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Research Article

Unveiling the interactive effect of green technology innovation, employment of disabilities and sustainable energy: A new insight into inclusive sustainability

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Abstract. The interaction between green technology innovation, employment of disabilities, and sustainable energy is a critical area of research that addresses the emergent need for inclusive sustainability. Nowadays, the interaction between sustainable energy and green technology innovation is considered an essential field of research that has been widely discussed in previous studies. However, the role of employment, especially of people with disabilities, on this effect is still inexistent despite its relative importance for the achievement of sustainable development goals. By unveiling the interactive effect between these factors, strategies can be defined to reduce and limit the negative impact on the environment while promoting employment. This study aims to fill this research gap by investigating the impact of green technology innovation and employment of disability on sustainable energy in 25 OECD countries from 1994 to 2020 using a dual methodological approach that integrates a parametric analysis: the panel vector autoregression (PVAR) model and a nonparametric assessment: the local linear dummy variable method (LLDV). The findings reveal (i) a significant positive correlation between the enforcement of green technology innovation and the increase in the employment rate of people with disabilities, (ii) a limited direct effect of green technology innovation on green energy consumption, and (iii) a positive impact of the interactive effect of employment of disabilities and green technology innovation, with a higher elasticity than that recorded by a separated effect. The outcomes address environmental challenges and promote social equity in the green economy. They also offer some critical recommendations for policymakers and researchers on sustainable energy.

Keywords: Employment of people with disabilities, green technology innovation, clean energy consumption, inclusive sustainability, Panel vector autoregression (PVAR) model

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1. Introduction

As the world grapples with the pressing challenges of environmental degradation, social inequality, and economic development, exploring innovative approaches to address these multifaceted issues is crucial. Industrialization poses a severe threat to nature, natural resources use, and the sustainable survival of the Earth (Khan, 2023; Voumik *et al.,* 2023). However, this industrial dynamic and development is required to develop economic activity. Making an economic profit is necessary but not enough to attain sustainability. Furthermore, sustainable development goals consider social and environmental sustainability, and all these aspects are needed to attain inclusive sustainability (Bilderback, 2024; Hariram *et al.,* 2023). For the most part, this new approach tries to define requirements and actions to balance economic profit, social advantages, and environmental sustainability. Recently, tremendous advancements in technology and industrialization have put pressure on the sustainability of the Earth due to the depletion of non-renewable energy resources and CO2 emissions (Akbar *et al.,* 2023). Therefore, in the current scenario, many countries are introducing and encouraging Green Technology Innovation, which balances industrialization and promotes a sustainable globe (Liao et al., 2023). Green Technology Innovation can act as an engine for economic value, environmental protection, and employment by creating new job opportunities. A growing body of previous studies insists on the importance of employment for social sustainability (Helena *et al.*, 2023), and many recent researches indicate that the employment of people with disabilities (PwD) is a potential field in developed and developing countries to attain social inclusion while promoting economic development (Stamm, 2023). By supporting and facilitating the employment of PwD, adopting new green technologies and innovation can enhance financial security, self-respect, and reciprocal relationships within society. Unfortunately, the employment rate of PwD in most developing countries is still relatively low (Morris, 2023). Some other academies limit the use and adoption of green technology innovation with sustainable development by reducing environmental impact, improving resource efficiency, and promoting renewable energy solutions. According to Zhang et al. (2024), green technology innovation can lead to the development of a new energy-use approach. This has also been employed by Song *et al.* (2024), who argue that using GTI improves energy efficiency and can transform sustainability. In addition, Chen *et al.* (2023) define it as a critical area in the face

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of growing concerns for sustainable development and climate change. Generally, there are no definitions that consider in the same time GTI, sustainable energy, and employment of disabled employees to achieve sustainable inclusion. There is no eventual agreement about using GTI in these research areas. Examining the effect of GTI and the employment of disabled employees in sustainable energy development to achieve sustainable inclusion can provide critical economic, social, and environmental issues by contributing to increasing knowledge in this field and creating a more equitable and sustainable future. Considering these methodological and theoretical gaps, this research investigates the importance of GTI and the employment of disabled people, rarely treated in the literature, on sustainable energy to define the new borders and significance of sustainable inclusion. In this context, green technology innovation can contribute to developing new technologies to reduce energy use while redefining and assisting PwD by providing adequate technology and delimiting the effect of disabilities in work and work accommodations. This research makes four critical contributions to this emergent research field. First, this research enriches sustainable energy knowledge in OECD countries in several ways. To the best of our knowledge, this study is the first innovative contribution that combines sustainable energy, employment of disabled people, and green technology innovation to quantify the eventual interaction between them. The relevant literature is still limited for OECD countries, and this effect is critical in a new area of research that needs to be deeply explored. Second, this research investigates the interactive effect of these variables using a panel vector autoregression model (PVAR) in 25 OECD countries from 1994 to 2020, and this has not been elaborated before under these circumstances while considering its dynamic during the time. Third, this study uses a dual methodological approach to address the multifaceted nature of these issues. The parametric analysis is conducted through a panel vector autoregression (PVAR) model to examine dynamic interactions among variables of interest, and a nonparametric assessment is carried out using the local linear dummy variable method (LLDV) to test the nonlinearity and heterogeneity inherent in the data. Fourth, a conceptual framework to explain different relationships between factors is developed and tested to define corresponding empirical evidence of this effect. It offers actionable insights to guide policymakers in OECD countries as they formulate and implement strategies to facilitate the transition toward sustainable energy systems. The findings are expected to make a meaningful contribution to the body of literature on environmental policy and clean energy consumption, enhancing our understanding of the drivers of sustainability in the energy sector. This research aims to define a new approach to sustainable energy based on an inclusive approach that integrates the employment of people with disabilities. It investigates how an interactive effect of green technology innovation and employment of disabilities can increase green energy consumption.

