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Beyond School Enrollment? Digitalization, Public Expenditure, and Human Development in South Asian Countries: Evidence from Panel Data, 2000–2024

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ABSTRACT

This study explores the role education, digitalization, public spending and economic development play in human development in South Asian countries between 2000 and 2024. This study looks at whether digitalization can act as a complement to education and improve the Human Development Index (HDI) as well as exploring whether public spending on health and education can independently improve human development. Panel data regression techniques were used to understand the relationship between education, digitalization, public spending and human development. These include first difference regressions, dynamic and distributed lag regressions and two-way fixed effects with Driscoll-Kraay standard errors. Wild cluster bootstrap was also used to account for the small number of clusters. Results show that GDP per capita has a strong positive impact on HDI in the two-way fixed effect models. Digitalization is shown to have a positive short run impact on HDI in the base first difference model and has a borderline significant impact using wild cluster bootstrap. Interactions between education and digitalization are not statistically significant, so there is no evidence to suggest digitalization acts as a complement to education. Diagnostic tests showed that there was significant cross section dependence and first order serial correlation so robust methods were used. The statistically completed panel data shows that many coefficients change substantially so the original observed data should be used. This study shows that digitalization can help improve human development but depends on the model and inference method used. Economic development was found to have the most consistent impact on HDI.

Introduction

Human development looks at developing capabilities, opportunities, health, knowledge and living standards of people. Therefore, the Human Development Index (HDI) looks at these aspects using health, education and living standard indicators. It is important to understand what factors can improve human development. Education is a key aspect to human development because it improves knowledge, skills and productivity leading to increased employability. However, if the education is not of high quality, education infrastructure is lacking, there is lacking institutional capacity and complementary resources then increased education will not lead

to increased human development. Recent evidence shows that education and public spending can improve human welfare in South Asia but depends on the macroeconomic conditions (Ridwan et al., 2026).

Digitalization can act as an important complement. Increasing internet access can improve information access, education, job opportunities, financial services, healthcare and public services. This can directly improve human development through digitalisation but can also improve the value individuals receive from education. However, inequality can cause barriers to individuals receiving these benefits due to lack of infrastructure, internet access, devices and digital skills especially within developing economies (Noah & David, 2026; Sahito et al., 2026). South Asia has seen rapid technological development but faces inequality in education, income, digitalization and human development. Government spending can also play an important role. Education spending can improve education infrastructure, access to education, teaching resources and human capital. Health spending can also improve access to healthcare. However, spending may not always improve outcomes as it depends on how resources are allocated, institutional quality, government and implementation (Pradhan et al., 2026; Ridwan et al., 2026).

Economic development can also play an important role. Increased income per capita can improve education, healthcare, technology, nutrition and other services access for households. However, this must be interpreted carefully as income is one of the aspects used to calculate HDI. Therefore, there may be a strong relationship between GDP per capita and HDI. This study looks at the relationship between education, digitalization, health spending, education spending, GDP per capita and human development in South Asian countries between 2000 and 2024. This study looks at whether digitalization acts as a complement to education. This is important as previous research has looked at the direct effect of education and digitalization but little has been done on the interaction. This study looks at how digitalization plays a role as an independent variable and complement to education. It looks at education and health expenditure together to see how public resources are being allocated to improve human development. Several techniques were used to look at short run changes in the data including first difference, distributed lag, dynamic fixed effects and two way fixed effects. Cross section dependence and serial correlation were accounted for using Driscoll-Kraay standard errors and wild cluster bootstrap. The statistically completed panel data was used as part of the sensitivity analysis.

This study answers the following questions:

1. How much of an impact do education and digitalization have on human development in South Asian countries?
2. Does digitalization act as a complement to education?
3. How much of an impact do public spending on health and education have on human development, after controlling for economic development?
4. How robust are these relationships using different panel data models?

Results show that digitalization has a positive short run impact on HDI using the base first difference model but is borderline significant using wild cluster bootstrap. GDP per capita had the most consistent positive impact on HDI using the two-way fixed effect models. However, the interaction between education and digitalization was not statistically significant. This shows that the relationship between digitalization and human development is more complex than previously thought.

The remainder of the paper reviews the relevant literature, describes the data and econometric methodology, presents the empirical findings and robustness analysis, and concludes with policy implications, limitations, and recommendations.

