management 14*, 1127.

[9] Kamssu, A. J., J. S. Siekpe, J. A. Ellzy, and A. J. Kamssu (2004). Shortcomings to globalization: Using internet technology and electronic commerce in developing countries. *The Journal of Developing Areas*, 151–169.

[10] Kapasia, N., P. Paul, A. Roy, J. Saha, A. Zaveri, R. Mallick, B. Barman, P. Das, and P. Chouhan (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 116*, 105194.

[11] Kumar, B. S. and S. S. Kumara (2018). The digital divide in india: Use and non-use of ict by rural and urban students. *World Journal of Science, Technology and Sustainable Development*.

[12] Pandey, N., A. Pal, et al. (2020). Impact of digital surge during covid-19 pandemic: A viewpoint on research and practice. *International journal of information management 55*, 102171.

[13] Poushter, J., C. Bishop, and H. Chwe (2018). Social media use continues to rise in developing countries but plateaus across developed ones. *Pew research center 22*, 2–19.

[14] Rizzato, F. (2020). Analyzing mobile data consumption and experience during the covid-19 pandemic. *Opensignal*.

[15] Scott Long, J. (1997). Regression models for categorical and limited dependent variables. *Advanced quantitative techniques in the social sciences 7*.

[16] Stewart, M. B. (1983). On least squares estimation when the dependent variable is grouped. *The Review of Economic Studies 50*(4), 737–753.

[17] Subudhi, R. and D. Palai (2020). Impact of internet use during covid lockdown. *Horizon J. Hum. & Soc. Sci 2*, 59–66.

[18] Tewathia, N., A. Kamath, and P. V. Ilavarasan (2020). Social inequalities, fundamental inequities, and recurring of the digital divide: Insights from india. *Technology in Society 61*, 101251.

[19] Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society*, 24–36.

[20] Vaidehi, R., A. B. Reddy, and S. Banerjee (2021). Explaining caste-based digital divide in india. *arXiv preprint arXiv:2106.15917*.