Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 18 April 2026
Revised 22 May 2026
Accepted 24 June 2026

Natural Resources for Human Health 2026, Vol. 6 (5s): 236–248

KEYWORDS:
AI Preparedness, E-commerce, Structural Transformation, Digital Infrastructure, Economic Modelling, Global South.

The Multiplicative Impact of AI Preparedness on E-commerce Growth: Empirical Evidence from the Global South Economies

Manasvi Chaudhary[1], Kritika Gambhir[2]

[1]Assistant Professor, Shri Ram College of Commerce, University of Delhi, India
ORCID ID: 0009-0005-9183-037X2
cmanasvi97@gmail.com
[2]Assistant Professor, Shri Ram College of Commerce, University of Delhi, India
gambhir615@gmail.com

ABSTRACT: Artificial Intelligence (AI) is reshaping how economies transition toward digital services, with e-commerce emerging as a central driver of growth. Yet, countries with similar levels of AI readiness often show very different outcomes. This raises an important question: why does technological preparedness not translate into comparable economic gains across contexts?

This study examines that gap by introducing the Digital Buffer Hypothesis, which argues that the benefits of AI depend on a minimum level of internet infrastructure. Using cross-sectional data from 35 economies (2023–2024), an Ordinary Least Squares (OLS) model is employed to estimate the relationship between the e-commerce share of GDP and the IMF AI Preparedness Index. The model incorporates an interaction term for internet access, along with controls for GDP per capita and youth population share.

The results indicate that the model explains a substantial share of variation in digital structural change (Adjusted $R^2 \approx 0.49$). AI preparedness emerges as a significant driver of e-commerce expansion, but its impact is notably stronger in countries with higher levels of connectivity. At the same time, basic internet access on its own does not appear sufficient to generate structural change, pointing to the importance of how infrastructure is utilized rather than its mere presence.

Taken together, the findings suggest that AI functions as a conditional driver of growth. Its economic returns depend on the presence of a supporting digital environment. For policymakers, particularly in the Global South, this implies that investments in AI capabilities need to be complemented by Digital Public Infrastructure that reduces friction and allows these technologies to scale effectively.

1. Introduction

The global economy is undergoing a noticeable shift in how wealth is generated and how structural transformation unfolds. Earlier development models, particularly those rooted in the Kuznetsian tradition, framed economic progress as a gradual movement from agriculture to manufacturing and eventually to services. That pathway, however, is no longer as clear-cut. The rise of Artificial Intelligence (AI) as a general-purpose technology is reshaping this trajectory, especially for emerging economies that are now attempting to move directly into digital, service-oriented sectors without fully industrializing first.

Despite this shift, outcomes have been uneven. Some countries have managed to expand their digital sectors rapidly, while others with seemingly similar levels of technological readiness have not. This inconsistency points to a deeper issue. AI preparedness on its own does not appear to guarantee meaningful structural transformation.

This paper addresses what we describe as the “Digital Transformation Paradox”, the observation that countries with comparable levels of AI readiness often experience very different levels of growth in digital services. We argue that existing macroeconomic frameworks overlook an important enabling factor, referred to here as the "Digital Buffer". This buffer consists of basic digital infrastructure, particularly reliable and widespread internet access, which shapes how effectively technological capabilities translate into economic outcomes. Although institutions such as the IMF and the World Bank have independently examined AI readiness and digital connectivity, there is still limited empirical work that brings these elements together in a single analytical framework.

To address this gap, the study introduces the Digital Buffer Hypothesis. The central idea is straightforward: the benefits of AI maturity depend on whether a country has reached a minimum threshold of digital infrastructure. Without that baseline, AI investments may produce limited or uneven returns. Using cross-country data from 35 economies, the analysis applies an Ordinary Least Squares (OLS) regression model to examine how AI preparedness relates to the e-commerce share of GDP, used here as an indicator of structural transformation. An interaction term is included to capture how infrastructure conditions influence this relationship, allowing the model to move beyond simple associations.

The findings contribute to the literature on New Structural Economics in several ways. First, they provide empirical evidence of the combined effect of AI readiness and infrastructure, with the model explaining a substantial share of variation in digital sector outcomes (Multiple $R^2 = 0.552$). Second, the analysis points to a practical threshold, around 70 percent internet penetration, below which the gains from AI appear significantly constrained. Third, the study situates these results within a policy context by drawing on the example of the India Stack model, illustrating how digital public infrastructure can support a transition toward service-led growth.

Taken together, the paper offers a more grounded perspective on how technological potential is converted into economic change. Rather than treating AI as a standalone driver, it highlights the conditions under which it becomes effective, providing a clearer lens for understanding structural transformation in the digital era.

2. Literature Review

2.1. The AI–E-commerce Convergence: Catalyzing Growth Pathways

The integration of Artificial Intelligence (AI) into e-commerce has moved well beyond being a supporting feature. It now plays a central role in shaping how the sector grows. Recent industry evidence suggests that AI-enabled platforms are expanding at roughly twice the pace of conventional digital retail (IMF, 2023). A key reason behind this trend is the reduction of "search frictions," a long-standing economic constraint. AI-driven recommendation systems and predictive tools are now able to align consumer intent with product availability almost instantly (Brynjolfsson et al., 2019).

