İŞLETME ARAŞTIRMALARI DERGİSİ
JOURNAL OF BUSINESS RESEARCH-TURK
2026, 18(3), 2209-2227
https://doi.org/10.20491/isarder.2026.2288

# Digital Competitiveness and Renewable Energy Investment Attractiveness: A Cross-Country Analysis

**Dilek ŞAHİN YOMRALIOĞLU** [a]

[a] Istanbul Medipol University, Faculty of Business Administration and Management Sciences, Istanbul, Türkiye, dilek.yomralioglu@medipol.edu.tr

**ARTICLE INFO**

**Keywords:**
Renewable Energy
Sustainability
Digitalization
International Business
Management

**Received** 30 September 2025
**Revised** 5 August 2026
**Accepted** 15 August 2026

**Article Classification:**
Research Article

**ABSTRACT**

**Purpose –** This research investigates the interplay between digital competitiveness and the attractiveness of countries for renewable energy, utilizing the "World Digital Competitiveness" scores (DCI) and "Renewable Energy Country Attractiveness" (RECAI) rankings.

**Design/methodology/approach –** This study examines the relationships between the RECAI rankings and the dimensions of digital competitiveness indicated by the DCI scores, which are Technology, Knowledge and Future Readiness. The analyses are conducted separately for the years 2023 and 2024 by using correlation and regression analysis. The data set is limited to 32 countries in 2023 and 36 countries in 2024.

**Findings –** The correlation results show that Technology is significantly associated with RECAI ranking in 2023, whereas Knowledge and Future Readiness in 2024. In the 2023 regression model, although the overall model is significant, DCI dimensions have no statistically significant effect on RECAI ranking. In 2024, Future Readiness emerged as the only significant predictor, with higher scores associated with better RECAI positions, and the analysis of 2023-2024 differences shows that differences in DCI scores cannot significantly explain differences in RECAI rankings.

**Discussion –** The data set is limited and some statistical results which are in the borderline may change with a larger data set. Additional independent variables may help to increase the explanatory power of the model.

## 1-INTRODUCTION

Concerns about climate change are increasing worldwide, prompting countries to prioritize environmental issues to mitigate the effects of rising global temperatures. The 2015 Paris Climate Agreement highlighted the importance of collective efforts to combat climate change, aiming to limit global temperature increases compared to pre-industrial levels (Ali, 2021). The Agenda for Sustainable Development, approved by all United Nations Member States in 2015, provides a shared framework aimed at fostering peace and prosperity for the future through the attainment of the 17 Sustainable Development Goals (SDGs). Achieving these goals necessitates the creation and application of new and effective tools that consider current global trends, including digitalization and the incorporation of sustainable development into all market activities and sectors. This idea drives the world's transformation by promoting innovative strategies to tackle complex issues related to climate change, resource depletion, and social inequalities (U.N., 2024). By embedding sustainability into the design, development, and implementation of digital platforms, organizations can effectively reduce their ecological impact and promote beneficial environmental results (Malhotra, 2023).

Contemporary manufacturing is a critical component of the global economy, yet it is also one of the sectors with the greatest environmental impact. Increasing production volumes and population growth have led to a significant rise in carbon emissions, waste generation, and energy consumption, creating substantial challenges, particularly in an era that demands sustainability. The widespread use of fossil fuels leads to a significant surplus of carbon dioxide emissions, exceeding the Earth's natural capacity to absorb them. This

**ETHICAL APPROVAL:** This study uses publicly available secondary country-level indices and does not involve human participants; therefore, ethics committee approval was not required.

**Suggested Citation**

Şahin Yomralıoğlu, D. (2026). Digital Competitiveness and Renewable Energy Investment Attractiveness: A Cross-Country Analysis, İşletme Araştırmaları Dergisi, 18 (3), 2209-2227.

phenomenon contributes to rising global temperatures, sea-level rise, and other critical sustainability challenges (Rizwanullah et al., 2024). Globally rising manufacturing activities foster higher energy consumption and carbon emissions throughout product life cycles, leading sustainable production to become a strategic priority for governments, industries, and international organizations. Artificial intelligence models are employed for energy consumption forecasting, and production scheduling optimization, while the digital twin provides continuous synchronization between physical manufacturing assets and their virtual counterparts (Punna et.al., 2026). The advancement of technologies like digital twins, and the Internet presents significant opportunities to enhance efficiency and support the transition to more sustainable manufacturing methods (Setyadi et al., 2025). By continuously synchronizing data between physical and virtual environments, digital twins enable manufacturers to simulate operational scenarios, predict system behavior, and optimize production performance before implementing physical changes. When combined with artificial intelligence, digital twins become powerful decision support tools capable of identifying inefficiencies, forecasting energy consumption, and recommending sustainability-orientated interventions in real time (Punna et al. 2026). These improvements allow engineers to perform "what-if" simulations on the digital twin to optimize operations, predict failures, and refine designs long before changes are implemented. For instance, if a manufacturer is considering altering a production line layout or adjusting machine settings, they can simulate these changes on the digital twin to assess their impact on efficiency, productivity, and potential failure points. This predictive capability not only enhances operational optimization but also significantly reduces downtime and maintenance costs by identifying issues before they manifest in the physical system. This iterative approach allows for continuous improvement and innovation, ultimately leading to more efficient production systems and higher-quality products (Görtz, 2026). Technological improvements and digital competitiveness are highly affected by regional regulations. Enhanced transparency and accessibility in regulatory processes build investor confidence, facilitating quicker project implementations. Effective regulatory frameworks reduce bureaucratic obstacles, enabling smoother operations in the renewable energy sector. Additionally, digital tools can help streamline compliance and reporting processes, further attracting investments by minimizing risks associated with regulatory uncertainties (Yang et. al., 2024).

The Resource-Based View presents a significant theoretical framework for understanding how environmentally oriented resources and capabilities can provide sustainable competitive advantages through their strategic interactions with both built and natural environments. However, the applications of this framework have primarily remained focused on firm-centric and efficiency-driven approaches, emphasizing the internal capabilities of firms to effectively utilize resources for competitive gain. Scholars are increasingly advocating for the integration of biodiversity into business strategies, not merely as a resource to be compensated for, but as a dynamic and regenerative asset. By considering businesses as major consumers of natural resources, this perspective expands the underlying assumptions of Natural Resource-Based View shifting from a firm-centric view of resource management to a relational, ecosystem-based understanding, where biodiversity influences strategy through its material, regulatory, and landscape-level dynamics (You et. al., 2025).

In this context, it is expected to associate a common objective belief that an effective energy transition is being realized, with renewable energy replacing fossil energy. However, since the 2008 financial crisis, many economies are still exploring diverse energy development models for economic growth, and the integration level of renewable energy is falling short of expectations (Yang et al., 2024). Digital competitiveness plays a crucial role in enhancing the attractiveness of renewable energy investments through various mechanisms. As mineral and energy resources become increasingly difficult to access, increased technology will be required to continue to achieve the same production levels that these industries have historically achieved (Hanga and Kovalchuk, 2019; Perrons and Jensen, 2015; Clifford et al., 2018). One of the primary mechanisms is the capacity for knowledge generation, which enables better data collection and analysis. This capability allows investors to make informed decisions based on accurate information and fosters innovation in renewable energy technologies, ultimately leading to improved efficiency and reduced costs. Additionally, a digitally skilled workforce is essential for the renewable energy sector's evolution, as it ensures that employees possess the necessary technical and creative skills to address emerging challenges (Liu et al., 2025). The development of wider regions reliant on the energy sector creates an ongoing demand for a workforce that is not only technically sufficient but also creative and adaptable to new challenges. This demand extends to the need for specialists in digital technologies, underscoring the importance of skills in sustainability and environmental management that intersect with the energy sector's digital and renewable transformation (Kuzmin et. al., 2024).

