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The Long-Run Dynamics of Green Technology, Ecological Footprint, and Health Vulnerability in Developed and Developing Countries

Muhammad Asif Amjad[1], Hafeez ur Rehman[2], Nabila Asghar[3]

[1] Scholar, Department of Economics and Statistics, University of Management and Technology, Lahore, Pakistan. Email: f2020330007@umt.edu.pk

[2] Professor, Department of Economics and Statistics, University of Management and Technology, Lahore. Pakistan. Email: hafeez.rehman@umt.edu.pk

[3] Associate Professor, Department of Economics, Division of Management and Administrative Science, University of Education, Lahore. Pakistan. Email: nabeela.asghar@ue.edu.pk

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ABSTRACT

Human activities have contributed to environmental degradation for decades, and ecological footprint is considered an effective tool for measuring natural resource consumption. The present study explores the moderating role of green technology to determine the impact of the ecological footprint on the health vulnerability of developed and developing countries from 1990 to 2020. The long-run results are estimated by using the Panel Quantile Regression model at lower, middle, and higher health vulnerability groups. The empirical results show a U-shaped relationship exists between ecological footprint and health vulnerability in all groups. The green technology is used as the moderator term, which shifts the turning point of the U-shaped curve at higher quantile groups of developed countries and middle quantile groups at middle quantiles. Which shows that green technology moderates health vulnerability by reducing the ecological footprint. Furthermore, this study shows that most developing countries fall in the lower health vulnerability group while most developed countries fall in the middle health vulnerability group. This study recommends that these selected countries' governments increase green technologies, reducing the ecological footprint and improving the health sector.

Corresponding Author's Email: hafeez.rehman@umt.edu.pk

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1. Introduction

Every country exploits its natural resources without caring about the environment to fulfil the massive human demand. Using natural resources has significant negative environmental impacts, which is considered the major obstacle to achieving sustainable development goals (SDG). The growing human demand is fulfilled by using the energy from burning natural resources, which adversely affects the environment (Asghar, Amjad, Rehman, Munir, & Alhajj, 2023).

In the previous literature, several studies measure environmental degradation by using proxies for carbon emissions and greenhouse gases (Rani, Amjad, Asghar, & Rehman, 2022b). These proxies measure only atmosphere pollution and ignore pollution of land and water resources. Burke (1997) resolved this problem by using ecological footprints (EFP), which account for all human activities on land, the atmosphere, and water resources. Global Footprint Network Network (2022) measures human activities on cropland, forest, grazing land, fishing, build-up land, and carbon footprint. It provides a comprehensive picture of human consumption of the planet's ecosystems to measure environmental degradation (Saud, Chen, & Haseeb, 2020).

Environmentalists and scientists have been raising awareness about the urgent need to address environmental degradation. They warn that if we fail to decline environmental degradation, it will lead to widespread pollution, loss of biodiversity, climate change, and other negative impacts that will be felt globally (Rani, Amjad, Asghar, & Rehman, 2022a). Therefore, it is imperative to take action now to mitigate the effects on the environment and ensure a sustainable future. It includes reducing greenhouse gas emissions, preserving wildlife habitats, reducing waste, and adopting sustainable practices in agriculture, energy production, and other industries (Sial, Arshed, Amjad, & Khan, 2022).

For this purpose, the COP27 conference has played a vital role in the fight against the adverse effect of climate change. This conference brought together representatives from worldwide countries to collaborate on addressing global warming and its impacts. At this conference, many countries announce and negotiate their commitments to reducing environmental degradation (Atwoli et al., 2022).

The present study asses the long-run dynamics of EFP to determine the health vulnerability and further extends its application by using green technology (GTECH) as the moderator in both developed and developing countries. Health vulnerability refers to the susceptibility of an individual or a population to adverse health outcomes, including diseases, disabilities, or death, due to various factors such as age, genetics, lifestyle, environment, or access to healthcare (Amjad & Asghar, 2021). Health vulnerability is often associated with socioeconomic status, living conditions, and access to resources which significantly increase the well-being of people. Addressing health vulnerabilities is essential to promoting health equity and improving the overall health of populations (Dai et al., 2022).

The impact of an EFP on human health is very significant. An excessive EFP lead to environmental degradation, which damages human health (Lenzen et al., 2020; Pata, Aydin, & Haouas, 2021).

Figure 1 shows the world's EFP per capita and biocapacity per capita from 1990 to 218. The upper line shows EFP consumption per capita which is an increasing trend, while the below line shows the biocapacity per capita, which is a declining trend. The difference between EFP consumption and biocapacity is increasing, which shows the biocapacity deficit. It is observed that the world’s biocapacity deficit is growing rapidly.

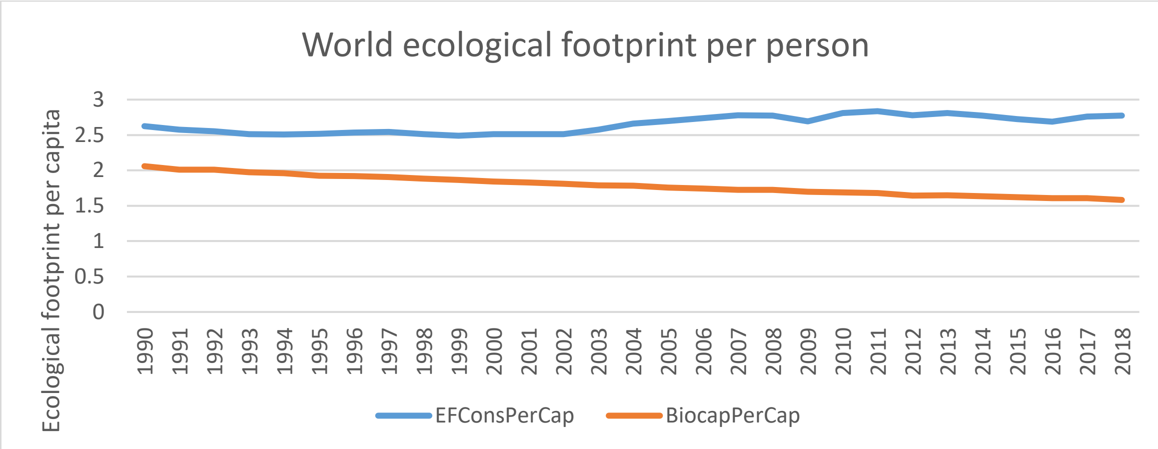

Figure 1: World Ecological Footprint Trend

This study uses Green technology (GTECH) as the moderator term. It refers to developing and implementing new technologies and products that are environmentally friendly and promote sustainability (Ouyang, Li, & Du, 2020). It includes solar and wind power to sustainable transportation systems like electric vehicles and high-speed rail to eco-friendly building practices and products. GTECH aims to improve human health and promote a more sustainable future (Ouyang et al., 2020).