2. Literature review

2.1 Green technology innovation and sustainable energy

A growing body of literature on this research topic confirms the pivotal role of Green technology innovation in advancing sustainable energy solutions and addressing environmental challenges while promoting economic growth. Integrating renewable energy sources, innovative engineering practices, and emerging technologies like blockchain enhances the efficiency and transparency of energy systems. This multifaceted approach mitigates climate change and fosters sustainable development (Ragmoun, 2024b; Farooq *et al.,* 2024), mitigating environmental impacts (Wang *et al.,* 2022; *Ai et al.,* 2021), and ensuring energy security (Song *et al.,* 2024; Ragmoun, 2023). Liu *et al.* (2022) demonstrated that green energy efficiency and climate technologies significantly reduce environmental pollution over the long term. Further, Saqib et al. (2024) explored how green technologies are essential in reducing ecological footprints and facilitating the transition to renewable energy sources. They confirmed the existence of this positive effect in the long and short term. One recent research related to this relationship was performed by Deng et al. (2024), who demonstrated that Green technology innovation, mainly blockchain, enhances the management of energy resources, promotes transparency, and supports sustainability goals by improving energy consumption monitoring and reducing carbon emissions. In the same line of idea, Kamran and Turzyński (2024), using a comprehensive review of existing literature and research, examined the effect of GTI on sustainable energy. The result provides theoretical evidence that Green technology innovation focuses on resource conservation and energy efficiency, playing a vital role in sustainable energy by minimizing environmental impact and enhancing business performance in Asia. Ghafoor et al. (2023) further advance the discussion by probing the interconnections between green growth, environmental quality, and energy consumption in OECD countries. Utilizing the Autoregressive Distributed Lag (ARDL) approach, their study challenges prevailing theories, such as the Environmental Kuznets Curve, by demonstrating that green growth does not adhere to the theory's predicted patterns, whereas non-green growth does. Their findings support the increasingly recognized notion that economic prosperity can coexist with environmental sustainability if the economic paradigm is reoriented to integrate green technologies and prioritize renewable energy sources. Based on most existing studies, green technology innovations have been identified as a significant driver for clean energy consumption, promoting sustainable future development (Shan *et al.,* 2021; Aneja *et al.,* 2024; Sheng *et al.,* 2024).

2.2 Green Technology Innovation and employment of people with Disabilities

The implication of GTI on the employment of people with disabilities has received limited interest from researchers, and the number of studies dealing with this empirical and theoretical impact is still very limited. The intersection of green technology innovation and the employment of people with disabilities (PwDs) presents significant empowerment and economic participation opportunities. Various studies highlight how assistive technologies and sustainable practices can create inclusive job opportunities for PwDs, enhancing their quality of life and financial independence (Setiadi *et al.,* 2024). By integrating green technologies, energy efficiency increases, environmental impact is limited, and sustainable development is promoted (Swain and Wallentin, 2019). However, the success of this process requires a diversified workforce (Olutimehin *et al.,* 2024). Integrating individuals with disabilities can enhance creativity and innovation (Redko, 2024; Frączek, 2024). Therefore, fostering an inclusive environment that actively employs individuals with disabilities can significantly contribute to the effectiveness of green technology initiatives. Using an explorative approach, Maritz and Laferriere (2016) demonstrated that Green technology innovation empowers people with disabilities by enhancing their entrepreneurial skills through accessible training and assistive technology, fostering independence and improving their economic quality of life. According to Setiadi et al. (2024), this approach is called green technopreneur. Their research investigated how an integrative approach with green technology innovation and employment of people with disabilities can be elaborated. They show that using green technology empowers people with disabilities to improve their quality of life. The research elaborated by Marín-Palacios et al. (2022) emphasized the need for inclusive design teams. It suggests that green technology innovation can benefit from employing people with disabilities and enhancing creativity and accessibility in solutions. The bibliographic analysis used in this research confirms that green technology innovation can limit inequalities in the workplace and increase people's well-being. Furthermore, Bricout et al. (2021) confirmed that green technology innovation can create equitable employment opportunities for people with disabilities, enhance their participation in the workforce, and benefit employers through diverse talent and improved productivity. Recently, Sovacool et al. (2022) investigated these outcomes and concluded that the Emerging green technology sectors present significant employment opportunities for people with disabilities, necessitating targeted training strategies to ensure equitable participation in this growing economy proportional to the nature and typology of inequality. Saarani et al. (2024) analyzed and discussed Hydroponic systems as another innovative avenue, allowing PwDs to engage in agriculture with minimal physical strain as a new trend for GTI-assisting PwDs. Using technology like Arduino to monitor plant growth empowers PwDs to manage hydroponic gardens effectively. These critical findings present a new opportunity to ample job opportunities for PwDs.

2.3 Employment of people with disabilities and sustainable energy

The employment of people with disabilities (PWD) in the sustainable energy sector offers many opportunities to enhance social inclusion and economic sustainability while promoting equity and understanding diverse needs. The study elaborated by Memmott et al. (2021) highlighted that energy insecurity significantly affects people with disabilities and emphasized the need for equitable access to safe and sustainable energy solutions for their well-being. Additionally, Graff et al. (2021) treated the effect of energy insecurity, which critically impacts the quality of life of people with disability, and developed recommendations and plans for energy justice. The results of Kosanic et al. (2022) about an inclusive future insisted on the importance of sustainable lifestyles, suggesting that inclusion is essential to promote sustainable energy initiatives. Within the same line of idea, they supported that environmental change places PwD in an economically and socially disadvantaged position. Salvatore and Wolbring's (2022) investigation confirmed that environmental issues impact PwD and insisted on integrating their experiences into sustainable energy decision-making. Stein and Stein's (2022) study emphasizes the need for disability-inclusive climate action to ensure an active involvement of PwD in sustainable energy initiatives. By examining the concept of Disability-inclusive climate solutions, Stein et al. (2024) confirmed that participating employees with disabilities in sustainable energy initiatives foster a more inclusive workforce and improves overall climate resilience. For Shaw et al. (2022), engaging disabled employees in sustainable energy projects can dismantle stereotypes and improve societal perceptions of disability. Fang et al. (2022) investigated the economic effect of renewable energy consumption while considering Disabled individuals. They identified their essential role as ecological citizens despite the barriers and difficulties they face.

3.Research method

Two main approaches are used to investigate the interdependence between the employment of disabled people and green technology innovation and sustainable energy. The first is based on the GMM-PVAR model to identify the eventual independent and dynamic effect. The second is Logistic Loss Data Visualization Embedding (LLDVE), which represents this effect and makes it easier to understand.

3.1 Data descriptions

This study gathered data from World Development Indicators databases and the Organization for Economic Co-operation and Development. All variables' descriptions are expressed in log differences or percentage changes to reduce heteroscedasticity (Charfeddine and Khediri, 2016). Sources, symbols, and definitions of research variables are arranged and detailed in Table 1. Seven variables were used. These include HC to

Table 1
Definitions and source of research variables

	Definitions	Unit	Source
CLEAN	Is defined as the contribution of clen energy to total primary energy supply (TPES).	%	Organization for EconomicCo-operation and Development
CO2	Carbon dioxide emissions	in metric tons	World Development Indicators
SP	Environmental policy stringency index ranges from 0 (not stringent) to 6 (highest degree of stringency)	Index	Organization for Economic Co-operation and Development
ENVLAW	Environmentally related taxes, % total tax revenue	%	Organization for Economic Co-operation and Development
$DE_{i,t}$	Employment rate of people with disabilities	Index	Penn world table 10.0
GDP	Market value of all final products produced by economic and social factors in a certain period, calculated at constant 2010 US dollars	calculated at constant 2010 US dollars	World Development Indicators
GTI	Patents in environment-related technologies	Number	Organization for Economic Co-operation and Development

Source: Author

measure the rate of disabled employees, TI for green technology innovation, and clean energy consumption. This encompasses the main measures: environmental policies, taxes, clean energy use, and CO2 emissions. GDP was also considered to evaluate the effect of this interaction on economic development.