Rooted in the theory of dynamic capabilities, strategic potentials related to digitalization and Artificial Intelligence facilitate optimization, serve as crucial precursors that bolster a firm's capacity to identify sustainability-related opportunities, capitalize on emerging market trends, and adapt marketing systems in response to changing sustainability requirements. This approach identifies organizational sustainability capability as the primary mediating factor, illustrating how insights and process driven by digitalization are transformed into sustainability-focused strategic practices that enhance long-term competitiveness (Htet et. al., 2026).

While there is substantial research on renewable energy policies and the effects of digitalization on energy security, sustainability, and equity, there has been insufficient focus on how these factors are interconnected within regional contexts. The challenges associated with the energy transition are multifaceted, encompassing financial, regulatory, and infrastructural obstacles that necessitate integrated approaches, along with strategies for incorporating Sustainable Development Goals and productive solutions (Ha and Kumar, 2021). Even if digital competitiveness is maintained, the attractiveness of the renewable energy investments necessitates additional factors such as, demand for energy, policy stability and the variety of natural resources. Digital competitiveness reflects the capacity of economic actors to develop, adopt, and effectively utilize new technologies, while the attractiveness of renewable energy investments is affected by interconnected factors such as technological innovation, regulatory capacity, business environment, and preparedness for the future. Therefore, examining the relationship between countries' levels of digital competitiveness and their international positions regarding renewable energy investments is important for understanding the potential connections between digital transformation and renewable energy transition (EY, 2024).

This study aims to assess the impact of digital competitiveness on renewable energy investment and development opportunities, exploring the interrelationship between these two factors using two global indices which are, "World Digital Competitiveness Index" (DCI) and the "Renewable Energy Country Attractiveness Index" (RECAI) .This study addresses a significant gap in existing literature by exploring the interconnections between digital competitiveness and renewable energy investments within regional contexts. While previous research has extensively examined renewable energy policies and the impacts of digitalization on energy security, sustainability, and equity, there has been limited focus on how these factors interact and influence each other in specific geographical settings. The study comparatively examines the relationships between countries' Renewable Energy Country Attractiveness Index (RECAI) rankings and the dimensions of digital competitiveness: Knowledge, Technology, and Future Readiness for the years 2023 and 2024 by using correlation and regression models. The study aims to assess whether countries' current levels of digital capacity and short-term changes in digital capacity yield different outcomes in terms of the attractiveness of renewable energy investments. The research is expected to offer a practical framework for assessing the impact of digital competitiveness on renewable energy investments which can be employed by businesses and investors to evaluate potential opportunities in different markets. This study not only contributes to the theoretical understanding of the interplay between digital competitiveness and renewable energy investment by applying the dynamic capabilities approach but also provides actionable insights for practitioners and policymakers, ultimately promoting a more sustainable and equitable energy future by identifying areas requiring improvement for enhanced sustainable energy implementation.

The paper is structured as follows: Section 2 offers a comprehensive literature review both bibliographic network cluster analysis and the updated overview of the relevant literature sources. Section 3 describes the data used in this paper and describes the data collection and processing, as well as explaining some methodological issues and limitations of the study. Section 4 summarizes the findings of the study, section 5 presents conclusions and recommendations, finally future study suggestions are given.

## 2- LITERATURE REVIEW

When listing the literature, studies in the field regarding the digital transformation of companies and shifts towards renewable energy implementation are reported as follows:

Studies related to renewable energy consumption and governance mechanisms both political and institutional;

Asongu and Odhiambo (2022), investigated the relationship between governance and renewable energy consumption in Sub-Saharan Africa. The findings indicate that both political and institutional governance are negatively correlated with renewable energy consumption in the countries studied. The study emphasizes the importance of accurately measuring governance indicators to prevent confusion between effective and ineffective governance.

Makpotche et al. (2024) concluded that effective governance mechanisms have a positive influence on renewable energy consumption. The study analyzed firm-level data from the Refinitiv Sustainable and Compustat databases, covering the years from 2002 to 2021. The findings provide evidence that various governance mechanisms significantly contribute to the transition toward renewable energy. These mechanisms include having a sustainability committee, implementing environmental, social, and governance (ESG) compensation policies, linking compensation to financial performance, conducting external sustainability audits, ensuring transparency, promoting gender diversity on boards, and maintaining board independence.

Velte (2025) conducted a comprehensive literature review that encompassed one hundred quantitative, peer-reviewed empirical studies examining the impact of gender diversity, sustainability board committees, sustainability-linked executive compensation, and sustainable institutional investors on carbon performance, reporting, and assurance. The review asserts that board gender diversity, as a key corporate governance factor, is positively associated with carbon reporting and performance.

Firm level studies regarding the impact of digitalization on renewable energy integration by considering size and ownership structure effects, consumption amount, collaboration and human capital metrics;

Rani and Haris (2024) conducted a study that explored how small and medium-size enterprises (SMEs) are adopting ESG (Environmental, Social, and Governance) practices in support of sustainable energy initiatives. Although larger corporations have made substantial investments to align with ESG principles, small and medium-size enterprises face challenges such as limited resources, a lack of expertise, and weaker regulatory compliance requirements, which impede their progress in integrating these practices.

Ren et al. (2023) conducted research that focused on publicly traded renewable energy companies in China from 2008 to 2021. The study concluded that the impact of digital transformation on the performance of these companies can differ based on factors such as ownership structure, geographic location, and company size. In particular, the effects of digital transformation on corporate performance are more significant in state-owned enterprises (SOEs) and larger companies.

Zhao et al. (2021) studied China's digital transformation in renewable power systems. The findings showed that digital transformation enhanced the efficiency of renewable energy usage.

Sahebi et al. (2025) conducted a literature review. The study's results highlight the importance of researchers embracing interconnected theoretical frameworks that consider the enabling and reinforcing impacts of different AI capabilities, along with the organizational and managerial factors that affect successful digital implementation.

Ezeanochie et al. (2021) created a model for the industry. The study concluded that the renewable energy industry needs to foster collaboration throughout the value chain to fully leverage the advantages of digital transformation. Alliances among manufacturers, technology suppliers, and regulatory agencies can accelerate the implementation of innovative solutions and ensure adherence to sustainability standards.

Kuzmin et al. (2024) address how investments in human capital influence the innovation and digital competitiveness of energy firms, which may drive the renewable energy transition, specifically concentrating on the Russian energy sector. The results not only emphasize the critical importance of human capital in the energy sector's transition but also propose policy initiatives to effectively facilitate this transformation.

Some of the studies focus on firm level economic efficiency and capital investment requirements as given below;

Tumin et al. (2022) used data from the Skolkovo Energy Center at the Moscow School of Management and the Energy Research Institute of the Russian Academy of Sciences (RAS). The study concluded that a successful shift to renewable energy sources can only occur if a favorable energy balance and positive economic efficiency in their utilization are achieved.

Bogdanov et al. (2021) conducted research that claims the new sustainable energy system incorporates storage technologies, enhanced flexibility, and the production of synthetic fuels. Consequently, this requires substantial capital investments, which not only facilitates the establishment of a sustainable energy system but also enhances socio-economic welfare.

Cao et al. (2024) conducted a study on two hundred enterprises globally. The implementation of digital twin technology (virtual simulation) has enhanced the return on investment (ROI) for businesses. Research indicates that companies utilizing digital twin technology in renewable energy projects achieve an average ROI of 18%, compared to just 13% for those that do not employ this technology.

Country level studies;

Hao and Shao (2021), investigate driving sources of renewable energy deployment in 118 countries. It is revealed that a country's vulnerability to climate change and carbon intensity are mostly correlated with its renewable energy deployment. In contrast, the impact of carbon tax policy adoption is statistically insignificant.

