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Nonlinear and Heterogeneous Effect of Digitalization on Foreign Direct Investment: Evidence from Developing Countries

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Abstract

This study aims to clarify whether digitalization has a nonlinear and heterogeneous effect on foreign direct investment (FDI) inflows in developing countries. We employ data from the period 2002–2023 and apply various econometric methods, including System Generalized Method of Moments (S-GMM), Dynamic Panel Threshold Regression (DTPR), and Method of Moment Quantile Regression (MMQR), to address the research question. The findings report an inverted U-shaped relationship between digitalization and FDI. Specifically, the effect of digitalization on FDI changes across different levels of digitalization. Initially, digitalization positively affects FDI, but beyond a certain threshold, its impact turns negative. This indicates that the benefits of digitalization for FDI are not unlimited but may be constrained by the risks and costs associated with excessive digital infrastructure expansion. Additionally, the MMQR analysis shows a heterogeneous effect of digitalization on FDI. Digitalization has a stronger impact on FDI at lower quantiles. However, as a country's development level increases, the effectiveness of digitalization in attracting FDI gradually diminishes. Policymakers need to identify and maintain an optimal level of digitalization to promote FDI. This requires not only investment in digital infrastructure but also in supporting factors such as improved governance quality and the development of legal frameworks to ensure a stable and conducive economic environment for FDI. Moreover, flexible policies tailored to different country or regional groups are necessary to maximize the benefits of digitalization without triggering negative impacts on long-term economic development.

Keywords:

Digitalization;
DTPR; FDI;
Heterogeneous Effect;
ICT;
MMQR;
Nonlinear Effect;
S-GMM.

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1- Introduction

In the era of globalization and the Fourth Industrial Revolution, digitalization has emerged as a crucial factor driving economic development and international integration. For developing countries, digitalization not only contributes to the modernization of the economy but also serves as a key to attracting FDI - one of the essential resources for promoting economic growth and improving quality of life [1–3].

On one hand, digitalization enables developing countries to enhance their international competitiveness, while facilitating both domestic and foreign enterprises in accessing new markets and optimizing production and business operations. Studies indicate that countries with higher digitalization levels attract more FDI, as investors prioritize locations with favorable digital environments that ensure information security and support business operations effectively [4, 5]. Furthermore, the advancement of digitalization strengthens transparency, minimizes transaction costs, boosts labor productivity, and enhances government efficiency, creating an attractive and sustainable investment

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environment [1, 2, 6, 7]. Digitalization serves as a catalyst for accelerating industrial progress, as it can rapidly reduce labor and intermediary product costs [8, 9] and facilitate cross-border transactions for companies, thereby providing them with new investment opportunities [10]. Digital information systems also enable FDI enterprises to expand their reach into new markets. Moreover, digitalization can assist governments in promoting themselves to attract more FDI capital [11]. Digitalization enhances FDI attractiveness by reducing the information costs required for cross-border investments. Specifically, if local digitalization levels are high, a market phenomenon has already been formed and recognized within the organization, meaning that more data sources are available and easier for investors to acquire and analyze. Collecting data on emerging markets also becomes more accurate, which aids companies in planning related investments [12]. Digitalized regions also help foreign companies quickly familiarize themselves with the market and the social conditions of the host country. Additionally, digitalization reduces the cost of talent search. Regions with higher levels of digital development often possess stronger technological and talent advantages, providing a significant human resource pool for multinational corporations [13]. Furthermore, digitalization can leverage information and communication technologies to bridge communication gaps, effectively reducing the communication costs associated with geographical distance in business activities, thus helping companies better integrate into the host country's market environment.

On the other hand, if not managed and developed appropriately, the rapid growth of digitalization can lead to issues such as increased investment costs, business process complications, and even cybersecurity risks. Ivanova et al. [14] and Radanliev et al. [15] point out that companies may struggle to manage their servers, exposing them to system failures or data loss risks. Moreover, emerging technologies may have negative environmental impacts, making digital FDI less appealing to host countries [11]. Tarafdar et al. [16] refer to the negative effects of information technology as a "set of negative phenomena", suggesting that the use of digital applications could impact the safety and well-being of individuals, organizations, and society. Previous researchers, such as Damgaard et al. [10], argue that digital transformation creates challenges not only in terms of geographically connecting investments but also in distinguishing genuine financial integration and diversification from financial engineering. This may reduce the attractiveness of the investment environment, particularly for foreign investors [14, 15]. Empirical studies have shown that, in certain cases, excessive reliance on information technology can create an unstable investment environment, thereby reducing the ability to attract FDI [3, 17–19].

While the impact of digitalization on FDI has attracted significant research attention, empirical findings remain inconclusive, highlighting several gaps that warrant further investigation.

First, existing studies have primarily focused on the linear impact of digitalization on FDI [1, 2, 11], yielding conflicting results. Recent research suggests that the relationship between digitalization and FDI is not strictly linear; rather, digitalization's impact on FDI inflows may shift from negative to positive once a certain development threshold is reached [3, 13, 17]. This nonlinearity adds complexity to the relationship; however, most previous studies have predominantly focused on linear effects, leaving a critical gap in the literature.

Second, the geographical scope of current research has been largely confined to developed economies, such as the 23 European countries, or single-country analyses in Denmark and China [3, 13, 17]. Consequently, there is a significant lack of studies addressing developing countries, where digitalization levels remain constrained and pose substantial challenges to FDI attraction. Inadequate telecommunications infrastructure, underdeveloped Internet networks, and technological disparities across regions hinder the potential benefits of digitalization in these economies. Moreover, developing nations face the dual challenge of adopting new technologies while improving the business environment and infrastructure [11, 20]. These countries also encounter intense competition for FDI due to limited domestic capital availability. Furthermore, previous studies indicate that the impact of digitalization on FDI is not uniform across all economies and regions [1, 2, 11]. Factors such as economic development levels, capital accessibility, infrastructure quality, and technological capabilities lead to heterogeneous effects. However, this heterogeneity remains underexplored in the existing literature.

Third, diverse measures of digitalization have been employed in prior studies, including internet coverage [4], the proportion of employees in computer and software services—reflecting the economy's reliance on digital technology and skilled labor [21], and telecommunications services such as broadband and mobile data, which are crucial for economic development and poverty reduction [22]. Other measures include mobile phone penetration [23] and government spending on science and technology (S&T) [24]. Despite the extensive use of these indicators, previous research has largely focused on isolated measures without integrating a comprehensive framework that captures the multifaceted nature of digitalization. Measurement inconsistencies across studies hinder an accurate assessment of digitalization's impact on FDI, underscoring the need for a holistic approach that integrates multiple metrics for improved evaluation.

In light of these gaps, further research is needed to examine the nonlinear effects of digitalization on FDI, extend the analysis to developing economies, and establish a comprehensive framework for measuring digitalization to provide more robust insights into its influence on FDI attraction.

This study seeks to address existing research gaps by analyzing a sample of 67 developing countries over the period 2002–2023. Employing the System Generalized Method of Moments (S-GMM) estimation, along with robustness checks using Dynamic Panel Threshold Regression (DPTR) and Method of Moments Quantile Regression (MMQR) techniques, the study investigates the non-linear and heterogeneous impact of digitalization on FDI inflows in developing economies.

The empirical findings reveal that digitalization exhibits an inverted U-shaped effect on FDI attraction. In the initial stages, digitalization facilitates increased FDI inflows to developing countries; however, beyond a certain threshold, the benefits diminish due to escalating operational costs and heightened security risks. Furthermore, the MMQR estimates highlight notable heterogeneities in the impact of digitalization across countries with different development levels. Specifically, less developed countries appear to leverage the benefits of digitalization more effectively compared to their more developed counterparts. These findings offer a nuanced and comprehensive understanding of the role of digitalization in attracting FDI to developing countries. The study provides a solid foundation for policymakers to formulate targeted strategies that maximize the positive impacts of digitalization while mitigating its potential drawbacks.

The remainder of this study is structured as follows: Section 2 presents the literature review. The methodology, including data, models, and methods, is detailed in Section 3. Section 4 discusses the results derived from S-GMM estimation and robustness checks across alternative digitization measures and estimation methods, including DPTR and MMQR. Finally, we conclude and outline several policy implications in Section 5.

2- Literature Review

Digitization has become increasingly critical in attracting FDI, particularly within the context of globalization and digital transformation. It encompasses various domains, such as internet connectivity, telecommunications infrastructure, and other technological services, which collectively provide the foundational infrastructure for businesses to operate and expand into new markets. The advancement of digitization significantly influences a country's ability to attract FDI by enhancing economic competitiveness, promoting international connectivity, and improving the overall business environment [1]. However, the impact of digitization on FDI is not uniform across all nations and industries. In some countries, if digital infrastructure is not synchronized or fully developed, it can create certain barriers for foreign investors. Risks related to information security also introduce potential costs of digitization in attracting FDI. Both theoretical and empirical research on the role of digitization in attracting FDI has produced mixed results.

2-1- Theoretical Framework

The relationship between digitalization and FDI is addressed by several economic theories concerning FDI behavior, including the Uppsala Model [25–27], the Transaction Cost Theory [28, 29], the Theory of Ownership Advantage [30], the Product Life Cycle Theory [31], and the OLI Paradigm [32].

According to the Uppsala model of firm internationalization, the process of entering foreign markets occurs gradually, based on the accumulation of experience and the mitigation of risks through local knowledge. The advancement of digitalization can bridge geographical gaps and enable firms to quickly access information about new markets without the need for immediate physical presence. This transformation alters firms' behavior in making investment decisions in foreign markets, thereby enhancing the ability of countries with higher levels of digitalization to attract FDI [25].

