

Digital Transformation and Economic Inequality: Trends, Clusters and Policy Impacts Across Economies

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Abstract

Digital transformation is reshaping economic structures worldwide, yet its implications for income inequality remain debated. This study examines the relationship between digital readiness (DR) and income inequality across twelve advanced and emerging economies from 2005–2024. Using panel regression, clustering, and machine learning approaches, the study explores trends, structural country groupings, and the determinants of inequality. The results reveal heterogeneous dynamics: emerging economies often experience inequality reductions as digital readiness improves, whereas the effects in advanced economies are weaker or insignificant. Fixed-effects models suggest that short-run increases in digital readiness may temporarily coincide with higher inequality. Clustering identifies two structural groups of countries with distinct digital and socioeconomic profiles. Overall, the findings suggest that digital transformation alone is insufficient to reduce inequality and must be complemented by policies promoting affordable connectivity, digital skills, and inclusive institutions.

Keywords: Digital readiness, income inequality, fixed effects panel regression, machine learning, cluster analysis

JEL Classification: O33, D63, I32, L96, O15

1. Introduction

Over the past two decades, global economic dynamics have undergone a profound transformation as digital technologies have reshaped production, service delivery, and market access (Matyushok *et al.*, 2021). In advanced economies, improved digital readiness has bolstered productivity and competitiveness, while in emerging markets, ICT diffusion has facilitated financial inclusion and new livelihood opportunities. Evidence from emerging markets shows that the interaction between platform digitalization and stronger intellectual property protection not only enables technology entrepreneurship but also reshapes the underlying opportunity structures (Du *et al.*, 2025). Technological progress plays a substantial role in economic development (Khan and Khan, 2024). Nevertheless, digital transformation is inherently ambivalent: while it can democratize access and reduce frictions, it may also amplify disparities in income and opportunity when adoption remains uneven (Xiao *et al.*, 2024). We add to this debate by providing an integrated, multi-method analysis of digital readiness and income inequality in both advanced and emerging economies over nearly two decades.

Income inequality remains a major economic challenge with profound implications for growth, equity, and social stability (Khan and Khan, 2024; Paddu *et al.*, 2025) and household-level well-being (Hong *et al.*, 2024). Traditionally shaped by labor markets, institutional frameworks, and fiscal policy, inequality now unfolds within a digitally mediated landscape where access to and usage of digital infrastructure become additional determinants. On one hand, digital technologies have delivered substantial welfare gains for underserved populations by expanding access to credit and labor markets (Magwedere and Marozva, 2025). On the other hand, a growing body of evidence, especially from advanced economies, highlights the risk of technological change intensifying inequality, particularly when adoption favors high-skilled workers or households (Antonelli and Tubiana, 2023). Against this background, this study offers an innovative perspective by jointly analyzing long-run trends, structural country groupings, and policy-relevant effects of digital transformation on income inequality.

Recent empirical literature attests to the complex relationship between digital transformation and inequality. The review by Christanti *et al.* (2024) reveals that digital divides go beyond mere access; they encompass usage proficiency, digital skills, and infrastructure quality, all of which systematically correlate with socioeconomic status. In the European Union, evidence shows that socially sustainable digital transformation correlates with lower inequality and progress toward Sustainable Development Goals (Nosratabadi *et al.*, 2023). Similar patterns emerge in global sustainable supply chain governance in emerging markets (Yongsheng and Yingquan, 2025). At the same time, policymakers face a dual challenge:

ensuring digital transformation promotes inclusion (Khan *et al.*, 2025) and supports broader ESG and sustainability goals in digitally intensive supply chains (Wu *et al.*, 2024), while avoiding scenarios where digital acceleration widens existing gaps.

Despite the growing interest, several empirical and conceptual gaps remain. First, most studies treat digital transformation as a static snapshot (Conway, 2015; Li *et al.*, 2018; Wu *et al.*, 2022), ignoring its evolving dynamics and how inequality co-evolves over time. Second, comparative analyses often focus on either advanced or emerging economies in isolation, limiting cross-context generalizability. Third, limited research adopts multi-method frameworks that combine trend analysis, structural classification (*e.g.*, clustering), and causal inference. Finally, rigorous causal studies, particularly those utilizing policy change as natural experiments, are sparse in this domain. These gaps constrain the development of nuanced, evidence-based policy recommendations that can leverage digital transformation for inclusive growth.

This study contributes to existing literature in three ways. First, the novelty of our study lies in the integration of descriptive, structural, and causal analyses within a unified panel framework spanning 2005–2024 and covering both advanced and emerging economies. We chart dynamic trends in digital readiness and income inequality, identifying divergent trajectories across contexts. Second, we apply clustering methods (k-means and hierarchical) to reveal groupings of countries with similar socioeconomic-digital profiles and use these clusters as policy-relevant typologies. Third, we leverage variation in the timing of digital policy adoption through event-study difference-in-differences designs to estimate the causal impact of digital reforms on inequality. This multi-method approach moves beyond traditional cross-sectional or bivariate correlations and offers richer insights into how digital transformations shape economic stratification across different stages of development.

The objectives of this paper are threefold. First, we document how a composite digital readiness index and income inequality coevolve over 2005–2024 in twelve advanced and emerging economies, identifying convergence and divergence patterns across countries. Second, we classify these economies into clusters using k-means and hierarchical algorithms based on digital readiness, GDP per capita, education, and urbanization to obtain policy-relevant country groupings with distinct socioeconomic and digital profiles. Third, we estimate the distributional impact of major digital policy adoptions on income inequality using an event-study difference-in-difference framework, assessing whether and how inequality changes in the year following such reforms.

2. Literature Review

Recent scholarship emphasizes that the digital divide is not only a matter of infrastructure but also deeply connected to socioeconomic inequality. For instance, Sanders and Scanlon (2021) frame digital inequality as a human rights issue, arguing that the lack of reliable broadband access disproportionately affects marginalized groups and perpetuates economic and educational disparities. Similarly, research by Ochillo (2022) documents a direct correlation between digital exclusion and intergenerational inequality in the U.S., underscoring how digital access shapes economic mobility.

At the aggregate level, studies illustrate the nuanced impact of digital transformation on income distribution. Xiao *et al.* (2024) use cross-country panel data (1995–2020) and advanced estimators to reveal that technological innovation's effects on inequality vary substantially, depending on broader socioeconomic contexts. In a complementary vein, Baffour Gyau *et al.* (2025) examine OECD countries (2004–2021) using GMM modeling and find that while digitalization has spurred economic progress, it also intensified inequality in certain subgroups, highlighting the need for balanced, inclusive policy frameworks. Configurational analyses of HRM systems at the organizational level suggest that differentiated digital HR bundles produce differentiated performance outputs, which could produce distributional effects (Xi *et al.*, 2025).

Understanding how countries cluster in digital readiness and inequality is vital for comparative policy design. In the EU context, Nosratabadi *et al.* (2023) introduce the concept of Social Sustainability of Digital Transformation (SOSDIT), demonstrating that countries with higher digital social sustainability also tend to achieve better SDG performance and lower Gini coefficients. Besides the range of digital indicators, civil-society players, such as environmental non-governmental organizations, can also affect the redistribution of activity regionally, thus adding another aspect of the sustainability-inequality nexus (Li *et al.*, 2024a). Similarly, Košíková and Vašaničová (2025) apply cluster analysis to identify distinct groupings of EU nations based on digital skill levels and infrastructure, offering policy-relevant typologies tailored to each cluster's developmental stage.

Few studies rigorously estimate the causal impact of digital policy on inequality using quasi-experimental designs. However, Li *et al.* (2024b) provide important empirical evidence that digital transformation reduces labor income's share of total income, suggesting displacement effects, possibly widening inequality in the absence of offsetting redistribution or skill development. Additionally, Zhang *et al.* (2024) examine how the digital economy enhances income distribution among industries through improvements in productivity

and human capital, and similar dynamics emerge in cross-border knowledge collaborations of multinational enterprises (Zhang *et al.*, 2025).

The literature reveals that digital inclusion is economically and socially essential (Sanders and Scanlon, 2021). Cross-country analyses elucidate macroeconomic trends (Bafour Gyau *et al.*, 2025; Xiao *et al.*, 2024), while clustering approaches highlight structural variation (Nosratabadi *et al.*, 2023). Causal studies begin to unpack policy effects. Yet, these contributions remain fragmented, such as (i) Temporal dynamics of digital readiness and inequality rarely feature in tandem, (ii) comparative classification across advanced and emerging economies remains underdeveloped, and (iii) robust causal inference using real policy variation is almost absent.

Considering these constraints, the present study provides three main contributions. First, it takes a dynamic approach by tracing the co-evolution between digital readiness and income inequality in the years 2005–2024, in twelve advanced and emerging economies. Second, it combines descriptive, clustering, and panel regression analyses into a single analysis framework, therefore connecting observed trends, country groupings, and determining conditional relationships between digital readiness and income inequality. Third, it examines the distributional effect of large-scale digital policy adoptions by an event-study difference-in-differences design. Overall, these features extend the existing work that has largely been based on cross-sectional correlations, single methodologies, or a limited number of national settings.

3. Research Methodology

3.1 Data and Variables

The empirical analysis is based on an unbalanced panel dataset covering the period 2005–2024 for a selection of advanced and emerging economies. The primary variables are Digital Readiness (DR_{it}), which is constructed as a standardized index (z-scores) of multiple digital infrastructure indicators, including internet usage (IU), fixed broadband subscriptions (FB), mobile subscriptions (MS), secure servers (SS), and electricity access ($ELEC$). Inequality (Inq_{it}) is measured by the Gini coefficient. GDP per capita ($GDPpc$, constant US\$), log-transformed ($\log GDPpc_{it}$), as well as other socio-economic variables, are considered as economic control variables. The panel structure allows us to examine both cross-country differences and within-country changes over time.

