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How Do Digital Readiness and Economic Growth Compare Across Income Groups?

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ABSTRACT

Research Originality: This study provides new empirical evidence on the global impact of digital readiness on economic growth by comparing high-, middle-, and low-income countries. Unlike previous studies focusing on single countries or regions, this research examines whether digital readiness contributes differently across income groups.

Research Objectives: This study aims to explore the development of digital readiness and analyze its effect on economic growth across countries by income level.

Research Methods: The study uses descriptive analysis and panel-data regression across 105 countries for 2019–2023. Digital readiness is measured by the Networked Readiness Index, comprising 46 indicators. PCA is applied to construct the index, and panel regression examines the relationship between digital readiness and economic growth across income groups.

Empirical Results: Digital readiness significantly boosts economic growth across all income groups, with the strongest effect in high-income countries, a moderate effect in middle-income countries, and the weakest in low-income countries.

Implications: The findings show that digital readiness has become a key driver of global economic growth, reflecting increasing access to and adoption of digital technologies across countries at different income levels.

Keywords:

cross-country analysis; digital infrastructure adoption; economic development; income group comparison; technological preparedness

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INTRODUCTION

The relationship between digital technology and economic growth has become one of the most contested and consequential debates in contemporary development economics (Ping et al., 2026). As globalization intensifies, Information and Communication Technology (ICT) has emerged as a structural driver of productivity, trade, and innovation. Yet, the mechanisms through which it translates into growth remain deeply contested, particularly across countries at different stages of development. Understanding why digital readiness produces divergent economic outcomes across income groups lies at the heart of this study (Sarsar & Echaoui, 2026). The world in the era of globalization faces major challenges that affect economic growth (Ahmed et al., 2026). Today, virtually everything can be controlled remotely across various regions via the internet using technological devices. This is inseparable from the influence of rapidly advancing Information and Communication Technology (ICT), which fosters the digital economy within a country (Cheng et al., 2026; Mukherjee, 2026).

The use of digital technology has been increasing, particularly since the onset of the COVID-19 pandemic in early 2020, which led to restrictions on various community activities. This situation has driven people to increase their use of digital technology to meet their needs, including working and learning from home, *online shopping,* and other activities that require it. This has led to an increase in demand for internet and mobile data services (WTO, 2020). We Are Social (2023) notes in its annual *Digital Report* that, as of January 2023, *digital traffic* trends have continued to rise post-COVID-19. Among these trends, 59.8% of global internet users are shopping online more frequently in the post-pandemic era, with the largest increase in online shopping occurring in the *fashion & food* categories, at 37%. The number of consumer transactions via online e-commerce also increased by 8.3%, totaling 4.11 billion.

The *Global Information Technology Report* (GITR), published by *the World Economic Forum* (WEF), examines various indicators of a country's readiness for digitalization. These individual indicators are aggregated to produce pillar scores, which are then combined to generate sub-index scores and ultimately merged to produce the *Networked Readiness Index* (NRI), also known as the Digital Readiness Index, as it is used to assess a country's ability to leverage the digital revolution. *The Networked Readiness Index* (NRI) underwent a model update in 2019. *The* 2023 *Networked Readiness Index* is the fifth edition of the updated NRI model published by the Portulans Institute in collaboration with the University of Oxford. The 2023 NRI comprises 58 indicators distributed across 12 sub-pillars and consolidated into 4 main pillars (aspects): the technology aspect, the human resources aspect, the governance aspect, and the SDG contribution aspect (NRI Model, 2023). This index aims to conceptualize the complex reality of information and communication technology (ICT) and identify common factors that enable countries to use technology effectively. The indicator framework in the NRI is intended to guide policymakers and civil society on the factors they need to consider and account for to leverage ICT in their growth strategies.

The top 10 countries with the highest NRI scores in 2023 are all *high-income economies,* comprising a mix of Asian countries (Singapore and South Korea) and European

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countries (Finland, the Netherlands, Sweden, Switzerland, Denmark, and Germany), as well as the United States. Europe remains the region with the most advanced technology, accounting for 7 of the top 10 countries in the NRI index. Among developing countries in Asia *(lower- and upper-middle-income),* the top five in overall digital readiness are China, Malaysia, Thailand, Vietnam, and Indonesia. In the Americas region, the top three developing countries are Brazil, Costa Rica, and Argentina. In the MENAP region *(Middle East, North Africa, and Pakistan)*, the United Arab Emirates (ranked 30th) and Saudi Arabia (ranked 41st) continue to lead the Arab world in network readiness. Meanwhile, among Sub-Saharan African countries—most of which are *low-* and *middle-income*—the highest NRI index is held by Kenya (ranked 70th), followed by South Africa (ranked 74th).

The differences in the impact of ICT on economic growth between developed and developing countries are illustrated in a study by the International Telecommunication Union (2018), which found that *fixed broadband* has had a significant impact on the global economy over the past seven years (2010–2017). A 1 percentage point increase in *fixed broadband* penetration results in a 0.08 percentage point increase in economic growth (GDP). Second, based on the *mobile broadband* model, a 1 percentage point increase in *mobile broadband* penetration results in a 0.15 percentage point increase in GDP. Third, the economic impact generated by *fixed broadband* penetration (through *the returns-to-scale* effect) is higher in more developed countries than in less developed ones. On the other hand, the economic impact of *mobile broadband* penetration is more significant in less developed countries than in more developed ones. Also demonstrates that ICT plays a major role in the growth of high-income and upper-middle-income countries, but fails to contribute to the growth of lower-middle-income countries.

