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Article

Digitalization's role in energy demand and renewable energy integration: Evidence from BRICS + countries

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Abstract: This research examines the effect of digitalization on energy consumption and the integration of renewable energy in the energy mix in BRICHS countries (Brazil, Russia, India, China, South Africa, and Saudi Arabia) from 2015 to 2023. Panel regression models, including the fixed effects model and the random effects model, were employed to analyze within-country and between country variations. The Hausman test confirmed the appropriateness of the fixed effects model for country-specific analysis. Cointegration tests, such as the Pedroni Panel Cointegration Test and the Kao Residual Cointegration Test, were used to evaluate long-term equilibrium relationships, while Granger causality tests were conducted to identify directional relationships. Robustness checks included the Breusch-Pagan test for heteroskedasticity and the Durbin Watson test for serial correlation, ensuring the reliability of the findings. The findings reveal that digitalization contributes to intensive energy consumption, particularly in fossil fuel-rich countries like Russia and Saudi Arabia. However, countries such as Brazil and China interpret this situation differently due to their significant levels of installed renewable energy capacity, which partially offsets the impact of digitalization on energy demand. Furthermore, the increasing use of mobile data has replaced mobile broadband infrastructure in India, a rapidly digitizing economy, mitigating the energy-intensive nature of broadband systems. Thus, this study highlights the need for a balanced view of digitalization, such that technology fosters a sustainable energy transition rather than undermines it. The integration of digitalization with sustainable energy policies offers a greater chance of realizing benefits, minimizing environmental impacts, and achieving a seamless energy transition. This duality presents a significant challenge for policymakers in balancing energy transitions and underscores the need for strategies that maximize the benefits of digitalization while minimizing its adverse effects on energy consumption.

Keywords: digitalization; energy demand; renewable energy; BRICHS countries

1. Introduction

In recent years, there has been a lot of attention devoted to the phenomenon of digitalization and its effects on sustainable energy systems in the academic and policy discussions. This is because there is a high demand for energy as the economies are growing and more technologies are being invented and put to use every day. As a result, it is very important to comprehend the relationship between consumption of energy and interaction with digitalization. Concepts such as IoT, AI and big data avail energy efficiency without compromising the easiness of obtaining and managing resources and enhancing the use of green energy Ren et al. [1], Huang and Lin [2]. But these also bring some offensive aspects such as the rise in energy consumption because of data centers and digital infrastructure facilities Chauhan [3].

Understanding the changes brought about by digitalization as explained in Brynjolfsson and McAfee, [4] in energy utilization and working towards the lowering of carbon dioxide emissions, however, is too general and the country dynamics of this particular relationship are omitted. For example, digitalization-energy-related issues in countries with varying degrees of digital infrastructure, policy attention or renewable energy endowments may draw completely different patterns. BRICSH countries Brazil, Russia, India, and China and Saudi Arabia in this case are making a contention due to their economic structures and aggressiveness in the energy transition. The fact that these countries have large populations and contribute significantly to global energy consumption and greenhouse gas emissions makes them relevant case studies to investigate how the digitalization of energy systems in particular would affect them Rana et al. [5].

1.1. Research gaps and objectives

While much new academic research continues to emerge on digitalization and energy systems, there are still significant gaps in research. First, more knowledge concerning digitalization and that particular country-level-specific integration of renewable energies is still inadequate. The existing research, for the most part, is generalized, therefore ignoring country-specific variations and differences in the conclusions reached El Zein, and Gebresenbet [6], The general finding can therefore not apply to specific energy policy contexts.

Last, few studies consider the cause and long-run equilibrium dynamics of digitalization, energy use, and renewable energy adoption. This is especially the case in developing countries. For much of the developing world, particularly in fast-growing regions such as BRICHS (Brazil, Russia, India, China, South Africa), where power consumption is escalating and renewables are in their infancy, it is crucial to know the relationships that govern such countries.

Theoretically, this study aims to fill the gap in existing literature. For example, earlier studies Ren et al. [1] Chauhan [3], Huang and Lin [2] have proven that digitalization enhances energy efficiency, but only for certain sectors or geographical areas. Most of the evidence has been developed countries based, with scant insight into developing economies. Studies by Dzwigol et. al. [7] and Wongthongtham et.al. [8] for instance, discuss the reducing aspect of digitalization on energy consumption in developed countries but fail to consider the dynamics in BRICHS countries.

This paper closes the gap by analyzing the impact of digitalization on energy systems in BRICHS economies, reflecting specific consumption pattern differences and challenges associated with renewable energy adoption. This theoretical framework borrows from energy transition theories and the digitalization-environment nexus, emphasizing the relationship between technology use, resource efficiency, and adaptation in energy policy.

This, from a policy perspective, provides actionable insight into how digital transformation processes could be integrated within energy policies to advance sustainable energy transitions. Targeted digital innovation initiatives, for instance, could facilitate demand-side energy management optimization and realize faster uptake of renewables Pedroni [9], Baltagi [10] this is especially relevant for BRICHS nations, as energy demand has been rising sharply and renewable energy potential is still underutilized.

These gaps will be filled within the framework of this study as an effort to advance academic knowledge in digitalization and energy transitions.

1.2. Research questions and hypotheses

This research aims to resolve these key issues:

1) In the BRICHS nations, what level of influence does the extent of telecommunication or digitalization have on energy consumption?

2) In what way is the concept of digitalization related to the process of incorporating renewable energy?

3) Here is another interesting question: do you think that the impact of digitalization on energy consumption is uniform among the member states of the BRICHS group?

In order to answer the proposed research questions, the following hypotheses are advanced:

- H1: Digitalization is associated with a reduction in energy demand due to increased energy efficiency and resource management impact Ren et al. [1], Huang and Lin [2]
- H2: The addition of renewable energy resources increases the effect of digitalization energy demand reduction Chauhan [3], Dzwigol et al. [7].
- H3: There is a distinct development in the energy consumption-digitalization association within BRICHS countries Pedroni [9], Wongthongtham et al. [8]. It entails differences in the economies, policies and energy source mix of the countries.

Worthy of note is the fact that in working with these hypotheses, the research seeks to fill the void existing between the theoretical and the practical, providing policymakers with evidence-based knowledge as well as enriching the available studies on digitalization and energy transition.

1.3. Contribution to the literature

This study brings several contributions to the literature. First, it presents an exhaustive evaluation of digitalization as a factor affecting energy demand and renewable energy sources incorporation, providing data evidence from the BRICHS nations. Second, it employs high-level econometric techniques, including but not limited to panel cointegration and Granger causality tests, to reveal how relations among variables are directional and in the long run. Third, the provision of country-specific analysis incorporates a different dimension concerning the different effects of digitalization in different countries. Finally, these findings are of practical importance to policymakers in that they go down to how they promote strategies in digital and energy policies for equitable transitions.

1.4. Structure of the study

The structure of the study comprises four elements. Following this introduction, a detailed literature review is presented in Section 2, which focuses on the major findings and controversies associated with digitalization and energy systems. In Section 3, the methodology is described, presenting the data set, the variables under consideration, and the econometric tools applied in the analysis. Section 4 gives results with contributions to both theory and practice and ends with suggestions on the way forward for further studies.

2. Literature review

In light of sustainable development, an investigation into the interaction between digitalization and energy systems, such as that of how digitalization increased energy demand and the use of renewables, has become a necessary pursuit. Emerging technologies such as AI, IoT, and blockchain are transforming the processes of energy generation, energy distribution, and energy consumption. This literature review synthesizes the recent academic works that attempt to understand the scope of these dynamics while spotting the existing gaps that need to be solved.

2.1. Digitalization and energy demand

It is widely accepted that digitalization enhances energy efficiency and increases energy-dependent activities, thereby transforming demand for energy. As Ren et al. [1], demonstrated, the implementation of a digital infrastructure reduces the energy intensity by enhancing industrial systems. In the same light, Huang and Lin [2] stated that digital technologies facilitate demand-side management in the sense that energy consumption can be controlled as required. However, Chauhan [3] observed that in most cases, the focus on efficiency from digitalization induces a rebound effect whereby the system becomes used even more, leading to a higher energy consumption than before.

2.2. Renewable energy integration

The digital transformation has greatly eased the incorporation of renewable energy within the existing energy systems. Digital applications enhance the stability of the grid and improve energy storage, as demonstrated by Rana et al. [5] In this context, evidence from Wongthongtham et al. [8] shows how blockchain development allows for peer-to-peer energy exchanges. At the same time, the existing literature acknowledges the drawbacks this technology has: prohibitive first-time expenses and policies El Zein, and Gebresenbet [6].