Formally, the digital readiness index is computed as:

$$DR_{it} = \frac{1}{K} \sum_{k=1}^K \frac{X_{kit} - \bar{X}_k}{\sigma_k} \quad (1)$$

where DR_{it} is digital readiness for country i at time t , K means number of indicators, X_{kit} denotes indicator k for country i at time t , $\bar{X}_k$ is mean of indicator k , and σ_k is standard deviation of indicator k .

3.2 Econometric Models

3.2.1 Correlation Models

We estimate simple bivariate correlation coefficients:

$$\rho^{(P)} = \frac{\sum_{t,i} (DR_{it} - \bar{DR})(inq_{it} - \bar{inq})}{\sqrt{\sum_{t,i} (DR_{it} - \bar{DR})^2 \sum_{t,i} (inq_{it} - \bar{inq})^2}} \quad (2)$$

for the Pearson correlation, and a rank-based equivalent for Spearman's $\rho^{(S)}$.

3.2.2 Panel Regression Model

To control for unobserved heterogeneity, we estimate the following fixed-effects panel model:

$$Inq_{it} = \alpha + \beta DR_{it} + \gamma \log GDPpc_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where μ_i denotes country fixed effects, and λ_t is year fixed effects.

3.2.3 Clustering Model

For the k -means clustering, we minimize within-cluster variance:

$$\arg \min_{\{C_j\}_{j=1}^k} \sum_{j=1}^k \sum_{i \in C_j} \|x_i - \mu_j\|^2 \quad (4)$$

where x_i is a data point and μ_j means centroid of cluster j .

3.2.4 Difference-in-Differences Event Study

To assess the causal impact of digital policy adoption, we apply a staggered DiD model using the fixest implementation of Sun and Abraham (2021):

$$Inq_{it} = \alpha + \sum_g \sum_{\tau} \beta_{\tau} \cdot 1\{G_i = g\} \cdot 1\{t - G_i = \tau\} + \gamma \log GDPpc_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where G_i is the adoption year for country i (or never treated), τ indexes the event time (years since adoption), and β_{τ} captures the dynamic treatment effect relative to the base period. Country μ_i and year λ_t fixed effects control for time-invariant heterogeneity and global shocks.

All estimations are conducted in R (version 4.4) using the packages tidyverse, fixest, and cluster for statistical modeling, and ggplot2 for visualization. Panel regressions are estimated with clustered standard errors at the country level.

4. Results and Discussion

Table 1 presents the descriptive statistics for the variables used in this study. Table 1 shows that advanced economies have higher and less dispersed digital readiness, while emerging economies display lower average readiness and greater variability in both digital indicators and inequality. Income inequality (Inq) exhibits considerable variation, with Gini coefficients ranging from 25.50 to 64.80 (SD = 10.14). Digital indicators display wide disparities: IU varies between 2.39% and 96.30% of the population, FB penetration ranges from 0.00 to 48.67 subscriptions per 100 people, and MS ranges from 7.81 to 178.43 per 100 people. The number of SS per million people shows extreme dispersion, from less than 1 to over 196,000; reflecting differences in digital security capacity. $ELEC$ spans from 46.80% to full coverage, while $GDPpc$ ranges from USD 710.49 to USD 85,809.90 (SD = 20,895.30), underscoring significant income-level disparities. These variations highlight the heterogeneous digital and economic landscapes across countries, providing a robust basis for analyzing the nexus between digital transformation and inequality.

Table 1: Descriptive statistics and source of the variables

Variables	Definition	Min	Max	SD	Source
<i>Inq</i>	Gini coefficient (0 = equality, 100 = inequality)	25.50	64.80	10.14	WB (2021)
<i>IU</i>	Individuals using the Internet (% of population)	2.39	96.30	29.32	WB (2021)
<i>FB</i>	Fixed broadband subscriptions (per 100 people)	0.00	48.67	15.88	WB (2021)
<i>MS</i>	Mobile cellular subscriptions (per 100 people)	7.81	178.43	32.43	WB (2021)
<i>SS</i>	Secure Internet servers (per million people)	0.61	196,554.13	32,917.33	WB (2021)
<i>ELEC</i>	Access to electricity (% of population)	46.80	100.00	13.39	WB (2021)
<i>GDPpc</i>	Gross domestic product per capita in current US\$	710.49	85,809.90	20,895.30	WB (2021)

Source: Authors’ own calculations

Figure 1 illustrates the trends and slopes of income inequality (*Inq*) and digital readiness (*DR*) from 2005–2024. Figure 1 displays inequality trends, showing a more heterogeneous pattern. Countries like Brazil, Mexico, and South Africa exhibit persistently high Gini coefficients, with only gradual improvements over time. Conversely, countries such as India, France, and Germany maintain lower inequality levels with modest declines. Some advanced economies (e.g., the United States) show stable but relatively high inequality, aligning with the findings of Antonelli and Tubiana (2023), who emphasize the structural persistence of inequality in high-income nations despite technological progress. The divergence between *DR* and inequality trajectories in certain cases suggests that digital transformation alone does not uniformly reduce inequality, echoing findings by (Baffour Gyau *et al.*, 2025). Similarly, the trend in *DR* shows a consistent upward trajectory across all countries, even at different paces. Advanced economies such as the United States, Germany, and the United Kingdom show a higher starting point and steeper growth, reflecting early investments in ICT infrastructure and innovation. Emerging economies, including India, Nigeria, and Indonesia, start from significantly lower *DR* levels but demonstrate strong growth momentum, suggesting catch-up dynamics in digital adoption.

Figure 1: Trend and slope in digital readiness and income inequality from 2005–2024

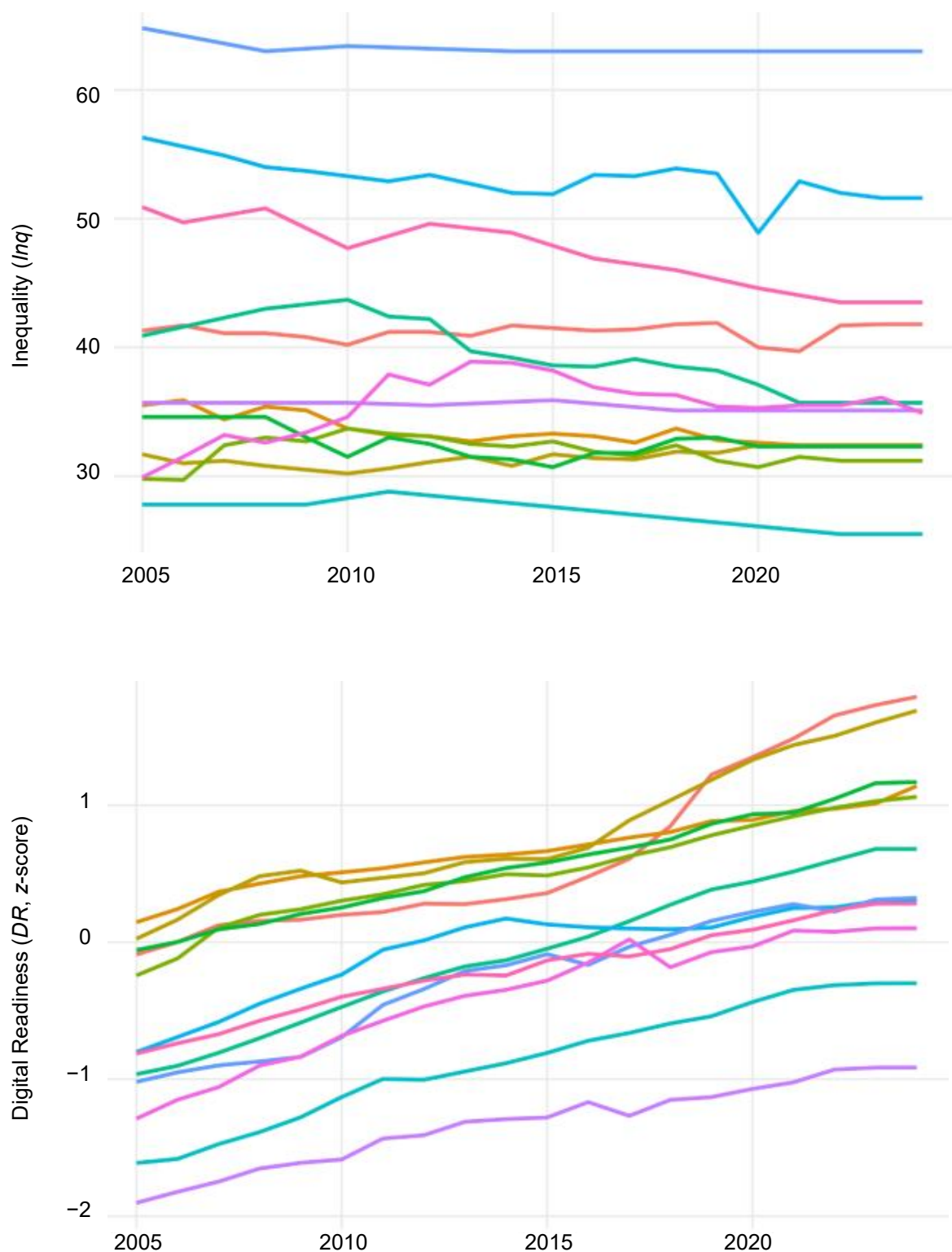
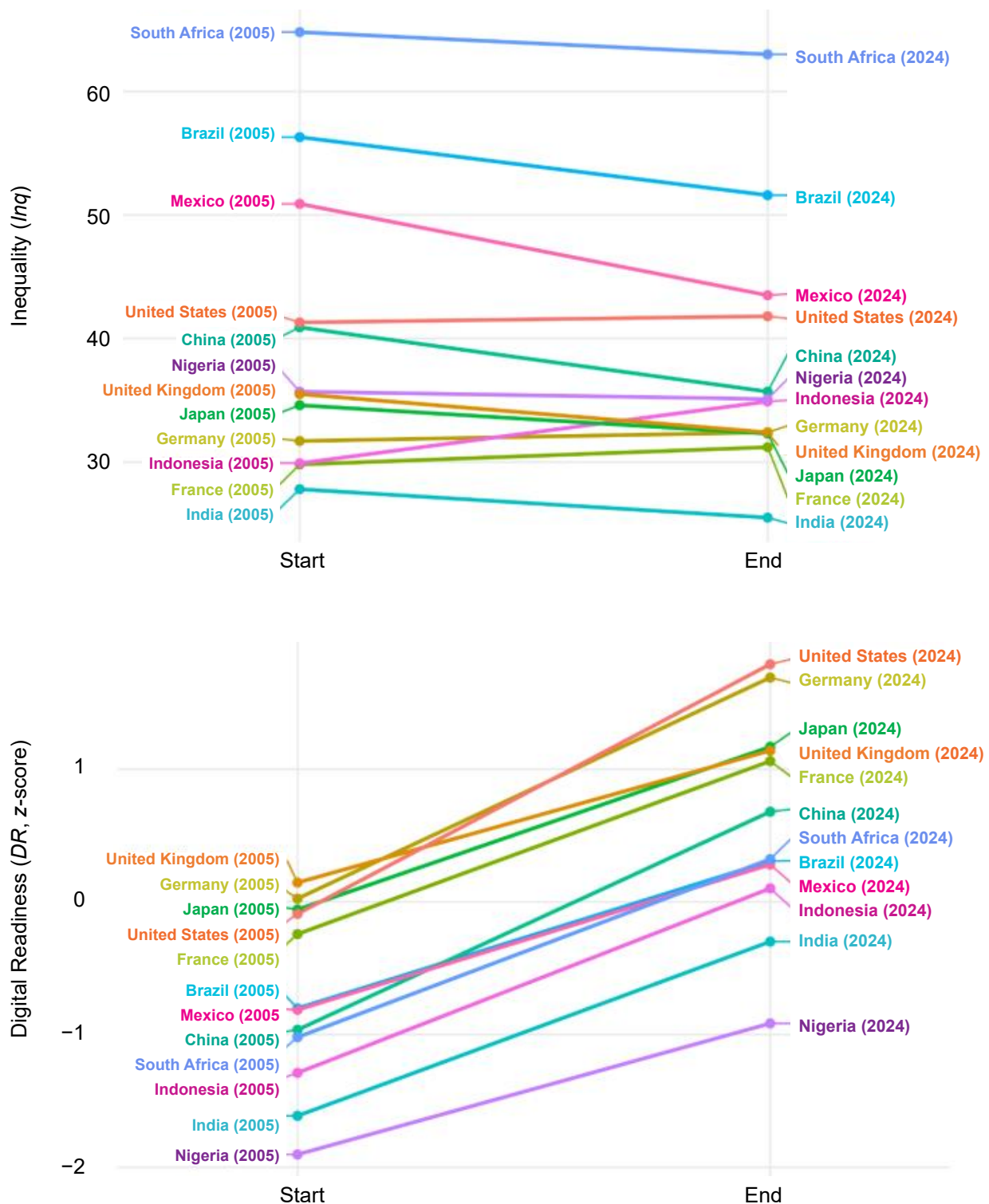


