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Measuring the Impact of Economic and Environmental Drivers on Human Development: A Comparison between Developed and Less Developed Countries

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ABSTRACT

The world faces a variety of environmental problems that have a significant impact on human development. In light of this, this study examines how environmental degradation affects human development while accounting for factors such as gender, income, and educational disparities, unemployment, GDPPC, institutional quality, and urbanization. The comparison between developed and developing nations is done between 1996 and 2021. Using both ecological footprints and carbon dioxide (CO2) emissions figures to measure the environmental impact on developed and less developed countries provides a more comprehensive approach to checking the environmental damage's impact on human development. Overall, the generalized moment's analysis method approves robust relationships between the study variables. The GMM analysis mentioned that environmental quality affects human development in the selected countries by increasing the ecological footprint and carbon emissions. Likewise, inequality in income, education, and gender has a huge negative impact on human development, as unemployment also has the opposite effect on human development in the case of less developed countries instead of developed countries. On the other hand, it has been proven that GDP, quality of institutions and urbanization confirm human welfare. Therefore, taking into account these main findings, some broad policies are required to contribute to enhancing human welfare.

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1. Introduction

Nature and the environment are responsible for goods and services essential to human development. Human well-being and worth of life depend critically on the quantity and quality of food, water, energy and biodiversity accessible to humans. In addition to contributing to air pollution, carbon emissions have been linked to cardiovascular and respiratory disorders. Lower life expectancy and a lower standard of living can affect HDI due to poor air quality. In addition, the hazards associated with floods, worse environmental condition and high heat level have increased due to climate change brought on by carbon emissions (Chen, Cai, & Ma, 2020). The advancement of nations in reaching high levels of human development is impeded by gender disparities in health and education. Obstacles preventing girls and women from obtaining high-quality education and improved health care might result in decreased life expectancy, lower literacy rates, fewer possibilities for skill development, and lower levels of economic involvement. Due to its limitations on the development of human capital and economic empowerment, gender disparity in health and education has a detrimental effect on HDI (Dijkstra & Hanmer, 2000; Gelard & Abdi, 2016). Additionally of the research uses metrics including GDP (Li & Wei, 2010), income (Qin, Cagas, Ducanes, He, Liu, & Liu, 2009), and industry concentration (Canfei He, Wei, & Pan, 2007) to study inequality in China from an economic perspective. A number of research concentrate on public issues, including gender (Cai He & Xiaoping, 2006), healthcare (Chou & Wang, 2009), and education (Cao, 2008). These studies analyzed a single measurement of socio-economic development and cannot reflect overall patterns of regional disparity. Health is a fundamental population indicator for measuring a country's environmental and economic situation. As a result, human contextual elements like social, medical, and genetic factors affect how the disease spreads (Goloshumova et al., 2019). As a result of population urbanization and environmental changes, there are more patients suffering from chronic dermatomes. Human physical and mental health are significantly impacted by the conditions of both the home and workplace (Sokolovskaya, Grinenko, Miroshkin, Udodov, Egorova, & Diatlova, 2019). An environment where people can live long lives, in excellent health, and with prosperity is what the Human Development Index (HDI) describes. As a result, it's critical to establish the financial means by which members of society can maintain a respectable quality of living. Better health, education, and living standards are combined to create the Human Development Index. Human development is influenced by a number of factors besides per capita wealth, though. According to Taqi, e Ali, Parveen, Babar, and Khan (2021), there is no evidence that raising per capita numbers improves people's standard of living. On the other hand, prospects to promote economic growth increase with human development levels. Scholars have long been concerned about the repercussions of income inequality (Aiyar & Ebeke, 2020). He places a strong emphasis on how income distribution affects capital accumulation and, in turn, economic expansion.

Conversely, Kuznets's study from 1955 mostly addresses the other way around, specifically the impact of growth or development phase on the circulation of income. Three transmission mechanisms exist through which inequality and income distribution might impede capital accumulation and growth. The findings indicate that economic complexity is positively impacted by institutional quality. Thus, nations with better-quality institutions are probably going to have more complicated economies. Factors measured in influential institutional quality include the effectiveness of the legal and regulatory framework, security of property rights, and governance (Olaniyi & Odhiambo, 2023). At the national level, human development index inequality has decreased in different regions of China. In other words, areas that may have had lower HDI values are communicable with areas with higher values. This study provides insights into the developing landscape of human development in China, highlighting both the overall HDI improvement and the attention to development in definite regions. ICT promotion in the GCC region significantly negatively impacts CO2 emissions. This suggests that the adoption and use of ICT technologies are associated with significant reductions in carbon emissions. Therefore, the advancement and increased use of ICT contribute to environmental sustainability by reducing carbon emissions (Islam, Rahaman, ur Rehman, & Khan, 2023). The study found a positive association between high levels of financial inclusion and reduced income inequality through improved human capital. This means that wider access to financial services and a more equitable distribution of income have a positive effect on human capital development. There are various ways in which this study stands out in this particular environment. Our objective was to perform a study that examined the effects of potential economic and ecological features on the Human Development Index (HDI) by segmenting global data according to the GNI per capita. Moreover, we discovered a paucity of research evaluating the ecological footprint's influence as an environmental factor on HDI. In addition, our research incorporates a comparative evaluation of worldwide data under the GNI per capita classification.

2. Literature Review

The relationship between economic density, human development, sophisticated innovation processes, and the use of renewable energy and their combined effect on the ecological footprint of the G-7 countries was outlined by (Balsalobre-Lorente, Nur, Topaloglu, & Evcimen, 2024). Long-term elasticity estimates indicate that the ecological footprint is less affected by economic density, human development, advanced innovation processes, and interaction variables. Thus, a unidirectional causal link between economic density, human growth, and ecological footprint was found in this study. This implies that the ecological footprint is significantly impacted by shifts in human development and economic density. The study also discovered a reciprocal association between the G7 countries' environmental footprint and their use of renewable energy. Addis and Cheng (2023) referenced the connection between the use of renewable energy, harm to the environment, and economic growth in OECD nations. This study estimated the effect of environmental damage on economic growth over the years 1995 to 2021 using a variety of methodologies, including FMOLS and DOLS. Research demonstrates the long-term connection between economic growth and energy use. Consumption of renewable energy does, however, positively affect economic growth, whereas CO_2 has a substantial negative effect. According to Yasin, Ahmad, Amin, Sattar, and Hashmat (2024), CO_2 has a detrimental overall effect on development and sustainable development. In Borowiec and Papież (2024) study, CO_2 emissions convergence in nations at several stages of development was compared, and the effects of globalization and the strictness of environmental regulations on CO_2 emissions convergence were given some thought. Panel data covering the years 1992–2019 from 38 countries were used in the study. According to the study, rising globalization affects emerging nations' CO_2 convergence processes. This study revealed that whereas average CO_2 levels rose quickly worldwide, they did so most quickly in developing nations. On the other hand, in developed countries, it decreases but at a slower speed. Thus, policymakers may need to consider not only the convergence of emissions but also the role of environmental policies and globalization in shaping the overall sustainability and impact of climate policies.