The Transaction Cost Theory posits that firms decide to invest internationally when the transaction costs in foreign markets are lower than the potential benefits. Digitalization plays a crucial role in minimizing these transaction costs by streamlining management processes, facilitating information exchange, and enhancing contract execution. Advanced information and communication technology (ICT) systems enable firms to manage cross-border operations more efficiently, thus reducing risks and costs for foreign investors. According to Williamson [28], firms are more likely to engage in direct investment in countries with a well-developed digital infrastructure, as this allows them to optimize management and operational costs while improving their ability to control business processes in foreign markets.

According to Hymer's Ownership Advantage Theory [30], multinational corporations (MNCs) will only engage in foreign investment if they hold substantial competitive advantages over local firms. Digitalization strengthens these advantages by enhancing information management, increasing production efficiency, and fostering product innovation. Countries with advanced ICT infrastructure tend to attract more MNCs aiming to capitalize on technological superiority to gain market dominance.

The Product Life Cycle Theory proposed by Vernon [31] explains that firms engage in foreign investment to leverage cost advantages and develop different stages of a product. Digitization plays a crucial role in technology transfer, enabling firms to efficiently scale production and manage global supply chains. Countries with advanced digital infrastructure are better positioned to support businesses in executing these transfer processes, thereby attracting increased FDI.

In the context of Dunning's OLI Paradigm [32], a firm's decision to pursue FDI is contingent upon three critical elements: ownership advantages (O), location advantages (L), and internalization (I). Digitization emerges as a pivotal factor in enhancing location advantages by providing advanced digital infrastructure. Countries exhibiting high levels of digitization confer substantial benefits upon international firms, including the reduction of operational costs and enhanced access to global markets. Furthermore, digitization streamlines the internalization process for firms, thereby optimizing profitability while simultaneously mitigating associated risks.

2-2- Empirical Evidence

2-2-1- Positive Impact of Digitalization on FDI

Digitization significantly alters the methods and speed of information transmission in today's era [33, 34]. Particularly for MNCs, digitization enhances the return on investment [35]. Profitability is a central consideration for businesses in general, and MNCs specifically, when making investment decisions [36]. Digitization improves the attractiveness of FDI by reducing the information costs that MNCs incur when investing across borders. Specifically, a high level of digitization in the host country, particularly when institutionalized, indicates transparency in data. This facilitates easier access to and analysis of information for investors contemplating entry into new markets, while also improving the accuracy of data collection on developing markets, thereby enabling MNCs to plan their investments more effectively [12, 35, 37]. Furthermore, a well-digitized country allows foreign firms to quickly acclimate to the local market and social conditions (World Economic Forum, 2021).

The development of digitization significantly reduces transaction costs for FDI enterprises. Services such as broadband internet and modern telecommunications systems facilitate connections with international business partners, optimize supply chains, and enhance information and data management capabilities. Research indicates that countries with advanced digitization typically exhibit higher levels of FDI. Moreover, digitization improves transparency and reliability in business management, thereby increasing investor confidence and lowering the costs associated with sourcing high-quality resources. Regions with higher levels of digitization often possess superior technological capabilities and better-quality labor, providing a more abundant supply of skilled workforce for multinational enterprises [13]. Additionally, digitization can shorten communication gaps and reduce costs arising from geographic distance, facilitating better integration into the local business environment.

Additionally, digitization enhances the business environment, thereby increasing the attractiveness of FDI. Countries with strong digitization typically offer online public services, minimizing administrative procedures and legal barriers, which facilitates foreign investment. Digitization also supports the development of digital banking and e-commerce, creating new opportunities for investors in high-tech, trade, and service sectors. According to Choi [4], digitization has a significant impact on labor market development and industrial sectors, thereby attracting foreign investors.

Previous studies have indicated that factors such as communication and internet infrastructure facilitate host countries in attracting FDI [38, 39]. According to Ha & Huyen [17], digitization plays a crucial role in attracting FDI in both the short and long term. They assert that digitization can help businesses overcome challenges posed by the COVID-19 pandemic, based on a study involving data from 23 European countries. Other research has also demonstrated a positive relationship between digitization and FDI attraction [38, 39]. Boermans et al. [38] found that provinces with robust communication infrastructure are more likely to attract foreign investors. Mensah & Traore [39] noted that integrating high-speed internet as a metric for evaluating infrastructure quality indicates that digitization will boost FDI in the banking and technology sectors in countries participating in the Belt and Road Initiative (BRICS). In a separate study, Sinha & Sengupta [40] observed that digitization significantly enhances productivity, efficiency, FDI inflows, and economic growth in developing countries. Asongu & Odhiambo [2] identified a close relationship between the increased adoption of digital technologies, such as mobile phones, and the rise in FDI inflows to sub-Saharan African countries, indicating a direct correlation between digitization improvement and FDI growth. Cuervo-Cazurra [6] also demonstrated that in transition economies, the development of digital technology is a crucial factor driving FDI flows. Furthermore, the report by Baller et al. [7] reinforces this perspective, revealing that higher levels of digitization correspond with a greater capacity to attract FDI in various countries.

2-2-2- Negative Impact of Digitalization on FDI

While numerous studies highlight the positive role of digitization in attracting FDI, some research suggests that digitization may have a random or even negative impact on a country's FDI inflows. Sangroya et al. [41] indicated that the adoption of cloud computing could adversely affect data security for service consumers. Similarly, Brougham & Haar [42] found that employees' perceptions of technological advancements are negatively correlated with their organizational commitment and job satisfaction. Consequently, this may render FDI less appealing from the perspective of host countries.

In alignment with this perspective, several previous studies have found that companies may struggle to manage their servers, potentially exposing them to risks of system failures or data loss, particularly when servers are in different countries in the context of e-commerce [14, 15, 43]. Furthermore, FDI firms may face compliance issues with environmental regulations if their systems emit excessive carbon [11]. Additionally, the advancement of digitization presents challenges in connecting geographically diverse investments and distinguishing between real financial integration and diversification through financial engineering [44]. Given the heavy reliance on intangible assets, digitization lacks a physical presence, complicating the valuation of investments in international markets. Damgaard et al. [44] argue that these valuation uncertainties may hinder firms dependent on intangible assets from raising capital through initial public offerings due to unreliable valuations, thereby affecting their cost of capital and potentially diminishing FDI inflows. Another reason for a potential decline in FDI flows relates to environmental issues. Emerging technologies may usher in a new era of disasters, including hazardous waste, greenhouse gas emissions, and other electronic waste. If these wastes are not adequately managed, the environment could suffer severe degradation [11, 20]. By investigating the impact of digitization on climate change in Switzerland, Hilty & Bieser [20] provide empirical evidence of the negative effects of digital infrastructure development on climate change issues.

3- Data and Methodology

3-1- Data

To evaluate the impact of digitization on FDI, we employ an annual balanced dataset comprising 67 developing countries from 2002 to 2023. A detailed list of these 67 developing countries is provided in Appendix 1. The data sources include the World Development Indicators (WDI) and the World Governance Indicators (WGI) from the World Bank. The selection of data was based on availability and the objectives of the study. A comprehensive description of the variables is presented in Table 1.

Table 1. Variables definitions and sources

Variables	Code	Measures	Sources
		Dependent variables	
Foreign Direct Investment	FDI	FDI, net inflows (% of GDP)	WDI
		Independent variables	
Digitalization	Mobile	Mobile cellular subscriptions (per 100 people)	WDI
	Internet	Individuals using the Internet (% of population)	WDI
	Telephone	Fixed telephone subscriptions (per 100 people)	WDI
	DIG_{PCA}	The composite index is calculated using principal component analysis (PCA) on three component indicators, which are standardized before the PCA procedure: • Mobile cellular subscriptions (per 100 people) (Mobile) • Individuals using the Internet (% of population) (Internet) • Fixed telephone subscriptions (per 100 people) (Telephone)	Author's calculations
	Broadband	For robustness check, this study employs Broadband subscriptions (per 100 people) as proxy for digitalization.	WDI
		Control variables	
Government Expenditure	GovExp	General government final consumption expenditure (% of GDP)	WDI
Trade openness	TRADE	Percentage of the sum of exports and imports of goods and services (% of GDP)	WDI
Financial development	FD	Domestic credit to private sector by banks (% of GDP)	WDI
Inflation	INF	Inflation, consumer prices (annual %)	WDI
Institutional Quality	IQ	The composite index is calculated using a simple average over on six indicators, ranging from -2.5 (weak) to +2.5 (strong): • Control of Corruption • Government Effectiveness • Political Stability and Absence of Violence/Terrorism • Rule of Law • Voice and Accountability • Regulatory Quality	Author's calculations

The dependent variable in the model is the inflow of FDI (see Table 1), which was collected directly from the World Bank's World Development Indicators (WDI) database. FDI is measured by the total net investment inflows, including equity capital, reinvested earnings, other long-term capital, and short-term capital, used to acquire 10 percent or more of a company in the host country.

The independent variable of interest is digitization (DIG). Based on recent studies representing digitization [45–48], we employ various measures, including: (i) the number of mobile subscriptions per 100 people; (ii) the percentage of individuals using the internet as a proportion of the population; (iii) the number of fixed-line subscriptions per 100 people; and a composite index derived by applying principal component analysis (PCA) to the three aforementioned indicators. To assess the robustness of our results, we utilize a new dataset, specifically broadband subscriptions (per 100 people), as a proxy for digitization. This measure is widely used in the literature to gauge digitization levels [49, 50]. All indicators are sourced from the World Development Indicators (WDI).

