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Do Digitalization and Innovation Accelerate Productivity? A Comparative Analysis of Four Asian Countries

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Abstract: *Productivity growth has remained slow in Asian countries. The study examines the impact of digitalization and innovation on output productivity in four Asian countries: China, India, Bangladesh, and Pakistan, using data from 1990 to 2022. The panel autoregressive distributed lag (ARDL) model was employed to investigate the long-run relationship between the variables. The study implements the Fully Modified OLS (FMOLS) method for robustness checks. The long-run results show that digitalization and innovation have a positive and significant impact on productivity in each country. Human capital, foreign direct investment (FDI), and trade openness also have a significant impact on productivity. The panel ARDL result shows that digitalization, innovation, human capital, trade openness, and FDI significantly affect productivity in the long run. The study recommends encouraging investments in digital infrastructure, inventions, and innovations across various economic sectors, including R&D activities, fostering industry-academia collaborations, and technological advancements. These countries should also invest in education, technical, and vocational training to improve labor productivity and efficiency.*

Keywords: Productivity, innovation, digitalization, human capital, FDI, panel ARDL, Aisa.

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1. Introduction

Productivity growth had been declining in Asia before the COVID-19 pandemic. Total factor productivity (TFP) and labor productivity (output per worker) are measures of economic efficiency, and both have been trending downward (Dabla-Norris et al. 2023). TFP growth in emerging and developing nations has slowed significantly since the global financial crisis, compared to advanced economies (Van Ark et al., 2008). As a result, the productivity levels of many Asian nations remain below the global productivity frontier, as measured by the total factor productivity (TFP) of the United States (Syverson, 2017). The productivity slowdown initially appears perplexing because it happened at the same time as observable improvements in digital technology and innovation in the area. Digital technology gives businesses access to new resources and methods for creating, producing, and distributing products and services. In recent years, technological advancements in various fields, including ridesharing, digital financial technology, e-commerce, and mobile app-enabled services, have sparked a new wave of innovation and a rapid rise in digitalization. Yet, the acceleration of digital technology and innovation has not been able to reverse the downturn in overall productivity in Asia (Brynjolfsson & Hitt, 2000).

Digitalization has a dynamic and wide-ranging effect on productivity. Digitalization can greatly increase productivity by streamlining procedures, reducing human error, and automating repetitive tasks. It is also encouraging innovation by opening new avenues for product development, new methods of working, and new business models that may be implemented across a variety of industries (Economic and Social Commission for Asia and the Pacific (ESCAP), 2024, p. 5). The productivity disparities between enterprises and the advancement of the technological frontier are both necessary for increasing overall productivity. Yet, a nation's TFP growth is contingent upon the extent to which technology and innovation are integrated among its firms. The disparity in TFP and technology across Asia's highest- and lowest-performing businesses is likely due to slow diffusion within countries. It is essential to analyze the factors that affect TFP dispersion acrossemployrs and the characteristics of lagging firms in Asian countries (Dabla-Norris et al. 2023).

In Asia, digitalization and innovation are significant forces that influence firm-level productivity. The association between innovation intensity, measured as research and development (R&D) costs per worker, and productivity at the firm level has long been acknowledged in economic literature. High R&D intensity results in technological advancements, thereby enhancing TFP. By improving the effectiveness of activities, the digitalization of manufacturing processes can boost total productivity. However, to fully reap the benefits of digitalization, it may be necessary to make complementary investments in factors and skills, such as software and data, which are significant components of many organizations' intangible capital (Nahar, 2024). Unlike tangible capital, intangibles are easily scaled up at a low cost and allow businesses to grow rapidly. According to studies conducted in other locations, businesses that invest heavily in intangible assets experience the fastest increases in productivity. Intangibles also help to translate technological advancements into higher output (Yuhn & Park, 2010; Mohnen & Hall, 2013).

Over the past few decades, many studies have looked at how innovations affect the employment and productivity of firms. It is expected that technological advancement will raise productivity, which is a measure of technology's economic contribution. The "productivity paradox" proposed by Brynjolfsson (1993) states that although firms in the 1990s were keen to invest in ICT, the productivity gains were small. A few possible factors include redistribution, profit-dispersal, learning and adapting, and ICT management. Many innovation types, such as organizational, marketing, process, and product innovations, significantly increase firm productivity (Mohnen & Hall, 2013; Fazlıoğlu et al., 2019).

The selected countries, i.e. China, India, Pakistan, and Bangladesh, are emerging and developing economies of the largest continent of Asia in the world. Each country has its own economic and political importance. All four countries are developing economies with a large population and a growing middle class. They are all located in South Asia, with strategic access to the Indian Ocean and potential trade routes. Each country has a rich cultural heritage and diverse linguistic, religious, and ethnic groups. China has the largest economy, followed by India, Pakistan, and Bangladesh. Bangladesh is a growing economy, largely dependent on textiles and remittances. China is a large and rapidly growing economy, driven by manufacturing, technology, and infrastructure development. India is a diverse economy with a growing service sector, significant agricultural production, and a large diaspora. Pakistan is a struggling economy, heavily reliant on agriculture, and faces challenges such as the law and order situation and political instability.

Bangladesh has a growing startup ecosystem, an increased focus on digitalization and ICT development, and government initiatives such as the “Digital Bangladesh” vision. China is the global leader in innovation and digitalization, with significant investments in AI, 5G, and renewable energy, large-scale adoption of digital payments and e-commerce, and government support for tech industries and startups. Similarly, India is a rapidly growing digital economy, with an increased focus on digitalization and innovation in industries such as IT and pharmaceuticals, as well as government initiatives like “Digital India” and “Startup India”. Pakistan is a growing startup ecosystem, especially in fintech and e-commerce, with an increased focus on digitalization and innovation in industries like textiles and agriculture, and government initiatives like the “Digital Pakistan” vision. However, Bangladesh, India, and Pakistan face challenges due to infrastructure limitations and low internet penetration. In recent times, these economies have been investing in innovation and digitalization, especially China and India. Each country aims to become a digital- and innovation-based economy.

The basic research question is: What are the impact mechanisms of digitalization (ICT) and innovation (patent applications) on productivity in selected Asian countries? This research question examines the interplay between digitalization, innovation, and productivity (the efficiency and effectiveness of economic output). The feasible option for a country to accelerate productivity growth is to have tangible capital, i.e., labor, capital, trade openness, human capital, and FDI, as well as intangible capital such as innovation and digitalization (ICT). The rapid growth of ICT has transformed the way businesses operate, governments function, and societies interact. In the context of developing countries, ICT has been touted as a key driver of productivity. Inventions and innovations in various sectors of the economy, such as R&D, and providing incentives for technological advancements to improve productivity. In addition, FDI inflow and trade openness increase productivity through the flow of inventions, capital, and expertise from industrialized to emerging nations. Moreover, trade allows countries to specialize in industries where they have a comparative advantage, potentially leading to higher productivity and competitiveness in those sectors. Additionally, FDI offers capital and resources that can be invested in R&D, education, and infrastructure, which are essential for accelerating TFP. A country invests in education and technical and vocational training to enhance its human capital, thereby boosting labor productivity and efficiency. Expenditure on tertiary education will further increase innovation, inventions, R&D activities, and the use of digitalization. Our results demonstrate that digitalization and innovation influence TFP positively in selected countries. Human capital, trade openness and FDI have a significant and positive impact on TFP in selected countries. These countries should invest in digital infrastructure, innovations in various sectors of the economy, such as R&D activities, and technological advancements. These countries should also invest in education and technical and vocational training to enhance labor productivity and efficiency. Our findings have significant ramifications for policy and practice, ultimately aiming to support the achievement of the United Nations' Sustainable Development Goals (SDGs) No. 8 (decent work and economic growth) and No. 9 (industry, innovation, and infrastructure).

