Digitalization and economic development: lessons from globalized developing countries

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Abstract

Purpose – This paper aims to empirically investigate the dynamic interlinkages among globalization, digitalization and economic development in the top 75 most globalized countries from 2000 to 2019. The selection of the 75 most globalized developing countries is based on the overall scores of the KOF Globalization Index (2021).

Design/methodology/approach – The research design is based on secondary data collected from the World Bank (2021), the International Telecommunication Union (2021) and the KOF Globalization Index (2021). The study uses panel unit root tests followed by the panel cointegration techniques. Further, the estimation uses panel fully modified ordinary least squares and panel dynamic ordinary least squares methods.

Findings – The empirical results reveal that the effect of globalization on economic development is sensitive to different estimation procedures; in some cases, but not in every case, the effect is positive and significant. However, the positive and significant effect of digitalization on economic development is robust across all estimated models. Long-run equilibrium relationships and bidirectional causalities strongly affirm the nexus among globalization, digitalization and economic development, substantiating the interconnectedness among 75 developing economies.

Originality/value – The study reinstates that the forces of globalization and digitalization will be instrumental in shaping the selected most globalized economies in the long run. Adopting various econometric methodologies takes care of the time-specific and cross-sectional dynamics, as evident in the panel framework considered in this study. The empirical findings truly ascertain the theoretical synergy among the forces of globalization leading to more digitalization and economic development. This makes the empirical interplay highly conducive to framing long-term policies to expand the information communication network in terms of its access and reach.

Keywords Digitalization, Globalization, Economic development, Most globalized countries, Panel data econometrics, Panel cointegration test

Paper type Research paper

JEL classification – F63, O12, O33

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1. Introduction

The interlinkage between globalization and digitalization is nothing but a dynamic rapport where each process amplifies and accelerates the other. This interplay has profound implications for economies, societies and cultures worldwide. Digitalization enables businesses to reach global markets through several advanced platforms. Conversely, globalization facilitates the transfer of digital technologies and innovations across borders. In this way, digitalization and globalization together promote inclusive economic growth by providing access to global markets and digital transformation. In this regard, developing countries must assess the dynamics of digitalization and economic development in the era of globalization, which has become one of the most considered factors in formulating strategic development policies. So, a particular research question stems from the issue regarding the symbiotic relationship between the drivers of globalization, digitalization and economic development and a robust cross-country empirical analysis would serve as guidance in formulating these policies, along with other factors to be considered, such as the unique socioeconomic characteristics of developing countries.

Developing economies necessitate digital transformation to revolutionize their industries and enable global reach and economic integration (Bukht and Heeks, 2017). Zhang *et al.* (2022) also argued that the digital economy heightens effectiveness in domains like capital and workforce, contributing to economic expansion. However, Bukht and Heeks (2018) explored the challenges developing nations face in tapping into the digital economy's potential. These challenges encompass inadequate and costly digital infrastructure, a shortage of human capabilities, insufficient financing, weak governance and issues of digital exclusion, inequality and other negative consequences. Rodrik (2019) also contended that the high cost of information and communication technology (ICT) development and infrastructure hinders progress, particularly in less developed nations. Despite the above challenges, previous studies have highlighted that the digital economy is a primary catalyst for economic expansion in developed as well as developing nations (Venturini, 2009; Vu, 2011; Huateng *et al.*, 2021). Remeikiene *et al.* (2021) present opposing viewpoints, arguing that transition economies typically have low living standards and inadequate infrastructure, which may hurt economic activity due to ICT development.

The motivation behind the present study appears to be the need to define the digital economy from a broader perspective (Ashmarina *et al.*, 2020). The quest for a broader canvas would contribute to the economic growth of countries with different levels of economic development. Besides directly focusing on the development impact of digitalization under the advanced phase of globalization, the previous researchers mainly analysed the global linked economic, technological and environmental impacts of ICT using its conventional measures like mobile-cellular subscribers, fixed broadband users and internet users, and those studies were mostly conducted at firm, country and regional levels (Qu *et al.*, 2017; Kirikkaleli *et al.*, 2018; Mgadmi *et al.*, 2021). However, those traditional measures of ICT need to capture the broader aspects of digitalization. These facts justify the need for a new empirical investigation on the most globally integrated developing nations employing cutting-edge measures of variables and advanced data sets.

In this context, the study delves into the hypothesis to assess the feedback loops between the channels of globalization and digitalization and their catalytic role in stimulating economic development. The motivation is substantiated by the changing investment climate driven by consistent flows in investment and improved communications across developing nations. The stimulating forces of the technologically driven ecosystem call for the interconnectedness between the policies related to openness augmented by improved access to connectivity. The study also provides a new approach to looking at the issue comprehensively, which is considered in constructing empirical analysis. Using a panel of a large number of developing countries which witness a substantial level of globalization, the panel unit root tests followed by a few panel cointegration techniques are employed to investigate the dynamic inter-linkages between globalization, digitalization and economic development and to provide substantial findings that can be used for policy analysis.