Elmassah (2023), had panel data analysis on 10 developed, 16 emerging countries for the period 1976-2018 to reveal short term and long-term renewable energy production determinants. The findings indicate a long-term elasticity between renewable energy (RE) and GDP in developed nations, along with short-term dynamics involving RE, oil prices, and $CO_2$ emissions. In contrast, for emerging economies, there are long-term relationships observed between RE and GDP, $CO_2$ emissions, and oil prices.

Bingixin et. al. (2025) investigate the nonlinear relationship between digitalization and renewable energy consumption with particular focus on the role of human capital as a moderating factor in the Belt and Road countries The study's findings reveal that the relationship between renewable energy consumption and digitalization is very dynamic, leading to important implications for various areas, including energy policy, sustainable development initiatives, and advancements in technology and human capital. The study further highlights that Foreign Direct Investment is crucial for undertaking substantial renewable energy projects, especially in the absence of the necessary technical expertise or resources.

Zuo and Ren (2025), study the impact of renewable energy consumption on digitalization by conducting a panel data analysis on Belt and Road countries. It is concluded that policies that encourage the integration of advanced technologies into energy systems could enhance the use of renewable resources and render energy grids more adaptable, flexible, and able to facilitate significant transitions toward more sustainable energy sources.

Lin and Huang (2025), investigate the moderating impact of digitalization on renewable energy integration in the electricity sector of 33 countries for the period 2000-2019. The results indicate that digitalization positively influences the integration of renewable energy, with the moderating effect being asymmetric. Digitalization has a moderate effect in developed countries, but no statistically significant results have been found in developing countries.

In examining the literature, it becomes evident that a significant number of studies focus on digitalization and the transition to renewable energy, with diverse perspectives being addressed both theoretically and empirically. This study aligns existing literature but differentiates itself by examining the effect of digitalization on renewable energy investment attractiveness by using two global indexes that have broadened evaluation criteria. The indexes used for this research are the "World Digital Competitiveness Index" (DCI) and the "Renewable Energy Country Attractiveness Index" (RECAI). Data are collected for the years 2023 and 2024 and analyzed using regression analysis and correlation matrix methods.

## 3- RESEARCH METHODOLOGY

This study is designed as a quantitative and comparative research based on secondary data. It examines the relationships between the Renewable Energy Country Attractiveness Index (RECAI) rankings, which represent the relative positions of countries in terms of renewable energy investments, and the dimensions of digital competitiveness indicated by the Digital Competitiveness Index (DCI). The analyses were conducted separately for the years 2023 and 2024; subsequently, a difference model was created based on the ranking and digital competitiveness score differences of the same countries over the two years. The main dependent variables of the study are the RECAI rankings for the years 2023 and 2024. The independent variables are the World Digital Competitiveness Index indicators in the dimensions of Knowledge, Technology, and Future Readiness. In the model created based on the differences between 2023 and 2024, the RECAI rankings are used as the dependent variable, while the annual score differences in the three DCI dimensions are used as independent variables. The scores of DCI dimensions are used while rankings are used for RECAI since there is no normalized scores are available.

**Data Collection**

The RECAI rankings used in the research are obtained from the Renewable Energy Country Attractiveness Index 62 and Renewable Energy Country Attractiveness Index 63 reports published by Ernst and Young (EY). RECAI ranks the world's 40 most attractive markets in terms of renewable energy investment and project development opportunities. Both the 2023 and 2024 reports include a total of 40 countries/markets.

The digital competitiveness data is sourced from the IMD World Digital Competitiveness Ranking reports. In the IMD reports, countries' digital competitiveness scores are evaluated across three main dimensions: Knowledge, Technology, and Future Readiness. The overall score documents indicate that 64 countries are included in the overall digital competitiveness ranking for 2023, and 67 countries for 2024.

In the process of creating the dataset, countries listed in the RECAI reports were matched with corresponding countries in the DCI data based on country names. Variations in country names observed between the reports, such as "Turkey–Türkiye," "Taiwan, China–Taiwan (Chinese Taipei)," and "China Mainland–China," were standardized prior to analysis. Although there are 40 countries in the RECAI reports for both years, the analyses are limited to countries for which relevant DCI sub-dimension data is available due to the absence of data for some RECAI countries. Accordingly, the 2023 analyses were conducted in 32 countries, while the 2024 analyses were conducted in 36 countries. It is noted that correlation and regression analyses in this study were also performed with these sample sizes. The countries that have existed in RECAI's ranking of 2023 but do not exist in DCI 2023 are; Morocco, Honduras, Egypt, Vietnam, Tunisia, Dominican Republic, Kenya, Panama and for 2024; these countries also have not existed but four countries are added which are Japan, Brazil, New Zealand and Switzerland.

In the 2023–2024 difference analysis, common countries with complete data for all variables in both years were used. Therefore, the difference model was created based on 32 countries. This approach prevents comparability issues that may arise from calculating difference values. The scores of digital competitiveness can be grouped into three factors that highlight the main areas analyzed. In Figure 1, the primary topics of the index are delineated, accompanied by emphasized subtitles. The use of subtitles enhances clarity and facilitates a deeper understanding of the thematic organization, thereby providing a comprehensive overview of the index's framework. Evaluation criteria depend on both survey data and hard data. Hard data is used to analyze digital competitiveness as it can be measured (e.g. Internet bandwidth speed) and survey data, which analyzes competitiveness as it can be perceived (e.g. Agility of companies). Hard criteria represent a weight of 2/3 in the overall evaluation whereas the survey data represent a weight of 1/3.

In Figure 1, it can be observed that the main headings are knowledge, technology and future readiness. The evaluation of knowledge, technology and future readiness that mainly consist of integration and application of knowledge, the effectiveness of regulations, the adoption of new technologies, and adaptation to required changes (IMD, 2024). Knowledge refers to the quality of education, talent management, and scientific concentration for achieving specific targets. Technology is evaluated based on environmental conditions such as the regulatory framework, capital, and technological infrastructure. It includes regulatory incentives for technological advancements. Future readiness is crucial for achieving a smooth digital transformation which requires company specific factors like agility, adaptive culture, etc. (Setiawati et al., 2022). In addition, two criteria are for background information only, which means that they are not used in calculating the overall digital competitiveness scores (i.e., Population and GDP).