This study addresses the research gap by providing a comprehensive comparative analysis of the relationship between innovation, digitalization, and productivity in four Asian countries, contributing to the literature in several ways: First, existing studies have primarily focused on developed economies or specific regions, overlooking the Asian context, particularly Bangladesh, China, India, and Pakistan. We are addressing the lack of research in this region. Second, the comparative case study approach provides rich contextual insights, enabling the identification of patterns, similarities, and differences across countries. Third, by employing both time series and panel analysis, this research offers a more nuanced understanding of the complex relationships between digitalization, innovation, human capital, trade openness, FDI, and productivity. Fourth, this study employs contemporary techniques, including cross-sectional dependency, CIPS, the Kao test for co-integration, and panel ARDL, to ensure reliable and robust results. Fifth, this research extends the theoretical understanding of digitalization, innovation, and productivity, offering implications for policymakers, practitioners, governments, and academicians.

The remaining article is presented as follows: The literature review is presented in Section 2. The empirical model and methodology are presented in Section 3. The results are discussed in Section 4, and the study's summary and conclusion are presented in Section 5.

2. Literature Review

2.1 Innovation and Productivity

In recent literature, numerous studies have shown that innovation (creativity) and productivity have a positive association (Gehringer et al. 2016; Saleem et al. 2019; Sobieraj & Metelski, 2021; Chakraborty et al. 2024). Similarly, Comin (2004) assessed the impact of R&D spending on productivity growth. Consequently, US productivity increases with an increase in R&D spending. Similarly, Rehman and Islam (2023) found that actions leading to higher levels of firms' productivity include human capital, FDI, trade openness, product innovation, and learning through exporting. Furthermore, previous studies found that productivity growth is affected by many factors such as innovation, digitalization, human capital, investment, trade openness, FDI and inflation (Seo & Lee, 2006; Gehringer et al. 2016; Saleem et al. 2019; Ahmad, 2021; Sobieraj & Metelski, 2021; Pradhan et al. 2021; Gaglio et al. 2022; Choi & Park, 2024).

Researchers examine various determinants of productivity growth to evaluate their impacts. Innovation is crucial for all types of businesses, whether new or established, as it plays a major role in production. The underperformance of Europe's innovation in comparison to the US has been traced to investments in ICT and R&D. Data from four consecutive waves of an Italian manufacturing company's panel data were used by Hall et al. (2013). Furthermore, the study adapts the CDM model to include R&D and ICT investment as the two main drivers of productivity and innovation. A significant association has been discovered between productivity and innovation. Investment in R&D and ICT is becoming increasingly important for productivity. In this connection, Friesenbichler and Peneder (2016) found that firm productivity appears to be most strongly driven by foreign ownership and innovation, using data from Eastern Europe and Central Asia. The exports, population density, and company size all have additional favorable effects on productivity. Another study by Morris (2018) analyzed the connections between innovation and the productivity of a firm using a cross-country panel dataset. According to the findings, innovative businesses exhibit significantly higher levels of economic productivity in the manufacturing and services sectors.

Similarly, Fazlıoğlu et al. (2019) examined Turkish manufacturing firms that differentiate between several innovation typologies and the systematic effects of firms' innovation efforts on productivity growth from

2003 to 2014. The study's conclusion suggests that there is variation among firms in their inclination to innovate, as well as their ability to profit from such endeavors. According to findings, innovation activity boosts a firm's productivity as compared to non-innovating enterprises. Another study by Saleem et al. (2019) analyzed factors affecting TFP in Pakistan. Manufacturing activities focused on exports and labor-intensive technologies have been the primary drivers of economic expansion. Nevertheless, TFP is determined from the Cobb-Douglas production function (CDPF). For this analysis, time series data were used from 1972–2016. The result found that Pakistan's productivity and economic growth were greatly affected by innovation. In the same way, Jitsutthiphakorn (2021) examined the relationship between business productivity and export survival, and innovation in influencing firm productivity. The panel database has been used to integrate productivity, innovation, and firm survival techniques to investigate their relationships in the six ASEAN countries. The result indicates that innovation, exports, firm size, and industry technology are the primary drivers of increasing company productivity in the six ASEAN developing nations.

H1: Innovation has a positive impact on the productivity of selected Asian countries.

2.2 Digitalization (ICT) and Productivity

Digitalization is considered the latest technological revolution, enhancing economic growth, productivity, competitiveness, and improving access to education, healthcare, and government services. Existing research has explored the relationship between ICTs and economic growth, productivity, and innovation (Katz & Koutroumpis, 2013; Jayaprakash & Pillai, 2022; Bahr et al. 2024). In this connection, Spiezia (2012) employed econometric techniques to calculate the impact of ICT investments in 26 industries across 18 OECD countries between 1995 and 2007. The results found that in Australia and Japan, ICT investments are estimated to contribute 1.0% and 0.4% of value-added growth in the business sector annually. Finland and Japan are the only two exceptions, where investments in ICT were more dynamically focused on software and communication equipment than computing equipment. In Germany, Slovenia, and the UK, ICT-producing industries contribute at least two-thirds of the rise in TFP, over 60% in the US, and slightly less than 50% in France and the Netherlands. Similarly, Hall et al. (2013) used panel data from four Italian manufacturing companies. Furthermore, the study adapts the CDM model to include R&D and ICT investment as the two main drivers of productivity and innovation. A significant association has been discovered between productivity and innovation. Investment in R&D and ICT is becoming increasingly important for productivity.

In the same way, Abri & Mahmoudzadeh (2015) evaluated the impact of ICT on Iran's manufacturing industries' productivity and efficiency. The data was gathered from 23 Iranian manufacturing sectors between 2002 and 2006, and techniques like panel data and DEA were applied for the analysis. The results discover that ICT positively and significantly impacts productivity of manufacturing industries. Similarly, Gehringer et al. (2016) analyzed the factors that influence productivity between nations and across industries. To achieve this, the study used a panel data collection spanning 17 European Union (EU) nations and 13 sectors from 1995 to 2007 using the augmented mean group and dynamic ordinary least-squares methods. Another study by Pieri et al. (2018) employed the stochastic frontier model to investigate the impact of R&D and ICT on productivity in industrialized countries from 1973 to 2007. According to their findings, ICT has been proven to lower production inefficiencies and create cross-industry spillovers. R&D accelerated technological advancement and encouraged knowledge spillovers within industries. Further, productivity in OECD nations increased by over 95% because of R&D and ICT. Similarly, Gal et al. (2019) analyzed the impact of digital technology adoption on the efficiency of businesses. Within an empirical framework, it combines industry-level data on the uptake of digital technology with productivity data from multinational corporations. The findings offer solid proof that a sector’s use of digital technology is linked to increases in business productivity. The findings show that the primary forces behind TFP are ICTs and human capital. In this connection, Bozkurt et al. (2022) conducted a study to illustrate how digitalization affects TFP from 2012 to 2020. The panel results indicate that digitalization significantly and favorably impacts TFP. The results imply that productivity is enhanced by digitalization. Another study by Gaglio et al. (2022) examined the relationships among productivity, innovation, and the utilization of digital communication technologies in a sample of 711 micro and small enterprises (MSEs) in South Africa by using Crepon-Duguet-Mairesse (1998) model and the 2SLS method.