Finally, following previous studies by Arvin et al. [51], the control variables in our model include: Government Expenditure (GovExp), defined as total government final consumption expenditure as a percentage of GDP; Trade Openness (TRADE), represented by the total volume of exports and imports of goods as a percentage of GDP; Financial Development (FD), measured by domestic credit to the private sector as a percentage of GDP; Inflation (INF), defined as the annual growth rate of the consumer price index; and Institutional Quality (IQ), measured as the average of six indicators: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Rule of Law, Voice and Accountability, and Regulatory Quality, sourced from the Worldwide Governance Indicators (WGI) [52]. These components capture both governance quality and the legal framework, offering a comprehensive measure of institutional strength. Incorporating specific legal metrics may enhance the robustness of the findings regarding the complementary roles of governance and the legal framework. These indicators range from -2.5 to +2.5, with -2.5 reflecting weak institutional quality and +2.5 indicating strong institutional quality.

3-2- Empirical Model

First, to explore whether the development of digitization has a direct impact on FDI, we establish a linear regression model to assess the effect of digitization on FDI as follows:

$$FDI_{it} = \gamma_0 + \gamma_1 DIG_{it} + \delta_j X'_{it} + (\mu_i + \varepsilon_{it}) \tag{1}$$

In this model, $\gamma_0, \gamma_1, \gamma_2$ and δ_j are the respective regression coefficients; i and t represent the country and time dimensions, respectively. FDI_{it} is the dependent variable representing foreign direct investment. DIG_{it} serves as the independent variable representing digitization. Next, X'_{it} includes the control variables utilized in the model, which comprise government expenditure (GovExp), trade openness (TRADE), financial development (FD), inflation (INF), and institutional quality (IQ). Finally, μ represents the fixed effects of the model, while ε denotes the estimation error, assumed to be independent and identically distributed with a mean of 0 and a constant variance $\sigma^2\left(\varepsilon_{it} \sim i.i.d(0, \sigma_\varepsilon)\right)$.

After confirming the existence of a relationship between digitization and FDI, we proceed to examine whether a nonlinear relationship exists between digitization and FDI. To this end, we include the squared term of digitization, hypothesizing that excessive digitization may constrain FDI inflows. Therefore, the empirical equation is reformulated as follows:

$$FDI_{it} = \gamma_0 + \gamma_1 DIG_{it} + \gamma_2 DIG_{it}^2 + \delta_j X'_{it} + (\mu_i + \varepsilon_{it}) \tag{2}$$

The nonlinear relationship reflects a reality in which initial investments in digitalization bring substantial benefits, such as increased connectivity, enhanced productivity, and reduced transaction costs, which attract FDI. However, as digitalization exceeds a certain level, the marginal costs, including those associated with cybersecurity risks, maintenance of digital infrastructure, and market saturation, begin to outweigh the benefits. This trade-off underpins the inverted U-shaped relationship identified in our analysis.

Incorporating both DIG and DIG² allows the model to capture the nonlinear relationship between digitalization and FDI. The positive coefficient of DIG reflects the initial benefits of digitalization in attracting FDI, while the negative coefficient of DIG² indicates diminishing returns as digitalization increases beyond an optimal threshold. This quadratic specification provides robust evidence of the nonlinear nature of the relationship, as confirmed by statistical significance across multiple models.

3-3- Method

3-3-1- Principal Component Approach (PCA)

The study employs PCA to construct a composite index for the digitization (DIG). PCA, first introduced by Pearson [53] and later expanded by Hotelling [54], involves extracting information from multidimensional datasets and transforming the original variables into new indices that reflect relevant information across distinct, uncorrelated dimensions. It operates by reducing a large set of variables while preserving as much of the original data as possible.

To derive the composite index for digitization (DIG), the first eigenvector or loading matrix from PCA was used as the necessary weights. Consequently, the following linear combination exists:

$$DIG = \vartheta_1 Mobile + \vartheta_2 Internet + \vartheta_3 Telephone \quad (3)$$

Here, ϑ_1, ϑ_2 and ϑ_3 represent the eigenvectors (weights) derived from PCA, while Mobile, Internet, and Telephone are the three primary components of digitization.

Since the component variables are measured on different scales, we normalized them before conducting PCA to ensure accurate and meaningful results. PCA relies on the variance of the variables, and if the variables have different scales, those with larger values will dominate the results, distorting the analysis. Normalization adjusts the variables to a common scale with a mean of 0 and a standard deviation of 1, eliminating the influence of measurement units and ensuring all variables contribute equally to the analysis. The formula for standardization is as follows:

$$x_{t.norm} = \frac{x_t - \mu}{\delta} \quad (4)$$

where $x_{t.norm}$ is the normalized value, x_t is the original value, μ is the mean, and δ is the standard deviation.

3-3-2- Cross-sectional Dependence (CD) Test and Slope Heterogeneity Test

A key characteristic of panel data is cross-sectional dependence, which arises when a common factor makes units (countries) interdependent. Identifying this dependence is vital for panel data analysis [55]. Neglecting cross-sectional dependence can result in biased and unpredictable outcomes [56], undermining the reliability of the findings [55]. To evaluate cross-sectional dependence among the variables, the Pesaran test was utilized. The formulation of the Pesaran test is as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{p=i+1}^{N} \rho_{pi} \quad (5)$$

In the equation above, T denotes the time dimension, N represents the panel size, and ρ_{pi} is the correlation coefficient. The null hypotheses for this test are no cross-sectional dependence. To further ensure the robustness of our analysis, we also employed the Friedman test to corroborate the presence of cross-sectional dependence.

The countries studied display diverse characteristics in the research data, indicating that each cross-section is heterogeneous. The slope homogeneity or heterogeneity is crucial for the accuracy of estimation results. Consequently, this study utilizes the slope heterogeneity test proposed by Pesaran & Yamagata (2008) [57], specified as follows:

$$\widetilde{\Delta_{SH}} = (\mathrm{N})^{\frac{1}{2}} (2K)^{-\frac{1}{2}} \left(\frac{1}{N}\tilde{S} - k\right) \quad (6)$$

$$\widetilde{\Delta_{ASH}} = (\mathrm{N})^{\frac{1}{2}} \left(\frac{2k(T-k-1}{T+1}\right)^{-\frac{1}{2}} \left(\frac{1}{N}\tilde{S} - k\right) \quad (7)$$

Among them, the adjusted delta tilde is $\widetilde{\Delta_{ASH}}$ and delta tilde is $\widetilde{\Delta_{SH}}$.

3-3-3- Stationary Test

After assessing cross-sectional dependence in the panel data, we conduct unit root tests to determine if a variable is I(0) or I(1). If the CD test indicates cross-sectional dependence among countries, we use second-generation unit root tests, namely the CADF and CIPS tests developed by Pesaran [58]. The CADF test accounts for cross-sectional dependence, ensuring valid regression estimates. Equation 8 presents the CADF model.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{k} \delta_{ik} \Delta \bar{y}_{t-j} + \sum_{j=1}^{k} \delta_{ik} \Delta y_{i,t-j} + \varepsilon_{it} \quad (8)$$

where $\Delta y_{i,t-j}$ và $\bar{y}_{t-1}$ characterize the differenced and lags of the variable being tested. After calculating CADF, CIPS is calculated by averaging CADF and introduced by Pesaran [58] as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF \quad (9)$$

If cross-sectional dependence is absent, we employ first-generation unit root tests, such as Im-Pesaran-Shin (IPS) [59], Levin-Lin-Chu (LLC) [60], Breitung test [61] and ADF-Fisher test introducted by Maddala & Wu [62].

3-3-4- Two-Step S-GMM

The study employs the Two-Step System Generalized Method of Moments (S-GMM) for estimation, a dynamic panel data technique introduced by Blundell & Bond [63] and Arellano & Bover [64]. This two-step GMM method is advantageous for preserving data integrity and preventing unnecessary data loss. It is especially effective for balanced panel datasets, providing more accurate and consistent coefficient estimates [64].

Several factors justify the use of the S-GMM approach. First, S-GMM is particularly effective when the number of cross-sectional units N exceeds the time periods T $(N > T)$. In our study, which includes data from 67 countries (N=67) over the period from 2002 to 2023 ($T = 22$), this technique is deemed appropriate.

Second, the model accounts for the potential endogeneity of the predictor variables, as lagged values of SD may correlate with past and current errors, leading to endogeneity issues. Third, the method handles country-specific fixed effects and potential collinearity among variables, which could be problematic if included variables are endogenous.

The S-GMM method also offers better explanatory power compared to traditional methods such as Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). It effectively manages endogeneity and collinearity, particularly when dealing with endogenous factors. The approach also addresses reverse causality and measurement error issues [65], which are tested using Hansen's test.

To verify the validity of the instruments used in the regression, p-values from Hansen and Sargan tests are compared to the 5% significance threshold to ensure there are no issues with over-identification. These tests are crucial for ensuring the accuracy of instrumental variable estimates in econometric models [66, 67]. Additionally, the p-values for AR(1) and AR(2) are checked against the 5% significance level to test for autocorrelation, with the null hypothesis of no autocorrelation being upheld if the p-value is greater than 0.05.

Based on Equations 1 and 2, the research model is reformulated using S-GMM as the analytical method, resulting in the following proposed model:

$$FDI_{it} = \gamma_0 + \delta_0 FDI_{i,t-1} + \gamma_1 DIG_{it} + \delta_j X'_{it} + (\mu_i + \varepsilon_{it}) \tag{10}$$

$$FDI_{it} = \gamma_0 + \delta_0 FDI_{i,t-1} + \gamma_1 DIG_{it} + \gamma_2 DIG^2_{it} + \delta_j X'_{it} + (\mu_i + \varepsilon_{it}) \tag{11}$$

where $FDI_{i,t-1}$ denotes the lagged dependent variable included in the regression model. The remaining indicators are explained similarly to Equation 1.

