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PAKISTAN'S PATH TO PROSPERITY: INTEGRATING DIGITIZATION AND EDUCATION FOR SUSTAINABLE ECONOMIC GROWTH

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Abstract
*Digitization and education are widely recognized as pillars of modern economic development. However, in the context of Pakistan, their interactive role in fostering sustainable growth is underexplored, with literature often treating them in isolation. This study addresses this research gap through an empirical analysis, utilizing ARDL methodology on time series data from 2005 to 2023. The result shows that in Pakistan, digitalization, education, interactive term of (DIGI*Edu) and gross fixed capital formation have positive effect on economic growth in long run. In contrast, inflation exhibits no significant long-run effect. The study concludes that for Pakistan to achieve higher economic growth, policymakers must concurrently invest in digital infrastructure, prioritize educational development, and foster a stable investment climate. The paper contributes to a more holistic framework for policymaking in the digital age.*

INTRODUCTION

In the contemporary landscape of rapid technological change and evolving economic paradigms, digitization and education have become indispensable drivers of sustainable economic growth. As the Fourth Industrial Revolution unfolds, nations that fail to synchronize their educational frameworks and technological infrastructure with these shifts risk economic obsolescence. For Pakistan, a country with a significant youth demographic and considerable human potential, the integration of digital tools into education is not merely an option but a critical prerequisite for achieving future prosperity. Empirical evidence consistently demonstrates that economic growth is positively influenced by both digitalization and education. Digital technology spurs innovation, enhances efficiency, and improves connectivity across various sectors (Yakubi et al., 2022; Hanif and Arshed, 2016). Concurrently, education equips individuals with the skills necessary to thrive in a digital economy, fostering creativity and boosting productivity. The synergy between these two domains is powerful; digital connectedness has transformed education, making learning more accessible and flexible through online platforms that overcome geographical barriers and build digital literacy (Haque et al., 2023; Nikolopoulou, 2023).

Digitalization is a recognized catalyst for economic growth, enhancing communication, facilitating financial transactions, and transforming e-commerce and business practices (Habibi and Zabardast, 2020). In developing nations, it has been pivotal since the early 2000s, reducing communication costs and extending services to underserved rural populations (Myovella et al., 2020). Pakistan exemplifies this potential, with internet usage surging from 20% in 2011 to 45.7% in 2024 and mobile subscriptions reaching 77.8% of the population (Global Digital Reports, 2024). However, this progress occurs against a backdrop of persistent challenges, including infrastructure deficits, gender inequality, and social equity issues that hinder resource mobilization (Ofori and Asongu, 2021). The COVID-19 pandemic further complicated this landscape, acting as a "great accelerator" for digital adoption by forcing rapid shifts to remote work and online education globally (Amankwah-Amoah et al., 2021). Yet, it also intensified the digital divide, exacerbating inequalities between privileged and underprivileged groups, urban and rural areas, and advanced and emerging economies (Beaunoyer et al., 2020; Karar, 2019). This disparity has limited access to digital opportunities in regions like Sub-Saharan Africa and the Middle East and adversely affected educational outcomes, as disadvantaged students face significantly greater challenges in remote learning compared to their wealthier peers (Deng and Hag, 2024; Miah, 2023).

Existing research provides robust evidence that digitalization and education independently promote economic growth in developing countries (e.g., Bibi et al., 2025; Habibi and Zabardast, 2020). However, within the specific context of Pakistan, a critical gap remains in understanding their interactive and dynamic effects specifically, how they jointly drive growth in both the short and long run. This study aims to fill that gap by investigating the synergistic relationship between digitization and education in accelerating Pakistan's economic growth.

Thus, this paper aims to fill that gap by investigating how the integration of digitization and education can accelerate economic growth in Pakistan and offering policy directions to realize this potential. The paper is structured as follows: a literature review, methodology, data analysis, conclusion and policy implications.