Hashmat, Ghouse, and Ahmad (2023) investigated the GMM analysis and confirmed that environmental quality affects human development in the selected countries by increasing the ecological footprint and carbon emissions. Similarly, inequality in income, education, and gender has negative effects on human development. Thus unemployment also has the opposite effect on human well-being. On the other hand, it has been proven that GDP, quality of institutions and urbanization guarantee people's well-being. Therefore, taking into account these main findings, it is necessary to recommend a series of policy measures related to people's well-being in selected national contexts. Nica, Poliakova, Popescu, Valaskova, Burcea, and Constantin (2023) described the impact of financial development, institutional quality and CO_2 emission on life expectancy for the period of 1990 to 2021. This study examined the association between financial development, institutional quality, CO_2, and life expectancy using quintile regression and ARDL. According to the study, life expectancy, fossil fuel consumption, and CO_2 emissions are negatively correlated. This finding demonstrates the beneficial effects of using renewable energy on health. Consequently, this study implies that a lower life expectancy is linked to higher CO_2 emissions and higher fossil fuel usage. This study shows that both environmental factors and health spending are important for increasing life expectancy. Islam et al. (2023) investigation of the asymmetric effects of information and communication technology (ICT) on carbon dioxide (CO_2) emissions took into account the economies of the Gulf Cooperation Council (GCC). The study's time frame was from 1995 to 2019. An unstable relationship between ICT and CO_2 emissions was revealed by the GLS results. Decreasing CO_2 emissions is linked to both positive and negative shocks of ICT and financial development. Energy consumption, however, increases CO_2 emissions. This shows that there are differences in the effects of financial and ICT development on CO_2 emissions.

In sub-Saharan Africa, Sarkodie and Adams (2020) revealed the connections between human development, political institutional environment, income level, and income disparity. Using nonparametric regression with Driscoll-Kraay standard errors indicates a statistical approach that is suitable for handling non-linear relationships and potential heteroscedasticity in the data. The time structure mentioned is from 1990 to 2017, indicating a longitudinal study capturing changes over a substantial period. The findings of the study summarized several key interactions and suggestions from the perspective of Sub-Saharan Africa. So, the study suggests that higher levels of income disparity are associated with reduced access to electricity. The study reveals that income inequality is related to a reduction in human development. The result of the study suggests that a more equal distribution of income is linked with better overall human development outcomes, as well as health and education. Thus, the study specifies that higher income levels are positively correlated with human development, and a favourable political system environment ensures access to clean and modern electricity. This suggests that political stability, good governance, and effective policy performance play a central role in supporting infrastructure development, including the provision of electricity. Other findings regarded the asymmetric effects in the series of returns and the existence of spillover effects of COVID-19 on returns and volatility on KMI 30 in each wave provide important insights into the dynamics of financial markets during the crisis. The ability of the E-GARCH model to capture these effects provides valuable information for understanding market behaviour and risk management strategies (Ghouse, Bhatti, Aslam, & Ahmad, 2023).

Niranjan (2020) investigated the spatial heterogeneity in human development and whether elements that are spatially dependent on humans have an impact on patterns of human development. Stated differently, the research endeavours to comprehend that the results of human development are influenced by geographic location. The outcome demonstrates that during the previous 20 years, the state's level of human development has significantly improved. However, the state also has to deal with distinct and growing discrepancies, namely when looking at intra-regional disparities. Therefore, the state's level of human development has significantly improved during the past 20 years. This improvement has recognized various factors, such as economic development, development in education and healthcare and social development advantages. Albuquerque (2014) indicated that there is a significant concentration of rheumatologists in state capitals and large communities creating visible differences between different states (UFs) and regions of states. The distribution of these skilled workers seems to be influenced by various factors, including GDP, the Human Development Index adjusted for inequality of the number of graduates from rheumatology residencies and the state capital. So, the study also suggests that income opportunities, as reflected in the GDP, and human development levels as indicated by human development, this thing play a role in determining the distribution of rheumatologists. Thus, professionals are more involved in areas with better economic predictions and higher human development standards.

Li (2012) focused on China's regional inequalities in human development. The main objective is to calculate the Human Development Index (HDI) for each province in China in 1990, 2000, and 2008. The HDI is a composite index that reflects factors such as life expectancy, better education, and per capita income. This step helps track changes in human development across different regions over time. The second objective focuses on the analysis of the spatial distribution of the HDI and its three component indices. This step aims to identify patterns and differences in human development and its components across provinces in China. Mapping and spatial analysis techniques were used to visualize and understand geographic differences. The third objective is to investigate how China's development has influenced human development in the region. Therefore, this analysis aims to reveal the impact of these transitions on differences in human development outcomes across states. Ghouse, Hashmat, and Athar (2021) cited an interaction term between CO_2 emissions and trade openness that shows a positive relationship with economic growth. This suggests that increased foreign trade is associated with economic growth. This relationship is not statistically substantial in the long run, suggesting that the interaction between carbon emissions and foreign direct investment may have a less strong effect on economic growth. This result highlights the need to carefully consider sustainability and environmental impacts when pursuing economic growth, especially in foreign trade and foreign direct investment.

Huang, Gu, Lin, Alharthi, and Usman (2023) pointed out income disparities in the growth of the financial sector in sub-Saharan African (SSA) countries. Key themes focus on the challenges of declining human capital, efforts to strengthen the financial sector, and the role of income inequality in shaping development trajectories. This study aims to investigate how income inequality affects the development of the financial sector in SSA countries. Therefore, this study mainly focused on investigating the relationship between unequal income distribution and the progress or challenges faced by the financial sectors of these countries. In this study, we used a GMM approach to investigate the individual effects of the impact of economic inequality and financial inclusion on human capital and considered potential endogeneity issues. Therefore, this methodology improves the ability of studies to draw meaningful and robust conclusions about the relationships between these variables. Another study compares the proposed methodology with existing co-integration methods and highlights its potential to improve analytical accuracy and reduce the complexity of testing procedures. By simplifying the Ghouse equations and eliminating potential sources of error, this methodology increases the power and reliability of the test, making it a more robust tool for analyzing the relationship between econometrics and statistics (Ghouse, Hashmat, & Athar, 2021). Bekele, Sassi, Jemal, and Ahmed (2024) discussed the empirical literature on human capital development and its role in sustainable economic development. For analysis, this study used panel data from 2000 to 2020. This suggests a long-term approach that takes into account changes over time. The use of appropriate instruments, consideration of quality aspects, and the presence of institutional and political factors increase the depth and relevance of research findings. This approach assumes that the broader global human capital challenge is a key driver of economic sustainability. In sub-Saharan Africa, this study seeks to advance knowledge of the relationship between economic sustainability and the development of human capital. This study attempts to capture the dynamic interactions between these variables using 20 years of panel data and offer insights that can guide plans and policies for regional sustainable development. This result suggests that human development and economic sustainability are inversely related. This means that as human capital development increases, economic sustainability decreases, and vice versa.