GTECH declines the EFP by promoting sustainability and reducing the impact of human activities on the environment (Feng, Chong, Yu, Ye, & Li, 2022). These innovations include renewable energy sources, efficient transportation systems, sustainable building practices, and environmentally friendly products. By reducing reliance on non-renewable resources and decreasing waste, GTECH helps to lower the overall EFP and promote a healthier, more sustainable future (Huang, Haseeb, Usman, & Ozturk, 2022).

The discussion shows that higher EFP causes environmental degradation, which is damaging human health badly. In contrast, GTECH improves ecological quality, ultimately improving human health. The key objective is to investigate the moderating role of green technology to determine the impact of EFP on health vulnerability from a global perspective.

This study is significant because it is the first study to examine the role of non-linear EFP on health vulnerability. In the previous literature, several studies investigate the linear effect of EFP on different human health-related problems (Fatima, Arshed, & Hanif, 2021; Gündüz, 2020; Hong et al., 2021; Kassouri & Altıntaş, 2020). Furthermore, this study uses GTECH as the moderator term with EFP to determine health vulnerability. Several scholars used the moderator term in the literature to shift the turning point of a U or inverted U-shaped curve (Sardar & Rehman, 2022). Additionally, this study is very novel because it uses the health vulnerability index of different groups as lower, middle, and higher health vulnerability groups.

2. Literature Review

The researcher and policymakers have failed to explore a suitable proxy to measure environmental degradation. Obtaining accurate and reliable data on environmental pollution is challenging, as pollutants are dispersed over large areas and difficult to detect and quantify. Despite these challenges, researchers are using a variety of proxies to measure environmental degradation. Several pieces of literature measure environmental degradation using carbon emissions (Bruckner, Hubacek, Shan, Zhong, & Feng, 2022). Several scholars pointed out that carbon emissions are not only one gas that is polluting the environment. There are so many other gases, like greenhouse gases which badly damage the environment quality (Shen et al., 2020). The EFP is the new term introduced by Rees (1992) that covers each aspect of the environment, like land, air, and water (Ullah, Ahmed, Raza, & Ali, 2021).

Greenhouse gases are considered an essential polluter of the global atmosphere, which badly damage the health of the inhabitants. Farooq, Shahzad, Sarwar, and ZaiJun (2019) examined that GHS caused higher health issues using quantile regression in China. Tan, Liu, Dong, Xiao, and Zhao (2022) conducted their study in 30 provinces of China and concluded that China is the largest culprit of GHS emissions, which adversely affects the health sector. Naiyer and Abbas (2022) evaluated that in the short-run human body copes with exposure to GHG, while in the long run, it adversely affects human health.

Assessment (2005) reported that human well-being is intrinsically connected with ecological conditions, and a neat and clean environment improves human health outcomes. Kassouri and Altıntaş (2020) examined the human well-being on EFP in 13-MENA countries from 1990-2016. The HDI is the proxy for human well-being. The study concluded that EFP, globalization, and bio-capacity significantly increased HDI.

Qaiser Gillani et al. (2021) researched Asian countries to explore the association between public health outcomes on EFP from 2000 to 2018. The Infant mortality was used to measure health outcomes. The Panel ARDL found that EFP significantly increased the infant mortality rate. Yang and Usman (2021) investigated that EFP, industrialization, and urbanization increased health expenditures. Fatima et al. (2021) noted that EFP and other factors on life expectancy from 1994 to 2017. The panel FMOLS revealed that ecological factors declined life expectancy. Nathaniel (2021) explained the role of EFP on human well-being by using HDI in N-11 countries. The study found that the EFP increased HDI except in Egypt.

Human activities are attributed to the increase in the EFP, a factor in environmental degradation. Most human activities are based on using natural resources like fossil energy. Greiner, York, and McGee (2022) reported that about 79% of the world relies on fossil energy which is considered the major contributor to the EFP. Lelieveld et al. (2019) determined that a 65% mortality rate is based on the use of dirty fossil energy.

In this study, green technology is used as a moderator to determine health vulnerability. Green technology practices motivate stakeholders to use environmentally friendly technologies that enhance public health. Mousa and Othman (2020) explored the link between green human resources and the health sector in Palestine based on primary data management. The study analysed that green human resources significantly improved the health sector. Jiang, Chang, and Shahzad (2022) studied the impact of green technology on life expectancy in BRICS countries from 1993 to 2019. ARDL panel analysis examined green technology-enhanced life expectancy in Russia and China over the long run. Khan, Aziz, and Khan (2022) described the impact of environmental technology on the life expectancy rate in GCC countries from 1990 to 2020. The study concluded that environmental technologies improved life expectancy. Madsen and Strulik (2023) examined technological progress in the fertility rate of 21 OECD countries from 1750 to 2000. This study measured technological progress through patents, R&D, investment in machinery, and intellectual property rights. The study concluded that technological progress reduced the fertility rate.

Industrialization deteriorates the health sector by releasing toxic chemicals, pollutants, and waste products into the environment, damaging public health, particularly in communities near industrial facilities. It leads to respiratory problems, congenital disabilities, cancers, and other illnesses Manisalidis, Stavropoulou, Stavropoulos, and Bezirtzoglou (2020) and Bauer, Im, Mezuman, and Gao (2019) found that industrialization caused environmental pollution, which damages human health. Safdar et al. (2022) also explore how industrialization increased infant mortality.