3-3-5- Robustness Checks

Robustness checks with Dynamic Panel Threshold Regression (DPTR)

Due to the potential issues of collinearity and multicollinearity in models that include squared terms, which may affect the regression results [68], we employ the dynamic panel threshold regression developed by Kremer et al. [69] to examine the nonlinearity of digitization on FDI. This approach is an extension of the original models proposed by Hansen [70] and Caner & Hansen [71], allowing for endogenous regressors within a panel data framework. This model addresses the limitations of the static threshold model suggested by Hansen [70]. According to Sikhawal [72], there are two unresolved issues in the conventional static threshold technique. First, in many cases, economic variables may be partly determined by their past behavior. Thus, incorporating the lagged coefficient of the dependent variable into the regression equation is essential to transform the static panel data model into a dynamic panel model. Second, the static threshold approach necessitates the selection of an entirely exogenous threshold variable, which may lead to biased estimates.

The dynamic panel threshold regression is an extension of the cross-sectional threshold model proposed by Caner & Hansen [71], in which GMM estimation techniques are employed to account for endogeneity. The general form of the dynamic panel threshold model is expressed as follows:

$$y_{it} = \mu_i + \delta y_{it-1} + \beta'_1 z_{it} I(q_{it} \le \gamma) + \beta'_2 z_{it} I(q_{it} > \gamma) + \varepsilon_{it} \tag{12}$$

In which the indices $i = 1, \dots, N$ represent countries, and $t = 1, \dots, T$ denotes the time index. μ_i represents the country-specific effects, and the error term ε_{it} follows an iid distribution, $\varepsilon_{it} \sim (0, \sigma^2)$. I (·) is an indicator function that determines the regime defined by the threshold variable q_{it} and the threshold level γ. The vector z_{it} is a m-dimensional vector of explanatory variables, which may include lagged values of y and other endogenous variables. The vector of explanatory variables is divided into a subset z_{1it}, which contains exogenous variables uncorrelated with ε_{it}, and a subset of endogenous variables z_{2it}, which are correlated with ε_{it}.

In addition to the structural Equation 12, the model requires a suitable set of $k \ge m$ instrumental variables x_{it} that includes z_{1it}. Next, we apply the dynamic panel threshold model to assess the nonlinear impact of digitalization on FDI. To achieve this objective, we consider the following threshold model:

$$FDI_{it} = \mu_i + \delta_0 FDI_{i,t-1} + \beta_1 DIG_{it} I(DIG_{it} \le \gamma) + \delta_1 I(DIG_{it} \le \gamma) + \beta_2 DIG_{it} I(DIG_{it} > \gamma) + \psi' Z_{it} + \varepsilon_{it} \tag{13}$$

In Equation 13, digitalization (DIG) serves as the threshold variable and is also a regime-dependent regressor. The threshold variable DIG_{it} divides the sample into regimes with different regression parameters, represented by β_1 and β_2. We utilize digitalization measures obtained through PCA method (DIG_{PCA}) and broadband subscriptions (DIG = Broadband) as representatives for digitalization to perform robustness checks.

Following the approaches of Bick [73] and Kremer et al. [69], we allow for differences in the intercepts across regimes, denoted by δ_1. FDI_{t-1} is considered an endogenous variable, meaning $z_{2it} = initial_{it} = FDI_{i,t-1}$, while z_{1it} includes the remaining control variables. This setup minimizes any potential biases in estimating the threshold and marginal effects.

The vector x_{it} consists of explanatory variables, which can be divided into a subset of exogenous variables x_{1it} that includes Government Expenditure (GovExp), Trade Openness (TRADE), Financial Development (FD), Inflation (INF), and Institutional Quality (IQ) that are uncorrelated with ε_{it}, and a subset of endogenous variables (z_{2it} $=FDI_{t-1}$) that are correlated with ε_{it}.

Therefore, based on the advantages of the Dynamic Panel Threshold Regression (DPTR) method, we use this method to determine the threshold value of digitization. This method not only ensures that the threshold is not arbitrarily determined but also allows for the calculation of a specific threshold value by dividing the data sample into different regimes based on the threshold variable. DPTR uses Generalized Method of Moments (GMM) estimation techniques to handle endogeneity problems and clearly determines the threshold value (γ) - that is, the digitization point at which its impact on FDI changes from positive to negative. This threshold value is determined based on empirical data and verified through confidence intervals, providing clear and reliable quantitative results for researchers and policy makers.

Robustness Checks with Method of Moments Quantile Regression (MMQR)

The MMQR approach proposed by Machado & Santos Silva (2019) [74] offers the advantage of not only capturing the heterogeneous characteristics of variables across different levels but also effectively addressing issues such as extreme outliers and heteroskedasticity. We believe that the potential heterogeneous relationship between digitalization and FDI across different segments of digitalization distribution can be best captured through the panel quantile regression framework. Therefore, this study adopts MMQR as a viable method that allows us to provide evidence of variations in digitalization across different quantiles, especially at higher levels of digitalization [75]. Moreover, several studies have reported that existing panel data-based approaches fail to account for heterogeneity and cross-sectional dependence over time [76], whereas the MMQR technique can effectively observe the impact of conditional heteroskedasticity [77]. Additionally, this approach can address the potential endogeneity within independent variables, making it suitable for cases where panel data models are affected by spillover effects. The method ensures robust results for nonlinear models and accommodates asymmetry based on location [74, 77].

According to Musa et al. (2024), the FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares) models are existing panel regression models capable of addressing correlation and endogeneity issues; however, these methods lack data on conditional mean values. Therefore, given the nonlinear and asymmetric relationship of the dependent variable, the MMQR approach can resolve both endogeneity and heterogeneity issues. The robustness of the MMQR method has been confirmed in recent studies, and it is capable of delivering reliable results despite irregularities in the data [75, 76, 78]. The MMQR equation takes the following form:

$$Q_y(\tau|X_{it}) = \left(\alpha_i + \delta_i(\tau)\right) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \tag{14}$$

Here, the vector of explanatory variables is denoted by X_{it}, $Q_y(\tau|X_{it})$ represents the vector of the explained variables. $X'_{it} - \alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ indicates a scalar coefficient, showing that quantile fixed effects τ differ from conventional least squares fixed effects in that individual effects do not shift the intercept. These parameters are independent of time variation, and their heterogeneous effects are influenced by changes in quantiles and different conditional distributions. The quantile sample τ, denoted as $q(\tau)$, is estimated by solving the obtained optimization problem.

$$min_q \sum_i \sum_t \rho\tau(R_{it} - (\delta_i + z'_{it}\gamma)q) \tag{15}$$

where the check function is denoted as $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$. Next, based on the model proposed in Equation 1, we reconstruct the model using the MMQR method by incorporating the variables from our research model. The details are presented in Equation 16. Figure 1 provides a graphical presentation of the empirical econometric modeling approach utilized in the present study.

$$Q_{FDI}(\tau|X_{it}) = \alpha_{it} + \beta_{1\tau}DIG_{it} + \beta_{2\tau}DIG^2_{it} + \beta_{3\tau}GovExp_{it} + \beta_{4\tau}TRADE_{it} + \beta_{5\tau}FD_{it} + \beta_{6\tau}INF_{it} + \beta_{7\tau}IQ_{it} + \varepsilon_{it} \tag{16}$$

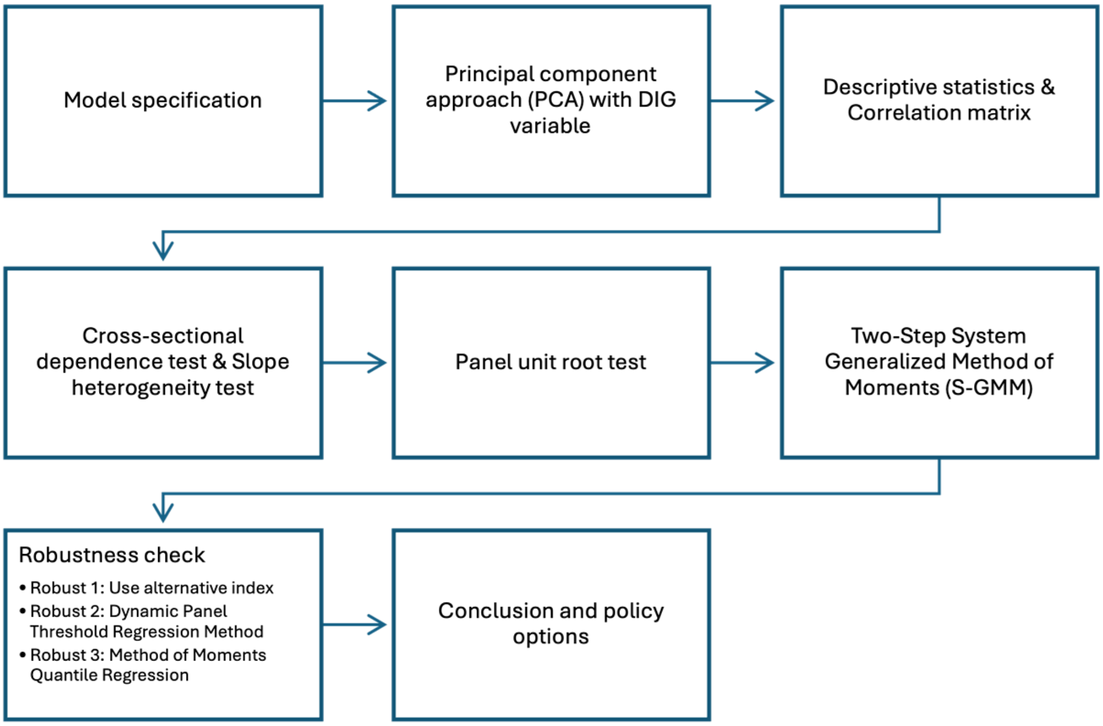

Figure 1. Estimation flow diagram

4- Empirical Results

4-1- PCA Results

Table 2 presents the PCA approach and the results of the correlation matrix for the digitization variable (DIG). First, we began by examining whether there is a certain degree of association among the indicators used to construct the DIG index. The results, presented in Panel (C), indicate that the indicators are significantly correlated. Consequently, the study proceeded to estimate PCA based on the correlated indicators [79].