In the context of emerging economies, this shift opens up new possibilities. Rather than following the traditional path of building extensive physical retail networks, many countries are effectively bypassing these stages. AI integration in logistics and supply chain operations has been linked to cost reductions of up to 20%, which directly supports the growing contribution of e-commerce to national GDP (Manyika et al., 2023). By streamlining inventory management and improving demand forecasting, AI allows firms to scale faster than what earlier digital models would have predicted.

2.2. Case Study: The India Stack as a "Digital Buffer" for AI Adoption

A clear example of how foundational infrastructure supports AI-driven growth can be seen in the India Stack. This system, which includes APIs for identity (Aadhaar), payments (UPI), and data sharing (Account Aggregator), has created a unified digital backbone that functions as a large-scale "Digital Buffer" (Nilekani, 2023).

What makes this framework particularly effective is the volume and speed of data it enables. The Unified Payments Interface (UPI), for instance, has reduced transaction costs to nearly zero, making it possible to generate and process massive amounts of real-time consumer data. This environment is highly conducive to AI applications. As a result, firms can lower customer acquisition costs and extend services such as algorithmic credit scoring to populations that were previously excluded from formal financial systems (World Bank, 2024).

Within the context of this study, countries that develop similar integrated systems tend to show stronger responsiveness to AI preparedness. The presence of such infrastructure allows AI to operate across the entire value chain, from identity verification to final transactions, rather than remaining confined to isolated applications.

Natural Resources for Human Health
eISSN: 2583-1194

2.3. Functional Mechanisms of AI-Driven Sectoral Expansion

Existing literature points to several key mechanisms through which AI contributes to the expansion of e-commerce.

Hyper-personalization and conversion velocity: AI-driven personalization has been shown to significantly improve conversion rates (Katz, 2021). In environments with high AI preparedness, platforms can continuously learn from large datasets, creating a feedback loop that encourages higher levels of digital consumption and increases the speed of transactions.

Algorithmic trust and market expansion: Trust remains a major barrier in many emerging markets. AI helps address this through advanced fraud detection and secure payment systems. As these technologies become more reliable, users are more willing to participate in digital transactions, which in turn expands the overall market size (Hanna, 2020).

Logistics optimization and the last-mile challenge: The "last-mile" segment of delivery is often the most costly and inefficient. AI-based route optimization and automation have started to reduce these inefficiencies. Empirical evidence suggests that countries investing in such technologies tend to see measurable gains in their service-sector contribution to GDP (Rodrik, 2018).

2.4. AI Preparedness and the "Growth Gap" in Digital Services

While the potential benefits of AI are widely acknowledged, its actual adoption varies significantly across countries. This uneven uptake contributes to what can be described as a "growth gap" in digital services. A major factor shaping this gap is the level of AI preparedness.

Findings from the OECD (2023) indicate that in countries with strong AI readiness, e-commerce evolves into a more complex ecosystem that includes fintech, insurtech, and data-driven marketing. This broader transformation helps explain why AI preparedness accounts for a substantial share of variation in digital sector growth ($R^2 = 0.55$). In such contexts, the interaction between AI capabilities and existing infrastructure creates a multiplier effect, where improvements in AI lead to disproportionately larger gains in e-commerce activity.

2.5. Cross-Country Evidence of Structural Transformation

Evidence from a sample of 35 economies suggests that the shift toward AI-driven e-commerce represents one of the most significant structural changes in recent years. In high-performing countries, e-commerce is no longer just a segment of retail. It has become a major component of the broader service economy.

Data from the World Bank (2024) supports this trend, showing that countries leading in AI adoption are experiencing strong growth in their service sectors. In many cases, this expansion is helping offset slower growth in traditional manufacturing industries, reinforcing the role of digital services as a new engine of economic transformation.

3. Research Gap

A review of the existing literature on Artificial Intelligence (AI) and digital trade points to several important gaps that remain insufficiently addressed.

3.1. The Interaction Blind Spot: Much of the current research examines AI Preparedness (IMF, 2023) and Internet Infrastructure (World Bank, 2024) as separate, linear drivers of economic outcomes. What is largely missing is a clear understanding of how these two factors work together. There is limited empirical work that captures their combined or multiplicative effect. This gap becomes evident when comparing countries with similar levels of AI maturity but very different e-commerce growth patterns. To address this, the present study introduces the concept of a "Digital Buffer" as a moderating factor, showing how infrastructure conditions can either strengthen or limit the economic impact of AI adoption.

