

Technological Advancement & Tertiary Education: An Econometric Analysis of the Indian Economy

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Digital technologies and capabilities are core instruments in building resilience in the field of tertiary education. India, with rising demographic dividend and technological transformation, is moving towards technology-driven education. The rationale behind digitalized education is to build skilled and competent youth of the nation by making knowledge accessible and affordable for all. The present study investigates the relationship between technological advancement and tertiary education in the Indian economy for the period 2001-2021 by using the Autoregressive Distributed Lag (ARDL) approach. It was found that the advancement in technology in recent times has a positive and significant impact on tertiary education.

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Introduction

India with the tradition of Gurukuls and Pathshalas treated education to be sacred and essential since the Vedic era. It demonstrates higher social and private returns and opens doors of new endeavors for individuals and for a nation as a whole. With 1113 Universities, 43796 Colleges and 11296 Stand Alone Institutions (AISHE, 2020-21), India aims to provide efficient infrastructure to encourage the youth of the nation and also attract students worldwide to attain education in India driven by skills and practicality. To bridge the gaps in tertiary education, the Government of India released the NEP 2020 and Education Quality Upgradation and Inclusion Program (EQUIP), a five-year education plan setting targets and objectives for a new educated India. The education sector in the recent era has faced a technological transformation driven by online teaching tools, courses and assignments providing affordable access to youth for higher education in far-fetched places across the globe. Also, it has led to the

shift of education techniques from teacher-centered to student-centric one, creating a more independent learning environment. Technological advancement and capabilities are essential to create a resilient tertiary education system. This technological progress attained a big push due to COVID-19, revealing that digital technologies are crucial for resilience in tertiary education and that it is essential for all education institutions to embrace and adapt to remote delivery infrastructure and online education setup. It is noteworthy that in India, post-adoption of technology in tertiary education, the layout of enrollment has widened from 9.69 percent in 2001 to 31.3 percent in 2021 (World Bank, 2023).

To illustrate the role of human capital in an endogenous growth model, Romer (1989) provided a theoretical and empirical framework. He believed education and knowledge to be consistent with the model, and that the initial level of literacy has a beneficial impact on investment rates and, indirectly leads to higher growth rates. Similarly, Kim and Lee (2011) emphasized the importance of human capital development in propelling a country to a higher growth path. Nations' growth paths are determined by the structure of human capital and the unpredictable nature of new technology. They considered new technology with unpredictable effects to adversely affect human capital accumulation and income development, trapping the economy in a state of low economic growth. The introduction of new technology into the economy shocks human capital investments in the short run as well as long-

term growth. Likewise, Ihugba, Austin, Okonkwo, and Duru (2021) emphasized in their study that internet use, digital infrastructure, and a good learning environment with digital technologies facilitate tertiary enrollment and student outcomes..

Review of Literature

Aristovnik (2012) applied Data Envelopment Analysis (DEA) technique to selected EU-27 and OECD countries to analyze the efficiency of input (Expenditure on ICT, Internet users) on output (enrollment rates of students) for the period 1999-2007. The results reflected diversity in ICT efficiency across the majority of EU and OECD nations, with Finland, Norway, Belgium, and Korea emerging as the most efficient nations in terms of the influence of ICT on educational outcomes. Overall, the study concluded that all nations have the capacity to boost ICT efficiency in enhancing educational outputs/outcomes. However, Karamti (2016), using survey data of 377 college students and teachers, found that ICT has a negative impact on academic performance in higher education in Tunisia. Moreover, Chauhan (2017) examined the role of technology in improving the efficiency of elementary students learning based on a meta-analysis of 215 mean scores and standard deviations of experimental and control groups from a total of 122 distinct studies. The study concluded that technology improved elementary students' learning effectiveness. Seethal and Baskaran (2019) too believed that digitalization would bring about a radical change in the educational land-

scape in the twenty-first century and India's economy would boom as a result of the income generated by digital education and a shift to an interactive, open-access learning approach.