Table 2. Principal component and correlation matrix results for DIG variables

Panel (A): Principal component results				
Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	1.978	1.19578	0.6593	0.6593
Component 2	0.782221	0.542441	0.2607	0.9201
Component 3	0.23978		0.0799	1.0000
Panel (B): Principal components eigenvectors results				
Variables	Component 1	Component 2	Component 3	Unexplained
Mobile	0.6220	-0.4024	0.6718	0
Internet	0.6507	-0.2117	-0.7292	0
Telephone	0.4357	0.8907	0.1301	0
Panel (C): Correlation matrix results				
Variables				
Mobile	1.0000			
Internet	0.7496*** (0.0000)	1.0000		
Telephone	0.2766*** (0.0000)	0.3904*** (0.0000)	1.0000	

Note(s): p-value in parentheses; *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

Based on Table 2, the first component was selected for the DIG variable as its eigenvalue exceeds 1 (1.978) and contributes the most to the total variance. The scree plot in Figure 2 further supports our findings.

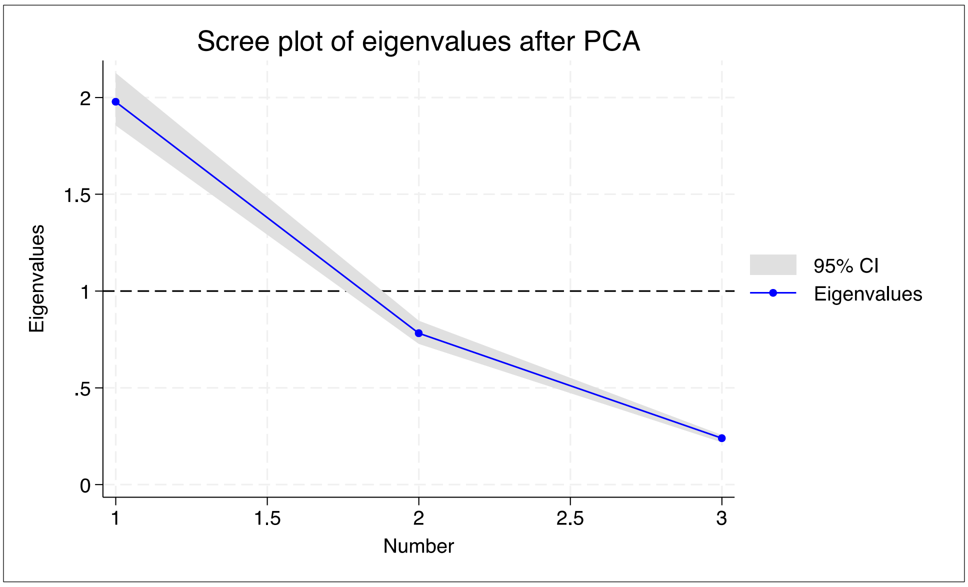

Figure 2. Scree plot of eigenvalues from the PCA

4-2- Descriptive Statistics

The descriptive statistics and correlation matrix presented in Table 3 provide a comprehensive overview of the study variables. FDI as a percentage of GDP has a mean value of 4.0433%. The range of FDI as a percentage of GDP spans from a minimum of -40.086% to a maximum of 106.53%, highlighting the diverse levels and significant volatility of FDI inflows across developing countries. Digitalization (DIG) exhibits a mean of 2.48e-10 and a standard deviation of 1.4064, indicating considerable dispersion in the levels of digitalization across the sample.

Table 3. Descriptive statistics and correlation matrix

Variables	FDI	DIG	GovExp	TRADE	FD	INF	IQ
Mean	4.0433	2.48e-10	14.689	77.893	39.333	6.0695	-0.2522
Std.Dev	6.2385	1.4064	4.8590	35.140	28.128	7.2167	0.5367
Min	-40.086	-2.4957	3.4603	22.106	3.4351	-7.1138	-1.3383
Max	106.53	3.1158	46.262	222.18	194.67	108.89	1.2523
Obs.	1,474	1,474	1,474	1,474	1,474	1,474	1,474
				Correlation matrix			
FDI	1.0000						
DIG	0.0699***	1.0000					
GovExp	0.0612**	0.2474***	1.0000				
TRADE	0.3266***	0.2407***	0.2866***	1.0000			
FD	0.0042	0.4207***	0.0758***	0.2539***	1.0000		
INF	0.0566**	-0.1161***	-0.0809***	0.0531**	-0.1931***	1.0000	
IQ	0.1228***	0.3892***	0.3400***	0.2749***	0.3209***	-0.1763***	1.0000

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

The correlation matrix reveals significant interrelationships among the variables. FDI is positively correlated with both DIG (0.0699, $p < 0.01$) and the control variables, providing initial indications that digitalization may enhance the attractiveness of FDI inflows in developing countries. The statistical evidence suggests strong correlations between the independent variables and the control variables in the model. However, all correlation coefficients are below 0.8, indicating that multicollinearity is not a severe concern in our regression model.

4-3- Cross-Section Dependence Tests and Panel Unit Root Tests Results

Table 4 reports the results of cross-sectional dependence tests for the variables under consideration, using both Pesaran's CD-test and Friedman's CD-test.

Table 4. Result of cross-sectional dependence

Variables	Pesaran's CD-test		Freidman CD-test	
	Statistics	p-value	Statistics	p-value
FDI	22.189***	0.0000	162.766***	0.0000
DIG	207.471***	0.0000	1310.736***	0.0000
GovExp	22.104***	0.0000	151.162***	0.0000
TRADE	33.503***	0.0000	233.740***	0.0000
FD	85.567***	0.0000	546.478***	0.0000
INF	63.509***	0.0000	353.293***	0.0000
IQ	0.954	0.3401	29.869	1.0000

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

The results indicate that FDI, DIG, GovExp, TRADE, FD, and INF all exhibit significant cross-sectional dependence. Both Pesaran's and Friedman's CD-test results confirm this at the 1% level of statistical significance, highlighting the increasing economic interdependence among countries in a globally integrated environment. In contrast, IQ does not show cross-sectional dependence across countries. Pesaran's CD-test statistic for IQ is 0.954 with a p-value of 0.3401, and Friedman's CD-test statistic is 29.869 with a p-value of 1.0000, indicating relative independence of institutional quality among the studied countries.

These findings guide the selection of appropriate unit root tests to ensure the accuracy and efficiency of data analysis, considering the presence or absence of cross-sectional dependence.

Table 5 presents the results of the slope heterogeneity test. The findings indicate significant slope heterogeneity based on both the Delta and adjusted Delta statistics. Specifically, the Delta statistic is 29.497, and the adjusted Delta statistic is 36.977, both statistically significant at the 1% level. These results demonstrate substantial variations in the regression slopes across different sections. In other words, the relationship between the dependent and independent variables is not homogeneous across the sample, and the coefficients vary significantly between different observations. This finding underscores the need to account for slope heterogeneity in the model specification to ensure reliable results.

Table 5. Slope heterogeneity test

Slope heterogeneity		
Delta	29.497***	0.000
Adj.	36.977***	0.000

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

Table 6 presents the results of the stationarity test using the CIPS method for variables with cross-sectional dependence. The findings indicate that FDI, DIG, and INF are stationary at the level (I(0)). Specifically, the CIPS values are -2.928, -2.185, and -3.057, respectively, all significant at the 1% level. In contrast, the variables GovExp, TRADE, and FD are stationary at the first difference (I(1)). These results highlight differences in stationarity among the variables, providing crucial information for selecting the appropriate analytical methods tailored to the characteristics of each variable.

Table 6. Results of the unit root test with CIPS

Variables	Level	First difference	Decision
FDI	-2.928***	-	I(0)
DIG	-2.195***	-	I(0)
GovExp	-1.746	-4.199***	I(1)
TRADE	-1.715	-4.090***	I(1)
FD	-1.955	-3.455***	I(1)
INF	-3.057***	-	I(0)

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

Table 7 presents the results of the stationarity tests for the IQ variable using various first-generation unit root tests. The results indicate that the IQ variable is not stationary at the level according to the Im, Pesaran, and Shin (IPS), ADF-Fisher, and Breitung tests, with p-values of 0.2330, 0.1831, and 0.9009, respectively. However, all methods consistently show that the IQ variable becomes stationary at the first difference, with statistical significance at the 1% level.

Table 7. Results of the unit root test for IQ variable

Methods	Level		First difference	
	Statistics	p-value	Statistics	p-value
Im, Pesaran and Shin (IPS) test	-0.7290	0.2330	-17.1965***	0.0000
Levin-Lin-Chu (LLC) test	-4.9175***	0.0000	-14.5403***	0.0000
ADF-Fisher test	148.6299	0.1831	706.8043***	0.0000
Breitung test	1.2864	0.9009	-8.5279***	0.0000

Note: *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

Based on the stationarity test results, the non-stationary variables are differenced to the first order to ensure stationarity before being included in the analytical model. This step is essential for maintaining the validity of the regression analysis and preventing spurious results.

4-4- Results of Two-Step S-GMM

To achieve the research objectives, we first examine the linear impact of digitalization on FDI. The results in part A of Table 8 indicate that digitalization has a significant positive effect on attracting FDI in developing countries, highlighting how advancements in digital infrastructure and technology can directly enhance a country's appeal to foreign investors. Digitalization improves the business environment by increasing connectivity, enhancing operational efficiency, and reducing transaction costs. These factors make a country more attractive to foreign investors.

