HOW DOES DIGITAL TRANSFORMATION DRIVE MANUFACTURING GROWTH IN DEVELOPING COUNTRIES?

NGUYEN NGOC MAI[1], THUY HIEN NGUYEN[2]

Summary

This study examines the impact of digital transformation on the manufacturing sector across 131 developing countries between 2010 and 2023. Employing an extended Cobb-Douglas production function and a Generalized Least Squares (GLS) regression model, the analysis reveals that digital exports, capital formation, and labor productivity significantly contribute to manufacturing growth, whereas inflation exerts a negative influence. The findings also suggest that e-government development has a particularly strong positive impact in less developed regions, such as Africa, by enhancing institutional efficiency. Overall, the study underscores that strategic investments in digital trade, governance, and infrastructure are crucial for policymakers seeking to foster sustainable industrial growth in developing economies.

Keywords: Digital transformation, manufacturing sector, developing countries

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INTRODUCTION

The ongoing wave of digital transformation is drawing increasing attention from scholars, policymakers, and manufacturers. It entails upgrading production through robotics, intelligent systems, and other digital technologies. The World Economic Forum projects that digital transformation could add up to $100 trillion to the global economy by 2030, largely through platform-driven interactions. Developing countries are also accelerating this trend. In Viet Nam, Decision No. 749/QD-TTg (2020) aims to build a robust digital economy and integrate into global supply chains.

The study aims to conduct a comprehensive investigation into the impact of digital transformation on the manufacturing sector in developing countries. Specifically, it seeks to enrich the current body of literature by systematically reviewing existing studies, identifying key research gaps, evaluating the adequacy and applicability of prevailing theoretical frameworks, and proposing new perspectives tailored to the realities of developing economies. Through this effort, the study aspires to contribute not only to academic knowledge but also to the formulation of more effective industrial policies and strategies to support digital transformation in manufacturing sectors among developing countries.

LITERATURE REVIEW

Digital transformation reshapes enterprise systems by embedding advanced technologies that boost innovation, efficiency, and smart ecosystems. Real-time analytics, Internet of Things (IoT), and Artificial Intelligence (AI) enhance flexibility and responsiveness, while cyber-physical systems improve maintenance, supply chain visibility, and cost efficiency (Lai, 2024). Yet, challenges such as resistance, skill gaps, and cybersecurity risks persist, underscoring the need for workforce upskilling and stronger digital security.

METHODOLOGY

Descriptive statistics

The descriptive statistics in Table 1 offer an essential overview of the data structure and reveal substantial variation across countries in key economic and technological indicators. The dataset reflects a wide range of economic and digital transformation indicators across developing countries from 2010 to 2023, highlighting substantial variation in both digital capacity and manufacturing performance.

Developing economies show wide disparities: EGOV ranges from 0 to 0.95, inflation from stability to 500%, and internet use from near zero to full access. Digital exports average $4.6 billion but are highly concentrated, while MVA spans from under $10 million to $4.9 trillion, with similar gaps in capital formation and labor productivity. These contrasts highlight structural heterogeneity and the need for econometric methods that account for digital, institutional, and macroeconomic differences.

The correlation matrix in Table 2 and Figure 1 provides meaningful insights into the relationships among the main variables included in the analysis. Manufacturing value added (dlnMVA) shows a positive association with labor productivity (dlnLabor_Production), suggesting that improvements in worker efficiency are accompanied by increases in industrial output. Positive correlations are also observed between dlnMVA and both capital formation (dlnCap) and digital exports (dlnDigiex), reflecting the potential complementary roles of investment and digital trade in supporting manufacturing growth.