Figure 1: Continuation



Source: Authors' own elaboration

Moreover, the slope chart for *DR* highlights substantial absolute gains for all countries. The steepest increases are visible for India, China, and Indonesia, reflecting the rapid adoption of broadband, mobile, and secure server infrastructure. In contrast, high-income countries show smaller relative gains due to already high baselines in 2005. This pattern aligns with the World Bank (WB, 2021) reports showing diminishing marginal returns of ICT investment in saturated markets, versus transformative impacts in underserved markets. The slope chart for inequality reveals mixed outcomes. Brazil and Mexico show notable reductions in inequality, possibly linked to targeted social programs and digital inclusion policies. Meanwhile, Nigeria and Indonesia exhibit increasing inequality despite gains in *DR*, highlighting that digital expansion without complementary redistributive measures may exacerbate disparities (González *et al.*, 2016). Advanced economies remain clustered with relatively low to mid-level inequality, indicating stability rather than major shifts.

Otieno and Busili (2024) and del Carpio *et al.* (2022) suggest that while technology adoption boosts productivity and connectivity, its inequality effects depend heavily on institutional quality, labor market inclusivity, and complementary policy interventions. Our findings support this, showing cases where *DR* improvements correspond to inequality reduction (*e.g.*, Brazil), but also instances where inequality persisted or widened (*e.g.*, Nigeria). Figure 1 illustrates that emerging economies start from low digital readiness but improve rapidly, whereas advanced economies begin at high levels and change more gradually, while inequality trends remain heterogeneous across countries.

Figure 2 collectively compares Gini inequality (panel A), income groups (panel B), digital readiness (panel C), urbanization (panel D), GDP distribution (panel E), and 2020 innovation scores across major economies (panel F). **Panel A** regarding the Gini map shows the highest inequality in South Africa and Brazil, moderate in the USA and China, and lowest in European nations and Japan. **Panel B** (income group map) classifies countries from high to lower-middle income, with high-income nations like the USA, UK, Japan, and Germany contrasted with lower-middle-income India and Nigeria. **Panel C** regarding digital readiness highlights advanced readiness in developed economies (USA, Germany, UK, Japan) and lower readiness in countries like Nigeria and India. Whereas **panel D** reveals that urban population percentages are highest in Japan, Brazil, and much of Europe/North America, while India, Nigeria, and Indonesia remain less urbanized. Studies of polycentric urban forms in Chinese cities show that city morphology determines equalization of basic public services (Cheng *et al.*, 2025), which means that urban form can interrelate with digital public infrastructure in creating inequality. Moreover, **panel E** emphasizes the economic dominance of the USA, China, and Japan, while GDP per capita disparities remain stark.

Furthermore, **panel F** regarding the 2020 innovation reveals that Germany, the UK, and the USA are the top performers, while Brazil and South Africa lag. Together, the figures depict intertwined patterns of wealth, inequality, digital capacity, urbanization, and innovation across global economies.