2. LITERATURE REVIEW

2.1. Theoretical Basis

Emerging in the 1980's, Endogenous Growth Theory (EGT) posits that economic development is generated from within the economic system, contrary to neoclassical models that rely on exogenous technological progress. Scholars like Lucas (1988) and Romer (1990) argued that investments in human capital, innovation, and knowledge are internal drivers of growth. Garicano and Rossi-Hansberg (2012) further demonstrated how businesses leverage communication technologies to manage information and knowledge, thereby fostering innovation and effective coordination. Theoretically, a strong positive correlation exists between human capital and labor productivity, underscoring education's critical role in enhancing labor quality, disseminating information, and facilitating technology adoption (Barro, 2013; Wang & Liu, 2016). Human Capital (HC) Theory reinforces this view, emphasizing that education, training, and skill development directly enhance individual productivity and, by extension, economic growth. This is aligned with the Sustainable Development Goals (SDGs), which stress the role of education in equipping individuals with the values, skills, and knowledge needed to address developmental challenges (Odhiambo, 2024). Robust human capital, cultivated through education, is a cornerstone of national economic success, driving growth, increasing incomes, reducing poverty, and boosting competitiveness (Hanif & Arshed, 2016). Complementing this, Technology Diffusion Theory (Rogers, 1962) explains how new technologies are adopted and integrated across a society. The theory holds that the pace and breadth of this adoption are critical to realizing productivity gains and growth. In Pakistan, the escalating penetration of mobile cellular subscriptions and internet access exemplifies this diffusion process. However, the benefits are not automatic; they are mediated by complementary factors including digital literacy, institutional quality, and the policy environment. The theory helps explain why the impact of digital tools may be uneven and delayed.

2.2. EMPIRICAL STUDIES

2.2.1. Digitization and Economic Growth

Digitization or ICT adoption has been shown in multiple global studies to boost growth via efficiency gains, new business models, and broader access to markets. Asma et al. (2024) employ panel data for 87 emerging economies (2000- 2023) and find that digital infrastructure significantly drives growth, especially when coupled with human- capital investments. Afonasova and Panfilova (2019) compared the digital economy of Russia with that of other European Union nations and concluded that in terms of Internet connectivity and its effects on GDP and social processes, the cross-country examination found considerable contrasts between Russia and the other EU countries. Results indicated that Russia is ranked among the top 10 nations in terms of ICT. Habibi and Zabardast (2020) compared the economic impact of education and ICT in ME and OECD countries using GMM and fixed-effect techniques on a dataset from 2000 to 2017. They found ICT positively influences economic growth in both regions. Mobile subscriptions have a greater impact in the ME, while internet users have less influence than OECD nations. Similarly, Myovella et al. (2020) examined the role of digitalization in SSA and OECD economies from 2006 to 2016 using GMM estimators. Their findings show digitization boosts economic growth in both regions, with mobile telecommunications having a greater impact in SSA, whereas broadband internet is more significant in OECD countries. Donou-Adonsou (2019) analyzed whether telecommunications infrastructure supports economic growth more in countries with better education access, using a panel of 45 SSA states from 1993 to 2015. The study found mobile phones do not significantly impact economic growth, but the internet does in better-educated nations. Mentsiev et al. (2020) claimed that it is almost impossible to imagine surviving in the past without access to the conveniences that modern society takes for granted. Novikova and Strogonova (2020) claimed that the digital economy is a key engine of economic growth and development in the Ural macro-region. In the context of digitalization, Nguyen (2023) stated that digital technology is an appropriate way for emerging economies to catch up with established economies. Progress in digital technology stimulates economic growth by lowering transaction costs and enhancing people's skills and knowledge. In order to promote long-term development, Liu et al. (2022) concluded that the digital economy has emerged as a critical tool for China's high-quality development, fostering technical innovation. Inna et al. (2021) looked over the impact of digital technologies on economic growth in Ukraine by focusing on areas that can accelerate digitalization to increase GDP. Stimulating IT development has significant prospects for activating digitalization processes and increasing GDP. The importance of the digital economy on Africa’s economic growth has been examined by Abendin and Duan, (2021) from year 2000 to 2018. The findings of the research have shown the positive effect of digitalization on trade and economic growth of African regions. In order to assess the growing trend of digitalization, Limna et al. (2022) found that the digital economy offers both opportunities and challenges to many countries' economic systems. Lu and Zhu (2022) executed research from 2013 to 2020 on the digital economy and high-quality development in 31 Chinese provinces. The researchers observed spatial correlation among optimal economic expansion, digital economy, and technological and scientific innovation. Moreover, the study suggested that high economic development could be sped up with digital economy development. The digital economy is growing at an exponential rate, particularly in underdeveloped countries. However, the digital economy's definitions and measures are inconsistent and constrained (Williams, 2023).

Some studies have posed a negative impact of digitalization on economic growth. For example, for 39 African nations, Solomon et al. (2020) examined how the use of digital technology affected nations. ICT usage has positive as well as negative impacts on growth. Furthermore, the study demonstrates that only individual usage has a positive influence.

2.2.2. Education and Economic Growth

Human capital theory positions education as a vital growth driver since it enhances labour productivity and innovation capability. Khan and Malik (2015) in their review found that education positively affects economic growth in Pakistan via multiple channels, though the magnitude varies by level of education and measurement proxies. More recently, Khan et al. (2023) observe that Pakistan's education system continues to fall behind regional peers, constraining growth prospects. Ahmad et al. (2022) indicated that prosperous economies are more common in nations with higher educational degrees.