Massive population growth negatively impacts human health because it strains the healthcare system, making it difficult for people to access quality medical care. Inadequate healthcare facilities and services increase illness and health issues. Sastry (2004) conducted his study in the states of Sao Paulo and Brazil between 1970 and 1991 and found that rural-urban gaps influence infant mortality. The fundamental reasons for low mortality rates in urban areas are access to electricity, clean drinking water, etc. Van de Poel, O'donnell, and Van Doorslaer (2009) examined a study in West sub-Saharan African countries and found a low mortality rate in urban areas and a high mortality rate in rural areas. Urbanization also affects the infant mortality. Ely, Driscoll, and Matthews (2017) evaluated a study in the U.S and concluded that the infant mortality had decreased due to urbanization. Bandyopadhyay and Green (2018) explored the connection between mortality rate and urbanization from 1955 to 2010. The study established a positive relationship between urbanization and health conditions. Thus, there exists an inverse relationship between urbanization and the mortality rate.

After reviewing the previous literature, it is found that EFP causes environmental degradation, which badly damages human health (Fatima et al., 2021; Gündüz, 2020; Hong et al., 2021; Kassouri & Altıntaş, 2020). We have not found any study in the previous literature that examined the non-linear analysis of EFP to determine health vulnerability. Furthermore, this study uses the moderating role of green technological innovation to determine the impact of EFP on health vulnerability.

3. Research Methodology

The present study chose 93 developed and 79 developing countries based on data availability, followed by Alam, Du, Rahman, Yazdifar, and Abbasi (2022) ranking. The annual panel data is taken from 1990 to 2020. In this study, the health vulnerability of Sarkodie, Ahmed, and Owusu (2022) is used as the dependent variable based on adaptive capacity, exposure, and sensitivity. Dai et al. (2022) used the health vulnerability index as the dependent variable in the literature. Furthermore, this study uses the three quantile groups as the lower health vulnerability index group, middle health vulnerability index group, and high health vulnerability index group in Q1, Q2, and Q3 quartiles. These quantile groups are built using the actual value of the health vulnerability index followed by the 25%, 50%, and 75% percentiles. The data source and description of the variables are discussed in Table 1.

Table 1
Description of the Variables

Symbol	Indicator	Units	Sources
HVI	Health Vulnerability	Index (0 to 1)	ND-GAIN (2022)
EFP	Ecological footprint	Gha per person	Global Footprint Networking (2022)
GTECH	Green technologies	Total, Percentage	OECD (2022)
IND	Industry value added	% of GDP	WDI(2022)
URPOP	Urban population	% of total	WDI(2022)
EXPO	Export of goods and services	% of GDP	WDI (2022)

Several studies pointed out that EFP badly affects human health (Fatima et al., 2021; Nathaniel, 2021).The bi-variate analysis between these variables confirms the non-linear behavior, which is not demonstrated here due to the non-availability of space. So, the multiple regression can be formed as follows:

$$HVI_{it} = \alpha_0 + \alpha_1(EFP)_{it} + \alpha_2(EFP)^2_{it} + \alpha_3(LNIND)_{it} + \alpha_4(LNURPOP)_{it} + \alpha_4(LNEXPO)_{it} + (\varepsilon)_{it} \quad (1)$$

In equation (1), HV_{it} Shows the health vulnerability, which is treated as the dependent variable. To capture the non-linearity, EFP is used as the linear and quadratic term, which proposes U or an inverted U-shaped curve. This study follows the green technology (GTECH) as the moderator variable to shift the turning point. Following Rani et al. (2022a) the moderator term can be used as follows:

$$HVI_{it} = \alpha_0 + \alpha_1(EFP)_{it} + \alpha_2(EFP)_{it}^2 + \alpha_3(GTECH)_{it} + \alpha_4(GTECH \times EFP)_{it} + \alpha_5(GTECH \times EFP^2)_{it} + \alpha_6(LNIND)_{it} + \alpha_7(LNURPOP)_{it} + \alpha_8(LNEXPO)_{it} + (\varepsilon)_{it} \quad (2)$$

The GTECH term is used as the interaction term with linear and quadratic terms of EFP. The moderator is used for shifting the turning point of the non-linear curve. To estimate the turning point of equation (2), the following estimation is used as follows:

$$\frac{\partial HV_{it}}{\partial GTECH_{it}} = \alpha_1 + 2\alpha_2 EFF_{it} + \alpha_4 GTECH_{it} + 2\alpha_5 GTECH_{it} EFP_{it} = 0$$

$$FFP_{it}^* = \frac{-\alpha_1 - \alpha_4 GTECH_{it}}{2(\alpha_2 + \alpha_3 GTECH_{it})} \quad (3)$$

The moving of turning point depends on the moderator GTECH. So, partial derivatives are used of equation (3) concerning GTECH as follows:

$$\frac{\partial FFP_{it}^*}{\partial GTECH_{it}} = \frac{(\alpha_1\alpha_5 - \alpha_2\alpha_4)}{2(\alpha_2 + \alpha_5 GTEC_{it})^2} \quad (4)$$

In equation (4), the quadratic denominator term is positive due to the quadratic term, so the shift of the turning point depends on the sign of the numerator $(\alpha_1\alpha_5 - \alpha_2\alpha_4)$. The positive value of the numerator expression shows that the turning point move to right side, while its negative value shows the turning point shift to the left side of the U or inverted U-shaped curve as GTECH increases. However, α_5 demonstrate the flattens and steepens of the curves. Its positive value shows that it steepens the curve, while its negative value flattens it (Haans, Pieters, & He, 2016).

The empirical findings are calculated using the Panel Quantile Regression (PQR) model. It is helpful in the context of outliers. The major benefit of the PQR model is reducing outliers when the error term is not normally distributed. The PQR model is utilised in this research since the health vulnerability differs among nations. This method is effective in reducing cross-sectional heteroscedasticity and autocorrelations (Sardar & Rehman, 2022).