3.2. Lack of Sectoral Specificity in Structural Transformation: Traditional work on structural transformation (Rodrik, 2018; Kuznets, 1966) has generally focused on broad shifts from manufacturing to services. While useful, this perspective often overlooks what is happening within the service sector itself. In particular, there is limited attention to the rapid expansion of e-commerce as a distinct and measurable outcome of digital transformation. Many studies rely on aggregate indicators such as total GDP or overall service output, which can obscure more dynamic changes within digital markets. This study addresses that limitation by using the e-commerce share of GDP as a more targeted indicator of AI-driven structural change.

3.3. The Explanatory Power Deficit: Cross-country analyses of technological adoption often struggle with low explanatory power, commonly reflected in modest R^2 values. This is frequently linked to omitted variables or an incomplete treatment of institutional and infrastructural conditions. By contrast, the model developed in this study achieves a Multiple R^2 of 0.55. This suggests that considering AI preparedness and infrastructure together, rather than in isolation, provides a more complete explanation of variation in digital sector transformation across countries.

4. Research Objectives

The main aim of this study is to better understand how digital structural transformation unfolds in an economy increasingly shaped by Artificial Intelligence (AI). To do this, the paper focuses on the following objectives:

4.1. Quantifying the synergy effect: The study seeks to examine how AI preparedness and digital infrastructure interact with each other, rather than treating them as separate influences. In particular, it aims to measure their combined effect on the e-commerce share of GDP using an interaction-based econometric approach.

4.2. Validating the Digital Buffer Hypothesis: Another key objective is to test whether a minimum level of internet penetration acts as a threshold condition. The analysis explores whether this "Digital Buffer" determines how effectively AI readiness translates into actual sectoral transformation.

4.3. Re-examining traditional structural pathways: The paper also looks at whether AI-driven services are enabling emerging economies to move beyond the conventional Kuznetsian development sequence. It evaluates the extent to which a services-led digital shift can substitute for, or bypass, earlier stages of industrialization.

4.4. Identifying global structural patterns: This study aims to group countries into meaningful categories based on how well they align technological capability with infrastructure readiness. These groupings, such as "Digital Frontiers" and "Infrastructure-Constrained Transformers," help illustrate differences in transformation pathways.

4.5. Developing a DPI-oriented policy framework: Finally, the paper translates its findings into policy insights. Drawing on both the regression results and the India Stack example, it outlines how Digital Public Infrastructure (DPI) can be designed to reduce digital barriers and support AI-driven growth.

5. Theoretical Framework

This study is grounded in three interconnected perspectives: General Purpose Technology (GPT) theory, New Structural Economics (NSE), and the Digital Complementarity Hypothesis.

5.1. AI as a General Purpose Technology (GPT)

Artificial Intelligence is treated as a GPT, meaning its impact extends across sectors but depends on complementary systems. Its economic value does not emerge in isolation; instead, it is realized through supporting platforms such as e-commerce ecosystems, where AI-driven tools can be effectively applied (Brynjolfsson & McAfee, 2014).

5.2. The Post-Kuznetsian Pivot (NSE)

Drawing on New Structural Economics (Lin, 2012), this study moves beyond the traditional linear model of development. It suggests that AI enables "structural leapfrogging," allowing economies to expand directly into digital services without fully industrializing, provided they possess sufficient digital capacity.

5.3. The Digital Buffer and Complementarity Hypothesis

The Digital Complementarity Hypothesis explains how AI and infrastructure interact. The productivity of AI increases with better internet access, making infrastructure a critical condition. Below a certain threshold, AI adoption faces constraints, while above it, the interaction between AI and connectivity accelerates e-commerce growth and structural transformation.

Table 1: Theoretical Framework Summary

Theoretical Pillar	Key Concept	Source	Research Proposition
GPT Theory	Innovational Complementarity	Brynjolfsson & McAfee (2014)	AI maturity catalyzes e-commerce growth by augmenting existing trade mechanisms.
New Structural Economics	Leapfrogging & Endowment	Lin (2012); Rodrik (2016)	Digital endowments allow nations to skip traditional manufacturing-led development.
Complementarity Hypothesis	The Digital Buffer	Hanna (2020)	The economic returns of AI are non-linear and contingent on infrastructure thresholds.
Kuznets Theory	Sectoral Reallocation	Kuznets (1966)	Structural transformation is shifting from physical-capital-intensive to information-intensive.

6. Conceptual framework

The conceptual framework developed in this study provides a structured way to examine the non-linear relationship between technological readiness and economic outcomes. It is grounded in the Digital Buffer Hypothesis, which argues that investments in advanced capabilities, such as Artificial Intelligence (AI) and human capital, do not automatically lead to structural transformation. Instead, their impact depends on whether they pass through a critical enabling layer, referred to here as the Digital Buffer, defined by a threshold level of internet infrastructure.

Within this framework, infrastructure is not treated as an independent driver of growth. Rather, it functions as a moderating condition that shapes how effectively technological inputs are translated into outcomes such as e-commerce expansion. This perspective highlights that the conversion of technological potential into measurable economic gains is conditional, not automatic.