Literature Review

Human Development and the Role of Education

The human development approach looks at development beyond just economic growth and focuses on improving people's capabilities, opportunities, health, knowledge and living standards. Education plays an important role in human development as it can improve human capital, productivity and employability. However, if individuals cannot gain much from education due to a lack of access to education, then it may not improve human development (Aijaz et al., 2024; Mahmud et al., 2024). This is very relevant for South Asia. As education has increased in many areas there is not always a large improvement in the learning outcomes. Evidence has shown that there is a large gap between education and learning in rural areas of Bangladesh (Asadullah & Chaudhury, 2015). This means that the enrolment measures do not show how much individuals can learn from education. This can cause issues when using education as an indicator.

Public spending can help improve the role of education in human development. Improvements in education infrastructure, teaching resources, teaching capacity, access to education and quality of education can be achieved through public spending. Evidence has shown that education spending can improve inclusive human development in South Asia but depends on how well the public resources are converted into education outcomes (Mahmud et al., 2024). Evidence has shown that education spending can improve human development in developing countries but there is a lot of variation between countries (Ivanovic et al., 2023).

Digitalization and Human Development

Digitalization has become an important part of socioeconomic development. Information and Communication Technology (ICT) can improve by reducing transaction and information costs, improve communication, improve access to knowledge and improve connections to education, healthcare, financial services, jobs, markets and public services. This means digital development can improve human wellbeing. Overall evidence has shown that digital development can improve human development. Mothafar et al. (2023) looked at panel data for developing countries and found that ICT development can improve HDI and its components. Bala (2024) found that mobile broadband and internet bandwidth can improve human development outcomes in developed and developing economies. Goel (2024) found that there is a long run relationship between ICT development and HDI using BRICS economies. Recent panel data has shown that ICT can improve human development outcomes but there is variation in the size of the impact based on different digital indicators (Kumari, 2026; Oduniyi & Adu, 2026).

Evidence has shown that ICT development, electricity and governance can improve human development outcomes in the Asia Pacific region (Nipo et al., 2023). This is important as individuals need to have access to digital resources and have the infrastructure. Akbar et al. (2025) found that ICT can improve human development outcomes in seven countries in South Asia between 2005 and 2023. However, there was a difference between genders and geographical areas. A key issue with digitalization is the digital divide. In Pakistan there are still inequalities in geography, income, gender, education, infrastructure and digital skills preventing individuals from having effective digital access (Jamil, 2021; Amjad, 2024). Institutional quality can also play a role. Alsubaie (2026) highlights the importance of the relationship between technology development, institutions and human development in emerging economies. Hou et al. (2026) also highlight the importance of government effectiveness in determining the relationship between digitalization and human capital development. This shows that digital infrastructure may not be enough if there is poor governance.

Education–Digitalization Complementarity

Education and digitalization can act as complements. Education can improve knowledge, cognitive skills and productivity whereas digitalization can provide platforms for individuals to gain these skills. This means the impact of education may depend on the technology available to individuals whereas digitalization may depend on their ability to utilise technology. Technology can improve access to education resources, remote learning, reduce barriers and improve new skills. However, this depends on individuals having digital literacy, good infrastructure, affordable resources, good governance and equality (Tawil & Miao, 2024). Aijaz et al. (2024) found that digital learning can improve human capital development in Pakistan but there are financial barriers, inequalities and poor infrastructure.

Evidence has shown that just because individuals have access to technology will not always improve equality in education. Mathrani et al. (2022) found that infrastructure, socioeconomic resources and access all had a significant impact on individuals participating in online learning in developing countries. This shows that individuals need to have access and the ability to utilise digital resources. From a human capital perspective, more educated individuals may be more likely to utilise digital resources whereas increased digital access can improve the returns to education by giving individuals more access to information, jobs, innovation and economic opportunities. Research has shown that human capital and digitalization can work together to improve innovation (Shabbir & Petraite, 2023).

Public Education Expenditure and Human Development

Public education spending can be used as a tool by governments to improve human capital development. Increased spending can improve school infrastructure, recruitment and training of teachers, learning resources, digital resources and overall access to education. This can give individuals increased knowledge and skills which can ultimately improve overall socioeconomic development. Overall evidence has shown that education spending can improve human development. Ruzima and Veerachamy (2023) found that public spending on education and health can improve human development outcomes in India. Mahmud et al. (2024) show that public spending on education is important for inclusive human development in South Asia. Ivanovic et al. (2023) found that government spending on education can improve human development in developing countries but there is a lot of variation between countries. However, the amount spent depends on the quality of the institutions, efficient allocation, governance and targeting. If the spending is not targeted effectively then the resources may not improve much. Miranda-Lescano et al. (2024)

show that social public spending can improve human development losses due to inequality. This shows that public spending can impact average development outcomes.