4. Result Discussion

Table 2 presents the summary statistics of all concerned variables in this study in developed and developing countries. Their standard deviation values are less than their corresponding mean values, showing these variables are under-dispersed. Furthermore, the higher Jarque-Bera value and significant probability value present that all series are not normally distributed. The high Kurtosis value shows the presence of outliers in the model (Amjad, Asghar, & Rehman, 2021; Amjad, ur Rehman, & Batool, 2022; Wang et al., 2022).

Table 2
Summary Statistics of the Developed Countries

	HVI	EFP	GTECH	LNIND	LNURPOP	LNEXPO
Mean	29.9389	4.4167	16.8475	3.3320	1.9378	3.9251
Median	30.0810	3.9591	10.7480	3.2890	1.9851	3.9914
Maximum	96.7990	17.7261	142.7400	4.6888	3.6584	5.9139
Minimum	-52.1110	0.0608	-156.6100	1.6232	-2.3026	-3.1130
Std. Dev.	13.7146	2.5978	22.2396	0.3929	0.7779	0.8739
Skewness	-0.0391	1.4838	1.8421	0.4060	-0.8646	-1.1759
Kurtosis	3.3060	6.2567	13.8552	3.7074	5.2423	7.2759
Jarque-Bera	10.75	2092.51	13518.55	125.02	864.31	2567.012
Probability	0.0046	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	77451.8	11426	41596.36	8619.968	5013.104	10154.35
Sum Sq. Dev.	486398.4	17451.35	1220671	399.175	1565.033	1974.833

Observations	2587	2587	2469	2587	2587	2587

Table 3
Summary Statistics of Developing Countries

	HVI	EFP	GTECH	LNIND	LNURPOP	LNEXPO
Mean	57.4203	1.6133	30.3652	3.1985	3.5392	2.7019
Median	61.3496	1.2511	20.0669	3.2221	3.5855	2.7777
Maximum	89.9382	7.8920	234.4750	4.2866	4.4878	4.0857
Minimum	0.0000	0.4599	0.0000	-0.0927	1.6894	-2.9133
Std. Dev.	18.9082	1.0964	30.0010	0.4032	0.5193	0.6617
Skewness	-0.8224	2.5253	2.0100	-1.0517	-0.5732	-2.2518
Kurtosis	3.3251	10.2494	8.3382	9.4922	3.1513	13.3432
Jarque-Bera	143.8376	3994.1890	2284.9120	2382.9740	68.4214	6511.7710
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	70512.12	1981.114	37288.51	3927.808	4346.193	3317.955
Sum Sq. Dev.	438676.5	1474.934	1104371	199.4479	330.9342	537.2641
Observations	1228	1228	1228	1228	1228	1228

Note. Author's own estimation

Figure 2 exhibits the correlation plot of the developed and developing countries. It shows red and blue color boxes. The light colors show weak correlation values. In Figure 3, all correlation boxes display light colors, which indicates a weak correlation between the variables (Asghar et al., 2023; Rafique, Hussain, Naushahi, Shah, & Amjad, 2023).

Developed countries Developing countries

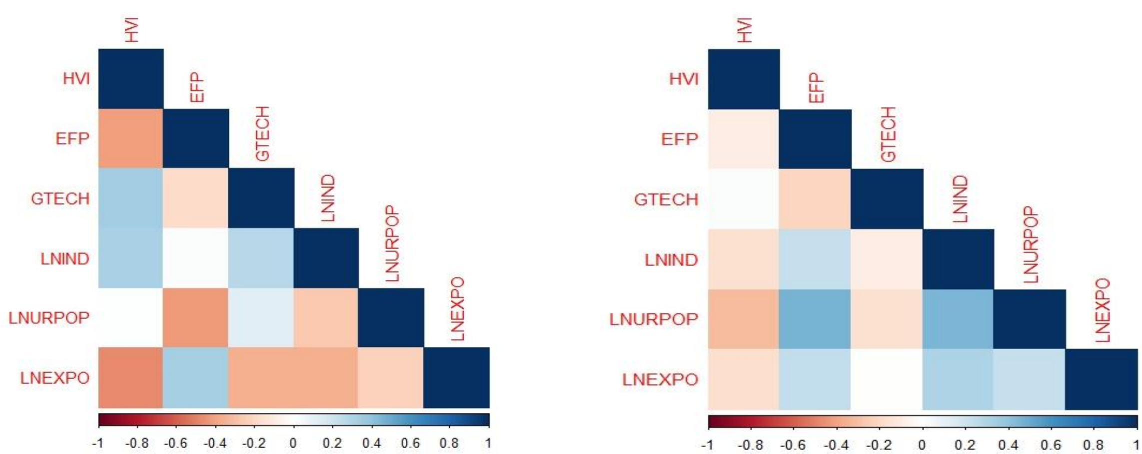

Figure 2: Correlation plot

Table 4 presents the long-run coefficients of the model by using the PQR model at lower, middle, and higher health vulnerability index (HVI) groups of both developed and developing countries. The level coefficient of EFP negatively impacts the HVI in lower, middle, and higher HVI groups. It shows a lower level of EFP improves human health. EFP measures how much natural resources are consumed against the earth's production ability. Lower EFP offers that natural resources are less consumed than their production, ultimately increasing human well-being (Nathaniel, 2021).

The square coefficient of EFP favourably affects the HVI in all quantile groups. It reveals a greater amount of EFP increases environmental deterioration, which significantly impacts the health sector (Fatima et al., 2021; Gündüz, 2020; Hong et al., 2021; Kassouri & Altıntaş, 2020; Nathaniel, 2021). The higher EFP shows the consumption of natural resources is greater than its ability to reproduce which causes environmental degradation.

The level coefficient of EFP is negative, whereas the square coefficient of EFP is positive, which suggests the U-shaped curve (Dawson, 2014). It shows higher EFP leads to health vulnerability because human consumption is more than natural resource production. A higher EFP causes air, land, and water pollution. Air pollution causes respiratory diseases such as asthma and other chronic obstructive pulmonary diseases. Water pollution from industrial activities, chemical fertilizers, and other sources origins various illnesses, such as diarrhoea, liver problems, and neurological disorders. Land pollution and biodiversity loss cause habitat destruction, and climate change lead to increased zoonotic diseases transmitted from animals to humans. High EFP contributes to climate change, which has a range of adverse health impacts, such as more frequent and severe heatwaves, droughts, and extreme weather events, which lead to injuries, death, and displacement of people.