3. Methodology

This study encompasses micro panel data for developing and developed countries from 1996 to 2021. The categorization is created on the GNI per capita. To avoid the inappropriate specification we used an empirical framework as the misspecification is a cause of spurious correlation (Ghouse, Rehman, & Bhatti, 2024).

3.1. Empirical framework

The United Nations Development Programme (UNDP) launched the most current and comprehensive attempt to assess the comparative state of socioeconomic development in both industrialized and developing nations in 1990 with its Human Development Annual Report series. The Human Development Index (HDI) was developed using these reports. A scale from 0 to 1 represents each country's HDI rank.

- 0 Represents the bottom human improvement
- 1 represents the very best human improvement

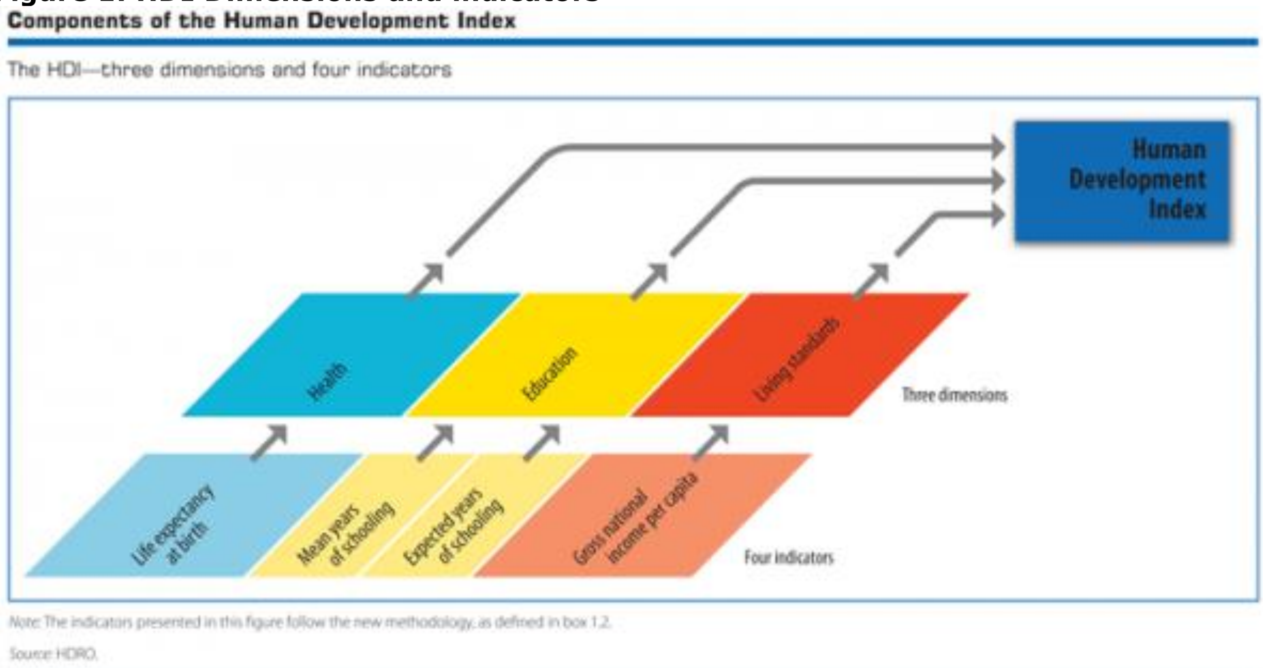
Thus, a nation's HDI is only the arithmetic mean of its three indexes:

$$\text{HDI} = \frac{1}{3}\,(\text{income index} + \text{longevity index} + \text{education index})$$

Or,

$$\text{HDI} = \tfrac{1}{3}\,(\text{income index}) + \tfrac{1}{3}(\text{longevity index}) + \tfrac{1}{3}(\text{education index})$$

Figure 1: HDI Dimensions and indicators



Source: Human Development Reports (HDR)

The basic model is:

$$Y_{it} = \beta_0 + X_{it}\beta_1 + V_{it}$$

In this instance, ɑi denotes the intercept, and Yit is defined as the human development condition at t=1….T, i=1…N. Vit is a time-varying, unobserved component (error term). Unobserved variables are permitted to have any kind of relationship with observed variables in fixed effects models (Allison, 2009). To extract these models, use this base model. The defined model, which may be further explained as follows, looks at how human growth is affected by the ecological footprint, CO2 emissions, unemployment, GDP per capita, urbanization, and institutions.

$$HDI_{it} = \beta_O + \beta_1 EnD_{it} + \beta_2 GINI_{it} + \beta_3 EI_{it} + \beta_4 GI_{it} + \beta_5 UN_{it} + \beta_6 GDPPC_{it} + \beta_7 INST_{it} + \beta_8 URBAN_{it} + \epsilon_{it} \quad (1)$$

HDI outlooks for "Human Development Index", EnD attitudes for "environmental degradation", GINI stands for "income inequality", EI denotes "education inequality", G1 is for "gender inequality", UN for "unemployment", GDPPC (Gross Domestic Product) per capita; INST stands for "institutional quality", and URBAN intended for "Urbanization".

$$HDI_{it} = \beta_O + \beta_1 EF_{it} + \beta_2 CO2_{it} + \beta_3 GINI_{it} + \beta_4 EI_{it} + \beta_5 GI_{it} + \beta_6 UN_{it} + \beta_7 GDPPC_{it} + \beta_8 INST_{it} + \beta_9 URBAN_{it} + \epsilon_{it} \quad (1.1)$$

The Human Development Index (HDI) refers to a state of well-being, affluence, and longevity for individuals. As a result, it's critical to establish the financial means by which members of society can maintain a respectable quality of living. Better health, education, and living standards are combined to create the Human Development Index. Human's well-being is influenced by several factors besides per capita wealth, though. This is because rising per capita numbers do not improve the lot of people (Taqi et al., 2021). On the other hand, chances for promoting economic growth expand with rising human development levels.