Prior studies have examined the relationship between ICT and economic growth using various approaches. Niebel (2014) found a positive relationship between ICT capital and GDP growth but did not identify statistically significant differences in the output elasticity of ICT across developing, emerging, and developed countries, thereby questioning the 'leapfrogging' hypothesis. Bahrini and Qaffas (2019) showed that mobile phone use, internet use, and broadband adoption positively and significantly affect economic growth, while fixed telephone use had a negative impact in developing country contexts. Myovella & Haucap (2020) found that digitalization contributes positively to economic growth in both groups of countries, with mobile telecommunications and broadband internet exhibiting different magnitudes of effect between OECD and SSA countries. Further studies using multi-country panel frameworks confirmed long-run relationships among ICT infrastructure, capital formation, labor force, and per capita GDP, highlighting that ICT investment supports sustained economic growth (Pradhan et al., 2018; Pradhan et al., 2021; Awad & Albaity, 2022). These studies highlight the significant but varied impact of ICT across regions and income groups, setting the stage for research on more comprehensive measures.

Building on this literature, recent studies have employed the Networked Readiness Index (NRI) to capture digital readiness more holistically. Silva et al. (2022) show that the NRI captures key dimensions of digital technologies and their implications for economic and social progress. However, debates remain on its capacity to address digital divides. Prasetyo & Mulyana (2025) examine the impact of the NRI's four pillars on GDP growth in 21 East Asia and Pacific countries (2019–2024), finding that Technology and Governance significantly influence economic growth, while People and Impact do not show statistically significant effects, highlighting the importance of digital infrastructure and effective governance. Hammache (2024) demonstrates a positive association between digitalization, measured by NRI sub-indexes, and economic growth in the Middle East and North Africa, although some human capital indicators show limited significance. Methodological studies also explore the structure and measurement of NRI. Tokmergenova & Dobos (2023) apply Principal Component Analysis to map relationships among NRI sub-pillars, providing insights into the dimensionality and clustering of digital-readiness patterns, while Bánhidi & Dobos (2024) propose alternative weighting approaches to rank digital development using NRI, emphasizing measurement challenges and comparative frameworks. Despite these advances, the literature rarely offers global comparisons of how overall digital readiness impacts economic growth across different income groups.

This study addresses these gaps through three contributions. First, it employs the NRI as a holistic, multidimensional measure of digital readiness, going beyond single-indicator proxies used in prior research. Second, it applies Principal Component Analysis (PCA) to identify the dominant NRI determinants driving digital readiness across country groups. Third, it simultaneously compares the impact of digital readiness on economic growth across high-, middle-, and low-income countries using panel data for 105 countries over 2019–2023. This period uniquely encompasses the COVID-19 digital transformation surge and its aftermath. Accordingly, this study pursues two objectives: (1) to explore the development of digital readiness as measured by the NRI across income groups, and (2) to analyze the differential impact of digital readiness on economic growth across high-, middle-, and low-income countries at the global level.

METHODS

This study uses secondary data obtained from existing sources (Hasan, 2002), specifically global data sources such as the World Bank and the Networked Readiness Index Report, spanning 5 years (2019–2023). The quantitative analysis methods employed include principal component analysis (PCA) and panel data regression (pooled data), processed using Stata software, supported by descriptive analysis drawing on scientific journals, books, and previous studies. The data used for this study are presented in Table 1.

Before the in-depth analysis, data cleansing removed duplicate, inconsistent, and incomplete records (including those with missing values), reducing the initial sample from 133 to 105 countries (28 removed) and the NRI indicators from 58 to 46 (12 removed). The final dataset comprises panel data from 105 countries (48 high-income, 52 middle-income, and 5 low-income) over 2019–2023, with 46 NRI indicators and 525 observations in total. These 5 years were used because complete and consistent NRI data were only available up to 2023, ensuring reliability and comparability across countries.

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Table 1. Variables and Data Sources

Variables	Description	Unit	Source
LnGDP	Gross domestic product	Million USD	World Bank
LnGCF	Gross capital formation	Million USD	World Bank
LnLF	Labor force population	People	World Bank
INFLCPI	Inflation	Annual %	World Bank
LnGE	Government spending	Million USD	World Bank
EDC	Minimum education attainment rate: bachelor's degree or equivalent	Annual %	World Bank
NRI	Digital readiness index	Score 0-100	NRI Report

This study employs three analytical methods to examine the impact of digital readiness on economic growth: principal component analysis (PCA), score plot analysis, and panel data regression using the Random-Effects approach. Principal Component Analysis (PCA) is used to reduce the 46 NRI indicators into a smaller number of new variables that represent the original set and capture the dominant factors shaping the NRI; the number of components formed equals the number of original variables (Supartoyo, 2018).

