Abstract

The aim of this paper is to analyse the evolution and structural interdependence of Sustainable Development Goals (SDGs) across 130 countries over the period 2019–2023, with a specific focus on the role of digital readiness in shaping sustainable development trajectories. Using a Generalized Q Analysis (GQA) framework, the study integrates ten normalized SDG indicators-including dimensions related to capital accumulation, growth, and digitally mediated capacities-into a multidimensional structure, generating $2^{10} = 1{,}024$ possible development profiles and 650 country-year observations.

The results reveal a strongly polarized two-dimensional structure. The first component-interpreted as Digital and Capital Readiness-accounts for nearly 90% of the total variance and reflects the joint accumulation of natural, human, productive, and digitally enabled institutional capital. The second component-associated with Short-Term Economic Stability and Growth Dynamics- explains about 5% of the variance and captures cyclical movements in growth, employment, and inflation. The first component is significantly stronger in developed economies characterized by higher institutional quality and digital capacity. By contrast, the second component exhibits greater volatility over time and is more pronounced in low-income countries, where growth dynamics are less supported by digital and institutional complementarities.

Overall, the findings highlight that contemporary sustainable development is increasingly shaped by digitally mediated interactions between capital accumulation, institutional capacity, and economic growth, and that digital transformation plays a critical role in determining both the resilience and direction of national development paths.

Keywords

Digital Transformation; Digital Readiness; Sustainable Development Goals; Generalized Q Analysis; Global and Regional Development

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O33; O47; R11; C38

1) Introduction

The Sustainable Development Goals (SDGs), adopted in 2015, provide a comprehensive global framework for addressing economic, social, environmental, and institutional challenges. Before the COVID-19 pandemic, although there had been progress in areas such as reducing extreme poverty and access to education, progress was too slow to meet the 2030 targets, particularly for climate action, reducing inequality, and protecting biodiversity (United Nations, 2019). Funding gaps and weak institutional capacity in some countries were the main constraints (Sachs et al., 2019).

In recent years, digital transformation has been identified as a transversal mechanism influencing the achievement of the SDGs, affecting productivity, service delivery, institutional efficiency, and social inclusion (Katz & Callorda, 2018). Digital technologies increasingly mediate economic, social, and environmental outcomes, making digital readiness a key structural factor in sustainable development performance (Cruz-Jesus et al., 2017). Consequently, the interaction between digital readiness, institutional capacity, and SDG performance has become central to understanding contemporary development dynamics.

The COVID-19 pandemic represented a widespread setbacks in the evolution of sustainable development indicators, particularly those related to poverty (SDG 1), health (SDG 3), education (SDG 4), and decent work (SDG 8) (United Nations, 2020; Wang et al., 2021), namely on socioeconomic objectives, with limited and short-term environmental benefits due to reduced economic activity. After the pandemic, recovery trajectories were uneven due to disparities in financing and institutional capacity (United Nations, 2022).

At the same time, the pandemic accelerated digital transformation worldwide, intensifying the reliance on digital platforms, remote work, e-government, and digital public services. Empirical studies show that countries with higher levels of digital readiness experienced greater economic resilience and continuity of services during the crisis (Katz et al., 2020; Soto-Acosta, 2020). This highlighted digital infrastructure, skills, and governance as key buffers against socioeconomic shocks.

Many short-term economic recovery measures undermined progress on climate action and responsible consumption (C. Li et al., 2023; Yuan et al., 2023). The 2023 Sustainable Development Goals Report stated that more than half of the SDG targets were stagnant or regressing (United Nations, 2023), with conflict, debt, and extreme weather events being the most significant constraints to achieving the SDGs. The aim of this paper is to add value on testing these interactions, thought focusing of the discovery of dynamic complementarities between sustainable indicators.

Within this context, digital transformation plays a dual role: it can amplify complementarities between SDGs by enhancing coordination, efficiency, and inclusion, but it may also exacerbate inequalities when digital capacities and institutions are unevenly distributed (Billon et al., 2017). Understanding how digital and non-digital indicators interact is therefore essential for identifying sustainable development paths and trade-offs between long-term structural capacity and short-term growth dynamics.

To address this, a new method is used that, instead of looking at the attributes/indicators of countries for a long time, looks at the evolution of complementary attributes in representative virtual countries identified by Principal Components of the Combined Attributes for all the countries. By incorporating indicators related to digital readiness, such as technological infrastructure, human capital, governance, and digital impact, allows the identification of latent digital transformation configurations and their complementarities with broader sustainable development outcomes (S. Dutta & B. Lanvin, 2020). This shifts the analysis from isolated indicators toward a structural understanding of digitally mediated development trajectories.

After a more specific literature review on place-based approaches to endogenous sustainable development in point 2, the methodology of Generalized Q Analysis of Sustainable Development Indicators is clarified in point 3. Point 4 present the results that are discussed in Point 5. Concluding remarks are suggested in Point 6.

2) Place-based approaches to endogenous sustainable development

Most of the analyses and policies that look into Sustainable Development Goals consider them as substituting and conflicting with each other. Adopting the scheme of an endogenous growth model at the local level (Barca, 2008), (Sass & Dentinho, 2023) point out that sustainable development goals can be approached knowing that they interact with each other within specific contexts of space and a long time. Rodríguez-Pose (2013) shows that sustainable development should be aligned with local human capital, and with local institutions that dynamically and wisely combine the different aspects of sustainable development (Rodríguez-Pose, 2020), namely redistributing education, health, equity, accessibility to services and welfare, plus means to invest locally on natural, built, creative and productive capital (OECD, 2021).

Digital transformation increasingly shapes these endogenous growth mechanisms by influencing how local capital is accumulated, coordinated, and redistributed. Digital infrastructure, skills, and governance enhance the productivity of local human and productive capital, strengthen institutional capacity, and facilitate access to services, thereby reinforcing the interaction between economic, social, and environmental dimensions of sustainable development (Cruz-Jesus et al., 2017; Katz & Callorda, 2018)

Endogenous sustainable development assumes that local but intrinsically networked capital – natural, social, human, productive and institutional - can promote economic, social and ecological sustainability (Horlings, 2015), demanding place-based policies (OECD, 2025) and requiring local stakeholders' attitudes and gestures that add value to local resources, named by (Sørensen, 2018) as "Place Capital".