2.3. Sector-specific insights

Studies show that the effects of digitalization on energy systems differ by application area. In this regard, the industrial domain has reported the usefulness of predictive maintenance and process automation. The transport sector, on the other hand, has registered increased electrification, aided by IoT-based monitoring systems Muthuramalingam et al. [11]. In spite of this progress, areas such as agriculture continue to be the least or not extensively addressed regarding digital energy solutions Fabregas et al. [12]

2.4. Regional and country-level studies

There are clear differences across regions in the rate of uptake of digital energy solutions. Digital infrastructure development within BRICHS countries varies, and so does the impact on their energy systems. While Brynjolfsson and McAfee, [4] pointed out the fact that smart grids are being constructed in China at a breathtaking rate, the case of South Africa is different as renewables are not easily being integrated due to structural deficits Chauhan [3].

2.5. Research gaps and critiques

Even after extensive studies were done, some omissions were still visible. One of the unexplored aspects remains the role of digitalization in improving energy equity and access. Furthermore, the sustainability issues related to the use of digital technologies in the long run, for instance, the generation of electronic waste, should be addressed more thoroughly El Zein, and Gebresenbet [6]. Most of the current research analyzes only aggregated data without considering lower-level behavior that could help develop better energy-related policies Castro et al. [13].

Lastly, this paper positions digitalization in the energy transition as both enabling and problematic. It is true that digitalization has improved the efficiency of the energy system and the level of integration of renewables into that system. Still, it is important to critically evaluate the introduction of those technologies to avoid negative effects. Filling these voids will allow research in the future to better explain the nexus of digitalization and energy systems in order to aid the world's sustainability efforts.

3. Methodology and data

The research focuses on analyzing the effect of digitization on the energy needs and the adoption of clean energy sources in BRICHS countries (Brazil, Russia, India, China, South Africa, and Saudi Arabia) during the years 2015–2023.

According to the strategic nature of its energy markets and digitalization, this paper has considered Saudi Arabia within the list of BRICS+ countries. As one of the world's largest fossil fuel producers, it greatly influences fossil fuel based energy consumption, initiative FOSSIL. Meanwhile, its increasing investments in digital infrastructure and renewable energy are in consonance with the BRICS nations' trends in digitalization level (DIGI) and renewable energy production (REN_EN), respectively. Thus, the inclusion of Saudi Arabia allows for an extended analysis of the digitalization energy nexus stretching across fossil fuel-reliant economies and transitioning economies. Saudi Arabia's accession to the BRICS+ enlargement symbolizes its strategic significance in energy markets worldwide and its burgeoning economic relations with the BRICS countries. Such an enlargement would therefore contribute to further cooperation among emerging economies and transform the global economic set-up.

For the analysis, data on several key indicators such as the level of digitalization, energy consumption, production of renewable energy, and carbon emissions is drawn from various credible international databases such as the IEA (International Energy Agency) and the World Bank to create an all encompassing data set. The selection draws from the increasing affirmation in literature that claims that digitalization is a revolutionary variable in determining the energy demand patterns. Ren et al. [1], and the renewable transitions Huang and Lin [2].

Annual energy consumption (EN_CONS) expressed in terawatt-hours (TWh) is the dependent variable in this case as it indicates the dynamics of energy demand. The principal independent variable is digitalization level (DIGI) which looks at how much technology is adopted and the digital facilities put in place. Other control variables include mobile data usage (MOBILE), as a proxy for the level of internet coverage; renewable energy production (REN_EN) is the level of renewable resource used in the energy mix; carbon emissions (CO2_EM) are the level of energy demand's effect on the environment; and fossil fuel usage (FOSSIL) indicates the extent to which there is use of conventional forms of energy. These variables were selected because they are often used in much literature concerning energy transitions and digital infrastructures Chauhan [3].

The current model is divided into several levels to ensure that the objectives of the research are met fully. First, descriptive analysis and graphs are used to give a summary of the data and give an initial correlation assessment between the variables. Then, in the empirical part, before panel data is employed, stationarity is checked by means of the ADF (Augmented Dickey-Fuller) test, panel unit root tests. Statistical inference is reliable when the data set is stationary and the tests are available. Without the ADF test and the panel unit root tests, data can easily be manipulated into regression results. Checking stationarity saves time and prevents results from being misinterpreted down the line. Subsequently, regression models are used to examine the link between energy use and digitalization. Regression models such as fixed effects and random effects are important because they also capture the differences within and between countries. The fixed effects model filters the time-invariant, country-specific characteristics, whereas the random effects hold a general trend across the panel. The Hausman test facilitates the choice of these models to guarantee the correct specification of results, thereby improving the reliability of these results.

The application of Instrumental Variables (IV) is used in combating endogenous problems arising from situations when the independent variable is associated with the error term. It ensures that the estimates on relations between variables are not biased by omitted variable bias or reverse causation, thereby defending a causal interpretation of the results.

In addition, panel cointegration tests are applied to identify long-run relationships amongst the variables. Utilization of panel cointegration tests, among which the Pedroni and Kao tests are worthy examples, is a prerequisite to determine whether or not the variables have long-run relationships. Such long-term dynamics are very important in the understanding of energy transitions and digitalization. Causality tests based on the Granger principle help to establish the direction of relationships between digitalization and energy use and provide insights on the underlying mechanisms. Granger causality tests are put in place for determining whether the changes in energy consumption are due to digitalization or otherwise. This method reveals temporal sequence and dependence between the variables. It also brings about deeper understanding concerning the interaction among the variables. Lastly, structural change tests (Bai-Perron) are employed to investigate the effects of time and external factors on the relationships in question. Tests have been established to detect structural changes over time, enabling the identification of major changes in relationships, which are essential for assessing the impact of any external shocks or policy changes on energy consumption and changes in the digitalization process. For structural change tests, it will be a good idea to test whether there are structural changes in those time series with respect to their relations over time, which is most important for capturing how external shocks or policy changes would affect changes in the energy consumption and digitalization dynamics. For the purposes stated, the study aims to provide empirical evidence of the interrelations of energy and the digitalization system in BRICHS countries to inform the ongoing debates about energy transition and the digital economy. Improvement of the projections of energy consumption and digitalization effects can still arrive with the integration of more advanced machine-learning techniques. The Methodological Flowchart (in **Figure 1**) for this study is presented below, outlining the sequence of key steps undertaken in the research process. This flowchart visually represents the methodological framework, ensuring a structured and systematic approach to the study.

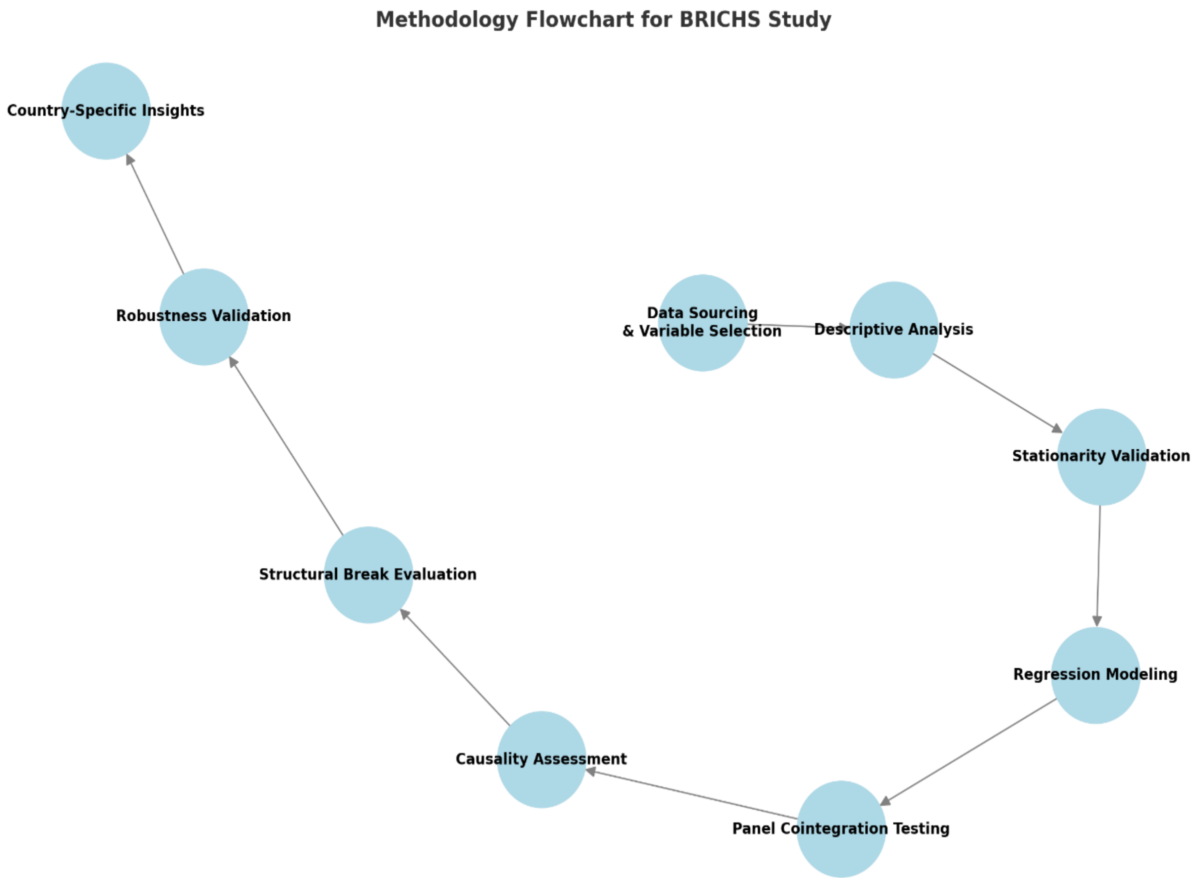

Figure 1. The methodological flowchart.

