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Green growth pathway through green innovation and human capital under low and high regime: From the perspective of energy intensity

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Green growth has recently become an interesting field of research, as the pairing of economic growth and environmental preservation is seen as an urgent need. Despite this importance, few studies have investigated the underlying factor of green growth (GG), especially those relating to green innovation (GI) and human capital (HCI) as catalysts of energy intensity (IE). The current study aims to investigate the repercussions of human facets and the green patents on energy intensity-driven green growth. We use the panel threshold regression (PTR) supported by the Exponential Panel Smooth Regression (EPSR) method spanning the period 1997-2019 to the case of 16 countries which include most and least eco-friendly countries. Our findings disclosed that below a threshold value of the human capabilities, green technological innovation remains without negative effects on EI. Our results also revealed that only the group of most eco-friendly countries (MEFC) is those which benefit from green innovation by moving from a low to high regime of human capital index. The group of least eco-friendly countries (LEFC) cannot benefit from green innovation to foster GG even by translating from low regime to high regime. In addition, human capital exerts an adverse effect on EI in the case of low regime; and therefore, for a low threshold value of the HCI. The outcomes of the present study can clarify the need to implement future action plans in terms of arbitration between the environmental quality in its different forms and savings in terms of energy consumption.

1. Introduction

Due to accentuate and increasing environmental degradation, all economies around the world are currently faced with the urgency of balancing between good management of natural resources and the urgency of achieving sustainable growth (Zia et al., 2021; Alkaraan et al., 2022). The importance of green growth in the pursuit of SDGs, job creation, and the discovery of new energy sources has been substantially investigated by previous studies but with controversial results (Sandberg et al., 2019; Yikun et al., 2023). According to Wiebe & Yamano (2016), green growth refers to the development and implementation of less pollution-intensive technologies in order to produce cleaner and eco-friendly goods. Technological advancement as well as renewable energy technologies enabled through technical efficiency are drivers for promoting GG by recording fewer external costs materialized by less pollution (Danish & Ulucak, 2020). Therefore, technological innovations in general can reduce the energy use during the production chain (Banerjee et al., 2003). Furthermore, Ling Guo et al. (2017) argued that GG is a strategy intended to save employee energy and reduce carbon emissions. As a result, GG is an effective tool for overcoming the rise in environmental degradation downstream and upstream of the production chain. Among the underlying factors, although it is little studied by existing literature, is that of green innovation which allows economies to use the energy provided by different natural sources through innovative and environmentally friendly processes. A particular form of technological advancement intended for environmental sustainability is that relating to green innovation and even Dai and Zhang (2017) have argued that environmental management struggles are conditioned by green innovation performance. However, the technological facet of GG is not the only possible configuration, but it also incorporates the human facet. Human activities, whether intentional or not, contribute positively or negatively to environmental performance and sustainable growth. It is under the effect of educational level, acquired skills, experiences at the workplace and awareness of

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environmental damage, that human capital can constitute a catalyst for GG (Iorember et al., 2020). Conceptually, green innovation qualified by other research as eco-innovation (Garcia-Granero et al., 2018) is linked to innovative ideas allowing the improvement of processes and the creation of products whose outcome is the mitigation of environmental damage. Furthermore, empirical studies have widely examined the effects of green innovation on carbon emissions (Lee & Min, 2015; Zhang et al., 2017; Yang and Li, 2017; De Jesus et al., 2018; Sun et al., 2021; Ding et al., 2021; Ji et al., 2021) and environmental quality (Hojnik & Ruzzier, 2016; Mensah et al., 2019), but little existing research has investigated its repercussions on GG. Many previous studies have analyzed the effects of HCI on carbon emissions (Huang et al., 2021; Jin et al., 2022) and the ecological footprint (Ahmed & Wang, 2019; Chen et al., 2022), but the question of its impact on GG remains insufficiently documented. Under human capabilities, the mastery and advancement of technology is easier, energy consumption becomes controlled (Shahbaz et al., 2019), and the costs of adopting these technologies are lowered (Kim & Lee, 2011). Moreover, the substitution of polluting energy sources by renewable sources is permitted under the impact of human skills, which consolidates energy security (Desha et al., 2015). In addition, the effects of green innovation on carbon emissions and the fight against the depletion of energy sources are conditioned by human qualifications (Huang et al., 2021). It emerges from what has been mentioned that a set of gaps can be understood concerning previous studies relating to the connectedness between, green innovation, human facet and EI: Firstly, several studies have focused on the impact of green innovation on environmental degradation and not on an essential bridge of environmental quality which concerns GG. Most previous research has adopted a generalist approach through output and focused on the impact of human capital on environmental quality through its repercussions on carbon emissions (Bano et al., 2018; Nathaniel et al., 2020) Huang et al., 2021, Jin et al., 2021), or ecological footprint (Ahmed et al., 2019; Mahmood et al.,2019; Yu and Guo, 2023). Environmental sustainability is no longer assessed solely by indicators of environmental degradation but potentially by environmental management- based GG, more particularly by the EI report. Second, the relationship between green innovation and GG has not previously been articulated with the threshold value of HCI. The effects of green innovation performance can be moderated by the level of skills, know-how, experiences, and the degree of awareness.

In light of these shortcomings, this research aims to fill in the gap in the literature by proceeding in this way: First, we explore the repercussions of GI and HCI on one of the components of GG that are linked to EI. The nexus between GI and the EI has been little analyzed, and attention has rather been attributed to the environmental effects of GI (Bashir et al.,2020). Second, the connectedness between GI and EI was approached by following the threshold approach, and we retained human capital, the extent of which is supposed to condition this impact study. Most of the existing research on GG has basically followed a green innovation-driven perspective, and the role played by human capital threshold values for GG has not received sufficient attention. Third, in order to better understand the relationship between GI, HCI and EI, this study was based on aggregated databases differentiating between most eco-friendly countries and least eco-friendly countries. In fact, controlling energy consumption was recommended during the Conference of Parties (COP26) established in Glasgow, by limiting the global temperature below 1.5 C, particularly in the case of countries seeking growth. Therefore, the benchmarking between these two sub-samples allows clarification on the underlying factors of GG which can be differentiated according to the efforts in terms of green innovation and also to avoid the results being skewed. Through the present study, we will try to answer the following axial questions: Does green innovation constitute an effective means to boost GG? Are the effects of GI on GG conditioned by the registered human capital threshold? Do the impacts of HCI and GI on EI differ between the most and least eco-friendly countries? The contribution of the study lies in the investigation of the impact of environment-related technologies on GG depending on human capital index. So, the objective of the current research is to examine whether the level of acquired qualifications and awareness of the need for economical use of natural resources, which characterize the human facet are crucial to allow green innovation to encourage the GG process.

The rest of the study is conducted in this manner: First, we present an overview of existing literature that has focused on the effects of human capital and green innovation on GG. Then, we explain the methodology adopted including the models retained. Subsequently, we interpret the results found. Finally, we present the concluding remarks and the main recommendations.