So, it is a concern for policymakers and environmentalists to pay focus on declining the EFP. It is quite challenging to reduce EFP, so this study diverts attention to moving green technology (GTECH) as the moderator term to moderate health vulnerability (HVI) by using the EFP. In Table 7.9, GTECH adversely impacts the HVI in all quantile groups in the whole sample (Jiang et al., 2022; Madsen & Strulik, 2023; Mousa & Othman, 2020).

The moderating role of GTECH in determining the impact of an EFP on HVI is becoming increasingly important as the world faces a growing environmental crisis. The interaction of GTECH with linear EFP significantly increases HVI, while the interaction of GTECH with quadratic EFP significantly declines HVI in at higher HVI groups in developed countries and middle HVI groups of developing countries. Figure 3 shows the quadratic two-way interactions coefficients.

The moderating role of GTECH with EFP to determine HVI is significant, as it provides solutions that minimize the adverse health effects of environmental degradation. The GTECH includes renewable energy sources, energy efficiency, and sustainable transportation, which are critical in reducing the EFP that mitigates health vulnerability. Furthermore, GTECH leads to improved air, water, and land quality, which helps to reduce the incidence of respiratory and cardiovascular diseases, cancer, and other health problems associated with environmental pollution.

Table 4
Long Run Coefficients by PQR Approach

Dependent variable: Health vulnerability index (HVI)						
	Developed countries			**Developing countries**		
	Lower HVI	**Middle HVI**	**Higher HVI**	**Lower HVI**	**Middle HVI**	**Higher HVI**
EFP	-4.8469*	-8.0241*	-7.5660*	-10.7041*	-18.1757*	-6.8861*
	(0.4286)	(0.3681)	(0.4378)	(3.7853)	(3.1359)	(2.4067)
EFP2	0.2599*	0.4649*	0.4388*	1.5319**	3.5247*	1.6274*
	(0.0334)	(0.0287)	(0.0341)	(0.6258)	(0.5184)	(0.3979)
GTECH	0.0915**	-0.0668*	-0.0721***	-0.3475*	-0.2851*	0.1894**
	(0.0424)	(0.0364)	(0.0433)	(0.1197)	(0.0992)	(0.0761)
GTECH× EFP	0.0226	0.0731*	0.0720*	0.2175***	0.2919*	-0.0530
	(0.0186)	(0.0160)	(0.0190)	(0.1221)	(0.1012)	(0.0776)
GTECH× EFP^2	-0.0028***	-0.0067	-0.0065*	-0.0091	-0.0585*	-0.0129
	(0.0015)	(0.0013)	(0.0016)	(0.0246)	(0.0204)	(0.0156)
LNIND	3.7820*	6.8604	5.5552*	-1.5778	-4.6201**	-3.2565**
	(0.8417)	(0.7230)	(0.8599)	(2.3476)	(1.9449)	(1.4926)
LNURPOP	-2.2405*	-3.1214	-2.1873*	-10.8950*	-12.2280*	-5.2819*
	(0.4158)	(0.3571)	(0.4248)	(2.0931)	(1.7340)	(1.3307)
LNEXPO	-4.3587*	-3.6704	-3.6649*	-3.3642**	-4.5824*	-2.3095*
	(0.3670)	(0.3152)	(0.3749)	(1.3275)	(1.0998)	(0.8440)
Const.	44.0341*	49.3392	56.5708*	113.9127*	146.6067*	108.4201*
	(4.0234)	(3.4559)	(4.1105)	(8.3285)	(6.8997)	(5.2951)

Pseudo R2	0.2486	0.3264	0.3444	0.1012	0.1223	0.0773

The moderator term is used for the shifting the turning-point. To estimate the shifting of the turning-point, the value of coefficients is plugged into the expression $(\alpha_1\alpha_5 - \alpha_2\alpha_4)$. When we plug the coefficient in the expression, it shows the positive sign that presents the turning point shift at the right side of the U-shaped curve (Haans et al., 2016). It shows that GTECH moderates the HVI with EFP in the whole sample. To check the flattens and steepens "α_5" value is used. The negative value of the "α_5" shows the flattening of the U-shaped curve.

Table 5
Moderation role of GTECH

	Quantile groups	Category	Changes in the turning point	Sensitivity
Developed countries	Group 3	High HV group	Right	Flattening
Developing countries	Group 2	Medium HV group	Right	Flattening