Scoreplot analysis, part of PCA, maps the 105 countries into quadrants I–IV based on each country's PC1 and PC2 values: Quadrant I (high PC1, high PC2), Quadrant II (high PC1, low PC2), Quadrant III (low PC1, low PC2), and Quadrant IV (low PC1, high PC2). Panel data regression combines cross-sectional and time-series data, allowing for control of unobserved heterogeneity and a more comprehensive analysis of dynamic effects among variables (Ghanim, 2026). Three general estimation models are commonly applied: the Common Effect Model (Pooled Least Squares), the Fixed Effect Model, and the Random Effect Model (Kwon, 2026). This study applies Generalized Least Squares (GLS) using the Random Effects approach, selected directly based on the purpose of the analysis, with model adequacy assessed using R^2, the F-test, and the t-test. The model used in this study is:

$$LnGDP_{it} = \alpha_{0i} + \alpha_1 \ln GCF_{it} + \alpha_2 \ln LF_{it} + \alpha_3 \ln flcpi_{it} + \alpha_4 \ln GE_{it} + \alpha_5 EDC_{it} + \alpha_6 NRI_{it} + \alpha_7 DhNRI_{it} + \alpha_8 DmNRI_{it} + u_{1it} \quad (1)$$

Where:

GDP = Gross Domestic Product/Economic Growth (million USD); GCF = Gross Capital Formation/Total Investment (million USD); LF = Total Labor Force/Working-Age Population (people); Inflcpi = Inflation (annual percentage); GE= Government Expenditure (million USD); EDC= Minimum educational attainment rate at bachelor's degree or equivalent (percent); NRI = Networked Readiness Index/Digital Readiness Index (index 1–100); DhNRI = Interaction dummy variable between NRI and high-income countries (1 = high-income country, 0 = other countries); DmNRI = interaction dummy variable between NRI and middle-income countries (1 = middle-income country, 0 = other countries); u = error term; i = country; i = 1, 2, 3, …, 105; and t = year; t = 1, 2, 3, 4, 5

RESULTS AND DISCUSSION

Principal Component Analysis (PCA) of the 46 indicator variables comprising the NRI yielded three new variables (principal components) that accounted for 60.90% of the total variance, indicating that the Digital Readiness Index (NRI) can be explained by just these three derived variables. The three new variables formed by the PCA analysis are PC1 (Digital Well-being and Social Connectivity), PC2 (Innovation Ecosystem and Digital Transformation), and PC3 (Technology Infrastructure and Digital Economy). These three variables are the factors that most influence the NRI index. The results of the scoreplot analysis at illustrate the digital readiness of 105 countries. PCA analysis confirms that high-income countries rank higher on the Digital Readiness Index in nearly all aspects (all indicators). The country with the lowest PC1 score is Ethiopia (in the low-income country category), indicating very low scores for Digital Well-being and Social Connectivity.

Meanwhile, the country with the lowest PC2 score is Greece (in the high-income country category), indicating very low scores in the Digital Innovation and Transformation Ecosystem. Indonesia itself is in Quadrant IV, meaning it has a fairly good PC2 score (Digital Innovation and Transformation Ecosystem) (> 0), but a poor PC1 score (Digital Well-being and Social Connectivity) (< 0). The results of the regression analysis examining the relationship between the Digital Readiness Index and economic growth (GDP) indicate that the Digital Readiness Index (NRI) significantly boosts economic growth across all income groups of countries, with the greatest impact in high-income countries (61.9%), followed by middle-income countries (30.4%), and low-income countries (0.2%). This study indicates that digital readiness has now become a relevant driver of economic growth across all income groups of countries, in line with the increasing access to and penetration of digital technology in recent years.

The final data (scores 0–100) were used to calculate the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, which assesses sample adequacy by comparing observed and partial correlations and must exceed 0.50 for PCA to proceed. The KMO result of 0.6038 indicates sufficient, though moderate, inter-variable correlation, confirming that the 46 NRI indicators capture a reasonably diverse yet interconnected set of digital readiness dimensions and justifying the use of PCA to condense them into fewer interpretable components without significant information loss. With the KMO check confirming the dataset's suitability, the PCA analysis proceeds by calculating correlations among variables (Li & Li, 2026), organizing them into a correlation matrix, and examining the eigenvalues (characteristic roots) of each variable. In this study, the new principal components are based on eigenvalues greater than 6, as shown in Table 2.

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Table 2. Eigenvalues and Variance Contributions by Indicator

Component	Eigenvalue	Cumulative	Variance (%)	Component	Eigenvalue	Cumulative	Variance (%)
Comp 1	19.2465	0.4184	41.84	Comp 24	0.1900	0.9713	0.41
Comp 2	6.0506	0.5499	13.15	Comp 25	0.1789	0.9752	0.39
Comp 3	2.7170	0.6090	5.91	Comp 26	0.1633	0.9788	0.36
Comp 4	2.1235	0.6552	4.62	Comp 27	0.1326	0.9817	0.29
Comp 5	2.0921	0.7006	4.55	Comp 28	0.1105	0.9841	0.24
Comp 6	1.5941	0.7353	3.47	Comp 29	0.1061	0.9864	0.23
Comp 7	1.5503	0.7690	3.37	Comp 30	0.0929	0.9884	0.20
Comp 8	1.1414	0.7938	2.48	Comp 31	0.0848	0.9902	0.18
Comp 9	1.0737	0.8172	2.33	Comp 32	0.0655	0.9917	0.14
Comp 10	0.7996	0.8345	1.74	Comp 33	0.0598	0.9930	0.13
Comp 11	0.7821	0.8515	1.70	Comp 34	0.0593	0.9943	0.13
Comp 12	0.6830	0.8664	1.48	Comp 35	0.0521	0.9954	0.11
Comp 13	0.6586	0.8807	1.43	Comp 36	0.0425	0.9963	0.09
Comp 14	0.6315	0.8944	1.37	Comp 37	0.0397	0.9972	0.09
Comp 15	0.5694	0.9068	1.24	Comp 38	0.0284	0.9978	0.06
Comp 16	0.4839	0.9173	1.05	Comp 39	0.0252	0.9983	0.05
Comp 17	0.4491	0.9271	0.98	Comp 40	0.0230	0.9988	0.05
Comp 18	0.4103	0.9360	0.89	Comp 41	0.0175	0.9992	0.04
Comp 19	0.3685	0.9440	0.80	Comp 42	0.0164	0.9996	0.04
Comp 20	0.3122	0.9508	0.68	Comp 43	0.0088	0.9998	0.02
Comp 21	0.2772	0.9569	0.60	Comp 44	0.0061	0.9999	0.01
Comp 22	0.2597	0.9625	0.56	Comp 45	0.0031	1.0000	0.01
Comp 23	0.2161	0.9672	0.47	Comp 46	0.0011	1.0000	0.01