2. Literature review

2.1. Human capital and green growth

The development of human capital has been considered an essential ingredient to limit energy ingestion and therefore, achieving efficiency in energy use (Bano et al., 2018). Two propagation channels through which human capital can influence GG: Since the study of Lucas and Robert (1988), the human factor is an important input for the production chain and can replace physical capital when economic structures change and according to Wang et al. (2022a), it constitutes a catalyst for the fight against pollution and the completion of GG. Economic development is only ensured in the presence of human capital during its different stages (Ding et al. 2021). The second mechanism is relating to the revival of labor productivity as well as those of other factors of production, including the energy productivity under the efficiency effect. The economic use of natural and energy resources is only possible by substituting these endowments in terms of human capital, and this is made by establishing an effective correspondence between the human facet and the energy facet. According to Sakamoto (2018), it is through the spillover effect that human capital can have an impact not only on its own productivity, but also and potentially on that of other production factors. The beneficial effects of human capital on GG are not only materialized in input but also in output. A human capital made aware of the dangers to the environment, well paid and educated, is perceived as a green consumer and vigilant of the damage that the nature of its consumption can lead to the environment (Fang & Chen 2017; Ulucak & Bilgili, 2018). Previous studies have not yielded conclusive results on the impact of HCI on EI. The majority of recent research has found positive effects of HCI on GG (Liu et al, 2023; Bano et al. 2018). By focusing on the innovation sector and referring to the simulation scenario, Xu (2021) showed a beneficial effect of HCI on green economic growth. For their part, Wang et al. (2021) classified human capabilities into three categories depending on education levels and they examined their effects on GG and found that only well-educated human resource is advantageous for GG. These authors found that only human capital having gone through the primary and secondary level, exerts moderating effects on GG. The bringing into play of the conscience about the acts necessary for the protection of the environment. The creation, mastery and development of eco-friendly technologies. These three forms of assets that can present the human facet in environmental terms depend on the forms of human capabilities. Indeed, according to Desha et al. (2015), human resource encompasses three ingredients: The stock of human capabilities materialized by the accumulation of past experiences and past educational courses. The second refers to knowledge specific to firms and acquired in the workplace. This latter form is embedded in the entrepreneurial culture of the organization by emphasizing the practice and attitudes of eco-friendly behavior (Azhar & Yang, 2021). The third concerns the skills and knowledge acquired from job-relating training. Referring to a sample of 30 Chinese manufacturing firms, Yuan and Zhang (2017) found that GG based on energy efficiency is possible through technological advancement and knowledge spillovers enabled through the provision of a high human capital staff. Pablo-Romero and Sanchez-Braza (2015) highlighted that human resource is a substitute for the energy use because well-educated, experienced and competent employees lead to technological advancement, which is more economical in energy terms, capable of reducing the costs of implementing modern technologies which can induce socially responsible and less polluting production (Kim & Lee, 2011). By focusing on three types of samples in the Asian region and applying truncated regression, Twum et al. (2021) revealed that the environmental efficiency index is high in the East Asia region compared to other regions and they highlighted the role of human capital in boosting environmental efficiency. Finally, well-educated employees, aware of the environment, and knowledgeable about energy security, allows monitoring of energy use (Shahbaz et al., 2019), more reliance on clean energy (Desha et al., 2015) and technological progress and decreasing costs of the use of green technologies (Kim & Lee, 2011). Alongside this line of research, another has shown that the human capital is not immune to negative effects on GG. Human resources are presented as a solution to make production greener, more economical in terms of energy used, less polluting and push for the implementation of environmental regulations (Yuan & Zhang, 2017). Based on a study carried out in Nigeria from 1971 to 2011, Adom (2015) found that human capital exerts a negative impact on energy use. For their part, Peng et al. (2023) examined the effects of different levels of human capabilities on green economic efficiency in the case of 280 Chinese prefecture-level cities, spanning the period 2003-2019. Their study revealed that, based on the baseline regression, the human facet boosts the green economic efficiency of prefecture-level cities. In addition, several past research have found perverse impacts of human capabilities on energy consumption (Shahbaz et al., 2019; Yao et al., 2019; Khan et al., 2020b; Gao et al., 2022; Shahbaz et al., 2022; Bouznit et al., 2023; Churchill et al., 2023; Pegkas, 2024) and few of them (Wang et al., 2022b) have shown positive effects. Table 1 presents a summary of recent research that has focused on the effects of HCI on energy consumption.

Table 1
Summary of recent studies on the effects of human capital on energy consumption

Authors	Samples (Periods)	Methods	Variables	Outcomes
Shahbaz et al. (2019	USA (1975-2016)	bootstrapping autoregressive-distributed lag (ARDL) cointegration approach	HC; GDP, ED ; EC; OP; NRR	$HC \overset{-}{\Rightarrow} EC$
Yao et al. (2019)	18 OECD countries (1965-2014)	AMG estimator	HC ; EC ; GDP ; EP ; IK; EIM; R&D; FD; UNION	$HC \overset{-}{\Rightarrow} EC$
Khan et al. (2020b)	G-7 economies (1995-2017)	AMG estimator	HC; EP; R&D; GDP; FD; MVA; IVA; TO; FDI; ECI; GFCF; EC	$HC \overset{-}{\Rightarrow} EC$
Gao et al. (2022)	China (2000-2019)	AMG estimator ; Panel threshold regression model	HC; GDP; K; ES; URB; FD; TO; EI; R&D; II; EC	$HC \overset{-}{\Rightarrow} EC$
Shahbaz et al. (2022)	China (1971-2018)	Bounds testing and VECM Granger causality approaches	HC; GDP; R&D; EC	$HC \overset{-}{\Rightarrow} EC$
Wang et al. (2022b)	China (1997-2018)	Fixed effects with instrumental variables and the Generalized Method of Moments	HC; GDP; ETP; TLI; URB; EX; EP ; EC	$HC \overset{+}{\Rightarrow} EC$
Bouznit et al. (2023)	Algeria (1970-2017)	OLS and FMOLS methods	HCI; GDP; K; URB; OP; EC	$HC \overset{-}{\Rightarrow} EC$
Churchill et al. (2023)	United Kingdom (1500-2020)	NARDL technique and 2SLS method	HC; EC; GDP; EP; URB; IK; TO; R&D; EC	$HC \overset{-}{\Rightarrow} EC$
Pegkas (2024)	Greece (1990-2021)	ARDL method	HC; GDP; K; EP; PAT; EC	$HC \overset{-}{\Rightarrow} EC$

Acronyms: EC: Energy consumption; ECI: Eco-innovation; ED: Export diversification; EIM: The ratio of net energy imports to total energy consumption; EI: Energy intensity EP: Energy prices; ES: Economic structure; ETP: Technological progress in the energy field; EX: Export FD: Financial development; FDI: Foreign direct investment ; GDP: Gross Domestic Product; GG: Green growth; GI: Green technology patents; GL: Globalization; HC: Human capital; II: Income inequality; IK: The ratio of investment to capital stock; IVA: Industry value-added; K: Physical capital stock; OP: Oil price; MVA: Manufacturing value-added; NRR: Natural resources; PAT: Energy patents; R&D: Research and development; TLI: Theil index; TP: Trade openness; UNION: The ratio of union membership to economy-wide employment; URB: Urbanization.

Although energy consumption reflects the GG process to the extent that the use of energy is reduced or integrated into the production chain more efficiently, environmental problems are prevented (Cihan and Değirmenci, 2024), this indicator remains restrictive and partial. We consider that EI constitutes a rigorous proxy for the GG process since it measures for each unit produced the units of energy used and, therefore, it indicates the energy inefficiency of an economy. Furthermore, the human facet can contribute to the sustainable development strategy depending on green innovation and, therefore, it can exert not only direct, but also moderating effects on GG through conditioning the impact of the environment related-technologies.