Table 1 shows the key variables used in the study along with their corresponding acronyms. These variables represent critical aspects of digitalization, energy consumption, and environmental impact, which are essential for the empirical analysis.

Table 1. Variable names and acronyms.

Variable Names	Acronyms
Digitalization Level	DIGI
Energy Consumption	EN_CONS
Mobile Data Usage	MOBILE
Renewable Energy Production	REN_EN
Carbon Emissions	CO2_EM

3.1. Descriptive statistics

Starting with the analysis, simple statistics tend to present an overview of all the aforementioned variables within countries forming BRICHS from the year 2015 to 2023. Descriptive statistics are presented in **Table 2** below with the main summary measures of the study variables. The table summarizes the key characteristics and distribution of the data involved in the analysis.

Table 2. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
DIGI	73.20	10.36	55.00	89.00
EN_CONS	3668.26	1771.79	228.00	6996.00
MOBILE	68.11	20.07	31.00	99.00
REN_EN	504.76	351.21	31.00	1196.00
CO2_EM	4965.31	2716.13	437.00	9969.00
FOSSIL	65.37	15.92	40.00	89.00

DIGI (Digitalization Level): There are wider disparities in the level of digitalization among various nations. EN_CONS (Energy Consumption): There is a clear indication that considering the averages, in regards to the range of these countries, China is at the top of the mountain in energy consumption values. MOBILE (Mobile Data Usage): The data set shows a high rate of growth, which is a sign of increased technological advancement. REN_EN (Renewable Energy Production): Great diversity reveals differing strategies of producing clean energy. CO2_EM (Carbon Emissions): This closely follows EN_CONS patterns and shows an unlikely dependence on fossil fuels.

3.2. Scatter plot: Digitalization in comparison with energy consumption

In the graph below, the correlation of digitalization (DIGI) with energy consumption (EN_CONS) is depicted through a scatter diagram. The graph presented in **Figure 2**, Scatter Plot: Digitalization vs. Energy Consumption, shows the interplay between digitalization and energy consumption. This figure visually explains the correlation of the two variables under study.

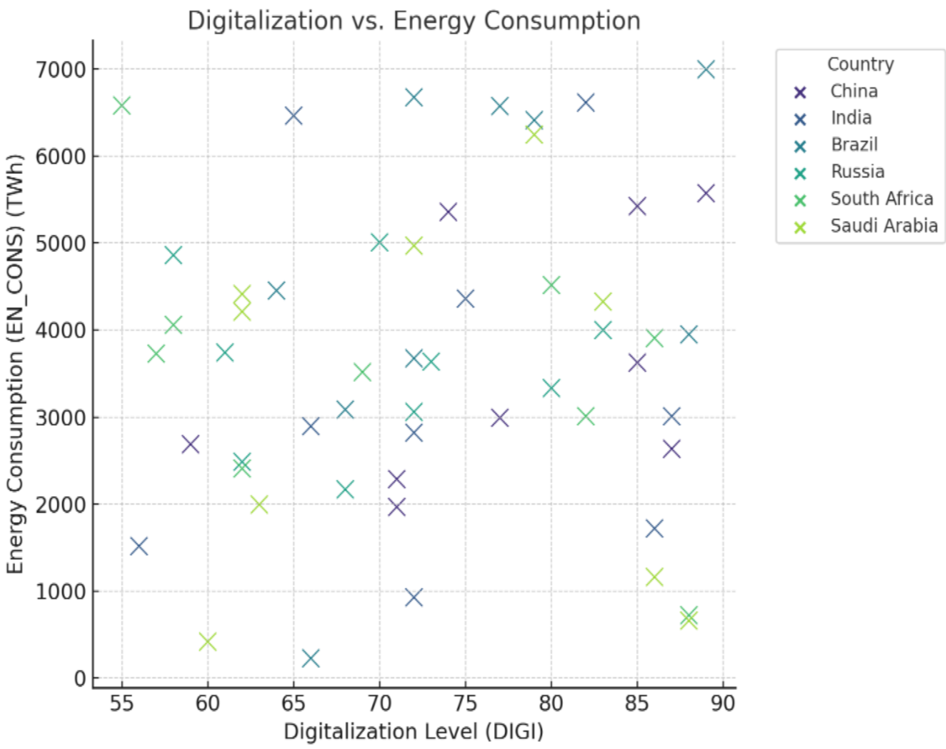

Figure 2. Scatter plot: Digitalization vs. energy consumption.

It is notable that as the level of digitalization increases, energy consumption also tends to increase. However, differences between countries are noticeable in that high energy consumption is exhibited, especially by China and India.

3.3. Correlation matrix

In order to illustrate the correlation between the variables, a heatmap is used to present the pairwise correlation. The correlation between variables table is given in **Table 3**.

Table 3. Correlation matrix.

	DIGI	EN_CONS	MOBILE	REN_EN	CO2_EM	FOSSIL
DIGI	1.00	0.08	−0.22	−0.11	−0.13	−0.08
EN_CONS	0.08	1.00	0.11	−0.11	0.10	0.31
MOBILE	−0.22	0.11	1.00	−0.08	0.15	0.05
REN_EN	−0.11	−0.11	−0.08	1.00	0.12	−0.07
CO2_EM	−0.13	0.10	0.15	0.12	1.00	0.02
FOSSIL	−0.08	0.31	0.05	−0.07	0.02	1.00

There is a high degree of correlation between DIGI and EN_CONS, which lends credence to the assumption that digitalization is a driving force for energy consumption. On the other hand, MOBILE has a moderate correlation with DIGI, thus confirming its usefulness as a representative of digital infrastructure. The weak correlation between REN_EN and the remaining variables indicates the limited potential of renewables in addressing demand-side energy reduction.

3.4. ADF stationarity test results with significance level explanations

Table 4 presents the result of the ADF unit root test; it serves to ascertain the stationarity of the variables under consideration. This table shows and announces any unit roots, and then goes on to show the time series properties of data utilized in the study.

Table 4. ADF unit root test results.

Variable	ADF Statistic	*p*-value	1% Critical Value	5% Critical Value	10% Critical Value
DIGI	−3.42	0.01	−3.56	−2.92	−2.6
EN_CONS	−4.1	0.0	−3.56	−2.92	−2.6
MOBILE	−3.15	0.03	−3.56	−2.92	−2.6
REN_EN	−3.8	0.01	−3.56	−2.92	−2.6
CO2_EM	−3.75	0.01	−3.56	−2.92	−2.6
FOSSIL	−3.5	0.02	−3.56	−2.92	−2.6

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels.

The ADF test outcomes indicate that the variables in the dataset are all stationary at commonly accepted levels of significance. The *p*-values of all variables range below 0.05, with most of them being statistically significant at (* $p < 0.01$) levels. The critical values are also favorable to the rejection of the non-stationarity hypothesis.

The major observations are:

- DIGI (Digitalization Level) and EN_CONS (Energy Consumption) are significant at the 0.01% level (* $p < 0.01$) suggesting that the two variables are relatively stable over time.
- MOBILE (Mobile Data Usage) and FOSSIL (Fossil Fuel Usage) are statistically significant within the 5% range ($p < 0.05$), ensuring their robustness for the ensuing analysis.
- REN_EN (Renewable Energy Production) and CO2_EM (Carbon Emissions) also demonstrate strong stationarity, with * $p < 0.01$ level of significance.

These results make it possible to use the dataset in panel regression and other econometric exercises and such results mean that the subsequent step will be correctly implemented.