Table 1: Explanation of variables and predictable signs

Variables Category	Symbols	Expected Signs	Data Sources
Dependent Variable			
Human Development Index	HDI		WDI/HDI reports
Independent Variable			
Ecological Footprints	EF	-ive	Global Footprint Network
Carbon Dioxide	CO2	-ive	WDI
Unemployment	UN	-ive	WDI/ILO
GDP Per capita	GDPPC	+ive	WDI
Income Inequality	GINI	-ive	WIID/WDI
Education Inequality	EI	-ive	UNDP/HDR
Institutions	INST	+ive	ICRG/WGI
Urbanization	URBAN	+ive	WDI

4. Results and Discussion

Descriptive statistics are used to analyze trends and associations between dependent and independent variables. It provides average trends and distributions of data, allowing you to expand your research scope and better predict future behaviour. The predicted outcomes are a useful tool for further analysis and policy influence. The statistics of various indicators such as HDI, EFcc, CO2mtc, income inequality, education inequality, gender inequality, unemployment, GDPPC, institutional quality, and urbanization are shown in the table. These statistics provide insight into the central tendency, variance, and shape of the distribution for each metric in the dataset. Skewness and kurtosis provide information about the asymmetry and tails of the distribution, and the Jarque-Bera statistic tests the regularity of the data. The probability associated with Jarque-Bera helps you assess whether your data follows a normal distribution.

Table 2 describes the variables of the variable used in this study for the case of developing countries. The average HDI is approximately 0.525, with a median of 0.515, suggesting a slightly positively skewed distribution. The slightly positive Skewness (0.042) indicates a longer right tail, implying that some entities may have higher HDI values.

Table 2: Descriptive Statistics of Key Variables for Less Developed Countries (1996-2021)

	HDI	EFcc	CO2mtc	GINI	EI	GI	UN	GDP	IQ	URBAN
Mean	0.525136	1.567482	0.922983	49.72225	9.069345	0.913078	5.992699	7.82E+10	-0.951142	38.36574
Median	0.515000	1.282952	0.480130	50.97550	6.893114	0.927000	5.039417	1.18E+10	-1.048273	35.97650
Maximum	0.806800	10.63942	7.934283	76.86300	58.02742	1.040000	1066.741	2.69E+12	2.355201	78.21700
Minimum	0.212000	-2.368206	0.000965	28.34100	-3.614103	0.423000	-255.7567	1.56E+08	-4.165656	7.412000
Std. Dev.	0.118027	1.089680	1.326991	9.399882	8.762928	0.069342	50.96926	2.25E+11	1.237670	16.76284
Skewness	0.041932	3.363182	2.870233	-0.082381	3.455370	-1.199928	11.99646	6.866463	0.307403	0.414134
Kurtosis	2.442850	19.72821	11.78752	2.311118	15.15382	6.424658	226.4412	62.62289	2.911971	2.265130
Jarque-Bera	23.33257	23893.15	8097.749	36.87526	14367.31	1285.338	3711868.	275145.9	28.35157	90.11551
Probability	0.000009	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000
Sum	926.3407	2765.038	1628.143	87710.06	15998.32	1610.670	10571.12	1.38E+14	-1677.814	67677.17
Sum Sq. Dev.	24.55922	2093.389	3104.475	155774.8	135378.8	8.476982	4580036.	8.96E+25	2700.611	495390.2
Observations	1764	1764	1764	1764	1764	1764	1764	1764	1764	1764

The kurtosis (2.443) suggests tails and a peak that is moderately different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a low probability (0.000009). The average EFCC is approximately 1.567, with a median of 1.283, suggesting a strongly positively skewed distribution. The strongly positive Skewness (3.363) indicates a significantly longer right tail. The kurtosis (19.728) suggests tails and a peak that is substantially different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a very low probability (0.000000). In the case of carbon emissions (CO2mtc), the average CO2mtc is approximately 0.923, with a median of 0.480, signifying a strongly skewed distribution. The strong positive Skewness (2.870) indicates a significantly longer right tail, implying that some entities may have much higher CO2mtc values. The kurtosis (11.788) suggests tails and a peak that is significantly different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a very low probability (0.000000). The average GINI coefficient is approximately 49.72, with a median of 50.98, suggesting a slightly negatively skewed distribution. The slightly negative Skewness (-0.082) indicates a slightly longer left tail. The kurtosis (2.311) suggests tails and a peak that is moderately different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a very low probability (0.000000). The average education inequality is approximately 9.069, with a median of 6.893, signifying a strongly skewed distribution. The strongly positive Skewness (3.455) indicates a significantly longer right tail, implying that some entities may have exceptionally high education inequality values. The kurtosis (15.154) suggests tails and a peak that is significantly different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a very low probability (0.000000).

The subsequent is gender inequality (GI), the average Gender Inequality coefficient is approximately 0.913, with a median of 0.927, signifying a negatively skewed distribution. The negative Skewness (-1.200) designates a longer left tail. The kurtosis (6.425) suggests tails and a peak that is significantly different from a normal distribution. The Jarque-Bera test indicates a significant deviation from normality with a very low probability (0.000000). The average (mean) value is 5.99, with a median of 5.04. The data has a wide range, as indicated by the maximum value of 1066.74 and a minimum of -255.76. There is considerable variability in the data, with a standard deviation of 50.97. The distribution is highly skewed (11.99) and exhibits significant kurtosis (226.44). The Jarque-Bera test suggests that the data does not follow a normal distribution (0.00). The average GDP is approximately 6.871 and the middle GDP value is 2.25. The highest GDP in the dataset is 2.692 and the lowest GDP is 1.5608. There is a standard deviation of approximately 7.8210, indicating significant variability. The

Skewness is 6.87, suggesting a highly skewed distribution and the kurtosis is 62.62, indicating heavy tails in the distribution. The Jarque-Bera test indicates a departure from normal distribution with a very low p-value (0.000000). The average IQ is approximately 2.91 and the middle IQ value is 1.24. The highest IQ in the dataset is 28.35 and the lowest IQ is -4.17. There is a standard deviation of approximately 2.36, indicating some variability. The Skewness is -0.95, suggesting a slight leftward skew and the kurtosis is -1.05, indicating a distribution with relatively flat tails. The Jarque-Bera test tests the assumption of normality, and the extremely low p-value (0.000001) suggests a departure from normal distribution. The average (mean) value is 38.37, with a median of 35.98. The data has a narrower range compared to the UN group, with a maximum of 78.22 and a minimum of 7.41. The variability in the data is moderate, with a standard deviation of 16.76. The skewness is 0.41, indicating a slight rightward skew. The kurtosis is 2.27, suggesting a distribution with moderate tails. The Jarque-Bera test also indicates a departure from a normal distribution (0.00). In short, the "UN" group has more extreme values, higher variability, and a highly skewed distribution compared to the "URBAN" group. Both groups show a departure from a normal distribution based on the Jarque-Bera test.