Using a panel dataset from 1996 to 2009, Reza and Widod (2013) employed the aggregate production function to assess education's impact on economic growth in Indonesia. Their findings indicate that economic growth significantly benefits from the educational attainment of workers. According to the panel model, a 1 % increase in average worker education correlates with a 1.56 % rise in production. Hanif and Arshed (2016) analyzed panel data from SAARC nations (1960–2013) and found that tertiary education enrollment has the highest impact on growth compared to primary and secondary enrollments. Sebki (2021) investigated 40 developing countries (2002–2016) using dynamic panel data estimators and the difference GMM estimator, revealing that tertiary education significantly boosts economic growth, while secondary education has a negative effect. Ogundari and Awokuse (2018) examined HC's impact on economic growth in SSA, using education and health as metrics. Based on balanced panel data from 35 nations (1980–2008) and using the System GMM dynamic model, their study found that both metrics positively influence economic growth, with health contributing more significantly than education. Therefore, Ahmad et al. (2022) indicated that prosperous economies are more common in Hassan et al, (2020) analyze the impact of different levels of education of employed persons on level and growth of national output, agriculture, industry & services sector output in Pakistan analysis time series data for the years, 1985-2018. The method of analysis is the autoregressive distributed lag model (ARDL). Each level of education is found to have a positive effect on the output per employed person both in the short-run and long-run except for agriculture sector. In the agriculture sector, each education level is negatively associated. The deeper analysis showed that the greater negative effect of employment evades the positive effect of education in the agriculture sector. The comparison of different sectors shows that primary education contributes more to the industrial sector. While the contribution of the secondary & tertiary education is highest in the services sector.

2.2.3. Integration of Digitization and Education

The intersection of digitalization and education (often termed digital learning or edtech) is an emerging focal area. Aijaz et al. (2023) present a critical review of digital learning in Pakistan, showing that while online education holds promise for human-capital development, digital divides and institutional weaknesses hamper outcomes. The COVID-19 pandemic further exposed these gaps, Jamil & Muschert (2023) point to severe infrastructure constraints in Pakistani universities during the shift to e-learning. Correa and Esquivias, (2025) analysed the impact of digitalization, education, and institutional quality on economic growth by comparing Sub-Saharan Africa (SSA) and Middle East (ME) economies. Using an annual panel dataset from 2005 to 2021 for 14 SSA and 9 ME countries and the Pooled Mean Group (PMG) model, the study finds that digitalization, education, and institutional quality positively influence economic growth in both regions. The interaction between digitalization and education has a negative insignificant (i.e weak) impact, while the interaction between digitalization and institutional quality positively influences economic growth in both regions.

Donou-Adonsou (2019) found that the interaction between the Internet and education positively impacts economic growth, while the interaction between education and mobile phones has no significant impact. The sign and magnitude may depend on the level of development of the country or the region.

3. METHODOLODY

3.1. Data

This study employs a quantitative approach to analyze the impact of digitalization, education, gross fixed capital formation, and inflation on Pakistan's economic growth. We utilize an annual time series dataset spanning from 2005 to 2021. The dependent variable, economic growth, is proxied by GDP per capita (constant 2015 US$). The independent variables include a digitization index, education (% Gross enrollments, i.e. Secondary + Tertiary Education (% gross)), gross fixed capital formation (% of GDP), and the annual consumer price inflation rate. All data,were sourced from the World Development Indicators (WDI).

3.2. Model Specification

The foundational model for this research posits that GDP per capita is a function of digitalization, education, their interaction, gross fixed capital formation, and inflation. This relationship is specified as follows:

GDPPC = f (DIGI, Edu, DIGI*Edu, GFCF, Inf)

Where;

Digital Index

To capture the multifaceted nature of digitalization, a comprehensive Digital Index (DIGI) was constructed using Principal Component Analysis (PCA). This index synthesizes three key indicators:

1. Fixed broadband subscription (per 100 people)
2. Individuals using the Internet (% of population)
3. Mobile cellular subscription (per 100 people)

$$\ln \mathrm{GDPPC} = \beta_0 + \beta_1 \ln(\mathrm{DIGI}) + \beta_2 \ln(\mathrm{Edu}) + \beta_3 \ln(\mathrm{DIGI} * \mathrm{Edu}) + \beta_4 \ln(\mathrm{GFCF}) + \beta_5 \ln(\mathrm{Inf}) + \varepsilon t \quad \ldots\ldots (1)$$

In the above model, DPPC (economic growth) is the dependent variable while DIGI (digitization index), education (School enrollment, secondary, tertiary (% gross)), Gross fixed capital formation (% of GDP), Inflation, consumer prices (annual %) are independent variables.