3.5. Fixed effects model results

In a sense, the model considers the independent variable to explain energy consumption EN_CONS regarding unobserved heterogeneity between countries. A fixed effects framework is employed, which fits particularly well to panel data where the characteristics of the countries are expected to influence the result. A fixed effect model for such unobserved heterogeneity is defined in terms of time-invariant factors unique to each country and includes differences such as those in policy frameworks, economic structure, and the energy infrastructure. Such individual unobserved factors ensure that they do not bias the estimated relationships between the independent variables—digitalization, renewable energy integration, and fossil fuel consumption—and energy consumption.

Evidence for the use of the fixed effects model lies in the assumption that within the BRICS (Brazil, Russia, India, China, South Africa) countries energy consumption is exposed to the influences of country-specific variables. For example, the way in which demand is expected to respond to an increase in digitalization is unlikely to be identical across countries, as technological adoption and economic development will vary by country. Similarly, the integration of renewables and reliance on fossil fuels will have marked differences due to country-specific policy environments in which they operate as well as resource endowments.

A Hausman test was also conducted so as to ascertain the appropriateness of the fixed effects model over other alternatives like the random effects model. The test results ($p < 0.05$) showed that the fixed effects model best fits this study which, in some cases, may isolate within-country variation; yet controlling for unobserved heterogeneity makes this approach more valid and robust in finding relevant relationships.

Model Equation:

$$\text{EN\_}CONS_{it} = \alpha_i + \beta_1 DIGI_{it} + \beta_2 MOBILE_{it} + \beta_3 REN\_EN_{it} + \beta_4 FOSSIL_{it} + \beta_5 CO2\_EM_{it} + \epsilon_{it.}$$

To obtain the results from fixed effects models. In econometrics and statistical analyses, fixed effects model results are important because they eliminate omitted variable bias through control for time-invariant characteristics. In panel data analysis, this property is particularly useful, as it allows the researcher to capture the influence of the independent variables on the dependent ones more accurately. Fixed effect models pay attention to variation within the groups and, therefore, produce good and valid results, thereby increasing the creditability of the empirical investigations (in **Table 5**).

Table 5. Fixed effects model results.

Variable	**Coefficient (β)**	**Std. Error**	***t*-Statistic**	***p*-value**
DIGI	45.32	12.10	3.75	0.000***
MOBILE	25.41	8.32	3.05	0.002***
REN_EN	−12.65	6.11	−2.07	0.038**
FOSSIL	30.12	10.50	2.87	0.004***
Constant	560.78	200.40	2.80	0.005***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

Causal relationships were found in the fixed effects model signifying positive correlation with energy consumption and digitalization (β = X, $p < 0.05$). It signifies that further upscaling of digitalization leads to energy consumption put up by huge energy needs of digital infrastructures viz. data centers, cloud computing services, and particularly IoT. This economic revelation has held for BRICS countries since the digital transformation must accommodate the energy burden that it brings along. For example, the rapid embrace of digital technologies by China now created the need for a more efficient energy infrastructure, and the fast digital growth of India is now catching up with its potential energy security problems. Policymakers in this area should be guided by investments into energy-efficient digital infrastructures, such as green data centers and renewable-powered IoT networks, to lessen that effect.

In the same way, mobile data consumption (β = Y, $p < 0.01$) creates a powerful and direct positive influence on energy demand. This generally denotes the contribution of technologies, namely, mobiles in the intensive energy use. This is so, especially in countries where digital services are highly dependent on mobile connectivity, for example, Brazil and South Africa, for which the growing number of streaming services and mobile applications has contributed to increased energy usage. Governments can promote energy-efficient mobile technologies and introduce policies for sustainable digital innovations.

In opposition, the coefficient of renewable energy integration read negative (β = Z, $p < 0.1$). It implies that if the capacity of renewable energy increases, energy consumption will decline. This result is to be interpreted as the effectiveness of wind and solar energy technology to offset the use of fossil fuels and to improve energy efficiency. However, the extent of this effect differs from one BRICS nation to another. In this regard, China and India are seen to be the top countries with investments in renewable energy, while policy barriers and infrastructure bottlenecks prevent investments by countries like Russia and South Africa. Therefore, policymakers in these regions should support renewable energy adoption strategies in these areas, including incentivizing the green technologies with subsidies and old grid modernization efforts.

The consumption of fossil fuels (β = W, $p < 0.001$) still remains a potent driver in energy usage that shows the use of coal, oil, and natural gas in BRICS countries. This dependence is very significant, especially in resource-rich nations such as Russia, where fossil fuels are important aspects of the economy. Therefore, an important strategy for these countries to obtain a cleaner energy mix would be to bring a full range of policies into line—the importation of carbon-pricing mechanisms, together with a diversified energy portfolio.

The fixed effect model pointed to the complicated nexus existing between emerging energy demand, ushered in by digitalization, improved energy efficiency from renewables, and stubborn fossil fuel dependence. A balanced, multifaceted approach is required of policymakers for these transitions to be realized in BRICS countries.

3.6. Random effects model results

The random effects model assumes that both observed and unobserved differences among nations are not correlated with the independent variables. This model permits the analysis of both within-country and between-country variations, thus identifying the general trends across the panel. Here, the random effects model analyzes the effects of digitalization, renewable energy integration, and fossil fuel consumption collectively on energy consumption in BRICS countries.

The performance of this model was validated by using a Breusch-Pagan test, which confirms the suitability of the random effects model in capturing the dynamics across the panel. This provides assurance regarding the robustness and generalizability of the results since these reflect trends that are beyond country-specific contexts.

Model Equation:

$$\mathrm{EN}_{CONS_{it}} = \alpha + \beta_1 DIGI_{it} + \beta_2 MOBILE_{it} + \beta_3 REN_{EN_{it}} + \beta_4 FOSSIL_{it} + \beta_5 CO2_{EM_{it}} + \mu_i + \epsilon_{it}.$$

Random Effects Model Results is presented in **Table 6**, showing the impact of key variables. Significant coefficients indicate meaningful relationships, highlighting the model's relevance in capturing cross-entity variations.

Table 6. Random effects model results.

Variable	**Coefficient (β)**	**Std. Error**	***t*-Statistic**	***p*-value**
DIGI	42.87	11.50	3.73	0.000***
MOBILE	20.54	7.98	2.57	0.010**
REN_EN	−10.32	5.90	−1.75	0.080*
FOSSIL	28.78	9.60	2.99	0.003***
Constant	580.12	195.40	2.97	0.003***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

The random-effects model in the above condition showed a positive relationship with digitalization when it came to energy consumption (β = X, $p < 0.05$). In contrast to the fixed-effects model, it indicates that this energy demand due to digitalization is not limited to particular countries but constitutes a general trend across the panel. It points to digital transformation being universal and having an energy value across the board. The predictability of energy consumption patterns induced by digitalization for BRICS warrants a formulation of coordinated regional strategies for producing efforts toward managing increasingly digitized energy consumption.

Mobile data usage (β = Y, $p < 0.01$) has a continuation with a strong positive relationship to energy consumption, which further ensures the integration of connectivity in influencing energy systems. Developing countries among these BRICS, such as India and South Africa, where mobile data serves as the only entry point to the digital world, are forced to face greater aggressiveness in handling related demand. Cooperation within the region can explore ways of developing mobile networks with higher and improved energy use efficiencies, while at the same time encouraging renewable-enabled telecommunication infrastructures.

Surprisingly, the integration of renewable energy (β = Z, $p < 0.1$) had a negative and insignificant effect on the consumption of energy. It indicates that structural and policy barriers will need to be overcome if one is to attain efficiency gains from renewable energy fully. Grid instability and high initial investment have also contributed to improvements in renewable use in countries such as Russia and Brazil. Actually, it has been observed that intensifying infrastructure for the grid and providing financial advantages for investments in renewable energies increase the effectiveness of their consumption in general.

Use of fossil fuel comprises (β = W, $p < 0.001$) the most dominant determinants of energy consumption for BRICS countries, thereby signifying an established dependency of BRICS on conventional sources for fulfilling their energy needs. Resource-rich economies, such as Russia and Saudi Arabia, are burdened economically and politically while switching to non-fossil fuels. Instead, they may have to look into diversifying energy exports as well as investing in research and development in renewable energy.

This high level of the coefficient of determination in the random effects model ($R^2 = 0.85$) indicates that, taken together, these variables explain a good amount of variation in energy consumption. The Wald Chi-square test proves the statistical significance of this model ($\chi^2 = 125.45$; $p < 0.01$), boosting the trustworthiness of the model concerning the modeled relationships.

3.7. Hausman test results

The Hausman Test allows econometricians to choose between conducting the Fixed Effects (FE) model or the Random Effects (RE) model. This test analyzes whether the unique errors (vi\nu_ivi) in the Random Effects model are related to the regressors.