This finding is consistent with previous studies by Asongu & Odhiambo [2] and accurately reflects the reality in many countries within this region. Evidence from countries like India, Vietnam, and Kenya reinforces these results. Data collected from the World Bank shows that in India, the Digital India initiative increased internet usage from 27% in 2015 to 50% in 2020, accompanied by a surge in FDI inflows from $45.15 billion in 2014-2015 to a record $64 billion in the fiscal year 2020-2021. Similarly, in Vietnam, the percentage of internet users rose from 27% in 2010 to nearly 70% in 2020, leading to an increase in FDI from $8 billion in 2010 to approximately $28.5 billion in 2020, primarily focused on high-tech and electronics manufacturing sectors. In Kenya, the robust development of the mobile payment system M-Pesa attracted FDI flows, which grew from $404 million in 2010 to $1.5 billion in 2019, particularly in the technology and telecommunications sectors.

These examples affirm that as countries enhance their digital infrastructure, they not only improve economic efficiency but also create a more attractive investment environment for foreign investors.

Next, we delve into whether this positive relationship is long-lasting by examining the nonlinear effects. The results in part B of Table 8 indicate that the coefficients of $[DIG_{PCA}]^2$, $Mobile^2$, $Internet^2$, and $Telephone^2$ are all negative and statistically significant, suggesting the presence of diminishing returns as the level of digitalization increases. In other words, digitalization exhibits a inverted U-shaped nonlinear effect on FDI, reflecting a complex relationship between these two factors. This implies that while FDI initially rises with increasing digitalization, it begins to decline after reaching a certain threshold.

Comparing with previous studies, these findings align with research affirming the positive impact of digitalization on FDI, while also contributing a new perspective on the nonlinear nature of this relationship. Prior studies, such as those by Asongu & Nwachukwu (2016) and Choi (2003), have indicated that advancements in digitalization can boost FDI. However, the current research reveals that this benefit is not always linear and may diminish as the level of digitalization rises, consistent with several recent findings [3, 17–19].

In the early stages, as digitalization begins to develop, it can stimulate FDI by enhancing business efficiency, reducing transaction costs, and creating new business opportunities. Foreign businesses often seek investment opportunities in countries with increasing levels of digitalization due to the growth potential arising from the adoption of new technologies and improved digital infrastructure connectivity. As digitalization continues to rise and reaches an optimal level, FDI is likely to increase significantly as the economic benefits of digitalization are fully realized. The business environment becomes more attractive to foreign investors thanks to advanced technological infrastructure, favorable regulatory frameworks, and expanding consumer markets [80].

Furthermore, digitalization can assist governments in promoting themselves to attract additional FDI [11]. Additionally, digitalization reduces the costs associated with talent acquisition. Regions with higher levels of digital development tend to possess stronger technological capabilities and a more skilled workforce, providing a substantial talent pool for multinational enterprises [13].

Table 8. Impact of Digitalization on FDI: S-GMM estimation

Dep.Var: FDI	A. Linear Impact of Digitalization on FDI				B. Nonlinear Impact of Digitalization on FDI			
	DIG = DIG_{PCA}	DIG = Mobile	DIG = Internet	DIG = Telephone	DIG = DIG_{PCA}	DIG = Mobile	DIG = Internet	DIG = Telephone
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
FDI_{t-1}	0.198*** [0.00451]	0.187*** [0.00433]	0.190*** [0.00622]	0.218*** [0.00871]	0.184*** [0.00494]	0.183*** [0.00443]	0.198*** [0.00550]	0.198*** [0.00613]
DIG_{PCA}	6.033*** [0.736]				0.228*** [0.0385]			
$[DIG_{PCA}]^2$					-0.864** [0.354]			
Mobile		0.118*** [0.0162]				0.181*** [0.0350]		
$Mobile^2$						-0.000615*** [0.000164]		
Internet			0.171*** [0.0350]				0.249*** [0.0772]	
$Internet^2$							-0.00209*** [0.000526]	
Telephone				3.103*** [0.168]				3.334*** [0.518]
$Telephone^2$								-0.0866*** [0.0136]
GovExp	-0.249** [0.115]	-0.0544 [0.118]	-0.175 [0.120]	-0.701*** [0.170]	-0.0423 [0.115]	-0.0995 [0.111]	-0.257** [0.127]	-0.409*** [0.142]
TRADE	0.0388*** [0.00295]	0.0392*** [0.00276]	0.0366*** [0.00373]	0.0285*** [0.00367]	0.0407*** [0.00294]	0.0404*** [0.00294]	0.0369*** [0.00358]	0.0419*** [0.00375]
FD	0.347*** [0.0514]	0.316*** [0.0467]	0.542*** [0.0511]	0.372*** [0.0545]	0.271*** [0.0459]	0.317*** [0.0425]	0.442*** [0.0544]	0.519*** [0.0623]
INF	0.179*** [0.0190]	0.0999*** [0.0233]	0.141*** [0.0223]	-0.0536** [0.0262]	0.153*** [0.0218]	0.117*** [0.0206]	0.197*** [0.0195]	0.142*** [0.0258]
IQ	1.610*** [0.252]	1.432*** [0.253]	1.782*** [0.260]	2.323*** [0.321]	1.770*** [0.297]	1.574*** [0.268]	1.923*** [0.239]	1.514*** [0.239]
Constant	-1.587*** [0.361]	-0.877*** [0.298]	-0.0361 [0.447]	1.893*** [0.410]	-1.234*** [0.360]	-0.876*** [0.307]	-1.018** [0.402]	-0.904** [0.383]
Obs.	1206	1206	1206	1206	1206	1206	1206	1206
No. of IVs	39	39	39	39	40	40	40	40
Countries	67	67	67	67	67	67	67	67
AR(1) test	(0.029)	(0.030)	(0.015)	(0.022)	(0.035)	(0.034)	(0.024)	(0.007)
AR(2) test	(0.336)	(0.327)	(0.319)	(0.442)	(0.333)	(0.330)	(0.333)	(0.316)
Hansen test	(0.150)	(0.142)	(0.078)	(0.173)	(0.089)	(0.055)	(0.109)	(0.042)

Note(s): Standard error in square brackets; p-value in parentheses; *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

However, once digitalization surpasses the optimal threshold, FDI begins to decline. This may be due to higher compliance costs associated with new technologies, increased complexity in data management and security, or market saturation [14, 15]. Additionally, businesses may struggle to adapt to the rapid pace of technological change, leading to reduced investment. Furthermore, excessive digitalization can create overwhelming competition between domestic and foreign firms, making it difficult to maintain profitability. Moreover, emerging technologies can have negative environmental impacts, potentially making digital FDI less attractive to host countries [11].

Thus, this inverted U-shaped relationship underscores the necessity of maintaining a balance in the digitalization process to optimize the benefits of FDI while avoiding negative repercussions when digitalization becomes excessive.

The control variables exhibit a significant impact on FDI, affirming that not only digitalization but also other macroeconomic and institutional factors play crucial roles in attracting foreign investment. Trade openness (TRADE) positively affects FDI across all models, aligning with economic theory and previous studies that suggest countries with higher trade openness attract more FDI. Foreign investors often seek markets with good access to other markets through international trade; thus, a high level of international integration enhances a country's attractiveness for FDI.

Financial development (FD) also has a strong positive impact on FDI. It improves access to capital, reduces transaction costs, and boosts investor confidence. A well-developed financial system provides necessary funding for investing businesses, optimizing investment opportunities and enhancing FDI inflows. In contrast, inflation (INF) has varying effects across models. In most cases, inflation positively correlates with FDI; however, in certain instances, particularly when measuring digitalization through fixed-line telephone usage (model 1d), inflation has a negative effect. This may indicate that moderate inflation can be seen as a sign of economic growth, creating opportunities for investors. Yet, excessively high inflation can lead to economic instability, diminishing the attractiveness of the investment environment.

Institutional quality (IQ) demonstrates a robust positive impact on FDI across all models, underscoring the critical role of institutional quality in attracting FDI. Institutional quality encompasses factors such as management efficiency, corruption levels, legal quality, and property rights protection. Foreign investors tend to favor countries with strong institutions, where property rights are safeguarded, administrative procedures are transparent, and policies are stable. This reduces investment risks and increases a country's attractiveness for FDI.

Conversely, government expenditure (GovExp) has a negative impact in most models, which may be attributed to inefficient public spending. For instance, public investment in unprofitable projects can erode foreign investors' confidence. Additionally, if government spending increases significantly without corresponding economic effectiveness, it could lead to budget deficits or increased public debt, creating macroeconomic risks that undermine the attractiveness of the investment environment.

Diagnostic tests, including the AR(2) test, show no second-order autocorrelation, and the Hansen test for the validity of instruments in GMM estimation indicates that the instruments are likely valid.

4-5- Robustness Checks

To assess the robustness of the impact of digitalization on FDI, we first replaced the digitalization measure with the level of "broadband subscriptions." Subsequently, we employed various methods to address challenges related to multicollinearity and slope heterogeneity, which result in non-uniform effects within the data, including the Dynamic Panel Threshold Regression Method and MMQR.

Using broadband subscriptions as a measure of digitalization allows for a more direct assessment of the technological infrastructure available to businesses, which can significantly influence foreign investment decisions. The Dynamic Panel Threshold Regression Method enables us to identify potential threshold effects, revealing how the impact of digitalization on FDI may vary across different levels of digitalization. Additionally, the MMQR method offers insights into the asymmetric relationships between variables, capturing the nuances of how digitalization affects FDI under varying conditions.

By implementing these approaches, we aim to confirm the initial findings and ensure that the observed effects of digitalization on FDI are not artifacts of specific measurement choices or methodological limitations. This comprehensive analysis will provide a clearer understanding of the dynamics at play and enhance the credibility of our conclusions regarding the role of digitalization in attracting FDI.