More specifically, on these main contributions, this study estimates the short-run and long-run panel vector error correction model (VECM) coefficients in cases of both without and with time trends. Dynamic fixed effect (DFE), dynamic ordinary least square (DOLS), fully modified ordinary least square (FMOLS), mean group estimator (MGE) and pooled mean group estimator (PMGE) methods are used to estimate the regression equations while taking cointegration among variables into account. Our study reveals significant positive correlations among globalization, digitalization and economic development in selected developing nations, indicating their interdependences in several dimensions.

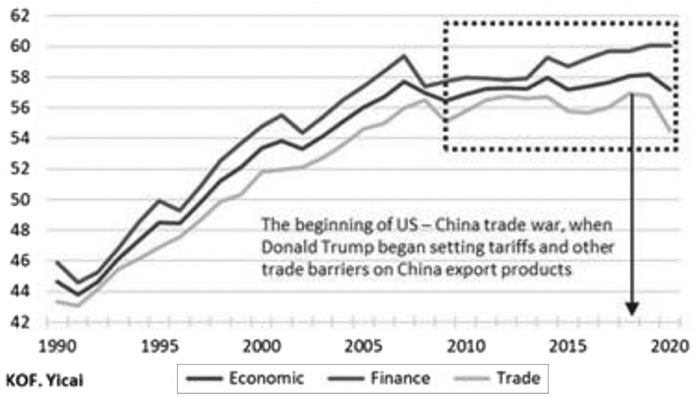
The subsequent part of the paper is structured as follows. Section 2 interprets some stylized facts and provides a conceptual framework. Section 3 documents the data and methodological issues, and Section 4 presents empirical findings and discussions. After that, Section 5 points out the concluding remarks of the paper.

2. Stylized facts and conceptual framework

The present study hypothesizes that the extent of the developmental impacts of digitalization and globalization are significant to be observed in developing countries. This is primarily due to the accumulated benefits from globalization and, subsequently, from digitalization that have occurred since the 1990s and 2000s, respectively. Hence, this study focuses on the interlinkages among globalization, digitalization and economic development since 2000 or after the Asian Economic Crisis. Globalization has been in retreat in the past decade due to the extent of the global financial crisis in 2009 and worsened after the US–China trade war that began in 2018, as reflected in Figure 1. The trade dimension of deglobalization is the central issue as it spills over to several developing countries.

Digitalization, however, has been growing significantly since the beginning of the 2000s, as shown in Figure 2. This rapid development is reflected by the increase in internet users in developed and developing economies. However, the upward trend of internet users relative to the population is steeper in the developed world and leaves a big gap between these two groups of countries. The convergence between globalization and digitalization in developing countries drives cross-border goods, services, information and capital flows, enabling businesses to tap into global networks, access new markets and leverage digital tools for productivity gains. This symbiotic relationship fuels economic development by fostering competition, driving innovation, creating jobs and increasing productivity in developing countries. Digitalization also levels the playing field for developing economies, enabling participation in global trade and attracting foreign investment.

The digital economy has been pivotal in abating economic setbacks and fostering recovery in developing countries amidst recent global challenges. Despite the digital transformation, the digital economy displays notable disparities across developing countries, resulting in unequal access to digital opportunities. Therefore, it is vital to assess the development of the digital economy in these countries, explore its effect on economic

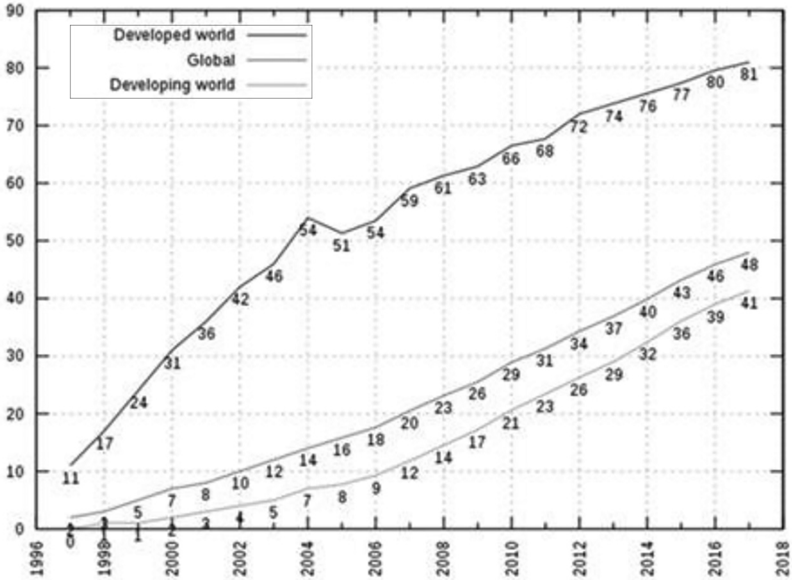


Notes: Figure 1 plots three dimensions (economic, finance and trade) of globalization in a group of developing countries across the globe over the period of 1990–2020
*KOF Globalization Index measures the economic dimension of globalization in 122 countries. Each index is a composite of de facto and de jure index. De facto index measures the actual flows and activities, while de jure measures the fundamentally policy-induced
Source: KOF Globalization Index, 2021