In this context, digital platforms and technologies enhance the networking capacity of places, allowing local resources and competencies to be embedded in wider innovation and value networks, which is particularly relevant for peripheral and small regions (Malecki, 2018).

There is evidence from case studies that place-based approaches to endogenous sustainable development have positive effects, such as the case of a Portuguese village that specialized on traditional linen (Vasta et al., 2019), although more top-down place-based policies may require a longer external support (Pan et al., 2023). More challenging is to achieve sustainable development in left-behind places (Benner et al., 2024), when networked capital is to some extend disconnected, furthermore when "places that don't matter" for innovation and economic dynamism are also unable to benefit from these specific sustainable development policies (Peñalosa & Castaldi, 2024).

Digital divides exacerbate these challenges, as left-behind places often lack the digital infrastructure and skills required to connect local capital to broader innovation systems. Empirical evidence shows that insufficient digital readiness limits the ability of lagging regions to benefit from place-based and endogenous development strategies, reinforcing spatial inequalities (Billon et al., 2017; Y. Li et al., 2020).

Notwithstanding this, the effects of place-based policies are highly heterogeneous because, as argued by OECD (2025), they are methodologically weak: with many case studies without counterfactuals, with many supports moving across space without a robust effect (Dentinho & Fortuna, 2019), or without long term required supports for depopulated places. Summing up, it is possible to put together endogenous sustainable development and place-based policies, but their success depends on local capacities (Margarian, 2011).

Digital transformation adds an additional layer to this heterogeneity, as differences in digital governance, institutional quality, and absorptive capacity shape the effectiveness of policy interventions. Regions with stronger digital institutions are more capable of translating policy support into sustainable outcomes, while digitally constrained regions may experience limited or delayed effects (Niebel, 2018).

The present paper argues that, to understand the complementarities between sustainable regional development and place-based policies, it is crucial to shift the analysis from the attributes of the objects of study, to the subjects or stakeholders of sustainable development, using Generalized Q Analysis (Dentinho et al., 2023), to define paths of sustainable development of complementary attributes and hoping that a change in one those attributes for specific places, will boost development and sustainability, learning from the commonalities with other similar places.

3) Data and Methods

3.1 - Data

The empirical dataset employed in this study combines information for 130 countries over the period 2019–2023. The data includes indicators from the Network Readiness Index (NRI) and key macroeconomic variables to characterize the level of digital and socio-economic development across years, regions and income groups (Table 1).

Table 1: Distribution of Data by Year, Region and Income

Year		Region		Income	
2019	121	Asia & Pacific	105	Highincome	245
2020	134	Europe	204	Lowincome	66
2021	130	Arab States	63	Lowermiddleincome	172
2022	131	The Americas	102	Uppermiddleincome	167
2023	134	Africa	143		
		CIS	33		
	650		650		650

The dataset includes 10 indicators presented in Table 2 with averages, minimums and maximums per indicator.

Table 2: Sustainable Development Goals Indicators for 2019 till 2023

	Average	Mínimum	Maximum
NRI score	50,59	12,33	82,75
Technology pillar score	44,58	6,45	88,18
People pillar score	45,64	5,48	84,11
Governance pillar score	58,30	10,79	91,30
Impact pillar score	53,87	19,54	88,33
GDP per capita, current prices (U.S. dollars per capita)	19126	260	136190
HDI	0,77	0,408	0,97
GDP growth (annual %)	2,37	-28,76	16,47
Unemployment, total (% of total labor force)	5,14	0	34,15
Inflation, GDP deflator (annual %)	10,46	-16,46	921,54

3.2 - Methodology

To ensure comparability, all variables were normalized within the interval [0,1] [0,1], using the observed minimum and maximum values of each indicator across the full period:

$$X_{i,t}^{*} = \frac{X_{i,t} - \min(X_i)}{\max(X_i) - \min(X_i)}$$

where $X_{i,t}^{*}$ denotes the normalized value of indicator i for country t.

This transformation eliminates the influence of scale differences and allows for the construction of composite structures across heterogeneous indicators.

The resulting dataset contains 10 normalized indicators capturing various aspects of economic, technological, and social development. The sample is representative of global heterogeneity, including countries from Europe, Asia & Pacific, the Americas, the Arab States, and Sub-Saharan Africa, grouped by four income levels (high, upper-middle, lower-middle, and low income) according to the World Bank classification.

Each country-year observation was encoded by a specific dummy configuration representing its regional and income identity. This allowed differentiation of patterns not only across indicators but also across structural classifications. For instance, a European high-income country in 2020 would take a unique dummy pattern distinct from an Asian lower-middle-income country in 2023.To ensure adequate variation, all possible combinations of dummy structures and normalized indicators were tested.

Given 10 indicators, the theoretical maximum number of configurations equals 2^{10} =1024 combined statements using 10 dummy variables (Table 3) and performing a Principal Component Analysis on the 650 countries/year's data set.

The formula to get the scores of the combined statements is the following:

$$S_{ikj} = \sum_{i=1}^{10} D_i \sum_{k=1}^{10} V_{kj} \text{ for all 1024 combinations (1)}$$

Where D_i = dummy for each indicator, V_{kj} = the score of each indicator k for country/year j, S_{ikj}= the combined score of indicators (ik) for country/year (j).

Table 3: Computation of Combined Normalized Indicators of Country/Years

	Statements										Country Year1	⋮	Country Year 650
1	NRI score										0,89		0,39
2	Technology pillar score										0,79		0,31
3	People pillar score										0,84		0,34
4	Governance pillar score										0,93		0,39
5	Impact pillar score										0,75		0,50
6	GDP per capita, current prices (U.S.										0,40		0,03
7	HDI										0,96		0,53
8	GDP growth (annual %)										0,68		0,64
9	Unemployment, total (% of total labour										0,85		1,00
10	Inflation, GDP deflator (annual %)										0,98		0,98
	1	2	3	4	5	6	7	8	9	10		…	
1	1	1	1	1	1	1	1	1	1	1	8,061087		5,109039
2	1	1	1	1	1	1	1	1	1	0	7,082331		4,126586

3	1	1	1	1	1	1	1	1	0	1	7,211674		4,109039
4	1	1	1	1	1	1	1	1	0	0	6,232918		3,126586
…													
1022	0	0	0	0	0	0	0	0	1	0	0,849413		1,000000
1023	0	0	0	0	0	0	0	0	0	1	0,978756		0,982453
1024	0	0	0	0	0	0	0	0	0	0	0,000000		0,000000

This new data set composed of 1024 observations on scores on combined indicators and 650 variables of country/years can finally be used to:

1. Dimensional reduction using Principal Component Analysis (PCA) within SPSS.

2. Extraction of components based on eigenvalues greater than 1 (Kaiser criterion) and analysis of the explained variance ratio, to be related with the dummies of combined indicators to name the components

3. Varimax rotation of components to enhance interpretability and to examine whether components correspond to specific regional or income structures.