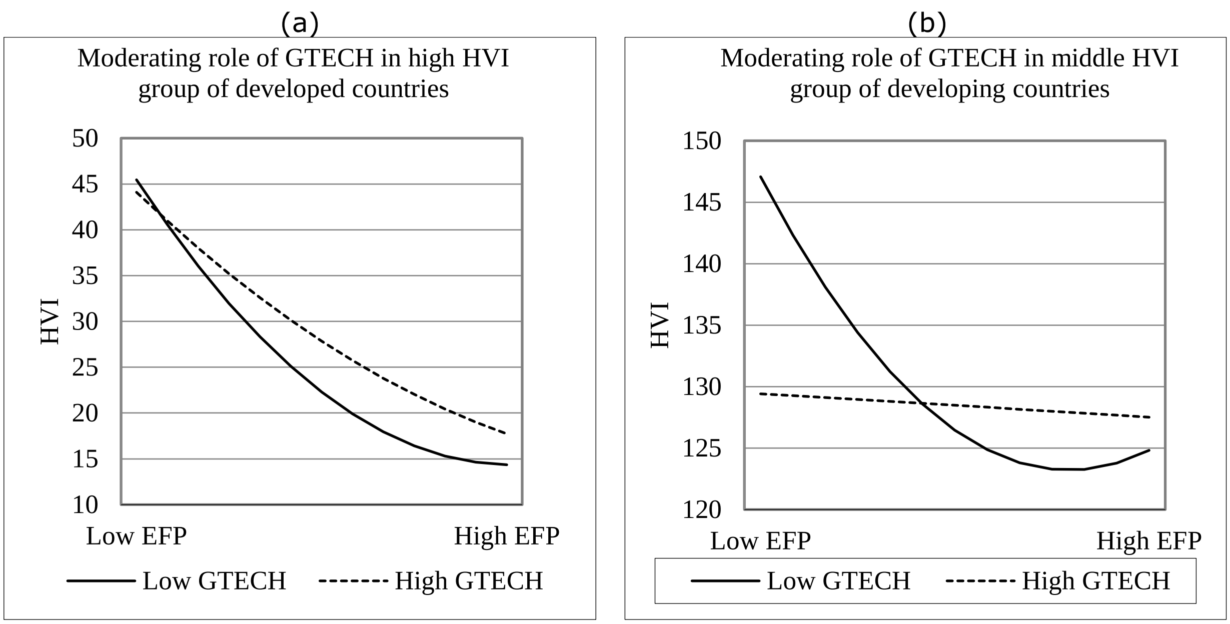

Figure 3: Two Way Moderating Role of Green Technology

This study includes three control variables: industrialization (LNIND), urbanization (LNURPOP), and exports (LNEXPO). LNIND significantly increases the health vulnerability index (HVI) in lower and higher HVI groups in developed countries (Bauer et al., 2019; Manisalidis et al., 2020; Naiyer & Abbas, 2022). In developed countries, LNIND negatively impacts the HVI in middle and higher HVI groups. The industrial sector deteriorates human health because most industries are using polluted energy, which causes environmental degradation. These industries contaminate the groundwater by discharging chemicals and other pollutants into waterways. LNURPOP declines HVI in most quantile groups in both models (Barcelos et al., 2020). (LNEXPO also reduces the HVI in both models (Byaro, Nkonoki, & Mafwolo, 2023; Panda et al., 2020).

5. Conclusion and Policy Recommendations

The present study examines the long-run dynamics of the moderating role of green technology to determine the impact of the ecological footprint (EFP) on health vulnerability. This study uses the panel data of 93 developed and 79 developing countries from 1990 to 2020. The PQR model is applied to estimate the long-run results by using three quantile groups as lower, middle, and higher health vulnerability index. The PQR estimation found a U-shaped relationship between EFP and health vulnerability in the sample. It shows higher EFP leads higher level of health vulnerability. The empirical results found that changes in green technology move the turning point to the right side of the U-shaped curve in higher HVI groups in developed countries and middle HVI groups in developing countries. These results show green technology moderates the health vulnerability of the whole globe. The dynamic panel quantile grouping shows most of the selected developing countries fall in lower health vulnerability index groups. In contrast, most developed countries fall in the middle health vulnerability index group.

This study recommends that governments adopt green technology through tax credits, subsidies, and other incentives that reduce ecological footprints and improve human health. Furthermore, governments should increase opportunities of green technology and the impact of the ecological footprint on public health. This can help to increase public support for policies that promote the use of green technology. International organizations should cooperate with countries having higher ecological footprints and motivate them to use green technologies.

Author contribution

Muhammad Asif Amjad: introduction section, Initial draft preparation, and original draft
Hafeez ur Rehman: interpretation of findings original draft and supervision
Nabila Asghar: Literature review and methodology, Analysis and explanation results

Conflict of Interests/Disclosures

The authors declared no potential conflicts of interest w.r.t the research, authorship and/or publication of this article.

References

Alam, A., Du, A. M., Rahman, M., Yazdifar, H., & Abbasi, K. (2022). SMEs respond to climate change: Evidence from developing countries. *Technological Forecasting and Social Change, 185*, 122087. doi:https://doi.org/10.1016/j.techfore.2022.122087

Amjad, M. A., & Asghar, N. (2021). Historical aspect of inflation in pre and post Covid-19 pandemic in Pakistan. *Perennial Journal of History, 2*(2), 383-401. doi:https://doi.org/10.52700/pjh.v2i2.80

Amjad, M. A., Asghar, N., & Rehman, H. U. (2021). Can financial development help in raising sustainable economic growth and reduce environmental pollution in Pakistan? Evidence from non linear ARDL model. *Review of Economics and Development Studies, 7*(4), 475-491. doi:https://doi.org/10.47067/reads.v7i4.406

Amjad, M. A., ur Rehman, H., & Batool, I. (2022). Nexus between Tourism and Economic Growth in Pakistan: Using Gregory Hansen and ARDL with Structural Break. *Review of Education, Administration & Law, 5*(3), 387-397. doi:https://doi.org/10.47067/real.v5i3.247

Asghar, N., Amjad, M. A., Rehman, H. u., Munir, M., & Alhajj, R. (2023). Causes of Higher Ecological Footprint in Pakistan: Does Energy Consumption Contribute? Evidence from the Non-Linear ARDL Model. *Sustainability, 15*(4), 3013. doi:https://doi.org/10.3390/su15043013

Assessment, M. E. (2005). *Ecosystems and human well-being* (Vol. 5): Island Press, Washington, DC.

Atwoli, L., Erhabor, G. E., Gbakima, A. A., Haileamlak, A., Ntumba, J.-M. K., Kigera, J., . . . Mulaudzi, F. M. (2022). COP27 Climate Change Conference: urgent action needed for Africa and the world. *The Lancet Oncology, 23*(12), 1486-1488. doi:https://doi.org/10.1016/S1470-2045(22)00645-3

Bandyopadhyay, S., & Green, E. (2018). Urbanization and mortality decline. *Journal of Regional Science, 58*(2), 483-503. doi:https://doi.org/10.1111/jors.12375

Barcelos, M. C., Ramos, C. L., Kuddus, M., Rodriguez-Couto, S., Srivastava, N., Ramteke, P. W., . . . Molina, G. (2020). Enzymatic potential for the valorization of agro-industrial by-products. *Biotechnology Letters, 42*, 1799-1827. doi:https://doi.org/10.1007/s10529-020-02957-3

Bauer, S. E., Im, U., Mezuman, K., & Gao, C. Y. (2019). Desert dust, industrialization, and agricultural fires: Health impacts of outdoor air pollution in Africa. *Journal of Geophysical Research: Atmospheres, 124*(7), 4104-4120. doi:https://doi.org/10.1029/2018JD029336

Bruckner, B., Hubacek, K., Shan, Y., Zhong, H., & Feng, K. (2022). Impacts of poverty alleviation on national and global carbon emissions. *Nature Sustainability, 5*(4), 311-320. doi:https://doi.org/10.1038/s41893-021-00842-z

Burke, B. M. (1997). Our Ecological Footprint: Reducing Human Impact on the Earth. In: JSTOR.