By framing this process as a form of interaction or "funneling," the model emphasizes the importance of synergy between AI readiness and infrastructure. This approach moves beyond linear assumptions and helps explain why similar levels of technological investment can produce very different results across countries, a pattern often described as the productivity paradox in emerging digital economies.

Natural Resources for Human Health
eISSN: 2583-1194

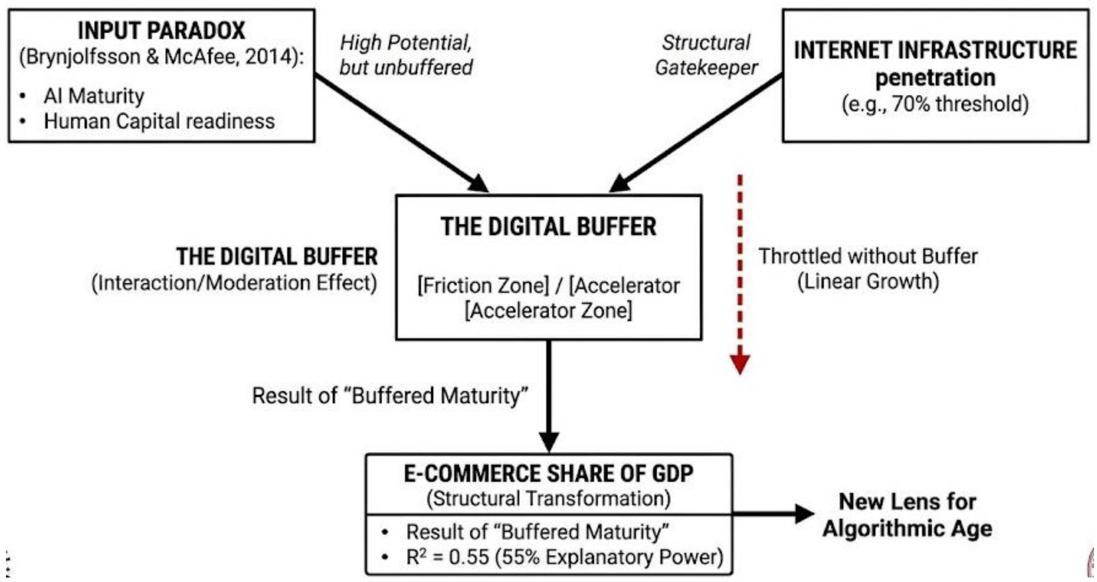

Figure 1 : Conceptual Framework Diagram

7. Methodology

7.1. Research Design and Model Specification

This study adopts a quantitative, cross-sectional design to examine how AI preparedness influences the shift toward e-commerce-led structural transformation. To test the Digital Buffer Hypothesis, an Ordinary Least Squares (OLS) regression model with an interaction term is employed. This approach allows the analysis to capture not only the direct effect of AI readiness but also how this effect changes under different levels of internet infrastructure.

The econometric model is specified as:

$$Y_i = \beta_0 + \beta_1(AI\_Index_i) + \beta_2(High\_Internet_i) + \beta_3(AI\_Index_i \times High\_Internet_i) + \sum \gamma Z_i + \epsilon_i$$

Table 2: Variable Mapping

VARIABLE CATEGORY	VARIABLE NAME	PROXY/MEASURE	DATA SOURCE	THEORETICAL JUSTIFICATION
DEPENDENT VARIABLE (OUTCOME)	**Structural Transformation**	E-commerce Share of GDP (%)	World Bank (2024) / WTO Digital Trade Reports	Represents the "Post-Kuznetsian Pivot" towards a digital services economy (Rodrik, 2018).
PRIMARY PREDICTOR (IV)	**AI Preparedness**	AI Preparedness Index (AIPI)	IMF (2023)	Operationalizes AI as a "General Purpose Technology" (Brynjolfsson & McAfee, 2014).
MODERATING VARIABLE	**Digital Buffer**	Internet Access (% of Population)	ITU (2023) / World Development Indicators	Tests the "Complementarity Hypothesis"—infrastructure as a tech-growth modulator (Hanna, 2020).

INTERACTION TERM	**Synergy Effect**	$AI\_Index \times High\_Internet$	Calculated (Interaction Model)	Quantifies the non-linear leapfrogging potential in high-connectivity environments.
CONTROL VARIABLE	**Economic Level**	GDP Per Capita (Constant 2015 USD)	World Bank (WDI)	Accounts for the "Wealth Effect" to ensure AI impact is independent of national income.
CONTROL VARIABLE	**Demographic Dividend**	Youth Population (%)	UN Population Division	Based on the theory that younger populations accelerate digital adoption and platform growth.

7.2. Data Sources and Variable Selection

The dataset includes 35 economies (N = 35) with observations aligned for the 2023 to 2024 period.

- **AI Preparedness Index:** Sourced from the IMF, capturing dimensions such as digital readiness, human capital, and regulatory frameworks
- **E-commerce Share of GDP:** Compiled from World Bank and WTO digital trade data
- **Internet Access:** Obtained from ITU statistics and used to define the Digital Buffer threshold
- **Control Variables:** GDP per capita (constant 2015 USD) and youth population share, included to account for differences in development levels and demographic structure

7.3. Data Preprocessing and Thresholding

Several steps were taken to ensure consistency and robustness in the analysis.