4. Saving the factor scores as regression variables, which represent the latent dimensions of global development and digital readiness.

4) Results

4.1 - Identifying Components

The extracted components were then regressed against regional, income-level, and temporal dummies to identify the structural determinants of each dimension. The regression results demonstrated a high degree of explanatory power (adjusted $R^2 \approx 0.99$), confirming the robustness of the GQA approach.

Two principal components were retained for interpretation (see Table 5):

Component 1 (Digital and Capital Readiness) — strongly associated with Technology, HDI, GDP per capita, and Governance indicators.

Component 2 (Economic Stability and Growth) more related to inflation, unemployment, and GDP growth dynamics.

Together, these two components explain approximately 94% of the total variance (Figure 1). This indicates that despite regional and income-level heterogeneity, the global patterns of digital transformation and economic performance are largely captured by two latent dimensions.

Table 4: Explained Variance

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	Non-rotated	Cumulative %	Total	Rotated	
1	582	90	90	582	90	90	349	54	54
2	28	4	94	28	4	94	249	38	92
3	4	1	94	4	1	94	6	1	93
4	3	1	95	3	1	95	6	1	94
5	3	0	95	3	0	95	5	1	95
6	3	0	96	3	0	96	3	0	95
7	2	0	96	2	0	96	3	0	96
8	2	0	97	2	0	97	3	0	96
9	2	0	97	2	0	97	3	0	96
10	2	0	97	2	0	97	2	0	97
11	1	0	97	1	0	97	2	0	97
12	1	0	98	1	0	98	2	0	97
13	1	0	98	1	0	98	2	0	98
14	1	0	98	1	0	98	2	0	98
15	1	0	98	1	0	98	1	0	98
16	1	0	98	1	0	98	1	0	98

Finally, the component scores were analyzed across years and regions to detect structural shifts over time. Regression of the component scores on year**,** region, and income-level dummies revealed that:

- High-income economies maintain stable digital capital accumulation (Component 1) with limited short-term fluctuation.
- Lower-income economies exhibit greater volatility in Component 2, reflecting sensitivity to macroeconomic shocks.
- Asia–Pacific and European countries show divergent trajectories — the former demonstrating strong catch-up potential, the latter consolidating already high digital capacity.

These patterns support the convergence hypothesis**:** lower-income countries tend to improve faster in digital capacity, while high-income economies sustain accumulated capital with slower marginal growth.

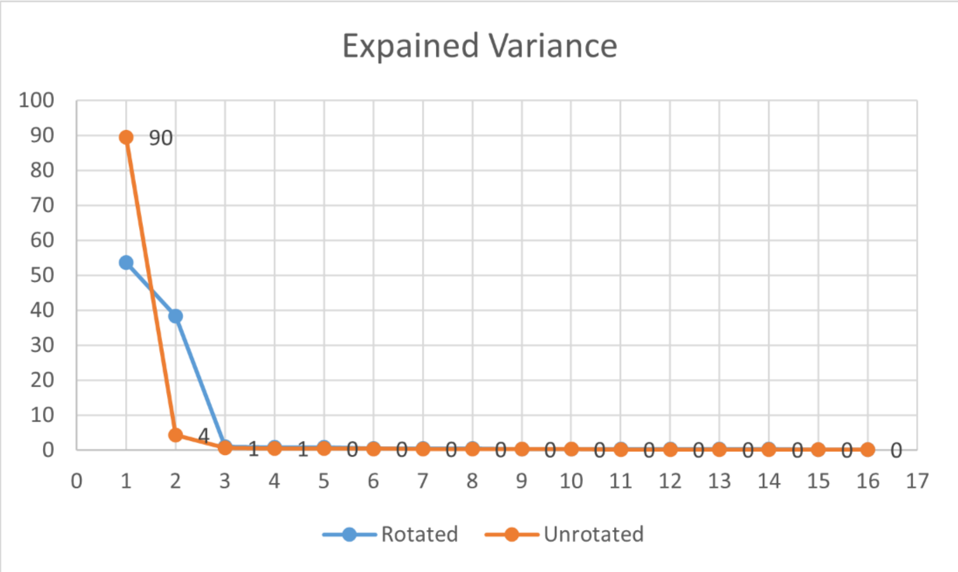


Fig. 1 Explained Variance

The figure presents the explained variance obtained from the principal component analysis (PCA). As shown in the graph, the first unrotated component explains approximately 90% of the total variance, indicating that most of the variation in the dataset can be captured by a single underlying dimension. After rotation, the first component retains around 54% of the explained variance, while the second component accounts for about 38%, together representing nearly 94% of the total variance. This distribution suggests a clear two-dimensional structure within the data.

The dominance of the first component implies a strong underlying factor related to capital accumulation and long-term development, encompassing indicators such as GDP per capita, HDI, and technological progress. The second component, which gains importance after rotation, reflects economic stability and short-term growth dynamics, characterized by variables like inflation and unemployment (inverted for interpretative consistency). The steep decline in explained variance after the second component demonstrates that additional components contribute negligibly to the overall variability, confirming the robustness of the two-factor solution.

Overall, the explained variance results validate the presence of two main latent dimensions in the dataset. The first captures sustainable capital and development capacity across countries, while the second reflects cyclical economic stability and resilience, particularly relevant for analyzing short-term fluctuations during events such as the COVID-19 crisis or geopolitical shocks.