Figure 2: Socioeconomic and developmental profiles of selected countries

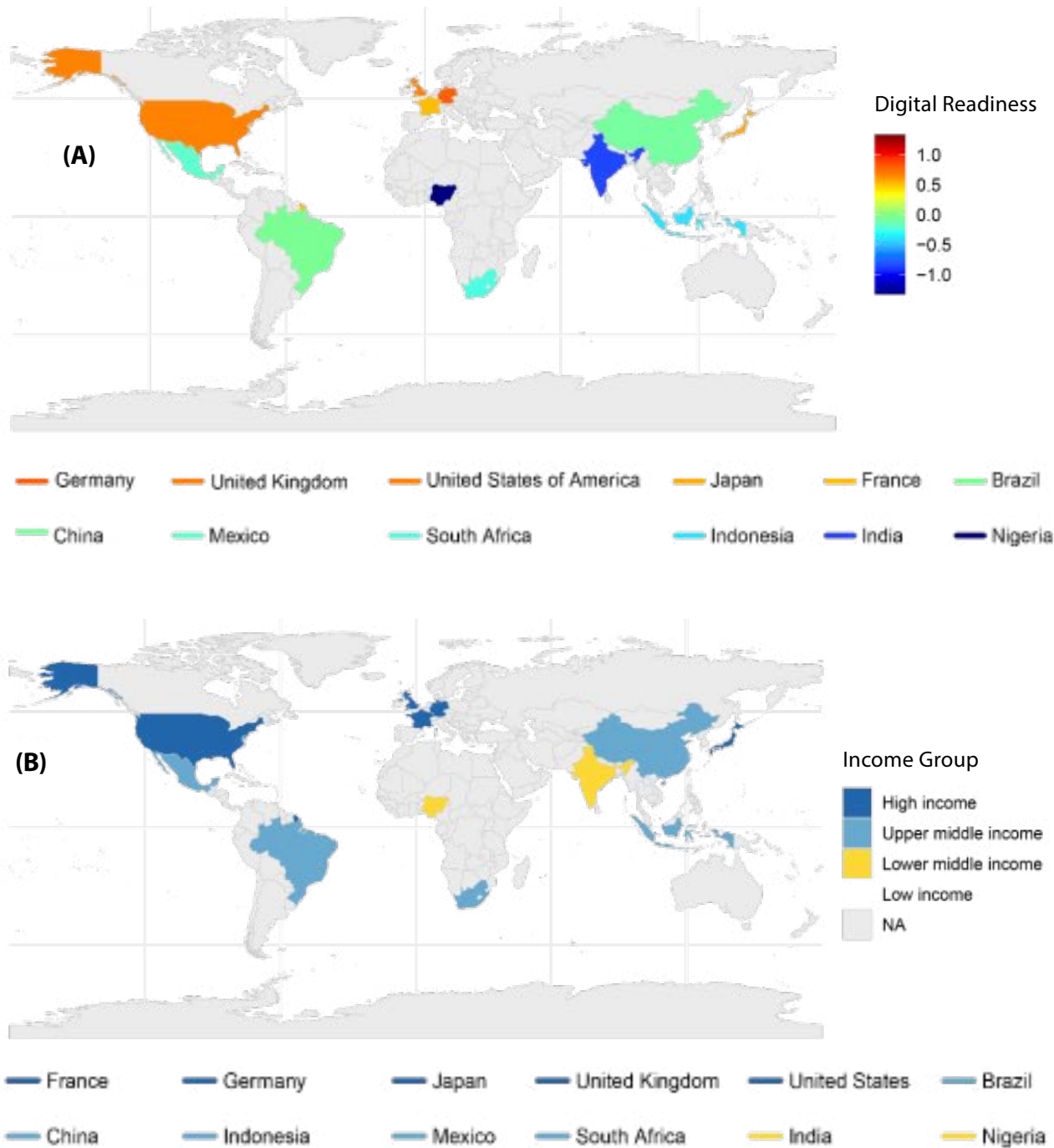


Figure 2: Continuation

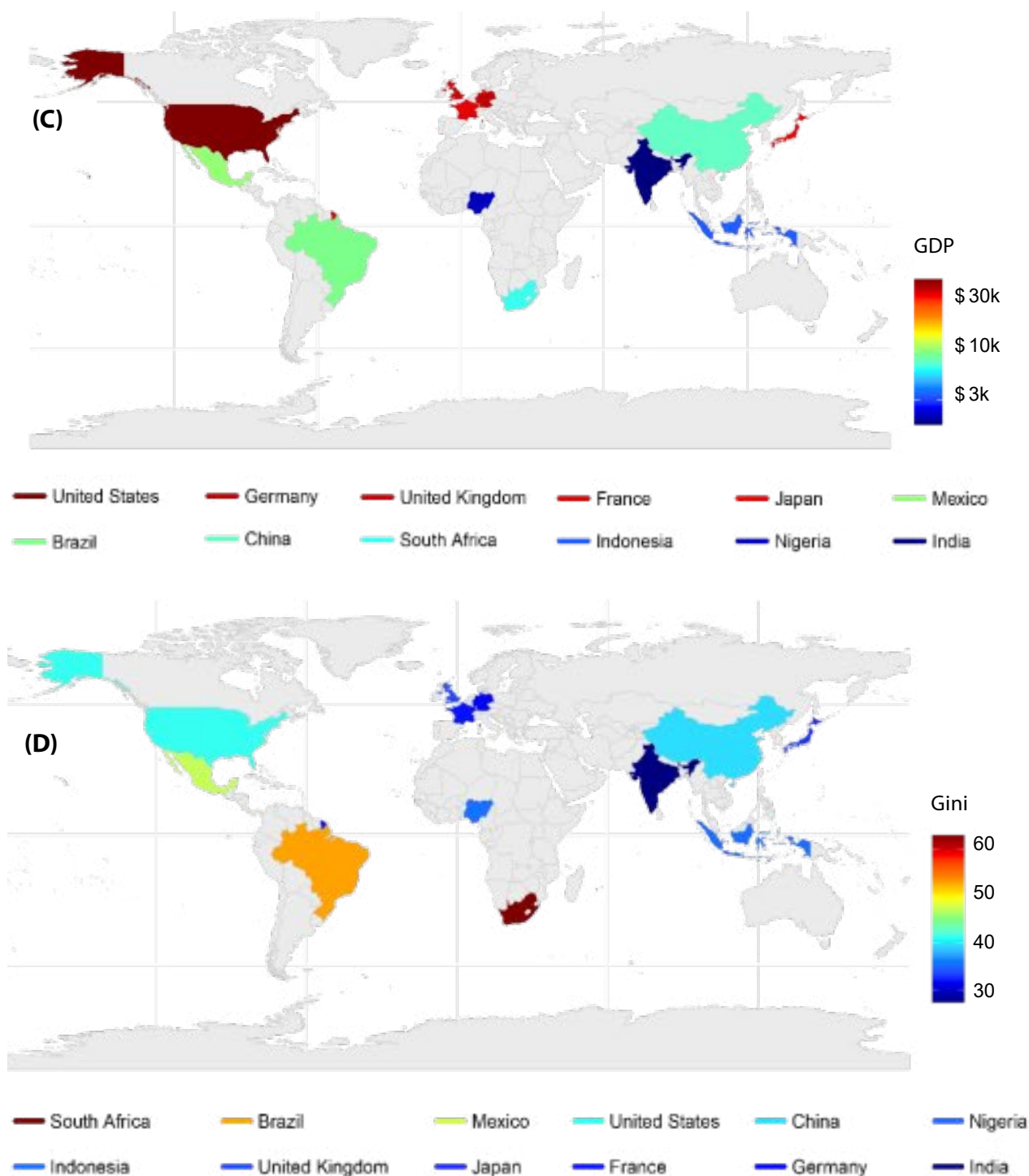
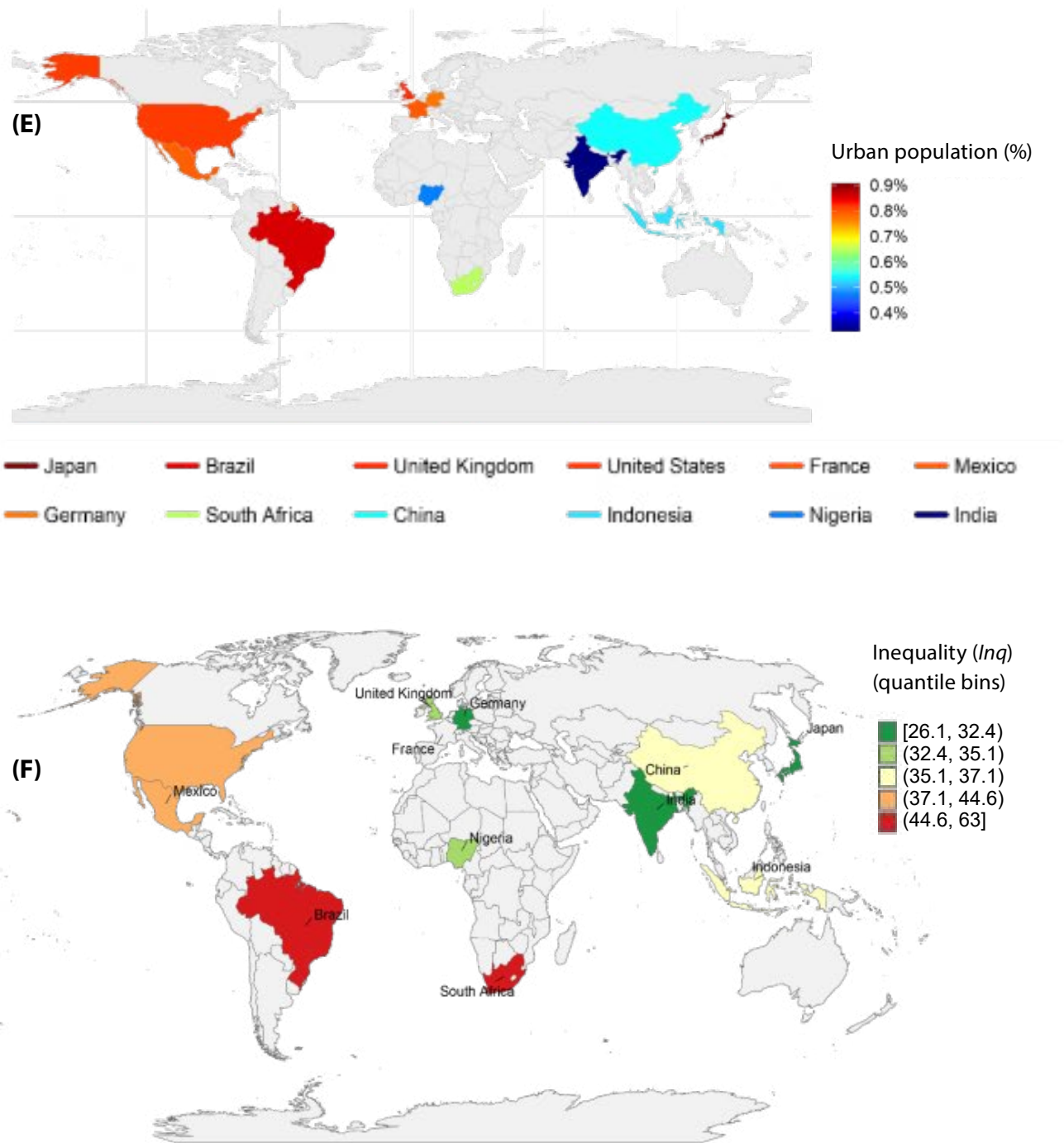