2.2. Geen innovation and energy intensity

The achievement of green growth has recently received increasing attention and several existing lines of research have addressed its underlying factors. Despite this orientation, studies on green innovation remain focused on its impacts on environmental degradation (Du et al., 2019; Khan et al. 2020a; Razzaq et al., 2021; Shao et al., 2021). According to Ullah et al. (2021), GG refers to a situation in which technological facets play a crucial vocation in monitoring the production chain and environmental degradation resulting from demand. This idea was highlighted by Mensah et al. (2019), who related GG to the vocation of environmental innovations in the field of energy production and distribution. Furthermore, an essential component revealing the trend towards GG is that relating to production efficiency which is enabled by green innovation. Under the challenges of carbon neutrality and the controlled exploitation of resource endowments, a branch of existing studies has focused on the most environmentally appropriate ways of eco-friendly achieving GG which have shifted the focus from technological innovation to clean innovation. In this regard, two opinions have arisen regarding the effects of GI on GG. The first vision is that achieving GG is possible due to the ability of green innovation to reduce environmental degradation, boost energy efficiency and reduce production waste (Ghisetti & Quatraro, 2017). The second vision emphasized the blessed vocation played by green innovation in waste recycling processes, thereby preserving the environment (Zhang et al., 2019). Kumari et al. (2021) showed that innovation in green processes makes it possible to preserve resource endowments, use renewable energy sources, and reduce waste through recycling. In addition, innovation in green products consists, according to Qu & Liu (2022), of mitigating environmental degradation resulting from manufacturing activities by integrating eco-friendly and renewable materials into existing products or by developing new products. Based on the fact that green innovation is a catalyst for GG in the energy sector (Ullah et al., 2021), environmental technologies not only allow the reduction of pollution and waste by implementing more efficient energy production processes, but also economical use and preservation of natural resources (Yikun et al., 2023). By focusing on the Chinese multivariate context spanning the period 1990-2018, Wang et al. (2021) applied the cointegration method and found that GG is positively mobilized by technological innovation in the long term among other factors relating to globalization, R&D spending, and economic growth. On an organizational level, green innovation is also a determinant of the organization's performance, if it is well ecological administered (Alhadid & As'ad, 2014). The development of GI can also lead to more energy efficiency as advocated by Abu Seman et al. (2019) who disclosed that green supply alongside GI substantially improves environmental quality and reveals the commitment of organizations to the environment. Likewise, Ahmed et al. (2023) referred to the SEM-based multivariate method applied to the textile industry in Pakistan and their findings revealed positive impacts of green innovation on organizational performance. Based on consumption-based pollution, Khan et al. (2020a) reached the conclusion that green innovation in the G7 economies is crucial for achieving GG by generating changes in the industrial fabric and economic structures. For their part, Wang et al. (2020) investigated the role of green innovation on GG in the G7 countries. These authors found perverse effects of export variety on GG, but they are attenuated by the presence of eco-innovation. Referring to aggregated country-level data related to 32 countries covering the period 1990-2013, Fernandes et al. (2021) showed that GG is boosted by sustainable innovation and sustainable technological innovation transfer, in turn allowing a revival of economic growth. Another line of research has revealed that technological innovations can constrain GG. These harmful impacts of innovations on sustainability and GG take the form of rebound effects resulting from the additional energy consumption and excessive exploitation of resources and therefore, more pronounced pollution which hinders GG (Zhang et al., 2018). In addition, companies are investing heavily in green innovations with the aim of maximizing revenues and for profit while saving capital and labor costs. This can overwhelm GG by causing more environmental degradation and wasted resource endowments (Zhang & Vigne, 2021). By applying the translog cost function, Wurlod and Noailly (2018) investigated the repercussions of green innovation on EI in the case of 14 industrial sectors specific to 17 OECD countries spanning the period 1975–2005. Their findings showed that GI reduced EI in most sectors and their quantitative results revealed that an increase in clean technologies led to a decline in EI. Moreover, Chakraborty and Mazzanti (2020) found that there is both a long and short-term connection between green energy innovation and EI although these relationships become insignificant over time and differ between the countries selected. Sun et al. (2019) discovered strong disparities in energy efficiency of 71 selected economies spanning the period 1990-2014. Their findings highlighted GI and institutional quality conditions favorably for energy efficiency. For their part, Ahmed et al. (2022) examined the underlying factors favoring sustainable economic progress and their findings revealed that green innovation act positively on the GG process.

In light of existing studies, the repercussions of GI on GG still remains questionable and inconclusive. The absence of the green outcome of environmental innovations is also justified by the lack of sufficient potential in terms of required skills and renewable and sustainable energy sources, particularly in developing countries. By referring to BRICS economies, Khattak et al. (2020) disclosed that green innovation and environmental quality are inversely correlated. Likewise, Weina et al. (2016) discovered the absence of effects of green technologies on environmental degradation in the Italian context spanning the period 1990-2010. Despite the fact that much previous research has found positive impacts of green innovation on GG, few of them have investigated the role of HCI in conditioning these effects. The current research attempts to explore the connectedness between GI and EI as a proxy for GG while examining the role played by the human capital threshold.

3. Methodology

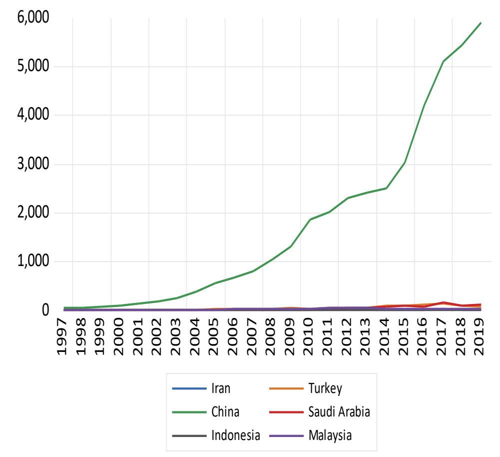
3.1. Data

The exploration of energy intensity-driven GG related to technology-related technology and the development of HCI was based on a database of core variables and a series of control variables. For this purpose, we used a variety of data sources covering the period 1997-2019. We refer to the database provided by OECD to collect the key variables related to EI and GI. We are based on EI, which is approximated by the total primary energy supply (TPES) per capita to measure GG. The use of EI as a proxy variable for GG is based on the assumption that the green character reflects not only the approaches used to limit environmental pollution but also the potential of countries in the economic use of energy during the production chain and, therefore, the capacity to restore resource endowments. We have retained green patents to measure environment-related technology which incorporates technologies reducing environmental pollution, water scarcity, and aiming at climate change mitigation. The use of patents related to the environment is a reliable proxy given their availability, its impartial character, and its centralization on the output of innovation activity. Furthermore, innovators in the green fields are only willing to register their patents when they are convinced that their inventions will be quickly commercialized, which allows them to reimburse the costs associated with filing patents in the different patent offices. Regarding all the variables relating to Internet use, mobile use and economic growth, they are all gathered from the WDI database and are proxied by Individuals using the Internet use (INTER), mobile cellular subscriptions (MOBI) and the GDP per capita growth GROWC), respectively. The human facet of GG was measured by the human capital index per person which is collected from the FRED database. In the current research, the impact of different core variables and covariates on GG is carried out in the context of 16 countries presenting extremely different outputs in terms of green innovation. Our sample includes the 10 most eco-friendly countries which are: Austria; Denmark; Finland; France; Ireland; Malta; Norway; Sweden; Switzerland and the United Kingdom. A second sub-sample concerns the least eco-friendly countries and includes the following countries: China; Indonesia Iran; Malaysia; Saudi Arabia and Turkey. The data on GG and all of their underlying factors and relating to the panel of countries mentioned above spanning the period selected have been compiled according to their availability. Table 2 presents all the variables retained, their measurements and a summary of descriptive statistics.