Table 5: Regression Coefficients of rotated component matrix on Dummies for Combined Indicators

Indicator	Component 1: Digital and Capital Readiness	Component 2 Economic Stability and Growth	Component 3 Economic Instability and

			Political Stability
NRI score	**0.388**	-0.054	**0.110**
Technology pillar score	**0.378**	-0.061	-0.231
People pillar score	**0.347**	-0.020	0.065
Governance pillar score	**0.389**	-0.002	**0.151**
Impact pillar score	**0.386**	-0.045	-0.007
GDP per capita, current prices (U.S. dollars per capita)	**0.235**	-0.081	-0.140
HDI	**0.443**	-0.117	0.091
GDP growth (annual %)	0.059	**0.463**	0.083
1-Unemployment, total (% of total labor force) (national estimate)	0.062	**0.643**	0.014
1-Inflation, GDP deflator (annual %)	**0.132**	**0.573**	-0.087

The table presents Regression Coefficients of rotated component matrix on Dummies for Combined Indicators, where bold intensity highlights the magnitude of each variable's loading across the three extracted components. The bold numbers indicate stronger positive associations, while the non-bold tones mark weaker or negative relationships. This visual design aids in quickly distinguishing which indicators most strongly define each latent factor.

As we can see, Component 1 is characterized by high positive loadings on HDI (0.443)**,** governance pillar (0.389)**,** impact pillar (0.386)**,** NRI score (0.388)**,** and technology pillar (0.378)**.** These variables reflect structural, developmental, and technological attributes, suggesting that Component 1 represents a dimension of digital capital and long-term socioeconomic development**.**

Component 2 has stronger relations with unemployment (0.643)**,** inflation (0.573)**,** and GDP growth (0.463)**,** capturing short-term macroeconomic conditions and performance dynamics. Because unemployment and inflation were inverted (1-value), higher scores indicate greater economic stability. Thus, Component 2 reflects a stability and growth dimension that complements the structural nature of Component 1.

Component 3 shows weak and inconsistent loadings, implying that it does not represent a distinct interpretable factor. Therefore, only the first two components are meaningful, together explaining approximately 94% of the total variance.

The loadings visually reinforce this two-dimensional structure: the first component clusters indicators of development and technological advancement, while the second groups those related to macroeconomic balance and short-term fluctuations, confirming the robustness of the factor solution and supporting the conceptual differentiation between digital capital and economic stability.

The two components are presented in the Graph of Figure 2 for the biggest countries. More developed countries like Australia, United States and Germany were not very much disturbed in their position from 2019 to 2023. It is also interesting to notice that South Africa is below its potential regarding both components. During the period Ukraine began to have a very good performance but after the war in 2022, decreased strongly in the second component and recover in 2023 losing ground in the first component. There are also major changes in Nigeria and in Angola. More steady paths are obtained by India and Indonesia, and, with higher level of sustainable development indicators, by China, Russia and Brazil.

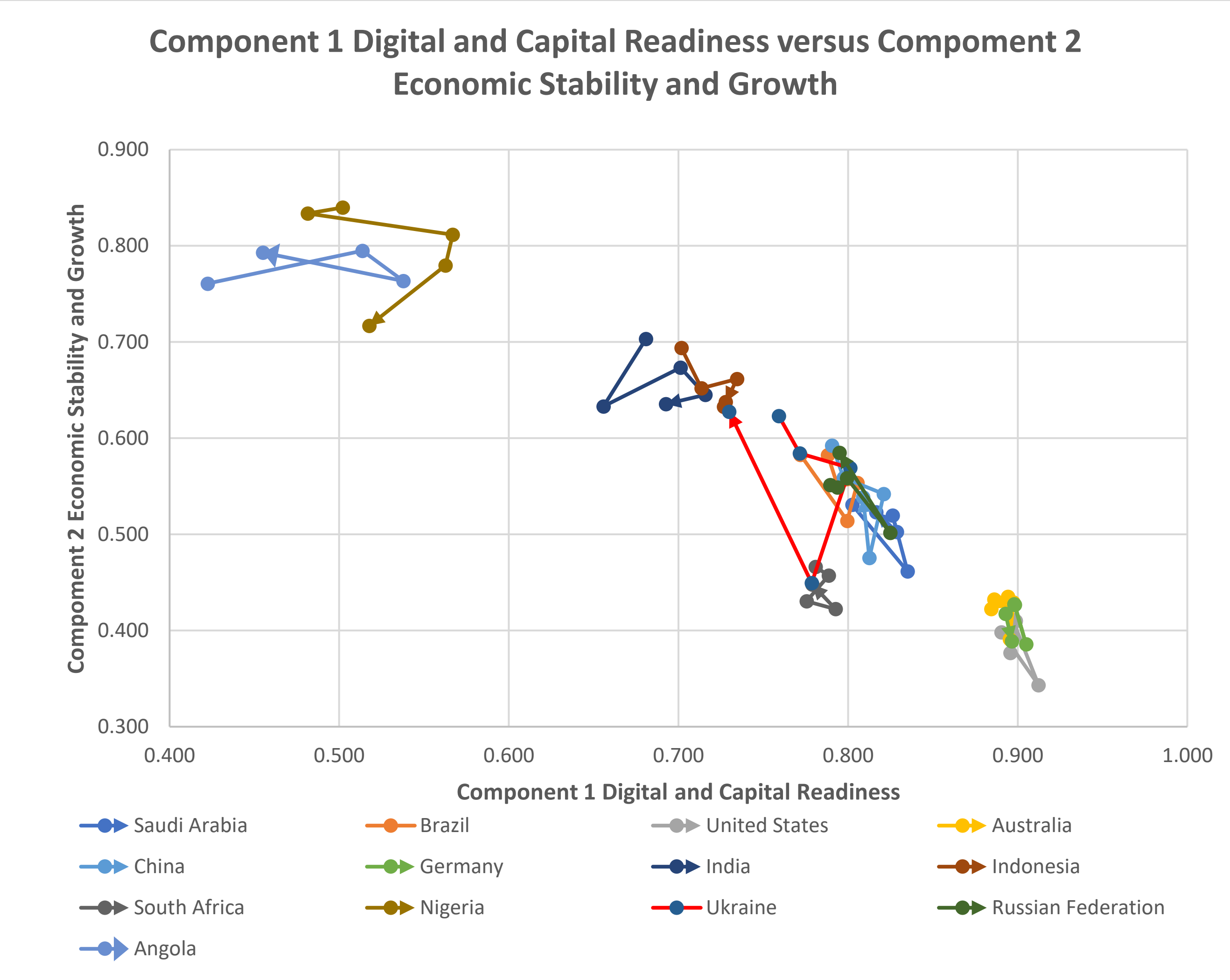


Fig. 2 Graph of Components 1 and 2 for Biggest Countries

4.2 - Explaining the Factors that influence Components

Component 1: Digital and Capital Readiness

Table 6 presents the Regression Model to Explain Component 1 Digital and Capital Readiness. The regression results for Component 1 indicate that income level represents the main structural determinant of digital and capital readiness across countries. The coefficients for low- and lower-middle-income groups are large and negative (B = -0.329 and -0.203, respectively), suggesting that these economies remain substantially below the digital readiness levels observed in the baseline category. Conversely, upper-middle- and high-income countries display smaller but still negative coefficients, reflecting a degree of digital maturity and saturation - implying limited potential for further marginal gains in the short term.

