

Article

Digital Infrastructure and Renewable Energy Innovation: The Moderating Role of Human Capital

Imène Chakroun ^{1,*}, Ghassen El Montasser ² and Hichem Saidi ^{3,*}¹ Tunis Business School, University of Tunis, El Mourouj 2074, Tunisia² ESCT Business School, University of Manouba, Campus Universitaire la Manouba, Manouba 2010, Tunisia; ghassen.elmontasser@esct.uma.tn³ Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh 11432, Saudi Arabia

* Correspondence: imene.chakroun@tbs.u-tunis.tn (I.C.); halsaidi@imamu.edu.sa (H.S.)

Abstract

Digital infrastructure enables green transformation, but its impact on renewable energy innovation depends critically on the availability of human capital. This study examines whether human capital acts as a mediator or moderator in the relationship between digital infrastructure and renewable energy innovation. Drawing on innovation systems and absorptive-capacity theory, we distinguish deployed human capital (advanced-educated labor) from human capital in formation (tertiary enrolment). Using dynamic panel data models for a sample of 22 countries (2000–2020), we find a positive association between digital infrastructure and renewable energy patenting. However, human capital does not mediate this link; instead, it conditions the relationship's strength. The estimated marginal association is highly sensitive to human capital levels, progressively diminishing at higher levels of both deployed and in formation human capital. These findings suggest that the innovation returns to digital infrastructure depend on the timing and deployment of capabilities within innovation systems. These findings suggest that the innovation returns to digital infrastructure depend not only on digital expansion but also on the timing and deployment of capabilities within national renewable innovation systems. Consequently, digital transformation and human capital development policies should be pursued to align existing and emerging skills with green innovation needs.

Keywords: digital infrastructure; renewable energy innovation; human capital; absorptive capacity; national innovation systems; green development



Academic Editors: Jianming Cai and Cristina Raluca Gh. Popescu

Received: 19 May 2026

Revised: 9 July 2026

Accepted: 14 July 2026

Published: 20 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The transition to low-carbon energy systems increasingly depends on countries' ability to generate and diffuse renewable energy technologies. Digital infrastructure is often expected to support this process by improving connectivity, data processing, coordination, and access to knowledge. However, the innovation benefits of digital infrastructure are not automatic. Countries with similar levels of digital expansion may differ considerably in their ability to translate digital capabilities into renewable energy innovation. More broadly, recent research suggests that green development outcomes are shaped not only by technological resources but also by the broader economic and institutional environment within which innovation takes place, highlighting the importance of understanding the conditions under which innovation-supporting resources generate sustainable outcomes [1].

This raises the following question for green development research: under what human-capital conditions is digital infrastructure associated with renewable energy innovation?

From a national innovation system perspective [2], digital infrastructure provides opportunities for knowledge access and coordination, but human capital may shape whether those opportunities can be recognized, absorbed, and translated into inventive activity [3]. This role is consistent with the absorptive-capacity view [4], which highlights the importance of skills and knowledge in enabling the identification, assimilation, and exploitation of new technological opportunities. However, human capital should not be treated as a single, homogeneous resource particularly in green innovation contexts where technological change and capability requirements evolve rapidly.

Prior studies have examined the importance of human factors in supporting sustainability-oriented outcomes [5], the role of digitalization in green innovation and energy-sector transformation [6,7], while others have emphasized the importance of education and skills for environmentally oriented innovation [8–10]. However, empirical evidence on three points remains limited. First, cross-country evidence on whether national digital infrastructure translates into renewable energy inventive activity is still developing. Second, human capital is often treated as a broad aggregate resource, even though skills already deployed in the labor force may differ from skills still being formed through tertiary education. Both constructs capture different stages of capability development and may influence innovation through different temporal mechanisms. This distinction is particularly relevant in digital–green innovation contexts, where capability development and capability deployment often follow different learning trajectories and time horizons, leading to heterogeneous innovation outcomes [11]. Third, while theoretical work distinguishes between mediation and moderation mechanisms, empirical comparisons of these two roles—particularly whether human capital transmits or conditions the digital infrastructure effect—are scarce. Distinguishing between these mechanisms is theoretically important because it determines whether human capital operates primarily as a channel through which digital infrastructure influences innovation or as a capability that shapes the effectiveness of digital resources. This distinction therefore contributes to broader debates on the role of complementary assets and absorptive capacity in digital-led green innovation [7,12].

This study addresses these gaps by asking three research questions. First, is digital infrastructure associated with renewable energy innovation? Second, do different forms of human capital contribute differently to renewable energy innovation? Third, does human capital mediate or moderate the relationship between digital infrastructure and renewable energy innovation? To answer these questions, we distinguish between two dimensions of human capital: deployed human capital, measured by the labor force with advanced education, and human capital in formation, measured by tertiary enrolment. This distinction allows us to move beyond aggregate treatments of human capital and to consider whether existing skills and future skill formation play different roles in shaping the relationship between digital infrastructure and renewable energy patenting.

Using panel data for 22 countries over the period 2000–2020, this study investigates the direct association between digital infrastructure and renewable energy patenting and tests the distinct roles of human capital in that relationship. The results show that digital infrastructure is positively associated with renewable energy patenting. However, the evidence does not support the mediating role of human capital. Instead, human capital appears to operate primarily as a conditioning factor. The interaction results suggest that the marginal association between digital infrastructure and renewable energy innovation is estimated to be lower at higher levels of both deployed human capital and tertiary

enrolment, consistent with an interpretation emphasizing the role of capability deployment and timing in shaping the innovation returns to digital infrastructure.

The paper makes three contributions. First, it contributes to the green innovation literature by examining digital infrastructure as a national enabling condition for renewable energy patenting. Second, it contributes to the human-capital and absorptive-capacity literature by distinguishing between deployed human capital, measured by the labor force with advanced education, and human capital in formation, measured by tertiary enrolment. Third, it contributes to debates on digital-led green development by providing empirical evidence comparing mediation and moderation mechanisms, thereby shedding light on whether human capital operates as a transmission channel or a conditioning factor in the digital infrastructure–innovation relationship.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 presents the data and variables. Section 4 outlines the methodology. Section 5 reports the empirical results. Section 6 discusses the findings and their implications for green innovation and development. Section 7 concludes.

2. Literature Review and Hypothesis Development

This section develops the theoretical foundation of the study. It first reviews the role of digital infrastructure as an enabling condition for renewable energy innovation. It then discusses human capital as a form of absorptive capacity within green innovation systems, distinguishing between deployed human capital and human capital in formation. Finally, it develops the argument that human capital may operate either as a mediating channel or as a moderating condition in the relationship between digital infrastructure and renewable energy innovation.

2.1. Digital Infrastructure as an Enabling Condition for Renewable Energy Innovation

Digital transformation is reshaping innovation systems by acting both as a technological driver and as an enabling infrastructure for ecosystem-level coordination. In National Innovation Systems, innovation outcomes reflect the quality of interactions among firms, universities, public agencies, and supporting infrastructures that govern knowledge creation, diffusion, and recombination [2,13]. From this perspective, digital infrastructure expands the connectivity and information-processing capacity of national ecosystems, strengthening knowledge recombination and cross-institutional coordination. Recent evidence supports this enabling role: ref. [14] shows that information technology agility and flexibility enhance innovation capability, while ref. [15] documents how digital technologies reshape innovation across inputs, processes, and outcomes. At the system level, these digital capabilities may lower coordination costs and accelerate experimentation cycles, increasing the likelihood that renewable-energy solutions are codified in patentable inventions.

In the energy domain, digitalization has been shown to support green innovation [16,17]. Digital tools can enhance value creation by improving energy-management systems and alleviating bottlenecks in the renewable-energy transition [18]. Digital platforms can also reconfigure energy ecosystems and enable business-model innovation. The adoption of digital technologies has supported consumer-centric value creation [19] and facilitated energy-as-a-service models that improve resource allocation, operational efficiency, and market opportunities [20,21]. These ecosystem and business-model shifts may create demand for novel technical solutions, including smart-grid algorithms, predictive maintenance protocols, and storage configurations, some of which may be codified in patent applications. Accordingly, we hypothesize:

Hypothesis H1. *Digital infrastructure is positively associated with renewable energy innovation.*

2.2. Human Capital as Absorptive Capacity in Green Innovation Systems

Human capital constitutes a core national capability that underpins sustainable innovation, yet studies examining its role in the energy sector remain underdeveloped [22]. Within a National Innovation System perspective, human capital strengthens system-level absorptive capacity through its coevolution with innovative capability [12]. It enables actors to recognize, assimilate, and exploit external knowledge [4], thereby improving the capacity to convert technological opportunities into renewable energy inventions.

The multifaceted nature of human capital, encompassing education, skills, and experience, enhances the capacity to generate, absorb, and apply new knowledge. At the national level, high concentrations of human capital, reflected in a skilled labor force and research capabilities, are associated with greater creativity, knowledge recombination, and the development of innovative solutions [23–25]. These capabilities are particularly relevant in renewable energy domains, where innovation is increasingly data-intensive and requires interdisciplinary problem-solving, engineering knowledge, digital skills, and coordination across ecosystem actors.