Figure 1. Screeplot of Eigenvalues Above Two

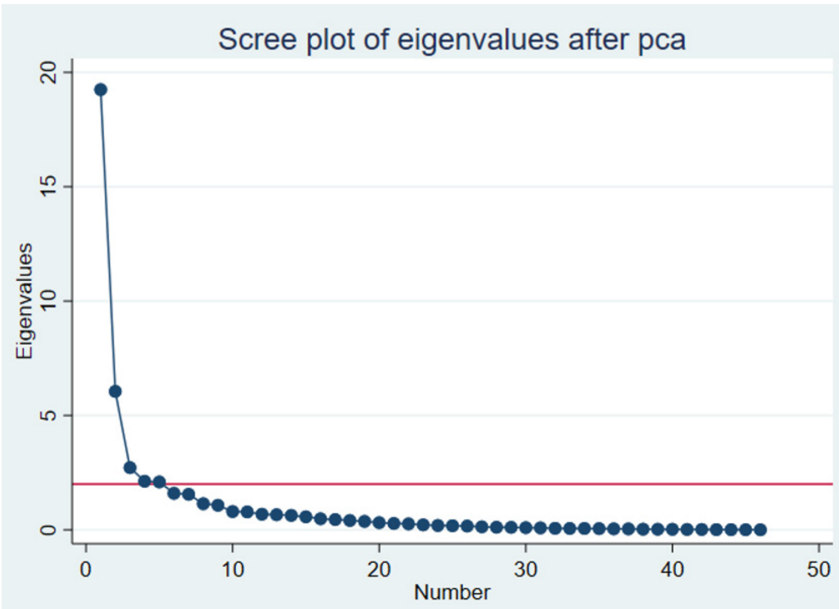

Table 2 shows the eigenvalues of each variable along with their variances. The table indicates that the PCA results yielded nine new variables (principal components) with eigenvalues greater than one. However, as shown in Figure 1, which displays the Screeplot of Eigenvalues above two, five principal components were selected as the new variables and by using one method to determine the number of new variables in PCA analysis, namely, drawing a line where the graph begins to flatten (a kink in the line), only three variables (three principal components) are selected as new variables. Eigenvalues greater than one indicate significant PC loading (Moniruzzaman, 2026).

A more detailed explanation is shown in the pie chart in Figure 2, which indicates that Component 1 accounts for 41.84% of the variance. When Components 2 and 3 are added, the total variance contribution exceeds 60%. Meanwhile, in that pie chart, it can be seen that the percentage of variance added by Component 4 and subsequent components is below 5% and continues to decrease (becoming increasingly insignificant). Therefore, this study will only use the three principal components (Components 1, 2, and 3) as new variables. These three new variables account for 60.90% of the data's variance (as seen in the total percentage of variance). To determine which variables are included in these three new variables and which truly influence the Networked Readiness Index (NRI), factor rotation (transformation) was performed using the varimax rotation method. Next, the factor loadings of each variable forming each principal component were examined. Variables with high factor loadings for a component indicate a strong relationship between that factor and the component (Bogaert et al., 2026; Anna et al., 2026).

Figure 2. Pie Chart of Contribution by Indicator

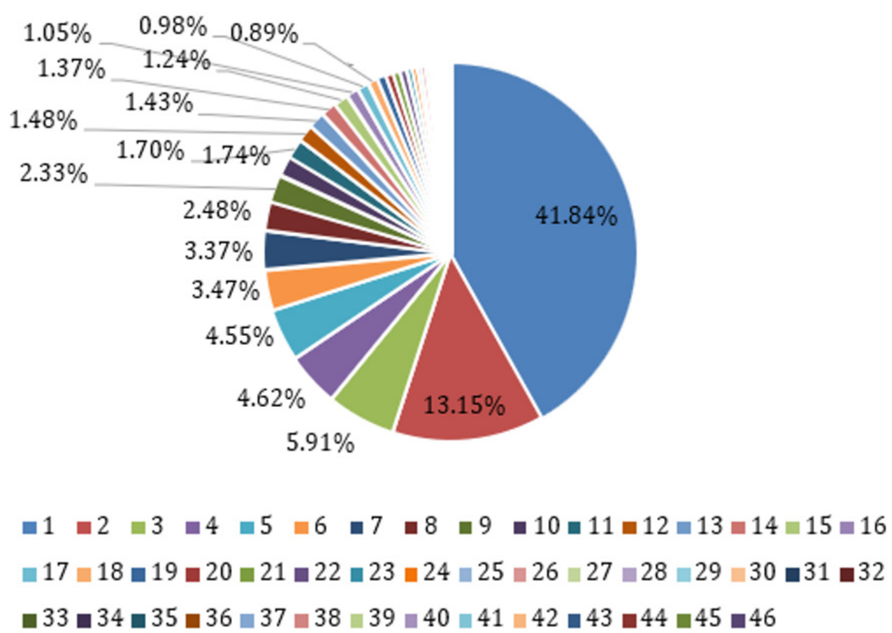

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Table 3. Factor Loadings per Indicator