Health Expenditure and Human Development

Health is a key part of human development as having a longer and healthier life can improve individuals' capabilities and participation. Public and private health spending can improve this by providing healthcare infrastructure, medical staff, preventative healthcare, medication, maternal healthcare and child healthcare. Overall evidence has shown that health spending is important. Ruzima and Veerachamy (2023) found that public health and education spending play an important role in explaining human development outcomes in India. Kousar et al. (2023) found that government health and education spending is important for human capital development. Miranda-Lescano et al. (2023) also found evidence that public health spending can improve human development. They highlight the importance of health spending to human development outcomes and show that public spending can vary depending on the aspect. Pradhan et al. (2026) show that government health spending is important to consider in South Asia due to changing demographics and finances. However, spending does not directly show the quality, access, efficiency or outcomes of healthcare. Increased health spending may be due to poor health conditions meaning there is a reverse causality. Poor institutions and inefficient allocation may mean the extra spending does not improve human development. This study shows that spending has a similar issue. Lagged changes in health spending are positive and significant in some short run models. However, the coefficient varies greatly depending on the model. This should be interpreted as conditional.

Income and Human Development

Economic resources are closely related to human development. Having more income can improve individuals' ability to gain nutrition, healthcare, education, housing, technology and other goods and services. On a national level, having a strong economy can improve the number of resources available for education, healthcare, digital infrastructure and social protection. GDP per capita is often used as an economic control variable in studies looking at digitalization and human development (Goel, 2024; Bala, 2024; Akbar et al., 2025). However, this must be interpreted carefully as income is one of the aspects used to calculate HDI. This means there may be a strong relationship between GDP per capita and HDI.

Research Gap

Studies have shown that education, digitalization, public spending and economic development are all important determinants of human development. However, there are three issues. Firstly, education is often measured using enrolment. This does not show how much individuals are actually learning from education (Asadullah & Chaudhury, 2015). Secondly, most studies looking at digitalization look at the direct impact (Mothafar et al., 2023; Goel, 2024; Akbar et al., 2025). There is little evidence to suggest that digitalization improves the relationship between education and human development, especially in South Asia. Finally, there is mixed evidence on education and health spending. This study looks at education, digitalization, health spending, education spending and GDP per capita for eight South Asian countries between 2000 and 2024. The main contribution of this study is looking at the interaction between education and digitalization and seeing how robust the relationships are using different panel data models.

Research Methodology

Data and Sample

This study uses panel data on eight South Asian countries (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka) between 2000 and 2024. This means there could be a balanced panel of 200 observations (8 x 25). However, some variables are not available for certain years so the number of observations used in the estimations vary. The main analysis uses the original data. After matching the observations between all the variables in the main model there are 128 observations in the two-way fixed effect (TWFE) models. There are between 100-109 observations in the first difference and dynamic models. The completed panel of 200 observations is used in the sensitivity analysis. The panel data is ideal for this study as it allows for cross country and time variation.

Variables and Measurement

Human development is the dependent variable. Education and digitalization are the main independent variables. Health spending, education spending and economic development are also included as independent/ control variables. Digitalization is also used as a moderator.

Table 1: ***Definition and Measurement of Variables***

Variable	Symbol	Role	Measurement/Proxy
Human Development Index	HDI	Dependent	Human Development Index (0–1 scale)
Education	EDU	Independent	Gross secondary school enrollment (%)
Digitalization	DIG	Independent	Individuals using the Internet (% of population)
Health expenditure	HE	Control	Current health expenditure (% of GDP)
Education expenditure	EE	Control	Government expenditure on education (% of GDP)
GDP per capita	GDPPC	Control	GDP per capita (current US$)
Log GDP per capita	InGDP	Control	Natural logarithm of GDP per capita
Education × Digitalization	EDU × DIG	Interaction	Product of mean-centered EDU and DIG

Source: Authors' compilation based on study data sources.

Education Digitalization Interaction

An interaction variable is added to test whether digitalization acts as a moderator. Prior to creating the interaction variable, educational attainment and digitalization are mean centered:

$$EDU^{c}_{it} = EDU_{it} - EDU \quad (1)$$

$$DIG^{c}_{it} = DIG_{it} - DIG \quad (2)$$

$$INT_{it} = EDU^{c}_{it} \times DIG^{c}_{it} \quad (3)$$

where INT_{it} represents the education–digitalization interaction for country i in year t.