Human capital may also support the alignment of technological innovation with sustainability goals. At the country level, green human capital can foster environmentally responsible practices and strengthen green innovation capabilities, thereby contributing to broader sustainable development objectives [8,26]. Human capital can also reinforce research and development capacity, promote knowledge exchange, and facilitate the diffusion of environmentally oriented knowledge, supporting green technology innovation [27]. However, the innovation contribution of human capital may differ depending on whether skills are already deployed in the economy or are still being formed through education. Deployed skills, reflected in the skilled labor force, represent immediate innovation capacity, whereas tertiary enrolment captures the formation of future capabilities. Recent research suggests that the contribution of higher education to innovation may unfold gradually, with stronger effects emerging over longer time horizons as educational investments are translated into productive and innovative activities [28]. Similarly, the authors of [29] argue that higher education supports technological innovation through human-capital accumulation and knowledge creation, although these benefits may not be reflected immediately in innovation outputs. As a result, periods of educational expansion may not necessarily coincide with higher current patenting activity when newly formed capabilities have not yet been absorbed into innovation processes. Consequently, human capital in formation may exhibit a weaker or delayed association with renewable energy patenting than deployed human capital.

Hypothesis H2. *Human capital is significantly associated with renewable energy innovation, but the direction and immediacy of this association may differ between deployed human capital and human capital in formation.*

2.3. Human Capital as Capability Formation, Transmission Channel, and Conditioning Factor

A central implication of National Innovation System theory is that infrastructures generate innovation returns only when complementary capabilities are present and effectively coordinated across the system. Human capital is one of the most important of these capabilities because it shapes the ability of actors to recognize, absorb, and exploit technological opportunities. However, human capital is not a homogeneous resource. Deployed human capital, reflected in the skilled labor force, represents capabilities already embedded in economic and innovation activities. By contrast, human capital in formation, reflected in tertiary enrolment, captures the development of future capabilities through higher education. This distinction is important because deployed skills may support the

immediate exploitation of digital opportunities, whereas tertiary enrolment may contribute more gradually as students enter the labor market and as education systems align with green and digital innovation needs.

Consistent with this framing, we argue that digital infrastructure may enhance the conditions for renewable energy innovation by expanding access to information, strengthening connectivity, and improving coordination possibilities across innovation actors. However, the extent to which these opportunities translate into patentable renewable energy innovations depends on human-capital conditions. Deployed skills may support the immediate exploitation of digital opportunities, whereas tertiary enrolment may capture a longer-term process of capability formation whose contribution to innovation emerges more gradually. This framing suggests that human capital may be more usefully understood as a conditioning capability than as a simple transmission channel through which digitalization affects innovation. This conditioning role need not imply that human capital always amplifies the marginal effect of digital infrastructure; it may also reflect diminishing returns, capability saturation, or differences in how digital and human-capital resources are aligned within national innovation systems.

The relationship between digital infrastructure, human capital, and renewable energy innovation can therefore be understood through two possible mechanisms. Recent evidence suggests that the effects of digital infrastructure on development outcomes may operate through both mediating and moderating mechanisms depending on the complementary conditions present within the system [30]. The first is a transmission, or mediation, pathway. Under this view, digital infrastructure may support learning, collaboration, resource allocation, and human-capital development, which in turn contribute to innovation. Human capital, in conjunction with technological change, may support the energy transition by accelerating renewable energy development [31]. Related studies suggest that digitalization can enhance learning and collaboration mechanisms that expand system-level absorptive capacity. For example, ref. [32] shows that digital transformation improves green innovation by enabling continuous learning and knowledge renewal, while ref. [33] finds that digital technologies contribute to the structural optimization of human capital, which subsequently promotes green innovation. Digital transformation has also been linked to increases in the number, efficiency, and quality of green patent applications [34]. Collectively, these studies suggest a plausible transmission pathway in which digital infrastructure may be associated with renewable energy innovation indirectly through human capital.

The second mechanism is a conditioning, or a moderation, pathway. From an absorptive-capacity perspective, the most immediate role of human capital may be to shape the innovation payoff from digital infrastructure rather than to transmit it. Digital infrastructure expands access to knowledge, data, and coordination opportunities, but innovation gains depend on whether the available skill base can exploit those opportunities. Consistent with this logic, several studies suggest that the influence of digitalization on green innovation depends on complementary human-capital conditions. Ref. [35] finds that digitally enabled environments deliver stronger green outcomes when supported by well-developed green human capital, while ref. [36] shows that human capital strengthens the relationship between digitalization and green innovation by improving the effectiveness of digital applications for sustainable development.

However, the conditioning effect may be nonlinear. A higher level of human capital does not necessarily imply that the marginal contribution of digital infrastructure will continue to increase. In more advanced innovation systems, additional digital infrastructure may produce diminishing marginal returns if basic connectivity and coordination constraints have already been reduced. Similarly, where skills are not effectively deployed toward renewable-energy sectors, or where tertiary education expands faster than labor-

market absorption, human capital may not amplify the digital infrastructure effect. These possibilities suggest that human capital may condition the digital infrastructure–renewable energy innovation relationship in ways that are positive, negative, or context-dependent. Accordingly, this study tests two alternative roles of human capital:

Hypothesis H3a. *Human capital positively mediates the relationship between digital infrastructure and renewable energy innovation, such that digital infrastructure is indirectly associated with renewable energy innovation through human capital.*

Hypothesis H3b. *Human capital moderates the relationship between digital infrastructure and renewable energy innovation, such that the marginal association between digital infrastructure and renewable energy innovation varies across human-capital conditions and may decline at higher levels of human capital.*

Building on these arguments, Figure 1 presents the theoretical framework of the study, showing how digital infrastructure and the two dimensions of human capital are expected to relate to renewable energy innovation.

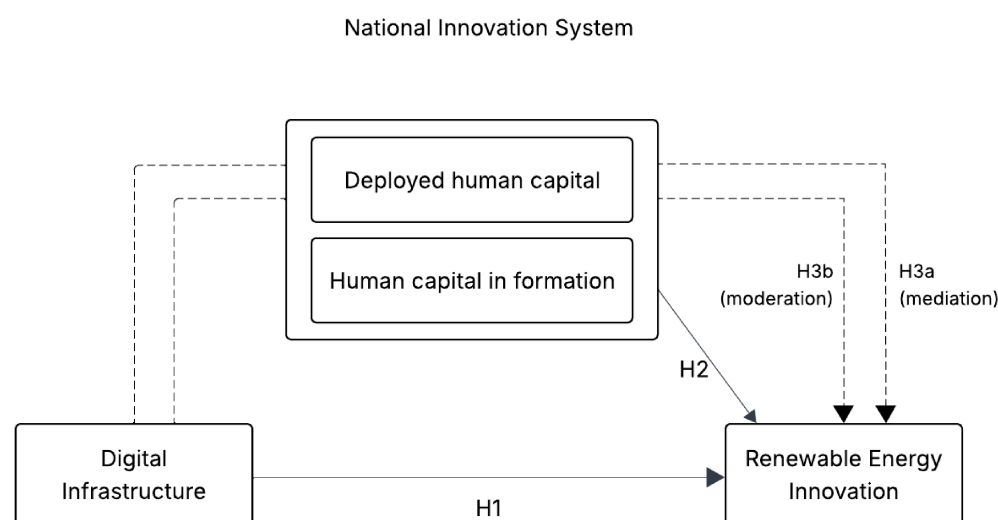


Figure 1. Theoretical model. Conceptual framework of digital infrastructure, human capital, and renewable energy innovation within a green national innovation system. Human capital is distinguished into deployed human capital and human capital in formation. H1 denotes the direct association between digital infrastructure and renewable energy innovation; H2 denotes the direct association between human capital and renewable energy innovation; H3a denotes the mediation pathway; and H3b denotes the moderating condition.

3. Data, Variables, and Measurement

This study draws on a country-level panel dataset comprising 22 countries over the period 2000–2020. The selected timeframe reflects both data availability and analytical relevance, as 2020 represents the most recent year for which comprehensive statistics on the labor force with advanced education are available for the studied countries. The final country sample is determined by the availability of consistent observations across renewable energy patenting, ICT indicators, human-capital measures, GDP per capita, and RD expenditure. The sample encompasses countries with varying levels of green innovation capability including top performers, emerging players, and transitional economies, thereby capturing a broad spectrum of development trajectories and institutional contexts. This diversity allows for a richer understanding of how digitalization and human capital interact to influence renewable energy innovation in different contexts. The countries included

are Argentina, Austria, Belgium, Czechia, Denmark, Finland, France, Greece, Italy, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, Norway, Poland, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. Countries in the sample vary considerably in innovation performance, digital development, R&D investment, and economic development. The sample thus includes both highly innovative economies and those with more limited innovation capabilities.

Consistent with a digital transformation perspective, digital infrastructure is operationalized as a foundational digital capability that supports connectivity and coordination across national innovation ecosystems. Human capital captures system-level absorptive capacity that enables knowledge identification, assimilation, and exploitation. The dataset integrates indicators corresponding to the study's conceptual framework: renewable energy patenting (REP), information and communication technologies (ICT), labor force with advanced education (LF), and tertiary school enrollment (SET). Gross domestic product (GDP) and research and development expenditure (RD) are included as control variables, consistent with prior innovation research [37].

Renewable energy innovation is measured by renewable energy patenting (REP), defined as the total number of patents in renewable energy technologies. This indicator captures renewable-energy inventive output, including technologies related to wind and solar energy, energy storage, efficiency, grid management, and electric transport. REP is interpreted as an indicator of renewable-energy technological output rather than a measure of technology diffusion, commercialization, or environmental impact.