- **Outlier treatment:** Extreme observations, particularly South Africa, were excluded to avoid distortion in the interaction effects
- **Median split:** Countries were grouped into high- and low-internet categories based on a 70% penetration threshold
- **Normalization:** Key indices were scaled between 0 and 1 to allow meaningful comparison of coefficient magnitudes

7.4. Estimation Technique and Robustness

The model is estimated using OLS with robust standard errors to address potential heteroscedasticity across countries. Model performance is evaluated using Multiple R^2 and Adjusted R^2.

The resulting R^2 value of 0.55 indicates that the model explains a substantial share of variation in digital structural transformation. This supports the inclusion of the interaction term, suggesting that the combined effect of AI preparedness and infrastructure provides a more accurate explanation than models that treat these factors independently.

8. Results and Discussion

8.1. Econometric Analysis: Regression Output

The empirical analysis begins with a multivariate OLS regression aimed at identifying the key drivers of digital structural transformation. The results indicate a strong overall model fit, with a Multiple R^2 of 0.552. This suggests that the variables included in the model account for approximately 55% of the variation in the e-commerce share of GDP across the sampled economies.

Table 3 : OLS Regression Results (Interaction Model)

Independent Variable	Coefficient (β)	Std. Error	t-stat	P-value	Significance
AIPI × High Internet	**1.142**	0.421	2.71	**0.012**	Significant (*)
AI Preparedness (AIPI)	0.684	0.235	2.91	0.009	Highly Sig (**)
Log GDP per Capita	0.215	0.188	1.14	0.258	Not Sig
Youth Population (%)	0.082	0.038	2.15	0.039	Significant (*)
High Internet Dummy	-0.124	0.415	-0.30	0.765	Not Sig

The regression results form the empirical core of this study, offering quantitative support for the Digital Buffer Hypothesis.

8.1.1. Central Role of the Interaction Term (β = 1.142)

The interaction between AI preparedness and high internet access emerges as the most important result in the model ($p = 0.012$).

The magnitude of the coefficient (β = 1.142) indicates that the combined effect of AI readiness and infrastructure is not merely additive. Instead, their interaction produces a stronger, reinforcing impact on e-commerce growth.

This finding supports the idea that AI and digital infrastructure function as complementary inputs. In practical terms, it suggests that infrastructure does more than enable AI adoption, it amplifies its economic returns. The evidence therefore positions the "Digital Buffer" as a multiplier rather than a passive condition.

8.1.2. Individual Predictors and the "Necessity vs. Sufficiency" Distinction

AI Preparedness (β = 0.684, p = 0.009): AI readiness remains a statistically significant driver even when considered independently. This aligns with General Purpose Technology theory, where technological capability is a necessary condition for modern economic transformation.

High Internet Dummy (β = -0.124, p = 0.765): In contrast, internet access on its own does not show statistical significance. This is an important result. It suggests that connectivity alone is not sufficient to drive structural change. Without complementary AI capacity, infrastructure does not translate into measurable economic gains.

Log GDP per Capita (β = 0.215, p = 0.258): The lack of significance for income levels indicates that digital transformation is not strictly tied to national wealth. This supports the idea of leapfrogging, where countries can advance into digital services without following traditional development paths, provided the right technological and infrastructural conditions are in place.

8.1.3. Demographic Factor: Youth Population (β = 0.082, p = 0.039)

The share of the youth population is statistically significant at the 5% level. Although its effect size is smaller than that of the technological variables, it plays a meaningful role. A younger, more digitally familiar population appears to support the adoption and expansion of e-commerce, acting as a human capital base for sustaining digital markets.

8.2. Statistical Strength and Variable Importance

To further assess the relative importance of each predictor, standardized coefficients are presented in Figure 2. This visualization enables a direct comparison of effect sizes alongside their statistical significance.