Table 2
Variable measurement and summary of descriptive statistics

Variable	EI	GI	HCI	INTER	MOBI	GROWC
Source	OECD database	OECD database	FRED database	WDI database	WDI database	WDI database
Maximum	7.42	5910.140	3.773	98.046	179.098	23.200
Minimum	0.67	0.500	1.611	0.032	0.618	-14.475
Mean	3.579	360.101	2.950	52.936	0.382	2.252
Median	3.51	129.950	3.086	58.000	97.363	2.015
Std.dev.	1.747	699.340	0.543	32.432	43.720	3.587
Skewness	0.300	4.616	-0.422	-0.263	-0.483	0.202
Kurtosis	2.302	30.342	2.010	1.596	2.364	7.892

Figs. 1-3 trace the developments recorded in terms of environment-related technology, human capital index and energy intensity in the case of MEFC and LEFC, respectively.



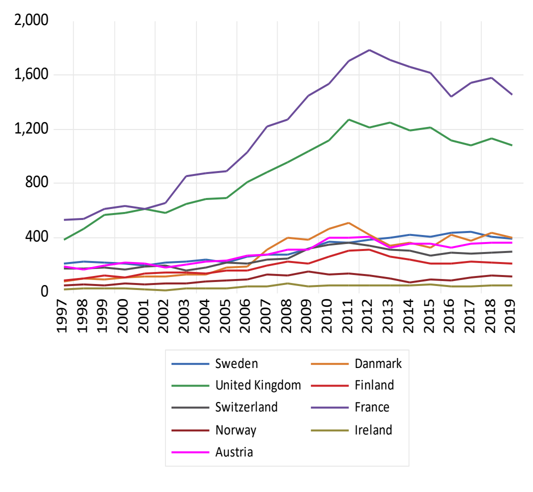


Fig. 1. Environment-related technologies in most eco-friendly countries and least eco-friendly countries

Fig. 2. Human capital index in most eco-friendly countries and least eco-friendly countries

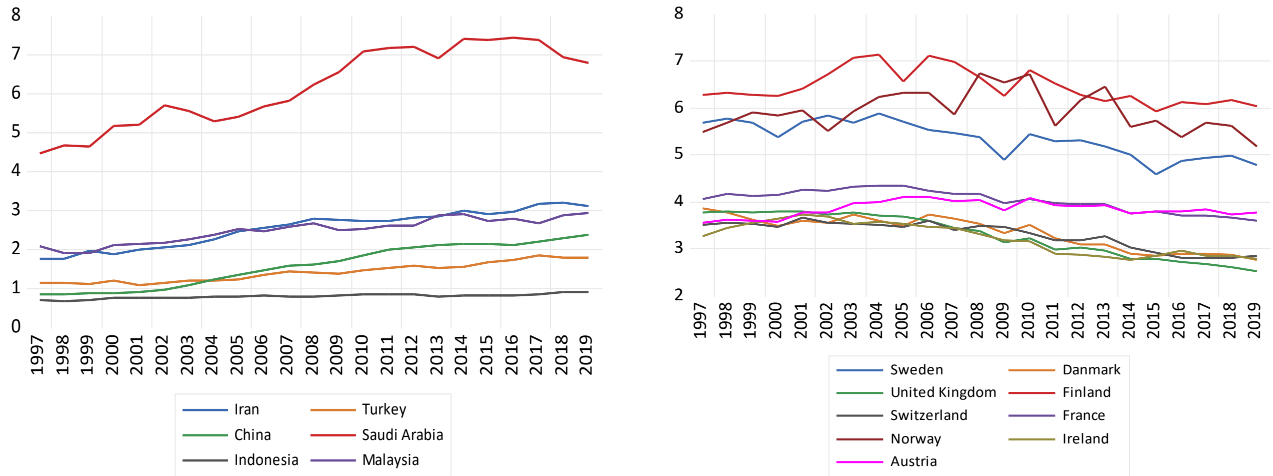


Fig. 3. Energy intensity in most eco-friendly countries and least eco-friendly countries

2.2. Threshold model

We investigate the connection between the human facet and the green innovation facet and the green governance while examining whether it is conditioned by the threshold value of the human capital index. The results differentiated according to the HCI threshold can reveal that the impact of the key variable relating to GI on GG is dependent on the level of human resource facet of the selected countries. Furthermore, we test whether the effects of green patents and HCI differ between the two subsamples of MEFC and LEFC. Then, we carry out a more advanced diagnosis by applying the Exponential Panel Smooth Regression (EPSR) method in order to test whether the effects of GI and HCI on EI differ between the linear and nonlinear parts. The model followed in the current study is part of the fixed effects model, and it effectively resolves the problem of heterogeneity characterizing nonlinear regressions. The category of PTR has the advantage, compared to other methods, that it distinctly allows the determination of regression coefficients having notable fluctuations between high and low regimes. The basic model is therefore traced by Eq. (1):

$$EI = f(GI\ ;\ HCI\ ;\ INTE\ ;\ MOBI\ ;\ GROWC) \tag{1}$$

The first formulation allows to test whether the threshold model is of type single or double which are traced by the following Eq. (2) and Eq. (3):

$$Y_{it} = \delta C + \beta_1 X_{it} I(q_{it} \leq \tau_1) + \beta_2 X_{it} I(\gamma_1 < q_{it} \leq \tau_2) + \beta_3 X_{it} I(q_{it} > \tau_2) + \vartheta_i + \omega_{it} \tag{3}$$

where C denotes the selected covariates, X indicated in our context the human capital. Y denotes the dependent variable related to EI. τ traces the threshold variable and q indicates its threshold value. I, ϑ, and ω trace the function indicator, the fixed constant through time, and the residues, respectively. The parameter specific to the threshold variable are traced by β. The following Eq. (4) reflects the residual sum of square:

$$S_r = \hat{e}(\tau)'\hat{e}(\tau) \tag{4}$$

Then, determining the nature of the model in question whether it is a single or double threshold requires recourse to LM statistics which involves testing the following hypotheses:

$H_0: \beta_1 = \beta_2$

$H_1: \beta_1 \neq \beta_2$

The approach consists of using this last equation to determine the authenticity threshold values which concern the human capital variable in this study. Once this hypothesis test is done, the next step consists of determining the LM statistic. This later is formulated by the following Eq. (5):

$$F_n(\tau) = \frac{S_0 - S_n(\hat{\tau})}{\hat{\sigma}^2} \tag{5}$$

where S_0 and $S_n(\hat{\tau})$ indicate the minimum sum and $\hat{\sigma}^2$describe the threshold regression residuals. The results of the null hypothesis tests make it possible to verify the existence or not of threshold impact. The statistics derived from the Eq. (6) allow, by testing the hypothesis $H_0: \hat{\tau} = \beta_0$, to conclude the authenticity of the threshold impact.