Indicator	Comp1	Comp2	Comp3	Indicator	Comp1	Comp2	Comp3
A1	0.1559	0.0498	0.0621	C4	0.2335*	0.0022	0.0001
A2	0.1728	0.0814	-0.0203	C5	0.1224	0.1997	-0.1179
A3	-0.0561	0.0530	0.3301*	C6	0.1630	-0.0586	-0.0980
A4	0.0515	0.1362	-0.0336	C7	0.0502	0.2946*	-0.0169
A5	-0.0347	0.0527	0.3248*	C8	0.1362	-0.0143	0.0431
A6	0.1410	0.1379	-0.1112	C9	0.1045	0.0472	-0.1997
A7	0.1162	0.1398	-0.1348	C10	0.1659	0.0409	0.0734
A8	0.1707	0.0164	0.0573	C11	0.1740	0.0176	0.0165
A9	0.0174	-0.0058	0.3480*	C12	0.1388	0.1677	0.0470
A10	0.0819	0.2504*	0.0382	C13	0.1303	0.0096	-0.0541
A11	-0.0256	0.3661*	0.0284	D1	-0.0087	0.1450	0.0781
A12	0.1695	-0.0599	0.1131	D2	0.1155	0.1538	-0.0045
B1	-0.0085	0.0332	0.3716*	D3	0.0661	-0.0093	0.3668*
B2	0.2532*	-0.0937	0.0319	D4	-0.0386	0.3174*	0.0914
B3	0.3020*	-0.2354*	0.0485	D5	0.0214	0.1198	-0.1145
B4	0.1889	0.0786	-0.1028	D6	0.1890	0.0253	-0.0364
B5	0.1047	-0.0300	0.3401*	D7	-0.1279	0.3361*	-0.0671
B6	0.1706	0.0458	0.0838	D8	0.0762	0.1046	-0.0775
B7	-0.0602	0.3656*	0.0596	D9	0.2629*	-0.0930	0.0079
B8	0.1349	0.1096	0.0484	D10	0.2609*	-0.0855	0.0634
C1	0.2288*	0.0076	-0.0082	D11	0.1549	0.0001	-0.1687
C2	0.0617	0.1405	0.1682	D12	0.0733	-0.0237	-0.1219
C3	0.1223	0.1531	-0.0587	D13	0.2226*	-0.0217	0.0012

Note: *) Factor values > 0.2 are taken as indicators with the highest correlation

Table 3 shows the factor loadings describing the correlations between the original variables (46 indicators) and the new variables (principal components 1, 2, and 3) resulting from PCA. The selected factor loadings are those above 0.2, which are considered sufficient to explain the variables influencing the NRI. Other variables with factor loadings below 0.2 are considered to have little or no influence on the NRI, and the resulting variables represent the 46 indicator variables in the original data. Table 4 provides a more detailed explanation of the variables influencing the NRI and the variance each variable explains.

Table 4 shows that PC1 accounts for 41.84% of the variance and is formed by seven variables with factor values above 0.2: B2 (use of social virtual networks), B3 (college enrollment rate), C1 (secure internet servers), C4 (online shopping), D9 (life expectancy at birth), D10 (SDG 3: good health and well-being), and D13 (SDG 11: sustainable cities and communities). PC1 is named Digital Well-being and Social Connectivity, as these indicators reflect the social and digital well-being dimensions of a country's population, implying that overall digital readiness is most strongly shaped by how well countries integrate digital access with human development outcomes, suggesting that infrastructure investment alone is insufficient without improvements in social well-being and inclusive connectivity.

Table 4. Summary of Principal Component Analysis Results

Principal components	Code	Variable name	Factor value	Explained variance
Pc1 (digital well-being and social connectivity)	B2	Use of virtual social networks	0.2532	41.84%
	B3	College enrollment rate	0.3020	
	C1	Secure internet servers	0.2288	
	C4	Online shopping	0.2335	
	D9	Healthy life expectancy at birth	0.2629	
	D10	SDG 3: good health and well-being	0.2609	
	D13	SDG 11: sustainable cities and communities	0.2226	
Pc 2 (innovation ecosystem and digital transformation)	A10	Adoption of new technologies	0.2504	13.15%
	A11	Investment in new technology	0.3661	
	B3	College enrollment rate	-0.2354	
	B7	Government incentives for investment in new technologies	0.3656	
	C7	Regulation of new technologies	0.2946	
	D4	The Rise of the gig economy	0.3174	
	D7	Freedom in making life choices	0.3361	
Pc 3 (digital technology and economic infrastructure)	A3	Internet subscription	0.3301	5.91%
	A5	International internet capacity	0.3248	
	A9	Ai publications	0.3480	
	B1	Domestic mobile *broadband* internet traffic	0.3716	
	B5	Annual Investment in Telecommunications Services	0.3401	
	D3	Domestic market size	0.3668	