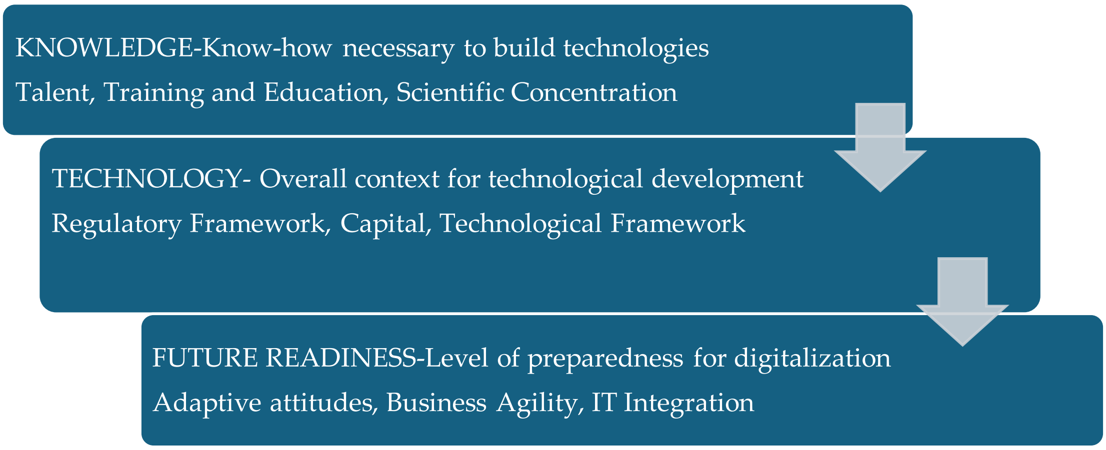


**Figure 1. Main index topics**

Resource: World Digital Competitiveness Index 2023

**Renewable Energy Country Attractiveness Index (RECAI)**

Ernst & Young (EY) publishes a wide range of statistics and reports aimed at its clients across various sectors. E.Y. (Ernst and Young) created the Renewable Energy Country Attractiveness Index (RECAI) and evaluates the world's top 40 markets according to the appeal of their investments in renewable energy. These index pillars highlight crucial elements such as the demand for energy, policy stability, project implementation (including capital accessibility), and the variety of natural resources. The index naturally benefits large economies. However, by normalizing with the gross domestic product (GDP) that is, dividing the “raw” RECAI scores by the log of GDP, we can see which markets are performing above the expectations for their economic size. In this way, the normalized index helps reveal ambitious plans for energy transition in smaller economies, creating some attractive alternatives for potential investors (E.Y., 2024). Since 2003, EY has ranked the world's top 40 renewable energy markets based on their attractiveness. This provides important information for investors, policymakers and firms which enhance sustainability strategies.

**Definition of Research Variables**

The RECAI ranking indicates the relative attractiveness of countries in terms of renewable energy investments and project development opportunities. In this variable, lower ranking values represent better performance, while higher ranking values indicate lower performance.

The DCI Knowledge dimension is considered as scored values that represent the capacity of countries in terms of the knowledge, skills, training, and human resources necessary for digital transformation; the Technology dimension supports the technological and regulatory infrastructure that facilitates the development and application of digital technologies; and the Future Readiness dimension reflects the countries' preparedness for adapting to digital transformation, agility, and the adoption of new technologies.

The ranking difference is calculated as follows:

$$\text{Ranking Difference} = \text{RECAI Ranking 2023} - \text{RECAI Ranking 2024}$$

According to this definition, positive values indicate that the country has improved its RECAI ranking, negative values indicate a decline, and zero indicates that the ranking has not changed. The DCI difference variables are calculated by subtracting the 2023 score from the 2024 score:

$$\text{DCI Difference} = \text{DCI 2024} - \text{DCI 2023}$$

Thus, positive values in the DCI change variables indicate an increase in the relevant dimension of digital competitiveness, while negative values indicate a decrease.

## 3.1-Data Analysis

Data analyses are conducted by using the R (Studio) programming language. Initially, country names and missing values were checked; only countries with complete RECAI rankings and all three DCI sub-dimensions for the relevant year are included. The statistical significance level is set at $\alpha = 0.05$ for all analyses.

The RECAI variable contains ordered values from 1 to 40. Due to this structure, the arithmetic mean and standard deviation of the RECAI rankings are deemed to provide limited information, as the average ranking would approach 20.5 in a complete dataset. Consequently, classical descriptive statistics for the RECAI ranking are not reported. Although DCI scores are continuous, the study focuses on their relationship with RECAI rankings, so a separate descriptive statistics table is not provided.

Given the ordinal nature of the RECAI variable, bivariate relationships between RECAI rankings and DCI sub-dimensions are assessed using the Spearman rank correlation coefficient. This method is also applied to examine differences in RECAI rankings and DCI sub-dimensions from 2023 to 2024.

Separate linear regression models are created for 2023 and 2024 to determine the explanatory power of the DCI sub-dimensions on RECAI rankings. The RECAI ranking is treated as an approximately numeric outcome variable. In the 2023 model, high multicollinearity among independent variables is identified, prompting the use of ridge regression for robustness. L2 regularization is applied, with the penalty parameter determined via leave-one-out cross-validation to stabilize predictions by shrinking coefficients of highly correlated variables.

Before regression modelling, the normality of residuals is assessed using the Shapiro-Wilk test, homoscedasticity is evaluated with the Breusch-Pagan test, independence of residuals is checked with the Durbin-Watson test, and linearity is evaluated using the Ramsey RESET test. Multicollinearity is examined through VIF and tolerance values, while outliers and influential observations are analyzed using studentized residuals, leverage values, and Cook's distances.

### *3.1.1. Correlation Analysis*

The presence of a significant relationship between the RECAI ranking values for 2023 and 2024 and the DCI sub-dimensions is measured using correlation analysis. The correlation values are assessed for both the data from 2023 and 2024, as well as for the differences between 2023 and 2024.

**Relationship Between the 2023 DCI Sub-Dimensions and RECAI Ranking**

Due to the variables not exhibiting a normal distribution and the ranking variable having an ordinal structure, the relationships between the variables are examined using the Spearman rank correlation coefficient. The analysis is conducted using data from 32 countries. The results of the analyses can be seen in Table 1 below.

**Table 1.** The relationship between the DCI sub-dimensions of the year 2023 and the RECAI ranking**.**

| Variables | Spearman ϱ | p |
|---|---|---|
| DCI Future Readiness – RECAI Ranking | -0.242 | 0.182 |
| DCI Knowledge – RECAI Ranking | -0.341 | 0.056 |
| DCI Technology – RECAI Ranking | -0.378 | 0.033 |

According to the results for 2023, there is a weak negative relationship between the RECAI ranking and the DCI Future Readiness is observed although it is not statistically significant ($\varrho = -0.242$; $p = 0.182$). This result indicates that while countries tend to improve their RECAI rankings as their level of future readiness increases, this relationship is not statistically significant.

A negative and low-to-moderate relationship is identified between the RECAI ranking and the DCI Knowledge dimension ($\varrho = -0.341$; $p = 0.056$). Although the direction of the relationship indicates that as the knowledge infrastructure strengthens, the RECAI ranking improves, the obtained p-value is greater than the 5% significance level, making it statistically insignificant. However, the borderline significance of the relationship ($p \approx 0.056$) suggests that this relationship could become significant with larger sample sizes.

The strongest relationship is found between the RECAI ranking and the DCI Technology dimension. The analysis results show a moderate, negative, and statistically significant relationship between the technology dimension and the RECAI ranking (ϱ = -0.378; p = 0.033). Since lower ranking values in RECAI indicate better performance, countries with high technological infrastructure and capacity rank higher in the RECAI ranking.

**Relationship Between the 2024 DCI Sub-Dimensions and RECAI Ranking**

In the analyses for 2024, the relationships between the variables are also examined using the Spearman rank correlation coefficient. The analysis is conducted using data from 36 countries. The results can be seen in Table 2 below.

**Table 2.** Relationship Between DCI Sub-Dimensions and RECAI Ranking for the Year 2024

| Variables | Spearman ϱ | p |
|---|---|---|
| DCI Future Readiness – RECAI Ranking | -0.402 | 0.015 |
| DCI Knowledge – RECAI Ranking | -0.389 | 0.019 |
| DCI Technology – RECAI Ranking | -0.321 | 0.057 |

According to the analysis results, there is a moderate, negative, and statistically significant relationship between the RECAI ranking and the DCI Future Readiness (ϱ = -0.402; p = 0.015). This indicates that countries with a high level of future readiness are more competitive in attracting investments in renewable energy and energy transition.

A moderate, negative, and statistically significant relationship is also identified between the RECAI ranking and the DCI Knowledge dimension (ϱ = -0.389; p = 0.019). This result shows that countries with high digital information infrastructure, education levels, and knowledge production capacity rank higher in the RECAI.

In contrast, although a negative relationship exists between the RECAI ranking and the DCI Technology dimension, this relationship is not statistically significant (ϱ = -0.321; p = 0.057).