[1] Foreign Trade University; Email: ngocmn@ftu.edu.vn

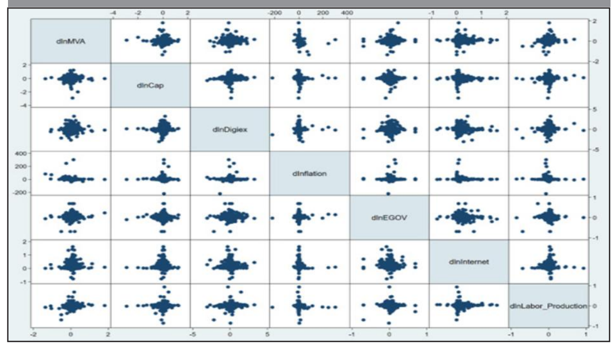
[2] Corresponding author, Foreign Trade University; Email: thuyhienng@ftu.edu.vn

TABLE 1: DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. dev.	Min	Max
MVA	1,721	50607.98	326106.6	8.9002	4909020
Internet	1,703	46.55562	28.63031	0.25	100
EGOV	1,834	0.493402	0.191623	0	0.9473
Digiex	1,688	4637.145	19044.18	1	288653
Inflation	1,698	6.481887	20.40904	-3.74915	557.2018
Cap	1,735	813000	2300000	23.3	15500000
Labor_ Production	1,742	19.18832	15.32852	1.42	79.66

Source: Author's calculation using Stata

FIGURE 1: SCATTERPLOT MATRIX



Source: Author's calculation using Stata

Empirical methodology

Linear Regression Model

The multivariable linear regression model is defined as:

$$Y = \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + u$$

Where Y is the dependent variable, $\vec{x} = (X_2, \ldots, X_k)$ are the independent variables, and u is the random error representing factors affecting Y but not included in the model.

This study uses the Cobb-Douglas production function to build the model. The Cobb-Douglas function is expressed as:

$$Y = A \cdot K^{\alpha} \cdot L^{\beta} \cdot D^{\gamma}$$

It can be transformed into a linear form by taking logarithms of both sides:

$$ln\, ln\, Q = \beta_1 + \beta_2\, ln\, ln\, K + \beta_3\, ln\, ln\, L + \beta_4\, ln\, ln\, D$$

Pooled, FE, RE and GLS Regression Models

The author applies econometric models to study the impact of technology and innovation on the operations of manufacturing enterprises. The models used for panel data analysis include POLS (Pooled OLS), the Random Effects model (RE), and the Fixed Effects model (FE).

The general form of these models is:

$$Y_{it} = \beta_0 + \beta_i X_{it} + \nu_{it}$$
$$\nu_{it} = a_i + u_{it}$$

Where:

- it: varies across space and time
- t: varies over time
- i: varies across space
- a_i: unobserved and time-invariant factors (unique characteristics of each observation) that may affect X and hence Y
- u_{it}: unobserved factors affecting Y but not X, satisfying OLS assumptions

Pooled OLS Model (POLS):

Assumes a_i does not exist, i.e., $v_{it}=a_i+u_{it}$ satisfies OLS assumptions. The POLS model is a simple regression estimated using ordinary least squares. It assumes that regression coefficients are constant across countries and over time. This assumption is a limitation since it might not hold in reality. Another critical assumption is that the independent variables are not correlated with past, present, or future values of the random error. This model often suffers from autocorrelation issues.

Fixed Effects Model (FE)

$$\{a_i \neq 0\; cov(a_i, X) \neq 0$$

Assume each country has unique characteristics that may affect explanatory variables. Developed from POLS, FE controls for country-specific differences. It assumes different intercepts for each country, fixed over time. Correlation may or may not exist between residuals and independent variables.

Random Effects Model (RE)

$$\{a_i \neq 0\; cov(a_i, X) \neq 0$$

Like the FE model, RE allows for different intercepts per country. However, it assumes no correlation between the residuals and independent variables. To choose the appropriate regression model, necessary diagnostic tests must be conducted.