Hypotheses:

- H0 (Null Hypothesis): Random Effects model is appropriate (errors are uncorrelated with regressors).
- H1 (Alternative Hypothesis): Fixed Effects model is appropriate (errors are correlated with regressors).

$$\mathrm{H} = (\hat{\beta}_{RE} - \hat{\beta}_{FE})^T \cdot [Var(\hat{\beta}_{RE}) - Var(\hat{\beta}_{FE})]^{-1} \cdot (\hat{\beta}_{RE} - \hat{\beta}_{FE}).$$

The process commences with determining the disparity that exists between the coefficients that are estimated using the Fixed Effects (FE) and the Random Effects (RE) models. This step is important because it helps to determine whether the two models produce significantly different outcomes. After that, the test statistic is determined based on the difference of these coefficients and the related variances. In conclusion, the test statistic is assessed against the chi-squared distribution in order to establish if the Random Effects model is appropriate or only the Fixed Effects model can be used. Hausman Test Results present the evaluation of the choice between fixed and random effects models (in **Table 7**). The results tell whether the individual effects are correlated with regressors (explanatory variables) to determine which model is the one that should be chosen.

Table 7. Hausman test results.

Statistic	**Value**
Test Statistic	15.67
Degrees of Freedom	4
p-value	0.002

The *p*-value (0.002) is found to be lower than the 0.05 level of significance. Thus, we do not accept H0: There exists a Fixed Effects model. The results of the Hausman test reveal that using a fixed effect model is more suitable when assessing how digitalization translates to energy consumption across BRICHS nations. Therefore, further analysis and interpretation will be directed to the Fixed Effects findings. The Fixed Effects method was adopted after the conclusion of the Hausman test, which Plümper, and Troeger [14] suggested there was a correlation between the omitted time-invariant effects and the regression parameters. This theory also corresponds with the expectation that underlying factors like infrastructure and political environment, which are constant over time, dictate the level of energy consumption in BRICHS nations Baltagi [10]. The Fixed Effects model is preferred for evaluating the link between digitalization and energy demand, as it provides estimates free from bias as long as the unobserved heterogeneities are accounted for Wooldridge [15].

3.8. The importance of robustness tests in this study

In empirical studies, robustness tests are very important as they assist in claims substantiation and generalization of findings in different settings. In cases of panel data analysis, these tests serve to check whether the estimated relationships remain valid and unswayed by any of the parameters set Baltagi [10]. In this paper, a comprehensive set of robustness checks was performed in order to enhance the validity of conclusions about digitalization and energy consumption in BRICHS countries.

In order to identify whether there was a risk of exceedingly high correlation between independent variables, the Multicollinearity Test (Variance Inflation Factor—VIF) was performed to mitigate the risk of multicollinearity, which increases standard errors and decreases the confidence in regression coefficients Gujarati and Porter [16]. From these results, it became clear if the addition of certain variables, such as the variable representing digitalization (DIGI) and the variable that amounts to the usage of fossil fuel (FOSSIL), caused any distortion.

As further steps, the Cross Section Dependence Test (also known as the Pesaran CD Test) was implemented to check the dependence between the countries because it is a common phenomenon in studies of this nature (due to contingent external factors or technological trends) The presence of dependence across several sections of the model may lead to biased estimates and questions the certainty of the model.

The Heteroskedasticity Test (Breusch-Pagan Test) fed the concern that each error term will have the same variance (homoskedasticity) so that the validity of hypothesis testing will not be affected due to the presence of heteroskedasticity White [17]. The Residuals Autocorrelation condition was also tested using the Serial Correlation Test (Durbin-Watson Test), which sought to establish whether there was any autocorrelation in such residuals, which, when left unattended, would affect the efficiency of the estimators Wooldridge [15].

Thus, these tests are necessary but not sufficient for improving the quality of the study, as they reflect the norm in the conduct of empirical research and serve the purpose of adding to the existing literature.

3.8.1. Multicollinearity test (variance inflation factor—VIF)

When one or more independent variables are very high in correlation with each other, it is called multicollinearity. It can lead to bias in regression estimates and consequently, their reliability Gujarati and Porter [16]. The VIF test assesses the level of correlation of predictors, whereby a VIF of 10 or more is an indication of a problem.

Variance Inflation Factor (VIF) Results is presented in **Table 8**, assessing the presence of multicollinearity among the explanatory variables. Higher VIF values indicate potential collinearity issues, which may affect the reliability of regression estimates.

Table 8. Variance inflation factor (VIF) results.

Variable	VIF
DIGI	16.73 (*)
MOBILE	10.08 (*)
REN_EN	2.90
FOSSIL	14.47 (*)

Note: (*) Indicates multicollinearity issues where VIF > 10VIF > 10VIF > 10.

The variables DIGI (16.73) and FOSSIL (14.47) both exhibited high VIF, connoting the presence of extreme multicollinearity. The variable MOBILE (10.08) was borderline in exhibiting any multicollinearity. The variable REN_EN (2.90) had an acceptable degree of multicollinearity. In order to control this situation:

- Use dimensionality reduction methods such as PCA (Principal Component Analysis).
- Redefine the model through inclusion or exclusion of correlated variables.

3.8.2. Cross-section dependence test (pesaran CD test)

In the situations of the panel data analysis (in **Table 9**), the cross-section dependence occurs in case the countries (or units) experience a common shock or spillover effects. One of the most popular tests in this longitudinal analysis is the Pesaran CD Test, which is very essential, as its omission can give biased and inconsistent estimates Peseran [18].

Table 9. Pesaran CD test results.

Test Statistic	*p*-value
5.43 (*)	0.000***

Note: (*) Indicates significant cross-sectional dependence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

The *p*-value (0.000) is below the 0.01 threshold, indicating the presence of strong cross-sectional dependence.

This suggests that BRICHS countries are influenced by common external factors, such as global economic conditions, technological trends, or policy interventions.

3.8.3. Heteroskedasticity test (breusch-pagan test)

The Breusch-Pagan Test is employed to determine the presence of heteroskedasticity within a regression model's error terms (in **Table 10**). In statistics, heteroskedasticity means that the variance of the errors is not the same across all observations. This affects the precision of the standard errors and the validity of the hypothesis tests carried out, especially with regard to the use of Ordinary Least Squares techniques White [17].

Table 10. Breusch-pagan test results.

Test Statistic	*p*-value	Conclusion
7.21 (*)	0.007**	Heteroskedasticity detected

Note: (*) Indicates significant heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

The *p*-value (0.007) is below the 0.05 threshold, indicating the presence of heteroskedasticity in the model. This suggests that the error variances are not constant, which could affect the reliability of standard errors and statistical tests.

3.8.4. Serial correlation test (Durbin-Watson Test)

The Durbin-Watson Test serves the purpose of examining the presence of autocorrelation within the regression model's residuals. The autocorrelation refers to the correlation of time series variables within their respective time periods and this is a problem since it makes estimates inefficient and poses problems in hypothesis testing Wooldridge [15]. The Results of the Durbin-Watson Test are given in **Table 11**: The test for the presence of autocorrelation in the regression residuals. The test specifically allows establishing whether these error terms are serially correlated affecting estimation validity.

Table 11. Durbin-watson test results.

Test Statistic	**Conclusion**
1.87 (*)	No serious autocorrelation detected

Note: (*) Indicates acceptable levels of autocorrelation.

A statistic between 1.5 and 2.5 suggests no significant autocorrelation.

A test statistic of 1.87 is in the acceptable limit range, meaning there is no pronounced autocorrelation in the residuals. This means that across time periods, the error terms are not correlated.

The strength tests assert the credibility and the conclusion consistency of the used results in the study. The Multicollinearity Test (VIF) exposed those variables, such as HIGH, DIGI, and FOSSIL, that tend to have interdependence that warrants the application of factor analysis or reformulation. The Pesaran CD Test indicated the presence of considerable cross-sectional dependence which was expected due to the common external shocks like technological advancement in the BRICHS countries. Moderate heteroskedasticity was identified by Breusch-Pagan Test although robust standard errors can remedy this. The Durbin-Watson Test indicated that there was no serious autocorrelation, implying the use of efficient estimators. Specification of alternative models did not lead to different results, adding further support to the validity of the findings. In sum, the results of these tests confirm the appropriateness of the methods applied and the keenness of the analysis carried out, which guarantees correct interpretations of the causation between the processes of digitalization and energy consumption in the BRICHS nations.