$$LR_n = \frac{S_n(\tau) - S_n(\hat{\tau})}{\hat{\sigma}^2} \tag{6}$$

In this last equation $S_n(\tau)$ indicates the unconstrained residual sum. Subsequently, the approach focuses on testing the following Eq. (7) in which the parameter θ refers to the level of significance retained:

$$LR_n \leq C\varphi = -2In\left[1 - \sqrt{1-\varphi}\right] \tag{7}$$

By replacing the core variables into Eq. (2) and Eq. (3), we obtain Eq. (8) and Eq. (9):

$$EI_{it} = \delta_{11}\, GI_{i,t} + \delta_{12} INTE_{i,t} + \delta_{13} MOBI_{i,t} + \delta_{14} GROWC_{i,t} + \beta_{11} HCI_{i,t} I(q_{it} \leq \tau) + \beta_{12}\, HCI_{i,t} I(q_{it} > \tau) + \vartheta_i + \omega_{it} \tag{8}$$

and

$$\begin{aligned} EI_{it} = {} & \delta_{11}\, GI + \delta_{12} INTE_{i,t} + \delta_{13} MOBI_{i,t} + \delta_{14} GROWC_{i,t} + \alpha_{11} HCI_{i,t} I(q_{it} \leq \tau_1) + \beta_{12} HCI_{i,t} I(\tau_1 < q_{it} \leq \tau_2) \\ & + \beta_{13} HCI_{i,t} I(q_{it} > \tau_2) + \vartheta_i + \omega_{it} \end{aligned} \tag{9}$$

2.2. Logistic and exponential PSTR model

The present study followed the approach of Gonzalez et al. (2005) who developed a particular configuration of the PTR model advanced by Hansen (2000) named the exponential panel Smooth threshold model. One of the specific forms of this model is its capacity to shed light on the linear and nonlinear effects of GI and HCI on EI. The advantage of this model is that it overcomes the problems of heterogeneity which characterize nonlinear regressions. In addition, these models take into consideration over time and individual changes in the effects of covariates. In the specific case of two regimes, the panel smooth threshold regression model is traced by Eq. (10):

$$y_{it} = \delta_i + \theta_0 x_{it} + \theta' x_{it} g(\tau_{it}, \gamma, c) + \mu_{it} \tag{10}$$

where *z* parameter denotes the threshold variable, *γ* denotes the transition function slope, and *c* the threshold parameter. The indices *i* and *t* denote the panel of countries selected and the time series, respectively. As a next step, we investigate the repercussions of GI and the HCI on EI in 21 countries from 1997 to 2019. We resort to the basic model described by the Eq. (8) and Eq. (9) in order to test the presence of nonlinearity between the variables. In this approach, the transition function presents two limit values 0 and 1. According to this approach, the logistic and exponential functions are formulated by Eq. (11) and Eq. (12), respectively:

$$g(\tau_i, \gamma, c) = \frac{1}{1 + exp[-\gamma(\tau_{it} - c]} \tag{11}$$

$$g(\tau_i, \gamma, c) = \frac{1}{1 + exp[-\gamma(\tau_{it} - c)^2]} \tag{12}$$

The transition function is equal to one if qit ≥ c and zero in case qit < c. The regression formulated by equations (8) and (9) presents fixed effects if γ→0. The sensitivity of the human capital index to EI as a function of cross-sections and time is formulated by the following Eq. (13):

$$\mu_{it} = \theta_0 + \theta_1 x g(\tau_{it}, \gamma, c) \quad (13)$$

The next step consists of examining whether the connection between HCI and EI is linear or nonlinear and therefore whether the use of the PSTR model is justified and takes following general form described by Eq. (14).

$$y_{it} = \delta_i + \theta_0^* Q_{it}\tau_{it} + \theta_1^* Q_{it}\tau_{it}^2 + \cdots + \theta_m^* Q_{it}\tau_{it}^m + \mu_{it}^* \quad (14)$$

In this last equation, the coefficients $\theta_0^*, \theta_1^* \dots, \theta_m^*$ are multiples of parmeter γ. This approach uses the Fischer LM test to test the null hypothesis. When the PSTR approach indicates the presence of at least 3 regimes, the model takes the form traced by Eq. (15):

$$y_{it} = \delta_i + \theta_0 Q_{it} + \theta_1 Q_{it} g_1(\tau_{it}, \gamma_1, c_1) + \theta_2 Q_{it} g_2(\tau_{it}, \gamma_2, c_2) + \mu_{it} \quad (15)$$

In this case, The null hypothesis has the following form H0: γ2 = 0. Starting from this approach, equation (16) is deduced and it is formulated as follows:

$$y_{it} = \delta_i + \theta_0^* Q_{it} + \theta_1^* Q_{it} g_1(\tau_{it}, \gamma_1, c_1) + \theta_{21}^* Q_{it}\tau_{it} + \cdots + \theta_{2m}^* Q_{it}\tau_{it}^m + \mu_{it}^* \quad (16)$$

4. Results and discussion

The present part of the research is devoted to analyzing the effects of GI and HCI on GG specific to the panel of countries selected while investigating whether this connectedness is dependent on the value of the HCI. The assessment of the impact is carried out through the threshold panel regression and concerns not only the entire sample but also each of the sub-samples of MEFC and that of LEFC. We also carry out a more advanced study by examining the linear and nonlinear part of all these effects by applying the Exponential Panel Smooth Regression. Before proceeding to explore the nexus between GI, HCI and energy intensity-based green growth, we carry out a rigorous and robustness check of the distribution of individuals and the time series. For this purpose, we will refer to the BDS independence test, CSD test, unit root and second-generation unit root tests. As presented in Table 3, the null hypothesis according to which time series is linearly dependent for all retained variables is clearly rejected and this reflects the inclusion of a hidden nonlinearity or nonstationarity.

Table 3
The outcomes of BDS independence test

Variable	Dimension 2		3		4		5		6	
	BDS Statistic	z-Statistic	BDS Statistic	z-Statistic	BDS Statistic	z-Statistic	BDS Statistic	z-Statistic	BDS Statistic	z-Statistic
EI	0.176***	59.350	0.298***	63.658	0.379***	68.336	0.429***	74.776	0.458***	83.379
GI	0.183***	23.295	0.309***	24.490	0.393***	25.915	0.447***	28.033	0.481***	30.904
HCI	0.193***	75.757	0.327***	80.562	0.417***	86.517	0.476***	86.517	0.514***	106.799
INTER	0.156***	65.184	0.252***	66.540	0.305***	68.304	0.329***	71.381	0.334***	75.801
MOBI	0.146***	43.267	0.234***	43.438	0.282***	44.040	0.303***	45.526	0.308***	48.044
GROWC	0.055***	10.157	0.097***	11.106	0.122***	11.695	0.133***	12.177	0.135***	12.704

Note: (***) describes significance at 1% threshold.