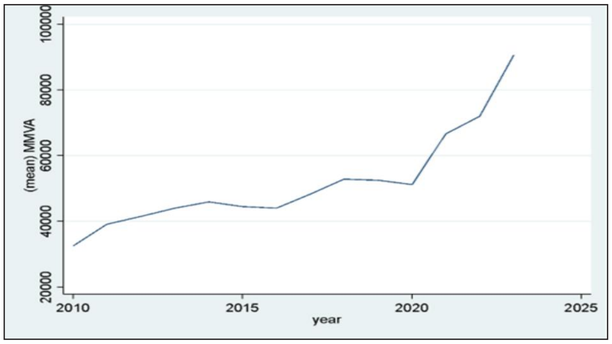
In the analysis of econometric and statistical data, the assumption of homoscedasticity and uncorrelated errors is central to the validity of Ordinary Least Squares (OLS) estimations. However, in many real-world scenarios, particularly in time series and panel data contexts, these assumptions are violated. When the error terms exhibit

TABLE 2: CORRELATION

	dlnMVA	dlnCap	dlnDigiex	dlnflation	dlnEGOV	dlnInternet	dlnLabor_ Prd
dlnMVA	1						
dlnCap	0.0905	1					
dlnDigiex	0.1071	0.0788	1				
dlnflation	-0.0844	0.0044	-0.0032	1			
dlnEGOV	0.0474	0.0126	0.0015	0.0475	1		
dlnInternet	0.073	-0.0089	-0.0297	-0.0213	-0.0257	1	
dlnLabor_Prd	0.1718	-0.0079	0.1147	-0.1087	0.0552	0.0764	1

Source: Author's calculation using Stata

FIGURE 2: MEAN OF THE MANUFACTURING SECTOR OF DEVELOPING COUNTRIES FROM 2010 TO 2023



Source: Author's calculation using Stata

heteroscedasticity or autocorrelation, OLS estimators remain unbiased but are no longer efficient, resulting in unreliable statistical inference. To address these challenges, the Generalized Least Squares (GLS) method provides a more robust framework for parameter estimation.

GLS is an extension of OLS that accounts for the presence of non-spherical error terms by transforming the regression model such that the transformed errors satisfy the classical assumptions of OLS. Specifically, GLS modifies the original model by applying a weighting matrix derived from the variance-covariance structure of the errors. This transformation ensures that the new model has homoscedastic and uncorrelated residuals, thereby allowing the use of OLS techniques on the transformed data to obtain efficient and consistent estimates.

Mathematically, the GLS estimator is defined as:

$$\widehat{\beta}_{GLS} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$$

where X is the matrix of explanatory variables, y is the dependent variable vector, and Ω is the variance-covariance matrix of the error terms. When Ω is the identity matrix, the GLS estimator reduces to the OLS estimator, highlighting GLS as a generalization of the classical approach.

The practical implementation of GLS requires knowledge of the structure of Ω. In many applications, this matrix is unknown and must be estimated. In such cases, the Feasible Generalized Least Squares (FGLS) method is employed, where a consistent estimate of Ω is used in place of the true matrix. Despite this approximation, FGLS often yields considerable improvements in estimation efficiency compared to OLS.

RESEARCH MODEL

Building on Chakrabarty and Chanda (2019), this study develops an empirical model to assess how digital transformation affects manufacturing in developing countries. Their framework informs the choice of manufacturing value added as the dependent variable and key drivers such as internet usage, digital exports, and e-government. Additional factors, labor productivity, capital investment, and inflation, are included based on Bekele (2020). The model is specified as follows:

$$\ln(MVA_{it}) = \beta_0 + \beta_1 \ln(Internet_{it}) + \beta_2 \ln(DDS_{it}) + \beta_3 \ln(EGDI_{it}) + \beta_4 \ln(LaborProd_{it}) + \beta_s \ln(Capital_{it}) + \beta_6 \ln(Inflation_{it}) + \mu_i + \lambda_t + \varepsilon_{it}$$