Table 3: Panel Generalized Method of Moments (Less Developed Countries)

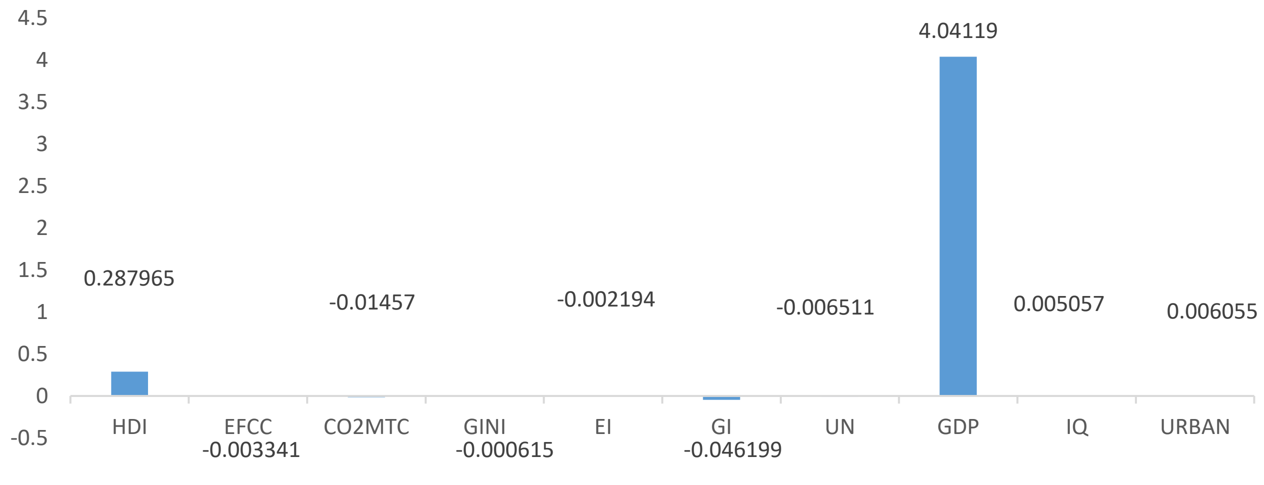
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI	0.287965	0.000299	963.0936	0.000000***
EFCC	-0.003341	0.000055	-60.85610	0.000000***
CO2MTC	-0.014570	0.000828	17.59661	0.000000***
GINI	-0.000615	0.000180	-3.416667	0.001100***
EI	-0.002194	0.000305	-7.193443	0.000000***
GI	-0.046199	0.008645	-5.343979	0.000000***
UN	-0.006511	0.002412	-2.670782	0.009500***
LOG(GDP1)	4.041190	0.083200	48.57199	0.000000***
IQ	0.005057	0.000229	22.08296	0.000000***
URBAN	0.006055	0.000163	-37.14723	0.000000***
J-statistic	42.5549			
Instrument rank	70			

*** , ** , and * designate signifcance levels of 1%, 5%, and 10%, respectively

According to Table 3's estimations in the form of the panel generalised method of moments (GMM) analysis, environmental degradation lowers the human development index (HDI) for developing nations by influencing the ecological footprint and CO2. Ecological footprint, on the other hand, negatively impacts HDI. The value of coefficient shows that a 1% increase in Ecological Footprints (EFcc) is expected to decrease HDI 0.003341%, separately, according to the results. At the 1% level, the coefficient of carbon emission (CO2mtc) is found to be considerable and negative. Thus, a 1% increase in CO2 emissions results in a 0.014570% drop in HDI. These outcomes are in line with the study's key findings by Huimin (2013) a negative correlation between ecological footprints and human development, establishing a causal relationship requires rigorous empirical research and statistical analysis. Moreover, the relationship may vary by region and socio-economic status. Researchers typically employ interdisciplinary approaches that consider environmental, economic, and social factors to better understand the complex interactions between ecological footprints and human development. According to a different study by Chen, Cai, and Ma (2020), air pollution, which can lead to a variety of illnesses like respiratory and cardiovascular disorders, is largely caused by carbon emissions. HDI may be impacted by inadequate quality of air, which can also worse overall quality of life and life expectancy. Furthermore, the effects of climate variation brought on by carbon emissions may worsen health hazards such as infectious diseases, heat-related ailments, food insecurity, and a lower standard of living. Each of the three measures of inequality income (GINI), education inequality, and gender inequality has a 1% adverse impact on HDI. According to the coefficient values, HDI is decreased by 0.000615%, 0.002194%, and 0.046199% for every 1% increase in GINI, EI, and GI values. It is therefore widely recognized that inequality has a negative impact on the progress of society as a whole. These inequalities can manifest in many ways, including economic inequality, differences in education, and differences in access to health care, and social class.

Scholars and researchers have extensively explored the detrimental effects of inequalities on human development, and the consequences are documented in numerous studies (Chetty, Friedman, & Rockoff, 2014; Sen, 2001). Reduced life expectancy, fewer opportunities for skill development, subordinate literacy rates, and lower levels of economic engagement can result from obstacles that girls and women encounter in obtaining high-quality education and improved health prospects (Gelard & Abdi, 2016). Due to its restriction on human capital development and economic empowerment, the gender gap in health and education might hurt the HDI (Dijkstra & Hanmer, 2000). The following indicator, unemployment (UN), is substantial at the 1% level and thus harms HDI. In particular, a 1% increase in the unemployment rate (UN) results in a 0.006511% decrease in the HDI. The findings of Dahliah and Nur's study from 2021 support these findings, which have a negative relationship with HDI. In this study, authors considered that unemployment is frequently negatively related to human development, particularly in developing countries. High levels of unemployment can have profound social, economic, and psychological consequences that hinder overall human development. Given that the coefficient is statistically significant and positive, the results shown in Table 3 on the other hand, suggest that GDPPC increased the HDI in economies with extremely high HDIs. A 1% increase in GDPPC is expected to result in a 4.041190% increase in HDI. Similar results were attested to in a few earlier investigations by Rahmawati and Intan (2020) unemployment often leads to a decrease in income for individuals and families, contributing to poverty and hindering economic well-being, especially in the case of developing countries This can result in limited access to necessities and services. The subsequent findings, which are positive with HDI and statistically significant at 1%, are displayed in Table 2. The HDI is expected to increase by 0.005057% for every 1% increase in institutional quality (IQ). Thi Cam Ha, Doan, Holmes, and Tran (2023) depicted that the relationship between institutional quality and development is complex and varies across countries, the consensus is that well-functioning institutions are crucial for sustained and inclusive development. In this context, improvements in institutional quality can indirectly contribute to positive changes in the components that make up the Human Development Index. Table 3 specifically shows that an increase in urbanization of 1% corresponds to a gain in HDI of 0.006055%. At the 1% significance level, the coefficient's value indicates a positive relationship between urbanization and HDI. Given how reliant on urbanization the very high HDI economies are, this result is expected. In low-income economies, urbanization may have a favorable impact on economic activity, the availability of healthcare services, and employment opportunities (Ahmed, Le, & Shahzad, 2022).