3.2 PVAR-GMM specifications

This study assesses the impact of GTI and disability employment on clean energy consumption in 25 OECD countries from 1990 to 2020. Our methodological approach was based on the PVAR methodology, which will be estimated using the GMM method (generalized method of moments). PVAR models are commonly used to analyze interdependent, dynamic relationships among variables across time and individuals.

According to Holtz Eakin (1987), the PVAR model is used to understand the interaction of different endogenous variables in the panel data. The corresponding vector autoregressive deals with the relationship between an endogenous variable and its lag term. Using the PVAR model, research fully considers the individual and the effect of time. Several advantages can be considered when using the PVAR model. First, it introduces the individual dimension to allow an increasing degree of freedom when the number of observations increases (Dutta and Saha, 2023). Second, the PVAR methodology allows the heterogeneity of individual countries while allowing dynamic relationships between multiple endogenous variables. Third, the introduction of lagged endogenous variables makes the usual estimators biased, and this is why GMM Estimation of Panel VAR Models is integrated. Fourth, each variable in the PVAR model is relative to its historical realization in addition to an absolute and objective simultaneity with other variables and their corresponding treatment. The PVAR-GMM technique is used in this case due to the dynamic correlation between endogenous and exogenous variables while considering the short and long run and considering unobserved variability between different regions and nations (Abrigo and Love, 2016).

The usual expression of the PVAR model can be represented as follows (Nguyen *et al.,* 2019) (Equation 1)

$$Y_{i,t} = \tau_i + \sum_{K=1}^{m} \Phi_{l,k}\, Y_{i,t-k} + \sum_{j=1}^{m} \psi_{l,j}\, X_{i,t-j} + \gamma i + U i,t. \quad (1)$$

In equation (1), Yi,t represents M × 1 vector with M as the observable variables of an individual (i) at a time (t), Xi,t is the vector of observable deterministic strictly exogenous variables, The matrix M x M is estimated by two coefficients matrix $\Phi_{l,k}$, $\psi_{l,i}$. γi is the unobservable individual fixed effect matrix of individual i, and the error term is ui,t.

$$Y_{i,t} = \tau_i + \sum_{K=1}^{m} \Phi_k\, Y_{i,t-k} + \sum_{j=1}^{m} \psi_j\, X_{i,t-j} + \gamma i + U i,t. \quad (2)$$

Three central Hypothesis can be defined for the model assumptions:

Hypothesis 1: Y1,t, Y2,t,..., YN,T is an observable variable for any number of persons N and period length T.

Hypothesis 2 : states that for any i=1, ..,N, t = 1,.., T, ui,t represents an independent variable identically distributed randomly with a covariance matrix of Ω and a random error term that satisfies zero expectations

Hypothesis 3: If the random error is orthogonal to Yi,t; Xi,t and γi, and s < t, this means that :

$$E[Y_{i,s}] = E[X_{i,s}] = E[\gamma i] = 0, (s < t). \quad (3)$$

Based on these theoretical hypotheses, a foundation for identifying the PVAR model in terms of coefficients and parameters is established. By identification, we mean estimating and judging corresponding parameters. This step was performed according to the recommendations of Hong et al. (2019).

For equation (2), the first-order difference is defined by :

$$\Delta Y_{i,t} = \Delta \sum_{K=1}^{m} \Phi_k\, Y_{i,t-k} + \Delta \sum_{j=1}^{m} \psi_j\, X_{i,t-j} + \Delta\, U i,t. \quad (4)$$

Based on equation (3), we admit that if s < t-1, we can obtain:

$$E[\Delta Y_{i,s}] = E[\Delta X_{i,s}] = 0, (s < t\text{-}1). \quad (5)$$

Supposing that $\mathcal{Y}_{i,t}^{j}$ represents j variable in $Y_{i,t}$ as an economic variable vector, the corresponding first-order difference model related to $\mathcal{Y}_{i,t}^{j}$ is expressed as follows :

$$\Delta Y_{i,t}^{j} = \sum_{K=1}^{m} \Phi_k^{j}\, \Delta Y_{i,t-k} + \Delta \sum_{j=1}^{m} \psi_l^{j}\, \Delta X_{i,t-j} + \Delta\, \nu_{i,t}^{j} \quad (6)$$

In equation (6), *the random error term is the* $\nu_{i,t}^{j}$. Following these steps and according to Destek and Aslan (2019), in addition to the literature review discussed below, the model created can be represented as follows with i represents countries (35 OECD) and t time (1994-2020).

$$CLEAN_{i,t} = \gamma 0 + \gamma_1\, CO_{2i,t} + \gamma_2\, SPi_{,t} + \gamma_3\, ENVREG_{i,t} + \gamma_4\, GDP_{i,t} + \gamma_5\, DE_{i,t} + \gamma_6\, GTI_{i,t} + U_{i,t}. \quad (7)$$

Where: $CLEAN_{I,t}$: the contribution of clean energy to the total primary energy supply; $CO2_{i,t:}$ the difference of carbon dioxide emissions (in metric tons); $SPi_{,t}$: the Environmental policy stringency index. This index ranges from 0 (not stringent) to 6 (highest degree of stringency); $ENVREG_{i,t}$: the Environmentally related taxes, as a percentage of total tax revenue; $GDP_{i,t}$: the Market value of all final products produced by economic and social factors in a certain period, calculated at constant 2010 US dollar, $DE_{i,t}$: the employment rate of people with disabilities based on the average years of schooling defined by Barro and Lee (2013). $GTI_{i,t}$: the technological innovation related to the environment measured as the number of Patents in the environment.

By considering all previous steps and equations, especially equation (2) the proposed PVAR model is represented as follows:

$$Y_{i,t} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \dots\dots\dots A_p Y_{i,t-p} \dots\dots + X_{i,t} B + u_i + e_{i,t}, i = 1 \dots\dots\dots\dots N;\ t = 1 \dots\dots\dots\dots\dots T_i \quad (8)$$

Yi,t is the dependent variable vector, Xi,t is a vector of exogenous variable, u and e are (1xu) vectors related to dependent variables, others parameters such as the matrices (u x u); A1, A2,……….B, and the matrix (X x l) have to be estimated. Furthermore, five stages are adopted according to the requirements of our methodological approach. The first step in the PVAR method is the root unit test, followed by the optimal lag order in panel VAR specification. As mentioned below, GMM is used to estimate the PVAR model. In this context, According to Andrews et Lu (2001), the appropriate conditions in terms of the correct model and moment have to be selected using model and moment selection criteria (MMSC) such as BIC