Similarly, Seclen-Luna et al. (2022) examined how the adoption of digital technologies impacts the productivity and net sales of businesses in a sample of 2,970 manufacturing and creative companies, using OLS techniques. The results show a positive association between digital technology and productivity. Nevertheless, these correlations may vary depending on the type of digital technology used, the company's size, and the gender distribution of managers. The statistical significance of these connections for net sales in large enterprises across both industry groups is higher. In both categories of sectors, SMEs are statistically more significant in terms of productivity. Another study by Falki & Mahmood (2023) analyzed the relationship between TFP and ICT in nine Asian developing economies from 2000 to 2018. Much attention has been paid to the productivity paradox, especially in the industrialized world. The PCA method was used in the empirical study to represent ICT access and other control variables that may affect the rise of TFP. The findings indicate that the TFP growth of the sample countries is influenced by R&D, investment, and ICT availability.

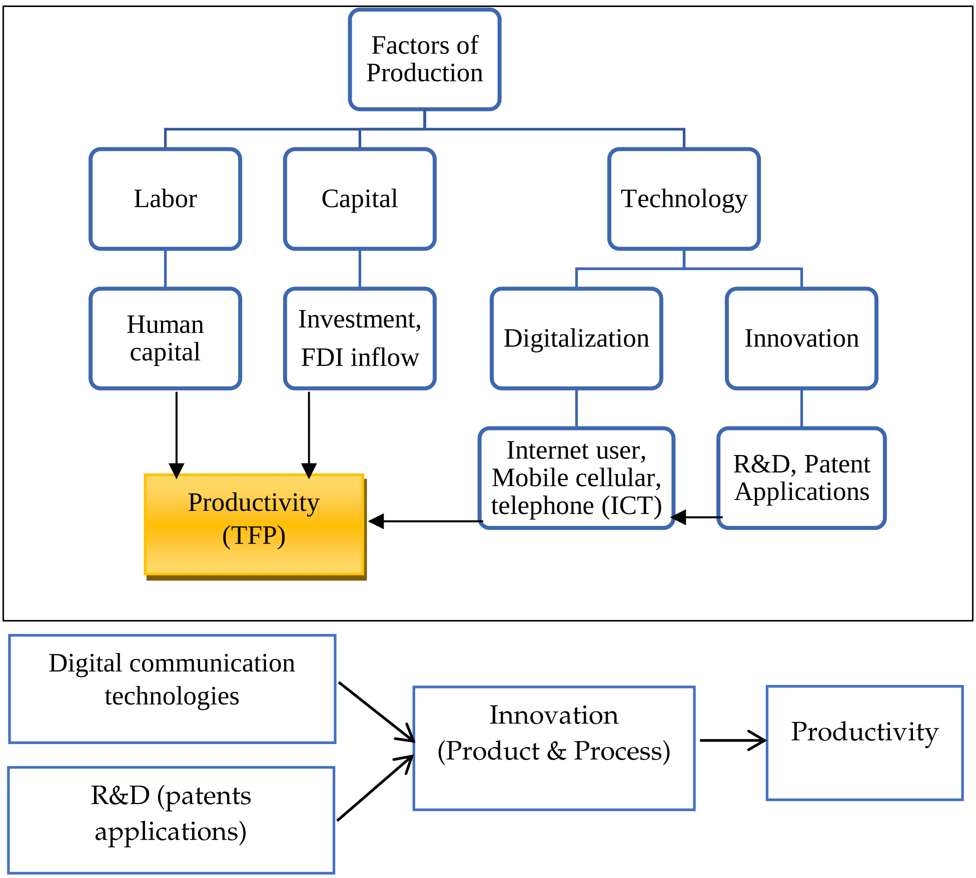
H2: Digitalization (ICT) has a positive influence on the productivity of selected Asian countries.

3. Theoretical and Methodological Framework

3.1 Theoretical framework

The foundations of productivity can be found in Solow's groundbreaking work from neoclassical growth theory, which identified productivity as a byproduct of the production function. According to Solow (1956), TFP growth is essential for a nation's sustained progress through innovations and technological change. Technology and knowledge have been recognized as important determinants of growth since the advent of endogenous growth theory (Romer, 1986, 1990; Lucas, 1988; Grossman & Helpman, 1991). Technology is the sole factor that has the potential to produce significant cross-country differences in terms of per capita income. Since the 1960s, there has been a growing consensus that technological gaps are the primary factor causing economic growth and development disparities (Abramovitz, 1986). Howitt & Aghion, (1998) also favored technology as a catalyst for TFP expansion. Later, individual education and training were considered essential to the total worth of human capital in nations (Schultz, 1961; Becker, 1962), and they can boost productivity significantly (Lee & Brahmasrene, 2019; Han & Lee, 2020). Romer (1990) emphasized that productivity is dependent on the amount of human capital already in place as an input, which creates new knowledge and facilitates the copying or adaptation of foreign technology. While Romer (1986) essentially models TFP is a function of the stock of R&D. Lucas (1988) and Coe & Helpman (1995) assume that TFP also depends on the R&D stock of foreign trading partners. According to research by Fare et al. (1995), Jones and Williams (1998), and Comin (2004), all of which show that R&D has a significant effect on TFP. Digitalization is considered the latest technological revolution. According to Brynjolfsson (1993), investment in ICT can promote productivity. The study used an expanded model of Crepon-Duguet-Mairesse (1998), to examine the impact of digitalization and innovation on productivity for selected Asian countries. The current study also investigates the effect of human capital, FDI, and trade openness on TFP.

Figure 1: ICT, R&D and Productivity based on CDM (1998)



Source: Authors' own construction.

3.2 *Measurement of TFP and Model Construction*

According to Awais & Amjid (2016), the growth accounting framework is frequently used to calculate the residual as proposed by Solow (1957). In contrast to the original neoclassical growth model, Romer

(1986) and proponents of the "new growth theory" see technological advancement as an endogenous variable that primarily results from the input of human capital to economic growth. CDPF is used to compute TFP in the absence of TFP data. According to Solow (1957), the growth accounting approach can be employed to calculate TFP. The production function is expressed as:

$$Y = A K^{\alpha} L^{1-\alpha} \quad (1)$$

In Equation (1), Y represents output; K is capital; L is labor, and A represents technology. The study also adds human capital to the model (Romer, 1990). The above model becomes as follows.

$$Y = AK^{\alpha}(LH)^{1-\alpha} \quad (2)$$

After taking the log and differential, Equation (2) becomes, in growth form, as follows.

$$\Delta\, ln(Y) = \alpha[\Delta\, ln(K)] + (1-\alpha)[\Delta\, ln(LH)] + \Delta\, ln(A) \quad (3)$$

Equation 4 estimates TFP growth using Equation 3.