Table 6: Regression Model to Explain Component 1 Digital and Capital Readiness

Model	R	R Square	Adjusted R Square	Standard Error of Estimate
1	0.919[a]	0.845	0.842	0.06158

ANOVA[a]					
Source	Sum of Squares	Df	Mean Square	F	Sig.
Regression	13.123	12	1.094	288.384	<,001[b]
Residual	2.416	637	0.004		
Total	15.539	649			

Coeffiecients[a]					
	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Error	Beta	t	Sig.
(Constante)	0.858	0.007		129.324	0.000
Y2019	0.007	0.008	0.017	0.855	0.393
Y2020	0.009	0.008	0.023	1.181	0.238
Y2021	0.017	0.008	0.043	2.197	0.028
Y2022	0.021	0.008	0.053	2.714	0.007
AsiaPacific	-0.013	0.008	-0.030	-1.561	0.119
Arab	-0.045	0.009	-0.087	-4.898	0.000
Americas	-0.050	0.008	-0.119	-6.269	0.000
Africa	-0.120	0.010	-0.321	-12.576	0.000
CIS	-0.020	0.012	-0.028	-1.600	0.110
Low-income	-0.329	0.012	-0.642	-28.349	0.000
Lower-middle-income	-0.203	0.008	-0.579	-26.522	0.000
Upper-middle-income	-0.092	0.007	-0.260	-13.266	0.000

Excluded Variables[a]					
Model	Beta In	T	Sig.	Correlation	Collinearity Statistics (Tolerance)
Y2023	,000[b]	0.000	1.000	0.000	5.118E-14
Europe	.[b]				0.000
Highincome	.[b]				0.000

Regional differences are also evident. The Arab States, Sub-Saharan Africa, and the Americas show significantly negative coefficients, pointing to comparatively lower structural readiness and weaker digital infrastructure foundations. In contrast, the Asia-Pacific and CIS regions exhibit small or statistically insignificant deviations from the reference category, indicating more balanced or transitional performance within the global digital landscape.

The regression results for Component 1 indicate that income level represents the main structural determinant of digital and capital readiness across countries. The coefficients for low- and lower-middle-income groups are large and negative (B = -0.329 and -0.203, respectively), suggesting that these economies remain substantially below the digital readiness levels observed in the baseline category. Conversely, upper-middle- and high-income countries display smaller but still negative coefficients, reflecting a degree of digital maturity and saturation - implying limited potential for further marginal gains in the short term.

Temporal effects (2019-2022) are modest and statistically insignificant, confirming that Component 1 primarily captures long-term structural and institutional characteristics rather than short-term fluctuations.

In summary**,** Component 1 reflects a dimension of accumulated digital capital and socioeconomic development, strongly influenced by income and regional structures, with limited temporal variation. This supports the interpretation of Component 1 as a stable, long-run indicator of digital and developmental capacity rather than a cyclical or period-specific factor.

Component 2 Economic Stability and Growth

The regression model for Component 2 (Table 7) also demonstrates strong explanatory power ($R^2 = 0.82$), indicating that regional and income-level factors play a substantial role in shaping short-term macroeconomic stability and growth dynamics. The results reveal positive and significant coefficients for several regions, notably the CIS, Sub-Saharan Africa, the Americas, and the Arab States (B = 0.302, 0.092, 0.057, and 0.049, respectively). These findings suggest that, during the analyzed period, these regions experienced relatively stronger cyclical recovery and greater resilience in maintaining economic stability compared to others.

Table 7: Regression Model to Explain Component 2 Economic Stability and Growth

Model	R	R Square	Adjusted R Square	Standard Error of Estimate	
1	,905[a]	0.819	0.816	0.06212	
ANOVA[a]					
Source	Sum of Squares	Df	Mean Square	F	Sig.
Regression	11.120	12	0.927	240.113	<,001[b]
Residual	2.458	637	0.004		
Total	13.578	649			
Coeffiecients[a]					
	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Error	Beta	t	Sig.
(Constante)	0.452	0.007		67.542	0.000
Y2019	0.007	0.008	0.020	0.959	0.338
Y2020	-0.026	0.008	-0.072	-3.402	0.001
Y2021	0.017	0.008	0.047	2.206	0.028
Y2022	-0.022	0.008	-0.061	-2.902	0.004
Asia Pacific	0.017	0.008	0.044	2.073	0.039
Arab	0.048	0.009	0.099	5.200	0.000
Americas	0.057	0.008	0.144	7.022	0.000
Africa	0.092	0.010	0.262	9.520	0.000
CIS	0.032	0.013	0.049	2.578	0.010
Low-income	0.302	0.012	0.631	25.805	0.000
Lower-middle-income	0.215	0.008	0.656	27.827	0.000
Upper-middle-income	0.112	0.007	0.339	16.017	0.000

Excluded Variables[a]					
Model	Beta In	T	Sig.	Correlation	Collinearity Statistics (Tolerance)
Y2023	,000[b]	0.000	1.000	0.000	5.118E-14
Europe	.[b]				0.000
Highincome	.[b]				0.000

Income-level effects further reinforce this pattern. Both low-income and lower-middle-income economies exhibit positive coefficients (B = 0.302 and 0.215), implying comparatively higher short-term performance or faster rebound capacity after global economic shocks. This may reflect the more flexible economic structures and adaptive labor markets that characterize many emerging economies.