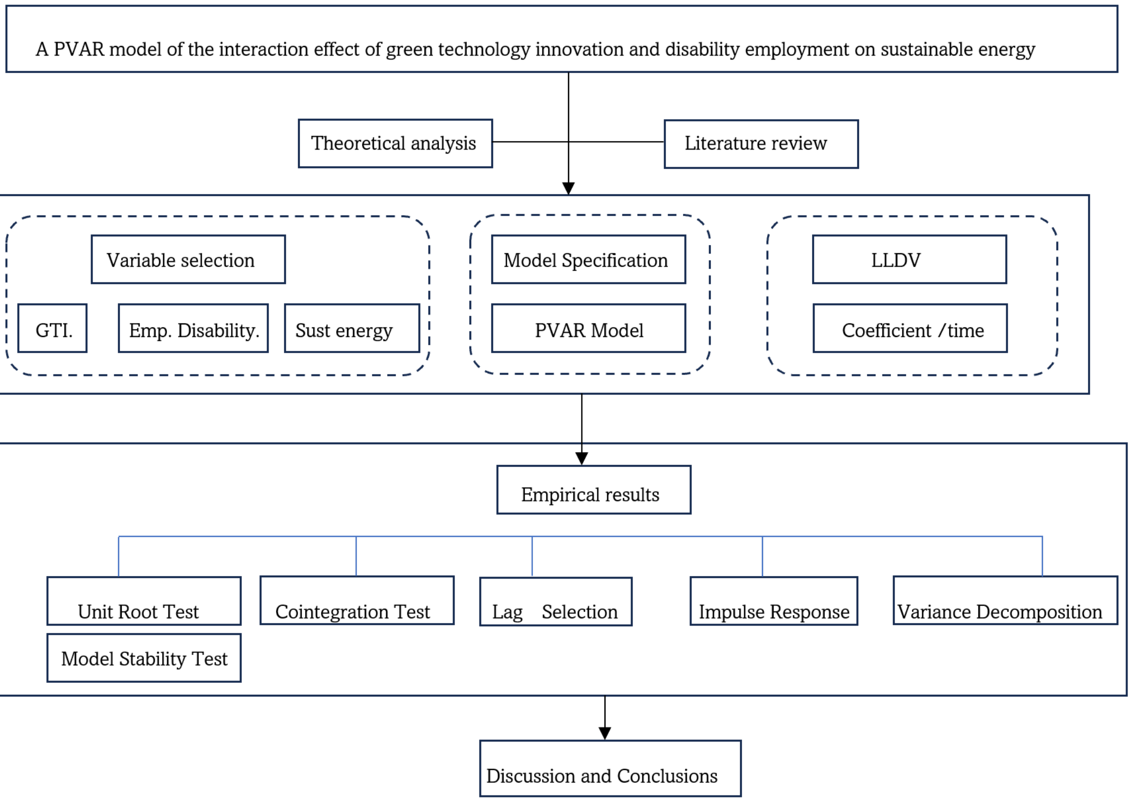

Fig. 1 Methodological approach

(the Bayesian Information Criterion), AIC (Akaike Information Criterion) and HQIC (Hannan-Quinn Information Criterion).

MMSC-BIC is often used to select the optimal lag length in PVAR models, where the complexity of including more lags can lead to overfitting. The Akaike Information Criterion (AIC) Measures the quality of a model based on the trade-off between goodness of fit and model complexity. It aims to find a model that best explains the data without overfitting by penalizing the addition of more parameters. MMSC-HQIC selects the optimal model specification in panel data or time series settings. It helps choose lag length in Panel Vector Autoregression (PVAR) models and select the best model structure and variable selection in dynamic panel models.

After this, the stability of panel VAR must be verified, and the third step is obtaining the impulse-response functions (IRF) and forecast-error variance decompositions (FEVD). Figure 1 details the steps and tests used in this research, as recommended.

3.3 Logistic Loss Data Visualization Embedding (LLDVE)

To estimate the impact of disability employment, green Technology innovation, and environmental regulation on clean energy, the LLDVE method is used, which allows us to obtain coefficients that vary over time (Hailemariam *et al.,* 2019). LLDVE aims to embed high-dimensional data into a lower-dimensional space to preserve the underlying structure and relationships between data points. The objective is to make patterns more interpretable for visualization and analysis. The non-parametric specification is written as follows:

$$G\_CLEAN_{i,t} = f(t) + \lambda_1(t)G\_CO2_{i,t} + \lambda_2(t)G\_SP_{i,t} + \lambda_3(t)G\_ENLAW_{i,t} + \lambda_4(t)G\_GDP_{i,t} + \lambda_5(t)G\_HC_{i,t} + \lambda_6(t)G\_TI_{i,t} + \alpha_i + u_{i,t}$$

Where $\boldsymbol{f(t) = f_i(t/T)}$ the individual trend functions are represented, $\boldsymbol{\lambda(t) = \lambda_j(t/T)}$ denote the time-varying coefficients. Philips (2001) supposes that $\sum_{i=1}^{N} \boldsymbol{\alpha_i = 0}$ and $\boldsymbol{f(t/T) = f_i(t/T)}$

3.3 PVAR Model

To apply the PVAR model, five main steps are typically involved

3.3.1 Panel unit root test

This is the first step in estimating the process before testing the PVAR framework. According to Liao et al. (2024), the panel unit root test aims to verify all series' data proprieties regarding stationery to determine if they suit the PVAR. Unit root tests determine if each series in the panel data is stationary (i.e., has a constant mean and variance over time) or non-stationary (i.e., contains a unit root).This study will use the Im et al. (2003) test (IPS) to verify the stationarity of the research variables.

3.3.2 Cointegration test

This test determines and measures the long-term relationship (Kao, 1999) and equilibrium between variables. Some researchers don't include this test and consider that the descriptive analysis of the correlation test is enough. (Kuang *et al.,* 2020).

3.3.3 Lag selection

This step is conducted to define the appropriate time for a dynamic interaction between variables related to the PVAR model (Shen and Li, 2023). In this way, "The optimal lag period"(Carrasco-Gutierrez and Ehrl, 2023) is calculated.

Selecting the optimal lag length is crucial to ensure that the model captures the dynamics without overfitting.

3.3.4 Impulse response analysis

IRFs examine the dynamic interrelation between the variables introduced in PVAR models. An impulse response function (IRF) diagrams are used to identify interactions in the corresponding model (Lin & Wang, 2019). This step helps us to understand how changes and shocks in one variable impact the other variables over time.

3.3.5 Variance decomposition

Used to quantify the interdependence and degrees of fluctuations between variables, it explains how one variable influence another (Lin & Wang, 2019) and helps to understand and appreciate the variability of the model according to the different variables.

If these steps are followed well, an effective PVAR model can be defined, and valuable insights can be generated regarding dynamic interaction relationships between variables (Mamipour *et al.,* 2019). Finally, in addition to these steps, a limited number of researchers admitted the relative importance of the Granger causality test (Khan *et al.,* 2020). The results of these tests will be presented and analyzed in the next section

4. Results and discussion

4.1 Descriptive statistics and correlation matrix

Table 2 displays the descriptive statistics results and shows that SP recorded the highest growth rate (+5.27%). The CO2 emissions variable recorded the lowest average growth rate (-0.32%). The growth rate of the GTI appears to be the most volatile, with the highest coefficient of variation. However, the employment of PwD (DE) rate is the least volatile variable with the lowest coefficient of variation.