$$\Delta\, ln(A) = \Delta\, ln(Y) - \alpha[\Delta\, ln(K)] - (1-\alpha)[\Delta\, ln(LH)] \quad (4)$$

Various researchers used different factor shares. The present study builds upon the work of Saddique (2022), where the labor and capital shares are assumed to be 0.48 and 0.52, respectively. However, it is also important to consider other factors. The extended econometric model of Equation (4) is as follows (Gehringer et al., 2016; Saleem et al., 2019).

$$TFP_t = \alpha_0 + \alpha_1\, INN_t + \alpha_2\, ICT_t + \alpha_3\, FDI_t + \alpha_4\, TOP_t + \alpha_5\, HUM_t + \varepsilon_t \quad (5)$$

The study transformed the above model into a log-linear format to estimate the equation and assess the direct elasticity.

$$ln(TFP)_t = \alpha_0 + \alpha_1\, ln(INN) + \alpha_2\, ln(ICT) + \alpha_3\, ln(FDI)_t + \alpha_4\, ln(TOP)_t + \alpha_5 (HUM)_t + \varepsilon_t \quad (6)$$

Whereas,

ln = Natural log, t = time/study period, TFP_t = total factor productivity of a country, INN_t = innovation, ICT_t = information and communication technology index, FDI_t = foreign direct investment inflows, TOP_t = trade openness, HUM_t = human capital, ε_t = Random error term

3.3 Data and Variables

The study utilizes panel and time series data from 1990 to 2022 to examine the impact of innovation and digitalization on productivity in Bangladesh, China, India, and Pakistan. The data on constant GDP, labor force, capital formation, innovation, digitalization, FDI, trade openness, and expenditure on education (human capital) were taken from World Development Indicators (WDI), the World Bank. All the data has been converted into log form except for the ICT index.

Table 1: Variables of the Study

Variables	Symbol	Definition/ measurement	Source	Variable used by
Productivity	TFP	Growth accounting framework	Calculated from Solow growth model	Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Sobieraj & Metelski (2021); Gaglio et al. (2022); Tan & Wei (2023)
Output	Y	GDP at constant 2015 US$	World Development Indicators,	Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Gaglio et al. (2022); Falki & Mahmood (2023)
Labor	L	Labor force, Total	World Bank, (2024)	Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Gaglio et al. (2022)
Capital	K	Gross fixed capital formation (constant 2015 US$)		Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Ahmad (2021); Gaglio et al. (2022); Falki & Mahmood (2023)
Digitalization	ICT	Internet user, Mobile cellular subscriptions, Fixed telephone subscriptions		Pradhan et al. (2021); Gaglio et al. (2022) Falki & Mahmood (2023), Choi & Park (2024); Zhang et al. (2024); Chandio et al. (2024)
Innovation	INN	Total patent applications (residents and non-residents)		Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Ahmad (2021); Rehman & Islam (2023); Xin et al. (2023)
Trade openness	TOP	Exports plus imports/ GDP		Teixeira & Fortuna (2010); Gehringer et al. (2016); Saleem et al. (2019); Sobieraj & Metelski (2021); Rehman & Islam (2023)
Foreign direct investment	FDI	Net inflow, foreign direct investment (US$)		Teixeira & Fortuna (2010); Gehringer et al. (2016); Sobieraj & Metelski (2021); Rehman & Islam (2023)
Human capital	HUM	Expenditure on education (as a % of GDP)		Gehringer et al. (2016); Ahmed (2017); Saleem et al. (2019); Sobieraj & Metelski (2021); Rehman & Islam (2023)

Source: Authors' compilation.

3.4 Estimation Procedure

3.4.1 Unit Root Test

Before performing a regression analysis on time series data, the series needs to be examined for stationarity or the integration order. Most time series data are thought to have a unit root, which indicates that they are non-stationary and can be differenced into stationary series. This study employed the Augmented Dickey-Fuller (ADF) test to assess the unit root of the data. Furthermore, for panel data, the study employed a second-generation unit root test, such as the cross-sectional augmented Im, Pesaran, and Shin (CIPS).

3.4.2 ARDL Model

The study employed the bounds test for co-integration to investigate the long-run relationship between the variables and determine how innovation and digitalization impact the productivity of selected Asian countries. Additionally, the study's long- and short-run results were estimated using the ARDL model. The modeling of Equations 1, 2, and 3 in the ARDL model constitutes the first stage of the ARDL bounds testing process. The following is the general ARDL model:

$$\Delta ln(TFP)_t = \beta_0 + \sum_{t=1}^{p} \beta_1 \, \Delta ln(TFP_{t-i}) + \sum_{t=1}^{p} \beta_2 \, \Delta ln(INN_{t-i}) + \sum_{t=1}^{p} \beta_3 \, \Delta ln(ICT_{t-i}) + \sum_{t=1}^{p} \beta_4 \, \Delta ln(FDI_{t-i}) + \sum_{t=1}^{p} \beta_5 \, \Delta ln(TOP_{t-i}) + \sum_{t=1}^{p} \beta_6 \, \Delta(HUM_{t-i}) + \lambda_1 ln(INN_{t-i}) + \lambda_2 ln(ICT_{t-i}) + \lambda_3 \, ln(FDI_{t-i}) + \lambda_4 ln(TOP_{t-i}) + \lambda_5 (HUM_{t-i}) + \varepsilon_t \qquad (7)$$

The number of lags, denoted as (i= 1, 2, 3, …...) is represented by $t-i$, β_0 denoted by the intercept term, error term is represented by ε_t. The error correction dynamics are denoted by β_1, β_2, β_3, β_4, and β_5, whereas the long-run dynamics is represented by λ_1, λ_2, λ_3, λ_4, and λ_5. If co-integration is present, the error correction model (ECM) can accurately represent the short-run dynamics of the variables (Maddala, 1992).

$$\Delta ln \, (TFP)_t = \beta_0 + \sum_{t=1}^{p} \beta_1 \, \Delta ln(TFP_{t-i}) + \sum_{t=1}^{p} \beta_2 \, \Delta ln(INN_{t-i}) + \sum_{t=1}^{p} \beta_3 \, \Delta ln(ICT_{t-i}) + \sum_{t=1}^{p} \beta_4 \, \Delta ln(FDI_{t-i}) + \sum_{t=1}^{p} \beta_5 \, \Delta ln(TOP_{t-i}) + \sum_{t=1}^{p} \beta_6 \, \Delta(HUM_{t-i}) + \Phi(ECT_{\mathrm{ti}}) + \varepsilon_t \qquad (8)$$

The pace at which long-run equilibrium is being adjusted is represented by the error correction term (ECT_{t-1}). If the (ECT_{t-1}) sign is significant and negative, it is suggested that the model is converging toward equilibrium.