4-5-1- Robustness Checks 1: Substituting the Measure of Digitalization

Table 9 presents the results of our first robustness test, wherein the number of broadband subscriptions is employed as a proxy for digitalization in analyzing the determinants of FDI. This measure reflects the level of access to and utilization of high-speed internet, which can significantly influence foreign firms' investment decisions. In several studies, such as those by Ha & Huyen (2022) [17] and Latif et al. (2018) [81], "the number of broadband subscriptions" has been utilized to gauge the extent of digitalization. Employing this measure enhances the robustness of our findings regarding the impact of digitalization on FDI and provides a more comprehensive understanding of the digital landscape's role in attracting foreign investment.

Table 9. Robustness check 1 - Using broadband subscriptions as a proxy for digitization

Dep.Var: FDI	Coefficient	Standard Error	*t*-statistics
FDI_{t-1}	0.1963561***	0.0053553	36.67
Broadband	0.8979082***	0.1655543	5.42
$Broadband^2$	-0.0331003***	0.0061046	-5.42
GovExp	-0.2153022	0.1503041	-1.43
TRADE	0.0394832***	0.0035259	11.20
FD	0.4094069***	0.0563139	7.27
INF	0.2159599***	0.025931	8.33
IQ	1.771009***	0.2231222	7.94
Constant	-1.229046***	0.3520175	-3.49
Obs.		1139	
No. of IVs		40	
Countries		67	
AR(1) test (p-value)		(0.025)	
AR(2) test (p-value)		(0.329)	
Hansen test (p-value)		(0.108)	

Note(s): p-value in parentheses; *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

The model employs dynamic panel data, incorporating various control variables and examining the potential existence of endogeneity issues using instrumental variables. The main results indicate that digitalization, represented by the number of broadband subscriptions, has a significant positive impact coefficient of 0.8979082 ($p < 0.01$), reflecting a strong and statistically significant influence of digitalization on FDI. The development of broadband not only enhances the connectivity of businesses but also improves operational efficiency and labor productivity, thereby increasing a country's attractiveness to foreign investors.

Considering the non-linear effects of digitalization on FDI, we find that the coefficient for the squared broadband subscriptions variable ($Broadband^2$) is -0.0331003 with statistical significance at the 1% level, indicating the presence of diminishing returns to the expansion of broadband infrastructure. Once a certain threshold is reached, further enhancement of broadband access may yield only marginal improvements in FDI.

The diagnostic tests for AR (2) (p-value = 0.329) and the Hansen test (p-value = 0.108) show no evidence of second-order autocorrelation, supporting the validity of the instrumental variables used for the lagged dependent variable and confirming that the identification constraints are valid, thus affirming the exogeneity of the instruments employed. These findings provide additional robust evidence of the inverted U-shaped relationship between digitalization and FDI in developing countries.

4-5-2- Robustness Checks 2: Substituting the Estimation Method - Dynamic Panel Threshold Regression Method

The nonlinear impact of digitization on FDI was identified in the S-GMM estimations. However, due to concerns related to collinearity and multicollinearity in models that include squared terms, as noted by Narayan & Narayan (2010), we employ threshold estimation on dynamic panel data to provide further robust evidence for our findings. Table 10 presents the results of the robustness check using threshold estimation for the dynamic panel data model, in which digitization (DIG) is represented by two variables: the composite index from principal component analysis (DIG_{PCA}) and the number of broadband subscribers. The results provide strong evidence of the nonlinear effect of digitization on FDI attraction in developing countries. Specifically, the threshold estimates for DIG_{PCA} is -1.775, with a 95% confidence interval ranging from [-1.839; -1.537], and the threshold for broadband is 4.002, with a confidence interval from [1.709; 18.846].

Table 10. Robustness check 2: Using Dynamic Panel Threshold Regression Method

Variables	DIG = DIG_{PCA}	DIG = Broadband
Threshold $\hat{\gamma}$	-1.775	4.002
Confidence interval (95%)	[-1.839; -1.537]	[1.709; 18.846]
$\widehat{\beta_1}\,(DIG \leq \gamma)$	0.104***	0.0751***
	[0.0274]	[0.0149]
$\widehat{\beta_2}\,(DIG > \gamma)$	-0.138**	-0.00870***
	[0.0153]	[0.00177]
FDI_{t-1}	0.232***	0.252***
	[0.0192]	[0.0203]
GovExp	-1.189***	-1.701***
	[0.220]	[0.233]
TRADE	0.363**	0.313***
	[0.130]	[0.116]
FD	0.444***	0.659***
	[0.124]	[0.127]
INF	0.0442**	0.0271**
	[0.00887]	[0.0110]
IQ	0.324***	0.0625
	[0.166]	[0.120]
Constant	0.495***	0.341***
	[0.048]	[0.0178]
$\hat{\delta}_1$	116.9231**	61.47919**
Boostrap	45.34377**	28.84291**
N	67	67
Observation	1407	1407

Note(s): The point estimates of the thresholds ($\hat{\gamma}$) and the corresponding 95% confidence intervals (C.I) are reported in the first two rows respectively. The regime-dependent marginal effects of DIG on FDI are denoted by $\widehat{\beta_1}$ and $\widehat{\beta_2}$. $\hat{\delta}_1$ is the threshold intercept. In [ ] is the standard error; *, **, *** represent statistical significance at 10%, 5% and 1%

Analyzing the impact of digitization below and above the threshold, we find that when the level of digitization is below the threshold (DIG ≤ γ), the effect of digitization on FDI is positive and statistically significant for both measures of digitization. However, when the level of digitization exceeds this threshold (DIG > γ), the effect on FDI turns negative. This result reaffirms the nonlinear relationship between digitization and FDI, wherein initial increases in digitization promote FDI, but beyond a certain threshold, this effect becomes negative due to diminishing returns as the digitization process reaches saturation, or due to the costs and potential risks associated with maintaining and excessively expanding digitization. Therefore, digitization development policies need to be carefully considered to optimize the level of digitization while ensuring that this level does not exceed the threshold that could harm FDI attraction.

Additionally, other control variables in the model also report results consistent with the initial estimations. The lagged FDI (FDI_{t-1}) exhibits a positive coefficient and is highly statistically significant ($p < 0.01$) in both models, indicating the persistence of FDI over time. Government expenditure (GovExp) has a significant negative effect on FDI, with a negative coefficient that is statistically significant at $p < 0.01$. Other variables, such as trade openness (TRADE) and financial development (FD), have positive and statistically significant impacts on FDI, while inflation (INF) shows a positive but weaker effect.

4-5-3- Robustness Checks 3: Substituting the Estimation Method – MMQR

In this section, we report the results of the new MMQR approach. This is necessary because the relationship between digitization and FDI is nonlinear and heterogeneous across the distribution of FDI. This implies that the impact of digitization on FDI may vary at different levels of FDI, and a single average estimate may not adequately capture the complexities of this relationship, especially when considering the heterogeneous characteristics of countries in relation to data generation processes [74]. Different countries or regions may experience varying degrees of impact from digitization on FDI depending on their position within the FDI distribution. For instance, countries with low levels of FDI may observe a stronger positive impact of digitization compared to those with high levels of FDI.

Quantile estimation allows for the examination of these differences and provides a more nuanced understanding of how digitization influences FDI in various contexts. Furthermore, due to the nonlinear nature of the impact of digitization on FDI, as evidenced in the results from Tables 8, 9, and 10, the effect of digitization on FDI may change at different levels of digitization. Thus, quantile estimation facilitates the identification and modeling of this variation, enabling an analysis of how the relationship between digitization and FDI shifts across the distribution. The MMQR approach also mitigates the influence of outliers in the data, thereby offering a more accurate portrayal of the relationship between digitization and FDI. Additionally, this method aids policymakers in gaining a clearer understanding of the impact of digitization on FDI at various levels of the distribution, allowing for the design of policies tailored to specific groups of countries or regions.

The results presented in Table 11 indicate that digitalization positively and significantly impacts the dependent variable across all quantiles from Q10 to Q80. The variable $[\mathrm{DIG_{PCA}}]^2$ also has a negative coefficient. It is statistically significant in most quantiles from Q10 to Q70, affirming the inverted U-shaped relationship between digitalization and the dependent variable. Specifically, the initial increase in digitalization yields a positive effect, but this effect diminishes as digitalization continues to rise. However, the level of impact gradually decreases when moving from lower to higher quantiles, suggesting that the influence of digitalization is strongest at lower quantiles and diminishes at higher ones. This relationship indicates that the effectiveness of digitalization decreases as FDI investment levels increase.

This can be explained as follows: at low investment levels, an increase in digitalization enhances operational efficiency and the quality of the investment environment. Multinational companies may find that improvements in technological infrastructure, workflow processes, and information management systems increase investment opportunities. Digitalization can help reduce transaction costs, improve access to information, and enhance management practices, creating a more attractive investment environment in the host country. Furthermore, countries or regions with high levels of digitalization may become more competitive in attracting FDI, as digitalization fosters a more conducive environment for businesses to operate. This is particularly important at low investment levels, where the fundamental aspects of digitalization can make a significant difference.

However, as FDI investment levels increase and reach high levels, the effectiveness of digitalization begins to wane. When FDI has reached a high level, additional improvements from digitalization may become less critical. At high investment levels, other factors such as tax policies, political stability, and quality infrastructure may become more significant. Once these factors are improved to a high degree, the increase in digitalization may no longer make a substantial difference in attracting additional investment. Moreover, when digitalization reaches a level of ubiquity or a high threshold, the incremental benefits of digitalization may diminish. For instance, countries with advanced technological infrastructure may not derive significant additional benefits from further increases in digitalization, as investors may not perceive a marked difference in these benefits compared to other factors. Ultimately, investors at high investment levels may have already achieved technological satisfaction and may no longer seek further improvements from digitalization. Focus may shift to other factors such as public policy or larger consumer markets rather than digitalization.