This table shows Skewness measures the asymmetry of data distribution, and Kurtosis measures the "tailedness" of the data distribution, indicating whether data points are concentrated around the mean or in the tails for each variable. The distribution of CLEAN and DE is perfectly symmetrical.

The correlation matrix (Table 3) shows a strong negative correlation between CLEAN and CO2 (-0.43). However, there are weakly positive correlations between CLEAN and the variables GDP and SP with coefficients of +0.18 and +0.08, respectively. The Pearson correlation matrix shows a negative effect between clean energy consumption and employment of disabilities as human capital (-0.005). This can be due to the impact of energy used to facilitate the employment process of people with disabilities, such as assistive technology and accommodations. The correlation between clean energy and green technology innovation is positive (0.037) but is considered low. The most important at this level is the identification of eventual interactions and effects between different variables. Our main objective is still the combined effect, not a separate impact.

4.2 Unit root test

The PVAR model is used in this research to analyze the interaction and effects of green technology innovation (GTI) and employment disability (DE) on sustainable energy appreciated by clean energy consumption (CLEAN). Table 4 shows the unit root test result as the starting point for the economic analysis. As shown, all variables are stationary.

Table 2
Descriptive statistics

	CLEAN	CO2	ENVREG	GDP	DE	SP	GTI
Mean	3,676328	-0,327283	-0,209527	1,960068	0,542925	5,275659	0,592721
Median	3,201240	-0,072356	-0,529878	1,872455	0,536790	1,284652	0,993438
Max	50,30454	15,38235	250,9846	21,51041	1,612121	155,8145	193,3660
Min	-49,19748	-15,82227	-86,72189	-10,55414	-0,314844	-36,77248	-218,4006
SD	9,410166	3,822043	11,79577	2,691267	0,326134	15,93429	29,89959
Skewness	0,241705	-0,07428	13,30612	-0,135358	0,666808	4,025416	-0,094043
Kurtosis	6,094888	4,302689	299,6238	9,179140	4,359086	29,01010	18,00028
CV	2,5640	11,9375	56,4115	1,3724	0,5894	3,0228	50,6610

Mean, average; SD (standard deviation); Max (maximum value); Min (minimum value); CV (coefficient of variation defined as the ratio of the standard deviation to the mean).

Table 3
Pearson correlation matrix

	CLEAN	CO2	ENVREG	GDP	DE	SP	GTI
CLEAN	1						
CO2	-0,4378	1					
ENVREG	-0,0756	0,0426	1				
GDP	0,1814	0,4189	-0,0802	1			
DE	-0,0056	0,1255	0,0360	0,1692	1		
SP	0,0819	0,0397	-0,0355	0,0524	0,0001	1	
GTI	0,0374	-0,0043	-0,0657	-0,0544	-0,0222	0,1154	1

Table 4
Unit root test, optimal lags, and stability of PVAR model

	With constant		With constant and trend	
	Value	p-value	Value	p-value
CLEAN	-14.42	0.00	-13.86	0.00
CO2	-14.97	0.00	-15.91	0.00
ENVREG	-15.23	0.00	-15.82	0.00
GDP	-12.74	0.00	13.67	0.00
DE	-2.91	0.00	-2.99	0.00
SP	-14.07	0.00	-14.11	0.00
GTI	-9.23	0.00	-10.14	0.00

Table 5
Lag order selection criteria.

lag	CD	J	J pvalue	BIC	AIC	HQIC
1	0.919326	200.7533	.392896	-987.7486*	-191.2467*	-505.7617*
2	0.7872107	135.9215	.733671	-755.4549	-158.0785	-393.9648
3	0.3440486	81.47896	.8859831	-512.772	-114.521	-271.7786
4	-137.6618	13.16094	.9999999	-283.9645	-84.83906	-163.4678

Notes: * $p < 0.05$.

4.3 Cointegration test

Investigating short- and long-run effects between variables was conducted to make this research more useful. You can refer to Table 6 for more details. The positive relationship between disability employment and clean energy usage remains significant until the fourth horizon, when a declining trend is noticeable. This indicates the natural saturation point of education and skills influencing energy consumption patterns. This result contradicts Pata et al. (2023), who supported a long-term positive effect of employment of disabilities on sustainable energy. Also, the consistent negative relationship between CO2 emissions and disability employment rate stresses the critical importance of education, skill development, and health investments, as previously supported by Stein et al. (2024). Such investments are pivotal in creating an environmentally conscious society and proactive in reducing CO2. Green Technological innovation, mainly oriented to environmental improvements, demonstrates a strong and positive influence on the growth of clean energy consumption (CLEAN), reaching its maximum in the fourth year. This finding is a testament to innovation's vital role in making clean energy more accessible, cost-effective, and efficient. However, the results also highlight that more than technological innovation is needed to drive the adoption of clean energy in the absence of supportive policy frameworks. This finding confirms that policymakers are encouraged to create and maintain regulatory environments that actively support technological advancements in clean energy.

4.4 Optimal lags, and stability of PVAR model

As discussed below, investigating this interaction effect requires determining the optimal lag order first. In this case, the results shown in Table 5 confirm the opportunity of the first-order panel VAR (one lag) because it has the smallest BIC, AIC, and QIC values. Details related to this step are represented in Table 5. The next step to perform before estimating the PVAR model is the determination of the stationary test. Therefore, this paper uses IP tests as a standard panel data unit root test method. A unit root test was performed to confirm the PVAR model's opportunity. As shown in the IPS test (Table 7), all variables introduced into the PVAR model are stationary. However, the IPS test values (regardless of the nature of the specification) appear to be lower than the critical value calculated at a 5% significance level (-1.64). The null hypothesis of a unit root is rejected, and the series is considered stationary.

Results issued from each variable's first-order difference and lag specification permit us to reject the null hypothesis with 1% as the significance level. All variables are stationary. As shown in Figure 2, the modulus of all eigenvalues is less than 1. Apart from that, Figure 2 shows that our PANEL-VAR is stable. The dynamic matrix's eigenvalues module is in the circle of units. Stability checks ensure that the estimated PVAR model generates consistent and bounded forecasts over time. This implies that the model's shocks decay over time rather than persist indefinitely. Stability indicates that the system will return to equilibrium after a shock.