Figure 1. Various indices of globalization

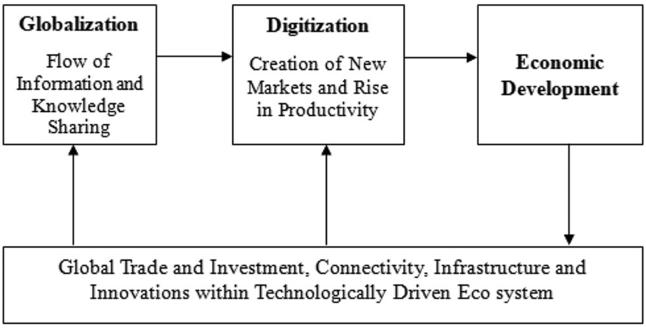
expansion and comprehend the recent events' influence on digital economy-related industries. This evaluation can guide future policies to strengthen digital economy cooperation among developing countries to bridge the digital divide with developing nations. The existing studies have yet to reach a unanimous conclusion about the influence of the digital economy and globalization on economic development. Therefore, the mechanisms underlying the relationship dynamism among globalization, digitalization and economic development require further investigation. The hypothetical relationship might be explained by a conceptual framework as mentioned below.

Figure 3 explores the dynamic interlinkages among globalization, digitalization and economic development and its feedback mechanism. Globalization enhances digitalization through improved information flow and communication. Digitalization fosters economic development by creating new markets and increasing productivity. Economic development supports further digitalization and globalization through global trade and investment flows, improved connectivity and robust, world-class infrastructure within the framework of an innovative, technologically driven ecosystem. The positive externalities of globalization can substantiate this. Globalization initiates the process with increased global trade and foreign direct investment, leading to market expansion, competition and innovation. Digitalization supports improved communication and trade, enhancing information flow and knowledge sharing, which feeds back into globalization. The continuous cycle of digitalization leading to economic development and economic development fostering further digitalization creates a synergistic relationship. This symbiotic relationship is manifested within the domains of globalization.



Notes: Figure 2 plots the number of internet users per 100 populations (an important indicator of digitalization) in the developing world, developed world and also at the global level over the period of 1996-2018
Source: International Telecommunication Union (ITU), 2021

Figure 2. Internet users per 100 populations



Notes: The flow chart in Figure 3 attempts to construct a theoretical framework to establish the dynamic relationships between digitalization, globalization and economic development
Source: Own presentation of authors

Figure 3. A flow chart presenting the conceptual framework

So, the study is planned to be conducted for exploring the intertwining of digitalization, globalization and economic development within an empirical framework. The dynamic interlinkage is deeply rooted in the different channels of globalization, which fuels digitalization and enables global communication and cross-border trade, boosting economic development by creating demand for digital solutions and connectivity.

3. Data and methodology

The study uses a balanced panel data set covering 2000–2019, including annual data sets on economic development (DEV), globalization (GLO) and digitalization (DIG) from the top 75 most globalized developing countries (see note 1) [1], collected from various secondary sources. The KOF Globalization Index (2021) ranks the countries based on the Globalization Index (overall), from where 75 middle-income countries are chosen. DEV is measured by the per-capita gross domestic product (GDP) growth, and the data is sourced from the World Development Indicators (WDI) of the World Bank (2021). GLO is quantified by the simple average of two important dimensions of globalization, namely trade and financial globalization, as presented by the KOF Globalization Index (2021). DIG is measured by the ICT development index, a cutting-edge statistic provided by the World Telecommunication/ICT Indicators (WTI) database of the International Telecommunications Union (ITU) (2021). The research period is significant for all variables, notably DIG, and the provided data on GLO, DIG and DEV are sufficient for regression analysis within the causality framework.

The empirical investigation of the dynamic interlinkage(s) among GLO, DIG and DEV in most globalized developing countries using the panel cointegration framework is the central objective of the study. In this connection, a system of linear equations would express the hypothetical causalities expressing the interconnectedness among variables. So, the linkages among economic development (DEV_{it}), globalization (GLO_{it}) and digitalization (DIG_{it}) are empirically explored by estimating the following fundamental models:

$$DEV_{it} = \beta_{01i} + \beta_{11i}DIG_{it} + \beta_{12i}GLO_{it} + \varepsilon_{1it} \quad (1a)$$

$$GLO_{it} = \beta_{02i} + \beta_{21i}DIG_{it} + \beta_{22i}DEV_{it} + \varepsilon_{2it} \quad (1b)$$

$$DIG_{it} = \beta_{03i} + \beta_{31i}GLO_{it} + \beta_{32i}DEV_{it} + \varepsilon_{3it} \quad (1c)$$

The dependences of DEV on DIG and GLO, GLO on DIG and DEV and DIG on DEV and GLO are represented by the equations (1a)–(1c), respectively, where the error terms ε_{1it}, ε_{2it} and ε_{3it} stand for the respective equations.

The unit root tests for panel data regression established by Levin *et al.* (2002) and Im *et al.* (2003) are used in this study to verify that the series of observations for the relevant panel variables exhibit stochastic behaviour. Levin *et al.* (2002) take into account a number of variables for freely wandering over the cross-sections, including autocorrelation order, intercepts, temporal trends and residual variances. The Levin *et al.* (2002) test is appropriate when time series are independently generated with equal sample sizes, and any individual autocorrelation of order one series has the same autocorrelation coefficients. Alternatively, different cross-section units in a heterogeneous panel may have different autocorrelation coefficients according to the Im *et al.* (2003) test. Conventional wisdom suggests that a large number of long-term panel variables exhibit stationarity issues; hence, we proceed with the econometrics technique descriptions, accounting for the likelihood that non-stationary stochastic processes produce the series.