PC2 accounts for 13.15% of the total variance. It is formed by seven variables: A10 (adoption of new technology), A11 (investment in new technology), B3 (college enrollment rate, with a negative loading), B7 (government incentives for technology investment), C7 (regulation of new technology), D4 (prevalence of the gig economy), and D7 (freedom to make life choices). PC2 is named the Innovation and Digital Transformation Ecosystem because its indicators reflect systemic readiness and support for innovation and digital transformation as a whole. B3's negative loading suggests that increased access to higher education does not necessarily correlate positively with digital readiness, consistent with Marginson's (2016) observation that the expansion of higher education is often not accompanied by improvements in curriculum quality or relevance to innovative industries; the OECD (2021) similarly stresses aligning higher education with 21st-century competencies and digital literacy. Together, these results suggest that strengthening the innovation and digital transformation ecosystem requires

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quality-oriented higher education reform, robust regulatory frameworks for emerging technologies, and government-backed incentives for technology investment, rather than simply expanding tertiary enrollment.

PC3 accounts for 5.91% of the total variance. It is formed by six variables: A3 (internet subscriptions), A5 (international internet capacity), A9 (AI publications), B1 (domestic mobile broadband internet traffic), B5 (annual investment in telecommunications services), and D3 (domestic market size). Named Technology and Digital Economy Infrastructure based on these characteristics, PC3 contributes the smallest share of variance, but its indicators are fundamental enablers of a digitally capable economy; countries with deficiencies in these hard infrastructure dimensions likely face a structural ceiling on the returns they can extract from digital readiness improvements captured by PC1 and PC2. In addition to generating the three principal components, the analysis mapped the positions of the 46 NRI indicators on PC1 and PC2 using a loading plot, illustrated in Figure 3.

Figure 3. Loading Plot Graph of 46 NRI Indicators

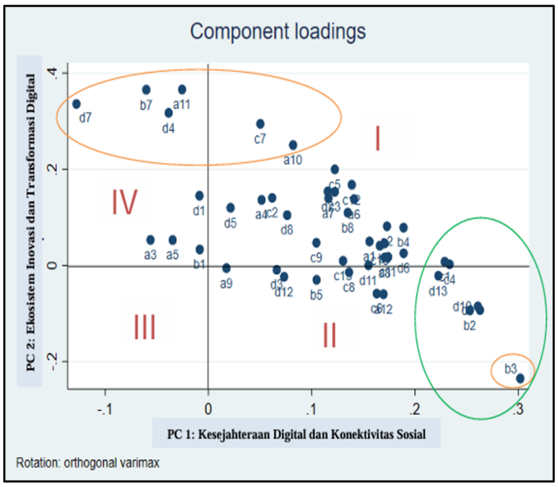
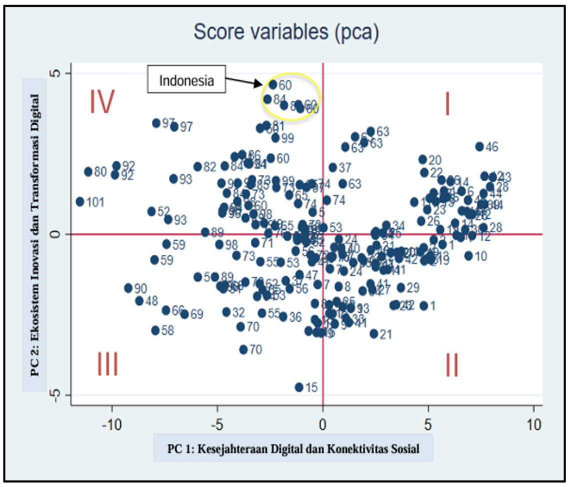


Figure 4. Scoreplot Graph of 105 Countries, 2019–2023



The seven indicators with eigenvalues > 2 on the far right of the loading plot (marked with green circles) are those forming PC1, while the six at the top and one at the bottom (orange circles) are those forming PC2, consistent with the indicators identified in Table 4. The loading plot shows that indicators in Quadrants I and II dominate PC1 (Digital Well-being and Social Connectivity), while those concentrated in Quadrant IV dominate PC2 (Innovation Ecosystem and Digital Transformation); the absence of indicators in Quadrant III indicates that all indicators contribute meaningfully to at least one component, reinforcing the validity of PCA as a dimension reduction method here.

Next, a scoreplot analysis was conducted to map the positions of 105 countries based on PC1 and PC2 values. Figure 4 illustrates the scoreplot graph in question. The group of countries in Quadrant I has high PC1 and PC2 values (> 0). Conversely, countries in Quadrant III have low PC1 and PC2 values (< 0). Countries in Quadrant II have high PC1 values (>0) but low PC2 values (<0). Finally, countries in Quadrant IV have high

PC2 values (>0) but low PC1 values (<0). The scoreplot graph shows that Quadrant I is predominantly occupied by high-income countries (country codes 1–47). Meanwhile, the countries in Quadrant III are mostly middle-income and low-income countries (country codes 48–105). These findings align with the fact that high-income countries generally have higher digital readiness indices than middle- and low-income countries. Whether in indicators reflecting digital readiness in terms of digital well-being and social connectivity (PC1), or in terms of the innovation ecosystem and digital transformation (PC2), high-income countries show positive values or are above 0. This spatial clustering indicates that the digital divide is not merely a function of internet access but a multidimensional gap encompassing social well-being, innovation capacity, and governance, dimensions that low- and middle-income countries must address simultaneously to meaningfully improve their NRI positioning.