Byaro, M., Nkonoki, J., & Mafwolo, G. (2023). Exploring the nexus between natural resource depletion, renewable energy use, and environmental degradation in sub-Saharan Africa. *Environmental Science and Pollution Research, 30*(8), 19931-19945.

Dai, H., Mamkhezri, J., Arshed, N., Javaid, A., Salem, S., & Khan, Y. A. (2022). Role of energy mix in determining climate change vulnerability in G7 countries. *Sustainability, 14*(4), 2161. doi:https://doi.org/10.3390/su14042161

Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of business and psychology, 29*(1), 1-19. doi:https://doi.org/10.1007/s10869-013-9308-7

Ely, D. M., Driscoll, A. K., & Matthews, T. (2017). *Infant mortality rates in rural and urban areas in the United States, 2014* (Vol. 285): US Department of Health and Human Services, Centers for Disease Control and ….

Farooq, M. U., Shahzad, U., Sarwar, S., & ZaiJun, L. (2019). The impact of carbon emission and forest activities on health outcomes: Empirical evidence from China. *Environmental Science and Pollution Research, 26*(13), 12894-12906. doi:https://doi.org/10.1007/s11356-019-04779-x

Fatima, R., Arshed, N., & Hanif, U. (2021). Do ecological factors dictate the longevity of human life? A case of Asian countries. *Ukrainian Journal of Ecology, 11*(8), 1-12. doi:https://doi.org/10.15421/2021_261

Feng, S., Chong, Y., Yu, H., Ye, X., & Li, G. (2022). Digital financial development and ecological footprint: Evidence from green-biased technology innovation and environmental inclusion. *Journal of Cleaner Production, 380*, 135069. doi:https://doi.org/10.1016/j.jclepro.2022.135069

Greiner, P. T., York, R., & McGee, J. A. (2022). When are fossil fuels displaced? An exploratory inquiry into the role of nuclear electricity production in the displacement of fossil fuels. *Heliyon, 8*(1). doi:https://doi.org/10.1016/j.heliyon.2022.e08795.

Gündüz, M. (2020). Healthcare expenditure and carbon footprint in the USA: evidence from hidden cointegration approach. *The European Journal of Health Economics, 21*(5), 801-811. doi:https://doi.org/10.1007/s10198-020-01174-z

Haans, R. F., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. *Strategic management journal, 37*(7), 1177-1195. doi:https://doi.org/10.1002/smj.2399

Hong, Y., Xu, X., Liao, D., Ji, X., Hong, Z., Chen, Y., . . . Zhang, H. (2021). Air pollution increases human health risks of PM2. 5-bound PAHs and nitro-PAHs in the Yangtze River Delta, China. *Science of the Total Environment, 770*, 145402. doi:https://doi.org/10.1016/j.scitotenv.2021.145402

Huang, Y., Haseeb, M., Usman, M., & Ozturk, I. (2022). Dynamic association between ICT, renewable energy, economic complexity and ecological footprint: is there any difference between E-7 (developing) and G-7 (developed) countries? *Technology in Society, 68*, 101853. doi:https://doi.org/10.1016/j.techsoc.2021.101853

Jiang, C., Chang, H., & Shahzad, I. (2022). Digital economy and health: does green technology matter in BRICS economies? *Frontiers in Public Health, 9*, 827915. doi:https://doi.org/10.3389/fpubh.2021.827915

Kassouri, Y., & Altıntaş, H. (2020). Human well-being versus ecological footprint in MENA countries: a trade-off? *Journal of environmental management, 263*, 110405. doi:https://doi.org/10.1016/j.jenvman.2020.110405

Khan, M. N., Aziz, G., & Khan, M. S. (2022). The impact of sustainable growth and sustainable environment on public health: a study of gcc countries. *Frontiers in Public Health, 10*, 887680. doi:https://doi.org/10.3389/fpubh.2022.887680

Lelieveld, J., Klingmüller, K., Pozzer, A., Burnett, R., Haines, A., & Ramanathan, V. (2019). Effects of fossil fuel and total anthropogenic emission removal on public health and climate. *Proceedings of the National Academy of Sciences, 116*(15), 7192-7197. doi:https://doi.org/10.1073/pnas.1819989116

Lenzen, M., Malik, A., Li, M., Fry, J., Weisz, H., Pichler, P.-P., . . . Pencheon, D. (2020). The environmental footprint of health care: a global assessment. *The Lancet Planetary Health, 4*(7), e271-e279. doi:https://doi.org/10.1016/S2542-5196(20)30121-2

Madsen, J., & Strulik, H. (2023). Testing unified growth theory: Technological progress and the child quantity-quality tradeoff. *Quantitative Economics, 14*(1), 235-275. doi:https://doi.org/10.3982/QE1751

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: a review. *Frontiers in Public Health, 8*, 14. doi:https://doi.org/10.3389/fpubh.2020.00014

Mousa, S. K., & Othman, M. (2020). The impact of green human resource management practices on sustainable performance in healthcare organisations: A conceptual framework. *Journal of Cleaner Production, 243*, 118595. doi:https://doi.org/10.1016/j.jclepro.2019.118595

Naiyer, S., & Abbas, S. S. (2022). Effect of greenhouse gases on human health. In *Greenhouse Gases: Sources, Sinks and Mitigation* (pp. 85-106): Springer.

Nathaniel, S. P. (2021). Ecological footprint and human well-being nexus: accounting for broad-based financial development, globalization, and natural resources in the Next-11 countries. *Future Business Journal, 7*(1), 1-18. doi:https://doi.org/10.1186/s43093-021-00071-y

Network, G. F. (2022). Open data platform. *York Univ. https://data. footprintnetwork. org/index. html#/. Accessed, 16*.