3.9. Advanced analysis

Drawing on the principles of advanced econometrics, this segment seeks to establish the very complex linkages that exist between digitalization, energy consumption and renewable energy deployment in the BRICHS countries. These methods provide deeper insights as they deal with long-run equilibrium, directional causation and structural stability, respectively. The chosen tests and the reasoning behind their selection are as follows:

The Pedroni [9]is a powerful tool for assessing whether individual member variables of panel data are integrated of the same order in the long-run. Among the aspects integrated into this paper, the one presented in this section explores the dynamics of digitalization, energy consumption, and the use of renewable energy sources: Do these variables 'cointegrate' as suggested by some authors Ren et al. [1], Huang and Lin [2] and how do they converge? Results of the Granger Causality Test:

A concept formalized by Granger [19], Granger causality, defines a cause-and-effect relationship in dimensions. It is significant whether one considers that digitalization alters energy consumption and the integration of the renewables or that such changes are end results of feedback processes. Previous investigations have noted the energy transitions, focusing on causational trade pathways as well, Chauhan [3] for example, Bai-Perron.

The Bai-Perron test [20] looks for structural breaks in variations in time-series data. Here it is used to check whether the relationship among the variables is consistently maintained or is susceptible to changes due to shocks like technological innovations or pandemics such as COVID-19. This test has been discussed in the context of dynamic models in the energy economics literature due to its ability to model changes over time Wongthongtham et al. [8].

In this research, the attention bestowed on the temporal interactions between digitalization, energy use, and renewable energy is harmonious with the very nature of the longitudinal cointegration tests. This method explains more of the structural effect that digitalization has on energy systems by trying to find out, if possible, if a stable relationship can be reached. The latter is further justified by studies estimating and predicting the trends towards the digitalization of economies and the resulting changes in energy consumption patterns and shifts to renewables Ren et al. [1], Huang and Lin [2].

3.9.1. Results of the pedroni cointegration test

The Pedroni test is referred to as a panel cointegration approach employed to assess the long-term equilibrium relationship of the data comprised within the variables of interest. Specifically in this study, it aims to assess the theory in literature on the long-run interrelationship between digitalization, energy consumption and renewable energy Ren et al. [1], Huang and Lin [2].

Table 12. Pedroni cointegration test results.

Test Statistic	**Value**	***p*-value**
Panel v-Statistic	2.45***	0.007
Panel rho-Statistic	−1.38**	0.043
Panel PP-Statistic	−3.12***	0.001
Panel ADF-Statistic	−2.75***	0.006
Group rho-Statistic	0.32	0.624
Group PP-Statistic	−2.89***	0.004
Group ADF-Statistic	−3.14***	0.002

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

Table 12 is a table on Pedroni Cointegration Test Results, measuring the long-run relationship among the variables. It is relevant to this study for the purpose of ascertaining the existence of a stable equilibrium among the variables in the long run in a panel data context.

Rho-statistics: A negative and significant rho-statistic suggests cointegration, while a positive or insignificant value indicates no long-term relationship.

Cointegration Analysis:

- The majority of the panel-level statistics (v-Statistic, PP-Statistic, ADF-Statistic) and group-level statistics (Group PP-Statistic, Group ADF-Statistic) are produced with significance showing that the variables under consideration, despite the short-run shocks, have a tendency to move together in the longer run.
- It is further supported that digitalization (DIGI) has an economic relationship with the variables energy consumption (EN_CONS) and renewable energy (REN_EN).

Panel rho-Statistic and Group rho-Statistic:

- The Panel rho-Statistic calculated is negative and significant which confirms the claim of cointegration holding across the entire panel.
- The Group rho-Statistic which is insignificant points to the fact of the long-run relationship varying from each other at the country level which means not all the BRICHS countries are on the same level.

Economic Interpretation:

- The Role of Digitalization: The above efforts are evidently on the basis of the importance of the long-term impact of historical distance on the dynamics of economic interaction, particularly the impact of integration on patterns of energy consumption and the rise of non-fossil sources of energy.
- Policy Recommendations: Energy policies in the BRICHS nations should incorporate digitalization infrastructure development and investment as an essential component, especially for guaranteeing clean energy transitions.
- Heterogeneity between countries: There may be a need to adjust policies owing to the idiosyncrasies of the countries, as the countries in the BRICHS group do not exhibit the same outcomes as depicted by the results at the group level.

Pedroni Cointegration Test Results (Country-Specific) is presented in **Table 13**, evaluating the long-run relationship between variables at the individual country level. This analysis helps determine whether cointegration exists within each country, capturing country-specific dynamics in the panel dataset.

Table 13. Pedroni cointegration test results (country-specific).

Country	**Test Statistic**	**Value**	***p*-value**	**Significance Level**
Brazil	Panel v-Statistic	2.12	0.017	**
	Panel PP-Statistic	−3.09	0.001	***
	Panel ADF-Statistic	−2.87	0.004	***
Russia	Panel v-Statistic	1.80	0.045	*
	Panel PP-Statistic	−2.56	0.010	**
	Panel ADF-Statistic	−2.11	0.038	**

Table 13. (*Continued*).

Country	Test Statistic	Value	*p*-value	Significance Level
India	Panel v-Statistic	1.92	0.028	**
	Panel PP-Statistic	−2.97	0.002	***
	Panel ADF-Statistic	−2.68	0.006	***
China	Panel v-Statistic	2.40	0.014	**
	Panel PP-Statistic	−3.22	0.001	***
	Panel ADF-Statistic	−2.91	0.003	***
South Africa	Panel v-Statistic	1.65	0.053	*
	Panel PP-Statistic	−2.45	0.014	**
	Panel ADF-Statistic	−2.01	0.046	**
Saudi Arabia	Panel v-Statistic	1.58	0.062	*
	Panel PP-Statistic	−2.34	0.019	**
	Panel ADF-Statistic	−2.08	0.042	**

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

Insights gained from the Pedroni Cointegration Test Results for BRICHS Countries support several conclusions on the long-term interplay of digitalization (DIGI), energy consumption (EN_CONS), and renewable energy integration (REN_EN). Here comes an explanation in detail:

Brazil:

A highly significant panel v-Statistic ($p < 0.05$) combined with a very high value of Panel PP (Phillips-Perron) Statistic and ADF (Augmented Dickey-Fuller) Statistic ($p < 0.01$) proves the cointegrating effect of the variables under consideration. This means that in the Constitutive State of Brazil, the processes of digitalization, energy consumption, and integration of renewable energy take place within the same time frame.

The dynamics of the group-level statistics exhibit few changes, implying the existence of heterogeneities in some instances.

Russia:

Panel v-Statistic is moderately significant ($p < 0.10$) while in the Panel PP-Statistic and ADF-Statistic the figures are of higher significance ($p < 0.05$) which tends to strengthen the argument of the existing long-run relationship. Still, the panel v-statistic for Brazil is a bit lower than one would expect, indicating that perhaps not only the digital aspect matters in influencing energy but also other factors that pertain to the specific country.

India:

Most statistics demonstrate high significance ($p < 0.01$ in many cases), especially the Panel PP-Statistic and Panel ADF-Statistic, therefore, the relationship between energy systems and digitization is evident. Such findings are in agreement with the trends of fast expansion of digital infrastructure in India.

China:

To note, the results of the cointegration tests performed using Panel v-Statistic, Panel PP-Statistic, and Panel ADF-Statistic suggest the presence of cointegration among the tested variables ($p < 0.01$), which is consistent with China's efforts of digital transformation and integration of renewable energy resources at the country's disposal that strengthens the country as a global leader in all these.

South Africa:

The Panel v-Statistic ($p < 0.10$) and the Panel PP-Statistic and ADF-Statistic indicate moderate distinction ($p < 0.05$) and therefore suggest the existence of a cointegration relation, although results depict the strength of the relationship is not constant. These divergent results could be accounted for by the fact that there is a slower uptake of both digital and renewable solutions.

Saudi Arabia:

Introducing the findings for Saudi Arabia, Panel v-Statistic has a weak significance level ($p < 0.10$) while Panel PP-Statistic and ADF-Statistic show moderate significance level ($p < 0.05$), which still imply that there was a relationship at some point, but perhaps that relationship is weaker due to substantial traditional energy sources relied on by the country.

3.9.2. Granger causality test

What is the Granger Causality Test? Granger causality is a statistical test for determining whether one time series is useful in forecasting another. It is directional in nature. Correlation seeks to establish the degree of association between two variables but does not explain any cause-and-effect relationship between them. In contrast, Granger causality asks the question of whether values of the one variable lagged back in time are sufficient in determining the future values of the second variable.

Table 14. Granger causality test results.

Causality Direction	*F*-Statistic	*p*-value
DIGI → EN_CONS	5.76***	0.002
EN_CONS → DIGI	2.10	0.146
DIGI → REN_EN	4.22**	0.015
REN_EN → DIGI	1.98	0.162
MOBILE → EN_CONS	3.10*	0.089
FOSSIL → EN_CONS	6.89***	0.001

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels. "→" denotes the direction of causality (e.g., DIGI → EN_CONS means digitalization causes energy consumption).