This persistent digital divide between high- and low-income countries, as reflected in the scoreplot results, is consistent with the broader empirical literature. Niebel (2018) confirmed that ICT capital is positively associated with GDP growth across all income groups, yet found no statistically significant evidence of 'leapfrogging' advantages for developing countries, implying that high-income countries retain structural advantages in translating digital readiness into growth. In a similar vein, Myovella et al. (2020) found that while digitalization contributes positively to economic growth in both groups, the magnitude of the effects of broadband internet and mobile telecommunications differs substantially between more and less developed countries. These findings collectively reinforce the present study's scoreplot results, which show that high-income countries consistently dominate the upper quartiles of both digital well-being (PC1) and innovation ecosystem (PC2) dimensions of the NRI.

In Figure 4, Indonesia (code 60) is positioned in Quadrant IV, with a fairly high PC2 value (> 0) but a low PC1 value (< 0), indicating that its innovation ecosystem and digital transformation, encompassing technology adoption, investment, and government support is sufficiently robust. However, it must still be matched by stronger digital well-being and social connectivity (PC1) to advance its digital readiness fully. The country with the lowest PC1 value is Ethiopia (code 101, low-income), reflecting very low digital well-being and social connectivity. In contrast, the country with the lowest PC2 value is Greece (code 15, high-income), reflecting very low readiness in its innovation ecosystem and digital transformation.

The model yields a strong overall R^2 of 0.9885, meaning 98.85 percent of the variance in economic growth (GDP) is explained by the model's variables, with all variables significant at the 1%–5% level (see Table 5). The variables GCF (public investment), LF (labor force), inflcpi (inflation), and GE (government spending) have a significant positive effect on growth, while EDC (minimum educational attainment of a bachelor's degree) significantly reduces it; digital readiness (NRI) significantly boosts growth across all income groups. Overall, these results are consistent with conventional macroeconomic theory: capital accumulation, labor mobilization, and government expenditure remain fundamental engines of growth, while the negative coefficient on tertiary education attainment points to a structural misalignment between educational output and productive labor market absorption across the 105 countries studied.

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Table 5. Regression Results (NRI on Economic Growth)

Dependent variable (lnGDP)	Coefficient
lnGCF	0.2942716***
lnLF	0.2644497***
Inflcpi	0.0010399***
lnGE	0.4605597***
edc	-0.0048649***
lnNRI	0.0018956**
DhNRI	0.6167026***
DmNRI	0.3020364***
Constant	2.976305***
R-squared	**0.9885**
Prob > chi2	**0.0000**

Note: ***Significant at the 1% significance level; **Significant at the 5% significance level; *Significant at the 10% significance level

Given its positive sign, the level of investment should indeed boost economic growth. From the equation above, if public investment increases by 1%, economic growth will increase by 0.294%. Furthermore, Okun's Law, which assumes that the unemployment rate can be used as a proxy for the labor force (LF) employed in the economy, has a negative relationship with real GDP; thus, the labor force (LF) has a positive relationship with real GDP (Bod'a et al., 2006). The regression results indicate that a 1% increase in the labor force is associated with a 0.264% increase in economic growth.

The inflation variable has a significant positive effect, indicating that higher inflation is associated with greater economic growth. Keynesian theory explains that in the short term, an aggregate rise in prices will increase output and boost economic growth; however, in the long term, high inflation rates will cause a decline in purchasing power, leading to a decrease in aggregate consumption, as well as reduced investment and government spending, thereby lowering economic growth. The regression results indicate that a 1% increase in inflation will raise economic growth by 0.1%. The government spending variable has a significant positive relationship with economic growth. This aligns with Keynesian theory, which states that government spending plays a crucial role in stimulating economic activity by increasing public spending to stimulate demand, create jobs, and drive economic growth (Wahyudi, 2020). The regression results indicate that if government spending increases by 1%, economic growth will rise by 0.46%.

The variable representing the minimum educational attainment level of a bachelor's degree or equivalent has a significant negative impact on economic growth. The regression results indicate that if the minimum educational attainment level, such as a bachelor's degree or equivalent, increases by 1%, economic growth will decrease by 0.5%. An increase in the number of college graduates does not automatically boost economic growth. Research conducted by Neycheva (2019) indicates that a high proportion of college graduates, coupled with insufficient job availability, leads to an oversupply of educated labor and negatively impacts economic growth. Siyi Gu (2024), through a comparative study in China, Germany, and the United States, demonstrates that higher education has a complex impact on economic growth. In China, for example, the rapid expansion of higher education has created challenges such as a talent mismatch, which can hinder economic growth. The mismatch between educational output and labor market needs, coupled with an oversupply of graduates, actually suppresses economic growth. A study of 78 countries indicates that quantitative expansion of higher education without improvements in quality and relevance can negatively impact economic growth, particularly in developing countries (Hemmati, 2020).