This study examines cointegration in series with panel heterogeneity using tests from Johansen (1995), Maddala and Wu (1999), Pedroni (2001) and Persyn and Westerlund (2008). The lag time is determined by applying the Akaike (1969) information criterion (AIC) to individual intercepts and trend elements. The cointegration test results show that there are long-term equilibrium relationships between DEV, GLO and DIG robustly rejecting the null hypothesis that cointegration does not exist.

The set of equation (1) [containing (1a)–(1c)] is estimated while accounting for cointegration between the pertinent variables using the DFE, DOLS, FMOLS, MGE and PMGE techniques. Using Pedroni's (2001) suggested methodology, the OLS estimate for serial correlation adjustment and the FMOLS estimator for heterogeneity correction with fixed effects are formulated as follows:

$$\widehat{\beta}^{*}_{\mathrm{NT}} - \beta = \left(\sum_{i=1}^{N} \widehat{L}^{-2}_{22i} \sum_{t=1}^{T} (x_{it} - \bar{x}_{i})^{2} \right)^{-1} \sum_{i=1}^{N} \widehat{L}^{-1}_{11i} \widehat{L}^{-1}_{22i} \left(\sum_{t=1}^{T} (x_{it} - \bar{x}_{i}) \mu^{*}_{it} - T \widehat{\gamma}_{i} \right) \tag{2}$$

The term $\widehat{L}_i$ indicates the lower triangular breakdown of the covariance matrix Ω_{I}; the term Γ_{I} represents a weighted sum of all autocovariances, with $\widehat{L}_{11i} = (\Omega_{11i} - \Omega^{2}_{21i}/\Omega_{22i})^{1/2}$ and $L_{22i} = \Omega^{1/2}_{22i}$ being the long term standard errors of the conditional procedure. The term $\widehat{\beta}_{NT}$ is described as an FMOLS estimator with a unique particular average of the format shown below:

$$\mu^{*}_{it} = \mu_{it} - \frac{\widehat{L}_{21i}}{\widehat{L}_{22i}} \Delta x_{it}, \widehat{\gamma}_{i} \equiv \widehat{\Gamma}_{21i} + \widehat{\Omega}^{o}_{21i} - \frac{\widehat{L}_{21i}}{\widehat{L}_{22i}} (\widehat{\Gamma}_{22i} + \Omega^{o}_{22i}) \tag{3}$$

The DOLS estimator proposed by Pedroni (2001) is represented as follows:

$$\widehat{\beta}_{\mathrm{iOLS}} = \left[N^{-1} \sum_{i=1}^{N} \left(\sum_{t-1}^{T} z_{it} z^{/}_{it} \right) \left(\sum_{t=1}^{T} z_{it} \overline{\mathrm{DEV}}_{it} \right) \right]_{1} \tag{4}$$

where z_{it} represents the $2(K+1) \times 1$ vector of regressors, where:

$$z_{it} = \left\{ (x_{it} - \bar{x}_{it}), \Delta x_{it-K}, \ldots\ldots, \Delta x_{it+K} \right\}; \overline{DEV}_{it} = DEV_{it} - \overline{DEV}_{i}$$

In the panel data series, endogeneity and serial correlation are linked by the addition of lags, which results in the series of the regressors' first-differenced form, or I(1). In this work, the dynamic panel model including DFE, MGE and PMGE is assessed using the non-stationary dynamic panel approach with parameter heterogeneity (Pesaran and Smith, 1995; Pesaran *et al.*, 1999). The dynamic panel model is represented by the following form: Endogeneity and serial correlation in panel data series are adjusted by adding lags and leads in the series of the first-differenced form of the regressors [i.e. I(1)].

Using a non-stationary dynamic panel approach that accounts for parameter heterogeneity, this work evaluates the dynamic panel model using DFE, MGE and PMGE estimators (Pesaran and Smith, 1995; Pesaran *et al.*, 1999). The dynamic panel model is stated as follows:

$$\Delta \mathrm{DEV}_{it} = \phi\left(\mathrm{DEV}_{i,t-1} - \phi_i^{/} \mathrm{X}_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \mathrm{DEV}_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}^{/*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (5)$$

The Auto-regressive Distributed Lag Model [ARDL (2)] is estimated using the following structure using the methodology suggested by Pesaran *et al.* (1999):

$$\mathrm{DEV}_{it} = \sum_{j=1}^{p} \lambda_{ij} \mathrm{DEV}_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}^{/*} \mathrm{x}_{i,t-j} + \gamma_i^{/} \mathrm{d}_t + \varepsilon_{it} \quad (6)$$