4.5 Impulse reaction functions (IRF) results

Fig. 2 provides RFID plots with 95% confidence bands, calculated using Monte Carlo simulations with 500 iterations. As might be expected, the impact of strict environmental policy on clean energy is positive between the first and third horizons, which is in line with those of Mihai *et al.* (2023), after which it becomes insignificant. Proportionally, environmental policy stringency has a negative and statistically significant effect on CO2 emissions. This finding indicates that the stringency of environmental policy will push people in OECD countries to use clean energy instead of fossil energy. Also, the results have shown a positive CLEAN response to employment of disability shocks and green technological innovation. That shock starts from the first horizon to the fourth horizon, and then it increases. Our results also confirm that CO2 emissions react negatively when followed by a positive impact on disability employment. The effect starts at the first horizon and reaches its maximum at the second year's level. This finding supports the results obtained by Sezgin et al. (2022), who suggested the impact of environmental policies and employment of disabilities on CO2 emissions for 1995–2015 in the Group of Seven and BRICS economies. These results permit us to conclude that the relationship between employment disability and CO2 emissions intertwines social equity (by defining an adequate regulatory framework) and environmental sustainability. People with disabilities often face significant barriers to employment, which

Table 6
Long-run Non-linear effect of TI and DE on CO2 emissions

	Long-run Non-linear effect of TI and HC on CO2 emission						
	CLEAN	SP	ENVREG	DE	TI	GDP	CO2
Ln_clean	0.722	-4.402***	-0.430**	0.360**	0.0833	-0.895***	-0.772***
	(0.610)	(0.454)	(0.207)	(0.164)	(0.228)	(0.182)	(0.211)
Ln_GDP	-0.119	3.382***	3.187***	4.824***	1.746***	1.980***	0.772*
	(2.352)	(0.561)	(0.546)	(0.830)	(0.478)	(0.499)	(0.454)
Ln_envreg	0.00384	-0.0942***	-0.0887***	-0.199***	-0.0198	-0.0381	-0.103***
	(0.111)	(0.0277)	(0.0277)	(0.0436)	(0.0235)	(0.0247)	(0.0233)
Ln_co2	0.672***	0.749***	1.423***	0.965***	1.359***	1.180***	1.208***
	(0.0897)	(0.0366)	(0.0529)	(0.0588)	(0.0422)	(0.0383)	(0.0439)
GTI+	-0.0164***						
	(0.00151)						
GTI-	-0.0449***						
	(0.0102)						
DE +		-0.0527***	0.00603	-0.0857***	-0.00036***	-0.0238*	-0.0136***
		(0.0140)	(0.0234)	(0.0182)	(0.000115)	(0.0137)	(0.00267)
DEc-		-0.0917***	-0.0379**	-0.00438	-0.0822***	-0.0971***	0.0126***
		(0.0285)	(0.0164)	(0.0186)	(0.0271)	(0.0159)	(0.00200)
Testing for Asymmetric Nonlinear Long-run	15.53(0.00)	8.94(0.00)	4.50(0.03)	23.31(0.00)	2.46(0.11)	96.56(0.00)	93.13(0.00)

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Or *p-value<0.10; **p-value<0.05; ***p-value<0.01. Testing for Asymmetric Nonlinear Long-run : p-value between parentheses H0 = Null hypothesis is rejected: confirms the presence of asymmetry, Ha = Null hypothesis cannot be rejected: No asymmetry confirmed. *Source: Authors' computations*

	Long-run Non-linear effect of TI and HC on CO2 emission						
	CLEAN	SP	ENVREG	DE	GTI	GDP	CO2
Constant	-0.270**	-1.508***	-8.919***	-9.138***	-11.97***	-5.361***	-0.0292
	(0.119)	(0.306)	(1.415)	(1.482)	(1.318)	(0.909)	(0.202)
	-0.0950**	-0.265***	-0.317***	-0.296***	-0.474***	-0.347***	-0.329***
Ln_clean							
	(0.0438)	(0.0515)	(0.0499)	(0.0471)	(0.0537)	(0.0593)	(0.0467)
Ln_GDP	3.213	1.905	-1.120	-4.285	4.489	-9.726	-5.047
	(11.30)	(9.000)	(3.166)	(6.480)	(5.960)	(7.408)	(3.909)
Ln_envreg	7.957	22.86*	6.484	-7.665	16.50	2.685	1.219
	(14.17)	(12.32)	(10.26)	(14.50)	(11.56)	(10.22)	(6.973)
Ln_co2	-0.353	-1.034*	-0.256	0.443	-0.758	-0.0864	0.0110
	(0.688)	(0.579)	(0.483)	(0.678)	(0.542)	(0.488)	(0.330)
GTI+	0.796***	0.721***	0.505***	0.616***	0.372***	0.544***	0.538***
	(0.100)	(0.0860)	(0.0959)	(0.102)	(0.0903)	(0.0872)	(0.0790)
GTI-	-0.00325*						
	(0.00191)						
DE +	0.0299*						
	(0.0161)						
DE -		-0.0200*	-0.00995	0.0336	-0.00792	-0.00709	0.0108**
		(0.0103)	(0.0211)	(0.0458)	(0.0476)	(0.0330)	(0.0491)
		-0.0340	-0.0525	0.00112	-0.0370	-0.00327	-0.00526
		(0.0644)	(0.0344)	(0.0146)	(0.0519)	(0.0397)	(0.0509)
Wald statistic Testing for Asymmetric Nonlinear Short run	2.80(0.09)	1.42(0.23)	0.36(0.54)	0.04(0.83)	0.00(0.96)	0.01(0.91)	3.33(0.06)
PMG versus MG	0.25	0.52	0.53	0.18	0.14	0.63	0.88
Observations	804	804	804	804	804	804	804

can exacerbate economic vulnerabilities and indirectly influence CO2 emissions. This connection is particularly evident in high unemployment rates, as increased unemployment correlates with higher CO2 emissions due to reduced economic activity and inefficient resource use (Mitić *et al.,* 2024). The main results show that ecological stringency policies and employment of disabilities had a decreasing impact on CO2 emissions. In addition, the CLEAN reacts positively to a positive effect on technological innovation linked to the environment. This impact reached its maximum level in the fourth year. This study confirms that the effects of regulation do not seem statistically significant as clean energy consumption in OECD countries and clean energy consumption reacts negatively to a positive shock of CO2 emissions for the first two years

Table 7
Variance decomposition analysis G_CO2

Horizon	CLEAN	SP	ENVREG	DE	GTI	GDP	CO2
0	0	0	0	0	0	0	0
1	.1398722	.0584448	.0000151	.0031699	.0034342	.1121955	.6828682
2	.122991	.0821018	.001094	.0466862	.0063599	.1307665	.6100007
3	.1146557	.0786017	.0010367	.0842833	.0068134	.1469438	.5676653
4	.1102811	.079603	.0025042	.1009747	.006832	.1524207	.5473842
5	.1077612	.0799758	.003387	.1133992	.0067555	.1537186	.5350028
6	.1062093	.0799445	.0038562	.1216544	.0067737	.1542853	.5272767
7	.1052421	.0799597	.0041985	.1268689	.0067845	.154511	.5224353
8	.1046297	.0799547	.0044183	.1302294	.0067924	.1546151	.5193604
9	.1042403	.0799486	.0045598	.1323807	.0067987	.1546703	.5174015
10	.1039916	.0799446	.0046512	.1337592	.0068028	.1547012	.5161495