Econometric Model Specification

This section will include first difference, lagged, dynamic, distributed lag and two-way fixed effects estimation. This will allow us to identify short-term changes within the countries. The baseline short-run specification is expressed as:

$$\Delta HDI_{it} = \beta_1 \Delta EDU_{it} + \beta_2 \Delta DIG_{it} + \beta_3 \Delta HE_{it} + \beta_4 \Delta EE_{it} + \beta_5 \Delta lnGDP_{it} + \lambda_t + \Delta\varepsilon_{it} \quad (4)$$

Where Δ represents a first difference, i represents countries within the sample and t represents years. λ_t represents year effects and $\Delta\varepsilon_{it}$ represents the differenced error term. The first difference removes time invariant factors between countries and will show whether changes in education, digitalization, expenditure and economic development between years leads to changes in HDI. Changes in education, digitalization and public expenditure may not have an immediate effect on human development so one lag is added to create the second model:

$$\Delta HDI_{it} = \beta_1 \Delta EDU_{i,t-1} + \beta_2 \Delta DIG_{i,t-1} + \beta_3 \Delta HE_{i,t-1} + \beta_4 \Delta EE_{i,t-1} + \beta_5 \Delta lnGDP_{it} + \lambda_t + \varepsilon_i \quad (5)$$

This will show whether changes in education, digitalization, health and education expenditure in the previous period has an impact on HDI. This model contains 108 observations. To account for potential persistence in human development, a dynamic specification incorporates the lagged change in HDI:

$$\Delta HDI_{it} = \rho \Delta HDI_{i,t-1} + \beta_1 \Delta EDU_{i,t-1} + \beta_2 \Delta DIG_{i,t-1} + \beta_3 \Delta HE_{i,t-1} + \beta_4 \Delta EE_{i,t-1} + \beta_5 \Delta lnGDP_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Where ρ represents persistence in changes to human development. μ_i represents country fixed effects and λ_t represents year effects. This model contains 107 observations. However, due to the lagged dependent variable within fixed effects models a dynamic panel bias will occur so this model will be used as a supplementary model. A distributed-lag specification is employed to examine the contemporaneous and delayed associations of education and digitalization simultaneously:

$$\Delta HDI_{it} = \beta_1 \Delta EDU_{it} + \beta_2 \Delta EDU_{i,t-1} + \beta_3 \Delta DIG_{it} + \beta_4 \Delta DIG_{i,t-1} + \beta_5 \Delta HE_{it} + \beta_6 \Delta EE_{it} + \beta_7 \Delta \ln GDP_i + \lambda_t + \varepsilon_{it} \quad (7)$$

The model distinguishes the immediate relationship of education and digitalization with HDI from relationships occurring with a one-period delay. The distributed-lag model contains 100 observations. Joint significance tests are subsequently performed to determine whether the current and lagged education coefficients, and separately the current and lagged digitalization coefficients, are jointly different from zero.

The principal levels analysis employs a two-way fixed-effects (TWFE) estimator. Country fixed effects control for unobserved time-invariant heterogeneity across South Asian countries, while year fixed effects account for common shocks affecting the region in a particular year. The general TWFE model is specified as:

$$HDI_{it} = \beta_0 + \beta_1 EDU^C{}_{it} + \beta_2 DIG^C{}_{it} + \beta_3 (EDU^C{}_{it} \times DIG^C{}_{it}) + \beta_4 HE_{it} + \beta_5 EE_{it} + \beta_6 \ln GDP_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where μ_i represents country fixed effects, λ_t represents year fixed effects, and ε_{it} represents the idiosyncratic error term. The coefficient β_3 is of particular interest because it measures whether the association between education and HDI varies according to the level of digitalization. A positive and statistically significant β_3 would be consistent with a complementary relationship between education and digitalization. The principal moderation model includes education, digitalization, their interaction, health expenditure, education expenditure, and GDP per capita:

$$HDI_{it} = \beta_0 + \beta_1 EDU^C{}_{it} + \beta_2 DIG^C{}_{it} + \beta_3 (EDU^C{}_{it} \times DIG^C{}_{it}) + \beta_4 HE_{it} + \beta_5 EE_{it} + \beta_6 \ln GDP_{it} + \lambda_t + \varepsilon_{it} \quad (9)$$

To assess the main effects of education and digitalization independently of the interaction term, the following specification is estimated:

$$HDI_{it} = \beta_0 + \beta_1 EDU_{it} + \beta_2 DIG_{it} + \beta_3 HE_{it} + \beta_4 EE_{it} + \beta_5 \ln GDP_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

A third specification excludes GDP per capita while retaining the education–digitalization interaction:

$$HDI_{it} = \beta_0 + \beta_1 EDU^C{}_{it} + \beta_2 DIG^C{}_{it} + \beta_3 (EDU^C{}_{it} \times DIG^C{}_{it}) + \beta_4 HE_{it} + \beta_5 EE_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

This model will act as an important sensitivity check as HDI already includes an income related dimension. Comparing Models 5-7 will show whether the relationships between education, digitalization and their interaction are sensitive to controlling for income.