Figure 2: Coefficients of Less Developed Countries Model



This graph indicates that in comparison to gender inequality, ecological footprints, carbon emissions, income inequality, unemployment, and education inequality (EI) have a adverse but minor impact. The GDPPC has a significant and advantageous effect on the HDI for emerging nations. On the other hand, urbanization (URBAN) has a positive effect on human well-being in the circumstance of less developed countries, but institutional quality (IQ) shows a optimistic but slight shift in human well-being.

Table 4 describes the variables of the variable used in this study for the case of developed countries. The provided statistics describe the distribution and characteristics of the Human Development Index (HDI) for a dataset with 2,249 observations.

Table 4: Descriptive Statistics of Key Variables for Developed Countries (1996-2021)

	HDI	EFCC	CO2MTC	GINI	EI	GI	UN	GDP1	IQ	URBAN
Mean	0.775975	4.107481	7.036657	39.76553	8.412274	0.925700	8.461569	6.02E+11	0.663364	68.46829
Median	0.786000	3.523022	5.269466	37.50000	9.112580	0.960000	6.936000	5.96E+10	0.688244	70.14400
Maximum	0.960500	17.72611	47.65131	74.22700	14.13215	1.043000	36.06379	1.99E+13	5.084053	100.0000
Minimum	0.329000	0.001440	0.180620	15.16200	0.559420	0.485000	-30.35544	9.641000	-5.793840	22.89700
Std. Dev.	0.103050	2.495849	6.602867	9.971571	3.658516	0.089503	6.380174	2.03E+12	2.598310	17.45377
Skewness	-0.635527	1.386291	2.308570	0.696281	-0.501982	-1.783937	0.735042	6.523019	-0.181108	-0.451931
Kurtosis	3.527268	6.113228	10.56831	3.013712	2.052247	6.505364	6.595089	50.34994	2.086888	2.672358
Jarque-Bera	177.4450	1628.595	7365.224	181.7397	178.6249	2344.329	1413.667	226044.7	90.42603	86.61605
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1745.169	9237.725	15825.44	89432.68	18919.20	2081.898	19030.07	1.35E+15	1491.906	153985.2
Sum Sq. Dev.	23.87214	14003.38	98007.98	223523.6	30088.89	18.00806	91508.47	9.29E+27	15176.74	684817.2
Observations	2249	2249	2249	2249	2249	2249	2249	2249	2249	2249

The average value is 0.775975, and the HDI for the observations is relatively high, indicating a moderate to high level of human development. The median HDI is 0.786000 slightly lower than the mean, suggesting that the distribution may be affected by some lower HDI values. This indicates that there might be a few countries with lower human development, bringing down the median. The highest HDI value in the dataset is 0.960500, indicating that at least one observation represents a country with a very high level of human development. This suggests diversity in development levels among the observed entities. The lowest HDI value in the dataset is 0.329000, indicating that there is a significant range in human development levels among the observed countries. The presence of a low minimum suggests disparities in development. The standard deviation is 0.103050 relatively moderate, suggesting some variability in human development levels across the observations. The moderate standard deviation indicates that HDI values are not extremely dispersed from the mean. The low p-value (0.000000) from the Jarque-Bera test suggests that the distribution of HDI values significantly deviates from a normal distribution. This reinforces the indication from skewness and kurtosis that the distribution is not symmetrical. The average value of EFCC is approximately 4.11, indicating the central tendency of the dataset.

The median value is 3.52, which is less than the mean. This suggests that the distribution may be positively skewed, with some higher values influencing the mean. The maximum value in the dataset is 17.73, indicating the presence of at least one observation with a very high EFCC value. The minimum value is 0.00144, which indicates that there are entities with very low EFCC values. The standard deviation is approximately 2.50 and indicates the degree of variation or spread of EFCC values around the mean value. A positive skewness of 1.39 indicates that the distribution of EFCC values is skewed to the right, with a tail with higher EFCC values, and a positive kurtosis of 6.11 indicates that the distribution is stronger, with a tail and more peaks than a normal distribution. Indicates that a Jarque-Bera test with a probability of 0.000000 indicates that the distribution deviates significantly from the normal distribution. This confirms the distortion and curvature results and indicates non-normality. The average carbon dioxide emissions per capita (CO2MTC) is approximately 7.04 tons. This represents the central measure of the distribution, and the median is 5.27, so it is below the mean. This suggests that the distribution of carbon dioxide emissions is positively skewed and higher values can influence the average value. The highest CO2MTC value in the dataset is 47.65, indicating that there is at least one observation with very high per capita carbon dioxide emissions. The minimum value for CO2MTC is 0.18, suggesting that some companies have very low carbon dioxide emissions per capita. The standard deviation is approximately 6.60, which indicates the degree of variation or spread of CO2MTC values around the mean value. A Jarque-Bera test with a probability of 0.000000 indicates that the distribution deviates significantly from the normal distribution. This confirms the distortion and curvature results and indicates non-normality. The average GINI coefficient of the observations is approximately 39.77, indicating average to high levels of income inequality. Also, the average GINI coefficient is below average at 37.50. This suggests that the distribution of the GINI coefficient is negatively skewed and higher values may influence the mean.

The maximum GINI coefficient in the dataset is 74.23, indicating the presence of at least one observation with very high levels of income inequality, and the minimum GINI coefficient is 15.16, indicating the existence of units with relatively low-income inequality. The standard deviation is approximately 9.97 and indicates the degree of variation or spread of the GINI coefficient around the mean value. A Jarque-Bera test with a probability of 0.000000 indicates that the distribution deviates significantly from the normal distribution. This confirms the Skewness and kurtosis results and suggests a non-normal distribution. The average GINI coefficient for income inequality is approximately 39.77, indicating a moderate to high level of income inequality on average. The average GINI coefficient was 37.50, suggesting that the distribution may be negatively skewed and higher values may be influencing the mean. The maximum GINI coefficient is 74.23, indicating the presence of at least one observation with a very high level of income inequality. The minimum GINI coefficient is 15.16, suggesting the presence of entities with relatively lower levels of income inequality. The standard deviation is approximately 9.97, indicating the amount of variability or dispersion in GINI coefficients around the mean. The positive Skewness (0.70) indicates that the distribution of GINI values in the GINI coefficient distribution is skewed to the right. The positive kurtosis (3.01) shows that the distribution is more peaked and has heavier tails than a normal distribution. The distribution considerably deviates from a normal distribution, according to the Jarque-Bera test with a probability of 0.000000, which supports the results of Skewness and kurtosis, which point to non-normality.