The country and time are indicated by the subscripts i and *t* (where i = 1, 2,…, 30 and *t* = 1, 2, …, 16). Here, x_{it} is a vector of independent variables that is "k × 1", and d_t is a vector of independent variables that is "s × 1". The error correction model that results from re-parameterizing equation (6) is shown as follows:

$$\Delta \mathrm{DEV}_{it} = \phi_i \mathrm{DEV}_{i,t-1} + \beta_i^{/} \mathrm{x}_{it} + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \mathrm{DEV}_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta \mathrm{x}_{i,t-j} + \gamma_i^{/} \mathrm{d}_t + \varepsilon_{it} \quad (7)$$

$$\text{where } \phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right), \beta_i = \sum_{j=0}^{q} \delta_{ij}, \lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}, j = 1, \ldots, p-1$$

$$\text{and } \delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}, j = 1, \ldots, q-1, i = 1, \ldots, N$$

In this analysis, the long-term relationship between variables is estimated according to the method proposed by Pedroni (2004) in the following manner:

$$\mathrm{DEV}_{it} = \alpha_i + \delta_i \mathrm{t} + \beta_{1i} \mathrm{x}_{1i,t} + \beta_{2i} \mathrm{x}_{2i,t} + \ldots + \beta_{Mi} \mathrm{x}_{Mi,t} + \mathrm{DIG}_{i,t} \quad (8)$$

The subscripts *t* (*t* = 1,…, T), i (i = 1,…, N) and m (m = 1,…, M) indicate the time, nation and variables to be used in the model of regression, respectively. The Panel VECM model that needs to be calculated once equation (7) has been estimated and long-term associations have been identified is as follows:

$$\Delta \mathrm{DEV}_{it} = \theta_{1i} + \lambda_{1i} \mathrm{EC}_{i,t-1} + \sum_{k=1}^{m} \theta_{11ik} \Delta \mathrm{DEV}_{i,t-k} + \sum_{k=1}^{m} \theta_{12k} \Delta GLO_{i,t-k}$$

$$+ \sum_{k=1}^{m} \theta_{13ik} \Delta \mathrm{DIG}_{i,t-k} + \mathrm{u}_{1it} \quad (9)$$

After estimating the VECM model, the lag length "m" [where, "m" = 2 in Schwarz (1978) Information Criterion or SIC] will be taken into account to assess the multivariate causality and look at both short-term and long-term causal linkages between variables.

Wald (1943) test for the null hypotheses H_{01}: $\theta_{12ik} = \theta_{13ik} = 0$, H_{02}: $\theta_{22ik} = \theta_{23ik} = 0$ and $H_{03} = \theta_{31ik} = \theta_{32ik} = 0$ for all i and k in equation (9), all of which show that the regressors in the regression model have no discernible effect on the dependent variable. In equation (9), we test the null hypothesis H_0: $\lambda_{1i} = \lambda_{2i} = \lambda_{3i} = 0$, which states that there is no consistent, long-term link between the independent regressors in the model and the dependent variable. The long-term associations between the independent and dependent variables are investigated in this test. Following equation (1a), equations (1b) and (1c) are also estimated in a comparable manner using the pertinent panel data econometric techniques as previously indicated.

4. Results

The empirical treatment, in tune with the methodology of the study, calls for descriptive statistics of the panel variables for the selected 75 developing nations for the time frame 2000–2019, shown in Table 1.

Table 1 shows that with 5.76 as the mean and 6.86 as the standard deviation, DEV ranges between 1.09 and 11.68 as the minimum and highest values, respectively, based on 1,500 data for all panel variables. Furthermore, GLO fluctuates between a minimum value of 26.69 and a maximum value of 83.70, with a mean and standard deviation of 62.07 and 37.55, respectively. Similarly, DIG has a range of values, with a mean of 48.33 and a standard deviation of 39.06, respectively, between 10.81, the lowest value, and 95.07, the largest value.

Table 2 illustrates the correlation matrix of underlying panel variables of the study, namely GLO, DIG and DEV, in the case of selected countries. High correlation coefficients are found in the data, with DEV and GLO at 0.78, DEV and DIG at 0.71 and GLO and DIG at 0.73, respectively. The strong correlation coefficients affirm that the three-panel variables, namely economic development (DEV), digitalization (DIG) and globalization (GLO), are interlinked in the sense that feedback loops exist between them. A globalized economy calls for transmitting knowledge and information through a digital interface, which augments the nation’s growth and development potential.

Table 1. Descriptive statistics of the panel variables

Variables	Mean	Median	Maximum	Minimum	SD	Observations
DEV	5.76	5.93	11.68	1.09	6.86	1,500
GLO	62.07	59.44	83.70	26.69	37.55	1,500
DIG	48.33	42.19	95.07	10.81	39.06	1,500

Notes: Table 1 reports the descriptive statistics for the study’s underlying panel variables across 75 selected developing countries from 2000 to 2019. These statistics, including mean, median, range and standard deviation

Source: Estimated by authors using KOF, WDI and WTI databases over 2000–2019

Table 2. Correlation matrix of underlying variables

Variables	DEV	GLO	DIG
DEV	1.00	0.78	0.71
GLO	0.78	1.00	0.73
DIG	0.71	0.73	1.00

Notes: Table 2 shows the correlation matrix of all underlying focussed variables of the study across selected countries. Significant correlations among variables are observed

Source: Estimated by authors using KOF, WDI and WTI databases over 2000–2019

The econometric treatment of panel variables should take care of their time-specific effects. This is more pronounced in the case of a data set where there is a possibility of any trend in the variable over the period. This calls for checking the time series properties of the panel variables. Ignoring the checking of stationarity properties will result in distorted estimation results.