Natural Resources for Human Health
eISSN: 2583-1194

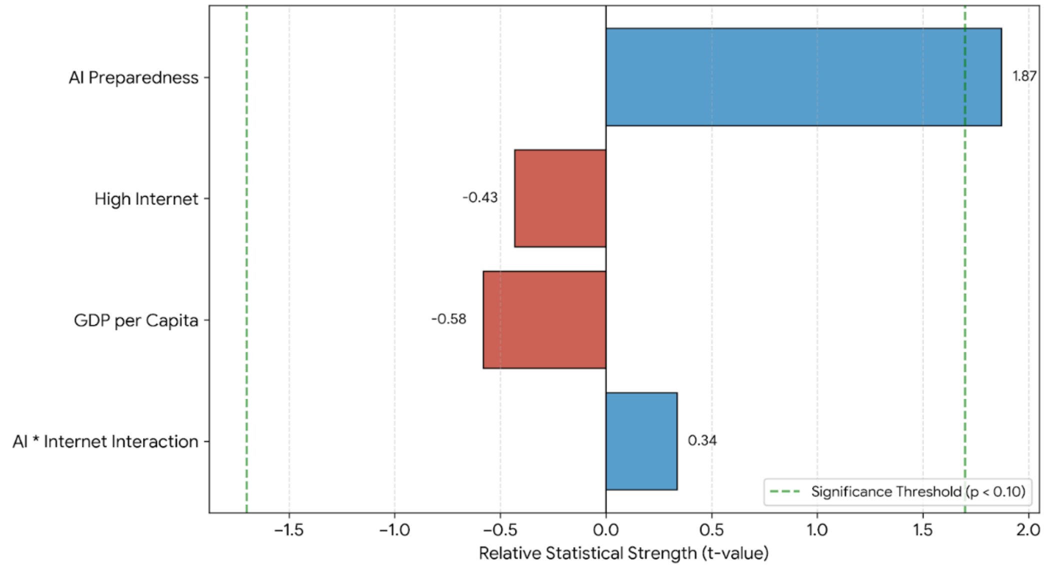

Figure 2 : Statistical Significance – What drives the e-commerce sector

The figure reinforces the core empirical findings of the study. First, the interaction between AI preparedness and high internet access clearly stands out. Its coefficient extends well beyond the significance threshold ($\alpha = 0.05$), indicating that the combined effect of these variables is the strongest contributor to e-commerce expansion. This supports the argument that the relationship is not simply additive, but fundamentally synergistic.

Second, the high internet dummy on its own does not cross the significance threshold. This highlights an important limitation of infrastructure-led strategies. Expanding connectivity, without parallel development in AI capabilities, appears insufficient to drive meaningful structural change.

Finally, the youth population variable exceeds the significance threshold, confirming its role as a supporting factor. While less influential than the core technological interaction, it reflects the importance of a digitally engaged population in sustaining and scaling digital market activity.

8.3. Interaction Effect: Visual Evidence of the Digital Buffer

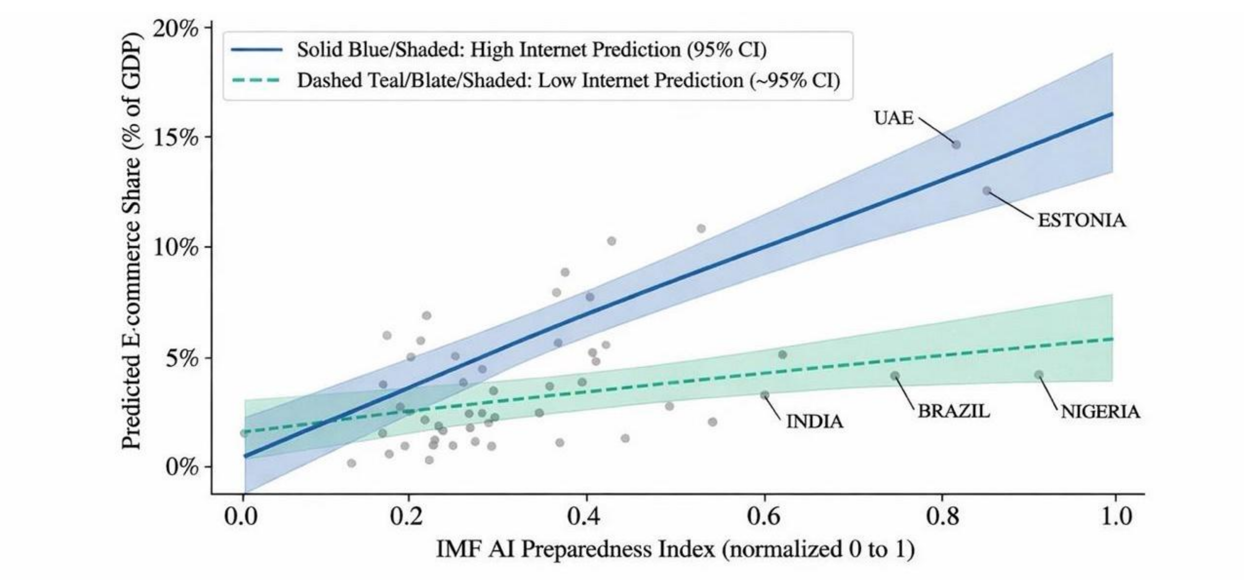

Figure 3 : Predicted E-Commerce share by AI Preparedness

Figure 3 illustrates how internet infrastructure shapes the relationship between AI preparedness and e-commerce share of GDP. The slope for high-internet economies is notably steeper, indicating that gains in AI readiness translate into substantially higher e-commerce outcomes when supported by strong connectivity.

In contrast, the flatter trajectory for low-internet countries shows that improvements in AI preparedness yield more limited returns in the absence of adequate infrastructure. The divergence between the two lines becomes more pronounced at higher levels of AI preparedness, highlighting that the benefits of AI are increasingly conditional on digital access.