3.4.3 Panel ARDL Model

The panel ARDL model is employed for panel data because there is a high degree of similarity and the possibility of cross-sectional dependency (CD) exists among the selected Asian countries. These countries are connected through trade integration, political relations, and globalization. The study utilized the panel ARDL model examine the long-run and short-run impacts of innovation and digitalization on productivity. The general form of the panel ARDL model is given below:

$$ln(TFP_{it}) = \beta_0 + \sum_{t=1}^{p} \beta_1\, ln(TFP_{it-1}) + \sum_{t=1}^{p} \beta_2 \ln(INN_{it-1}) + \sum_{t=1}^{p} \beta_3 \ln(ICT_{it-1}) + \sum_{t=1}^{p} \beta_4 \ln(FDI_{it-1}) + \sum_{t=1}^{p} \beta_5 \ln(TOP_{it-1}) + \sum_{t=1}^{p} \beta_6\, (HUM_{it-1}) + \lambda_1 ln(INN_{it-1}) + \lambda_2 ln(ICT_{it-1}) + \lambda_3 ln(FDI_{it-1}) + \lambda_4 ln(TOP_{it-i}) + \lambda_5 (HUM_{it-1}) + \varepsilon_{it} \quad (9)$$

Whereas i represents a country, t represents time, p denotes maximum lags, *t-i* represents number of lags (i= 1, 2, 3, ...), β_0 denotes the intercept term, ε_{it} represents the error term. The error correction dynamics are denoted by β_1, β_2, β_3, β_4, and β_5, whereas the long-run dynamics is represented by λ_1, λ_2, λ_3, λ_4, and λ_5. If co-integration is present, the ECM can represent the short-run dynamics (Maddala, 1992). The study assesses the robustness of the long-run estimations derived from the panel ARDL estimator, utilizing Phillips and Hansen's (1990) FM-OLS.

4. Result and Discussion

4.1 Panel ARDL Results (Aggregate Analysis)

Table 2 presents the descriptive statistics of the data. Data are converted into log form except for the ICT index and human capital. Descriptive statistics consist of mean, standard deviation, minimum, and maximum values in the data. The average growth of TFP is 1.5498, the maximum growth is 1.6454, and the minimum growth is 1.4693, respectively. Similarly, the mean value of ICT is 0.8157, the maximum value is 3.7393, and the minimum value is -1.7489, respectively. Similarly, the mean value of INN, FDI, TOP, and HUM is 8.5887, 22.045, 0.3538, and 2.7680, respectively. In the same way, the maximum values of INN, FDI, TOP, and HUM are 14.277, 26.564, 0.6448, and 4.6351, respectively. On the other hand, the minimum values of INN, FDI, TOP, and HUM are 4.6728, 14.145, 0.1551, and 1.4257, respectively.

Table 2: Descriptive Statistics

	TFP_{it}	ICT_{it}	INN_{it}	FDI_{it}	TOP_{it}	HUM_{it}
Mean	1.5498	0.8157	8.5887	22.045	0.3538	2.7680
Median	1.5561	1.1500	7.7995	21.624	0.3434	2.5679
Maximum	1.6454	3.7393	14.277	26.564	0.6448	4.6351
Minimum	1.4693	-1.7489	4.6728	14.145	0.1551	1.4257
Std. Dev.	0.0519	1.4755	2.7365	2.7315	0.1028	0.8743
Skewness	0.1457	-0.2743	0.5214	-0.4396	0.5875	0.3486
Kurtosis	1.5841	2.0579	2.1302	3.1031	3.0350	1.8296
Jarque-Bera	11.493	4.5562	10.144	4.3097	7.6006	10.207
Probability	0.0032	0.1025	0.0063	0.1159	0.0224	0.0061

Source: Authors' computation.

The most important phase in panel data analysis is to examine the Pesaran (2007) cross-sectional dependency (CD) among the nations. All the countries of the world are connected through liberalization and globalization. Any shocks in one country may affect another country. Therefore, it is essential to determine whether CD is present in the countries. Table 3 presents the Pesaran CD results. The test's null hypothesis typically states that there is no cross-sectional dependency. All variables in the CD results reject the null hypothesis of cross-sectional independence among the four countries except for HUM.

Table 3: Cross sectional Dependency test Results

Variables	TFP_{it}	ICT_{it}	INN_{it}	TOP_{it}	FDI_{it}	HUM_{it}
CD Test	9.66	12.80	9.26	3.91	12.17	-1.01
p-value	0.00	0.00	0.00	0.00	0.00	0.31

Source: Authors' computation.

The first-generation unit root result is ineffective when CD exists between the countries. Therefore, this research employed a second-generation unit root test, such as the CIPS. The second-generation unit root results are shown in Table 4. The results indicate that TFP, ICT, INN, HUM, and TOP show unit roots at the level but become stationary at the first difference at a 1% significance level. Other variables, such as FDI, exhibit stationarity at the level. Upon rejecting the null hypothesis regarding the existence of a unit root, it is ascertained that every variable exhibits stationarity at different orders such as I(0) and I(1). The critical values of

CIPS provided by Pesaran (2007) are -2.82 for 1%, -2.52 for 5%, and -2.39 for 10% respectively.

Table 4: CIPS Unit Root results

Variables	Level	First Difference
TFP_{it}	3.0188	-8.3706^{***}
ICT_{it}	2.0449	-3.1068^{***}
INN_{it}	-0.4604	-9.2306^{***}
TOP_{it}	-0.5716	-7.0987^{***}
FDI_{it}	-1.6326^{**}	----
HUM_{it}	-0.8139	-13.0685***

Source: Authors' calculation.
Note: *** & ** shows significance level at 1% and at 5%

After ensuring that there is stationarity in the data, the study uses the Kao co-integration test to look at the long-run relationship between the variables. The co-integration results are shown in Table 5. The alternative hypothesis positing the existence of co-integration or a long-run relationship between the selected variables is accepted instead of the null hypothesis, which asserts the absence of co-integration among the variables.

Table 5: Kao Co-integration Test

	t-Statistic	Prob.
ADF	-2.5180^{***}	0.0059

Source: Authors' calculation.
Note: *** shows significance level at 1%

After establishing a long-run association, the study employed a panel ARDL model to analyze both short- and long-run results. Table 6 displays the panel results for the long run. At the 1% significance level, ICT has a favorable and significant effect on TFP. This suggests that in selected countries, a 1% increase in ICT will result in a 0.0241 increase in TFP. A similar result was found by Seo and Lee (2006) for 38 OECD and EU countries, Gehringer et al. (2016) for 17 European Union countries, and Falki and Mahmood (2023) for nine developing economies in Asia; Choi and Park (2024) for South Korea. Similarly, INN exerts a positive and significant influence on TFP in the selected countries. This indicates that a 1% rise in INN will result in a 0.0404% increase in TFP in the long run. Similar results were found by Teixeira and Fortuna (2010) for Portugal, Gehringer et al. (2016) for 17 European Union countries, Saleem et al. (2019)

for Pakistan, Sobieraj and Metelski (2021) for 41 developed countries, and Rehman and Islam (2023) for BRICS economies.

At the 5% significance level, TOP has a significant and positive effect on TFP. This indicates that a 1% increase in TOP will lead to a 0.3579% rise in TFP over the long run in selected Asian countries. This result aligns with the findings of Seo & Lee (2006) for 38 OECD and EU countries, Teixeira & Fortuna (2010) for Portugal, Feenstra et al. (2013) for the US, Saleem et al. (2019) for Pakistan, and Sobieraj & Metelski (2021) for 41 developed countries, as well as Rehman & Islam (2023) for BRICS economies. Similarly, at the 5% significance level, the coefficient of FDI shows a positive and significant impact on TFP. A 1% increase in FDI boosts TFP by 0.0109% in the long run. This finding is consistent with Teixeira & Fortuna (2010) for Portugal, Gehringer et al. (2016) for 17 European Union countries, Saleem et al. (2019) for Pakistan, Sobieraj & Metelski (2021) for 41 developed countries, and Falki & Mahmood (2023), as well as Rehman & Islam (2023) for BRICS economies.