When considering the years 2023 and 2024 together, an interesting change is observed. In 2023, only the Technology dimension shows a significant relationship with the RECAI ranking, while in 2024, the Technology dimension lost its significance; conversely, the Future Readiness and Knowledge dimensions become significant. This indicates that the competitiveness of investments in renewable energy has become more closely related over time not only to technological capacity but also to information infrastructure and future readiness levels.

**Relationship Between Differences in RECAI Ranking and in DCI Dimensions**

To examine the relationship between the differences in the digital competitiveness dimensions of countries during the 2023-2024 period and the differences in the RECAI ranking, a Spearman rank correlation analysis is conducted. The results of the analysis can be seen in the table below (Table 3).

**Table 3.** Relationship Between the differences in RECAI Ranking and DCI Dimensions

| Variables | Spearman ϱ | p |
|---|---|---|
| Future Change – Ranking Change | -0.014 | 0.942 |
| Knowledge Change – Ranking Change | -0.128 | 0.485 |
| Technology Change – Ranking Change | -0.325 | 0.069 |

According to the analysis results, there is no significant relationship between the differences in the RECAI ranking and the differences in Future Readiness (ϱ = -0.014; p = 0.942). This finding indicates that the differences in countries' levels of preparedness for the future do not explain the differences in their RECAI rankings in the short term.

Similarly, no statistically significant relationship has been found between the differences in Knowledge and the differences in the RECAI ranking (ϱ = -0.128; p = 0.485). This result suggests that developments in knowledge infrastructure do not have a significant impact on the RECAI ranking differences in the short term.

The highest correlation coefficient is obtained between the differences in Technology and the differences in the RECAI ranking (ϱ = -0.325; p = 0.069). Although this relationship is not significant, the presence of a negative and low-to-moderate correlation suggests that developments in the technological framework may be related to improvements in the RECAI ranking. It is believed that this relationship can become statistically significant in studies conducted with larger samples.

### 3.1.2. Regression Analysis

The extent to which the RECAI ranking values for 2023 and 2024 can be explained by the DCI sub-dimensions has been measured using multiple linear regression analysis. The regression models are assessed for both the data of 2023 and 2024, as well as for the differences between 2023 and 2024.

**Evaluation of Assumptions Before Regression Analyses of 2023 Data**

Before starting the regression analysis, the fundamental assumptions of multiple linear regression are examined. To ensure reliable results, it is necessary for the residuals to show a normal distribution, error variances to be constant (homoscedasticity), residuals to be independent, the model to represent a linear structure, and no severe multicollinearity among independent variables.

Normal Distribution: Assessed using the Shapiro-Wilk test, which indicates normal distribution of residuals ($W = 0.958$, $p = 0.238$).

Constant Variance: The Breusch-Pagan test ($\chi^2 = 3.960$, $p = 0.266$) shows constant error variances and no heteroscedasticity.

Linearity: Evaluated with the Ramsey RESET test ($F = 1.333$, $p = 0.281$), confirming the model's linear structure.

Multicollinearity: VIF values for DCI Knowledge (VIF = 7.58), DCI Technology (VIF = 7.90), and DCI Future Readiness (VIF = 9.62) indicate moderate to high multicollinearity.

Independence: The Durbin-Watson test ($DW = 0.682$, $p < 0.001$) suggests potential positive autocorrelation, though less critical for cross-sectional data.

Overall, the fundamental assumptions are largely met, but there is a relatively high level of multicollinearity among the independent variables. To address this, ridge regression analysis is also applied to mitigate multicollinearity effects.

**Multiple Linear Regression Analysis for 2023 Data**

A multiple linear regression analysis is applied to determine the dimensions of digital competitiveness that affect the RECAI 2023 ranking. The dependent variable is the RECAI 2023 ranking, while the independent variables are the DCI Knowledge, DCI Technology, and DCI Future Readiness dimensions (E.Y., 2023).

The model is found to be statistically significant overall ($F(3,28) = 3.766$, $p = 0.022$). When examining the explanatory power of the model, it is observed that the independent variables explain approximately 28.7% of the total variance in the RECAI ranking ($R^2 = 0.287$). The adjusted coefficient of determination is calculated to be 21.1% (Adjusted $R^2 = 0.211$).

When examining the coefficients related to the independent variables, although the regression coefficient for the DCI Knowledge variable is negative, it is not statistically significant ($B = -0.430$, $\beta = -0.650$, $p = 0.150$). Similarly, the DCI Technology variable also has a negative effect but is found not to be significant ($B = -0.446$, $\beta = -0.666$, $p = 0.149$). In contrast, the DCI Future Readiness variable has a positive coefficient ($B = 0.565$, $\beta = 0.875$), which is not statistically significant at the 5% level, but shows a significant borderline relationship ($p = 0.088$).

Considering that lower ranking values in the RECAI ranking represent better performance, the negative coefficients for the Knowledge and Technology variables are consistent with theoretical expectations. Accordingly, it can be stated that as the knowledge and technology capacity increases, countries tend to rank higher in the RECAI ranking. However, it is assessed that the high correlation among the independent variables prevents the coefficients from reaching statistical significance.

The positive coefficient for the Future Readiness variable initially appears to contradict theoretical expectations. The primary reason for this is the high correlation of the Future Readiness variable with the other two DCI dimensions, which may cause the coefficient to change direction under the influence of multicollinearity. Indeed, while correlation analyses indicate a negative relationship between Future

Readiness and the RECAI ranking, the coefficient changes direction when the effects of the other variables are controlled in the regression model. This situation is considered one of the classic signs of multicollinearity (Hair et al., 2019).

**Ridge Regression Analysis for 2023 Data**

Due to high VIF values in the classical multiple linear regression, ridge regression is applied to test robustness. Using leave-one-out cross-validation, the optimal penalty parameter s $\lambda = 0.602$, minimizing cross-validation error. A stronger regularization ($\lambda_1SE = 4999.721$) reduces coefficients nearly to zero, so focus remained on the $\lambda min$ model.

Ridge regression coefficients show that DCI Knowledge (βridge = -0.286), DCI Technology (βridge = -0.289), and DCI Future Readiness (βridge = 0.280) retain the same directions as in the classical model. Standardized coefficients indicate Knowledge and Technology have similar negative impacts ($\beta = -0.431$ and $\beta = -0.430$), while Future Readiness has a positive impact ($\beta = 0.430$).

Cross-validation reveals decreased explained variance ($R^2 = 0.086$) and increased RMSE (10.73). The relationship between predictions and actual rankings is not statistically significant ($\varrho = 0.228$; $p = 0.210$), suggesting limited generalizability due to the small sample size and high variable correlation.

Ridge regression reduces multicollinearity's impact but does not alter coefficient directions. Knowledge and Technology have negative effects, while Future Readiness a positive one. However, low cross-validation performance suggests digital competitiveness indicators alone cannot fully explain the RECAI ranking. Adding variables related to economic, institutional, or energy policies may improve explanatory power.

**Evaluation of Assumptions Before Regression Analyses for 2024 Data**

Before conducting regression analysis to explain the 2024 RECAI ranking via digital competitiveness dimensions, key assumptions are evaluated.

Normal Distribution: The Shapiro-Wilk test indicates normal distribution of residuals ($W = 0.977$; $p = 0.632$).

Homoscedasticity: The Breusch-Pagan test confirms homoscedasticity ($BP = 0.012$; $p = 0.912$).

Linearity: The Ramsey RESET test shows no significant nonlinearity ($F = 1.087$; $p = 0.349$). However, the Durbin-Watson test suggests positive autocorrelation ($DW = 0.385$; $p < 0.001$), though data is cross-sectional.