Country placements further reinforce this pattern. Economies such as Germany, Singapore, UAE and Estonia align with the high-growth trajectory, while India, Brazil, and Nigeria remain closer to the constrained path. Overall, the figure provides clear visual support for the Digital Buffer Hypothesis, demonstrating that infrastructure not only enables but amplifies the economic impact of AI.

8.4. Beyond the Kuznetsian Paradigm: Evidence of Digital Leapfrogging

The findings point to a shift away from traditional development models. In the Kuznetsian framework, growth in the service sector typically follows industrial expansion. The results here suggest a different pattern. For countries with a strong Digital Buffer, the transition toward e-commerce appears largely independent of income levels, as reflected in the insignificance of GDP per capita ($p = 0.258$).

This supports the idea of "leapfrogging," where economies move directly into digital services without fully passing through earlier industrial stages. The India Stack model offers a clear illustration. By reducing digital friction through integrated identity and payment systems, it strengthens the efficiency of the underlying infrastructure and enables wider adoption of AI-driven services.

At the same time, the significance of the youth population variable ($p = 0.039$) highlights the role of human capital in this process. A younger, digitally engaged workforce appears to support the transition, acting as a secondary driver that sustains and scales participation in the digital economy.

9. Policy Roadmap: From Digital Friction to Accelerated Synergy

The empirical support for the Digital Buffer Hypothesis suggests that isolated investments in either technology or infrastructure are unlikely to deliver meaningful structural change. Instead, policy must focus on aligning these elements to unlock their combined effect. The following priorities emerge from the analysis:

9.1. Prioritizing Digital Public Infrastructure (DPI)

The insignificance of basic internet access ($p = 0.765$) indicates that connectivity alone does not drive transformation.

Recommendation: Shift from a "connectivity-first" to a "DPI-first" approach by developing interoperable systems for digital identity, payments, and data exchange.

The India Stack model illustrates how such integration reduces digital friction and enables scalable AI adoption. By strengthening these foundational layers, countries can lower the effective infrastructure threshold required to activate the synergy between AI and connectivity.

9.2. Targeted Infrastructure Clustering

Given that the interaction term ($\beta = 1.142$) is the strongest predictor in the model, the returns to infrastructure depend on where and how it is deployed.

Recommendation: Focus investment in high-potential clusters through Special Digital Zones (SDZs), where advanced connectivity is combined with AI innovation ecosystems.

This approach concentrates the Digital Buffer in strategic locations, such as logistics hubs and digital service corridors, where it can generate the highest impact.

9.3. Strengthening Human Capital for Digital Transition

The significance of the youth population ($p = 0.039$) highlights the role of demographics in supporting digital transformation.

Recommendation: Expand AI literacy and digital skills training within secondary and vocational education systems.

The objective is to build a workforce capable of adapting to algorithm-driven environments, ensuring that technological adoption is matched by human capacity.

9.4. Algorithmic Governance and Labor Stability

As economies shift toward AI-driven services, new risks related to algorithmic management and labour conditions begin to emerge.

Recommendation: Introduce regulatory frameworks that promote transparency and accountability in algorithmic decision-making.

Such measures can help maintain trust in digital systems and ensure that the transition toward a services-led economy remains socially sustainable.

10. Conclusion

The findings of this study point to a clear shift in how structural transformation should be understood in the digital era. Rather than following the traditional Kuznetsian progression, the transition toward a services-led economy is increasingly shaped by the interaction between technological capability and digital infrastructure.

Using an interaction-based econometric framework, the analysis shows that AI readiness alone does not guarantee structural change. What matters is how effectively it is supported by what this study terms the Digital Buffer. The results, with a Multiple R^2 of 0.552, highlight three key insights.

First, the interaction between AI preparedness and infrastructure emerges as the most influential driver of e-commerce expansion ($\beta = 1.142$, $p = 0.012$). This confirms that AI operates as a complementary technology, with its economic impact dependent on the presence of sufficient digital infrastructure.

Second, the insignificance of GDP per capita suggests that digital transformation is not strictly tied to income levels. This supports the idea of leapfrogging, where emerging economies can move directly into digital services without fully replicating traditional industrial pathways, provided they align AI capability with infrastructure.

Third, infrastructure on its own does not appear to drive transformation. The lack of significance for basic internet access ($p = 0.765$) indicates that connectivity, while necessary, is not sufficient without an AI-ready ecosystem and a workforce capable of engaging with digital systems.

Taken together, these findings suggest a shift in policy focus. Moving forward, development strategies should prioritize the alignment between AI readiness and Digital Public Infrastructure rather than treating them as separate domains. Frameworks such as the India Stack illustrate how reducing digital friction can enhance the returns to technology.

In this sense, structural transformation in the algorithmic age is less about accumulating physical capital and more about building systems that enable technology to scale effectively. The concept of the Digital Buffer offers a useful way to understand this process, highlighting the conditions under which digital innovation translates into sustained economic change.