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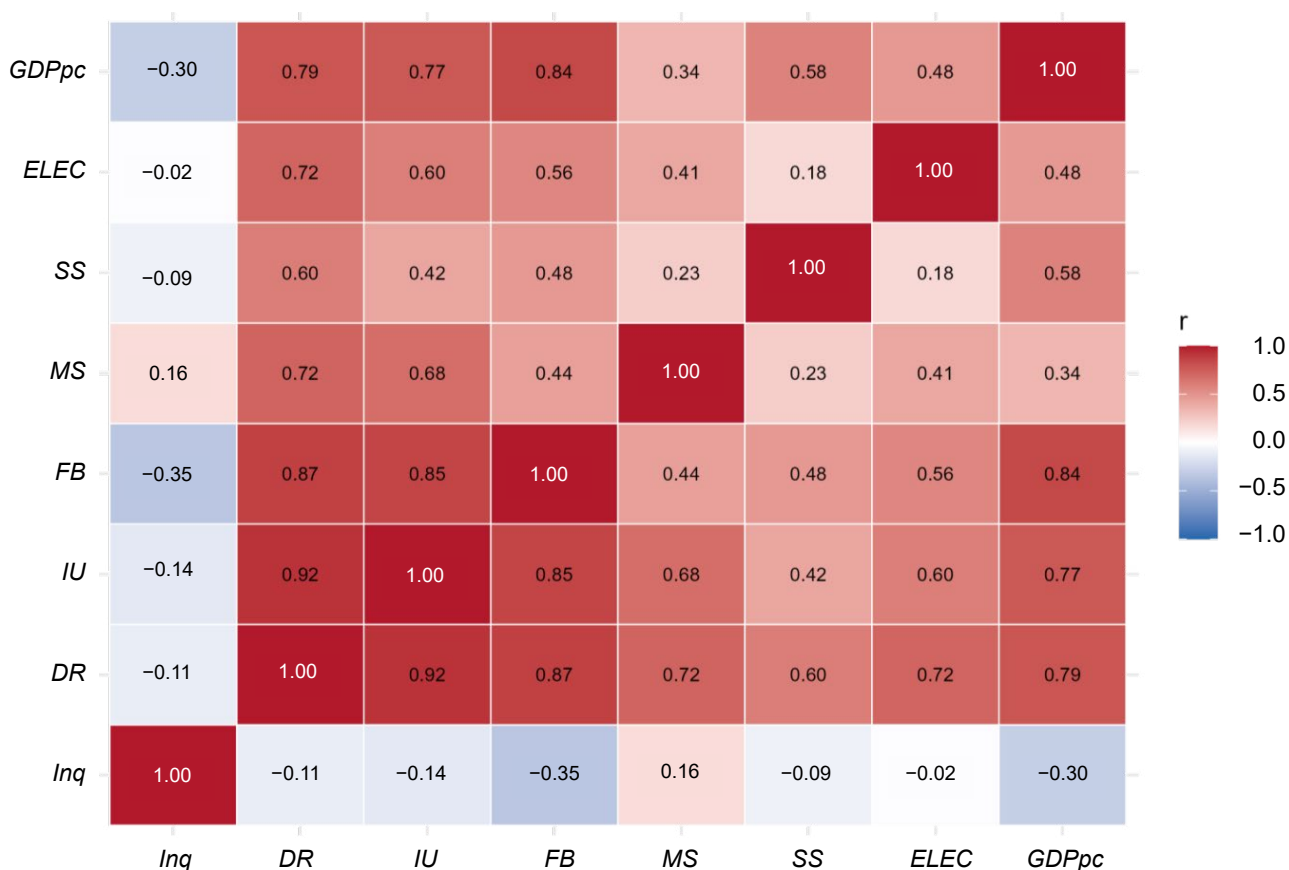


Notes: (A) Digital readiness indicating capacity for technology adoption and resilience, highest in most high-income states. (B) World Bank income groups classifying countries by economic tier. (C) GDP distribution mapping the economic weight of major economies. (D) Gini coefficient showing global inequality. (E) Urban population share highlighting urbanisation patterns. (F) World inequality map (2020) summarizing income disparity patterns globally.

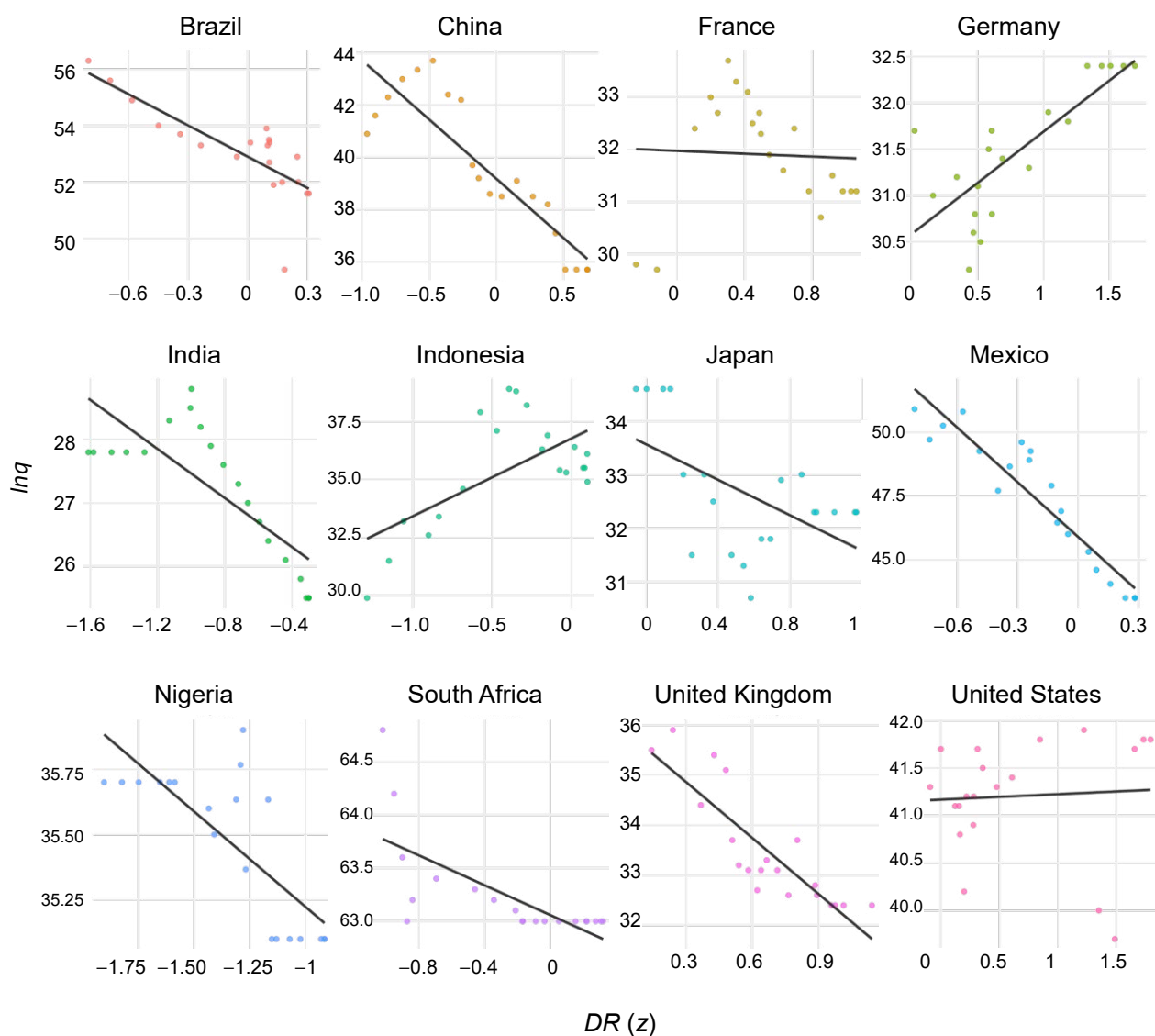
Source: Authors' own elaboration

Figure 3 demonstrates the Pearson correlation matrix and offers important preliminary insights into the relationships among the selected variables. *DR* exhibits a weak but negative correlation with income inequality (-0.11), suggesting that, on average, countries with greater digital preparedness tend to experience slightly lower inequality. *DR* is significantly and positively correlated with *GDPpc* with a coefficient of 0.79 , *IU* (0.92), and *FB* subscriptions (0.87), highlighting the substantial co-movement between digital infrastructure, economic development, and overall readiness. Among all predictors, *FB* penetration shows the strongest inverse correlation with inequality (-0.35), indicating its potential role as a critical lever for inclusive growth.

Figure 3: Pearson correlation of the variables



Source: Authors' own elaboration

Figure 4: Country-specific scatter plots between digital readiness and income inequality