Table 4
The outcomes of CSD test

	BP-LM		PS-LM		Biaised corrected scaled-LM		Pesaran-CD	
Variable	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
EI	1256.943	0.000	79.491	0.000	79.150		2.301	0.021
GI	1461.509	0.000	93.608	0.000	93.267		37.488	0.000
HCI	2225.948	0.000	146.359	0.000	146.018		46.977	0.000
INTER	1878.534	0.000	122.385	0.000	122.044		42.969	0.000
MOBI	1934.195	0.000	126.226	0.000	125.885		43.774	0.000
GROWC	558.280	0.000	31.279	0.000	30.938		16.795	0.000

Table 4 revealed that all the variables retained in the study have reflected their significant results at 5% which allows us to reject the null hypothesis. Therefore, the outcomes show the presence of CD across the panel and this is validated by the Breusch-Pagan LM (BP-LM), Pesaran scaled LM (PS-LM), Biased corrected scaled-LM and Pesaran-CD tests. The existence of CD between individuals leads to checking the unit root properties. Table 5 presents the outcomes of unit root tests and shows that the core variables of the study are stationary in level and in first difference with the exception of the variable relating to HCI which is not stationarity at level according to the ADF test.

Table 5
Unit root tests

Test	ADF test		PP test		Result
Variable	Level (p-value)	First difference (p-value)	Level (p-value)	First difference (p-value)	
EI	-2.939** 0.041	-18.408*** (0.000)	-3.216** 0.019	-18.420*** 0.000	I(0)
GI	-4.775*** 0.000	-18.415*** 0.000	-4.906*** 0.000	-20.487*** 0.000	I(0)
HCI	-2.363 0.153	-18.802*** 0.000	-2.357 0.154	-18.835*** 0.000	I(1)
INTER	-4.917*** 0.000	-18.583*** 0.000	-4.917*** 0.000	-19.535*** 0.000	I(0)
MOBI	-5.154*** 0.000	-18.329*** 0.000	-5.755*** 0.000	-18.328*** 0.000	I(0)
GROWC	-6.552*** 0.000	-16.733*** 0.000	-13.797*** 0.000	-86.701*** 0.000	I(0)

Notes: (***) and (**) describe significance at 1 and 5% thresholds, respectively.

Regarding the second-generation unit root test, the study refers to the Pesaran (2007) CIPS (cross-sectional augmented IPS) test. Table 6 presents the CIPS test outcomes together with truncated CIPS. The use of these tests is justified by the fact that they take into account cross-sectional dependencies unlike the ADF and PP tests (Hosfield, 2010). In this regard, Banerjee et al. (2005) highlighted that in the case cross-sectional dependencies are disregarded, there may be a discrepancy between the empirical size and the nominal size. The results shown in Table 6 support the findings of the ADF and PP test once we account for potential cross-sectional dependencies.

Table 6
Outcomes of second generation panel unit root tests

Model 1	Level	Δ	Result
	t-Stat	t-Stat	
CIPS test	-5.337***	-4.771***	I(0)
Truncated CIPS test	-4.296***	-4.296***	I(0)

Note: (***) describes significance at 1% threshold.

The findings in Table 7 show that the Weighted F-statistic and Scaled F-statistic in both the model with single threshold (87.909) and the model with double threshold (93.361; 80.761, respectively) are higher than the Critical Value (20.08, 17.37, respectively which indicates that the most appropriate model admits two threshold values and hence we retain the model with two threshold values (2.423; 3.171).

Table 7
Outcomes of multiple threshold test

		Threshold number test			Threshold value
Model	Threshold tests	Weighted F-statistic	Scaled F-statistic	Critical Value	
Model: EI= f(GI; HCI; INTER; MOBI)	Single threshold	87.909	87.909	20.08	3.171
	Double threshold	93.361	80.761	17.37	2.423 3.171

Our findings presented in Table 8 reveal that GI has negative effects on EI but only above a threshold value of 2,423 of HCI. Above this threshold value, a 10% increase in GI leads to a fall of 0.01% in EI. Conversely, environment-related technology has no significant effect on EI below this threshold value. Green innovation as a catalyst for GG through control of the energies employed in the production chain therefore requires a minimum of skills, know-how and awareness revealed by human resources. These results confirm those of Wang et al. (2020) but partially given that GG is only boosted by GI in the presence of a threshold value of human capabilities as advocated by Sun et al. (2022). Likewise, the HCI exerts negative effects on EI only when its threshold value is above 3.171. An increase of 1% in the HCI leads to a fall of 3,265% in EI. These results support those of Yuan and Zhang (2017) who argued that human capital staff makes it possible to produce technological advancement and generate new knowledge spillovers which boost GG based on EI. Concerning information and communication technologies (ICTs), their impacts on EI differ depending on the tool used. Indeed, the beneficial effects of mobile use do not require high threshold values for them to have a negative impact on EI. The mobile use reduces the EI only when the threshold value is below 2.423. Likewise, Internet use does not have positive effects on GG for very low or very high values of the HCI. As for GDP growth, it has a negative impact on EI only when the HCI is lower than 3,171. GG is driven by economic growth but independent of high HCI.

Table 8
Outcomes of panel discrete threshold regression

Variable	HCI ($q_{it} \leq 2.423$)		HCI ($2.423 < q_{it} \leq 3.171$)		HCI ($q_{it} > 3.171$)	
	Coefficient	t-Student	Coefficient	t-Student	Coefficient	t-Student
HCI	1.203	1.447	1.133**	2.059	-3.265***	-4.852
GI	-0.001	-0.614	-0.001**	-2.004	-0.001***	-4.767
INTER	0.018	1.352	-0.032***	-4.290	0.026***	2.799
MOBI	-0.011**	-2.063	0.027***	5.972	-0.009	-1.444
GROWC	-0.081**	-2.478	-0.065**	-2.172	-0.009	-0.174
Constant	-0.193	-0.112	-0.043	-0.027	15.315***	6.730

Notes: (***) and (**) describe significance at 1 and 5% thresholds, respectively.

By referring to the partial regression leverage plot on the effects of key variables on EI, as traced in Fig. 4, we note that the impacts of the GI and HCI on EI admit a flat plot effect if the HCI exceeds the threshold values. These results reflect that the repercussions of these key variables on EI are significant for high threshold values of the human capital index.