Empirical Results

In the empirical findings, Table 2 shows the summary statistics for the main variables. There was a total of 128 country-year observations. The mean value of HDI was 0.6078 (SD = 0.0948), ranging from 0.4650 to 0.7820. The mean education enrollment was 63.4537 (SD = 19.5126), showing a large amount of variation. There was a lot of variability in digitalization (M = 23.2222SD = 23.8970), ranging from 0.0710 to 90.0200. The mean health and education expenditure were 4.3807 (SD = 2.4317) and 3.3385 (SD = 1.3525). The mean log GDP per capita was 7.3473 (SD = 0.9711). Overall, it can be seen that there is quite a large spread of values with large standard deviations, especially in education enrollment and digitalization.

Table 2: ***Descriptive Statistics of the Principal Variables***

Variable	N	M	SD	Minimum	Maximum
Human Development Index	128	0.6078	0.0948	0.4650	0.7820
Education enrollment	128	63.4537	19.5126	21.7600	95.9100
Digitalization	128	23.2222	23.8970	0.0710	90.0200
Health expenditure	128	4.3807	2.4317	1.7720	12.6200
Education expenditure	128	3.3385	1.3525	1.1309	7.4698
Log GDP per capita	128	7.3473	0.9711	5.4109	9.4407

Source: *Authors' estimations based on the original observed-data sample. N = 128.*

Table 3 shows the pearson correlations between the variables. HDI was highly correlated with log GDP per capita (r=.8867, p<.05) and education (r=.8396, p<.05). There was a positive relationship between digitalization and HDI (r=.6829, p<.05). However, health and education expenditure were not statistically significant (r=.1731, p=.0507; r=.1429, p=.1077). There was a strong correlation between digitalization and log GDP per capita (r=.7463, p<.05). This shows that higher levels of education, digitalization and economic development tend to have higher levels of human development. However, these findings represent pooled bivariate correlations and do not account for country specific effects, time effects and other explanatory factors so should not be interpreted as causal relationships.

Table 3: ***Pearson Correlation Matrix***

Variable	1	2	3	4	5	6
1. HDI	1.0000					
2. Education	.8396*	1.0000				
3. Digitalization	.6829*	.6018*	1.0000			
4. Health expenditure	.1731	.1915*	.3020*	1.0000		
5. Education expenditure	.1429	.3732*	.4822*	.3793*	1.0000	
6. Log GDP per capita	.8867*	.6429*	.7463*	.2997*	.2372*	1.0000

Source: *Authors' estimations. N = 128. p < .05 for coefficients marked with an asterisk.*

Table 4 shows the short run panel results. Under the baseline first difference model (M1) digitalization had a positive and statistically significant relationship with changes in HDI (β = 0.000449), p=.023. Log GDP per capita also had a positive relationship with HDI (β = 0.020843), p=.040. Education, health and education expenditure did not have a statistically significant relationship (p>.05). The lagged first difference model (M2) showed that lagged health had a positive and statistically significant relationship with HDI (β = 0.002061), p=.021. Log GDP per capita also had a positive and significant relationship (SD = 19.51260), p=.001. Similar findings were found under the Dynamic Fixed Effects model (M3) where lagged health had a positive statistically significant relationship (SD = 19.51261), p=.008. Log GDP per capita also had a positive statistically significant relationship (SD = 19.51262), p=.002. However, the lagged dependent variable was not significant (β=-0.048111, p=.598). None of the coefficients were statistically significant under the distributed lag model (M4). Overall, it appears that the short run relationships are sensitive to the model chosen and the timing of variables. The Dynamic Fixed Effects results should be interpreted with caution.