The ICT variable is operationalized as a composite index constructed through principal component analysis (PCA) of four underlying indicators: fixed broadband subscriptions, internet users, mobile cellular subscriptions, and fixed telephone subscriptions. PCA is used because digital infrastructure is multidimensional and cannot be fully captured by a single indicator. Before applying PCA, the four ICT indicators are standardized to account for differences in units of measurement. The first principal component is retained as the ICT index because it captures the largest share of common variation across the indicators. Higher values of the index indicate stronger digital infrastructure. For transparency, the PCA loadings, eigenvalue, and explained variance should be reported in an appendix. Human capital is measured using two indicators that capture different stages of capability availability. Labor force with advanced education (LF) captures deployed human capital because it reflects advanced skills already available in the labor market and therefore more directly connected to current innovation activity. Tertiary school enrollment (SET) captures human capital in formation because it reflects future capability development through higher education. This distinction allows the analysis to examine whether existing skills and future skill formation relate differently to renewable energy innovation.

Table 1 provides detailed definitions of all variables, their measurement approaches, abbreviations, and data sources.

To ensure the validity of this dynamic specification, prior to estimation we confirm the stationarity of the renewable energy patenting (REP) variable using second-generation panel unit root tests that account for cross-sectional dependence, specifically [38] the cross-sectionally Augmented Im–Pesaran–Shin test.

Table 2 summarizes the panel data variables. Renewable energy patents (REPs) exhibit substantial cross-sectional and temporal heterogeneity (mean = 314.73; range = 0–2291), indicating wide variation in countries' innovation performance over time. The ICT index fluctuates around zero on average. The labor force with advanced education (LF) remains relatively stable throughout the period, while tertiary school enrollment (SET), gross domestic product (GDP), and research and development intensity (RD) display considerable

dispersion, reflecting pronounced differences in human capital accumulation, economic development, and research effort across countries and years.

Table 1. Variables, abbreviations, and sources.

Variable	Definition	Measurements	Abbreviation	Sources
Total number of patents in renewable energy technologies	Renewable energy sources include wind and solar, energy storage, efficiency, grid management, and electric transport.	Total number of patents	REP	https://ourworldindata.org/grapher/patents-for-renewables-by-country accessed on 10 May 2025
ICT (composite index)	Composite measure of national digital infrastructure.		ICT	
Fixed broadband	Fixed subscriptions to high-speed access to the public Internet (a TCP/IP connection), at downstream speeds equal to, or greater than, 256 kbit/s.	Subscriptions (per 100 people)		International Telecommunication Union (ITU)/ICT Indicators Database
Individuals using the Internet	Internet users in the last 3 months.	(% of population)		
Mobile cellular subscriptions	Subscriptions to a public mobile telephone service providing access to the PSTN using cellular technology.	Subscriptions per 100 people		
Fixed telephone subscriptions	Sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones.	Subscriptions per 100 people		
Labor force with advanced education	Percentage of the working age population with an advanced level of education in the labor force.	(% of total working-age population with advanced education)	LF	International Labour Organization, ILOSTAT database
School enrollment, tertiary	Ratio of total enrollment.	(% gross)	SET	UNESCO Institute for Statistics (UIS)
GDP per capita (constant 2015 US\$)	Gross domestic product divided by midyear population.	Economic output per person (per capita)	GDP	World Bank national accounts data, and OECD National Accounts data files.
Research and development expenditure	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP.	(% of GDP)	RD	UNESCO Institute for Statistics (UIS)

Table 2. Summary statistics of the studied variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
REP	459	314.7342	460.548	0	2291
ICT	462	6.10×10^{-11}	0.2630318	−0.7073134	0.4722339
LF	462	80.23717	3.39764	73.6304	89.9739
SET	462	66.26787	21.06128	9.85431	143.9627
GDP	462	36,031.29	24,657.73	6336.383	112,417.9
RD	462	1.658813	0.9310237	0.27606	3.8738

4. Methodology

To examine the relationship between digital infrastructure and renewable energy innovation, this study employs a dynamic panel-data framework. The baseline model is written as follows:

$$REP_{it} = c_i + \alpha REP_{i,t-1} + \beta ICT_{it} + \delta x'_{it} + \varepsilon_{it}, \quad (1)$$

In Equation (1), REP denotes the total count of patents related to renewable energy technologies that measures renewable energy innovation while ICT refers to a composite index capturing the level of information and communication technology development that measures digital infrastructure. The term x'_{it} denotes a row vector of control variables, specifically GDP per capita and expenditures on research and development (RD).

This specification clearly reflects the structure of a dynamic panel data model, characterized by the inclusion of a lagged dependent variable. The rationale for this inclusion is strongly grounded in the recent academic literature, which emphasizes the persistence and path-dependence of innovation processes, particularly in the renewable energy sector. For instance, ref. [39] emphasizes that past technological choices often lead to self-reinforcing innovation trajectories due to existing infrastructure, institutional learning, and cumulative investments that shape subsequent technological paths. Consequently, mature technologies such as solar and wind continue to dominate, even as emerging alternatives gain momentum.

Recognizing the potential endogeneity of the lagged patenting variable $REP_{i,t-1}$, we adopt the system Generalized Method of Moments (GMM) estimator. This approach provides consistent and efficient estimation of the model's parameters by addressing the inherent simultaneity and unobserved heterogeneity issues common in dynamic panel frameworks.

After estimating the parameters of model (1), we obtain initial insights into the effect of ICT on REP . In a subsequent step, we investigate whether the two dimensions of human capital considered in this study—labor force with advanced education (LF), representing deployed human capital, and tertiary school enrolment (SET), representing human capital in formation—exert a moderating or mediating influence on the relationship between ICT and REP .

To examine whether LF and SET moderate the relationship between digital infrastructure and renewable energy innovation, the baseline model is extended by introducing interaction terms between ICT and each human-capital dimension:

$$REP_{it} = c_i + \alpha REP_{i,t-1} + \beta ICT_{it} + \lambda HC_{it} + \varphi (ICT \times HC)_{it} + \delta x'_{it} + \varepsilon_{it}, \quad (2)$$

Equation (2) is estimated separately using LF (labor force with advanced education) and SET (tertiary enrolment) as alternative measures of human capital. The interaction terms are therefore $ICT \times LF$ and $ICT \times SET$. If φ is statistically significant ($p < 0.05$), this indicates a moderating effect of the human-capital variable considered (LF or SET).

To assess whether labor force with advanced education (LF) and tertiary school enrolment (SET) mediate the relationship between information and communication technologies (ICT) and renewable energy innovation (REP), two key conditions must first be established. First, we need to confirm that the coefficient associated with ICT denoted by β in model (1) is statistically significant, thereby indicating a robust baseline relationship. Second, following the classical mediation analysis of ref. [40], we verify two empirical conditions. By investigating the first one, we estimate a regression in which the hypothesized mediator—either human capital in formation [SET] or deployed human capital [LF]—is regressed on ICT and the set of control variables.

For analytical consistency, this regression is also estimated within a dynamic panel data specification. This approach is substantiated by prior research suggesting that current levels of human capital are influenced by their past values, a dynamic underscored, for instance, refs. [41,42]. The following equation formalizes this intermediate step:

$$HC_{it} = c_i + \kappa HC_{i,t-1} + \tau ICT_{it} + \delta x'_{it} + \varepsilon_{it}. \quad (3)$$

In Equation (3), ICT is expected to exert a statistically significant influence on LF or SET, depending on the specification estimated. The analysis culminates with the examination of this model to investigate the second empirical condition if the first one is verified:

$$REP_{it} = c_i + a REP_{i,t-1} + b ICT_{it} + d HC_{it} + \delta x'_{it} + \varepsilon_{it}, \quad (4)$$

where d in (4) should be significant. If coefficient b in (4) becomes statistically insignificant, this indicates the presence of full mediation. Conversely, if b is reduced in magnitude relative to the coefficient estimated in Equation (1) but remains statistically significant, this is indicative of partial mediation.

All empirical analyses, including the System GMM estimations, mediation and moderation tests, and marginal-effect plots, were conducted using Stata 17.

5. Empirical Results

This section presents the empirical results in three steps. First, Model (1) is estimated to examine the baseline association between digital infrastructure (ICT) and renewable energy patenting (REP). Second, Model (2) is used to assess whether human capital, captured by labor force with advanced education (LF) and tertiary enrolment (SET), moderates the ICT–REP relationship. Third, Models (3) and (4) are estimated to examine whether human capital operates as a potential mediating channel.

5.1. Digital Infrastructure and Renewable Energy Patenting

The analysis begins by examining the association between ICT and REP, controlling GDP and RD expenditure, while excluding the human capital variables (LF and SET) from the dynamic panel specification. The results are presented in Table 3.

Table 3. GMM estimation results, dependent variable REP.

Independent Variable	Coefficient	Std. Err.	Z	$p > z $
Rep L1	0.993791	0.1261156	7.88	0.000
ICT	53.6832	9.50145	4.65	0.001
GDP	0.0001696	0.0002098	0.81	0.428
RD	−57.269165	16.2696	−3.52	0.017
_cons	7.984554	21.96673	0.36	0.720
Observations	437			
Number of groups (countries)	22			
Number of instruments	8			
L(2/4).L.rep collapsed				
Arellano-Bond test for AR(1) in first differences	$z = -2.17$ (0.030)			
Arellano-Bond test for AR(2) in first differences	$z = 1.76$ (0.179)			
Hansen test of overid. Restrictions statistic: chi2(3)	$=6.12$ (0.917)			

Table 3 presents the system GMM estimation results with REP as the dependent variable. The coefficient on the lagged dependent variable (L1.REP) is close to unity and

highly significant. The coefficient on the lagged dependent variable is close to unity, reflecting the highly persistent but stationary nature of renewable energy patenting activity over time. ICT is positively associated with REP, significant at the 1% level, and provides support for H1. GDP per capita is positive but statistically insignificant. By contrast, RD expenditure is negatively and significantly associated with REP. The diagnostic tests indicate no evidence of second-order serial correlation and fail to reject the validity of the instruments, thereby supporting the robustness of the estimates.