However, Sousa, Karimova, and Gorlov (2020) found digital (computer) literacy to be 76.2% in Kazakhstan, leaving room for further growth, with digitalization having a transformative effect on education ranging from e-textbooks to educative online portals, information databases, and online and distance learning courses. Similarly, Mhlanga and Molo (2020) noted that the pace of digital transformation in education intensified in South Africa due to Covid-19. Several tertiary and higher education institutions have been compelled to transition to online learning and use technological platforms like YouTube, Microsoft Teams, Zoom, Skype, and WhatsApp. However, Ihugba et al. (2021) found no evidence of any significant effects of internet usage, infrastructure, environment, or government policy on tertiary school enrollment in Nigeria for the period 1996–2019 using the Vector Autoregression (VAR) technique. The report suggested increasing budgetary spending to upgrade infrastructure, offer free internet access, and improve educational quality.

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After reviewing several studies, it is concluded that the literature on the impact of ICT/technological advancement

on education is inconclusive. Further, the majority of the conducted research is descriptive in nature, and only limited studies have empirical backing. Thus, in this context, the current study aims to analyze the relationship between technological advancement and tertiary education with a particular focus on the Indian economy for the period 2001-2021.

Methodology

To examine the interrelationship between technological advancement and tertiary education, the present study uses yearly time series data for the Indian economy during 2001-2021. Fixed broadband subscriptions (lnBD) and mobile cellular subscriptions (lnMB) have been used as proxy variables to evaluate technological advancement, whereas tertiary school enrollment (percentage, gross) (lnTE) has been used to measure education. The data for the variables has been obtained from World Development Indicators, World Bank, 2023.

Using the models listed below, the relationship between technological advancement and tertiary education is examined, wherein the variables are transformed into natural log form for the analysis as follows:

$$\text{Model 1: } \ln TE_t = \theta_0 + \gamma_0 \ln BD_t + \varepsilon_{1t}$$

$$\text{Model 2: } \ln TE_t = \theta_1 + \gamma_1 \ln MB_t + \varepsilon_{2t}$$

Empirical Findings

Using yearly data for the Indian economy, a time series analysis is per-

formed, with the first being determining the stationarity of the variables using unit root tests. In this study, we have applied Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, the results of which are presented in Table 1. The results demonstrate that fixed broadband subscriptions and mobile cellular subscriptions are stationary at level, $I(0)$, but tertiary enrolment is stationary

at first difference, $I(1)$, according to both ADF and PP tests. Thus, as the variables are integrated of order $I(0)$ and $I(1)$, Autoregressive Distributed Lag (ARDL) Approach (Pesaran, Shin, & Smith, 2001) is applied to examine the relationship between the variables. Additionally, a dummy variable is also included in the model to consider the impact of COVID-19.

Table 1: Unit Root Tests

I. Augmented Dickey-Fuller (ADF) Test						
Variables	At Level			At First Difference		
	With C & T	With C	Without C & T	With C & T	With C	Without C & T
lnBD	-1.4506 (0.8123)	-3.9198*** (0.0079)	-	-	-	-
lnMB	-3.1744 (0.1174)	-9.9608*** (0.0000)	-	-	-	-
lnTE	-2.2017 (0.4590)	-1.4601 (0.5286)	-	-	-2.8807* (0.0663)	-

II. Phillips-Perron (PP) Test						
Variables	At Level			At First Difference		
	With C & T	With C	Without C & T	With C & T	With C	Without C & T
lnBD	-1.4756 (0.8037)	-4.0049*** (0.0066)	-	-	-	-
lnMB	-3.6358* (0.0521)	-10.0328*** (0.0000)	-	-	-	-
lnTE	-1.1017 (0.9032)	-0.9485 (0.7505)	-	-	-2.8152* (0.0748)	2.0301** (0.0433)

Notes: (i) Figures in parenthesis of type () are p-values.

(ii) *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

(iii) C stands for Constant and T stands for Trend.

Source: Computed

To investigate the relationship between technological advancement and tertiary education, the ARDL model first analyses the following equations, which checks for the existence of a long-run relationship between the variables:

$$\Delta \ln TE_t = \alpha_1 + \sum_{(i=1)}^k \delta_{1i} + \Delta \ln TE_{t-i} + \sum_{(i=0)}^k \delta_{2i} \Delta \ln BD_{t-i} + \eta_1 \Delta \ln TE_{t-i} + \eta_2 \Delta \ln BD_{t-i} + \varepsilon_{1t} \dots \dots \dots (1)$$

$$\Delta \ln TE_t = \alpha_2 + \sum_{(i=1)}^k \tau_{1i} + \Delta \ln TE_{t-i} + \sum_{(i=0)}^k \tau_{2i} \Delta \ln MB_{t-i} + v_1 \Delta \ln TE_{t-i} + v_2 \Delta \ln MB_{t-i} + \varepsilon_{2t} \dots \dots \dots (2)$$

Through the above equations, the F-Bounds Test is used to test the hypotheses listed below. The null hypothesis is rejected if the calculated F-value is greater than the upper bound critical

value; otherwise, the null hypothesis cannot be rejected.