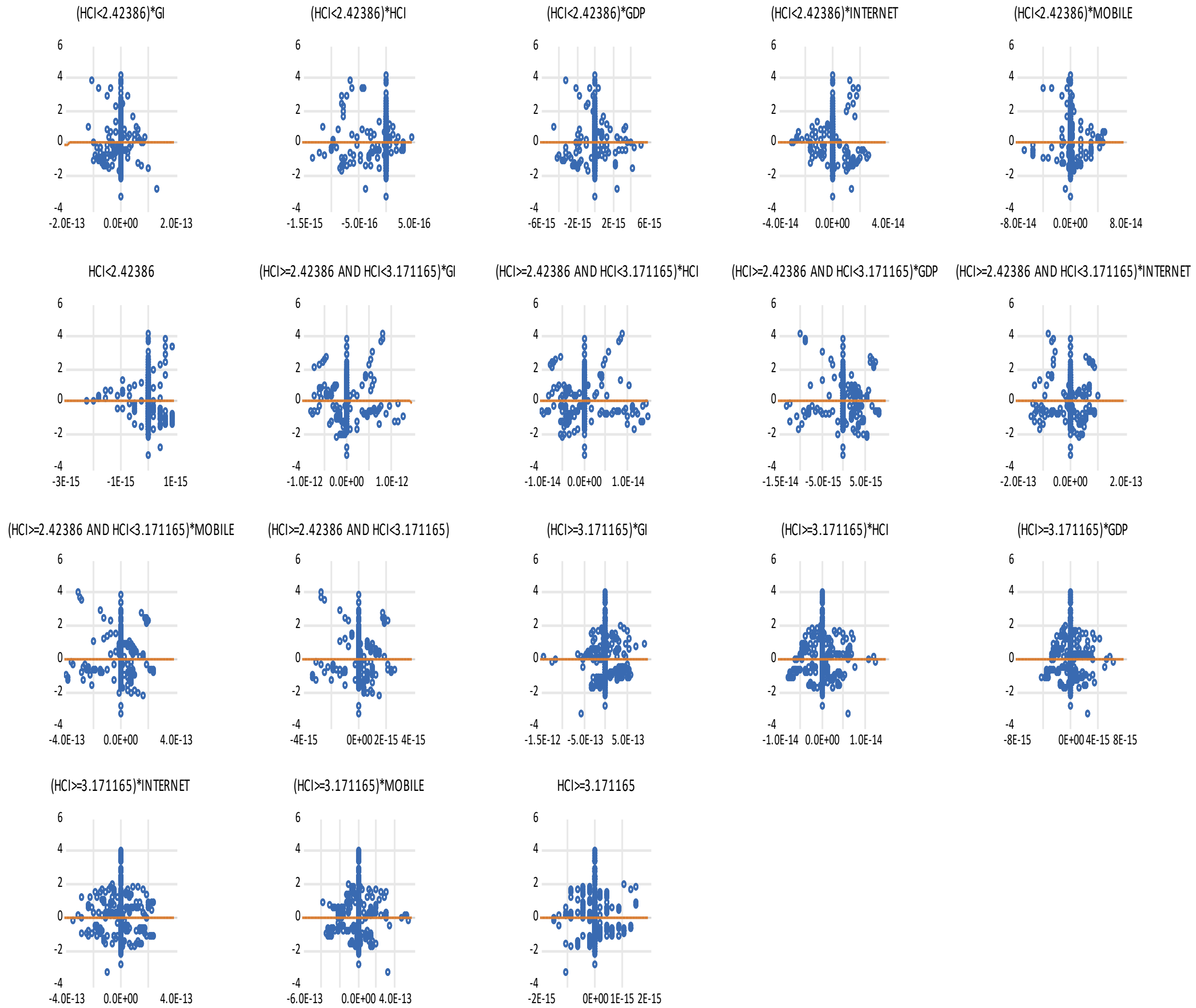


Fig. 4. Partial regression leverage plot on the effects of covariates on energy productivity

In this part of the study, we follow an in-depth analysis by distinguishing the linear part from the non-linear part in order to examine the repercussions of GI and HCI on GG. For this purpose, we carry out the linearity test. Table 9 indicates the rejection of the null hypothesis according to which the relationship between GI and EI is linear. Therefore, the exponential panel smooth regression model constitutes an appropriate model for the effects of the core variables on green growth. Regarding the Smooth Threshold Remaining Nonlinearity Test, it indicates that the model retained presents one transition or two regimes.

Table 9
Linearity and remaining nonlinearity tests

Sample	Least eco-friendly countries		Most eco-friendly countries	
	F-statistic	P-value	F-statistic	P-value
Smooth Threshold Linearity Test	5.534	0.000	11.359	0.000
Smooth Threshold Remaining Nonlinearity Test	1.867	0.105	1.192	0.314

The results displayed in Table 8 show that most of the nonlinear coefficients are significant. This reflects that the effects of GI and HCI on EI are of a nonlinear nature and they are conditioned by a rental parameter of 2.725 of HCI for the sub- sample related to LEFC and 2,959 for the group of MEFC. When the HCI<2.725 and HCI<2.959, the exponential panel smooth threshold regression is in its first regime qualified as low regime for the LEFC and the MEFC, respectively. The slope parameters for the two groups of countries are 22.756 and 24.907 which reflects a smooth transition from low regime to high regime.

Table 10
Outcomes of panel smooth threshold regression

	Least eco-friendly countries				**Most eco-friendly countries**			
Variables	Linear part		Non-linear part		Linear part		Non-linear part	
	Coefficient		Coefficient		Coefficient		Coefficient	
HCI	-14.024*	-1.763	15.135*	1.918	8.426**	2.283	-11.464 ***	-3.381
GI	-0.001	-3.229	0.001***	0.340	0.001**	2.471	-0.003***	-3.8931
INTER	0.007***	0.314	-0.008	-0.301	-0.081***	-2.619	0.107***	3.355
MOBI	0.061***	2.838	-0.066***	-2.2350	0.034*	1.682	-0.043 **	-2.042
GROWC	-0.001	-0.008	-0.087	-0.613	-0.064	-0.976	0.057	0.630
Constant	36.207*	-6.809	-36.286*	-1.793	-21.206**	-1.917	35.765 ***	3.567
Slopes	22.756	2.378			24.907	2.259		
Threshold	2.725***	42.145			2.959***	89.215		
Location parameter	2.725					2.959		

Notes: (***); (**); & (*) describe significance at 1, 5 and 10% thresholds, respectively.

As presented in Table 10, the effects of green innovation differ between the low and the high regime and this is confirmed for the two groups of countries. It also appears that the LEFC countries cannot benefit from green innovation to foster GG even by improving the human capital index. Although the strategic orientations to mitigate environmental degradation differ between the sample of least eco-friendly countries retained in this research and which includes China; Indonesia Iran; Malaysia; Saudi Arabia and Turkey, it emerges that GI in these economies are mainly targeted to reduce pollution and waste than to ensure non-abusive consumption of natural resources and energy. Regarding the second group of MEFC, by moving from low to high regime, green innovation has negative effects on EI and, therefore, contributes to boosting GG. For countries advanced in terms of green technologies, which include in the current study Austria; Denmark; Finland; France; Ireland; Malta; Norway; Sweden; Switzerland and United Kingdom., they can save energy use via advanced technologies and multiple renewable energy sources. Our findings also reveal that the effects of HCI between the two regimes differ between the two groups of countries. Indeed, human capital can only materialize through gains in terms of EI in the case of low regime and therefore for a low threshold value of the human capital index. These results illustrate the mismatch between technological advances in LEFC and their human resources. Indeed, the low environmental technology progress in this group of countries requires correspondingly low human skills for it to materialize in lower energy demand. These findings in the case of LEFC, consolidate those of Twum et al. (2021) who disclosed that HCI boosts energy efficiency, but only at the linear regime. Contrary results were reported in the case of MEFC in which the transition from low regime to high regime leads to a significant and negative effect of HCI on EI. In the sub-sample of MEFC, an increase of 1% in the HCI leads to a drop of 11,464% in EI, and therefore, a recovery in GG. As shown in Fig. 5 and Fig. 6, the continuity of the points relating to the threshold weight function going from low to high regime clearly illustrates the gentle transition process for the two groups of countries selected.