5.2. Moderation Results: The Conditioning Role of Human Capital

To evaluate whether LF moderates the relationship between ICT and REP, the previous specification is augmented by including an interaction term ($ICT \times LF$) among the explanatory variables. The results are presented in Table 4.

Table 4. Impact of ICT on REP with Labor Force with advanced education as a Moderator.

Independent Variable	Coefficient	Std. Err.	Z	$p > z $
Rep				
L1	0.9945045	0.123263	8.07	0.000
ICT	−670.5549	236.9451	−2.83	0.041
LF	8.23071	2.354989	3.65	0.022
ICTLF	−13.02478	4.635153	−2.81	0.025
GDP	0.0001459	0.000211	0.69	0.497
RD	−25.025078	5.52429	−4.53	0.015
_cons	−88.93077	152.6779	−0.58	0.566
Observations	437			
Number of groups (countries)	22			
Number of instruments	10			
L(2/4).L.rep collapsed				
Arellano–Bond test for AR(1) in first differences	$z = -2.18$ (0.029)			
Arellano–Bond test for AR(2) in first differences	$z = 1.78$ (0.175)			
Hansen test of overid. restrictions statistic: chi2(3)	$=9.28$ (0.929)			

Table 4 reports the system GMM estimates assessing the impact of ICT on renewable energy patents (REPs), accounting for labor force with advanced education (LF) as a moderating factor. The lagged dependent variable is positive and highly significant ($L1.REP = 0.994$), indicating strong persistence in renewable energy innovation activity over time, which justifies the use of a dynamic panel specification.

The coefficient on LF is positive and statistically significant at the 5% level, suggesting that a higher share of highly educated labor enhances renewable energy patenting. However, the direct coefficient on ICT is negative and significant, and the interaction term between ICT and LF is also negative and significant at the 5% level. This implies that the marginal effect of ICT on renewable energy patenting is negative in this specification and becomes even more negative as the proportion of highly educated labor force increases. This indicates that the estimated association between ICT and renewable energy patenting is highly sensitive to the level of human capital.

Among control variables, GDP does not exhibit a significant effect, while RD expenditure shows a negative and statistically significant coefficient (The negative coefficient associated with R&D expenditure should be interpreted with caution. Although innovation studies generally report a positive relationship between R&D investment and patenting activity, this result reflects variance absorption by the highly persistent lagged dependent variable in the dynamic specification. Because the lagged dependent variable captures the vast majority of the long-run cumulative effects of R&D, the short-run coefficient captures

only transitory fluctuations or efficiency shocks. Since R&D is included strictly as a control variable, we do not investigate this relationship further.) Diagnostic tests support the validity of the model: the Arellano–Bond test confirms the presence of first-order autocorrelation and the absence of second-order autocorrelation, while the Hansen test indicates that the instruments used are valid. Overall, the results suggest a conditional relationship between ICT, human capital, and renewable energy innovation. Table 5 reports the results on the moderating role of SET in the relationship between ICT and REP.

Table 5. GMM estimation results (dependent variable: REP, including SET interaction).

Independent Variable	Coefficient	Std. Err.	z	p > z
Rep	0.9956603	0.1306471	7.62	0.000
L1				
ICT	310.0994	71.94881	4.31	0.017
SET	−2.942662	0.3618927	−3.12	0.012
ICTSET	−3.6463668	0.7249238	−5.03	0.005
GDP	0.000227	0.0003163	0.72	0.481
RD	−21.283879	9.836636	−1.94	0.097
_cons	4.170496	36.0964	0.12	0.909
Observations			437	
Number of groups (countries)			22	
Number of instruments			10	
L(2/4).L.rep collapsed				
Arellano–Bond test for AR(1) in first differences			z = −2.16 (0.031)	
Arellano–Bond test for AR(2) in first differences			z = 1.76 (0.179)	
Hansen test of overid. restrictions statistic: chi2(3)			=8.36 (0.951)	

Table 5 reports on the system GMM estimation results incorporating tertiary education (SET) and its interaction with ICT. The lagged dependent variable is positive and highly significant, confirming strong persistence in renewable energy patenting and supporting the dynamic panel specification. ICT exhibits a positive and significant coefficient at the 5% level, indicating that digitalization plays an important role in supporting renewable energy innovation. In contrast, tertiary education (SET) enters with a negative and significant coefficient, suggesting that higher enrollment in tertiary education does not immediately translate into greater patenting activity.

Notably, the interaction term between ICT and SET is negative and strongly significant, implying that the positive impact of ICT on renewable energy patenting diminishes as tertiary education enrollment increases. This finding points to a moderating role of tertiary education, whereby ICT-driven innovation gains are relatively stronger in contexts with lower levels of tertiary enrollment.

Overall, the results highlight a clear moderating role of human capital in the ICT–innovation nexus. Both advanced labor force (LF) and tertiary education enrollment (SET) significantly condition the impact of ICT on renewable energy patenting. While ICT exerts a positive effect on innovation, its marginal contribution decreases as the availability of highly educated labor or tertiary-educated individuals increases, as reflected by the negative interaction terms. The results indicate that both LF and SET significantly condition the relationship between ICT and renewable energy patenting, as reflected in the negative interaction terms.

5.3. Mechanism Disentanglement: Transmission vs. Conditioning Pathways

While the preceding section established the conditioning role of human capital, digital infrastructure may also influence renewable energy innovation indirectly by altering human

capital dynamics. To explore this possibility and empirically rule out a simple transmission channel, we test the mediation conditions for both the advanced labor force (LF) and tertiary enrollment (SET). Across all specifications reported in this section, diagnostic tests confirm model validity, showing no evidence of second-order autocorrelation and valid overidentifying restrictions.

We first regress LF and SET on ICT to verify the initial conditions for mediation in Tables 6 and 7.

Table 6. Testing the first step of mediation: ICT effects on LF.

Independent Variable	Coefficient	Std. Err.	z	$p > z $
LF	0.8833701	0.3014915	2.93	0.068
L1.				
ICT	−2.364644	3.800944	−0.62	0.541
GDP	−0.0001408	0.0001392	−1.01	0.323
RD	−0.1853886	2.540655	−0.07	0.943
_cons	14.05921	39.23915	0.36	0.724
Observations			440	
Number of groups (countries)			22	
Number of instruments			7	
L(1/5).L.lf collapsed				
Arellano–Bond test for AR(1) in first differences			z = −2.19 (0.028)	
Arellano–Bond test for AR(2) in first differences			z = 1.57 (0.117)	
Hansen test of overid. restrictions statistic: chi2(2)			=0.70 (0.705)	

Table 7. Testing the first step of mediation: ICT effects on SET.

Independent Variable	Coefficient	Std. Err.	Z	$p > z $
SET	0.99347	0.0499984	19.87	0.000
L1.				
ICT	−2.106034	0.788776	−2.67	0.027
GDP	0.000038	0.0000436	0.87	0.383
RD	−0.9963465	0.6837451	−1.46	0.145
_cons	−3.016524	4.040938	−0.75	0.455
Observations			440	
Number of groups (countries)			22	
Number of instruments			7	
L(2/3).L.set collapsed				
Arellano–Bond test for AR(1) in first differences			z = −2.61 (0.009)	
Arellano–Bond test for AR(2) in first differences			z = −1.71 (0.310)	
Hansen test of overid. restrictions statistic: chi2(2)			=9.56 (0.968)	

For LF, the coefficient on ICT is statistically insignificant (Table 6), indicating that digitalization does not significantly influence the proportion of workers with advanced education within the sample period. Consequently, the first condition of Baron–Kenny for LF mediation procedure is not met [40].

The coefficient on L1.SET is close to unity and highly significant, confirming strong persistence in tertiary enrollment over time. ICT is negatively and significantly associated with SET at the 5% level, indicating that greater digitalization is associated with lower tertiary enrollment in the short term.

To complete the mediation test for SET, we proceed to the second stage of the mediation analysis in Table 8.

Table 8. Mediation analysis—step 2: effect of ICT on REP controlling for SET.

Independent Variable	Coefficient	Std. Err.	Z	$p > z $
Rep	0.9947619	0.1323744	7.51	0.000
L1.				
ICT	134.21479	27.33498	4.91	0.002
SET	−3.0393531	1.454235	2.09	0.030
GDP	0.0002316	0.0003699	0.63	0.538
RD	−25.37179	13.78901	−1.84	0.064
_cons	4.604301	44.05414	0.10	0.918
Observations	437			
Number of groups (countries)	22			
Number of instruments	9			
L(2/4).L.rep collapsed				
Arellano–Bond test for AR(1) in first differences	$z = -2.16$ (0.031)			
Arellano–Bond test for AR(2) in first differences	$z = 1.72$ (0.167)			
Hansen test of overid. Restrictions statistic chi2(3)	$=7.31$ (0.954)			

Table 8 reports the results including SET as an additional regressor. Controlling for SET causes the ICT coefficient to increase substantially, a pattern indicative of a suppression effect rather than traditional mediation. Additionally, SET exhibits a negative and significant association with renewable energy patenting. The diagnostic tests confirm model validity. Because controlling for SET amplifies rather than absorbs the digital effect, these results do not support a mediating role for tertiary enrollment.