The temporal coefficients capture the macroeconomic cycle associated with the COVID-19 pandemic and its recovery phase. The years 2020 and 2022 display negative and statistically significant coefficients, corresponding to the initial pandemic-induced contraction and subsequent post-recovery adjustments. In contrast, 2021 presents a positive coefficient, representing the rebound phase following the sharp downturn of 2020. The Asia-Pacific and Europe regions, which serve as baseline categories, maintain neutral to slightly positive performance levels, consistent with their relatively stable macroeconomic environments.

In summary, Component 2 reflects a dimension of short-term economic stability and cyclical recovery, capturing variations associated with pandemic-related disruptions and subsequent rebounds. The results highlight a pattern of macroeconomic volatility mitigated by resilience, particularly within emerging and developing regions, thereby complementing the long-term structural insights provided by Component 1.

4.3 – Spatial and Temporal Analysis of Components

The empirical analysis in this study was conducted using the GeoDa platform, which performs multivariate spatial decomposition of country-level data. GeoDa applies a generalized component extraction procedure that identifies latent spatial dimensions- referred to as components- that summarize the dominant patterns of variation in the dataset across countries and over time.

To visualize these results, GeoDa automatically generates maps in which each country is colored according to its loading value. A diverging color scale is used to represent the full numerical range of loadings. For each year in the dataset (2019-2023), GeoDa illustrates two major components that together represent the principal latent structures underlying global variation.

These components are orthogonal, meaning they describe independent patterns in the data. The resulting maps allow for both cross-sectional analysis (geographic comparison within a given year) and temporal analysis (stability and evolution of patterns across years).

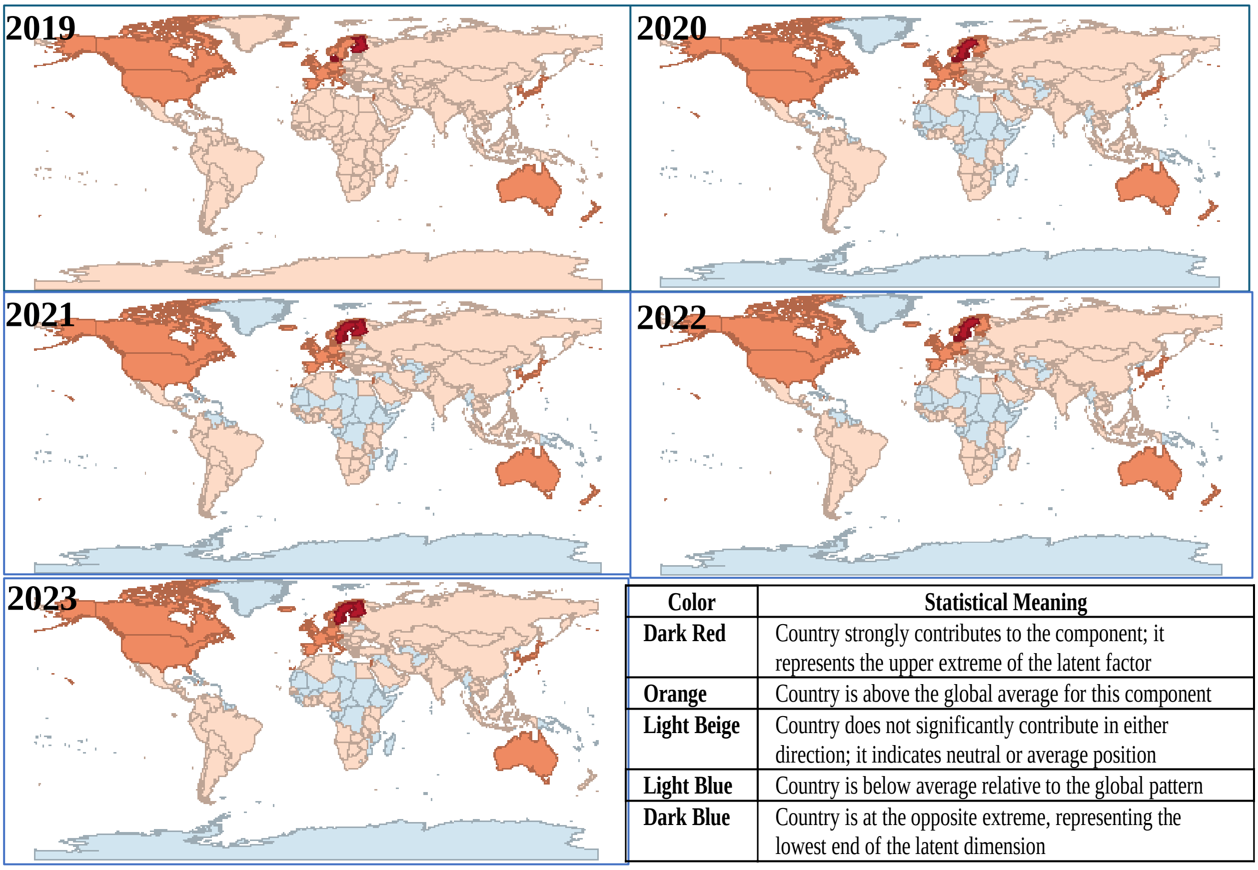
The method was chosen because it (1) captures multidimensional patterns that cannot be identified through single indicators, (2) provides spatially interpretable outputs, and (3) preserves cross-year comparability by applying the same extraction parameters across the entire period.

This makes GeoDa particularly suitable for analyzing structural global inequalities, development trends, and spatial clusters of vulnerability.

The GeoDa maps use a diverging color scale, where countries are shaded from dark blue to dark red depending on their loading values on each component. This color scheme reflects the strength and direction of its contribution to a given component.

For Component 1, the red and orange colors represent countries with high levels of development, strong institutional and economic capacity, technological advancement, and deeper integration into the global economy. In contrast, blue shades indicate low development, limited institutional capacity, and weaker economic and technological performance. Dark red areas such as Western Europe, the United States, Canada, and Australia reflect the strongest positive positions on this development dimension. Dark blue regions, particularly in Sub-Saharan Africa, correspond to the lowest values on development-related indicators. Countries shaded in beige generally occupy a middle position, typically reflecting middle-income or transitional economies.