Initial multicollinearity checks in the full model show high VIF for DCI Knowledge (VIF = 10.527), DCI Technology (VIF = 7.394), and DCI Future Readiness (VIF = 6.739), indicating strong interrelations. After stepwise selection, only DCI Future Readiness remains, eliminating multicollinearity concerns (VIF = 1.000). This does not imply the other dimensions lack relevance but rather share variance with Future Readiness.

Influential observations are noted, with Cook's distances for observations 2 and 35 exceeding the threshold, and observation 1 showing high leverage. Despite these, no data errors justified removal, thus all observations are retained.

**Linear Regression Analysis for 2024 Data**

To identify the digital competitiveness dimensions that explain the 2024 RECAI ranking, a bidirectional stepwise linear regression is conducted. Initially including DCI Knowledge, DCI Technology, and DCI Future Readiness, the model ultimately keeps only Future Readiness. This indicates Future Readiness is the key variable contributing independently to the RECAI ranking.

The final model is statistically significant, $F(1,34) = 6.937$; $p = 0.013$, with an $R = 0.412$ and $R^2 = 0.169$, meaning Future Readiness explains about 16.9% of the variance in RECAI rankings. The adjusted $R^2$ is 14.5%, suggesting moderate explanatory power. Much of the variance may relate to factors beyond digital readiness, such as energy policies and market conditions.

The effect of Future Readiness on RECAI ranking is negative and significant ($B = -0.328$; $\beta = -0.412$; $p = 0.013$). A one-unit increase in Future Readiness correlates with a 0.33 rank improvement, indicating better positioning in renewable energy investment attractiveness.

Comparing 2023 and 2024, all three DCI dimensions are in the 2023 model, but multicollinearity affects significance. In 2024, Knowledge and Technology are removed, highlighting a shift towards digital readiness as a critical factor for competitive positioning in renewable energy investments.

### 3.1.3. Evaluation of Assumptions Before Regression Analysis of Differences Between 2023 and 2024

To determine whether the differences in the DCI sub-dimensions of countries during the 2023–2024 period explain the differences in the RECAI ranking, the assumptions are examined prior to the analysis. The examination reveals that the non-significant result of the Shapiro-Wilk test indicates that the residuals do not show a significant deviation from normal distribution ($W = 0.984$; $p = 0.899$). Accordingly, the assumption of normality of the residuals has been met.

The constancy of the error variances is examined, and the test result is found to be non-significant ($BP = 1.658$; $df = 3$; $p = 0.646$). This finding indicates that the error variance does not systematically change at different levels of the predicted values, thus confirming the homoscedasticity assumption.

When examining the independence of the residuals, it is shown that there is no statistically significant autocorrelation among the residuals ($DW = 2.224$; $p = 0.482$). Therefore, no evidence is found against the assumption of independence of the residuals.

The non-significance of the RESET test indicates that there is no clear evidence against the establishment of a linear model ($F = 1.264$; $p = 0.299$). Thus, it is assessed that it is appropriate to address the relationship between the variables using a linear model (Ramsey, 1969).

Multicollinearity among the independent variables is examined through VIF and tolerance values. The values obtained for Knowledge difference (VIF = 1.017; tolerance = 0.983), Technology difference (VIF = 1.014; tolerance = 0.986), and Future Readiness difference (VIF = 1.031; tolerance = 0.970) indicate that there is no multicollinearity problem. The VIF values being well below 5 and the tolerance values being above 0.20 suggest that the independent variables provide sufficiently independent information to the model (Hair et al., 2019).

When examining outliers and influential observations, it is found that no observation exceeded the absolute studentized residual threshold of 3.

In conclusion, it is observed that the assumptions of normality, constant variance, independence, linearity, and multicollinearity have been met.

**The Impact of Differences in DCI Dimensions on RECAI Ranking Differences**

A multiple linear regression analysis using the Enter method is conducted to determine if differences in DCI Knowledge, Technology, and Future Readiness from 2023 to 2024 explain differences in the RECAI ranking. The model is statistically non-significant, $F(3,28) = 0.655$; $p = 0.586$, indicating limited explanatory power of these differences for short-term RECAI ranking shifts.

The findings suggest that annual RECAI ranking differences are more influenced by direct factors like renewable energy policies, regulatory incentives, investment volume, financing costs, and international economic conditions, rather than short-term digital competitiveness differences. Additionally, ranking differences depend on relative performance among countries; even with improved DCI scores, a country may not rise if others progress faster.

In summary, while cross-sectional analyses for 2023 and 2024 show significant relationships between some DCI dimensions and RECAI rankings, annual differences in these indicators do not correlate with ranking differences. This suggests digital capacity levels relate to renewable energy investment attractiveness, but differences in short term may not immediately impact RECAI rankings. Longer-term panel data analyses can provide more insights into the delayed effects of digital transformation investments on renewable energy markets.

## 4- FINDINGS AND DISCUSSIONS

The aim of the study is to find out the interaction of digital competitiveness by considering its sub-topics which are technology, knowledge and future readiness with the ranking of 40 renewable energy attractive countries.

"Based on the correlation analysis of the 2023 data, the RECAI ranking is not significantly associated with DCI Future Readiness. The relationship with the DCI Knowledge dimension is negative and low-to-moderate in magnitude but does not reach statistical significance. However, its p-value is close to the conventional significance threshold, suggesting that this relationship may warrant further examination in larger samples. The strongest relationship is observed for the DCI Technology dimension, which is negatively and significantly associated with the RECAI ranking. Since lower RECAI ranking values indicate better positions, this finding suggests that higher Technology scores are associated with greater renewable energy investment attractiveness.

Based on the correlation analysis of the 2024 data, moderate, negative, and statistically significant relationships are identified between the RECAI ranking and both DCI Future Readiness and DCI Knowledge. These findings indicate that countries with stronger future readiness and knowledge-related capabilities tend to occupy better positions in the RECAI ranking. In contrast, the relationship between DCI Technology and the RECAI ranking is negative but does not reach statistical significance ($p = 0.057$). Although this result is close to the conventional significance threshold, it should not be interpreted as statistically significant. The observed pattern may nevertheless be examined further using larger samples. These findings are broadly consistent with Yang and Liu (2025), Nazari and Musilek (2023), and Bingxin et al. (2025), who emphasize the relevance of knowledge and technological capabilities in supporting sustainability and energy-related outcomes.

Based on the multiple linear regression analysis of the 2023 data, none of the three DCI dimensions Knowledge, Technology, and Future Readiness have a statistically significant individual effect on the RECAI ranking. The relatively high correlations among the independent variables may have reduced the stability of the individual coefficient estimates and contributed to their lack of statistical significance. Therefore, ridge regression is additionally conducted as a robustness analysis to address the multicollinearity among the predictors. The ridge regression results do not substantially alter the overall findings, as no clear independent contribution of the DCI dimensions emerged. Despite the lack of significant individual predictors, the overall multiple regression model is statistically significant and explains approximately 28.7% of the variance in the RECAI ranking ($R^2 = 0.287$). These findings are consistent with El Zein and Gebresenbet (2024), who suggest that the contribution of digitalization to renewable energy implementation depends on a broader set of factors, including societal and regulatory frameworks, cybersecurity, and access to attractive financing.

For the 2024 data, bidirectional stepwise linear regression is conducted by initially including DCI Knowledge, DCI Technology, and DCI Future Readiness. The final model retains only Future Readiness, indicating that it is the only DCI dimension making a statistically significant independent contribution to the RECAI ranking. Future Readiness has a significant negative effect on the RECAI ranking, meaning that higher Future Readiness scores are associated with better RECAI positions. Specifically, a one-unit increase in Future Readiness is associated with an approximately 0.33-position improvement in the RECAI ranking. The final model is statistically significant and explains 16.9% of the variance in the RECAI ranking ($R^2 = 0.169$), indicating relatively limited explanatory power. This finding is consistent with Dubey et al. (2026), who identify awareness and green technology readiness as important factors in supporting the development of the green energy industry."