To formally evaluate the indirect effects, we employ Sobel–Aroian–Goodman tests and cluster bootstrap inference (Tables 9 and 10).

Table 9. Asymptotic tests of the indirect effect.

LF					SET				
Short-term indirect effect = −20.068213					Short-term indirect effect = 6.401				
Long-term indirect effect = −10,875.273109					Long-term indirect effect = 187,136.960				
Mediation Test	Indirect Effect	Std. Error	Z value	p-value	Mediation Test	Indirect. Effect	Std. Error	Z-value	p-value
Sobel	−20.068213	32.27218	−0.622	0.534	Sobel	6.401	3.889	1.646	0.100
Aroian	−20.068213	32.23495	−0.623	0.533	Aroian	6.401	3.716	1.722	0.085
Goodman	−20.068213	32.30937	−0.621	0.535	Goodman	6.401	4.055	1.578	0.114

Table 10. Cluster bootstrap mediation test.

LF		SET	
Replications	5000	Replications	5000
95% IC (short term indirect effect)	[−7.840; 10.265]	95% IC (short term indirect effect)	[−6.289; 4.518]
95% IC (long term indirect effect)	[−6881.329; 5528.169]	95% IC (long term indirect effect)	[−2429.565; 2642.152]
Bootstrap mean effect (short term indirect effect)	0.267	Bootstrap mean effect (short term indirect effect)	−0.275
Bootstrap mean effect (long term indirect effect)	763.353	Bootstrap mean effect (long term indirect effect)	113.101

As reported in Tables 9 and 10, the results for LF fail to detect a significant indirect effect, and the bootstrap confidence interval includes zero, confirming the absence of mediation. For SET, the asymptotic tests suggest a marginally significant indirect ef-

fect. However, the bootstrap confidence interval includes zero, rendering the evidence supporting a mediating role of SET inconclusive.

Overall, these results do not support a robust mediating role for human capital. Instead, they empirically rule out simple transmission, confirming that human capital operates primarily as an active boundary condition (moderator) rather than a passive conduit.

To further illustrate this conditioning role, we plot the marginal effects of ICT across varying levels of human capital (Figures 2 and 3).

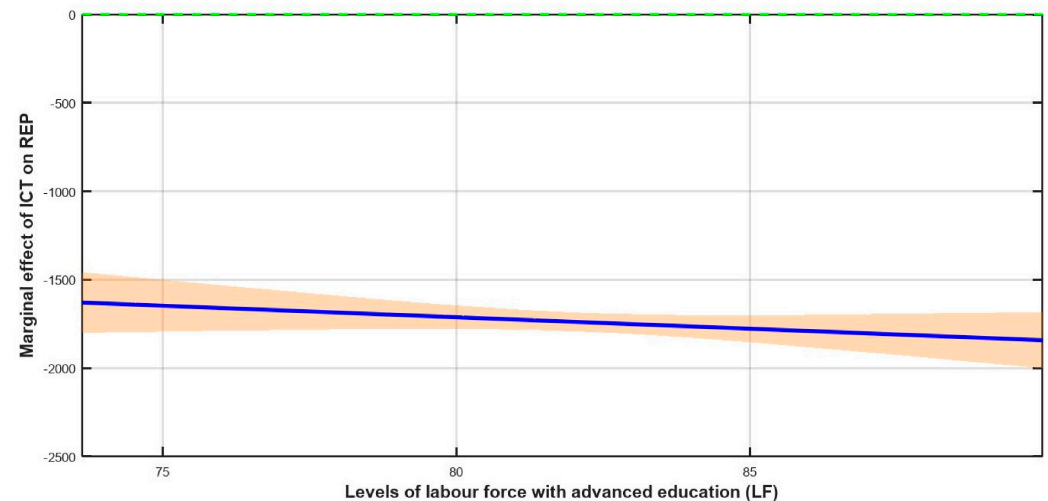


Figure 2. Marginal effects of ICT on renewable energy innovation across levels of LF.

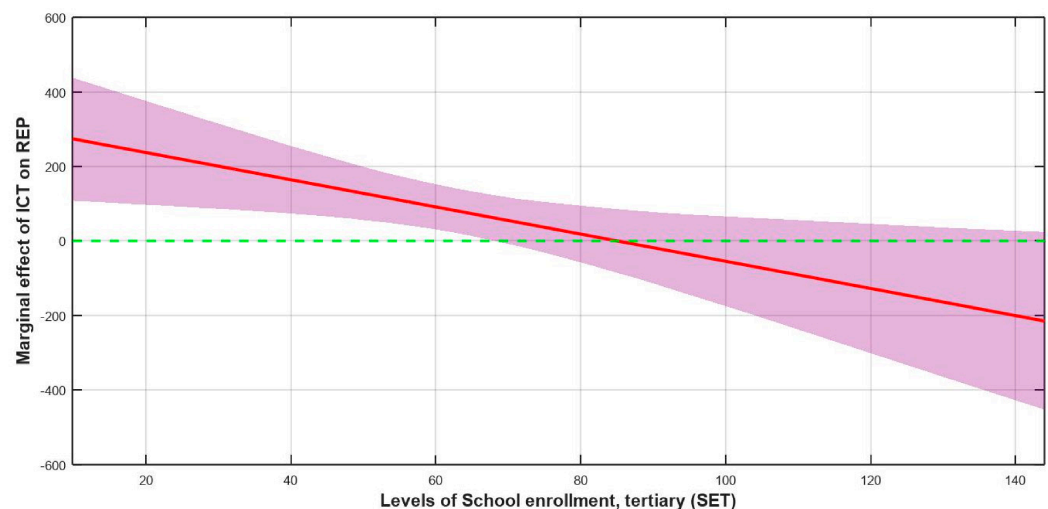


Figure 3. Marginal effects of ICT on renewable energy innovation across levels of SET.

Figures 2 and 3 illustrate the marginal effects of ICT on renewable energy innovation across varying levels of labor force with advanced education (LF) and tertiary education enrollment (SET), respectively. The marginal effects are derived from the interaction models as the partial derivative of renewable energy patenting with respect to ICT and are evaluated over the full observed support of LF and SET. The 95% confidence intervals are computed using the Krinsky–Robb method [43].

While both figures demonstrate that the marginal effect of ICT declines as human capital increases, the specific patterns differ based on the underlying coefficients. For tertiary education enrollment (Figure 3), the marginal effect of ICT is positive and statistically significant at lower levels of SET, but it progressively weakens, becoming statistically insignificant and eventually negative at higher levels of enrollment. This reflects the positive main effect of ICT combined with the negative interaction term reported in Table 5.

In contrast, for the labor force with advanced education (Figure 2), the marginal effect of ICT is negative and significant across the entire observed range of LF and becomes increasingly negative as the share of advanced education increases. This pattern is consistent with the negative coefficients for both the direct effect of ICT and the interaction term (ICT $\times$ LF) in Table 4.

Overall, these patterns illustrate that the association between digital infrastructure and renewable energy patenting is highly sensitive to the specific type and level of human capital, reinforcing the complex conditioning role of human capital in the digital innovation nexus.

6. Discussion

The empirical analysis reveals a nuanced relationship between digital infrastructure and human capital in renewable energy innovation across 22 countries. Rather than operating through a simple additive logic, these drivers interact in ways shaped by the structure of national innovation systems, the timing of capability formation, and the absorptive capacity available to convert digital opportunities into invention outputs. The findings are consistent with the view that digital infrastructure provides the backbone for ecosystem connectivity and coordination, but its translation into renewable energy patenting appears to depend on whether human capital enables knowledge exploitation at the right time and in the right institutional context. The discussion examines the direct role of digital infrastructure, the distinct roles of the two human capital dimensions, and the evidence for moderation without mediation, before articulating the theoretical and empirical limits of the analysis.

6.1. Confirming the Enabling Role of Digital Infrastructure

Digital infrastructure is positively associated with renewable energy innovation, consistent with the view that digital transformation can strengthen national innovation systems by improving information flows, coordination, and problem-solving capacity. By enabling data processing, real-time analytics, and computational capabilities, digital infrastructure may support green technology development, experimentation and more iterative R&D trajectories [7,44]. This interpretation is also consistent with recent research highlighting the role of technological innovation as a key driver of green development and environmental performance [45].

In the energy sector, the mechanism is not only technological but also business-ecosystem oriented. Intelligent systems, such as AI-enabled energy optimization and IoT-based grid monitoring, can increase operational efficiency and potentially create more favorable conditions for innovation activities [46]. Digital platforms further extend this effect by widening the networked architecture of innovation through data sharing, coordination, and co-creation across firms, utilities, research organizations, and regulators [25]. Consumer-centric value creation [20] and “energy-as-a-service” models [20,21] may create demand for new technical solutions (e.g., optimization algorithms, predictive maintenance protocols, storage configurations), some of which may be codified into patent applications.