In this model, the dependent variable is the natural logarithm of manufacturing value added ln(MVA_{it}), which captures the net output of the manufacturing sector in country i at time t. The key explanatory variable is ln($Internet_{it}$), representing internet users per 100 people, is used as a proxy for digital access and adoption. ln(DDS_{it}) reflects the value of digitally deliverable services exports, such as software, IT, and digital communication, which enhance industrial productivity through service-manufacturing linkages. The e-government development index *ln(EGDIit)* accounts for the digital capacity of public institutions to provide infrastructure and policy support. Labor productivity *ln(LaborProdit)* measures output per worker or per hour and reflects workforce efficiency, while *ln($Capital_{it}$)* denotes the physical and technological investment in the sector. Inflation *ln($Inflation_{it}$)* is included as a control variable to account for macroeconomic instability, which may distort investment and production. The model also controls unobservable heterogeneity across countries through country-specific fixed effects μ_i and for time-specific shocks through time effects λ_t. The error term ε_{it} captures idiosyncratic disturbances. This log-log specification allows interpretation of the coefficients as elasticities, facilitating a clearer understanding of the relative impact of each variable on manufacturing performance.

RESULTS

Current status of the manufacturing sector in developing countries

The manufacturing sector is central to economic development in many developing countries, driving jobs, exports, and industrial transformation. Yet it still faces challenges

TABLE 3: CURRENT STATUS OF IMPACT OF DIGITAL TRANSFORMATION ON THE MANUFACTURING SECTOR IN DEVELOPING COUNTRIES

Year	MVA (Million USD)	EGOV	Internet (%)	Digital exports (Million USD)
2010	32490.840	0.397	25.519	2514.659
2011	39062.730	0.420	28.543	2960.768
2012	41433.460	0.442	31.142	3184.960
2013	44003.220	0.435	34.099	3432.589
2014	45859.130	0.428	37.137	3836.440
2015	44406.650	0.443	40.663	3755.161
2016	43940.910	0.458	43.751	3829.270
2017	48261.360	0.489	47.994	4184.024
2018	52860.520	0.519	52.491	4801.750
2019	52435.570	0.547	55.581	4992.549
2020	51202.090	0.575	59.830	5063.230
2021	66531.810	0.581	65.301	6401.622
2022	71960.880	0.587	67.606	7467.713
2023	90584.860	0.587	75.380	10838.381

Source: Author's calculation using Stata

TABLE 4: THE OLS, RE, FE, AND GLS MODELS

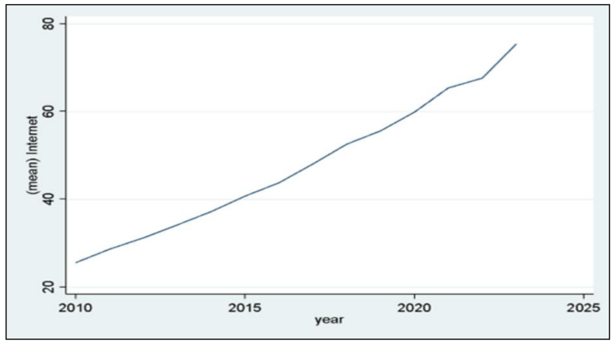
	OLS	RE	FE	GLS
	(1)	(2)	(3)	(4)
	dlnMVA	dlnMVA	dlnMVA	dlnMVA
dlnCap	0.0544**	0.0544**	0.0780***	0.0565***
	(0.0214)	(0.0214)	(0.0247)	(0.0214)
dlnDigiex	0.0378***	0.0378***	0.0342***	0.0371***
	(0.0124)	(0.0124)	(0.0130)	(0.0123)
dInflation	-0.000721**	-0.000721**	-0.00117***	-0.000712**
	(0.000344)	(0.000344)	(0.000386)	(0.000349)
region_ code=Afica	0	0	0	0
	(.)	(.)	(.)	(.)
region_ code=Asia	0.00468	0.00468	0	0.00472
	(0.0123)	(0.0123)	(.)	(0.0128)
region_ code=Europe	-0.00217	-0.00217	0	-0.000482
	(0.0140)	(0.0140)	(.)	(0.0145)
region_ code=North America	0.00476	0.00476	0	0.00449
	(0.0157)	(0.0157)	(.)	(0.0163)
region_ code=South America	-0.0152	-0.0152	0	-0.0156
	(0.0211)	(0.0211)	(.)	(0.0219)
dlnEGOV	0.207***	0.207***	0.208***	0.200***
	(0.0678)	(0.0678)	(0.0705)	(0.0677)
region_ code=Afica # dlnEGOV	0	0	0	0
	(.)	(.)	(.)	(.)
region_ code=Asia # dlnEGOV	-0.130	-0.130	-0.118	-0.131
	(0.159)	(0.159)	(0.167)	(0.161)
region_code= Europe # dlnEGOV	-0.423**	-0.423**	-0.424*	-0.455**
	(0.215)	(0.215)	(0.222)	(0.217)
region_ code=North America # dlnEGOV	-0.291	-0.291	-0.272	-0.279
	(0.207)	(0.207)	(0.214)	(0.209)
region_ code=South America # dlnEGOV	-0.613*	-0.613*	-0.639*	-0.616*
	(0.344)	(0.344)	(0.356)	(0.348)
dlnInternet	0.0634**	0.0634**	0.0516	0.0653**
	(0.0289)	(0.0289)	(0.0329)	(0.0290)
dlnLabor_ Production	0.454***	0.454***	0.420***	0.445***
	(0.0834)	(0.0834)	(0.104)	(0.0839)
Constant	0.0225**	0.0225**	0.0246***	0.0228**
	(0.00930)	(0.00930)	(0.00649)	(0.00955)
Observations	1159	1159	1159	1157