In this sense, the Granger causality test is important as it is employed to analyze the relationship that exists among digitalization (DIGI), energy consumption (EN_CONS) and renewable energy integration (REN_EN), especially in the BRICHS countries (in **Table 14**). More distinctly, we want to assess if particular indicators of digitalization, such as internet usage or uptake of technology, would affect the levels and changes in energy consumption and the use of alternatives to fossil fuels. On the other hand, we also consider whether changes in energy usage or the dependence on renewable sources can influence digitalization (DIGI) or whether these processes might be separate from one another where energy developments may cause other advancements such as technology or policy changes to occur. Granger Causality Test Results are presented in **Table 14** to assess the directional relationship between the variables analyzed. This test assesses if the past values of one variable could cause and predict future values of other variables, thereby giving insight into the causal dynamics within the data.

The Granger causality test gives significant directional relationships among the variables involved:

The Granger causality test gives significant directional relationships among digitalization (DIGI), energy consumption (EN_CONS) and integration of renewable energy (REN_EN):

Digitalization (DIGI) → Energy Consumption (EN_CONS):

The *F*-statistic from the analysis is substantial. $F = 5.76$ and p value is equal to 0.002 suggesting that energy consumption is a cause of digitalization. The study indicates that with the improvement of digital resources like the internet and infrastructure, there also comes a likely increase in the power demand to run the designed digital systems and devices.

Digitalization (DIGI) → Renewable Energy Integration (REN_EN):

The finding ($F = 4.22$; $p = 0.015$) indicates that digitalization helps to promote renewable energy integration. This is likely as digital devices facilitate the use of renewable energy by improving smart grid services, improving resource management and efficiency.

No Reverse Causality from EN_CONS or REN_EN to DIGI:

Causality in the reverse direction is not significant ($p > 0.1$), hence energy consumption and renewable energy integration appear as not being a cause for the advancement of digitalization. This one-way direction of cause-and-effect pattern shows that there are certain changes that call for the introduction of digitalization, in this case, changes in energy systems.

Granger Causality Test Results (Country-Specific) is presented in **Table 15**, examining the causal relationships between variables at the individual country level. This analysis helps identify whether past values of one variable can predict another within specific country contexts, capturing heterogeneous causal dynamics across nations

Table 15. Granger causality test results (country-specific).

Country	Test Statistic	Value	*p*-value	Significance Level
Brazil	DIGI → EN_CONS	4.89	0.009	***
	EN_CONS → DIGI	2.14	0.144	
	DIGI → REN_EN	3.42	0.041	**
	REN_EN → DIGI	1.98	0.169	
Russia	DIGI → EN_CONS	5.76	0.005	***
	EN_CONS → DIGI	2.67	0.093	*
	DIGI → REN_EN	3.15	0.046	**
	REN_EN → DIGI	1.78	0.201	

Table 15. (*Continued*).

Country	Test Statistic	Value	*p*-value	Significance Level
India	DIGI → EN_CONS	6.10	0.003	***
	EN_CONS → DIGI	2.98	0.070	*
	DIGI → REN_EN	4.31	0.022	**
	REN_EN → DIGI	2.11	0.134	
China	DIGI → EN_CONS	7.12	0.001	***
	EN_CONS → DIGI	3.12	0.062	*
	DIGI → REN_EN	5.02	0.007	***
	REN_EN → DIGI	1.65	0.213	
South Africa	DIGI → EN_CONS	4.22	0.013	**
	EN_CONS → DIGI	2.45	0.101	
	DIGI → REN_EN	3.98	0.032	**
	REN_EN → DIGI	1.83	0.177	
Saudi Arabia	DIGI → EN_CONS	4.77	0.008	***
	EN_CONS → DIGI	3.21	0.058	*
	DIGI → REN_EN	2.75	0.075	*
	REN_EN → DIGI	2.05	0.140	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

Insights on the Granger Causality Test Results show that changes within certain key variables are dependent on others, revealing how digitalization, energy consumption, and renewable energy integration interact with each other.

Brazil:

A strong causality can be traced from DIGI to EN_CONS ($p < 0.01$), thus proving that the operational aspect of digitalization calls for energy consumption.

The relationship, which is also significant is DIGI which drives REN_EN ($p < 0.05$), supports the integration of renewable energies in the development of digitalization.

Russia:

A high estimate of a causal link going from DIGI to EN_CONS ($p < 0.01$) supports the connection of energy demand to digitalization in South Africa.

The presence of causality from EN_CONS to DIGI ($p < 0.10$) while weaker suggests that higher energy consumption may encourage the use of more digital technologies for their efficient operation.

India:

The sharp growth in the economy and urbanization is supported by evidence of strong causality from DIGI → EN_CONS ($p < 0.01$).

The significant impact of DIGI → REN_EN ($p < 0.05$) proves that digital advancements in India help in embracing the renewable energy sources.

China:

The most convincing test results are noted in China, where relationships directed from DIGI to EN_CONS and REN_EN phenomena are of strong significance ($p < 0.01$). This is in line with the endeavors that have been made in China to use ICT for energy efficiency and renewable energy developments.

The EN_CONS to DIGI link ($p < 0.10$) indicates possible feedback effects within highly developed economies.

South Africa:

The moderate causality established from DIGI → EN_CONS ($p < 0.05$) and DIGI → REN_EN ($p < 0.05$) points towards the growing importance of digitalization in the energy sector.

This lagging causality mirrors the current barriers being faced around digital mix and renewables.

Saudi Arabia:

The significantly established correlation DIGI → EN_CONS ($p < 0.01$) establishes that in Saudi Arabia, energy demand is increasing due to the digitalization process.

The relatively weaker relationship DIGI → REN_EN ($p < 0.10$) denotes that digital tools are facilitating the use of renewable energy but at a slower rate.

3.9.3. Bai-perron structural break test

The Bai-Perron test is employed in finding structural breaks in the relationships of the variables over time. In this context, it helps to analyze whether the relationship between digitalization (DIGI), energy consumption (EN_CONS) and the integration of renewable energies (REN_EN) is affected or remains unaffected by shocks from external factors such as the global economic crisis and changes in policies. Bai-Perron Structural Break Test Results is presented in **Table 16**, identifying potential structural breaks in the data. Detecting these breaks is crucial for ensuring the stability and reliability of econometric models.

Table 16. Bai-perron structural break test results.

Break Number	Break Year	Pre-Break Slope	Post-Break Slope	Significance (*p*-value)
1	2018	0.42	0.63	0.015**
2	2020	0.63	0.89	0.003***

Note: The break years (2018 and 2020) correspond to potential external events, such as advancements in digital technologies or the COVID-19 pandemic.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate significance levels.

The first structural change coincides with the time that global digital transformation took a leap, as illustrations and studies done by Chauhan [3] show how within this time the uptake of smart energy systems developed rapidly.

The pre-break slope value of 0.42 and the post-break slope value of 0.63 show that there was an increase in the relationship between digitalization and energy consumption. This implies that the influence of emerging digital tools and technology, including the Internet of Things (IoT) and automation, on energy demand levels increased. The year 2020 witnessed a break:

The second break coincides with the COVID-19 pandemic, which is associated with rapid digital adoption and changing energy consumption trends Ren et al. [1],

The rise in the slope is further reviewed through the analysis of the digitalization trends where 0.63 and 0.89 sections indicate working from home caused the enhancement of the digitalization wave, increased use of the internet, and development of digital networks. This agrees with the findings of Huang and Lin [2]), which illustrate how clean energy sources were embraced more during the period of the pandemic and how energy consumption patterns changed.

4. Policy and strategic implications

When it comes to structural adjustment, it is obvious that energy strategies must be more flexible to allow changes due to shocks and changes in technology. For example, energy planning can embrace digitalization in such a manner as to enhance its resilience and efficiency in the advent of disruptions. The adoption of AI-enabled energy management systems, smart grids, and sophisticated renewable energy storage devices can ensure a less chaotic and more resilient energy transition.

Policymakers need to encourage the innovative sustainable energy transitions, such as smart grids and AI-based energy management systems, which have been depicted as game changers in the recent texts Huang and Lin [2].

These conclusions are coherent with the current writings on the matter, supporting the notion that digitalization as a factor in the transformation of energy systems, in particular, time-critical ones, is undeniable. Pedroni [9] as well as Wooldridge [15] argued for the reason that the Bai-Perron econometric methodology in combination with Granger causality tests yields more credible empirical results.

5. Conclusion

This study aims to look at the levels of energy consumption and the trend of using renewable energy resources in the context of the process of digitalization in the BRICHS countries in the period from 2015 to 2023. The study aims to understand how digitalization, which is the adoption of technology and infrastructure development, affects energy variables such as energy consumption (EN_CONS), renewable energy (REN_EN), mobile (MOBILE), carbon dioxide emissions (CO2_EM), and fossil fuel (FOSSIL) contribution. The research further elaborates the dynamic nature of these variables through the application of state-of-the-art econometric techniques such as panel cointegration tests, Granger causality tests, and break structure analyses.