6.2. Differentiated Roles of Deployed Human Capital and Human Capital in Formation

Human capital is expected to matter for renewable energy innovation, but the results indicate that its association with patenting depends on how human capital is measured and whether skills are already deployed or still in formation. This finding aligns with the absorptive capacity interpretation: innovation outcomes reflect not only the “amount” of education, but also whether skills are available and deployable for knowledge exploitation in green technological domains. When the labor force is already advanced-educated, skilled

workers embedded in national innovation systems may be better positioned to translate digital and climate-related knowledge into patentable low-carbon innovations [47]. This deployed human capital may strengthen green absorptive capacity and support renewable energy patenting [48,49].

Tertiary enrolment captures human capital in formation and may reflect transitional dynamics where education pipelines expand faster than labor markets and innovation systems can absorb and deploy new competencies. In contexts where curricula and training pathways lag the evolving demands of digitalized green sectors, short-run effects can appear weak or negative, consistent with temporal misalignment [50]. This creates a practical tension between the stock of available expertise (proxied by LF) and the flow of emerging talent (proxied by SET), especially when the green digital economy requires rapidly changing competencies. This should not be interpreted as evidence that tertiary education reduces innovation, but rather as an indication that education-based capability formation may not translate immediately into patenting. This timing misalignment is further evidenced by the negative short-run effect of digital infrastructure on tertiary enrolment itself (Table 7). In the short term, rapid digitalization may pull emerging talent directly into the labor market or alter educational pathways, temporarily depressing formal tertiary enrolment rates before these new competencies fully mature into patentable innovations.

Related evidence supports this timing interpretation. Recent research has shown that the contribution of higher education to innovation may unfold over different time horizons, with educational investments not necessarily translating immediately into innovation outputs [28]. Similarly, recent research emphasizes that the benefits of education depend not only on educational attainment itself but also on the accumulation and effective absorption of knowledge over time [51]. From this perspective, tertiary enrolment reflects the development of future capabilities whose contribution to innovation may emerge only gradually as newly acquired skills are integrated into innovation and production activities. Consequently, human capital in formation may exhibit a weaker association with current renewable energy patenting than deployed human capital, even though it remains important for longer-term innovation capacity.

Overall, the evidence implies that human capital matters for renewable energy innovation, but its contribution depends on the deployment, timing, and alignment of skills with the needs of the digital–green innovation ecosystem.

6.3. Conditioning Rather than Transmission: The Role of Human Capital in the Digital Infrastructure–Renewable Energy Innovation Relationship

The results are more consistent with a conditioning interpretation of human capital than with a transmission interpretation. Thus, H3a is not supported, whereas H3b is supported. The mediation tests do not provide support for the view that digital infrastructure is indirectly associated with renewable energy innovation through measurable changes in human capital over the period observed. More specifically, the Baron–Kenny conditions for mediation are not satisfied for either mediator, though for distinct reasons. For LF, the first-stage path—the effect of ICT on LF—is not statistically significant, structurally precluding a meaningful indirect effect. For SET, the coefficient on ICT increases in magnitude upon inclusion of the mediator, a pattern inconsistent with mediation and indicative of a suppression effect. These conclusions are further corroborated by the Sobel–Aroian–Goodman tests and cluster bootstrap procedure, both of which fail to establish a robust indirect effect for either variable. By contrast, the interaction results indicate that the estimated association between digital infrastructure and renewable energy innovation varies with the level of human capital. This pattern suggests that human capital functions primarily as a capability that shapes the extent to which digital opportunities are translated into renewable energy innovation.

From an absorptive-capacity perspective, this finding is plausible. Digital infrastructure may expand access to information, coordination opportunities, and technological possibilities, but the ability to convert those opportunities into inventive output depends on the skills available within the system [4,12]. This interpretation is also consistent with studies suggesting that digitalization generates stronger innovation outcomes when supported by complementary capabilities, including human capital and absorptive capacity [35,49,52]. At first glance, these findings may appear to differ from studies reporting a positive moderating role of human capital in the relationship between digitalization and innovation. One possible explanation is that previous studies often examine broader innovation outcomes or contexts in which human-capital accumulation remains a key constraint. By contrast, our distinction between deployed human capital and human capital in formation suggests that the timing and utilization of capabilities may be as important as their availability. In this context, the challenge may lie less in expanding human-capital stocks than in effectively deploying and aligning capabilities with renewable-energy innovation activities.

The negative interaction terms indicate that the estimated marginal effect of digital infrastructure is highly sensitive to the level of human capital, progressively diminishing or becoming increasingly negative as human capital increases. Specifically, in the context of the advanced labor force (LF), the direct effect of ICT is negative when the interaction is introduced, and this negative association is further amplified as the share of highly educated workers increases. This suggests that the innovation payoff from digital infrastructure is not uniform across human-capital contexts. Although the present analysis does not allow the underlying mechanisms to be observed directly, the evidence appears most consistent with an explanation based on the deployment and timing of human-capital development.

While digital infrastructure expands access to information and coordination opportunities, its contribution to renewable energy patenting depends on whether relevant skills are already available and embedded within innovation activities. This interpretation is supported by the contrasting roles of LF and SET in the empirical analysis. Whereas LF captures skills already deployed in the economy, SET reflects capabilities still in formation, whose contribution to innovation may emerge only gradually as newly acquired competencies are absorbed and mobilized within innovation systems. This reading is broadly consistent with research showing that digital transformation, innovation, and skill formation may evolve along different trajectories and time horizons [50], and with studies suggesting that the effect of education on green innovation may vary depending on the broader innovation environment [31,53]. Although the evidence appears most consistent with a deployment-and-timing interpretation, other mechanisms discussed in the literature, such as differences in skill alignment, diminishing marginal returns to digital investments, or variation in innovation-system maturity, may also contribute to the observed patterns and warrant further investigation.

Overall, the main implication is that digital infrastructure appears to generate innovation opportunities whose association with renewable energy patenting depends on complementary skill conditions. This reinforces the broader conclusion that digital-led renewable energy innovation depends not only on the expansion of digital resources, but also on the capability conditions under which those resources are used.

7. Conclusions

This study examined how digital infrastructure and human capital are associated with renewable energy patenting across 22 countries over the period 2000–2020. Drawing on National Innovation Systems theory and the absorptive-capacity perspective, it distinguished between deployed human capital, represented by labor force with advanced education, and human capital in formation, proxied by tertiary enrolment. The findings

show that digital infrastructure is positively associated with renewable energy patenting, but that this relationship is not automatic. Human capital operates more clearly as a moderating condition than as a mediating channel, indicating that the innovation payoff from digital infrastructure depends on how skills are deployed, formed, and aligned with renewable-energy innovation needs. These findings should be interpreted as evidence of conditional associations rather than definitive causal relationships, despite the use of a dynamic panel framework designed to mitigate endogeneity concerns. More specifically, the study contributes by distinguishing between deployed and in-formation human capital as two different stages of capability availability and by demonstrating that these dimensions shape the digital infrastructure–renewable energy innovation relationship primarily through conditioning rather than transmission mechanisms.

7.1. Theoretical Implications

The study contributes to the literature in three ways. First, it extends research on digitalization and green innovation by examining digital infrastructure as a national enabling condition for renewable energy patenting. This supports the view that digital transformation can improve knowledge recombination, coordination, and innovation capacity across ecosystems [54–56].

Second, it contributes to human-capital and absorptive-capacity research by showing that human capital should not be treated as a homogeneous stock. Deployed human capital and human capital in formation capture different stages of capability availability and therefore relate differently to renewable energy innovation. This distinction is consistent with the view that innovation outcomes depend on how complementary capabilities are formed, deployed, and integrated with technological change [23,57].

Third, the study clarifies the role of human capital in the digital infrastructure–innovation relationship by showing that human capital operates more clearly as a conditioning factor than as a transmission channel. This qualifies simple complementarity arguments and highlights the importance of capability alignment in digital-led renewable energy innovation. In this sense, the results align with ecosystem perspectives emphasizing that value creation increasingly depends on collaboration across interconnected systems rather than isolated organizational capabilities [58].

7.2. Policy and Practical Implications

From a policy perspective, the findings suggest digital infrastructure and human-capital policies are more effective when designed jointly. Policy priorities may nevertheless differ across national contexts. In countries where digital infrastructure remains relatively underdeveloped, efforts to expand connectivity, digital access, and innovation-supporting infrastructure may yield important benefits for renewable energy innovation. By contrast, in countries where digital infrastructure is already well established, additional investments in digital technologies may generate smaller innovation gains unless accompanied by measures that improve the deployment and alignment of human capital. In such contexts, strengthening university–industry collaboration, supporting the development of digital-green competencies, and facilitating the integration of skilled workers into innovation activities may be particularly important.

For policymakers, expanding human-capital stocks alone is insufficient. Greater attention is needed on how capabilities are deployed for digital-green transformation, including reducing coordination failures through sector-specific mobility incentives, innovation clusters, collaboration platforms, and university–industry partnerships. Prior research similarly shows policy effectiveness depends on interactions between mandates, market conditions, and network structures [59], while cross-sector collaboration and supply-chain integration

strengthen digitalization and green innovation [17,60]. For firms and ecosystem actors, digital infrastructure investment should be a capability-enablement strategy, not a standalone upgrade. In higher-skill contexts, the key challenge shifts from connectivity to skill deployment, organizational learning, and cross-sector collaboration, consistent with research on digital transformation and organizational capabilities [54,57].