Standard errors in parentheses

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

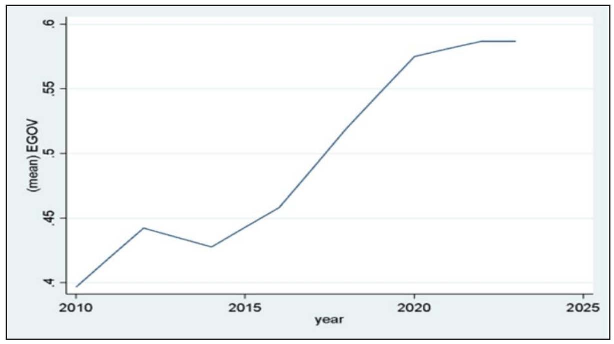
Source: Author's calculation using Stata

FIGURE 3: MEAN OF INTERNET USAGE OF DEVELOPING COUNTRIES FROM 2010 TO 2023



Source: Author's calculation using Stata

FIGURE 4: MEANS OF E-GOVERNMENT OF DEVELOPING COUNTRIES FROM 2010 TO 2023



Source: Author's calculation using Stata

such as low productivity, limited technology adoption, poor infrastructure, and reliance on labor-intensive methods.

Figure 2 shows average Manufacturing Value Added (MVA) in developing countries rising from USD 30 billion in 2010 to 50 billion in 2014, remaining flat until 2018, then surging to nearly 100 billion in 2023. This sharp post-2019 growth reflects recovery policies, supply chain shifts, and industrial modernization, supported by India's Production-Linked Incentive scheme, rising FDI in Southeast Asia, and pandemic-driven digital transformation.

Current status of digital transformation in developing countries

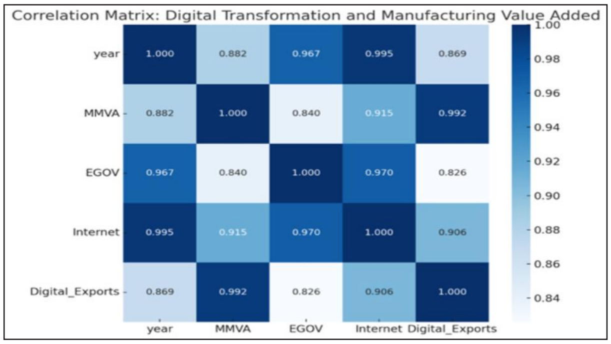
Digital transformation is a key priority for developing countries, driving modernization and global integration. Despite advances in infrastructure and policy, progress remains uneven due to financial, technological, and institutional gaps. In manufacturing, adoption of automation and AI is slow, yet governments and firms increasingly see digitalization as essential for productivity and

TABLE 5: MODEL VALIDATION TESTS

Tests	Results
Hausman test	p-value=0.5218
Breusch and Pagan Lagrange Multiplier	p-value=0.00
Wooldridge test for autocorrelation	p-value=0.0120

Source: Author's calculation using Stata

FIGURE 5: CORRELATION MATRIX: DIGITAL TRANSFORMATION AND MANUFACTURING VALUE ADDED



Source: Author's calculation using Stata

competitiveness.