3.3. Empirical Strategy: The ARDL Approach

To investigate both short-run and long-run dynamics, this study employs the Autoregressive Distributed Lag (ARDL) cointegration technique introduced by Pesaran et al. (2001). This method is selected for several key advantages: it can be applied irrespective of whether the variables are integrated of order I(0) or I(1) or a combination of both (Pesaran and Pesaran 1997). It performs well in small samples; and it allows for the derivation of a robust Error Correction Model (ECM).

The current study utilizes the ARDL (Autoregressive Distributed Lag) model, initially introduced by Pesaran et al. (2001), due to its flexibility in application regardless of whether the variables are integrated at level I(0), first difference I(1), or a mix of both (Pesaran & Pesaran, 1997). A key advantage of the ARDL model is its ability to incorporate an appropriate number of lags to effectively capture the dynamics of the data-generating process within a general-to-specific modeling framework (Laurenceson & Chai, 2003). Furthermore, the ARDL model allows for the derivation of an Error Correction Model (ECM) through a straightforward linear transformation (Banerjee et al., 1993). This ECM structure is valuable because it captures short-run dynamics while maintaining the long-run equilibrium relationship among variables (Pesaran & Shin, 1999). In addition, the ARDL technique demonstrates superior performance in small sample sizes compared to the Johansen and Juselius cointegration method (Pesaran & Shin, 1999). The ARDL approach to cointegration is carried out by estimating the following model:

$$\Delta \mathrm{GDPPC} = \beta_0 + \sum_{i=1}^{p} \psi_i \Delta \mathrm{GDPPC}_{t-1} + \sum_{i=1}^{p} \phi_i \Delta \mathrm{DIGI}_{t-1} + \sum_{i=1}^{p} \grave{W}_i \Delta \mathrm{Edu}_{t-1} + \sum_{i=1}^{p} \eta_i \Delta \mathrm{DIGI{*}Edu}_{t-1} + \sum_{i=1}^{p} \mu_i \Delta \mathrm{GFCF}_{t-1} + \sum_{i=1}^{p} \omega_i \Delta \mathrm{Inf}_{t-1} + \theta_1 \mathrm{GDPPC}_{t-1} + \theta_2 \mathrm{DIGI}_{t-1} + \theta_3 \mathrm{Edu}_{t-1} + \theta_4 \mathrm{DIGI{*}Edu}_{t-1} + \theta_5 \mathrm{GFCF}_{t-1} + \theta_6 \mathrm{Inf}_{t-1} + U_t \quad \ldots\ldots (2)$$

Where, β_0 represents the drift component, the variables retain their previously defined meanings, and U_t denotes the white noise error term. The first step in applying the ARDL bounds testing approach is to assess whether a long-run relationship exists among the variables using F-tests. The null hypothesis H_0: $\ddot{Y}_1 = \ddot{Y}_2 = \ddot{Y}_3 = \ddot{Y}_4 =$

$\ddot{Y}_5 = 0$ implies that no long-run relationship exists, while the alternative hypothesis H_1: $\ddot{Y}_1 \neq 0$, $\ddot{Y}_2 \neq 0$, $\ddot{Y}_3 \neq 0$, $\ddot{Y}_4 \neq 0$, $\ddot{Y}_5 \neq 0$ suggests the presence of such a relationship.

To evaluate this, the calculated F-statistic is compared against two critical value bounds provided by Pesaran et al. (2001): one assuming all variables are I(0), and the other assuming I(1). If the F-statistic exceeds the upper bound, the null hypothesis is rejected, confirming cointegration. If it falls below the lower bound, the null cannot be rejected. If it lies between the bounds, the result is considered inconclusive. To determine the optimal lag length for each variable, the ARDL approach estimates $(p+1)^k$ regressions, where p is the maximum lag and k is the number of regressors. Model selection is based on Schwarz Bayesian Criterion (SBC) and Akaike Information Criterion (AIC). If a long-run relationship is confirmed, the corresponding Error Correction Model (ECM) is then estimated.

$$\Delta GDPPC = \beta_0 + \sum_{i=1}^{p} \psi_i \Delta GDPPC_{t-1} + \sum_{i=1}^{p} \phi_i \Delta DIGI_{t-1} + \sum_{i=1}^{p} \grave{W}_i \Delta Edu_{t-1} + \sum_{i=1}^{p} \eta_i \Delta DIGI{*}Edu_{t-1} + \sum_{i=1}^{p} \mu_i \Delta GFCF_{t-1} + \sum_{i=1}^{p} \omega_i \Delta Inf_{t-1} + \alpha\, ECM_{t-1} + U_t \quad (3)$$

The ECM outcome shows the speed of adjustment back to long-run equilibrium after a short-run shock.