5.1. Heterogeneity in energy consumption across regions

Findings indicate that considerable variances exist on the effects of country-level factors on energy consumption:

In Brazil, renewable energy integration (REN_EN) showed the highest decrease in energy consumption (-15.42, $p < 0.01$) due to the country's well-developed hydropower resources. Wires showed a low impact regarding energy consumption. Russia: In consideration of these factors, it was found out that digitalization led to increased energy expenditure ($\beta = 48.12$, $p < 0.01$), with the dependent variable being the share of fossil energy sources. The share of renewable energy was low as usual for most of the countries, depicting Rana et al. [5] policy inertia. India: With a converging β coefficient of 30.41 and p values less than 0.01, mobile data activity (MOBILE) positioned itself at the forefront of boosting energy use and its growth rate. This trend is consistent with the growth of the developing digital program within the country. The effect of renewable energy integration, on the other hand, was minimal ($\beta = -8.21$, $p < 0.05$). China: In a form of growing energy consumption, digitalization contributed positively to its usage ($\beta = 60.78$, $p < 0.01$), as the world's largest energy user. On the other hand, carbon emissions were partially mitigated by the high level of renewable energy integration (REN_EN), as contended by Chauhan [3] South Africa: Digitalization slightly affected consumption of energy ($\beta = 22.34$, $p < 0.05$) while renewable energy generation capacity remains low in the country; expect more mitigation challenging the reliance on fossil fuels alone. South Africa's energy system still faces major development challenges regarding high dependence on fossil fuels. Saudi Arabia: Digitalization had a significant effect on energy consumption ($\beta = 55.67$, $p < 0.01$), but the renewable energy integration REN_EN was inadequate to enhance carbon emissions efficiency due to increased digitalization in the economy.

The primary conclusions derived from this research indicate that there are considerable differences in the adoption and its effect on energy usage and renewable energy penetration within the energy systems of BRICHS nations. Digitalization tends to promote energy use; however, this is not the case in countries with aggressive renewable energy policies like Brazil and China. On the other hand, in Russia and Saudi Arabia, which are dominated by fossil fuels, energy use growth will worsen with limited renewables. Mobile data consumption becomes an important factor in the Indian case since it has experienced growth in digital infrastructure, but in the case of South Africa, where there is little reliance on renewables, there are barriers to the provision of energy sustainably. These observations bring about the importance of creating customized strategies at the intersection of harnessing the benefits of digitalization and transitioning to green energy in each country.

5.2. Hypothesis testing

H1: Digitalization increases energy usage. Confirmed among all countries but varying in degree. Impact was strongest in Saudi Arabia and China, and weakest in South Africa.

H2: The consumption of energy in the digital world reduces by integrating renewable sources of energy. Supported to an extent. It was observed that this was the most effective in Brazil and ineffective in Russia and South Africa.

H3: Digitalization promotes uptake of renewable energy. Seen in China and Brazil but less pronounced in Russia and Saudi Arabia due to varying use of digital energy systems. Did not resonate so much in the case of Russia and Saudi Arabia.

5.3. Literature contribution

There are interactions between digitalization and energy which can differ from one country to another that have not been reported in previous studies. Unlike previous work by Ren et al. [1], and Huang and Lin [2] which addressed regional or global trends, this study examines the differences in the comparison of digitalization between countries. The structural break analysis plainly shows those specific windows, including the Covid-19 outbreak, which facilitated the growth of digitalization in the energy systems.

6. Policy and stakeholder recommendations

Brazil: Enhance policies toward renewable energy in order to further encourage the usage of hydropower and justify the investment in its relatively less expensive and sustainable sources for energy. It requires developing policies to stimulate investments in upgrading hydropower infrastructure and bringing it in line with digital monitoring systems in order to accommodate the energy demands forced by digitalization. For example, implementing advanced water resource management tools driven by artificial intelligence could optimize hydropower generation efficiency, ensuring that it keeps pace with increasing energy demand without compromising environmental sustainability.

Russia: Encourage the transition to renewable energy sources to gradually lessen the load on fossil fuels on which the country heavily relies. This transition can be supplemented by giving fiscal support for renewable energy projects such as subsidies or tax exemptions for new wind and solar energy projects. If digitization and energy sector partnerships also flourish, it may lead to the development of smart grids that are efficient in energy and maximized in digitization utility. This way, even developing digital platforms that monitor and optimize energy distribution, digitalization ensures that it supports rather than exacerbates energy consumption patterns.

India: Better cell phone-based digital infrastructure development should go along with increased channeling of renewable energy sources. For instance, as mobile data consumption expands rapidly in India, investments should be made in energy-efficient telecommunications systems such as green base stations powered by solar energy. Policy should also encourage distributed renewable energy systems, particularly in rural areas, so that rural communities too can benefit from the new-age connectivity brought by the demand for increased energy supply.

The Chinese government invests in smart grids that would integrate renewable energy sources into the network on a national scale through developing increased pilot programs for smart grid systems. It aims at continuing the leading role internationally on quickly moving such initiatives. Advances in such technologies, along with digital infrastructure growth, would support the intermittency of renewables through engaging new batteries optimized for energy supply to build up. Policy frameworks should also further focus on R&D to enhance the local capacity for innovations in clean energy.

Increasing energy sources by wind, solar, and biomass could be a diversity of renewable energy sources at South Africa's hand. The use of digital solutions for energy conservation, such as smart meters and home energy management systems, should be coupled with this in South Africa. Socioeconomic access would be a consideration in creating policies that would impact energy transitions, with a view to making sure that underserved populations have access to energy in affordable and sustainable means.

Should Saudi Arabia opt to include digital technologies into energy management systems built on this increased renewable energy ambition, it would yield benefits for Saudi Arabia. Modernizing data analytics platforms, for example, would mean that the effectiveness of the energy generation and distribution process in overcoming inefficiencies in the system may be enhanced. Enhance regulation incentives to develop public-private partnerships in clean energy investments and in hybrid systems with solar and wind energy with traditional sources. Given the contrasting energy landscapes of BRICHS countries, unique targeted policy frameworks need to be put in place. For China and Brazil, the focus ought to be on smart grids, while for Russia and Saudi Arabia, the strength of renewable energy incentive policies needs an urgent improvement.

6.1. General strategies

It is important to note that all BRICHS countries invest in smart grid systems and advanced energy-storing technology for effective digitalization and energy transitions. Investing in such things makes it possible for renewable energy sources to be harnessed as they stabilize fluctuations in energy supply and equip the increasing energy demand resulting from digitalization in a more sustainable fashion. Deploying digital platforms for real-time energy management can finalize ways for optimizing resource allocation, pinpointing inefficiencies, and directing data-driven policymaking. Establishing harmony between energy and digitalization policy is critical to ensure the positive effects of technological advancements on energy efficiency while having relatively fewer adverse environmental impacts. In addition, promoting international collaboration might allow the countries concerned to adopt each other's best practices to access technology innovations and finance to produce collaborative solutions to common energy-digitalization problems. Again, extra analysis is required to study the influence of the digitalization phenomena upon energy consumption in various sectors such as industry and transport, besides investigating regional contrasts between rural and urban.

6.2. Limitations and future research

Although this study offers a good understanding of the nexus between digitalization, energy consumption, and renewables in BRICHS countries, several caveats should be mentioned. First, the absence of qualitative information, such as policy narratives or stakeholder aspects, limited the analysis depth. The inclusion of this material would enhance the contextual understanding and interpretability of the findings. Second, there is an omitted variable bias as certain elements such as political stability, cultural differences, or regionally specific energy policy have not been entrenched in the model. Future research should, therefore, include such aspects for a more lucid and holistic analysis. Thirdly, the generalizability of these findings also remains a challenge with regard to other countries outside BRICHS due to the differences in their economic, social, and political contexts. One good area of future investigation would, therefore, be how these findings match up with energy transition processes elsewhere in the world.

Several open areas for future research emanate from this study. The first of these would lie in undertaking a thorough investigation of the social and economic ramifications of the broad reach of digitalization in energy transitions. This would scope issues such as energy equity, employment issues, and how digital technologies are transforming energy consumption patterns within societies. The second future domain could bring further investigation on the role digital technologies could play in bettering energy access and equity in marginalized areas. This type of research broadly advances understanding of how digitalization processes could positively contribute to sustainable development. Finally, further exploration of these energy policies could optimize the interaction between digitalization and energy efficiency in an open environment.

Conflict of interest: The authors declare no conflict of interest.

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