When linked to the level of development of countries attracting FDI, the heterogeneous impact of digitalization on FDI across different groups of developing countries can be further examined through the lens of quantitative effects. In low-income countries, where FDI is typically limited, enhancements in digital infrastructure and connectivity can crucially boost investment attraction, as even small improvements can lower transaction costs, enhance market access, and increase operational efficiency. In contrast, middle-income countries, which usually have higher FDI inflows, may experience diminishing returns from digitalization due to existing digital saturation and more complex factors like regulatory quality. These countries are also better equipped to integrate digital technologies, resulting in a subtler impact on FDI at higher quantiles. Therefore, it is essential to customize digitalization strategies according to the specific economic contexts of developing countries to optimize their ability to draw in foreign investments.

Examining the effects of the control variables, government expenditure (GovExp) has a negative impact on the dependent variable at quantiles ranging from Q10 to Q70, with the effect diminishing as we move to higher quantiles. This suggests that public spending may be ineffective or exhibit diminishing returns at lower quantiles, while at higher quantiles, the impact becomes less negative or even potentially positive. In contrast, trade (TRADE), financial development (FD), inflation (INF), and institutional quality (IQ) have a positive and statistically significant effect across all quantiles of FDI.

Table 11. Results of the MMQR

Variables	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG_{PCA}	0.159***	-0.0662***	0.267***	0.220***	0.194***	0.172***	0.151***	0.132***	0.113***	0.0892**	0.0576
	[0.0368]	[0.0253]	[0.0652]	[0.0507]	[0.0437]	[0.0390]	[0.0358]	[0.0342]	[0.0342]	[0.0361]	[0.0419]
$[DIG_{PCA}]^2$	-0.0149**	0.00621	-0.0251**	-0.0207**	-0.0182***	-0.0162**	-0.0142**	-0.0124**	-0.0106*	-0.00841	-0.00545
	[0.00595]	[0.00409]	[0.0105]	[0.00819]	[0.00707]	[0.00632]	[0.00578]	[0.00553]	[0.00552]	[0.00584]	[0.00677]
GovExp	-0.283***	0.219***	-0.642***	-0.486***	-0.399***	-0.328***	-0.258***	-0.195***	-0.131*	-0.0531	0.0519
	[0.0774]	[0.0533]	[0.138]	[0.107]	[0.0918]	[0.0821]	[0.0753]	[0.0719]	[0.0720]	[0.0761]	[0.0881]
TRADE	0.957***	-0.0511	1.041***	1.005***	0.984***	0.968***	0.952***	0.937***	0.922***	0.904***	0.879***
	[0.0601]	[0.0413]	[0.106]	[0.0827]	[0.0713]	[0.0638]	[0.0584]	[0.0558]	[0.0557]	[0.0590]	[0.0683]
FD	-0.355***	0.0939***	-0.508***	-0.442***	-0.404***	-0.374***	-0.344***	-0.317***	-0.290***	-0.256***	-0.211***
	[0.0449]	[0.0309]	[0.0797]	[0.0618]	[0.0533]	[0.0477]	[0.0437]	[0.0417]	[0.0417]	[0.0441]	[0.0511]
INF	0.0900***	0.0297*	0.0416	0.0625*	0.0744**	0.0840***	0.0935***	0.102***	0.111***	0.121***	0.135***
	[0.0248]	[0.0170]	[0.0439]	[0.0341]	[0.0294]	[0.0263]	[0.0241]	[0.0230]	[0.0230]	[0.0243]	[0.0282]
IQ	0.172***	-0.0702***	0.286***	0.237***	0.209***	0.186***	0.164***	0.144***	0.123***	0.0981***	0.0646***
	[0.0219]	[0.0151]	[0.0390]	[0.0302]	[0.0260]	[0.0232]	[0.0213]	[0.0204]	[0.0204]	[0.0215]	[0.0249]
Constant	-0.702***	0.0487	-0.781***	-0.747***	-0.727***	-0.712***	-0.696***	-0.682***	-0.668***	-0.650***	-0.627***
	[0.139]	[0.0955]	[0.245]	[0.191]	[0.165]	[0.147]	[0.135]	[0.129]	[0.129]	[0.136]	[0.158]
N	1412	1412	1412	1412	1412	1412	1412	1412	1412	1412	1412

Note(s): Standard errors in [ ]; *, **, *** represent statistical significance at 10%, 5% and 1%, respectively.

5- Conclusion and Policy Recommendations

Digitalization has become a core driver of global economic development, influencing how businesses operate, connect, and expand internationally. It reduces transaction costs, enhances transparency, and improves operational efficiency, thereby attracting foreign investors. Concurrently, digitalization plays a crucial role in enhancing national competitiveness. Therefore, understanding the impact of digitalization on FDI enables policymakers to design and implement appropriate strategies to attract investment, improve the quality of economic growth, and promote sustainable development. This is particularly important for developing countries, where limited domestic resources and intense competition for FDI necessitate economic transformation and adaptation to rapid global technological changes. In this study, we employ various econometric methods, including S-GMM, Threshold Regression, and MMQR, to estimate the nonlinear effects of digitalization on FDI in developing countries from 2002 to 2023.

The research results indicate a nonlinear relationship between digitalization and FDI, where the impact of digitalization on FDI varies at different levels of digitalization. As the level of digitalization increases from low to high, its initial effect on FDI is positive; however, once a certain threshold is surpassed, this effect turns negative. This suggests that the benefits of digitalization for FDI are not limitless but rather can be constrained by the risks and costs associated with excessive digitalization. Policymakers need to recognize that in promoting digitalization to attract FDI, it is essential to identify and maintain an optimal level of digitalization, avoiding the threshold beyond which the impact of digitalization becomes negative. This necessitates investments not only in digitalization but also in complementary factors such as enhancing governance quality and developing a robust legal framework to ensure a stable and conducive economic environment for FDI. Furthermore, flexible policies tailored to specific groups of countries or regions are required to maximize the benefits of digitalization while preventing adverse effects on long-term economic development.

Furthermore, the MMQR analysis results indicate the heterogeneous impact of digitalization on FDI. Specifically, digitalization has a more significant positive effect on FDI at lower quantiles, where FDI levels are still low. However, as FDI increases, the effectiveness of digitalization diminishes. Therefore, in countries with low FDI levels, governments should invest heavily in digital infrastructure, information management systems, and digital initiatives. Improvements in digitalization can enhance efficiency, making these countries more attractive to foreign investors. In contrast, in countries or regions that have achieved high levels of FDI, governments should recognize that digitalization may have reached a saturation point, and further investments in digitalization may not yield the expected growth in FDI. Instead, the focus should shift to other factors, such as improving the legal environment, strengthening the infrastructure, or developing the human resources needed to maintain and continue attracting FDI.

For instance, Vietnam, a country with lower FDI levels, serves as a notable example where investments in digital infrastructure have significantly contributed to attracting FDI. The Vietnamese government has prioritized the development of information and communication technology (ICT) infrastructure and introduced favorable policies such as tax incentives and administrative reforms to facilitate digital adoption. As a result, Vietnam has become a key destination for foreign investors in the electronics and high-tech manufacturing sectors, with major corporations like Samsung and Intel establishing operations in the country. Conversely, Singapore, which has already achieved high levels of FDI, has shifted its focus from merely expanding digitalization to improving the regulatory environment and governance quality. The country has introduced comprehensive regulations on data protection, intellectual property rights, and cybersecurity while promoting innovation in emerging fields such as artificial intelligence and financial technology (FinTech). This strategic shift is consistent with the study’s finding that in economies with high FDI inflows, further investments in digitalization may yield diminishing returns, necessitating a focus on legal frameworks and governance to sustain investment attractiveness.

Additionally, governments should develop flexible digital strategies based on the economic development level and current FDI status of the country. For countries that are just beginning to digitalize, the focus should be on developing basic technologies and facilitating the adoption of new technologies. Meanwhile, advanced digitalized countries should concentrate on optimizing and maximizing the benefits of digitalization, while integrating other strategies to remain competitive in attracting FDI. Ultimately, to continue attracting FDI even when digitalization has reached a high threshold, governments should encourage innovation and creativity in industries, such as high-tech development, artificial intelligence, and other advanced technology sectors. Similarly, India's 'Digital India' initiative illustrates how developing economies can leverage digitalization to attract FDI by integrating digital solutions across various sectors, such as finance, education, and healthcare, while simultaneously investing in human capital to support long-term sustainable development. This approach will help sustain the country’s attractiveness to foreign investors, even as the benefits of traditional digitalization begin to wane.

Although this study makes important contributions to analysing the impact of digitalization on FDI in developing countries, a significant limitation is that it does not fully analyse the impact of the COVID-19 pandemic on digitalization and FDI inflows, even though this factor could have significantly altered these trends during the study period. The COVID-19 pandemic triggered a major transformation in the global economy, accelerating the reliance on digital technologies, while simultaneously causing substantial disruptions to international investment flows. Therefore, future research could focus on a more in-depth analysis of the pandemic's impact on the relationship between digitalization and FDI, particularly in developing countries.

6- Declarations

6-1- Author Contributions

Conceptualization, T.L.H. and T.H.H.; methodology, L.H.N.; software, L.H.N.; validation, T.L.H., T.H.H., and L.H.N.; formal analysis, T.L.H. and T.H.H.; investigation, L.H.N.; resources, L.H.N.; data curation, T.L.H.; writing—original draft preparation, T.L.H., T.H.H., and L.H.N.; writing—review and editing, T.L.H.; visualization, T.H.H.; supervision, T.L.H.; project administration, T.L.H.; funding acquisition, T.L.H., T.H.H., and L.H.N. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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