The effect of the NRI variable (digital readiness) on the three income groups of countries, when analyzed alongside its dummy variables, was found to be significant and positive across high-, middle-, and low-income countries. In high-income countries, the NRI significantly boosts economic growth; a one-point increase in the NRI index raises economic growth by up to 61.9% (the sum of the NRI coefficient's elasticity and the DhNRI coefficient). In middle-income countries, the NRI has a significant positive effect; a 1-point increase in the NRI index boosts economic growth by 30.4% (the sum of the NRI coefficient and the DmNRI coefficient), and in low-income countries, it increases by 0.2% (only the NRI coefficient's elasticity, as Dh and Dm are zero). The stark income gradient, where the NRI effect in high-income countries is approximately 310 times that in low-income countries, reflects the role of complementary factors such as advanced digital infrastructure, strong institutions, deep financial systems, and a skilled labor force in amplifying the economic returns to digital readiness; this underscores that digital readiness alone is necessary but not sufficient for growth in resource-constrained settings

The findings of this study indicate a shift in results from a previous study by Yugo (2020), which examined the relationship between the digital readiness index and its impact on economic growth, unemployment, and labor absorption using data from 2013–2016. That study concluded that the digital readiness index (NRI) has a positive impact only in high-income countries, but has a negative impact in middle- and low-income countries. This difference can be explained by the updated data period and current post-pandemic conditions, where the adoption of digital technology has become increasingly widespread and equitable, even in middle- and low-income countries. The analysis period in this study (2019–2023) captures the broader phenomenon of digital transformation, including increased investment in digital infrastructure, internet penetration, and technology adoption by economic actors. These results reinforce Solow's growth theory, which holds that technological change can enhance labor productivity and long-run economic growth. Thus, this study offers a new contribution to the literature by demonstrating that digital readiness has now become a relevant growth driver across all income groups of countries, in line with the increasing access to and penetration of digital technology in recent years.

Interestingly, not all prior evidence points in the same direction regarding which income group benefits most from ICT. Appiah-Otoo & Song (2021) found that while ICT increases economic growth in both rich and poor countries, poor countries (middle- and low-income) tend to gain more from the ICT revolution. This contrasts with the present study's finding that the NRI effect is strongest in high-income countries. Habibi & Zabardast (2020) similarly found a positive association between ICT and economic

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growth in both Middle Eastern and OECD countries. Furthermore, Nguyen (2021) found that digitalization and governance each independently promote economic growth; however, their interaction significantly impedes it, indicating that in developing countries with poor institutional quality, government restrictions on digital platforms tend to limit the growth-enhancing potential of digitalization. This dynamic helps explain the weaker NRI growth effect observed in low-income countries in the present study.

A broader body of cross-national panel evidence further supports the income-differentiated pattern of NRI effects on economic growth. Farhadi et al. (2012) found a consistently positive and significant relationship between ICT and economic growth across all income groups. Critically, their income-stratified estimates revealed that the ICT coefficient was highest for the high-income group (0.11) and progressively declined to 0.09 for upper-middle, 0.06 for lower-middle, and only 0.02 for low-income countries, which means that a 1% improvement in ICT use raises a high-income country's GDP per capita by 5.5 times that of a low-income country. This income gradient directly parallels the present study's finding that the NRI raises economic growth by 61.9% in high-income countries compared to just 0.2% in low-income countries. Cheng et al. (2021) found that ICT diffusion positively and significantly improves economic growth only in high-income countries. This directly reinforces the present study's finding that the NRI's growth effect is strongest in high-income countries. From a regional perspective, Sassi and Goaied (2013) found a positive and significant direct effect of ICT on economic growth. They identified that the interaction between ICT penetration and financial development is also positive and significant.

Principal Component Analysis (PCA) of the 46 indicator variables comprising the NRI yielded three new variables (principal components) that accounted for 60.90% of the total variance, indicating that just these three derived variables can explain the Digital Readiness Index (NRI). The three new variables formed by the PCA analysis are PC1 (Digital Well-being and Social Connectivity), PC2 (Innovation Ecosystem and Digital Transformation), and PC3 (Technology Infrastructure and Digital Economy). These three variables are the factors that most influence the NRI index. The results of the scoreplot analysis illustrate the digital readiness of 105 countries. PCA analysis confirms that high-income countries rank higher on the Digital Readiness Index in nearly all aspects (all indicators). The country with the lowest PC1 score is Ethiopia (in the low-income country category), indicating very low scores for Digital Well-being and Social Connectivity. Meanwhile, the country with the lowest PC2 score is Greece (in the high-income category), indicating a very low score for the Digital Innovation and Transformation Ecosystem. Indonesia itself is in Quadrant IV, meaning it has a fairly good PC2 score (Digital Innovation and Transformation Ecosystem) (> 0), but a poor PC1 score (Digital Well-being and Social Connectivity) (< 0).

CONCLUSION

The relationship between the Digital Readiness Index (NRI) and economic growth indicates that digital readiness significantly boosts GDP across all income groups, with the greatest impact in high-income countries (61.9%), followed by middle-income countries

(30.4%) and low-income countries (0.2%). Digital readiness has become a relevant driver of economic growth, in line with the increasing access to and adoption of digital technology in recent years.

Governments and policymakers should therefore implement strategies tailored to the income level. (1) High-income countries, which already have strong digital readiness, should sustain and enhance their position by investing in emerging technologies such as AI, IoT, and 5G, strengthening innovation ecosystems, maintaining data security and privacy, and ensuring inclusive digital programs so all societal segments benefit. (2) Middle- and low-income countries require targeted measures: (a) increasing investment in ICT infrastructure to ensure equitable, reliable broadband access, including in rural and underserved areas; (b) expanding adoption of high-tech solutions through domestic R&D and technology transfer from developed countries to foster innovation and productivity; and (c) strengthening workforce skills through formal and informal education aligned with labor market needs, including digital literacy, coding, and digital entrepreneurship training. These strategies would allow governments across income groups to leverage digital readiness as a sustainable driver of growth while reducing digital inequalities and ensuring inclusive participation in the global digital economy.

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