Difference analysis is conducted to determine if differences in DCI Knowledge, Technology, and Future Readiness from 2023 to 2024 explain differences in the RECAI ranking. The model is statistically non-significant, indicating limited explanatory power of these changes for short-term RECAI ranking shifts.

## 5- CONCLUSION

The present study endeavors to investigate the interplay between digital competitiveness particularly its constituent elements of technology, knowledge, and future readiness and the rankings of 40 countries regarding their attractiveness for renewable energy investments. "The correlation results show that Technology is significantly associated with the RECAI ranking in 2023, whereas Knowledge and Future Readiness are significantly related to the RECAI ranking in 2024. In the 2023 regression model, although the overall model is significant, none of the individual DCI dimensions have a statistically significant effect on RECAI ranking. In 2024, Future Readiness emerges as the only significant predictor, with higher Future Readiness scores being associated with better RECAI positions. Finally, the analysis of 2023–2024 differences shows that score differences in Knowledge, Technology, and Future Readiness cannot significantly explain differences in RECAI rankings."

The findings suggest that dimensions of digital competitiveness, with a notable emphasis on future readiness, contribute to the determination of a country's appeal for renewable energy investments. It can be concluded that the attractiveness of renewable energy investments is increasingly linked not solely to technological infrastructure but also to the capacity for knowledge production and the preparedness for digital transformation. However, the difference model for the 2023–2024 period indicates that short-term fluctuations in the dimensions of digital competitiveness do not significantly account for short term differences in the RECAI ranking.

The results imply that, to enhance a country's attractiveness in renewable energy, it is crucial to adopt a multifaceted approach that builds on the findings of the study. Strengthening technological infrastructure through increased investment in research and development will foster innovation in renewable energy technologies. This should be complemented by initiatives aimed at enhancing future readiness, such as promoting digital transformation and developing skill-building programs to prepare the workforce for emerging technologies. Additionally, fostering knowledge production through collaborations between academia and industry can drive innovation and attract investment on renewable energy alternatives.

## FUTURE RESEARCH

By establishing the interrelationship between digital competitiveness and renewable energy investment, this study opens avenues for future research. It encourages scholars to further investigate the mechanisms through which digital technologies can facilitate energy transitions, particularly in underrepresented regions by adding different independent variables like availability of technical staff, which are not considered in this study.

## DECLARATIONS

**Generative Artificial Intelligence Statement:** Generative artificial intelligence tools were used solely to support language editing and improve the clarity and readability of the manuscript. These tools were not used to generate research data, conduct statistical analyses, interpret the findings, or develop the scientific conclusions. The author critically reviewed and revised all AI-assisted content and takes full responsibility for the accuracy, integrity, and originality of the published work.

**CRediT Authorship Contribution Statement:** Dilek Şahin Yomralıoğlu: Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing. The author read and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

**Conflict of Interest Statement:** The author declares that there is no financial, commercial, personal, or professional conflict of interest that could have influenced the research, analysis, interpretation, or publication of this study.

**Data Availability Statement:** The data used in this study were obtained from publicly available international index sources (World Digital Competitiveness Index and Renewable Energy Country Attractiveness Index). The compiled dataset and analysis files are available from the corresponding author upon reasonable request.

**Funding Statement:** The author received no financial support for the research, authorship, or publication of this article.

**Ethics Committee Approval:** This study uses publicly available secondary country-level indices and does not involve human participants; therefore, ethics committee approval was not required.

## REFERENCES


Ali, E. (2021). Climate change and agricultural development in West Africa: Role of renewable energy and trade openness. *Environmental Economics*, *12*(1), 14.

Asongu, S., & Odhiambo, N. M. (2022). Governance and renewable energy consumption in Sub-Saharan Africa. International Journal of Energy Sector Management, 16(2), 209-223.

Bingxin, W., Qamri, G. M., Hui, G., Ameer, W., & Majeed, M. A. (2025). From digitalization to renewable energy: How the tech-energy connection drives the green energy in belt and road countries. *Energy Economics*, *144*, 108324.

Bogdanov, D., Ram, M., Aghahosseini, A., Gulagi, A., et al. (2021). Low-cost renewable electricity as the key driver of the global energy transition towards sustainability. *Energy, 227*, Article 120467.

Cao, M., Song, W., & Xu, Y. (2024). Research on the impact of enterprise digital transformation based on digital twin technology on renewable energy investment decisions. *Energy Informatics*, *7*(1), 142.

Clifford, M. J., Perrons, R. K., Ali, S. H., & Grice, T. A. (Eds.). (2018). *Extracting innovations: Mining, energy, and technological change in the digital age*. CRC Press.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Sanchez Chico, A., & Stantcheva, S. (2025). Fighting climate change: International attitudes toward climate policies. *American Economic Review*, *115*(4), 1258-1300.

Diwanti, D. P., & Nawai, N. (2022). A systematical review of readiness for change of human and organization resources a case study in health organization. *JMMR (Jurnal Medicoeticolegal dan Manajemen Rumah Sakit)*, *11*(2), 164-179.

Dubey, S., Sachdeva, C., Katoch, R., & Mphande, C. L. (2026). Assessing the impact of green technology readiness and awareness on job performance in the green energy sector using technology acceptance model. *Discover Sustainability*, *7*(1), 462.

Elmassah, S. (2024). Determinants of renewable energy production in emerging and developed countries. *International Journal of Energy Sector Management*, *18*(5), 1014-1040.

El Zein, M., & Gebresenbet, G. (2024). Digitalization in the Renewable Energy Sector. *Energies*, *17*(9), 1985. https://doi.org/10.3390/en17091985

EY. (2023). *Renewable energy country attractiveness index: Top 40 ranking* (Report No. 62). https://www.ey.com/content/dam/ey-unified-site/ey-com/en-gl/insights/energy-resources/documents/ey-recai-62-v9-final.pdf

EY. (2024). *Renewable energy country attractiveness index: Top 40 ranking* (Report No. 63). https://www.ey.com/content/dam/ey-unified-site/ey-com/en-gl/insights/energy-resources/documents/ey-gl-recai-63-top-40-ranking-06-2024.pdf

Ezeanochie, C. C., Afolabi, S. O., & Akınsooto, O. (2021). A conceptual model for Industry 4.0 integration to drive digital transformation in renewable energy manufacturing. Iconic Research and Engineering Journals, 5(1), 1-12.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics* (4th ed.). Sage.

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models* (3rd ed.). Sage.

Görtz, M. (2026). Digital twins: past, present and future. *Scientific Reports*, *16*(1), 10510.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Hanga, K. M., & Kovalchuk, Y. (2019). Machine learning and multi-agent systems in oil and gas industry applications: A survey. *Computer Science Review*, *34*, 100191.

Hao, F., & Shao, W. (2021). What really drives the deployment of renewable energy? A global assessment of 118 countries. *Energy Research & Social Science*, *72*, 101880. https://doi.org/10.1016/j.erss.2020.101880

Ha, Y. H., & Kumar, S. S. (2021). Investigating decentralized renewable energy systems under different governance approaches in Nepal and Indonesia: how does governance fail. *Energy Research & Social Science*, *80*, Article 102214.

Heine, D., Faure, M. G., & Dominioni, G. (2020). The polluter-pays principle in climate change law: An economic appraisal. *Climate Law*, *10*(1), 94-115.

Htet, Y. W., Amin, M. R. M., Septiarini, E., & Wolor, C. W. (2026). Artificial Intelligence (AI) and 21st-Century Sustainable Marketing: A Dynamic Capabilities Approach to Sustainable Competitive Advantage. *Strategic Business Research*, 100166.