Table 6: Panel ARDL Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long run results				
INN_{it}	0.0404*	0.0209	1.9298	0.0628
ICT_{it}	0.0241***	0.0041	5.8888	0.0000
FDI_{it}	0.0109**	0.0047	2.3276	0.0266
HUM_{it}	0.0126*	0.0073	1.7353	0.0926
TOP_{it}	0.3579**	0.1481	2.4177	0.0217
Short run results				
$\Delta(ICT_{it})$	0.0043	0.0054	0.7947	0.4329
$\Delta(INN_{it})$	0.0146**	0.0073	2.0017	0.0541
$\Delta(TOP_{it})$	0.0277	0.0490	0.5657	0.5757
$\Delta(FDI_{it})$	-0.0065*	0.0034	-1.9018	0.0665
$\Delta(HUM_{it})$	0.0018	0.0066	0.2773	0.7834
ECM(-1)	-0.1857***	0.0414	-4.4849	0.0000

Source: Authors' calculation.

Note: * ** and ***shows significance level at 10%, 5% and 1%

Human capital affects TFP at the 10% significance level. This suggests that a 1% increase in educational spending will ultimately lead to a 0.0126% rise in TFP. A similar result was found by Seo & Lee (2006) for 38 OECD and EU countries, Teixeira & Fortuna (2010) for Portugal, Gehringer et al. (2016) for 17 European Union countries, Saleem et al. (2019) for Pakistan, Sobieraj & Metelski (2021) for 41 developed countries, and Falki & Mahmood (2023); Rehman & Islam (2023) for BRICS economies.

The short-run results are shown in the lower part of Table 6. The findings indicate that TFP is positively but insignificantly impacted by ICT, and TOP in the selected countries. Similarly, at a 5% level of significance, INN has a positive and significant short-run impact on TFP. On the other hand, in the short term, FDI has a negative and significant effect on TFP. At the 1% level of significance, the ECM(-1) term is significant and negative. The short-run speed of adjustment or disequilibrium is represented by the ECM term. The value of ECM is -0.1857, indicating that a 19% adjustment will take place to reach equilibrium in one year in the selected countries.

Table 7: The FMOLS results for Robustness

Variables	Coefficient	Std. Error	Prob.
INN_{it}	0.1369***	0.0208	0.0000
ICT_{it}	0.0555***	0.0060	0.0000
FDI_{it}	0.0274***	0.0082	0.0012
HUM_{it}	0.0759**	0.0332	0.0238
TOP_{it}	0.0822*	0.0141	0.0725

Source: Authors' calculation.
Note: *** and ** shows significance level at 1% and 5%

The robustness of the long-run coefficients between the variables was determined by the study, considering two different complementary estimators. Using Phillips and Hansen's (1990) methodology, the study determined FMOLS. Table 7 provides evidence that the calculated coefficients of innovation, digitalization, FDI inflow, human capital, and trade openness under FMOLS confirm the long-period estimates derived from the panel ARDL estimator.

4.2 Country-wise Time Series Results (Disaggregate Analysis)

In this section, the study presents empirical results, i.e., unit root, bounds test for co-integration, and ARDL for short and long-run coefficients for individual countries. Table 8 shows the ADF results for the unit root.

Table 8: ADF Unit Root Results

Country	Bangladesh		China	
Variables	**Level**	**First difference**	**Level**	**First difference**
TFPt	0.4856	-3.7920***	-1.0350	-6.4976***
	(0.9835)	(0.007)	(0.7285)	(0.000)
ICTt	-0.7919	-4.9844***	-0.9955	-2.8461*
	(0.9871)	(0.002)	(0.7419)	(0.0639)
INNt	-2.1314	-7.8851***	-1.5799	-4.8746***
	(0.2343)	(0.000)	(0.4810)	(0.000)
TOPt	-1.8351	-4.1638***	-1.8873	-4.2834***
	(0.3575)	(0.004)	(0.3336)	(0.002)
FDIt	-1.7818	-5.3448***	-3.6257***	----
	(0.3824)	(0.000)	(0.011)	
HUMt	-2.7355*	----	-1.6043	-7.3696***
	(0.079)		(0.4689)	(0.000)
Country	**India**		**Pakistan**	
TFPt	-0.2581	-5.1039**	0.0559	-5.5618***
	(0.9205)	(0.039)	(0.9570)	(0.000)
ICTt	-1.0998	-2.5136**	-0.2718	-4.8448***
	(0.7021)	(0.012)	(0.9185)	(0.000)
INNt	-1.4462	-4.3772***	-2.0327	-4.6869***
	(0.5469)	(0.002)	(0.2721)	(0.000)
TOPt	-1.3271	-4.8637**	-2.0656	-4.9511***
	(0.6017)	(0.027)	(0.2591)	(0.000)
FDIt	-2.7834***	----	-1.8040	-4.6223***
	(0.003)		(0.3791)	(0.000)
HUMt	-0.4272	-8.4855***	-2.7298*	----
	(0.2639)	(0.000)	(0.080)	

Source: Authors' calculation.
Note: ***, ** and *denotes significance level at 1%, 5% and 10%.

In the case of Bangladesh, the results show that HUM is stationary at the level, while TFP, ICT, INN, TOP, and FDI become stationary at the first difference. Comparably, China's ADF results indicate that TFP, ICT, INN, TOP, and HUM become stationary at the first difference, whereas FDI remains stationary in levels. The ADF results for India indicate that FDI is stationary at level, while the other variables become stationary at first difference. Similarly, the ADF results for Pakistan show that HUM is stationary at level, while TFP, ICT, INN, FDI and TOP become stationary at first difference. The ADF test yields mixed results, indicating both I(0) and I(1) processes. Therefore, the ARDL bounds test is an appropriate model for co-integration.

Table 9 shows the ARDL bounds results. The results demonstrate that co-integration is present among the variables in all four countries: Bangladesh, China, India, and Pakistan, respectively. The computed F-statistic values are 26.96, 9.77, 10.90, and 4.02 in the selected countries. The computed F-statistic values exceed the F-statistic critical values at 2.5% and 1%, respectively. Based on the findings, the null hypothesis that there is no co-integration is rejected. As a result, the ARDL bounds result verified that the variables have a long-run relationship.

Table 9: Bound's Test for Co-integration

Country	F-statistic value	I(0) Bound	I(1) Bound	K
Bangladesh	26.9573****	3.15	4.43	5
China	9.7725***	3.41	4.68	5
India	10.9041****	3.15	4.43	5
Pakistan	4.0161***	2.75	3.99	5

Source: Authors' calculation.
Note: I(0) and I(1) show lower bound and upper bound; k represents independent variables.
**** and *** shows significance level at 1% and at 2.5%.