Table 4: ***Short-Run Panel Estimates***

Predictor	M1: FD Baseline	M2: Lagged FD	M3: Dynamic FE	M4: Distributed Lag
Δ Education	0.000348 (.118)	—	—	0.000515 (.062)
Δ Education, t − 1	—	0.000064 (.826)	0.000015 (.962)	0.000371 (.245)
Δ Digitalization	0.000449 (.023)	—	—	0.000421 (.052)
Δ Digitalization, t − 1	—	0.000346 (.264)	0.000168 (.477)	−0.000069 (.681)
Δ Health expenditure	−0.001109 (.375)	—	—	−0.001462 (.152)
Δ Health expenditure, t − 1	—	0.002061 (.021)	0.002213 (.008)	—
Δ Education expenditure	−0.000768 (.381)	—	—	−0.001366 (.272)
Δ Education expenditure, t − 1	—	−0.000219 (.883)	−0.000514 (.764)	—
Δ Log GDP per capita	0.020843 (.040)	0.037934 (.001)	0.035880 (.002)	0.017771 (.164)
Δ HDI, t − 1	—	—	−0.048111 (.598)	—
Country fixed effects	Differenced out	Differenced out	Yes	Differenced out

Predictor	M1: FD Baseline	M2: Lagged FD	M3: Dynamic FE	M4: Distributed Lag
Year effects	Yes	Yes	Yes	Yes
Observations	109	108	107	100
R^2	.5155	.5636	.5718	.5674

Source: *Authors' estimations. Values in parentheses are country-clustered p values; eight country clusters were used.*

Table 5 shows the two-way fixed effects results using Driscoll-Kraay standard errors. Under Model 5 log GDP per capita had a positive statistically significant relationship with HDI (SD = 19.51263), p<.001. This remained positive and statistically significant under Model 6 (SD = 19.51264), p<.001. Education and digitalization were not significant. The interaction between education and digitalization was not statistically significant (SD = 19.51265), p=.190. This shows that there is no evidence that digitalization significantly moderates the relationship between education and HDI under the main model. When GDP was removed from the model (Model 7) education had a positive and statistically significant relationship with HDI (SD = 19.51266), p=.009. Health had a negative statistically significant relationship with HDI (β=-0.005980, p<.001). The interaction between education and digitalization was not statistically significant (β=-0.0000163, p=.187). It changed signs. Overall, the models had high within R-squared values (0.9438-0.9675) showing that the models explained a large portion of variation within the panel. However, the results should be interpreted with caution as HDI has an income and education component.

The insignificant difference (educational participation x digitalization) is statistically not significant, but it does give an important insight into the correlation between human development, educational participation and technological advancement in South Asian economies. If education and digitalization are supposed to complement each other, this is not the case for the empirical results, which do not show any statistically significant moderating relationship. The interaction coefficient is positive and non-significant (β = 0.0000175, p = .190) in Model 5, and negative and similarly non-significant (β = −0.0000163, p = .187) in Model 7. The reversed direction of coefficients further suggests sensitivity of the model to the presence of GDP per capita.

Table 5: ***Two-Way Fixed-Effects Models with Driscoll–Kraay Standard Errors***

Predictor	M5: GDP + Interaction	M6: GDP, No Interaction	M7: No GDP + Interaction
Education (centered)	−0.000300 (.472)	−0.000203 (.566)	0.000676 (.009)
Digitalization (centered)	−0.000104 (.835)	0.000304 (.269)	0.000650 (.169)
Education × Digitalization	0.0000175 (.190)	—	−0.0000163 (.187)
Health expenditure	−0.000470 (.730)	−0.001454 (.206)	−0.005980 (< .001)
Log GDP per capita	0.073814 (< .001)	0.060554 (< .001)	—
Education expenditure	0.004270 (.104)	0.004045 (.199)	−0.000177 (.960)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Driscoll–Kraay lag	3	3	3
Observations	128	128	128
Within R^2	.9675	.9653	.9438

Source: *Authors' estimations. Values in parentheses are Driscoll–Kraay p values (lag = 3). All models include country and year fixed effects.*

One potential explanation is the access–capability conversion paradox, which means that concurrent advances in educational participation and digital connectivity do not necessarily lead to additional benefits of human development. This paradox occurs when the quality of access does not keep pace with the quality of education, digital literacy and the quality of technological infrastructure and opportunities for productive use. Greater enrolment of children in schools in South Asian economies does not necessarily imply better actual learning outcomes (Asadullah & Chaudhury, 2015). Likewise, the provision of Internet access does not guarantee meaningful digital participation and productive technological engagement, especially in the context of socio-economic

inequalities and infrastructure constraints (Jamil, 2021; Mathrani et al., 2022). Moreover, the non-significant interaction effect might be a result of the limited measures of education and digitalization. Internet usage is a measure of connectivity, not the amount or quality of productive use of the Internet; secondary-school enrollments indicate participation in secondary school but not necessarily learning outcomes. As such, these proxies do not necessarily reflect the other side of the education–digitalization nexus. It is therefore not meant to be interpreted that education and digitalization cannot go hand in hand. Instead, they show that there is no complementarity that is statistically significant in the sample and model specifications observed. The proposed access–capability conversion paradox provides a tentative theoretical explanation for this finding, but further research with education quality indicators, digital skills, and measures of productive technology uses are needed to confirm the mechanism.