To ascertain if the variables DEV, GLO and DIG exhibit stationarity, the study used panel unit root tests recommended by Levin *et al.* (2002) and Im *et al.* (2003). Table 3, which displays the findings of these panel unit root tests, demonstrates that while all variables have unit root problems at the level, their initial differences eventually become stationary.

Table 3 presents the panel unit root test results of the concerned variables. These findings confirm that the panel variables are first-difference stationary. That implies that after taking the one-period differencing, the mean and variance of the panel variables are found to be time-independent. Im *et al.* (2003) assume that the panel auto-correlation coefficients differ across cross-sections and are allowed to vary such that the heterogeneity across panel variables is considered. Levin *et al.* (2002) assume that the auto-correlation coefficients do not vary across cross-sections and are pooled to equal a constant value. This is in tune with the homogeneity assumption of the panel variable. In this case, both the results of the tests are robust because the panel variables are integrated into order one.

The quest for a long-run relationship among the variables calls for a panel VECM procedure. This is conducted in a framework with synergy among the concerned variables. The application of the Multivariate Granger (1969) causality technique is found in the study of Pao and Tsai (2011), where the impact on environmental degradation was examined by economic growth and financial development for a panel of Brazil, Russia, India and China nations between 1980 and 2007. This was carried out to examine the presence of dynamic interlinkages.

The existing literature (Gholipour *et al.*, 2014; Chen *et al.*, 2024) substantiates the application of Pedroni's (2004) test procedure to look for any cointegrating relationships in analysing dynamic interlinkages. For a set of Organisation for Economic Co-operation and Development (OECD) nations between 1995 and 2008, Gholipour *et al.* (2014) inferred that the dynamic interrelationships between Foreign Direct Investment (FDI) in real estate, economic growth and property prices can be empirically tested using Pedroni's panel cointegration technique. The empirical findings exhibit that FDI in real estate causes a rise in the property prices of the selected OECD nations both in the short and long run, respectively. Chen *et al.* (2024) applied Pedroni's procedure to capture the interlinking dynamics between natural resources, financial development and energy intensity for emerging seven nations. The results confirm the significant associations among the variables. Similar studies (Chotia

Table 3. Findings from the panel unit root tests

	Levin *et al.* (2002)		Im *et al.* (2003)	
Variables	*Level*	*First difference*	*Level*	*First Difference*
DEV	−1.22 (0.17)	−6.31*** (0.00)	1.97 (0.66)	−3.38*** (0.00)
GLO	−2.01 (0.21)	−5.81*** (0.00)	0.66 (0.39)	−2.86** (0.03)
DIG	1.19 (0.18)	−6.77*** (0.00)	1.55 (0.61)	−2.94** (0.02)

Notes: Table 3 presents the results of Levin *et al.* (2002) and Im *et al.* (2003) panel unit root tests at the level and first difference for all considered variables. Results indicate that variables are non-stationary at level but stationary at first difference. ** and ***denote the statistical significance levels at 5% and 1%, respectively
Source: Estimated by authors using KOF, WDI and WTI databases over 2000–2019

and Rao, 2017; Zhang *et al.*, 2023) analysing dynamic interlinkages in a panel framework confirm the Pedroni test procedure's application.

The current study applies the Multivariate Granger Causality test procedures and VECM estimation procedures. Table 4 presents the findings of the Multivariate Granger (1969) causality investigation, which were derived from the outcomes of the unit root tests, the panel data procedures that were previously mentioned and the VECM estimation results.

The panel data regression estimation outcomes suggest a long-term relationship between DIG, GLO and DEV among the chosen developing nations. This result applies to various panel data estimate techniques, including Pedroni's (2004) method and the panel FMOLS and DOLS procedures for cointegration in heterogeneous panels, all of which reject the null hypothesis (H_0: $\beta_i = 0$). As shown by the FMOLS and DOLS results, the null hypothesis, which suggests a lack of cointegration, is rejected at both the individual and panel levels. This finding is insensitive to different methodologies adopted. Hence, the presence of cointegrating relationships is robust to different methodologies. The bidirectional panel causality runs from GLO to DEV and between DEV and DIG, which also encompasses the bidirectional panel causality between GLO and DIG, respectively. This finding is in tune with the theoretical foundation of the study, which emphasizes the interlinkages between the three-panel variables. The never-ending process of digitalization fosters economic development, and thereby, the level of economic development reinstates digitalization and creates a synergistic bonding within the positive externalities of global trade and investment flows as stimulated by the forces of globalization. Further, the estimation results under FMOLS are presented for the cointergrating relation. The estimation results are reported in Table 5.