The average value for the variable education inequality (EI) is approximately 8.41 and the median value is 9.11, which is less than the mean, suggesting that the distribution of EI values may be negatively skewed. The maximum and maximum values for EI are 4.13 and 0.56. The standard deviation is approximately 3.66, indicating variability in EI values around the mean. The negative Skewness (-0.50) suggests that the distribution of EI values is skewed to the left, indicating a tail of lower EI values and the positive kurtosis (2.05) indicates that the distribution has tails that are less heavy than a normal distribution. With a probability of 0.000000, the Jarque-Bera test suggests non-normality by showing a large deviation of the distribution from a normal distribution. The gender inequality (GI) variable has a median value of 0.96 and an average value of around 0.93. GI has a minimum value of 0.49 and a maximum value of 1.04. With a standard deviation of roughly 0.09, the variability of GI values around the mean is quite minimal. The distribution of GI values appears to be skewed to the left, with a tail of lower GI values, according to the negative Skewness (-1.78), and the strong positive kurtosis (6.51) suggests that the distribution is extremely peaked and has very heavy tails. With a probability of 0.000000, the Jarque-Bera test reveals a significant deviation of the distribution from the normal distribution, suggesting non-normality.

The next variable is unemployment and the average UN value is approximately 8.46. The median UN value is 6.936, suggesting that the distribution may be positively skewed, with some higher values influencing the mean. The maximum UN value is 36.06379 and the minimum UN value is -30.35544, indicating the presence of negative values. The standard deviation is approximately 6.38, indicating variability in UN values around the mean. The positive Skewness 0.735 suggests that the distribution of UN values is skewed to the right, indicating a tail of higher UN values and the negative kurtosis -0.181 indicates that the distribution has tails that are less heavy than a normal distribution. The Jarque-Bera test with a probability of 0.000000 indicates that the distribution significantly deviates from a normal distribution, suggesting non-normality. The average GDP value is approximately 6.0211 and the median GDP value is 5.9610. The maximum GDP value is 1.9913 and the minimum GDP value is 9.641000. A significant degree of variability in GDP numbers around the mean is shown by the standard deviation, which is roughly 2.0312. The high positive kurtosis (50.35) shows that the distribution has very heavy tails and is very peaked, while the positive

Skewness (6.523) indicates that the GDP values are substantially skewed to the right, indicating a tail of higher GDP values. With a probability of 0.000000, the Jarque-Bera test suggests non-normality by showing a large deviation of the distribution from a normal distribution. The median institutional quality (IQ) value is 0.688244, whereas the average is about 0.66. 5.084053 is the maximum IQ value, and -5.793840 is the lowest. The IQ levels are variable around the mean, as indicated by the standard deviation, which is roughly 2.60. The distribution of IQ scores appears to be slightly skewed to the left, as indicated by the negative Skewness (-0.181) and the positive kurtosis (2.087), which shows that the distribution has larger tails than a normal distribution. With a probability of 0.000000, the Jarque-Bera test suggests non-normality by showing a large deviation of the distribution from a normal distribution. There are approximately 68.47 URBAN values on average. Seventy-four is the median URBAN value. The variable is probably a percentage or proportion because the maximum URBAN value is 100.000, and the minimum URBAN value is 22.897. The URBAN values exhibit heterogeneity around the mean, as seen by the standard deviation of around 17.45. The distribution of URBAN values appears to be slightly skewed to the left, as indicated by the negative Skewness of -0.452 and the positive kurtosis of 2.672, which means that the distribution has heavier tails than a normal distribution. With a probability of 0.000000, the Jarque-Bera test suggests non-normality by showing a large deviation of the distribution from a normal distribution.

Table 5: Panel Generalized Method of Moments (Developed Countries)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI(-2)	0.449864	0.002119	212.3001	0.000000***
EFCC	-0.002621	0.000054	-48.80819	0.000000***
CO2MTC	-0.000154	0.000008	-18.73479	0.000000***
GINI	-0.000709	0.000080	-8.873592	0.000000***
EI	-0.013087	0.000400	-32.71750	0.000000***
GI	-0.049009	0.006991	-7.010299	0.000000***
UN	-0.000299	0.000010	-28.75000	0.000000***
GDP	4.046760	0.042900	94.33007	0.000000***
IQ	0.007294	0.000149	48.95302	0.000000***
URBAN	0.002387	0.000152	15.70394	0.000000***
J-statistic	81.29908			
Instrument rank	89			

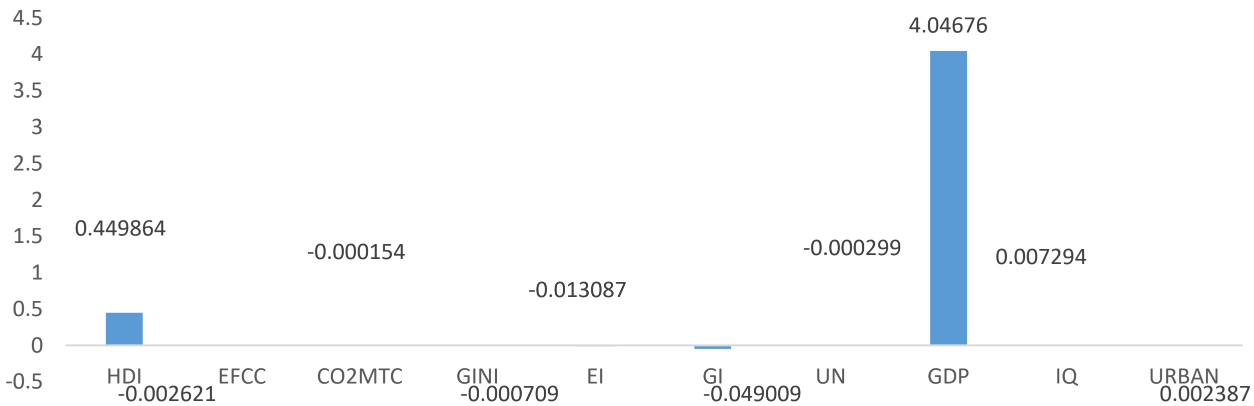
***, ** , and * designate significance levels of 1%, 5%, and 10%, respectively.