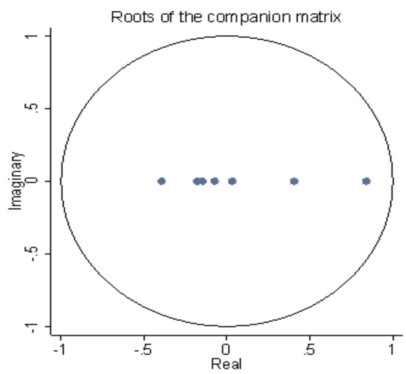

Fig. 2 Stability of the PVAR model

4.6 Variance decomposition analysis

In the PVAR model, this analysis supports and complements the Impulsive Response analysis and explains the effect of structural shock on each endogenous variable. To accurately analyze the value of mutual influence between GTI, DE, and CLEAN, this variance decomposition method is usually used to measure the effect of each variable on itself and the relative variance contribution caused by other variables as a rate. Tables 7 provide the FEVDs of the benchmark specification with seven variables. As can be seen from this table, 10.3 % of the variation in clean energy is explained by CO2, and GDP can explain 3.3% for a four-year horizon. The contribution of technology innovation and disability employment shocks is about 1.1%. This implies that while policy measures and disability employment are crucial, the overall economic performance and current emissions levels play a more dominant role in influencing the trajectory of clean energy trends. This supports the importance of the financial contribution of disabled individuals, who are often overlooked despite their potential to enhance productivity and reduce emissions through inclusive practices, as supported by Vornholt et al. (2018).

Similarly, GDP shocks explain 15.2% of the variation in CO2 emissions, and disability employment can explain 10% of GDP and 7.9% of CO2 emissions. This underscores the complex interplay between economic growth, human capital development, and environmental outcomes.

4.7 The integrative effect: LLDV Method

The results shown in Figure 4 detail estimated time-varying parameters for all variables. As supported by Ragmoun (2024a), a positive effect of environmental stringency policies on clean energy was confirmed between 1994 and 2006. The effect became zero or even negative during the global crisis, then positive after 2015. The impact of environmental taxation was negative from 1994 to 2005 and then became positive during the remaining period. This confirms the opportunity for a reglementary framework that sustains energy sustainability proportionally to the employment of PwD.

Disability employment had a positive effect during the same period, with higher elasticity than recorded by Environmental stringency policies and environmental taxation. Green technology innovation (GTI) showed an insignificant impact except for the periods of the global crisis from 2018 to 2019.

Another aspect that our study considers is the interaction between CO2 emissions and clean energy consumption. The observed negative response of clean energy consumption to increased CO2 emissions within the first two years is particularly interesting. This suggests an inherent inertia or delay in adopting clean energy following increased carbon emissions. Such a lag could be attributed to the entrenched infrastructure, existing investments, and societal habits that resist rapid change. This resistance poses a significant challenge