For education systems, tertiary enrolment's contribution to patenting emerges only after students enter the labor market with green-digital competencies. Thus, curriculum reform, interdisciplinary training, work-integrated learning, and stronger university–industry links are needed, aligning with studies on sustainability competencies and transdisciplinary design [61–64]. Policy design should also account for national cultural contexts, as trust, cooperation, and risk-taking shape innovation outcomes [65]. Coordination mechanisms must therefore adapt to local cultural and institutional environments.

7.3. Limitations and Future Research

This study contributes to understanding how digital infrastructure and human capital jointly shape renewable energy innovation, but several limitations suggest future research directions.

First, the ICT indicator captures broad digital infrastructure and access conditions but does not directly measure advanced digital capabilities such as artificial intelligence, cloud computing, industrial internet applications, or the quality of digital adoption. The renewable energy patent counts measure inventive quantity rather than quality, diffusion, or commercial impact. The human-capital indicators (LF and SET) represent broad dimensions of educational attainment and may not fully capture the green- and digital-specific competencies most relevant for renewable energy innovation. Future research could employ more specialized measures, including AI-readiness indicators, digital technology adoption measures, citation-weighted patents, technology diffusion indicators, and green- or digital-specific skill measures to provide a more refined understanding of the relationship between digital infrastructure, human capital, and renewable energy innovation.

Second, the macro-level design does not allow direct observation of the mechanisms linking digital infrastructure, human capital, and renewable energy innovation. The current empirical design does not permit differentiation among the competing explanations, including skill alignment, diminishing returns to digital investments, and differences in innovation-system maturity. Each of these mechanisms is consistent with the observed moderation patterns, and the available data do not provide sufficient leverage to isolate their relative contributions. Future research could investigate these mechanisms using firm-level, sector-level, network-based, or qualitative approaches capable of tracing how digital resources and human capital are mobilized within innovation activities.

Third, although the dynamic System GMM estimator helps address persistence and endogeneity concerns, the results should be interpreted with caution. While we applied a strictly constrained instrument strategy—collapsing the instrument matrix and restricting lag depths to prevent instrument proliferation—the relatively small cross-sectional dimension (22 countries) and short time span inherently limit the degrees of freedom for the Hansen test. This results in high p -values that, while indicative of a tightly constrained model, reduce the statistical power of the overidentification test. Furthermore, while lagged instruments help mitigate reverse-causality concerns, they do not fully eliminate the possibility that more innovative countries attract greater digital investment and infrastructure development. Future research could help consolidate the findings using longer panels, alternative estimators, restricted instrument sets, lagged explanatory variables, panel cointegration techniques, external instruments, or other identification strategies designed to strengthen causal inference.

Fourth, the negative coefficient associated with R&D expenditure warrants acknowledgement as a limitation. Although this result is not without precedent in the green innovation literature, the current study does not provide a definitive explanation for this finding. Model-specific factors, including the dynamic specification and the composition of the country sample, may contribute to this result, and future research should examine the R&D–innovation relationship more directly in this context.

Fifth, although the sample captures substantial variation in renewable energy innovation, digital infrastructure, and human-capital conditions, it is concentrated in relatively advanced innovation systems and exhibits some heterogeneity in institutional arrangements and digital-development trajectories across countries. Consequently, the findings may not fully generalize to countries characterized by different institutional configurations, innovation-system maturity levels, or skill compositions. Future research could extend the analysis to a broader and more homogeneous range of countries to assess the observed relationships across different innovation-system contexts.

Author Contributions: I.C.: conceptualization, investigation, writing—original draft, visualization, formal analysis, data curation; G.E.M.: investigation, methodology, visualization, formal analysis, writing—original draft, software, supervision; H.S.: software, funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2604).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is available upon request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

REP	renewable energy patenting
HC	human capital
ICT	information and communication technologies
LF	labor force with advanced education
SET	tertiary school enrollment
GDP	Gross Domestic Product
RD	research and development expenditure
PCA	principal component analysis
GMM	Generalized Method of Moments
R&D	Research and Development

References

1. Ding, W.C.; Keoy, K.H. Green growth at risk: The role of geopolitical risk and economic policy uncertainty on green production practices. *Humanit. Soc. Sci. Commun.* **2026**. [\[CrossRef\]](#)
2. Lundvall, B.Å. National innovation systems—Analytical concept and development tool. *Ind. Innov.* **2007**, *14*, 95–119. [\[CrossRef\]](#)
3. Benhabib, J.; Spiegel, M.M. Human capital and technology diffusion. In *Handbook of Economic Growth*; Aghion, P., Durlauf, S.N., Eds.; Elsevier: Amsterdam, The Netherlands, 2005; Volume 1A, pp. 935–966.
4. Cohen, W.M.; Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [\[CrossRef\]](#)
5. Ding, W.; Muhammad, R. The Effect of Perceived Organisational Support Towards the Green Loyalty: The Mediating Effect of Green Trust and Green Satisfaction. *J. Inf. Knowl. Manag.* **2026**, *25*, 2550085. [\[CrossRef\]](#)

6. Lin, B.; Huang, C. Promoting variable renewable energy integration: The moderating effect of digitalization. *Appl. Energy* **2023**, *337*, 120891. [\[CrossRef\]](#)
7. El Zein, M.; Gebresenbet, G. Digitalization in the renewable energy sector. *Energies* **2024**, *17*, 1985. [\[CrossRef\]](#)
8. Ni, L.; Ahmad, S.F.; Alshammari, T.O.; Liang, H.; Alsanie, G.; Irshad, M.; Ayassrah, A.Y.B.A. The role of environmental regulation and green human capital towards sustainable development: The mediating role of green innovation and industry upgradation. *J. Clean. Prod.* **2023**, *421*, 138497. [\[CrossRef\]](#)
9. Song, W.; Meng, L.; Zang, D. Exploring the impact of human capital development and environmental regulations on green innovation efficiency. *Environ. Sci. Pollut. Res.* **2023**, *30*, 67525–67538. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Degirmenci, T.; Aydin, M.; Bozatli, O.; Ahmed, Z. Consolidating sustainable development in OECD countries: The role of green energy transition, green innovation, environmental policy stringency, and human capital. *Sustain. Dev.* **2025**, *33*, 823–835. [\[CrossRef\]](#)
11. Tsai, K.H.; Liao, Y.C. Innovation capacity and the implementation of eco-innovation: Toward a contingency perspective. *Bus. Strategy Environ.* **2017**, *26*, 1000–1013. [\[CrossRef\]](#)
12. Castellacci, F.; Natera, J.M. The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. *Res. Policy* **2013**, *42*, 579–594. [\[CrossRef\]](#)
13. Bui, T.T.; Pham, T.D.P. National innovation systems and corporate intangible investment as a driver of sustainable development: A cross-country study. *Sustain. Dev.* **2025**, *33*, 9226–9244. [\[CrossRef\]](#)
14. Abera, M.; Marvadi, C.; Suthar, D. Digitization strategy and innovation performance of microfinance institutions: Mediating role of innovation capability. *J. Account. Organ. Change* **2025**, *21*, 250–277. [\[CrossRef\]](#)
15. Agostini, L.; Galati, F.; Gastaldi, L. The digitalization of the innovation process: Challenges and opportunities from a management perspective. *Eur. J. Innov. Manag.* **2020**, *23*, 1–12. [\[CrossRef\]](#)
16. Ning, J.; Jiang, X.; Luo, J. Relationship between enterprise digitalization and green innovation: A mediated moderation model. *J. Innov. Knowl.* **2023**, *8*, 100326. [\[CrossRef\]](#)
17. Cheng, W.; Li, Q.; Wu, Q.; Ye, F.; Jiang, Y. Digital capability and green innovation: The perspective of green supply chain collaboration and top management's environmental awareness. *Heliyon* **2024**, *10*, e32290. [\[CrossRef\]](#) [\[PubMed\]](#)
18. Loock, M. Unlocking the value of digitalization for the European energy transition: A typology of innovative business models. *Energy Res. Soc. Sci.* **2020**, *69*, 101740. [\[CrossRef\]](#)
19. Karami, M.; Madlener, R. Business model innovation for the energy market: Joint value creation for electricity retailers and their customers. *Energy Res. Soc. Sci.* **2021**, *73*, 101878. [\[CrossRef\]](#)
20. Hu, B.; Zhou, P.; Zhang, L.P. A digital business model for accelerating distributed renewable energy expansion in rural China. *Appl. Energy* **2022**, *316*, 119084. [\[CrossRef\]](#)
21. Iria, J.; Soares, F. An energy-as-a-service business model for aggregators of prosumers. *Appl. Energy* **2023**, *347*, 121487. [\[CrossRef\]](#)
22. Adepoju, O.O.; David, L.O.; Nwulu, N.I. Analysing the impact of human capital on renewable energy penetration: A bibliometric review. *Sustainability* **2022**, *14*, 8852. [\[CrossRef\]](#)
23. Bresnahan, T.F.; Brynjolfsson, E.; Hitt, L.M. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Q. J. Econ.* **2002**, *117*, 339–376. [\[CrossRef\]](#)
24. Agarwalla, M.; Sahu, T.N. Do human capital development and innovation matter in sustaining economic development? Panel data evidence from selected developing economies. *Sustain. Dev.* **2024**, *32*, 6864–6880. [\[CrossRef\]](#)
25. Li, H.Y.; Liu, Q.; Ye, H.Z. Digital development influencing mechanism on green innovation performance: A perspective of green innovation network. *IEEE Access* **2023**, *11*, 22490–22504. [\[CrossRef\]](#)
26. Meng, C.; Shi, D.; Wang, B. The impact of green human capital of entrepreneurs on enterprise green innovation: A study based on the theory of pro-environmental behavior. *Financ. Res. Lett.* **2023**, *58*, 104453. [\[CrossRef\]](#)
27. Chen, D.; Chen, S. Patent protection policy and firms' green technology innovation: Mediating roles of open innovation and human capital. *Sustainability* **2024**, *16*, 2217. [\[CrossRef\]](#)
28. Szczepanska-Woszczyna, K.; Lyulyov, O.; Pimonenko, T.; Infante-Moro, A.; Zimbhoff, A.; Solodovnikov, S. The Contribution of Higher Education to Innovation Development: Long-Term and Short-Term Analysis. *Forum Sci. Oeconomia* **2024**, *12*, 8–29.
29. Zhou, G.; Luo, S. Higher education input, technological innovation, and economic growth in China. *Sustainability* **2018**, *10*, 2615. [\[CrossRef\]](#)
30. Zhang, J.; Yang, Z.; He, B. Does Digital Infrastructure Improve Urban Economic Resilience? Evidence from the Yangtze River Economic Belt in China. *Sustainability* **2023**, *15*, 14289. [\[CrossRef\]](#)
31. Zhang, Y.; Alharthi, M.; Ali, S.A.; Abbas, Q.; Taghizadeh-Hesary, F. Eco-innovative technologies, human capital, and energy pricing: Evidence of sustainable energy transition in developed economies. *Appl. Energy* **2022**, *325*, 119729. [\[CrossRef\]](#)
32. Wang, X.; Zhong, X. Digital transformation and green innovation: Firm-level evidence from China. *Front. Environ. Sci.* **2024**, *12*, 1389255. [\[CrossRef\]](#)