Ouyang, X., Li, Q., & Du, K. (2020). How does environmental regulation promote technological innovations in the industrial sector? Evidence from Chinese provincial panel data. *Energy Policy, 139*, 111310. doi:https://doi.org/10.1016/j.enpol.2020.111310

Panda, T. K., Kumar, A., Jakhar, S., Luthra, S., Garza-Reyes, J. A., Kazancoglu, I., & Nayak, S. S. (2020). Social and environmental sustainability model on consumers' altruism, green purchase intention, green brand loyalty and evangelism. *Journal of Cleaner Production, 243*, 118575. doi:https://doi.org/10.1016/j.jclepro.2019.118575

Pata, U. K., Aydin, M., & Haouas, I. (2021). Are natural resources abundance and human development a solution for environmental pressure? Evidence from top ten countries with the largest ecological footprint. *Resources policy, 70*, 101923. doi:https://doi.org/10.1016/j.resourpol.2020.101923

Qaiser Gillani, D., Gillani, S. A. S., Naeem, M. Z., Spulbar, C., Coker-Farrell, E., Ejaz, A., & Birau, R. (2021). The nexus between sustainable economic development and government health expenditure in Asian countries based on ecological footprint consumption. *Sustainability, 13*(12), 6824. doi:https://doi.org/10.3390/su13126824

Rafique, F., Hussain, S. W., Naushahi, M. M., Shah, S. K. H., & Amjad, M. A. (2023). Analyzing the Pump Diesel and Gasoline Prices on Inflation in Pakistan: A New Evidence from Non-Linear ARDL. *Journal of Social Sciences Review, 3*(2), 372-381. doi:https://doi.org/10.54183/jssr.v3i2.270

Rani, T., Amjad, M. A., Asghar, N., & Rehman, H. U. (2022a). Exploring the moderating effect of globalization, financial development and environmental degradation nexus: a roadmap to sustainable development. *Environment, Development and Sustainability*, 1-19. doi:https://doi.org/10.1007/s10668-022-02676-x

Rani, T., Amjad, M. A., Asghar, N., & Rehman, H. U. (2022b). Revisiting the environmental impact of financial development on economic growth and carbon emissions: evidence from South Asian economies. *Clean Technologies and Environmental Policy, 24*(9), 2957-2965. doi:https://doi.org/10.1007/s10098-022-02360-8

Rees, W. (1992). Appropriated carrying capacity: what urban economics leaves out. *Environment and Urbanization, 4*(2), 123-130.

Safdar, M. B., Naveed, M., Razzaq, M., Wasif, H. M., Tahir, A., & Ejaz, M. (2022). Knowledge of Medical Students about Infant Feeding Practices. *Pakistan Journal of Medical & Health Sciences, 16*(04), 691-691. doi:https://doi.org/10.53350/pjmhs22164691

Sardar, M. S., & Rehman, H. U. (2022). Transportation moderation in agricultural sector sustainability—A robust global perspective. *Environmental Science and Pollution Research, 29*(40), 60385-60400. doi:https://doi.org/10.1007/s11356-022-20097-1

Sarkodie, S. A., Ahmed, M. Y., & Owusu, P. A. (2022). Global adaptation readiness and income mitigate sectoral climate change vulnerabilities. *Humanities and Social Sciences Communications, 9*(1). doi:https://doi.org/10.1057/s41599-022-01130-7

Sastry, N. (2004). Urbanization, development and under-five mortality differentials by place of residence in São Paulo, Brazil, 1970-1991. *Demographic Research, 2*, 355-386. doi:https://doi.org/10.4054/DemRes.2004.S2.14

Saud, S., Chen, S., & Haseeb, A. (2020). The role of financial development and globalization in the environment: accounting ecological footprint indicators for selected one-belt-one-road initiative countries. *Journal of Cleaner Production, 250*, 119518. doi:https://doi.org/10.1016/j.jclepro.2019.119518

Shen, M., Huang, W., Chen, M., Song, B., Zeng, G., & Zhang, Y. (2020). (Micro) plastic crisis: un-ignorable contribution to global greenhouse gas emissions and climate change. *Journal of Cleaner Production, 254*, 120138. doi:https://doi.org/10.1016/j.jclepro.2020.120138

Sial, M. H., Arshed, N., Amjad, M. A., & Khan, Y. A. (2022). Nexus between fossil fuel consumption and infant mortality rate: a non-linear analysis. *Environmental Science and Pollution Research, 29*(38), 58378-58387. doi:https://doi.org/10.1007/s11356-022-19975-5

Tan, X., Liu, Y., Dong, H., Xiao, Y., & Zhao, Z. (2022). The health consequences of greenhouse gas emissions: A potential pathway. *Environmental geochemistry and health, 44*(9), 2955-2974. doi:https://doi.org/10.1007/s10653-021-01142-3

Ullah, A., Ahmed, M., Raza, S. A., & Ali, S. (2021). A threshold approach to sustainable development: nonlinear relationship between renewable energy consumption, natural resource rent, and ecological footprint. *Journal of environmental management, 295*, 113073. doi:https://doi.org/10.1016/j.jenvman.2021.113073

Van de Poel, E., O'donnell, O., & Van Doorslaer, E. (2009). What explains the rural-urban gap in infant mortality: household or community characteristics? *Demography, 46*, 827-850. doi:https://doi.org/10.1353/dem.0.0074

Wang, H., Asif Amjad, M., Arshed, N., Mohamed, A., Ali, S., Haider Jafri, M. A., & Khan, Y. A. (2022). Fossil energy demand and economic development in BRICS countries. *Frontiers in Energy Research, 10*, 1-15. doi:https://doi.org/10.3389/fenrg.2022.842793

Yang, B., & Usman, M. (2021). Do industrialization, economic growth and globalization processes influence the ecological footprint and healthcare expenditures? Fresh insights based on the STIRPAT model for countries with the highest healthcare expenditures. *Sustainable Production and Consumption, 28*, 893-910. doi:https://doi.org/10.1016/j.spc.2021.07.020