4. EMPIRICAL RESULTS

4.1. DESCRIPTIVE STATISTICS

Prior to empirical testing, descriptive statistics are calculated to summarize the core properties of the dataset. The analysis covers the period 2005–2023 and includes the following variables: the dependent GDP per capita (constant 2015 US$), the key independent variables are Digitization index (DIGI), education (% Gross enrollments, i.e. Secondary + Tertiary Education (% gross)), gross fixed capital formation (% of GDP), and inflation rate. Table 1 summarizes the descriptive statistics for these variables, providing measures of central tendency (mean, median), dispersion (standard deviation), and distributional shape (skewness, kurtosis). The Jarque-Bera statistic is also reported to test for normality. This initial overview aids in comprehending the dataset's fundamental properties and its suitability for subsequent econometric analysis which help to comprehend the statistical impact of integrating Digitization and Education on the economic growth of Pakistan.

Table 1: Descriptive Statistics

	LNGDPPC	DIGI	LNGSE	LNDIG*GSE	LNGFCF	LNINF
Mean	7.236021	0.2347642	3.663768	-0.503768	2.652306	2.201810
Median	7.202890	-0.067900	3.693534	-2.830919	2.646241	2.250893
Maximum	7.403841	0.838472	3.981163	28.88705	2.807728	3.426479
Minimum	7.091104	-1.949032	3.131767	-44.66098	2.518091	0.927954
Std. Dev.	0.107187	0.676385	0.239709	22.85099	0.085852	0.608509
Skewness	0.289041	-1.163368	-0.653286	-0.501900	0.363036	-0.11698
Kurtosis	1.473075	4.575675	2.710492	2.120742	2.037030	2.929007
Jarque-Bera	2.110330	6.251355	1.417831	1.409728	1.151473	0.047327
Probability	0.348135	0.043907	0.492178	0.494176	0.562291	0.976614
Sum	137.4844	0.0222324	69.61033	-9.571593	50.39382	41.83439
Sum Sq. Dev.	0.206802	8.234945	1.034286	9399.019	0.132671	6.665093
Observations	**19**	**19**	**19**	**19**	**19**	**19**

Source: Author's own computations

4.2. CORRELATION OF KEY VARIABLES FOR PAKISTAN

A correlation analysis was conducted to examine the preliminary bilateral relationships between the variables and to check for potential multicollinearity. The results, presented in Table 2, reveal the initial associations. Economic growth (EG) shows a strong positive correlation with its primary drivers: the Digitization index (DIGI), Gross School Enrollment (lnGSE), their interactive term (DIGI*GSE), and Gross Fixed Capital Formation (GFCF). Conversely, Inflation (lninf) is negatively correlated with economic growth, indicating its adverse impact. As a rule of thumb, a correlation coefficient exceeding 0.80 suggests significant multicollinearity. Since all pairwise correlations in our model remain below this critical value (see Table 2), we conclude that multicollinearity is not a severe issue for the subsequent regression analysis.

Table 2: Correlation Matrix

	lnGDPPC	DIGI	lnGSE	DIGI*GSE	lnGFCF	lnInf
lnGDPPC	1					
DIGI	0.3176644	1				
lnGSE	0.68457237	0.02817378	1			
DIGI*GSE	0.54873903	0.50023726	-0.2160028	1		
lnGFCF	0.44155834	0.15402041	-0.6465509	0.25455935	1	
lnInf	-0.0476206	-0.0540040	0.09894069	-0.1696672	-0.1549333	1

Source: Author's own computations

4.3. RESULTS OF VARIANCE INFLATION FACTOR

The results of the Variance Inflation Factor (VIF) analysis are presented in Table 3. The recorded VIF values for all independent variables are substantially below the commonly accepted threshold of 10. This provides strong evidence that the model is free from harmful multicollinearity, ensuring the reliability of the coefficient estimates.