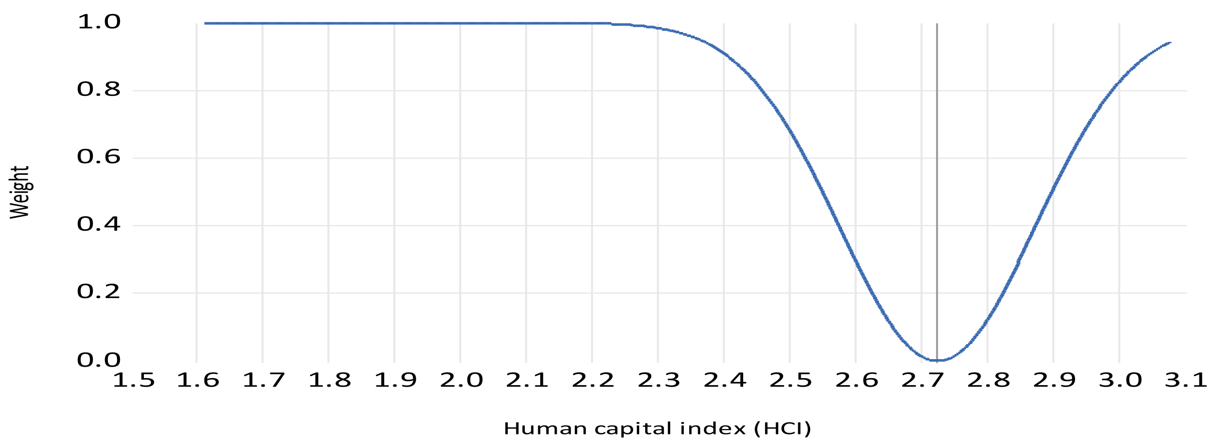


Fig. 5. Threshold weight function (Exponential ; c=2.725) for least eco-friendly countries

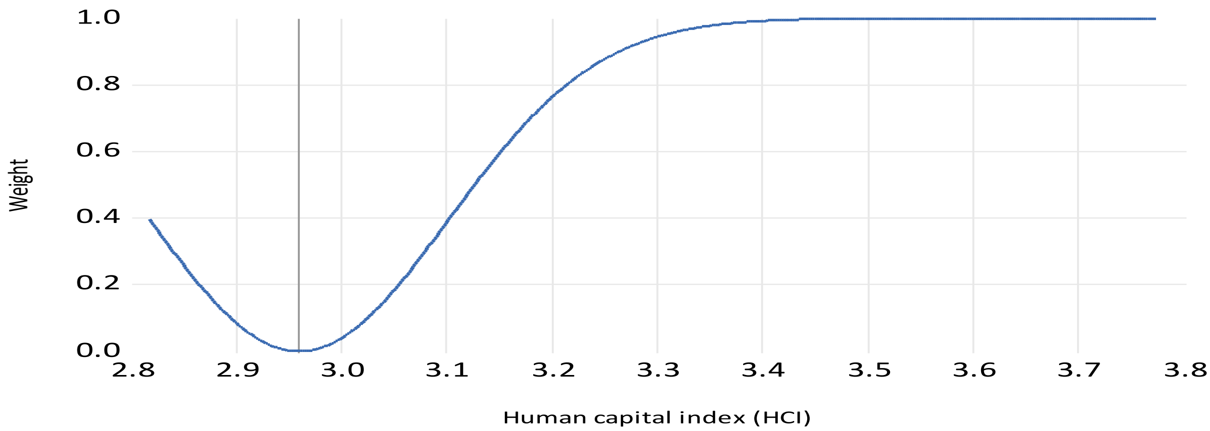


Fig. 6. Threshold weight function (Exponential ; c=2.959) in the case of most eco-friendly countries

5. Conclusion

Although there are numerous studies devoted to GI and HCI when it comes to their environmental impact, those devoted to investigating their impact on green growth are few. This study aims to shed light on the impact of green patents and human capabilities to boost EI. The findings based on the PTR applied to the context of 16 countries showed that the beneficial effects of GI on GG require a minimum threshold value of the HCI. Our results indicate that a 10% increase in GI leads to a fall of 0.01% in EI and therefore, the revival of green growth but only where the HCI is above 2.423. Below this threshold value, environment-related technology remains without negative effects on EI. The importance of the presence of a minimum level of human capabilities as a driver of green growth is also supported by our study given that their beneficial effects in reducing EI require the presence of a critical level of HCI. Furthermore, this research follows an in-depth study of the impact of green innovation and human capital on green growth by investigating their effects by moving from the linear part to the nonlinear part. Our findings reveal that the impact of GI differs between the low and the high regime, and this is confirmed for the two groups of least eco-friendly countries and most eco-friendly countries. However, only the group of top green innovation countries are those which benefit from green innovation by moving from low to high regime of human capital index. By positioning at the high regime of human capital, a 10% increase in GI lowers EI by 0.03% in the specific case of the most eco-friendly countries. The group of least green countries cannot benefit from green innovation to foster green growth even by improving the human capital index and therefore by translating from low regime to high regime. Our results also show that the contribution of human capital to reduce EI is not the same between the two regimes and also between the two groups of countries. Indeed, human capital can only materialize through EI-based green growth in the case of low regime and therefore for a low threshold value of the human capital index. These findings reflect the mismatch between technological advances in least eco-friendly countries and their human capabilities. Indeed, the low environmental technology advancement in this group of countries requires only low human skills for it to materialize in lower energy demand. Different results are observed in the context of MEFC countries in which by translating from low regime to high regime of the HCI leads to a significant and negative effect of HCI on EI. Based on the outcomes of the study, it appears that green innovation does not always constitute a lever to ensure green growth since this is only recorded in the presence of a minimal level of human capital index. In addition, the positive repercussions of environment-related technologies as well as human capital on the green growth process differ substantially between least and most eco-friendly countries given that the first group develops targeted skills for the revival of productivity and, therefore, guided by the imperatives of economic growth, while the second group is more framed by commitments to the environment. Despite the importance of these clarifications on the impact of GI and HCI on GG, a number of inadequacies can be pointed out: In this study, to assess green innovation, we rely on environmental-related technologies based on patent indicators. However, not all inventions are trademarked. Moreover, examining the impact of GI on energy productivity remains enough and must be consolidated by effort towards the mitigation of pollution and reduction of waste size. So, future veins of research must integrate additional aspects of green growth besides EI.

In light of the results found in this study, the concretization of efforts in terms of GI and HCI, by controlling the energies used in the production chain and, therefore, the revival of green growth requires the appropriate actions among which: 1/The least eco-friendly countries are required to develop green innovation activities aimed not only at mitigating pollution and recycling waste but, also encouraging inventions intended for economical use of natural resources. Indeed, our findings indicated that this subgroup of countries does not benefit from green patents in terms of GG. 2/Most eco-friendly countries must implement more green laws governing business activities in terms of waste and carbon emissions. These standards at the output of the production chain can be reflected downstream and therefore, allow control of raw material resources. 3/ The development of human capital is an ex-ante factor for green innovation to have a positive impact on energy management. In this regard, the outcomes of the study showed that in order to benefit from environment-related technologies in terms of green growth, it is essential to have a minimum threshold level of human capital index. 4/ The human resources training cycles and courses as well as the learning must be established on a large scale and in line with the technological advances of the countries in the field of the environment. Indeed, the results found showed that human capital does not have beneficial effects on the green growth process when it is under the low regime. Moreover, the mismatch between human capital and countries' green innovation remains without effect on actions in favor of environmental management 4/ Encourage financing for renewable energy projects by granting more payment facilities and reducing administrative procedures, which allows the expansion of the technological facet. 5/ Root the awareness of employees towards energy management as an entrepreneurial culture that can result in shining the image of the company within society and also control of production costs.

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