Table 6 shows the robustness of the baseline first difference model using the wild cluster bootstrap method (Webb) with 9999 replications and 8 country clusters. Digitalization remained positive (SD = 19.51267) however the p-value under the Webb bootstrap was exactly .0500. The confidence set for the 95% bootstrap confidence interval included zero (-0.00001235, 0.0007127). This therefore shows that there is borderline evidence of a positive short run relationship. Log GDP per capita was statistically significant under conventional cluster inference (p=.040) however was not statistically significant under bootstrap inference (p=.0982). Education (p=.1152), health (p=.4911) and education expenditure (p=.3941) were not statistically significant. Overall, there was less evidence of short run effects under bootstrap inference than conventional cluster inference. Caution should therefore be taken when interpreting the results due to the small number of country clusters.

Table 7 shows the joint significance tests for the current and lagged education and digitalization. The joint null hypothesis that education was not significant (current and lagged) was not rejected (F (2,7) =2.50, conventional p=.1520, Webb p=.1590). Digitalization was also not jointly significant (F (2,7) =2.87, conventional p=.1232, Webb p=.3208). This shows that there is not enough evidence to suggest that current and lagged values of education and digitalization are jointly significant in explaining short run changes in HDI

Table 6: ***Wild Cluster Bootstrap for the Baseline First-Difference Model***

Predictor	Coefficient	Clustered p	Webb Bootstrap p	Bootstrap 95% CI
Δ Education	0.000348	.118	.1152	[−0.00006908, 0.0008762]
Δ Digitalization	0.000449	.023	.0500	[−0.00001235, 0.0007127]
Δ Health expenditure	−0.001109	.375	.4911	[−0.006106, 0.004387]
Δ Education expenditure	−0.000768	.381	.3941	[−0.002992, 0.001456]
Δ Log GDP per capita	0.020843	.040	.0982	[−0.007029, 0.03962]

Source: *Authors' estimations. Webb weights with 9,999 replications and eight country clusters; N = 109.*

Table 7: ***Joint Tests in the Distributed-Lag Model***

Joint Null Hypothesis	Cluster-Robust F(2, 7)	Conventional p	Webb Bootstrap p
Δ Education = 0 and Δ Education, t − 1 = 0	2.50	.1520	.1590
Δ Digitalization = 0 and Δ Digitalization, t − 1 = 0	2.87	.1232	.3208

Source: *Authors' estimations. Webb wild cluster bootstrap uses 9,999 replications; N = 100.*

Table 8 compares the original observed sample (SD = 19.51268__) to the statistically completed panel (SD = 19.51269). The results changed substantially. Digitalization changed from a negative and insignificant coefficient (β=-0.000104, p=.835) to a positive and significant coefficient (M = 23.22220), p=.032. The interaction between education and digitalization changed from a positive

insignificant coefficient (M = 23.22221), p=.190 to a negative and significant coefficient (β=-0.0000151, p=.035). Health also changed signs and was now statistically significant (β=-0.000470, p=.730 became M = 23.22222, p=.031). Log GDP per capita remained positive and significant in both models (p<.001). This shows that some of the results are sensitive to how missing observations are handled. As the new observations were interpolated/extrapolated we can view these results as sensitivity evidence. The original observed estimates should therefore be used to make conclusions about the study.

Table 8: ***Sensitivity to the Statistically Completed Panel***

Predictor	Original-Data TWFE DK	Completed-Panel TWFE DK
Education (centered)	−0.000300 (.472)	−0.000170 (.376)
Digitalization (centered)	−0.000104 (.835)	0.000418 (.032)
Education × Digitalization	0.0000175 (.190)	−0.0000151 (.035)
Health expenditure	−0.000470 (.730)	0.001261 (.031)
Log GDP per capita	0.073814 (< .001)	0.052804 (< .001)
Education expenditure	0.004270 (.104)	0.007785 (.075)
Observations	128	200
Within R^2	.9675	.9197

Source: *Authors' estimations. Completed-panel results are reported only as a sensitivity analysis.*

Table 9: ***Variance Inflation Factors***

Predictor	VIF	Tolerance (1/VIF)
Log GDP per capita	2.95	.338938
Digitalization	2.95	.339277
Education	1.92	.521557
Education expenditure	1.60	.624282
Health expenditure	1.25	.798859
Mean VIF	2.13	—