33. Yang, P.; Sun, W. How does digital technology facilitate the green innovation of enterprises? Evidence from China. *Int. Rev. Appl. Econ.* **2023**, *37*, 621–641. [\[CrossRef\]](#)
34. Dong, C.; Shen, Y.; Geng, G. Green innovation driven by digital transformation: An innovation chain perspective. *Systems* **2024**, *12*, 349. [\[CrossRef\]](#)
35. Abbas, J.; Najam, H. Role of environmental decentralization, green human capital, and digital finance in firm green technological innovation for a sustainable society. *Environ. Dev. Sustain.* **2025**, *27*, 19763–19777. [\[CrossRef\]](#)
36. Javeed, S.A.; Yang, X.; Latief, R.; Ong, T.S.; Li, J. Digital Technologies and Sustainable Development: An Insight from the Corporate Sector. *Sustain. Dev.* **2025**, *33*, 4248–4264. [\[CrossRef\]](#)
37. Li, S.; Shao, Q. How do financial development and environmental policy stringency affect renewable energy innovation? The Porter hypothesis and beyond. *J. Innov. Knowl.* **2023**, *8*, 100369. [\[CrossRef\]](#)
38. Pesaran, M.H. A simple panel unit root test in the presence of cross-section dependence. *J. Applied Econom.* **2007**, *22*, 265–312. [\[CrossRef\]](#)
39. Eitan, A.; Hekkert, M.P. Locked-in transition? Towards a conceptualization of path-dependence lock-ins in the renewable energy landscape. *Energy Res. Soc. Sci.* **2023**, *106*, 103316. [\[CrossRef\]](#)
40. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173–1182. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Bellakhdhar, A. L'accumulation du capital humain: Modèle théorique et évaluation dans le cas de la Tunisie. *Rég. Dév.* **2019**, *49*, 25–46.
42. Romer, P.M. Endogenous technological change. *J. Polit. Econ.* **1990**, *98*, S71–S102. [\[CrossRef\]](#)
43. Krinsky, I.; Robb, A.L. On approximating the statistical properties of elasticities. *Rev. Econ. Stat.* **1986**, *68*, 715–719. [\[CrossRef\]](#)
44. Wu, L.; Shi, J. From peer influence to green cognition: How digital transformation fosters renewable energy innovation in manufacturing. *Energy Econ.* **2025**, *148*, 108691. [\[CrossRef\]](#)
45. Du, M.; Antunes, J.; Wanke, P.; Chen, Z. Ecological efficiency assessment under the construction of low-carbon city: A perspective of green technology innovation. *J. Environ. Plan. Manag.* **2022**, *65*, 1727–1752. [\[CrossRef\]](#)
46. Liu, Y.; Li, W. From technological empowerment to green performance: Empirical evidence on digitalization-driven energy conservation and emission reduction in logistics enterprises—A case study of SF Holding. *Energy Inform.* **2025**, *8*, 105. [\[CrossRef\]](#)
47. Popp, D.; Vona, F.; Grégoire-Zawilski, M.; Marin, G. The next wave of energy innovation: Which technologies? Which skills? *Rev. Environ. Econ. Policy* **2024**, *18*, 45–65. [\[CrossRef\]](#)
48. Akhtar, S.; Li, C.; Sohu, J.M.; Rasool, Y.; Hassan, M.I.U.; Bilal, M. Unlocking green innovation and environmental performance: The mediated moderation of green absorptive capacity and green innovation climate. *Environ. Sci. Pollut. Res.* **2024**, *31*, 4547–4562. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Kastelli, I.; Dimas, P.; Stamopoulos, D.; Tsakanikas, A. Linking digital capacity to innovation performance: The mediating role of absorptive capacity. *J. Knowl. Econ.* **2024**, *15*, 238–272. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Ciarli, T.; Kenney, M.; Massini, S.; Piscitello, L. Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Res. Policy* **2021**, *50*, 104289. [\[CrossRef\]](#)
51. Maranzano, P.; Cerdeira Bento, J.P.; Manera, M. The role of education and income inequality on environmental quality: A panel data analysis of the EKC hypothesis on OECD countries. *Sustainability* **2022**, *14*, 1622. [\[CrossRef\]](#)
52. Lee, M.J.; Kim, Y.; Roh, T. Exploring the role of digital servitization for green innovation: Absorptive capacity, transformative capacity, and environmental strategy. *Technol. Forecast. Soc. Change* **2024**, *207*, 123614. [\[CrossRef\]](#)
53. Li, L.; Li, G.; Ozturk, I.; Ullah, S. Green innovation and environmental sustainability: Do clean energy investment and education matter? *Energy Environ.* **2022**, *34*, 2705–2720. [\[CrossRef\]](#)
54. Konopik, J.; Jahn, C.; Schuster, T.; Hoßbach, N.; Pflaum, A. Mastering the digital transformation through organizational capabilities: A conceptual framework. *Digit. Bus.* **2022**, *2*, 100019. [\[CrossRef\]](#)
55. Huang, L.; Liu, H.; Li, X.; Mancino, F.; D'Amato, A. Boosting green collaborative innovation among manufacturing firms with digital technology: The role of knowledge recombinative potential within supply chain network. *J. Knowl. Manag.* **2025**, 1–32. [\[CrossRef\]](#)
56. Shen, L.; Shi, Q.; Parida, V.; Jovanovic, M. Ecosystem orchestration practices for industrial firms: A qualitative meta-analysis, framework development and research agenda. *J. Bus. Res.* **2024**, *173*, 114463. [\[CrossRef\]](#)
57. Heubeck, T. Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance. *Digit. Bus.* **2023**, *3*, 100053. [\[CrossRef\]](#)
58. Lingens, B.; Huber, F. Heading the orchestra of innovation: How firms align partners in ecosystems. *Innovation* **2023**, *25*, 257–281. [\[CrossRef\]](#)
59. Baldwin, E.; Tang, T. Hierarchies, markets, and collaborative networks in energy governance: Multilevel drivers of renewable energy deployment. *J. Environ. Manag.* **2021**, *290*, 112614. [\[CrossRef\]](#) [\[PubMed\]](#)

60. Wang, S.; Zhang, H. Inter-organizational cooperation in digital green supply chains: A catalyst for eco-innovations and sustainable business practices. *J. Clean. Prod.* **2024**, *472*, 143383. [[CrossRef](#)]
61. Filho, W.; Sima, M.; Sharifi, A.; Luetz, J.M.; Salvia, A.L.; Mifsud, M.; Olooto, F.M.; Djekic, I.; Anholon, R.; Rampasso, I.; et al. Handling climate change education at universities: An overview. *Environ. Sci. Eur.* **2021**, *33*, 109. [[CrossRef](#)] [[PubMed](#)]
62. Olsson, D.; Gericke, N.; Boeve-de Pauw, J. The effectiveness of education for sustainable development revisited: A longitudinal study on secondary students' action competence for sustainability. *Environ. Educ. Res.* **2022**, *28*, 405–429. [[CrossRef](#)]
63. Iqbal, M.; Ul-Durar, S.; Arshed, N.; Shahzad, K.; Ayub, U. Connecting higher education and renewable energy to attain sustainability for BRICS countries: A climate Kuznets curve perspective. *Int. J. Emerg. Mark.* **2025**, *20*, 2042–2060. [[CrossRef](#)]
64. Liu, J.C.; Kan, T. A comprehensive review of environmental, sustainability and climate change curriculum in Taiwan's higher education institutions. *Int. J. Sustain. High. Educ.* **2024**, *25*, 375–389. [[CrossRef](#)]
65. Chakroun, I.; Saidi, H.; Montasser, G.E. The role of national culture in renewable energy development and green innovation dynamics: A cross-country analysis. *Discov. Sustain.* **2025**, *6*, 1244. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.