In the case without a time-trend, the mean group (MG) estimator results confirm that the effect of GLO on DEV is insignificant. In this case, the MG estimator allows the intercepts, slope coefficients and error variances to differ across panels. This specification estimates separate regressions for each group and calculates a simple arithmetic average of the coefficients. This estimator produces consistent estimates of the parameters average, assuming that both the intercepts and the slopes vary across panels, allowing heterogeneity in

Table 4. Findings of Wald (1943) F-test from estimated panel VECM models

Regressand		(ΔDEV)			(ΔGLO)			(ΔDIG)	
	SR	LR	JR	SR	LR	JR	SR	LR	JR
(Constant)		2.77***			43.29**			0.41**	
(ΔDEV_{t-1})		0.12***			6.98**			0.09**	
(ΔDEV_{t-2})		0.08**			11.73**			0.05***	
(ΔGLO_{t-1})		0.01***			0.48**			0.01	
(ΔGLO_{t-2})		0.01**			0.23**			0.00	
(ΔDIG_{t-1})		0.34***			10.19**			0.77**	
(ΔDIG_{t-2})		0.11***			12.66***			0.29***	
(EC_{t-1})		0.59**			8.55**			0.06***	
		DIG→DEV			DIG→GLO			GLO→DIG	
	31.41***	28.29**	239.11***	50.06***	8.02**	28.31**	43.88***	10.55**	32.22**
Directions of causalities		GLO→DEV			DEV→GLO			DEV→DIG	
	46.31**	21.33**	244.08***	27.66**	9.11**	21.33**	2.81	8.93**	10.11**

Notes: Table 4 reports the outcomes of Wald's (1943) F-test derived from estimated panel VECM models with equations (1a), (1b) and (1c). SR, LR, JR and EC represent the short-run, long-run and joint causality, along with the coefficient of error-correction term. XigYi indicates the null hypothesis that Xi does not Granger (1969) cause Yi. ** and ***denote the statistical significance levels at 5% and 1%, respectively

Source: Estimated by authors using KOF, WDI and WTI databases over 2000–2019

Table 5. Estimated coefficients of the short-run and long-run panel models

					Without time-trend					
	MGE	PMGE	Panel FMOLS	Panel DOLS	DFE	PMGE	MGE	FMOLS	DOLS	DFE
Long-run coefficients										
(GLO)	−0.002	−0.003**	0.025**	0.021**	–0.002**	–0.003***	–0.002	0.025**	0.021**	–0.002**
(DIG)	0.241	0.496***	0.412***	0.109***	0.476**	0.496***	0.241	0.412***	0.109***	0.476**
Error corrections	–0.776**	–0.677**			–0.811**	–0.677**	–0.776**			–0.811**
Short-run coefficients										
(ΔGLO)	0.004	−0.006			–0.002	–0.006	0.004			–0.002
(ΔDIG)	–0.232	–0.316			–0.051	–0.316	–0.232			–0.051
Constant	2.878***	1.599***			1.866**	1.599**	2.878***			1.866**
Long-run coefficients					With time-trend					
(ΔGLO)			0.008***	0.010***				0.008***	0.010***	
(ΔDIG)			0.449***	0.421***				0.449***	0.421***	
Hausman (1978) test	4.672 (0.161)					4.672 (0.161)				

Notes: Table 5 interprets the estimated coefficients of the short-run and long-run panel models, namely, PMGE, MGE, FMOLS, DOLS and DFE, in cases of both without and with time trends. ** and ***denote the statistical significance levels at 5 and 1%, respectively
Source: Estimated by authors using KOF, WDI and WTI databases over 2000–2019

short- and long-run relationships. However, in the case of the PMGE, the pooling and averaging of coefficients are done to allow the intercepts, short-run coefficients and error variances to differ across panels similar to the MG estimator but constrain the long-run coefficients to the same across panels. Under PMGE, the GLO estimated coefficient appears to be negative and significant in the long run. This similar finding is also observed in the DFE estimator, where GLO's estimated coefficient is negative and significant. Under the DFE estimation procedure, the time-series data for each cross-section are pooled, and only the intercepts are allowed to differ across panels. This specification requires the strong assumption that the slope coefficients and error variances are identical, meaning that all panel responses are the same in the long and short run.

To augment the panel cointergrating relationship obtained, Panel DOLS specifications conduct regression with lags and leads of the short-run terms. Unlike the PMGE and MG estimator, serial correlation and asymptotic endogeneity are corrected, making the cointegrating equation's error term orthogonal to stochastic regressor innovations. Moreover, the panel FMOLS present an asymptotically unbiased estimator that eliminates problems caused by the long-run correlation between stochastic regressor innovations and the cointegrating equation. Using panels FMOLS and DOLS (without time trend), the estimated coefficients for GLO are 0.025 and 0.021, respectively. In this case, the degree of responsiveness to economic development stimulated by trade and financial globalization channels for a selected sample of 75 developing economies is found to be 0.025 under panel FMOLS and 0.021 under panel DOLS. This implies that a one-percent rise in the index of financial globalization (GLO) will result in a 0.025% rise in economic development. These calculated coefficients demonstrate that GLO favours DEV and are statistically significant in the long run. This finding reinstates the theoretical underpinnings in the sense that the channels of financial globalization instrumented by trade channels will augment economic development. Hence, the estimated coefficient of GLO is positive and significant only under panel DOLS and panel FMOLS but not in the case of PMGE and DFE. This finding may be attributable to the sample's heterogeneous cross-sectional dynamics of the selected countries.