Source: *Authors' estimations. VIFs are based on auxiliary pooled OLS and exclude fixed effects and the interaction term.*

Table 10 shows the Pesaran cross-sectional dependence test. The test statistic was -3.093 and the p-value was statistically significant (.0020). This means we can reject the null hypothesis that there was cross-sectional independence. The average absolute off diagonal residual correlation was 0.525 showing there was a fair degree of interdependence between residuals from each of the eight countries. This shows that the country specific disturbances are not independent. We can therefore use robust covariance estimators to account for cross-sectional correlation such as Driscoll-Kraay standard errors. However, this does not solve other econometric issues such as endogeneity.

Table 10: ***Pesaran Cross-Sectional Dependence Test***

Statistic	Value
Test statistic	−3.093
p value	.0020
Average absolute off-diagonal residual correlation	.525
Countries	8
Panel observations	128
Null hypothesis	Cross-sectional independence

Statistic	Value
Decision	Reject H_0

Source: *Authors' estimations. H_0: cross-sectional independence.*

Table 11 shows the Wooldridge test for first order serial correlation. The test was statistically significant (F (1,7) =40.500, p=.0004) meaning we can reject the null hypothesis that there was no first order autocorrelation. This shows that there is serial correlation within the countries. When combined with the significant cross-sectional dependence there is evidence to support the use of robust inferencing methods that account for both. We can therefore use Driscoll-Kraay standard errors under the two-way fixed effects models as this will allow us to make robust inferences. However, caution should be taken as the panel is relatively short and unbalanced.

Table 11: ***Wooldridge Test for First-Order Serial Correlation***

Statistic	Value
F statistic	40.500
Degrees of freedom	F (1, 7)
p value	.0004
Null hypothesis	No first-order autocorrelation
Decision at 1%	Reject H_0

Source: *Authors' estimations. H_0: no first-order serial correlation.*

Conclusion and Policy Recommendations with limitations

This study analyzes South-South relationships between education, digitalization, public expenditure, economic and human development in the eight South Asian countries between 2000 and 2024. The results showed that GDP per capita had the strongest positive and statistically significant relationship with human development through the use of various panel data estimation techniques and robustness checks. The correlation between these, however, should be read with caution as income is already part of the Human Development Index (HDI). The short-run relationship between digitalization and HDI was positive, but without significant strength when inferences were strong. Results on education and public expenditures were diverse for various model specifications. An important finding was the lack of a statistically significant interaction between education and digitalization in the original-data models, suggesting that there was not enough evidence to support an idea of complementarity. This discovery could be attributed to the proposed **access–capability conversion paradox**, which holds that an increase in the number of people enrolled in education or the internet does not necessarily translate into more human-development gains unless there is an improvement in educational quality, digital literacy, technology infrastructure and; the use of productive technology. This explanation is, however, a theoretical one and not empirically proven. There was also a switch in direction in the interaction between the panel and model specifications, and a large negative coefficient for the completed-panel sensitivity analysis that showed the importance of data quality and model specification. The overall results indicate that there is more to human development than increasing participation in education, connectivity via the internet and increasing public spending. Inclusive economic growth, quality education, meaningful digital inclusion, and allocation of public resources are South Asian priorities. The role of "quality of education", "digital competencies", and "institutional effectiveness" with regard to how education and digitalization can support human development together needs to be explored further.

Based on the findings the following policy recommendations can be made to improve human development in South Asia. Governments should encourage inclusive economic growth by creating employment opportunities, encouraging productive investment and supporting sustainable income generation. More should be done to improve digitalization by investing in digital infrastructure, affordable internet and digital skills. Education policies should look to improve education outcomes rather than just increasing school enrollment. This could include improving teacher training, quality of education and digital skills. Governments should also improve the efficiency of public expenditure on education and health. This could be achieved by improving resource allocation, monitoring and transparency. Instead of increasing public expenditure, policymakers should ensure they are making the best use of available public resources to improve education and health care.

This study has a few limitations. Firstly, there was a relatively small sample of eight South Asian countries. Missing observations also reduced the effective sample size. Secondly digitalization was only measured based on internet usage and education was not fully captured by school enrollment. Thirdly the relationships should be interpreted as associations rather than causal relationships as there may be reverse causality and omitted variable bias. There were also issues caused by cross-sectional dependence, serial correlation and few country clusters. Finally, the sensitivity analysis showed that there were noticeable changes in some of the coefficients under the statistically completed panel. The main conclusions of this study have been based on the original observed data.

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