Table 3: Variance Inflation Factor

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
DIGI	0.001839	41.12773	41.12773
lnGSE	0.002009	1397.005	5.642701
DIGI*GSE	0.00000167	42.68379	42.66191
lnGFCF	0.006407	2328.341	2.308825
lnInf	0.00008213	22.02183	1.485956
C	0.126968	6552.541	NA

Source: Author's own computations

4.4. STATIONARITY ANALYSIS

To determine the order of integration, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were conducted. The results, summarized in Table 4, indicate that the series are a mixture of stationary and non-stationary processes. Specifically, Digitalization (DIGI) and Education (lnEdu) were found to be stationary at level I(0). The remaining variables, namely GDP per capita (lnGDPPC), the interaction term (DIGI*Edu), Gross Fixed Capital Formation (lnGFCF), and inflation (inf), contained a unit root at level but achieved stationarity after first differencing, confirming they are I(1). This mix of I(0) and I(1) variables satisfies a key precondition for employing the Autoregressive Distributed Lag (ARDL) modeling approach, which is well-suited for analyzing cointegration and the short- and long-run relationships in such datasets.

Table 4: Results of Unit Root Tests

Variables	At Level		1st Difference		Conclusion
	ADF	PP	ADF	PP	
lnGDPPC	-0.318597	-0.354235	-3.262937**	-3.222323**	I(I)
DIGI	-3.272049**	-3.272049**	-7.150588***	-17.91686***	I(0)
lnEdu	-3.410079**	-3.770158**	-4.183944***	-4.183944***	I(0)
DIGI*Edu	-1.367477	-1.821155	-3.629221***	-6.067009***	I(I)
lnGFCF	-1.403547	-1.403547	-4.5956688***	-4.626817***	I(I)
lnInf	-1.026399	-1.079545	-4.117703**	-4.117542**	I(I)

Source: Author's own computations

4.5. Bounds Test for Cointegration

To investigate the existence of a long-run equilibrium relationship among the variables, the ARDL bounds testing approach was employed. As reported in Table 5, the calculated F-statistic is 9.446, which is greater than the upper critical values at all conventional significance levels (1%, 2.5%, 5%, and 10%). This leads to the rejection of the null hypothesis of no cointegration, confirming a stable long-run relationship. This finding justifies the subsequent estimation of both the long-run coefficients and the short-run error correction model.

Table 5: Bound Test

F-Bound test	Null Hypothesis = No levels relationship	
F-statistic = 9.446255		
Significance	Lower bound I(0)	Upper bound I(I)
10%	3.02	3.51
5%	3.62	4.16
2.5%	4.18	4.79
1%	4.94	5.58

Source: Author's own computations

4.6. Long run estimation of coefficients

The long-run coefficients derived from the ARDL model are presented in Table 6. The analysis reveals the following key findings on the drivers of economic growth in Pakistan:

The coefficient for digitization (DIGI) is positive and highly significant. A 1% increase in the digitization index leads to a 0.19% rise in GDP per capita, significant at the 1% level. This aligns with existing literature (e.g., Habibi & Zabardast, 2020; Myovella et al., 2020), confirming that technological adoption fosters economic growth. Digital advancement results from enhanced infrastructure investment, government initiatives, and improved access to technology and education. Education (EDU) demonstrates a strong positive impact, with a 1% increase associated with a 0.59% rise in economic growth (significant at the 1% level). This finding supports the pivotal role of human capital, as emphasized by Hanif & Arshed (2016) and Wang & Liu (2016), wherein education enhances productivity, technological absorption, and innovation.

Education (EDU) has a greater positive impact on economic growth. It means that Education (EDU) increases economic growth by 0.59 significant at the 1 % level, supporting (Hanif & Arshed, 2016; Wang & Liu, 2016), who noted education's critical role in economic growth. The benefits from advanced education systems, better alignment with labor markets, and superior economic resources, enhancing educational investment. This boosts economic growth (EG), improves living conditions, and reduces Indigenous poverty. Education also influences technology absorption and local innovation Sebki (2021), shaping employment and income growth (Woessmann, 2016). Ignoring education threatens future prosperity, leading to poverty and social isolation. Habibi and Zabardast (2020) highlighted that education positively influences economic development, employability, and behavior, fostering a supportive environment for investments. While fostering a conducive environment for investments.

Contrary to expectations, the interaction term between digitization and education (DIGI*EDU) has a significant negative coefficient. A 1% increase in this term reduces economic growth by 0.04%. This adverse effect may stem from significant skill-job mismatches in the labor market, where the workforce's education does not align with the demands of a digitizing economy (Zainal Abidin et al., 2024; Correa and Esquivias, 2025). Furthermore, a pervasive digital divide may be exacerbating inequality and limiting the broader economic benefits of digital transformation. This divide effects dependence of industries on digital technologies, decreasing work opportunities resultantly enhancing unemployment. improper connectivity of net impedes investment, lowering economic growth, and spread socioeconomic discrepancy, perpetuating rising mobility (Beaunoyer et al., 2020; Karar, 2019).