The findings of the ARDL bounds test confirmed a long-run relationship between the variables. Table 10 presents the estimated long-run results. At the 1% significance level, ICT has a significant and positive impact on TFP in Bangladesh, China, India, and Pakistan. In Bangladesh, TFP is expected to rise by 0.0063% for every 1% increase in ICT. A 1% increase in ICT will lead to a 0.1175% increase in TFP in China and a 0.0099% rise in TFP in India. In Pakistan, a 1% increase in ICT will ultimately result in a 0.0142% rise in TFP. Digitalization, or ICT, can enhance labor productivity by improving human capital through online courses, vocational training, and the provision of various IT skills. TFP can be boosted by digital financing, online shopping, online marketing, freelancing, and digital banking, which offer easy access to loans and credit for investors. ICT also enhances labor efficiency through fast networking, global internet connectivity, online trading, and FOREX. Similar results were found by Seo and Lee (2006) for 38 OECD and EU countries, Gehringer et al. (2016) for 17 European Union countries, and Falki and Mahmood (2023) for nine developing economies in Asia; Choi and Park (2024) for South Korea.

Table 10: Long Run Results

Variables	Bangladesh	China	India	Pakistan
ICT_t	0.0063***	0.1175***	0.0099***	0.0142***
	(11.2476)	(5.0529)	(7.2079)	(26.3830)
INN_t	0.0369***	0.1412***	0.0259***	0.0319***
	(23.6877)	(6.0844)	(3.9368)	(7.9537)
TOP_t	0.0235**	0.3053***	0.0682*	0.1415***
	(5.5759)	(5.7902)	(2.0891)	(4.1251)
FDI_t	0.0031**	0.0011	0.0042	-0.0219***
	(5.2374)	(0.1836)	(1.4435)	(-7.1515)
HUM_t	0.0118*	0.0208***	0.0091*	0.0332**
	(3.9121)	(6.5040)	(2.1819)	(2.9814)

Source: Authors' calculation.
Note: ***, **& * indicates significance level at 1%, 5% and 10%.

At the 1% level of significance, the positive coefficient values of INN significantly affect TFP in the four selected countries. In Bangladesh, China, India, and Pakistan, a 1% increase in INN will lead to a corresponding long-run increase in TFP of 0.0369%, 0.1412%, 0.0259%, and 0.0319%, respectively. This may be due to research and development activities in the IT and industrial sectors, as well as the publication of technical scientific research articles in research institutions and universities. R&D expenditure on patent applications and research publications contributes to innovation, inventions, and the generation of new ideas. The new growth theory by Romer (1985), Lucas (1988), and many others also emphasizes R&D and innovations in economic growth and TFP. Similar results were found by Teixeira and Fortuna (2010) for Portugal, Gehringer et al. (2016) for 17 European Union countries, Saleem et al. (2019) for Pakistan, Sobieraj and Metelski (2021) for 41 developed countries, and Rehman and Islam (2023) for BRICS economies.

The coefficients of trade openness (TOP) significantly and positively impact total factor productivity (TFP) in Bangladesh, China, India, and Pakistan. Accordingly, TFP in Bangladesh is projected to increase by 0.0235% for every 1% rise in TOP. In China, a 1% increase in TOP will enhance TFP by 0.3053% in the long run. Similarly, a 1% increase in TOP will lead to a 0.0682% boost in TFP in India. In Pakistan, a 1% rise in TOP will ultimately result in a 0.1415% increase in TFP. Trade openness (TOP) can elevate TFP by transferring capital, knowledge, and innovations from developed to developing countries. Moreover, trade exposes domestic firms to international competition, enabling them to learn from more advanced foreign competitors, which can drive innovation and enhance TFP. Furthermore, trade allows countries to specialize in sectors where they hold a comparative advantage, potentially resulting in greater productivity and competitiveness in these areas. Similar results were found by Seo & Lee (2006) for 38 OECD and EU countries; Teixeira & Fortuna (2010) for Portugal; Feenstra et al. (2013) for the US; Saleem et al. (2019) for Pakistan; and Sobieraj & Metelski (2021) for 41 developed countries; Rehman & Islam (2023) for BRICS economies.

At a 5 percent significance level, FDI significantly and positively affects TFP in Bangladesh. Over time, a 1% increase in FDI raises TFP by 0.0031%. In the cases of China and India, FDI influences TFP positively, but insignificantly. Similarly, Pakistan's TFP is significantly and negatively impacted by FDI, which may be due to a large inflow of FDI in consumption-oriented goods and services in the country. Advanced technologies and management techniques are often transferred from industrialized to developing nations as part of FDI. This technology transfer can boost TFP and enhance the host nation's innovation capacity. Furthermore, FDI provides funds and resources that can be utilized for research and development (R&D), education, and infrastructure, which are crucial for accelerating TFP. This finding aligns with Teixeira & Fortuna (2010) for Portugal, Gehringer et al. (2016) for 17 European Union countries, Saleem et al. (2019) for Pakistan, and Sobieraj & Metelski (2021) for 41 developed countries; Rehman & Islam (2023) for BRICS economies.

The coefficient values of HUM significantly and favorably affect TFP in Bangladesh, China, India, and Pakistan. This indicates that a 1% increase in education expenditure will raise TFP by 0.0118% in Bangladesh in the long run. Similarly, in China, a 1% rise in education expenditure will result in a 0.0208% increase in TFP. In India, a 1% rise in education expenditure will boost TFP by 0.0091% in the long run. For Pakistan, a 1% increase in educational spending will enhance TFP by 0.0332% over the long term. This could be attributed to the considerable investment in education (primary, secondary, and tertiary) as a percentage of GDP. Additionally, spending on technical and vocational training and skill development will improve labor productivity and efficiency, thereby enhancing a country's human capital. Investing in tertiary education will further promote innovation, inventions, R&D activities, and the adoption of digital technologies. Similar findings were reported by Seo & Lee (2006) for 38 OECD and EU countries; Teixeira & Fortuna (2010) for Portugal; Gehringer et al. (2016) for 17 European Union countries; Saleem et al. (2019) for Pakistan; and Sobieraj & Metelski (2021) for 41 developed countries; Rehman & Islam (2023) for BRICS economies.

Table 11 presents the short-run results. The findings demonstrate that ICT and INN significantly and favorably impact TFP in Bangladesh. In the short term, TFP is also positively and significantly affected by HUM, FDI, and TOP. At the 10% level of significance, the ECM (-1) term is significant and negative. The short-run speed of adjustment or disequilibrium is represented by the ECM term. Since the ECM value is -0.7479, it will take a 75% adjustment to bring Bangladesh to equilibrium within a year. The model fits the data well, as the R-squared value indicates that the independent variables account for approximately 99% of the variation in the dependent variable. The model is also checked for serial correlation and autocorrelation using the Lagrange Multiplier (LM) test. The outcome of the LM test indicates that serial correlation is not an issue for the model. Similarly, normality is assessed using the Jarque-Bera test, which shows that the data follows a normal distribution. The Jarque-Bera value is 1.21, and the probability value is 0.54, which exceeds 5%. Consequently, the null hypothesis cannot be rejected, affirming that the residuals have a normal distribution. To ensure the reliability and accuracy of the econometric model, the study employed the Ramsey RESET test to detect stability and specification errors. The Ramsey RESET result indicates that there is no problem of specification error in the model.