The panel generalised method of moments (GMM) analysis results, which are shown in Table 5, show that environmental degradation which is brought on by the ecological footprint (EFCC) and carbon emission level (CO2mtc) deteriorates the human development index (HDI) for emerging nations. Conversely, ecological footprint has a negative effect on HDI. Based on the statistics, it is projected that a 1% increase in Ecological Footprints (EFCC) will result in a 0.002621% fall in HDI. The coefficient is found to be negative and statistically significant at 1%. These outcomes are related to the study of Pata, Aydin, and Haouas (2021) which shows that the negative impact of ecological footprints on the environment, including deforestation, depletion of natural resources, and pollution, can have long-term consequences for human well-being. Environmental degradation can impact air and water quality, biodiversity, and ecosystem services essential to human health and livelihoods. It is found that, at the 1% level, the carbon emission factor (CO2mtc) is considerable and negative. The HDI rises by 0.000154% for every 1% increase in CO2 emissions. These results are in line with research by Chen, Cai, and Ma (2020), which found that among other things, carbon emissions can lead to respiratory and cardiovascular disorders and cause air pollution. HDI may be impacted by Poor air quality can also harm overall life satisfaction and life expectancy. Furthermore, the effects of climate transformation brought on by carbon emissions may worsen health threats such as infectious diseases, heat-related ailments, food insecurity, and a lower standard of living.

The impact of education inequality (EI), income inequality (GINI), and gender inequality (GI) on HDI is negative at 1% apiece. According to the coefficient values, HDI is reduced by 0.000709%, 0.013087%, and 0.049009% for every 1% increase in the values of GINI, EI, and GI. So, inequalities are widely recognized as harming overall societal progress. These inequalities can manifest in various forms, including economic disparities, educational gaps, healthcare access differences, and social stratification. Unequal distribution of income can result in differing living standards among different segments of the population. High levels of income inequality may lead to poverty, limited access to basic needs, and reduced opportunities for personal and professional development (Wilkinson & Pickett, 2006). Osher, Cantor, Berg, Steyer, and Rose (2021) depicted that disparities in educational opportunities obstruct human development. Limited access to quality education, especially among marginalized groups, has led to lower levels of educational attainment, reducing overall human capital development in a society.

At the 1% level, unemployment (UN), the following indicator, similarly has a negative correlation with HDI. More specifically, an increase of 1% in the unemployment rate (UN) results in a 0.000299% decrease in the HDI. The findings of Dahliah and Nur's study from 2021 support these findings, which have a negative relationship with HDI. In this study, authors considered that unemployment is frequently negatively related to human development, particularly in developing countries. High levels of unemployment can have profound social, economic, and psychological consequences that hinder overall human development. On the other hand, Table 5's results demonstrate that GDPPC increased the HDI in economies with extremely high HDIs, as the coefficient is both positive and statistically significant. A 1% increase in GDPPC is expected to result in a percentage gain in HDI. Studies from the past have attested to similar results by Jakovljevic et al. (2020) showing that GDP has a positive relation with human development as GDP measures the economic output of a country. Higher GDP generally implies a larger pool of economic resources that can be allocated to various social services, including healthcare, education, and infrastructure. Adequate economic resources can contribute to improved human development outcomes. The subsequent findings, which are positive with HDI and statistically significant at 1%, are displayed in Table 5. The HDI is expected to increase by 0.007294% for every 1% increase in institutional quality (IQ). Zallé (2019) shows that strong institutional quality is generally associated with positive human development outcomes. On the other hand, the quality of institutions can vary within developed countries, influencing regional disparities in human development but overall it has a positive impact on human development. Particularly, table 5 shows that an increase in urbanization of 1% corresponds to a gain in the HDI of 0.002387%. At the 1% significance level, the coefficient's value indicates a positive relationship between urbanization and HDI. Given how reliant on urbanization the very high HDI economies are, this result is expected. Greater access to healthcare facilities, job possibilities, and economic activity are all possible benefits of urbanization (Ahmad et al., 2020).

Figure 3: Coefficients of Developed Countries Model



This graph indicates that, albeit not as strongly as gender inequality (GI), ecological footprints, carbon emissions, income inequality, unemployment, and inequality in education all have bad effects. When applied to industrialised countries, GDPPC significantly and favourably affects HDI. Conversely, in developed economies, urbanisation (URBAN) has a marginally positive effect on human development, whereas institutional quality (IQ) shows a marginally favourable shift in human development.

5. Conclusion and Policy Implications

The world faces a variety of environmental problems that have a significant impact on human development. In light of this, this research looks at how environmental degradation affects human development while accounting for factors including urbanization, GDPPC, income and education inequality, gender inequality, and unemployment depending on the comparison between developed and developing countries from 1996 to 2021. Using CO2 emissions and ecological footprint figures to measure the environmental impact on developed and less developed countries provides a more comprehensive approach to checking the environmental damage's impact on human development. Overall, the generalized moment's analysis method approves a robust relationship between the variables of this study. The GMM analysis mentioned that environmentally friendly quality affects human development in the selected countries by increasing the ecological footprint and carbon emissions. Likewise, inequality in income, education, and gender have a huge negative impact on human well-being, and unemployment similarly has the opposite impact on human growth when compared to less developed nations instead of developed countries. On the other hand, it has been proven that GDP, quality of institutions and urbanization confirm human welfare. Therefore, taking into account these main findings, some broad policies are required to contribute to enhancing human welfare. Firstly, bearing in mind that the significance of environmental dilapidation in the procedure of ecological footprint and carbon dioxide emissions harms human well-being in both developed and less developed countries, especially for less developed countries, it is important to improve the rules and regulatory measures that have been enacted. It simultaneously restricts the impact of emissions on humans well-being. The basic idea overdue these strategy interferences is that improvements in human development will be facilitated if damage to the environment is reduced through enforcement and compliance with environmental laws. Secondly, differences in all inequalities in terms of gender and education, unemployment and education inequality also devise negative effects on human well-being. Eliminating these inequalities from the economy automatically leads to improved quality of life.

Thirdly, Dasic et al. (2020) depicted that both in developed and developing nations, accounting for GDPPC has been shown to promote human development, according to earlier research. The Human Development Index, which measures quality of life in 2020, is a sophisticated composite indicator. The availability of proper education and medical services raises the quality of life together with income levels. Fourth, human well-being is strongly impacted by higher-quality institutions. Furthermore, there is a stronger correlation between institutions devoid of corruption and higher living standards, such as access to adequate healthcare and education. In the end, it is discovered that urbanization works effectively in both established and developing nations since healthy and well-balanced urbanization is a major contributor to improved human development. In industrialized economies, urbanization may have a favorable effect on employment prospects, health facility accessibility, and economic activity (Rahim, Niaz, Shaheen, Asma, & ALMAS, 2022). On the other hand, urbanization and human development are positively correlated in less developed nations. According to Tripathi (2019), to raise their HDI rankings, developing nations must encourage balanced urbanization while enhancing essential services in urban areas. Previous research has demonstrated that one of the main causes of low quality of life is uncontrolled urbanization but balanced urbanization provides all facilities for health, education and employment in both developed and less developed countries.

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