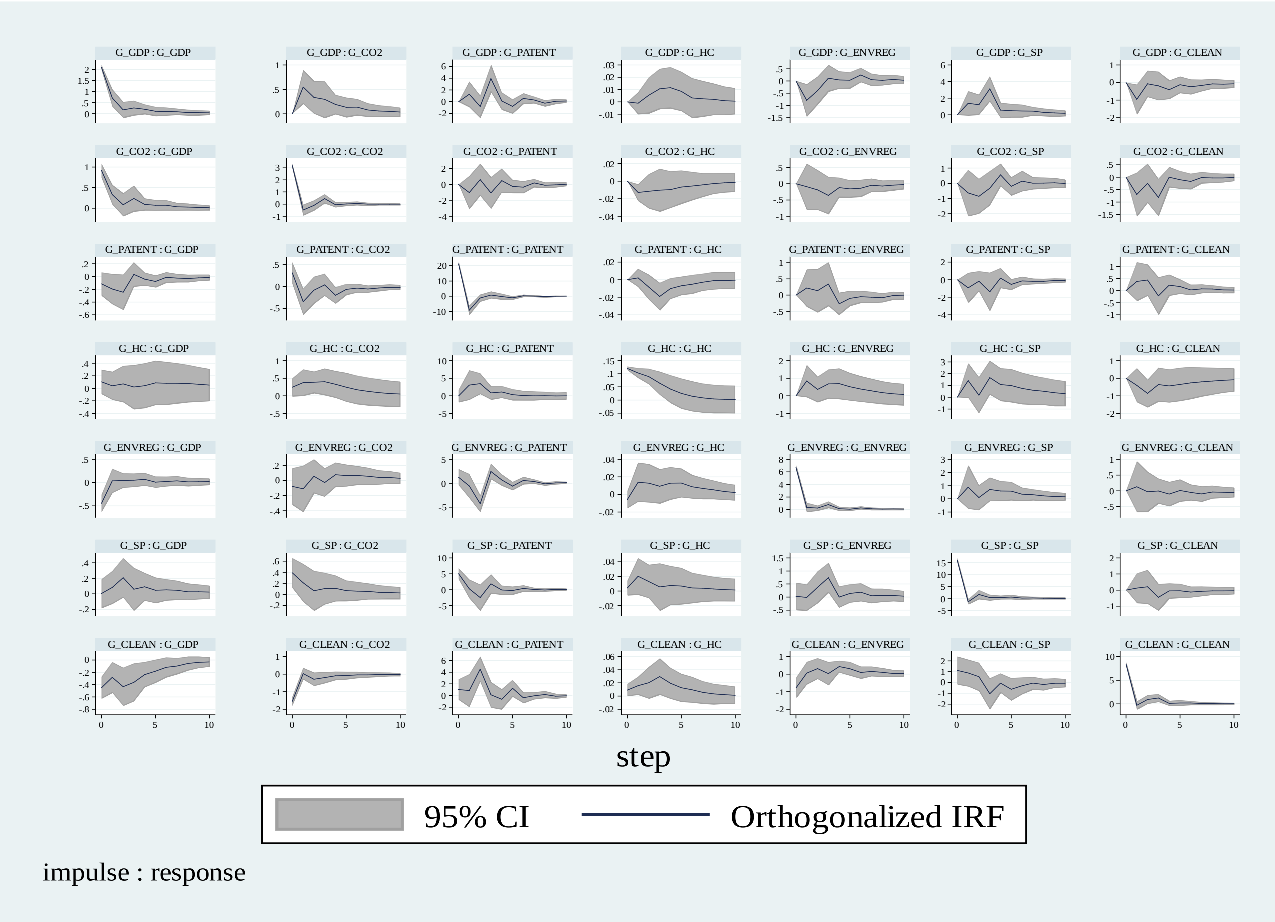

Fig. 3 Impulse response estimates

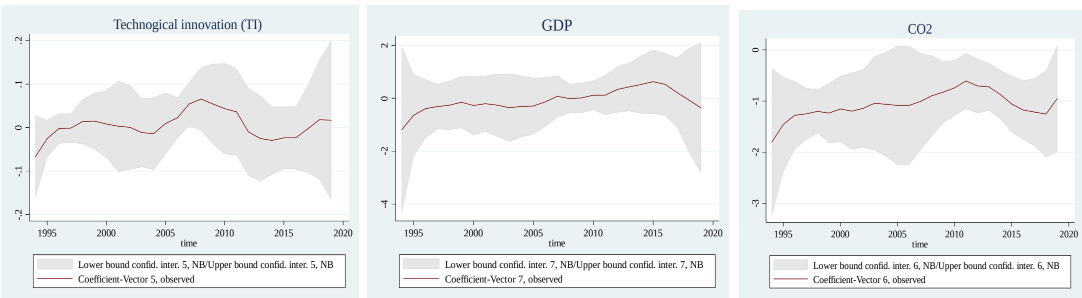

Fig. 4 LLDV estimates (all variables)

to policymakers striving for prompt transitions to clean energy in response to mounting environmental concerns.CO2 emissions negatively impacted the study period; the lowest effect was recorded during the global financial crisis. Finally, GDP's impact on clean energy remained positive only during the post-international financial crisis period.

5. Conclusion

The primary objective of our research was to delve into the intricate relationship between environmental policies as a regulatory framework, employment of disabilities, and green technological innovation and their collective impact on clean energy consumption as an indicator for sustainable energy and CO2 emissions within the context of OECD countries. The findings reveal a multifaceted and nuanced interaction among the studied variables. A robust positive correlation between environmental policies and sustainable energy exists, but this effect is still significant for a short period. Simultaneously, the stringent ecological policies have shown a consistent and enduring negative impact on CO2 emissions. This indicates that stringent regulations are effective and necessary for curbing CO2 emissions in the short to medium term. The study also confirms the significant roles played by the employment of disabilities and green technological advancements in environmental enhancement. These factors are essential to increase clean energy consumption and can alter the patterns of CO2 emissions in a favorable direction. As we can see, positive effects between variables exist, but it still depends on time. A negative impact of disability employment exists on CO2 emission, and a positive impact on clean energy consumption is recorded during a limited period. Green technology innovation, which creates new opportunities for the employment of people with disabilities, reinforces this effect while protecting the environment. Also, research findings underscore the pivotal role that environmental policies, disability employment, and green technology innovation collectively play in increasing sustainable energy and the nuanced influences between variables over time. Our results show that clean energy consumption depends on GTI, which depends on environmental policies and disability employment, but this effect varies over time. This research enriches theories about sustainable energy development based on the interaction between technology, human aspects, and policies for inclusive sustainability development. This effect has been treated quantitatively to define new procedures that combine many factors with high consistency. Still, in our case, this interactive effect was treated according to a short and long time to identify corresponding dynamics and conditions. Further, this research reveals the existence of a bidirectional causality between the employment of disabilities and sustainable energy, contrary to the results of existing studies. This impact still constitutes one of the main critical contributions of our research.

5.1 Practical implication

Based on these findings, some policies can be recommended, and it will be easier to understand how to invest more in renewable energy for a short and long time. Also, the results provide additional directives for reducing CO2 emissions. Investing more in green technology innovation while defining adequate environmental policies will increase sustainable energy for a short and immediate effect. Still, to maintain this benefit, the employment of disabilities is critical. However, investing in renewable energy resources can present some financial development and income difficulties for governments. Through a comprehensive examination of the complex relationships among environmental policy stringency, technological innovation, disability employment, and clean energy consumption within OECD countries, this study seeks to illuminate the pathways toward a more sustainable and environmentally conscious future based on an inclusive approach.

First, studying the interactive effects of Green Technology Innovation, Employment of People with Disabilities, and Sustainable Energy opens a new dimension of inclusive sustainability by integrating social, environmental, and economic aspects. Integrating disabled individuals into the workforce while focusing on green technology fosters a more inclusive economy, reducing inequalities in access to employment. Job opportunities generated in green technology sectors (such as renewable energy, sustainable manufacturing, and eco-friendly service sectors) offer employment avenues tailored to varied abilities. This inclusion supports social equality and enhances economic resilience. Second, companies embracing green technology and including people with disabilities in their workforce demonstrate a robust commitment to corporate social responsibility, enhancing their public image and community relations. Businesses can become leaders in social equity by aligning disability-inclusive hiring practices with sustainability goals, and fulfilling environmental and social obligations. Third, transitioning to sustainable energy is often labor-intensive and requires a diverse workforce. By actively including people with disabilities, the sector benefits from an expanded workforce equipped with unique problem-solving skills and perspectives. This approach also improves community support for sustainable energy initiatives, as local populations see tangible social benefits alongside environmental gains. Fourth, a diverse and inclusive workforce is more adaptable and resilient. By employing disabled individuals in green technology sectors, businesses can achieve continuity through diverse skills and perspectives, which are essential for innovation under changing environmental regulations and market demands. This resilience translates to sustainable operations, where businesses are prepared to adapt to evolving technological and ecological landscapes while supporting inclusive growth. Companies that lead in green technology and inclusive employment can achieve competitive advantages by differentiating their brand, attracting sustainability-conscious investors, and benefiting from a diverse and innovative workforce. Fifth, policymakers can use insights from this interaction to shape policies that encourage disability-inclusive employment within green industries, facilitating access to funding, tax incentives, or support for companies that drive sustainability and social equity. In summary, exploring the interaction between green technology innovation, sustainable energy, and employment of people with disabilities presents an integrated path toward inclusive sustainability. It bridges environmental responsibility with social justice, creating opportunities for equitable economic development, fostering resilient and adaptable businesses, and encouraging a broader, more inclusive approach to achieving sustainability.

5.2 Future perspective

One of the main shortcomings of this research is the heterogeneity of this dynamic-integrative process. Thus, further studies may address an extensive approach to sustainable energy by considering other determinant factors such as culture. Also, this research focuses on OECD countries, investigating these interactions in different geographic areas and evaluating economic development levels, which can guarantee a higher level of reliability and facilitate the generalization of results. Other possible future research can contribute by providing frameworks and metrics to measure the combined social and environmental impact of inclusive sustainability practices, guiding corporations toward a new corporate social responsibility standard that values ecological stewardship and social equity. Additionally, it will be interesting to explore how emerging technologies like AI, robotics, and automation can help accommodate disabilities while advancing energy sustainability, ultimately promoting inclusive technological growth and increased workforce diversity. In the long term, a focus on inclusive sustainability may help shift societal values towards a more holistic understanding of development, and it seems essential to explore the broader societal benefits of these practices, such as enhanced quality of life, reduced poverty, and improved public health, all contributing to more sustainable energy and equitable societies.

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