H₀: No long-run relationship exists between the variables (Equation 1: $\eta_1 = \eta_2 = 0$; Equation 2: $v_1 = v_2 = 0$)

H_a: A Long-Run Relationship exists (Equation 1: $\eta_1 \neq \eta_2 \neq 0$; Equation 2: $v_1 \neq v_2 \neq 0$)

Table 2 shows the results of the F-Bounds Test. The calculated F-value (11.7884 & 10.4227) in all models is more than the upper bound critical value (6.76) Narayan (2005), indicating that the null hypothesis (H₀) can be rejected. As a result, the existence of a long-run relationship between the variables is confirmed.

Table 2: ARDL F-Bounds Test

Trend specification: Restricted Constant and No Trend		
	Model 1 ARDL (4,0)	Model 2 ARDL (3,2)
F-value	11.7884	10.4227

Source: Computed

Before analyzing the relationship between the variables, diagnostic tests for serial correlation and heteroscedasticity are run to ensure the models' reliability. The results in Table 3

show that the models are appropriately defined, with no problems of serial correlation or heteroscedasticity, as the p-value is statistically insignificant in all of them.

Table 3: Diagnostic Tests

	Model 1	Model 2
Serial Correlation (LM)	7.0447 (0.1335)	8.4036 (0.2100)
Heteroscedasticity (BPG)	2.5777 (0.4614)	7.1212 (0.3098)

Note: Figures in the parenthesis of the type () are p-values.

Source: Computed

As the reliability of the model is confirmed, further, the long-run and short-run coefficients of models 1 and 2 are examined. For the short-run coefficients, the below mentioned equations are analyzed, which also confirms the stability of the estimated models depending on the value of lagged Error Correction Term (ECT(-1)). The coefficient of ECT(-1) must be negative and statistically significant for the model to be stable.

$$\Delta \ln TE_t = \omega_1 + \sum_{(i=1)}^{\kappa} \delta_{1i} + \Delta \ln TE_{t-i} + \sum_{(i=0)}^{\kappa} \delta_{2i} \Delta \ln BD_{t-i} + \Phi_1 ECT_{t-i} + \varepsilon_{1t} \dots \dots \dots (3)$$

$$\Delta \ln TE_t = \omega_2 + \sum_{(i=1)}^{\kappa} \delta_{1i} + \Delta \ln TE_{t-i} + \sum_{(i=0)}^{\kappa} \delta_{2i} \Delta \ln BD_{t-i} + \Phi_2 ECT_{t-i} + \varepsilon_{2t} \dots \dots \dots (4)$$

The long-run and short-run coefficient estimates are presented in Table 4. The results demonstrate that in the long-run, tertiary enrollment is positively and significantly related with both fixed broadband and mobile cellular subscrip-

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tions, highlighting the importance of technological advancement in tertiary education sector, allowing digital infrastructure to positively contribute to growth by enhancing educational access.

Further, the results of the short-run estimates reveal that the coefficient of ECT(-1) is negative and statistically significant at 1% level in both the models, thereby, confirming the stability of the observed long-run relationships. In model 1 and 2, the speed of adjustment is 44.80 percent and 53.95 percent per annum, respectively, indicating that in the event of any short-run disequilibrium, the adjustment towards long-run equilibrium will take around 2.23 years in model 1 ($1/\Phi_1$) and 1.85 years model 2 ($1/\Phi_2$).