Without accounting for any historical trend, the predicted DIG values in the FMOLS and DOLS models are 0.412 and 0.109, respectively, and are statistically significant at the 1% level. This shows that DIG has had a notably favourable effect on economic development as assessed by DEV. When the temporal trend is considered, the predicted DIG coefficients in FMOLS and DOLS become 0.449 and 0.421; these values are nonetheless significant at a 1% level. Therefore, the effect of DIG on DEV among the examined emerging economies is unaffected by the addition of the temporal trend. Additionally, for all 75 countries, it is seen that increasing DIG has a considerable beneficial impact on DEV.

Given that PMGE outperforms MGE estimators under the long-term null hypothesis of homogeneous coefficients, favouring PMGE over MGE estimators is supported by the Hausman (1978) test statistic, whose estimated value for selecting between PMGE and MGE estimators is found to be 4.672. The computed results indicate that the long-run PMGE coefficients for both DIG and GLO are statistically significant at the country level. DIG also has a positive and considerable impact on DEV; its PMGE and DFE values are 0.496 and 0.476, respectively.

The panel VECM results are consistent with PMGE, MGE, FMOLS, DOLS and DFE computations. Furthermore, statistical significance is found for the estimated long-run coefficients for DIG and GLO. The estimated long-run coefficients for GLO and DIG often converge around the estimated values in PMGE, which are 0.008 for GLO and 0.449 for DIG. This significant finding empirically shows a long-term correlation between GLO, DIG and DEV in the selected largely globalized developing countries. The panel VECM cointegration results provide more evidence for the long-term link between these three variables. In other words, the empirical manifestations adequately justify the strong theoretical symbiotic relationships among these variables.

In order to check the robustness of the outcomes obtained from various panel cointegration models, as mentioned and discussed above in detail, an advanced approach, as recommended by Pedroni (2019), has been applied. The issues related to endogeneity are the severe and primary concerns here. The results of the Pedroni (2019) test in the case of all underlying models confirm that our findings are robust. The directions of causalities among variables are also authenticated in the same process.

5. Concluding remarks

This paper investigates the dynamic interlinkages among globalization, digitalization and economic expansion to establish how globalization drives economic growth, promotes inclusivity and shapes the digital economy. It employs panel data regression models to clarify how the digital economy impacts economic expansion. Different econometric techniques were used, including unit root tests, cointegration analysis and panel data regression. The findings can contribute to informed policymaking to strengthen digital economy cooperation and bridge the digital divide among nations.

The findings revealed a strong positive correlation among globalization (GLO), digitalization (DIG) and economic development (DEV), indicating their interdependence. The panel unit root tests confirmed that the variables were non-stationary at the level but became stationary after the first differencing. The cointegration analysis supported the presence of long-run equilibrium relationships among DEV, GLO and DIG.

The results demonstrated a positive influence of GLO on DEV only under Panel DOLS and panel FMOLS, with statistically significant coefficients. However, these findings varied under MG and PMG estimation procedures. However, DIG showed a significant favourable effect on DEV across all estimation procedures. This finding is more robust. The findings from the panel VECM estimation supported the long-run correlation between GLO, DIG and DEV. The estimated coefficients remained significant across different econometric methods, providing empirical evidence of the interplay between these variables in the selected developing nations.

The research insights reflected in this study are in tune with the empirical findings of Arsić (2020), Myovella *et al.* (2020) and Zhang *et al.* (2022). These studies corroborate the notion that digitalization dynamics measured through various indicators are expedited through the channels of globalization for a set of selected developing countries. This calls for a policy-oriented approach to expanding the information communication network in terms of its access and reach. This will be instrumental in accelerating economic growth in the long run.

The policies designed for the globalized economies are in tune with the measures to improve digital connectivity, literacy, skills, regulations related to cyber-security norms and more excellent digital collaborations. Most digitalized economies like Malaysia focus on strengthening digital skills, whereas less digitized economies like Indonesia and Vietnam focus on digital infrastructure to reap the benefits of financial globalization. The cyber-security laws in the case of Malaysia are not well defined. The enactment of such laws will attempt to address the bottlenecks. The data protection provisions are not structured in Vietnam and must be addressed. This is the same for most of the globalized economies taken in this study. Countries can benefit from globalization if their digital infrastructure is well-equipped with advanced and updated connectivity, technical skills, good governance and a structured regulatory framework. This will also enhance regional collaboration regarding technology transfer among the globalized economies.

The findings imply that policies promoting global integration and digital advancements can foster economic growth and development. Globalized economies strive for better and equipped technology followed by growth-enhancing factors channelized by globalization. These insights provide valuable implications for policymakers and practitioners aiming to design effective strategies for the sustainable progress of the economy for globalized economies. Further research can delve into the specific mechanisms and channels through which globalization and digitalization influence economic development, considering country-specific factors and policy implications.

Note

1. *List of 75 most globalized developing countries:* Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Cabo Verde, Cambodia, Cameroon, China, Colombia, Congo, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, Fiji, Georgia, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kyrgyzstan, Lao PDR, Lebanon, Malaysia, Maldives, Mauritius, Mexico, Micronesia, Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Oman, Pakistan, Peru, Philippines, Samoa, Senegal, Solomon Islands, South Africa, Sri Lanka, Tajikistan, Thailand, Timor-Leste, Togo, Türkiye, Turkmenistan, Ukraine, Uzbekistan, Vanuatu, Venezuela, Vietnam, Zambia and Zimbabwe.

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