**IMD.** (2024). *World Digital Competitiveness Ranking 2024*. IMD Business School. https://www.imd.org/wcc/world-competitiveness-center/rankings/world-digital-competitiveness-ranking/

Kuzmin, E., Vlasov, M., Strielkowski, W., Faminskaya, M., & Kharchenko, K. (2024). Digitalization of the energy sector in its transition towards renewable energy: A role of ICT and human capital. *Energy Strategy Reviews*, *53*, Article 101418.

Lin, B., & Huang, C. (2023). Promoting variable renewable energy integration: the moderating effect of digitalization. *Applied Energy*, *337*, 120891. https://doi.org/10.1016/j.apenergy.2023.120891

Liu, C., Niu, H., Hayyat, M., & Hao, V. (2025). Understanding the relationship between ecological footprints and renewable energy in BRICS nations: An economic perspective. *International Journal of Hydrogen Energy*, *118*, 46-57.

Makpotche, M., Bouslah, K., & M'Zali, B. B. (2024). Corporate governance mechanisms and renewable energy transition. Corporate Governance: The International Journal of Business in Society, 24(3), 627-662.

Malhotra, Y. (2023). AI-Machine learning-data management governance & controls cloud computing best practices: Why ChatGPT-LLMs-generative AI cannot be trusted: Why we still need to advance R&D on them: Beyond AI hype: Advancing beyond limitations of ChatGPT, large language models, and generative AI. *2023 New York State Cybersecurity Conference, 25th Anniversary Cybersecurity Conference, New York State Capitol, Albany, New York, June 6-7, 2023.* Available at SSRN: https://ssrn.com/abstract=4444658

Maroufkhani, P., Desouza, K. C., Perrons, R. K., & Iranmanesh, M. (2022). Digital transformation in the resource and energy sectors: A systematic review. *Resources Policy*, *76*, Article 102622.

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & information systems engineering*, *57 (6)*, 339-343.

Nazari, Z., & Musilek, P. (2023). Impact of digital transformation on the energy sector: A review. *Algorithms*, *16*(4), Article 211.

Perrons, R. K., & Jensen, J. W. (2015). Data as an asset: What the oil and gas sector can learn from other industries about "Big Data". *Energy Policy*, *81*, 117-121.

Punna, S. K., Pusuluru, S., Ravikumar, M., & Menaa, F. (2026). AI-integrated manufacturing of advanced materials for energy storage, catalysis, and environmental applications. *Frontiers in Chemistry*, *14*, 1864044.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least squares regression analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, *31*(2), 350–371.

Rani, A., & Haris, M. (2024). Legal assessment of environmental, social, and governance integration for renewable energy success in Malaysia. *International Journal of Research and Innovation in Social Science, 8*(12). https://doi.org/10.47772/IJRISS.2024.8120306

Ren, Y., Li, B., & Liang, D. (2023). Impact of digital transformation on renewable energy companies' performance: Evidence from China. *Frontiers in Environmental Science*, *10*, Article 1105686.

Rizwanullah, M., Shi, J., Nasrullah, M., & Zhou, X. (2024). The influence of environmental diplomacy, economic determinants, and renewable energy consumption on environmental degradation: Empirical evidence of G20 countries. *PLoS ONE*, *19*(3), e0300921. https://doi.org/10.1371/journal.pone.0300921

Sahebi, I. G., Edalatipour, A., Dabaghiroodsari, M., Hasheminasab, S. M. H., Masoomi, B., & Kamali, S. E. (2025). Navigating the AI-powered transformation of renewable energy supply chains: A strategic roadmap to digitainability. *Energy for Sustainable Development*, *85*, 101663.

Setiawati, R., Eve, J., Syavira, A., Ricardianto, P., & Endri, E. (2022). The Role of Information Technology in Business Agility: Systematic Literature Review. *Calitatea*, *23*(189), 144-149.

Setyadi, A., Soekotjo, S., Lestari, S. D., Pawirosumarto, S., & Damaris, A. (2025). Trends and Opportunities in Sustainable Manufacturing: A Systematic Review of Key Dimensions from 2019 to 2024. *Sustainability*, *17*(2), 789.

Silva, D. S., Yamashita, G. H., Cortimiglia, M. N., Brust-Renck, P. G., & ten Caten, C. S. (2022). Are we ready to assess digital readiness? Exploring digital implications for social progress from the Network Readiness Index. *Technology in Society*, *68*, 101875.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.

Tsao, Y. C., Thanh, V. V., Lu, J. C., & Wei, H. H. (2021). A risk-sharing-based resilient renewable energy supply network model under the COVID-19 pandemic. *Sustainable Production and Consumption*, *25*, 484-498.

Tumin, V. M., Kharlanov, A. S., Zenkina, E. V., Kostromin, P. A., & Trifonov, V. A. (2022, February). Digital Transformation of Oil and Gas Sector during Transition to Renewable Energy Sources. In *International Scientific and Practical Conference Strategy of Development of Regional Ecosystems "Education-Science-Industry" (ISPCR 2021)* (pp. 484-489). Atlantis Press.

Tyagi, K., Rane, C., & Manry, M. (2022). Regression analysis. In *Artificial intelligence and machine learning for EDGE computing* (pp. 53-63). Academic Press.

United Nations. (2024). *Summit of the Future 2024*. https://www.un.org/en/summit-of-the-future?ysclid=mainw5qb1s185455507

World Competitiveness Index. (n.d.). *World digital competitiveness ranking*. https://www.imd.org/centers/wcc/world-competitiveness-center/rankings/world-digital-competitiveness-ranking/

Wooldridge, J. M. (2020). *Introductory Econometrics: A Modern Approach* (7th ed.). Cengage.

Xiao, C. (2025). Exploring and Overcoming Challenges for Digital Transformation in the Energy Sector Toward Carbon Neutrality. *Geological Journal*. https://doi.org/10.1002/gj.5156

Xu, X., Wei, Z., Ji, Q., Wang, C., & Gao, G. (2019). Global renewable energy development: Influencing factors, trend predictions and countermeasures. *Resources Policy*, *63*, 101470.

Velte P (2025;), "Sustainable corporate governance and corporate carbon outputs. Status quo of empirical research and further improvements". *Journal of Financial Reporting and Accounting*, Vol. ahead-of-print https://doi.org/10.1108/JFRA-10-2024-0743

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of business research*, *122*, 889-901.

Yang, G., Zha, D., Cao, D., & Zhang, G. (2024). Time for a change: Rethinking the global renewable energy transition from the Sustainable Development Goals and the Paris Climate Agreement. *Innovation*, *5*(2).

Yang, Y. X., & Liu, J. Y. (2025). Empowering green growth: The role of corporate digital transformation in boosting renewable energy investment in China. *Economic Analysis and Policy*, *86*, 590-605.

You, J. J., Hudson, P., White, P. C., Harrison, L. J., Armstrong, A., Treasure, L., & Lee, H. K. (2025). Biodiversity as a Social–Ecological Capability: Extending the Natural Resource-Based View in Renewable Energy Systems. *Business Strategy and the Environment*.

Yu, Y., Ren, F., Ju, Y., Zhang, J., & Liu, X. (2024). Exploring the role of digital transformation and breakthrough innovation in enhanced performance of energy enterprises: fresh evidence for achieving sustainable development goals. *Sustainability*, *16*(2), 650.

Zhao, Y., Xia, S., Zhang, J., Hu, Y., & Wu, M. (2021). Effect of the digital transformation of power system on renewable energy utilization in China. *IEEE Access*, *9*, 96201-96209.

Zuo, L., & Ren, Y. (2025). How renewable energy consumption and digitalization contribute to environmental sustainability: evidence from one belt one road countries. *Journal of Environmental Management*, *380*, 124379. https://doi.org/10.1016/j.jenvman.2025.124379