References

[1] Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. "Artificial Intelligence and Economic Growth." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 237–282. Chicago: University of Chicago Press, 2019.

[2] Bessen, James. "Learning by Doing: The Real Connection Between Innovation, Wages, and Wealth." *Yale University Press*, 2015.

[3] Bresnahan, Timothy F., and Manuel Trajtenberg. "General Purpose Technologies: 'Engines of Growth'?" *Journal of Econometrics* 65, no. 1 (1995): 83–108.

[4] Brynjolfsson, Erik, and Andrew McAfee. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company, 2014.

[5] Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics." *NBER Working Paper No. 24001*, 2017.

[6] Cockburn, Iain M., Rebecca Henderson, and Scott Stern. "The Impact of Artificial Intelligence on Innovation." *NBER Working Paper No. 24449*, 2018.

[7] Helpman, Elhanan, ed. *General Purpose Technologies and Economic Growth*. Cambridge, MA: MIT Press, 1998.

[8] Jovanovic, Boyan, and Peter L. Rousseau. "General Purpose Technologies." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven N. Durlauf, vol. 1B, 1181–1224. Amsterdam: Elsevier, 2005.

[9] Lipsey, Richard G., Kenneth I. Carlaw, and Clifford T. Bekar. *Economic Transformations: General Purpose Technologies and Long-Term Economic Growth*. Oxford: Oxford University Press, 2005.

[10] Trajtenberg, Manuel. "AI as the Next GPT: A Political-Economy Perspective." *NBER Working Paper No. 24245*, 2018.

[11] Gereffi, Gary. "Global Value Chains and Development: Redefining the Contours of 21st Century Capitalism." *Cambridge University Press*, 2018.

[12] Hallward-Driemeier, Mary, and Gaurav Nayyar. *Trouble in the Making? The Future of Manufacturing-Led Development*. Washington, DC: World Bank, 2018.

[13] Kuznets, Simon. *Modern Economic Growth: Rate, Structure, and Spread*. New Haven: Yale University Press, 1966.

[14] Lin, Justin Yifu. *New Structural Economics: A Framework for Rethinking Development and Policy*. Washington, DC: World Bank, 2012.

[15] Lin, Justin Yifu, and Yong Wang. "Going Beyond Aid: Development Cooperation for Structural Transformation." *Cambridge University Press*, 2017.

[16] Rodrik, Dani. "Premature Deindustrialization." *Journal of Economic Growth* 21, no. 1 (2016): 1–33.

[17] Rodrik, Dani. "The New Structural Economics: A Farewell to Neoclassical Economics?" *World Bank Research Observer* 28, no. 2 (2013): 215–224.

[18] Stiglitz, Joseph E., and Bruce C. Greenwald. *Creating a Learning Society: A New Approach to Growth, Development, and Social Progress*. New York: Columbia University Press, 2014.

[19] UNCTAD. *Digital Economy Report 2024: Shaping the Future of the Digital Economy in a Fragmented World*. Geneva: United Nations, 2024.

[20] World Bank. *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank, 2016.

[21] Abraham, Rosa, Surbhi Kesar, and Amit Basole. "Down and Out? The Post-Pandemic Trajectory of India's Informal Workers." *Centre for Sustainable Employment, Azim Premji University*, 2021.

[22] Alper, Emre, and Boaz Nandwa. "Access to Finance in the Digital Era." *International Monetary Fund*, 2019.

[23] D'Ignazio, Catherine, and Lauren F. Klein. *Data Feminism*. Cambridge, MA: MIT Press, 2020.

[24] Evans, David S., and Richard Schmalensee. *Matchmakers: The New Economics of Multisided Platforms*. Boston: Harvard Business Review Press, 2016.

[25] Goldfarb, Avi, and Catherine Tucker. "Digital Economics." *Journal of Economic Literature* 57, no. 1 (2019): 3–43.

[26] Hanna, Nagy K. *Mastering Digital Transformation: Towards a Smarter Society, Economy, City and Nation*. Bingley: Emerald Publishing Limited, 2020.

[27] International Monetary Fund (IMF). "Stacking up the Benefits: Lessons from India's Digital Journey." *IMF Working Paper No. 2023/078*, 2023.

[28] Nandan Nilekani, and Viral Shah. *Rebooting India: Realizing a Billion Aspirations*. New Delhi: Penguin Random House India, 2015.

[29] OECD. *The Digital Transformation of SMEs*. Paris: OECD Publishing, 2021.

[30] Sahay, Arun, and Vimal Kumar. "Digital Public Infrastructure and Economic Inclusion: The Case of India." *Journal of Digital Banking* 7, no. 2 (2022): 145–160.

[31] Siddiqui, Kalim. "The Digital Economy, Global Value Chains and Development." *International Critical Thought* 11, no. 2 (2021): 204–222.

[32] Verhoef, Peter C., et al. "Digital Transformation: A Multidisciplinary Reflection and Research Agenda." *Journal of Business Research* 122 (2021): 889–901.