The spatial patterns displayed in the GeoDa maps for Component 2 are consistent with the results of the regression model and reflect a dimension associated with short-term macroeconomic stability, cyclical volatility, and pandemic-related recovery dynamics. In the maps, countries shaded in red and orange represent high positive loadings, indicating that their short-term economic trajectories during the analyzed period were characterized by stronger cyclical movements- either sharper rebounds after downturns or more pronounced year-to-year fluctuations in growth. This pattern is especially visible in regions such as the CIS, Sub-Saharan Africa, the Americas, and the Arab States, where the GeoDa maps show persistent red/orange shading corresponding to the positive regression coefficients identified for these regions.



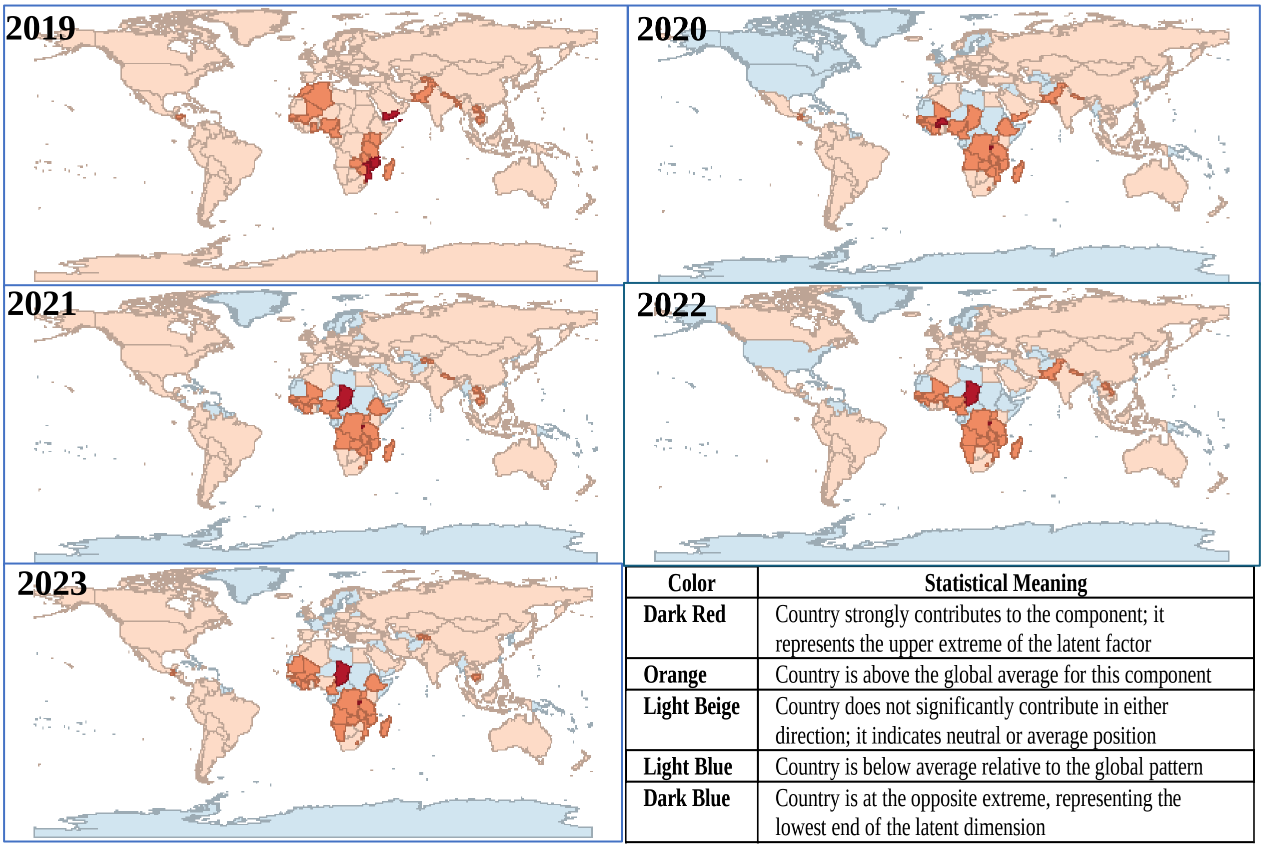
Color	Statistical Meaning
Dark Red	Country strongly contributes to the component; it represents the upper extreme of the latent factor
Orange	Country is above the global average for this component
Light Beige	Country does not significantly contribute in either direction; it indicates neutral or average position
Light Blue	Country is below average relative to the global pattern
Dark Blue	Country is at the opposite extreme, representing the lowest end of the latent dimension

Fig. 3 Spatial Representation of the Scores of Component 1 Digital and Capital Readiness

By contrast, blue shades represent negative loadings, reflecting countries with more stable short-term macroeconomic behavior and less pronounced cyclical variation. These regions-most notably Europe, Japan, Australia, and parts of the Asia-Pacific-appear consistently in blue on the maps, aligning with their relatively moderate or neutral regression estimates and their well-documented macroeconomic stability during the period surrounding the COVID-19 shock.

The temporal sequence of GeoDa maps further reinforces this interpretation. The shift in map intensities in 2020 and 2022 corresponds to the statistically significant negative year coefficients associated with the pandemic contraction and the subsequent adjustment period. The spatial expansion of red areas in 2021 matches the positive year coefficient indicating global rebound dynamics. Thus, the GeoDa visual output captures the same short-term economic cycle identified in the regression model: contraction in 2020, rebound in 2021, and adjustment in 2022.

Altogether, the GeoDa maps demonstrate that Component 2 represents a spatial-temporal pattern of short-term economic variation, where red shading indicates countries and regions experiencing stronger cyclical responses to global shocks, while blue shading marks those with more stable economic trajectories. This visually derived interpretation fully aligns with the econometric findings, confirming that Component 2 reflects a cyclical stability–volatility axis rather than a long-term structural development dimension.



Color	Statistical Meaning
Dark Red	Country strongly contributes to the component; it represents the upper extreme of the latent factor
Orange	Country is above the global average for this component
Light Beige	Country does not significantly contribute in either direction; it indicates neutral or average position
Light Blue	Country is below average relative to the global pattern
Dark Blue	Country is at the opposite extreme, representing the lowest end of the latent dimension

Fig. 4 Spatial Representation of the Scores of Component 2 Economic Stability and Growth

5) Discussion

This study applies Generalized Q Analysis (GQA) to examine the joint evolution of Sustainable Development Goal (SDG) indicators for 130 countries over the period 2019-2023, shifting the focus from isolated indicators to multidimensional development configurations and national trajectories. The empirical results reveal a remarkably stable two-dimensional structure. This clear separation between structural development capacity and short-term macroeconomic dynamics provides strong empirical support for the view that sustainable development is primarily driven by long-term capital formation processes rather than by short-run growth performance alone.