Table 11: Short Run Results

Variables	Bangladesh	China	India	Pakistan
$\Delta(ICT_t)$	0.0240**	0.0359***	0.0175***	0.0111***
	(6.0299)	(6.2535)	(8.1799)	(4.1986)
$\Delta(INN_t)$	0.0459**	0.0137***	0.0151***	0.0073*
	(5.3639)	(4.5137)	(6.0042)	(2.0522)
$\Delta(TOP_t)$	0.0525*	0.1718***	0.0249*	0.0600**
	(4.0842)	(15.5074)	(1.9728)	(2.6471)
$\Delta(FDI_t)$	0.0033**	0.0116***	-0.0093***	0.0092***
	(4.3687)	(7.3064)	(-7.1551)	(4.9866)
$\Delta(HUM_t)$	0.0434**	0.0128***	0.0065***	0.0057**
	(5.7766)	(5.0944)	(4.6040)	(2.7598)
ECM(-1)	-0.7479*	-0.6153***	-0.5874***	-0.7801***
	(-2.1619)	(-6.2950)	(-12.9493)	(-9.5926)
Diagnostic Tests				
R-squared	0.9973	0.9789	0.9557	0.9926
Adjusted R-Squared	0.9607	0.9618	0.9083	0.9835
F-statistic	27.2594	7.1623	8.5375	109.037
	(0.0001)	(0.0015)	(0.0067)	(0.0000)
LM Test	1.8169	1.4482	1.5098	2.3578
	(0.4063)	(0.2906)	(0.3247)	(0.1506)
Jarque-Bera Test	1.2146	2.1384	0.7654	0.6795
	(0.5448)	(0.3433)	(0.6820)	(0.7119)
Ramsey RESET Test	0.3189	0.4065	0.3065	0.5247
	(0.7355)	(0.8244)	(0.7064)	(0.9052)

Source: Authors' calculation.

Note: ***, **& *shows significance level at 1%, 5% and at 10%.

The short-run results for China show that ICT, INN, TOP, FDI, and HUM have a positive and significant impact on TFP at the 1% significance level. The ECM(-1) term is negative and statistically significant at this level. The ECM value is -0.6153, indicating that a 62% adjustment will occur to reach equilibrium in one year in China. At the 1% and 10% significance levels, the results for India indicate that TFP is positively and significantly influenced by ICT, INN, FDI, and HUM. The negative and significant ECM(-1) term represents the short-run rate of adjustment. The ECM value is -0.5874, suggesting that a 59% adjustment will occur to reach equilibrium in one year in India.

At the 1%, 5%, and 10% levels of significance, the short-run results for Pakistan demonstrate that ICT, INN, TOP, FDI, and HUM have a positive and significant influence on TFP. The short-run negative and significant disequilibrium is represented by the ECM(-1) term. The value of ECM(-1) is -0.7801, indicating that a 78% adjustment will occur to reach equilibrium in one year in Pakistan. The LM test results show that the model has no issues with serial correlation. Similarly, the data is also assessed for normality. The results indicate that the Jarque-Bera value is 0.68 and the probability value is 0.72, which is greater than 5%. Consequently, the null hypothesis is not rejected, and the residuals display a normal distribution.

5. Conclusions and Policy Recommendations

Productivity growth is influenced by tangible capital (labor and capital) as well as intangible capital such as innovation and digitalization. This research examines how digitalization and innovation affect the productivity of selected Asian nations, including Bangladesh, India, China, and Pakistan, from 1990 to 2022. The empirical results indicate that China's productivity is more affected by digitalization compared to India. This is because China's productivity growth has been stronger than India's due to its advanced technology and skilled labor force. Similarly, productivity in Pakistan is more influenced by digitalization than in Bangladesh. The findings reveal that productivity in Bangladesh, China, India, and Pakistan is positively and significantly impacted by innovation. In China, productivity is more influenced by innovation than it is in the other three nations.

Additionally, trade openness significantly and favorably impacts productivity in Bangladesh, China, India, and Pakistan. Trade openness has a greater effect on TFP in China compared to India, as China engages in trade with more countries than India. Similarly, trade openness influences productivity more in Pakistan than in Bangladesh. The results demonstrate that FDI positively and significantly affects productivity in Bangladesh. FDI influences productivity in China and India positively, but significantly. Conversely, FDI significantly and negatively impacts productivity in Pakistan. This may be due to the substantial FDI inflow in consumption-oriented goods in Pakistan. Furthermore, human capital has a positive and significant long-term influence on productivity in Bangladesh, China, India, and Pakistan. Additionally, the panel results show that digitalization and innovation positively and significantly affect productivity at the 1% level of significance in the selected countries. Trade openness has a significant and positive effect on productivity across these countries. FDI also positively and significantly influences productivity at the 1% level of significance. Human capital impacts productivity positively and significantly at the 1% level of significance.

The findings recommend that selected countries focus on formulating policies and plans that enhance digitalization and accelerate digital economies to boost productivity. These initiatives should promote investments in digital infrastructure, such as high-speed internet connectivity and telecommunications networks, to enable digital financing, online shopping, online marketing, freelancing, and digital banking. Consequently, this will enhance both overall productivity and labor productivity in a country. The governments of selected countries should prioritize investments that foster inventions and innovations across various sectors of the economy, including research and development (R&D) activities, collaboration between industries and academia, and incentives for technological advancements. The selected countries should also cultivate strong relationships with neighboring countries to attract foreign direct investment (FDI) inflows and open their economies to the world. This will ensure the flow of inventions, capital, and expertise from industrialized to emerging nations. Furthermore, trade enables countries to specialize in industries where they hold a comparative advantage, potentially increasing productivity and competitiveness in those areas. Advanced technologies and managerial techniques are often transferred from industrialized to developing nations as part of FDI. This technology transfer can enhance productivity and strengthen the host nation's capacity to innovate. Additionally, FDI provides capital and resources that can be allocated to R&D, education, and infrastructure, all of which are crucial for boosting productivity. The governments of selected countries should invest in education and in technical and vocational training to enhance human capital, labor productivity, and national efficiency. Expenditure on tertiary education will further drive innovation, inventions, R&D activities, and the adoption of digitalization. These countries should also uphold macroeconomic stability, as strong macroeconomic conditions create a favorable environment for investment and attract FDI inflows, resulting in increased output. Thus, macroeconomic stability accelerates a country's productivity. A country's efficiency, labor productivity, and human capital can all be improved through government investments in technical and vocational training and education. The investment in postsecondary education will contribute to growth in R&D, innovation, and the utilization of digitalization.

The present study has some limitations that present further opportunities for future investigation. First, only four Asian countries were included in this analysis. Future research will focus on alternative regions and economies, including but not limited to Asian countries, as well as low and medium-income economies worldwide, while also examining other macroeconomic and institutional factors. Second, this study analyzed various aspects such as innovation (both residential and nonresidential patents), digitalization, trade openness, foreign direct investment (FDI), and human capital. It is advised that scholars and researchers consider other measures of innovation and digitalization, including but not limited to product, process, and marketing innovation, R&D spending, big data, and artificial intelligence (AI). Third, our study is based on aggregate-level analysis. Therefore, it would be interesting to conduct research at the firm level by looking at the dynamic relationship between innovation, digitalization, and firm productivity. Fourth, a single equation modeling technique is employed in this work to assess the impact of innovation, digitalization, and several macroeconomic variables on productivity. A simultaneous equation modeling technique could be utilized in future studies to overcome this limitation.

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