Table 4: ARDL Long-Run and Short-Run Estimates

Long-Run Estimates		
Variables	Model 1	Model 2
lnBD	0.3883*** (0.0000)	-
lnMB	-	0.2399*** (0.0001)
Constant	-3.1370 *** (0.0000)	-1.6210* (0.0677)
Short-Run Estimates		
Variables	Model 1	Model 2
D(lnTE(-1))	0.1607 (0.2622)	-0.0153 (0.9261)
D(lnTE(-2))	-0.4763*** (0.0047)	-0.2575* (0.0764)
D(lnTE(-3))	0.2045 (0.1289)	-
D(lnMB)	-	-0.2228*** (0.0056)
D2020	-0.0035 (0.8753)	0.0417 (0.1202)
ECT(-1)	-0.4480*** (0.0001)	-0.5395*** (0.0001)

Notes: (i) Figures in parenthesis of type () are *p-values*. (ii) * and *** denotes significance at 10% and 1% level, respectively.

Source: Computed

Conclusion

The study concludes that availability of technological infrastructure significantly boosts education. It enhances capacity building and enriches students' creativity. India has tapped the technology driven education and initiated a shift from chalk and talk teaching technique to online/ distance mode of teaching. This has led to rise in enrollment at tertiary level of education in a large scale. The findings suggest quantum investment in technology upgradation in India to play an influential role in building strong, competent and skilled human capital. Thus, using ARDL approach, our results signify that advancement in technology in recent times has a positive and significant impact on tertiary education. To connect students from the remote rural and sub urban areas it is crucial for policy makers to work towards building strong technological infrastructure. This will pave the way for India to achieve its growth potential driven by skilled and competent youth of the nation.

References

- Aristovnik, Aleksander (2012). "The Impact of ICT on Educational Performance and Its Efficiency in Selected EU and OECD Countries: A Non-parametric Analysis." *The Turkish Online Journal of Educational Technology*, 11 (3):144-52.
- Chauhan, Sumedha (2017), "A Meta-analysis of the Impact of Technology on Learning Effectiveness of Elementary Students", *Computers & Education*, 105:14-30. *Science Direct*, doi: 10.1016/j.compedu.2016.11.005
- Ihugba, Okezie, Emenogu Austin, Okonkwo, O.N & Duru, E. (2021), "Impact of Internet Usage on Nigera Secondary School Students Performance: VAR Approach", *IJRDO-Journal of Educational Research*, 6(7): 58-70.
- Karamti, Chiraz, "Measuring the impact of ICTs on academic performance: Evidence from higher education in Tunisia." *Journal of Research on Technology in Education*, vol. 48, (4) 2016, pp. :322-37. *Taylor & Francis Online*, doi:10.1080/15391523.2016.1215176.
- Kim, Yong Jin, & Jong-Wha Lee (2011), "Technological Change, Human Capital Structure, and Multiple Growth paths." *The Japanese Economic Review*, 62(3): 305-30. *Springer Link*, doi:10.1111/j.1468-5876.2009.00507.x
- Mhlanga, David & Tankiso Moloi (2020) "COVID-19 and the Digital Transformation of Education: What are We Learning on 4IR in South Africa?" *Education Sciences*, 10 (7) *MDPI*, doi: 10.3390/educsci10070180
- Ministry of Education, Government of India (2021), All India Survey on Higher Education 2020-21,
- Narayan, Paresh Kumar (2005), "The Saving and Investment Nexus for China: Evidence from Cointegration Tests." *Applied Economics*, 37(17):1979-90. *Taylor & Francis Online*, doi: 10.1080/00036840500278103
- Romer, Paul M. (1989), "Human Capital and Growth: Theory and Evidence", *National Bureau of Economic Research Working paper 3173*
- Pesaran, M. Hashem, Yongcheol Shin & Richard J. Smith (2001), "Bounds Testing Approaches to the Analysis of Level Relationships", *Journal of Applied Econometrics*, 16 (3):289-326. *Wiley Online Library*, doi: 10.1002/jae.616
- Seethal, K. & Menaka Baskaran (2019), "Digitalization of Education in 21ST Century: A

Boon or Bane”, *International Journal for Research in Engineering Application & Management*, ISDOMP’19, 140-43. *Research Gate*, doi: 10.18231/2454-9150.2019.0436

Sousa, Rui Dinis, Beybitkul Karimova Sergey Gorlov (2020), “Digitalization as a New Direction in Education Sphere.” *E3S Web of Conferences*, 159, Doi: 10.1051/e3sconf/20201590