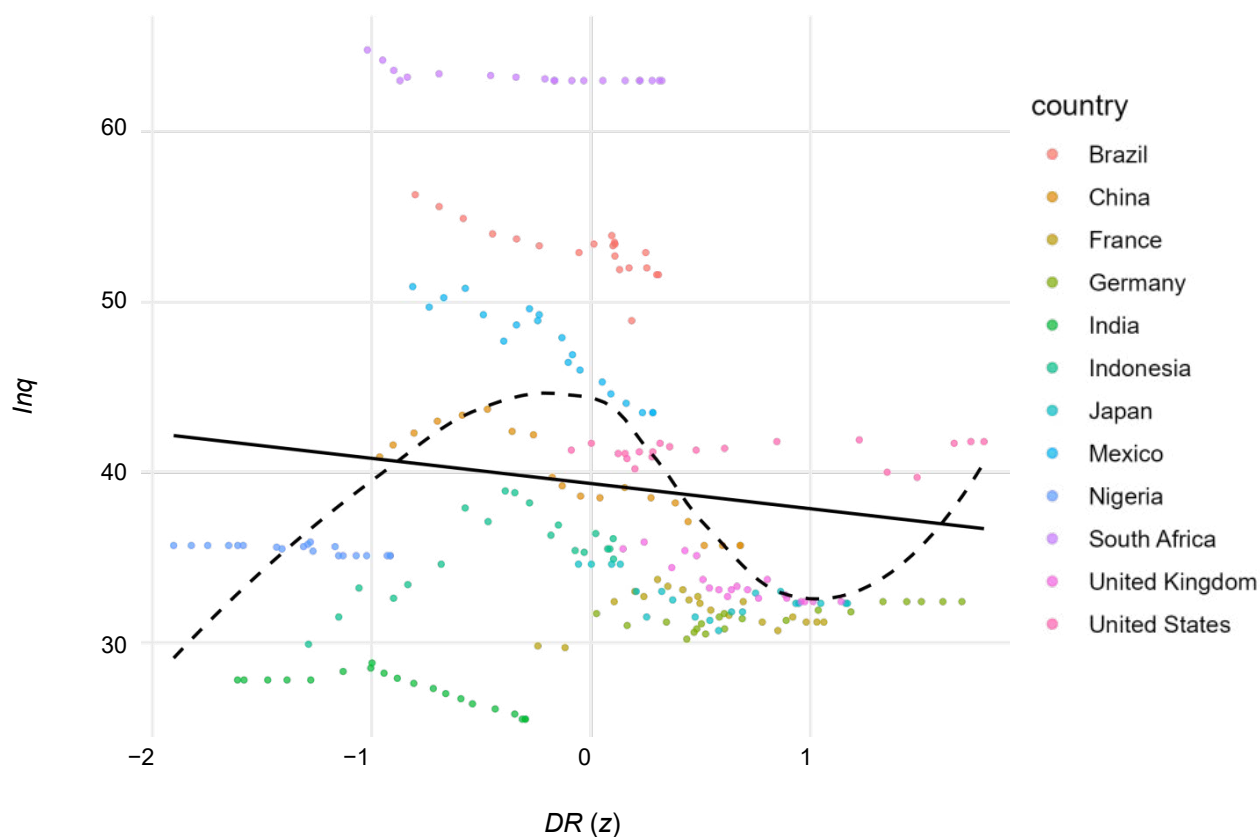
Source: Authors' own elaboration

Figures 4 and 5 illustrate the relationship between DR and income inequality (Gini index) across countries, both at an overall level and individually for each country. The faceted plots reveal heterogeneity in the nature and magnitude of this relationship; a higher DR score is associated with lower inequality in most cases, as observed in Brazil, China, India, and Mexico, where negative slopes dominate. In contrast, countries like Germany show a positive slope, suggesting that technological advancements might initially benefit higher-income groups more, thereby widening inequality in certain contexts. The overall scatter plot consolidates these trends, showing that while the global tendency leans towards a neg-

ative association, substantial variations exist between countries. This aligns with literature suggesting that digital transformation can reduce inequality by enhancing access to information, education, and economic opportunities (Hassan and Naoual, 2024; Medhioub and Boujelbene, 2024), but that benefits are unevenly distributed depending on institutional readiness, complementary infrastructure, and policy environments (Imran, 2023). Similar findings have been reported in recent empirical analyses of the digital divide's impact on economic disparity (Ateeq, 2024). Figure 3 indicates that digital readiness, income, and education are moderately to strongly negatively correlated with inequality, suggesting that these factors jointly shape distributional outcomes.

The country-level scatter plots (Figure 4) complement these aggregate patterns by revealing heterogeneity in the *DR-Inq* relationship. OLS slope coefficients show that in emerging economies such as Brazil ($\beta = -4.21, p < 0.05$), China ($\beta = -5.08, p < 0.01$), India ($\beta = -3.64, p < 0.05$), Mexico ($\beta = -6.34, p < 0.01$), Nigeria ($\beta = -2.45, p < 0.10$), and South Africa ($\beta = -1.87, p < 0.10$), increases in *DR* are significantly associated with reductions in inequality. In contrast, advanced economies such as France ($\beta = -0.42$), Germany ($\beta = 0.18$), Japan ($\beta = -0.67$), the United Kingdom ($\beta = -0.53$), and the United States ($\beta = 0.09$) display statistically insignificant slopes, suggesting that once a high threshold of *DR* is reached, its marginal impact on inequality diminishes.

The pooled scatter plot (Figure 5) consolidates this evidence, showing a negative but moderate overall association between *DR* and *Inq* ($\beta = -2.91, p < 0.05$). While many low-*DR* economies cluster at higher inequality levels, several high-*DR* countries still maintain moderate inequality, underscoring the role of complementary institutional, labor market, and redistributive policies. These findings indicate that digital readiness acts as an enabling factor for inequality reduction, especially in countries at earlier stages of digital transformation, guaranteeing equitable income distribution.

Figure 5: Overall scatter plot of digital readiness versus income inequality across selected countries

Source: Authors' own elaboration

The correlation and scatter plot analyses provide an initial, visually supported indication of the $DR-Inq$ relationship, highlighting both its direction and its cross-country variation. However, these bivariate associations cannot account for potential confounding effects from other socio-economic and infrastructural variables. Therefore, to formally assess the magnitude, statistical significance, and robustness of these relationships while controlling for factors such as $GDPpc$, electricity access, and urbanization, we estimate a series of multivariate regression models. This econometric approach enables a more rigorous evaluation of whether the observed negative association between DR and Inq persists once broader structural determinants are taken into account. The scatter plots in Figures 4 and 5 depict a slight negative relationship between digital readiness and inequality, but the cross-country variation is very high, making it clear that the strength and direction of the given association vary across contexts.

Table 2 demonstrates the results from the fixed-effects regressions, which suggest that the estimated relationship between *DR* and *Inq* varies substantially depending on model specification. In the simplest model (FE: *DR*), the *DR* coefficient is positive ($\beta = 1.695$) but statistically insignificant ($p = 0.374$), indicating no clear evidence of an association when *GDPpc* is omitted. However, once *GDPpc* is included as a control (FE: *DR* + $\log GDPpc$), the *DR* coefficient increases in magnitude ($\beta = 2.832$) and becomes statistically significant ($p = 0.012$). This suggests that, conditional on income levels, higher *DR* is associated with higher measured inequality.

Table 2: Fixed-effects regressions

Model	β (<i>DR</i>)	SE (<i>DR</i>)	<i>p</i> (<i>DR</i>)	β ($\log GDPpc$)	SE ($\log GDPpc$)	<i>p</i> ($\log GDPpc$)	Obs.	Adj. R^2	Within R^2	RMSE
FE: <i>DR</i>	1.70	1.83	0.37	–	–	–	240	0.98	0.03	1.33
FE: <i>DR</i> + $\log GDPpc$	2.83*	0.95	0.01	–1.42	1.58	0.39	240	0.98	0.07	1.30
FE: lag (<i>DR</i>) + $\log GDPpc$	2.65*	0.95	0.02	–1.81	1.47	0.24	228	0.98	0.08	1.21

Notes: Dependent Variable is *Inq*. Standard errors clustered by country. Country and year fixed effects included in all models. * denotes statistical significance at the 5% level.

Source: Authors' own calculations

A similar pattern emerges when *DR* is lagged by one year (FE: lag(*DR*) + $\log GDPpc$). The lagged *DR* coefficient ($\beta = 2.652$, $p = 0.017$) is also positive and significant, indicating that the effect persists over time, and potentially reflecting a delayed impact of digital readiness on inequality outcomes. *GDPpc* itself remains statistically insignificant across specifications, and the within R^2 values (ranging from 0.028 to 0.083) indicate that *DR* explains a modest share of within-country variation after accounting for fixed effects.

Table 3 presents the results of clustering analysis applied to twelve countries based on a set of indicators capturing *DR*, *GDPpc*, education (*EDU*), urbanization (*URB*), *ELEC*, and digital infrastructure metrics, including *IU*, *FB*, *MS*, and *SS*. The analysis grouped countries into two clusters ($k = 2$). Cluster 1 consists primarily of emerging economies such as India, Indonesia, and Nigeria. These countries exhibit lower *DR* scores (negative or near zero), lower *GDPpc*, and significantly lower penetration rates of *FB*, *SS*, and *IU* compared to advanced economies (Khan, 2024). Although some indicators like *MS* (e.g., Indonesia at 129.4 per 100 people) are high, these are often driven by prepaid, low-data usage plans, which may not

translate to effective digital inclusion (Friederici *et al.*, 2020).

Table 3: K-Means clustering of countries by *DR* and socio-economic indicators

Country	<i>DR</i>	<i>GDP</i>	<i>EDU</i>	<i>URB</i>	<i>ELEC</i>	<i>IU</i>	<i>FB</i>	<i>MS</i>	<i>SS</i>	<i>k</i>	<i>h</i>
Brazil	0.18	8.86	104.13	87.07	99.70	81.30	17.42	98.65	3,144.87	2	1
China	0.44	9.27	93.31	61.43	100.00	70.10	33.91	120.50	948.46	2	1
France	0.85	10.58	104.57	80.98	100.00	84.70	46.47	110.39	36,107.84	2	2
Germany	1.33	10.77	101.31	77.45	100.00	89.80	43.30	128.43	97,517.57	2	2
India	−0.44	7.55	77.63	34.93	96.50	43.40	1.64	82.25	472.19	1	3
Indonesia	−0.03	8.26	98.04	56.64	97.00	53.70	3.93	129.40	1,868.76	1	1
Japan	0.93	10.60	102.84	91.78	100.00	90.20	34.84	154.43	22,848.72	2	2
Mexico	0.09	9.09	102.58	80.73	99.40	71.50	17.75	96.92	328.20	2	1
Nigeria	−1.07	7.61	45.89	51.96	55.40	31.90	0.03	95.44	71.23	1	4
South Africa	0.22	8.63	110.02	67.35	90.00	72.10	2.15	158.45	14,123.27	2	1
UK	0.89	10.61	114.65	83.90	100.00	94.80	40.58	117.31	36,636.63	2	2
US	1.35	11.07	100.51	82.66	100.00	90.30	35.72	103.86	140,775.77	2	2

Source: Authors' own calculations

Cluster 2 is composed of advanced economies such as the United States, United Kingdom, Germany, France, and Japan, along with several upper-middle-income countries, including Brazil, China, South Africa, and Mexico. These countries share higher *DR* values, higher *GDPpc*, and better digital infrastructure (Feng and Qi, 2024). Notably, secure server density is orders of magnitude higher than in Cluster 1, with Germany reaching 97,517 compared to Nigeria's 71. Education indices are also higher, reflecting stronger human capital readiness for digital transformation.