At the same time, the results highlight the coexistence of complementarities and trade-offs among development dimensions. This pattern is consistent with endogenous and place-based development frameworks (Barca, 2008; Sass & Dentinho, 2023), which emphasize that development outcomes emerge from cumulative and context-specific interactions among different forms of capital rather than from isolated sectoral progress. In this sense, the empirical dominance of the first component confirms that sustainable development paths are fundamentally shaped by structural capabilities rather than by temporary macroeconomic accelerations.

Although institutional quality is not directly modelled in the empirical specification, the spatial patterns of Component 1 strongly suggest a close association between digital-capital readiness and institutional effectiveness, in line with the arguments of Rodríguez-Pose (2013; 2020) and the OECD (2021). Countries that occupy the highest positions on Component 1 are also those with stronger capacities to redistribute income, provide public services, and reinvest in natural, human, and productive capital.

The structure of Component 1 is also fully consistent with the concept of networked or place-based capital, which integrates natural, social, human, productive, and institutional assets into a cumulative and territorially embedded development capacity (Horlings, 2015; Sørensen, 2018). In this perspective, digital infrastructure, skills, and governance can be seen as critical connective layers that increase the density, reach, and effectiveness of these capital networks. The strong association between Component 1 and crisis resilience further suggests that such networked capital configurations provide not only higher long-run development levels but also greater robustness in the face of systemic shocks.

At the same time, the heterogeneous trajectories observed across countries illustrate that development paths remain strongly conditioned by structural and geopolitical contexts. Economies benefiting from natural resource rents or sustained external support- such as Angola, Nigeria, or large emerging economies operating under long-term strategic investment regimes- may temporarily compensate for structural weaknesses, while conflict-affected countries such as Ukraine show how abrupt political shocks can disrupt even relatively stable trajectories. Conversely, many “left-behind” countries and regions (Benner et al., 2024) remain unable to benefit effectively from either place-based or sectoral development policies (Peñalosa & Castaldi, 2024), precisely because their underlying capital and institutional networks are too fragmented.

In this context, digital divides play a critical reinforcing role. Uneven access to digital infrastructure, skills, and governance capacities limits the ability of lagging countries and regions to mobilize local resources, connect to broader innovation systems, and participate in global value and knowledge networks. The results therefore suggest that differences in digital readiness are not only a consequence of development gaps but also an important mechanism through which these gaps are reproduced over time. This helps explain why similar policy instruments often produce highly divergent outcomes across countries and regions.

Methodologically, the paper demonstrates the analytical value of moving from an indicator-based perspective to a subject- or trajectory-based approach using Generalized Q Analysis (Dentinho et al., 2023). Rather than asking whether individual SDGs progress or regress, the proposed framework identifies structurally coherent development configurations and traces how countries move within this multidimensional space over time.

Overall, the discussion suggests that the current global difficulties in advancing the SDGs are less the result of inherent conflicts between economic, social, and environmental objectives and more the consequence of slow, uneven, and path-dependent processes of capital and institutional accumulation. Digital transformation does not override these structural constraints, but it increasingly conditions the speed, coherence, and resilience with which countries can build and coordinate their development capacities.

6) Conclusion

This paper set out to analyse the interactions between sustainable development goals by examining the joint evolution of combined SDG indicators for 130 countries over the period 2019–2023 using a Generalized Q Analysis Technique, that allowed to track each country in the two representative components allowing a clearer path for sustainable development. This representation provides a coherent and intuitive interpretation of how national development paths were disrupted by the COVID-19 pandemic in 2020 and subsequently reshaped by asymmetric shocks such as commodity price fluctuations (e.g., Angola and Nigeria), geopolitical conflict (Ukraine), and persistent institutional constraints (e.g., South Africa).

From a digital transformation perspective, this approach also allows the identification of how digital readiness and digitally mediated capacities condition the resilience of countries to systemic shocks and shape their ability to remain on sustainable development trajectories during periods of disruption. Countries with stronger digital, institutional, and human capital foundations were better able to absorb the pandemic shock and preserve their structural development positions, whereas economies with weaker digital and institutional capacities exhibited greater volatility and more fragile recovery paths.

To some extend it was shown that problem relies more on weak institutional capacity (Sachs et al., 2021) and on the existence of disconneted capital netwworks of people and places left behind (Rodríguez-Pose, 2020). These weaknesses are increasingly intertwined with uneven digital capacities, as limited digital infrastructure, skills, and governance further constrain institutional effectiveness and reinforce the disconnection of capital networks in lagging countries and regions. More than conflicts between economic, social, and environmental goals highlighted by (C. Li et al., 2023; United Nations, 2020, 2021; Wang et al., 2021; Yuan et al., 2023) what seems to happen is the absence of analysing, understanding and assuming the specificity of ecah country in each context. Digital transformation reinforces the need for such context-sensitive analysis, as the impacts of digitalization on growth, inclusion, and sustainability vary significantly across countries depending on institutional quality and absorptive capacity. SDG targets may be stagnant or regressing (United Nations, 2023) but the process of creating natural, social, productive and institutional capital is slow and changeable as it is possible to forseen in the finding of commonalities of the Principal Components of the Generalized Q Analyis. In this sense, digital transformation should be interpreted as a cumulative and path-dependent process that interacts with these forms of capital, rather than as a short-term accelerator capable of offsetting structural weaknesses on its own.

Future research should therefore focus on the comparative evolution of countries occupying similar positions in the two-component space, in order to identify the contextual and policy-related factors that drive divergent trajectories. Particular attention should be given to politically actionable conditions, such as conflict resolution (e.g., Ukraine), improved governance of natural resource rents (e.g., Angola and Nigeria), and institutional preparedness for systemic shocks such as pandemics.

Finally, such future research should explicitly consider digital policy dimensions-including investments in digital infrastructure, skills development, and digital governance reforms-as politically actionable factors that may strengthen endogenous sustainable development and enhance the effectiveness of place-based strategies. In this way, digital transformation can be repositioned not as a short-term technological fix, but as a core component of long-term institutional and developmental resilience.

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