As anticipated, Gross Fixed Capital Formation (GFCF) has a significant positive impact, with a coefficient of 0.332. This underscores the continued importance of sustained investment in infrastructure, technology, and capital goods for driving long-term economic growth. The reason may be that a country has capacity to save and expend more on investment beyond the given total income, which promote to surge yield, income export, and employment opportunity and stimulate economic well-being (Zahir and Rehman, 2019).

The coefficient for inflation is small and insignificant negative relationship with economic growth suggests that inflation has no effect. Hussain (2020), who contended that inflation, leads doubts in economic decision-making, decreasing consumer and business expenses because of reduced purchasing power. This harmful influence of inflation is also buoyed by Moodley and Pillay (2024), who witnessed same tendencies in South Africa, where high inflation rates linked with decreased economic growth.

Table 6: Long Run ARDL Estimations

	Dependent variable = ln GDP per capita			
Variable	coefficient	Std. Error	t-stat	p-value
C	7.250933	0.009796	740.1936	0.0000
DIGI	0.199742	0.009970	-20.03477	0.0000
lnEDU	0.594497	0.062155	9.564781	0.0000
DIGI*Edu	-0.041308	0.000326	-12.70533	0.0000
lnGFCF	0.332139	0.080044	4.149476	0.0011
lnInf	-0.005696	0.008803	-0.647103	0.5280

Source: Author’s own computations

4.7. Short Run Equilibrium Model

The short-run analysis revealed that GDP per capita (GDPPC) was significantly influenced by digitization, education, the interaction of digitization and education (DIGI*Edu), gross fixed capital formation (GFCF), and inflation. Digitization exhibited small but mixed effects on economic growth, positively impacting GDPPC in the current period, while continuing to show a positive effect in the first and second lags. This trend highlights a time lag in skill utilization, where foundational education gradually enhances productivity and delivers benefits over time.

The coefficient of the first difference in education (D(lnEdu)) was positive and significant, indicating that increased enrollment in secondary and tertiary education had an immediate positive impact on economic growth in Pakistan.

However, the interactive term of digitization and education (DIGI*Edu) presented a mix pattern. In the first difference, it was negative and insignificant; in the first lag, positive but insignificant; and in the second lag, negative and significant. This suggests that digitization alone may not foster growth when educational attainment is low or when its benefits are delayed due to implementation lags or skill gaps.

Gross Fixed Capital Formation (GFCF) showed a positive effect on GDPPC in the short run, especially in its first difference and first lag. This implies that increased investment in infrastructure, industry, and capital assets enhances short-term output, employment, and income has critical drivers for a developing economy like Pakistan.

Inflation had a minor, negative, and statistically insignificant impact on GDPPC in both the first difference and first lag, suggesting that while low to moderate inflation may have minimal effect, higher inflation levels could be detrimental to growth.

Overall, the model demonstrated strong explanatory power, accounting for 73.32% of the variation in GDPPC (R-squared = 0.733268). The Durbin-Watson statistic of 2.196124 confirmed the absence of autocorrelation, reinforcing the reliability of the model's findings. The results reveal that the Error Correction Model has a negative value of -0.5728, showing that when disequilibrium happens, it will be corrected within 57% of a year.

Table 7: Short Run ARDL Estimations

	Dependent variable = ln GDP per capita			
Variable	**coefficient**	**Std. Error**	**t-stat**	**p-value**
D(lnGDPPC(-1))	0.326310	0.177455	1.838828	0.1032
D(lnGDPPC(-2))	0.238643	0.220907	1.080287	0.3115
D(lnGDPPC(-3))	0.981304	0.267646	3.666430	0.0063
D(DIGI)	-0.061036	0.025054	-2.436157	0.0507
D(DIGI (-1))	0.057428	0.028011	2.050194	0.0862
D(DIGI (-2))	-0.033814	0.015442	-2.189692	0.0711
D(lnEDU)	0.549220	0.232656	-2.360649	0.0459
D(DIGI*Edu)	-0.001523	0.000641	-2.376686	0.0550
D(DIGI*Edu (-1))	0.000207	0.000646	0.320217	0.7597
D(DIGI*Edu (-2))	-0.001796	0.000524	-3.429864	0.0140
D(lnGFCF)	0.141955	0.064925	2.186441	0.0650
D(lnGFCF(-1))	0.257519	0.085810	3.001045	0.0199
D(lnInf)	-0.011645	0.010164	-1.145754	0.2786
D(lnInf(-1))	-0.024971	0.013110	-1.904781	0.0859
CointEq (-1)	-0.57280	0.167296	-6.146952	0.0008
R-squared	0.733268		**Durbin-Watson stat**	2.196124
Adjusted R-squared	0.585084		**F-stat (Prob)**	99.1690 (0.0000)

Source: Author's own computation

4.8. DIAGNOSTIC TESTS

4.8.1. MODEL DIAGNOSTICS

To ensure the robustness of the ARDL model, standard post-estimation diagnostic tests were performed. As summarized in Table 8, the results are satisfactory. The null hypothesis of no serial correlation is not rejected by the Breusch-Godfrey test, and the Breusch-Pagan-Godfrey test finds no evidence of heteroskedasticity. Furthermore, the Ramsey RESET test supports the correct functional form of the model. The absence of these common econometric issues confirms that the estimated relationships between the variables are statistically reliable.