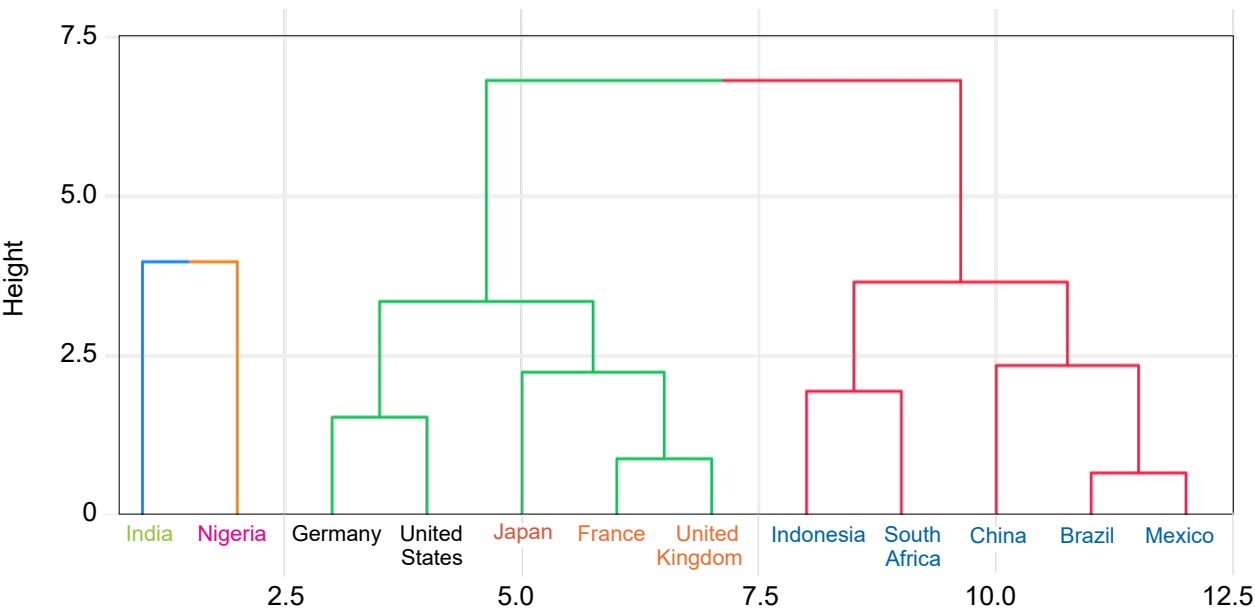
The clustering highlights structural divides in *DR* between advanced and emerging economies, consistent with the global digital divide noted in recent literature (Guha and Mukerji, 2021). Countries in Cluster 1 face challenges not only in economic capacity but also in critical enablers such as ICT infrastructure, broadband affordability, and quality of education, which are essential for leveraging digital technologies for inclusive growth (Deganis *et al.*, 2021). The inclusion of Brazil, China, South Africa, and Mexico in Cluster 2 suggests that

upper-middle-income economies can bridge parts of the digital divide despite not matching the *GDPpc* levels of advanced nations. This finding aligns with evidence that strategic digital investments and targeted policy interventions can accelerate digital readiness regardless of income level (Moeini Gharagozloo *et al.*, 2022). For instance, China's aggressive broadband rollout and Brazil's universal access policies have significantly improved Internet penetration rates since the mid-2010s (González *et al.*, 2016). The clustering results in Table 3 distinguish a group of low-DR countries with higher and more volatile inequality from a group of high-DR countries with lower and more stable inequality.

Disparities in *SS* reveal a further cybersecurity and e-commerce readiness gap. Previous research has shown that *SS* availability is strongly correlated with digital economy development, online financial services, and cross-border e-commerce adoption (Baller *et al.*, 2016). This explains why nations such as Germany, the US, and the UK dominate in high-value digital services exports. The results suggest that improving *DR* for countries in Cluster 1 requires multidimensional interventions: expanding ICT infrastructure, increasing electricity reliability, making broadband more affordable, and boosting human capital through digital skills programs (Magoutas *et al.*, 2024). Without such comprehensive measures, the divide between the two clusters is likely to persist, further exacerbating global inequality. Figures S1 and S2 further illustrate key aspects of K-means clustering analysis, including the elbow method and silhouette scores.

Figure 6 depicts the hierarchical clustering dendrogram and visually groups countries based on similarities in *DR* and socio-economic indicators. Two primary clusters emerge, where the first includes advanced economies, which exhibit high *DR*, strong economic performance, and robust ICT infrastructure. The second cluster comprises emerging economies, which demonstrate moderate *DR* but varying infrastructure development and income levels. Notably, India and Nigeria form a separate sub-cluster, indicating relatively lower *DR* and socio-economic development compared to other nations in the dataset.

Figure 6: Hierarchical clustering dendrogram



Source: Authors' own elaboration

These findings align with Inegbedion (2021) and Khanal *et al.* (2021), highlighting the persistent digital divide between advanced and emerging economies. Advanced economies tend to have greater ICT penetration, higher *GDPpc*, and more mature policy frameworks supporting digital transformation, enabling them to sustain competitiveness in the digital era (Xu *et al.*, 2023). In contrast, emerging economies face structural challenges, including unequal access to infrastructure, limited affordability, and skill gaps, which slow digital adoption and exacerbate income inequality (Rydzewski, 2025). The distinct placement of India and Nigeria in a separate cluster corroborates findings that countries with significant rural populations and lower electricity access face additional hurdles in achieving digital inclusivity (Nosike, 2024; Sindakis and Showkat, 2024).

Our results contribute to the growing evidence that *DR* is strongly associated with economic advancement and inequality reduction, as indicated by studies showing that countries investing in broadband expansion, digital skills, and institutional capacity experience faster convergence toward higher income levels (Katz and Callorda, 2018).

Figure 7 shows the world map, which represents the clustering of countries based on their *DR* and other socio-economic variables, as determined by the K-means clustering technique. In the map, countries are colored to denote their respective clusters, with orange representing countries with higher *DR* and green indicating those with lower *DR*. The countries in the orange cluster typically exhibit higher levels of technological infrastructure and

A world map illustrating the geographical distribution of three clusters. The map uses a color-coded legend to identify the clusters across various countries. Cluster 1 is represented by green, Cluster 2 by orange, and Cluster NA by gray. The map shows a clear separation of these clusters across different continents, with Cluster 2 primarily in North and South America, Cluster 1 in South and Central Asia, and Cluster NA in Australia and parts of Europe and Africa.

Cluster	Color	Geographical Distribution
1	Green	India, parts of Southeast Asia, parts of Africa
2	Orange	United States, Canada, Mexico, Brazil, parts of Europe and Africa
NA	Gray	Australia, Russia, and many other countries

Source: Authors' own elaboration

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in this cluster generally have lower levels of *DR*, *GDPpc*, *EDU*, *URB*, *ELEC*, *IU*, *FB*, *MS*, and *SS*. This finding aligns with Rao and Pachauri (2017), who showed that countries in lower-income groups tend to lag in digital transformation and economic development. These countries typically face economic inequality and limited access to essential infrastructure, which impacts their digital readiness (Musa *et al.*, 2025). Similarly, Cluster 2 represents a set of countries with higher average values across the same variables. These countries generally have higher *DR*, better education levels, and greater urbanization, along with advanced infrastructure. The countries in this group have invested significantly in their digital infrastructure, contributing to economic growth and reduction in inequality through better access to technology (Suhraab *et al.*, 2024). These findings are aligned with Nosike (2024) and Bayumi *et al.* (2024), which emphasize the critical role of digital infrastructure and economic investment in addressing disparities across nations.

Table 4 presents the performance metrics of two machine learning models, OLS and Ridge, to predict *Inq*. The Root Mean Squared Error (RMSE) for the OLS model is 6.77, while the Ridge model shows a slightly higher RMSE of 7.15, indicating that Ridge regression introduces more complexity but does not significantly improve predictive accuracy. Similarly, the Mean Absolute Error (MAE) is lower for OLS (5.52) compared to Ridge (6.03), suggesting that OLS provides a more accurate prediction in terms of absolute error.

Table 4: Machine Learning Model Results: Predicting Inequality.

Model	RMSE	MAE	abs_beta
OLS	6.77	5.52	8.29
Ridge	7.15	6.03	8.28

Source: Authors’ own calculations

Table 5 demonstrates the absolute beta coefficients; the variables *FB* and *DR* have the highest influence, with values of 8.29 and 8.28, respectively, suggesting that these variables are most significant in predicting inequality. *URB*, *EDU*, and *IU* also show notable influence, with coefficients of 8.11, 7.78, and 6.79, respectively, indicating their importance in understanding income inequality. The variable *MS* has the smallest impact with a coefficient of 1.33, and *SS* shows no significant influence in this model. Our findings are consistent with (Medhioub and Boujelbene, 2024; Murthy *et al.*, 2021), who revealed that broadband adoption and digital readiness contribute substantially to economic growth and income distribution. Additionally, variables such as urbanization, education, and internet usage have

been identified as key enablers in promoting inclusive development (Doloi, 2025). However, factors like mobile subscriptions and secure servers appear to play a lesser role in this specific model, aligning with findings that emphasize the importance of quality over mere availability of digital tools (Currier *et al.*, 2004). Table 5 shows that fixed broadband, overall digital readiness, urbanization, and education are the most influential predictors of inequality, while other digital indicators play a smaller role.

Table 5: Variable importance in predicting inequality from machine learning model

Variables	Absolute beta
FB	8.292
DR	8.278
URB	8.109
EDU	7.776
IU	6.794
ELEC	6.041
GDPpc	3.444
MS	1.327

Source: Authors' own calculations

Table 6 presents the distribution of income inequality (measured by the Gini coefficient) across countries categorized by their digital readiness (*DR*) level, divided into three groups such as low, medium, and high. The low *DR* group has a mean income inequality of 38.53 with a standard deviation of 11.52, suggesting a considerable variation in inequality levels within countries that exhibit lower digital readiness. The medium *DR* group shows a higher mean of 45.81 with a standard deviation of 9.60, indicating that countries in this category have a higher level of inequality but with a relatively narrower spread compared to the low *DR* group. In contrast, the high *DR* countries have the lowest mean inequality of 33.67 and the smallest standard deviation of 3.26, reflecting less disparity and a more uniform economic environment in countries with high digital readiness. This supports the growing evidence in literature that digital infrastructure and readiness can play a role in reducing inequality by promoting inclusive growth through technological advancements

and access to digital resources (Adam *et al.*, 2025; Musa *et al.*, 2025). Specifically, when complemented by targeted financial tools like green credit that support real-sector development (Jiang and Yuan, 2025).