Figure 3 shows a steady rise in internet usage in developing countries, from about 40% in 2015 to nearly 80% in 2023, with the sharpest increase between 2018 and 2023. This reflects rapid digital transformation driven by better infrastructure, affordability, and supportive policies, creating a stronger base for e-governance, e-commerce, and digital trade.

Figure 4 shows e-government (EGOV) in developing countries rising from 0.40 in 2010 to about 0.59 by 2023. After a brief slowdown around 2014, growth resumed with policy support and ICT investment, but recent stagnation suggests that further progress will depend on institutional reforms and infrastructure upgrades.

Current status of the impact of digital transformation on the manufacturing sector in developing countries

Figure 5 and Table 3 show MVA rising from $32.5 to over $90.5 billion between 2010 and 2023, closely linked to digital exports (r = 0.99), internet usage (r = 0.91), and EGOV (r = 0.84). Digital exports and internet penetration surged after 2020, while EGOV advances supported governance. Emerging technologies such as cloud computing, IoT, AI, and big data have reshaped manufacturing, driving efficiency, automation, and global competitiveness.

Recent empirical studies confirm that digital transformation is having a measurable and positive impact on manufacturing enterprises in developing economies. Through a quantitative analysis of 60 manufacturing firms, it demonstrated that digital transformation initiatives accounted for 42% of the improvement in operational efficiency, 38% in enhanced decision-making, and 34% in enterprise system flexibility. These findings highlight the tangible organizational gains linked to the adoption of digital technologies and underscore their role in improving enterprise-level performance and agility.

Regression results

Table 4 shows the results of OLS, RE, FE, and GLS models. The comparison of the four regression models, Model 1 (OLS), Model 2 (RE), Model 3 (FE), and Model 4 (GLS), shows strong consistency in the significance and direction of the main explanatory variables. Capital formation (dlnCap), digital exports (dlnDigiex), e-government development (dlnEGOV), and labor productivity (dlnLabor-Production) all have positive effects on the manufacturing sector (dlnMVA). These effects are stable across all models. The results confirm the critical role of both structural and digital factors in driving industrial growth.

Table 5 reports diagnostic tests for model selection. The Hausman test (p = 0.52) supports random effects over fixed effects, while the LM test (p = 0.00) confirms random effects but shows no heteroskedasticity, offering no clear advantage over OLS. The Wooldridge test (p = 0.012) reveals first-order autocorrelation, making OLS, RE, and FE inefficient. To address this, GLS was applied, correcting for autocorrelation and heteroskedasticity. Thus, Model 4 (GLS) is the most appropriate specification for analyzing digital transformation's impact on manufacturing value added.

CONCLUSION

Digital transformation integrates technologies like automation, AI, IoT, cloud computing, and big data into manufacturing, improving efficiency, quality, and adaptability. For developing countries, it is a strategic necessity to drive industrial growth, innovation, and global value chain integration.

This study analyzes how digital transformation affects manufacturing in developing countries, focusing on digital exports, internet usage, labor productivity, capital formation, and e-government. All 5 factors show positive and significant effects, boosting productivity, competitiveness, and market access, while inflation exerts a negative impact by raising costs and uncertainty. Results also reveal spatial variation: e-government's marginal effect is lower in mature regions like Europe and South America but more transformative in less industrialized areas such as Africa. Overall, the findings highlight digital capabilities as key drivers of industrial growth, with e-government effectiveness shaped by regional context.

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