Table 8. Diagnostic Test of Model

Problem	Estimation	F. Test	Prob.	Results
Autocorrelation	LM Test	0.256368	0.7784	Accepted Null Hypothesis/ No Autocorrelation
Heteroskedasticity	Breusch-PaganGodfrey	0.104321	0.9894	Accepted Null Hypothesis/ No Heteroscedasticity
Specification of Model	Ramsey Reset Test	0.026542	0.7254	Accepted Null Hypothesis/ No Specification error

Source: Author's own computations

4.8.2. STABILITY TEST

The model's parameter stability was assessed using the CUSUM and CUSUM of Squares tests. The results indicate that the cumulative sum of recursive residuals and their squares both remained within the 95% confidence bands for the entire study period. This confirms the absence of significant structural breaks and validates the model's robustness, thereby supporting the use of its estimates for deriving policy implications.

Figure 1

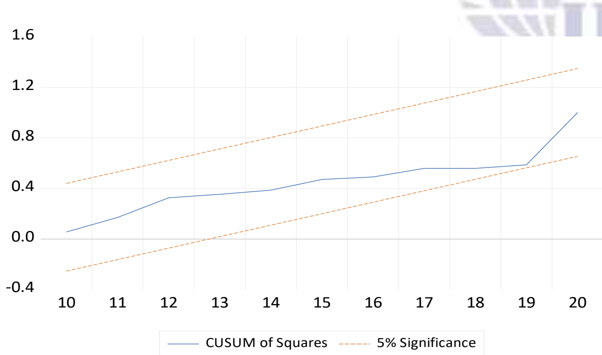
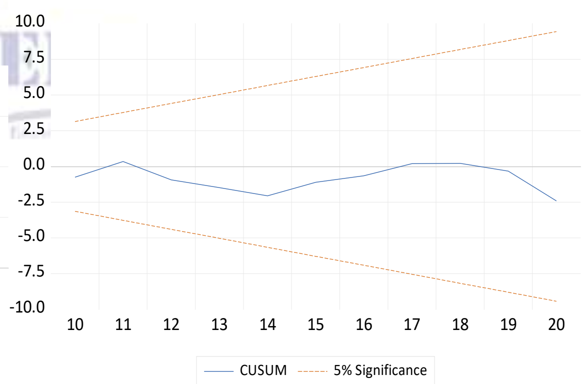


Figure 2



5. CONCLUSION

This study used the ARDL cointegration approach to examine the impact of integrating digitization and education, gross fixed capital formation (GFCF) and inflation on Pakistan's economic growth. Key findings include:

In the long run

- ➢ Digitization positively influenced economic growth (GDPPC).
- ➢ Education had significant positive impacts on economic growth (GDPPC).
- ➢ Interactive term of digitization and education (DIGI*Edu) has a positive and significant relationship with economic growth (GDPPC).
- ➢ Gross fixed capital formation (GFCF) had a significant positive effect on economic growth (GDPPC).
- ➢ Inflation was found to have an insignificant long-run impact on economic growth (GDPPC).

In the Short Run

➢ Digitization showed small but mixed effects on GDPPC.

➢ Education is positive and significant in the short run. This suggests that education boosted economic growth in Pakistan with immediately.

➢ Interactive term of (DIGI*Edu) is insignificant indicating digitalization fails to boost growth when education is low, or the benefits are delayed.

➢ Gross Fixed Capital Formation (GFCF) positively affected GDPPC in the short run.

➢ Inflation had a negative and insignificant impact on per capita GDP. This suggests that low/moderate inflation has negligible effect, but high inflation harms growth.

POLICY RECOMMENDATIONS

The study's findings suggested the following policy implications:

➢ Investments in digital infrastructure and technology utilization should be made to boost the growth of Pakistan economy.

➢ The government should prioritize education highlight for better education facilities within the country to achieve higher economic growth.

➢ Encouraging investment (public & private) can enhance growth quickly.

➢ Keep inflation low to moderate to avoid harmful side-effects.

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