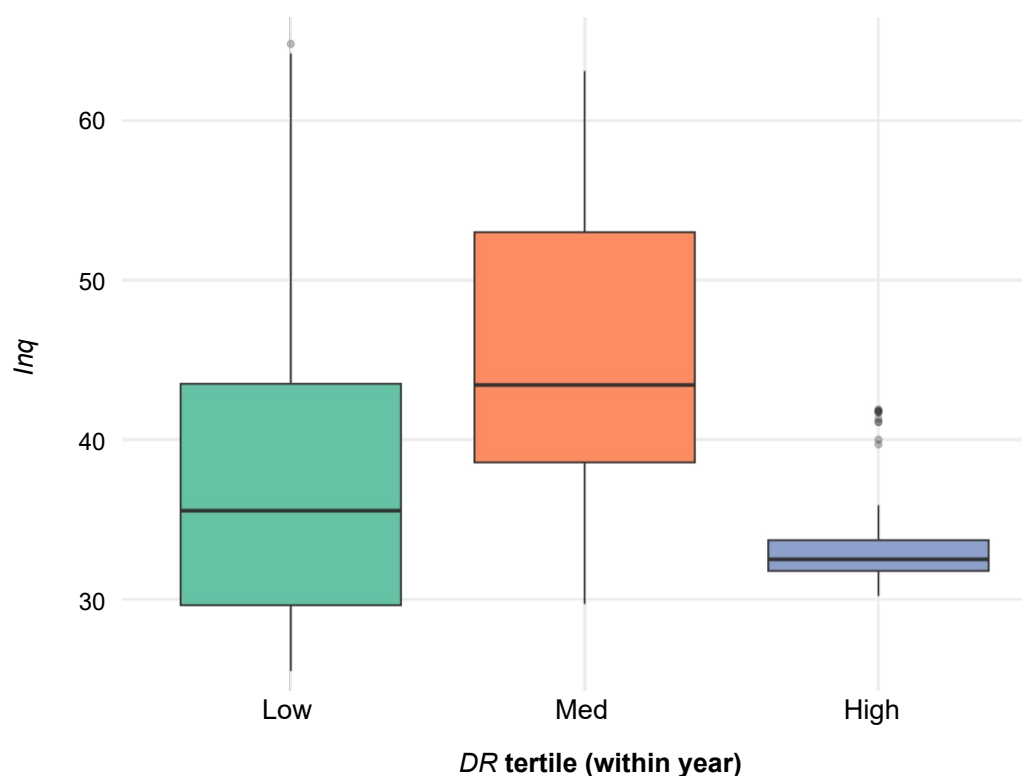
Table 6: Summary statistics of income inequality grouped by digital readiness levels

<i>DR_lab</i>	<i>n</i>	<i>Mean_Inq</i>	<i>SD_Inq</i>
Low	80	38.53	11.52
Med	80	45.81	9.60
High	80	33.67	3.26

Source: Authors’ own calculations

Figure 8 depicts a boxplot showing income inequality across countries grouped into low, medium, and high digital readiness (*DR*) tertiles. Countries in the low *DR* group exhibit the highest median inequality and the widest spread, indicating greater heterogeneity in inequality levels within this group. The medium *DR* group also displays relatively high inequality, though with less dispersion compared to the low *DR* group. In contrast, the high *DR* group shows the lowest median inequality and minimal variation, suggesting that higher levels of digital readiness are associated with more equitable income distribution. These results align with prior research highlighting the role of digital infrastructure and readiness in reducing economic inequality through enhanced access to education, innovation, and market opportunities (Shenglin *et al.*, 2017). Moreover, studies have found that digital adoption can amplify inclusive growth by fostering labor productivity and creating new economic opportunities, particularly when complemented by supportive institutional frameworks (Confetto and Covucci, 2024).

Table 6 and Figure 8 show that the low-digital readiness (low-*DR*) cohort has the highest mean Gini coefficient with the largest dispersion, and the high-digital readiness (high-*DR*) cohort has the lowest mean coefficient with significantly smaller dispersion, though the medium-digital readiness (medium-*DR*) cohort takes the middle values. These findings support the existing hypothesis that higher digital readiness is linked to more desirable inequality patterns. Figure 8: Income inequality across countries grouped by digital readiness tertiles

Figure 8: Income inequality across countries grouped by digital readiness tertiles

Source: Authors' own elaboration

5. Conclusion, Policy Implications, Limitations, and Future Research Directions

5.1 Conclusion

Drawing on a balanced panel of twelve diverse economies from 2005 to 2024, this study investigated the relationship between digital readiness (DR) and income inequality using an integrated methodological framework comprising spatial mapping, correlation analysis, clustering, predictive modelling, and causal inference. While DR has improved steadily across all observed countries, inequality trajectories remain heterogeneous, with evidence of a nonlinear association. Countries in the high-DR group recorded the lowest average inequality (mean = 33.67, SD = 3.26), whereas those in the medium-DR group exhibited the highest levels (mean = 45.81, SD = 9.60). This pattern suggests that transitional economies may experience temporary inequality spikes when digital adoption accelerates without accompanying inclusive policy measures. Spatial analysis further shows that high-DR

economies align with higher GDP per capita and greater urbanization, while low-DR countries such as India and Nigeria struggle with structural deficits in infrastructure and access.

Pearson correlations revealed a weak negative association between DR and inequality ($\rho = -0.11$). However, fixed-effects and lagged models indicated that short-run DR gains are associated with increased inequality ($\beta = 2.83$ and $\beta = 2.65$, respectively; $p < 0.05$), consistent with the skill-biased nature of early technological diffusion. Clustering distinguished a low-DR, high-inequality group from a high-DR, low-inequality group, while machine learning analyses identified fixed broadband ($\beta = 8.29$), DR ($\beta = 8.28$), urbanization ($= 8.11$), and education ($= 7.78$) as the most influential predictors. GDP per capita ($= 3.44$) and mobile subscriptions ($= 1.33$) played smaller roles. Event-study analysis revealed no immediate inequality reduction following digital policy adoption, suggesting that equity benefits may emerge only in the longer term.

5.2 Policy Implications

The findings carry direct implications for Sustainable Development Goals (SDGs) 9 (Industry, Innovation and Infrastructure) and 10 (Reduced Inequalities). The main policy implications can be summarized in four points. Specifically, first, low-DR countries must prioritise foundational enablers such as reliable electricity, basic backbone connectivity, and affordable entry-level internet access before scaling advanced digital services. These investments are essential to prevent rapid digitalization from simply amplifying existing spatial and income divides. Second, medium-DR economies, which in our sample display the highest and most volatile inequality, should pair broadband expansion with targeted inclusion policies. Priority measures include universal affordable internet, rural access programs, digital literacy and skills initiatives, and redistributive labour-market interventions, including transparency reforms, which reshape innovation incentives (Gao *et al.*, 2023), to mitigate transition-phase inequality spikes. Third, high-DR economies should focus on sustaining equitable access and preventing new forms of digital exclusion. This requires curbing excessive digital market concentration, enforcing pro-competitive regulation, and fostering lifelong learning so that workers can adapt to ongoing technological change and avoid skill obsolescence. Fourth, across all country groups, fixed broadband, overall digital readiness, urbanization, and education emerge as key levers for shaping inequality. Effective strategies, therefore, need to combine infrastructure rollout with human capital development and progressive regulatory frameworks that translate enhanced connectivity into genuinely equitable opportunities.

5.3 Limitations of the Study and Future Research Directions

Despite the above contributions, the current study has some limitations that underscore relevant paths toward further investigation. This study uses a sample of twelve countries in an unbalanced panel dataset, which allows meaningful comparative analysis, but this design can limit the applicability of results to other areas beyond the current sample, especially in low-income economies. An extension of the analytical framework to include a broader sample of countries and the inclusion of subnational information would help to support the patterns identified. Though the composite digital readiness index generated by the study provides an overall evaluation, its development is limited by the amount of available data and focuses more on the indicators of infrastructure and access. Therefore, future studies must attempt to incorporate smaller-scale measures related to quality of usage, digital skills, and user interaction with the digital environment.

Moreover, the event-study design used in this paper is based on observable policy adoptions, and it cannot fully negate the chance of policy endogeneity. The existing methodology could be complemented by micro-level data, distributional sensitive approaches such as functional-coefficient quantile regression for panel data with latent group structures (Yang *et al.*, 2024), and comprehensive case-studies of specific programs to provide a more comprehensive explanation of the particular mechanisms. Lastly, the discussion focuses on income inequality, thus overlooking what digital transformation has done to wealth inequality, social mobility, and non-monetary measures of well-being. Future research would effectively deal with these dimensions.

Acknowledgement

Funding: This research was supported by Soft Science Research Project of Henan Province (Grant No.252400411094), Key Scientific Research Project of Higher Education Institutions of Henan Province (Grant No. 25A790006), the Social Sciences Association Project of Henan Province (Grant No.SKL-2026-825) and Nanyang Normal University Project (Grant No. 2024BS008).

Conflicts of interest: The authors hereby declare that this article was neither submitted nor published elsewhere.

AI usage statement: The authors confirm that no artificial intelligence (AI) or AI-assisted tools were used in the creation of this manuscript.

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