Exploring Comprehensive Human Development: Beyond Economics and Education

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Abstract

The following report aims to show a comprehensive analysis of the human development index compared to other indices proposed by the United Nations Developing Program. Such indices are mainly focused on modern issues such as environment, gender inequalities, and wealth disproportions. The data take all the countries of the world in a date span from 1990 to 2021 showing the indices at each date. The primary objective of this study is to find the latent relations between the *HDI* and all the others to propose a new set of indices describing a nation's well-being. We are searching for a more complete understanding of the quality of life in a state, regarding not only the economics or schooling factors but focusing on more modern problems. To conduct this analysis, we carefully consider the semantics of each indicator and comprehend to the fullest all the aspects of it. To achieve this, we exploit statistical learning techniques to understand correlations and outliers. We hope to find some form of positive correlation between *HDI* and "green indicators" and likes with inequality factors.

Keywords: Human development indicators, Inequality, Sustainability, Gender inequality, Correlation

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1. Introduction

We live in a society driven by data and economic indicators are prior factors in political decision-making. In this context the Pakistani economist Mahbub ul Haq and Indian economist Amartya Sen proposed in the 90's the Human Development Index in order to measure the level of human development of countries, considering various factors such as life expectancy, education, and per-capita income and it is used by the United Nations to assess the well-being and development of nations. Anyway, it's thirty years since the *HDI* was proposed for the first time but time has changed and the modern world faces new problems that the index can't stand. Plus the Covid pandemic struck worldwide and, for the first time, the *HDI* of the world stopped improving and started decreasing. This was mostly due to the quarantines that made the *GNI* index drop drastically.

In the 00s third-world countries started to rise economically and socially, their *HDI* exploded and some of them could face the Western world. The "Bricks" nations are enough powerful to have a sphere of influence with a rising economy and an improvement in the standard of living. Anyway, these countries still face many problems that the *HDI* don't cover directly like pollution and wealth inequality and gender representation and empowerment. These aspects not covered undermine the quality of life of the people.

However, it is crucial to recognize that the construction and interpretation of complex concepts like gender development or inequality are susceptible to biases and cultural differences that influence happiness. Different cultures perceive and prioritize freedom differently, influenced by their unique historical, religious, and social contexts. Consequently, the metrics and criteria used in political freedom indexes may reflect Western values and modern expectations, potentially undervaluing or neglecting the perspectives and experiences of other cultures. For example, in the category of gender inequality, we find problematic indices such as the adolescent birth rate or the percentage of secondary education among males and females. It's important to acknowledge that cultural biases may distort the accuracy and impartiality of its findings.

1.1. Research Question

Our data have a period of 30 years, from 1990 to 2021. To gain a comprehensive understanding of the indices involved, we aim to consider all the countries in 2021: having one single year will permit us to study the behaviors more precisely without worrying about autocorrelation phenomena. Moreover, the reason for this was that with the advent of the Covid-19 pandemic, many of the previous historical values changed abruptly leading to a shift in gear not previously considered. A study of the correlation is done to ensure that the relations don't change drastically through time.

At first, we will focus more on the categories of each index to estimate the potential of each of them and see which of them has the strongest relation. We have the data linked to *IHDI*, *GII*, and *GDI* plus their components. Anyway, some of them have strong collinearity with the *HDI* or carry the same information, so, as the first layer, we carefully selected the covariates that are our interest and then applied statistical learning techniques to study the relations with *HDI*. In the final, the best covariate will be selected and we will decide if the best option is to keep them separated or synthesize them in one single index. This work hopes to reveal latent relations between the indices hoping that they will be used in the future to better explain the quality of life in the countries of the world leading to a future where economic matters are less central to development policy than social ones.

2. Data Exploration

2.1. First Pre-Processing

Initially, our data set was quite large, consisting of a table with 207 rows and 1008 columns. This large number of columns was because we had 13 different indexes for each year, covering the period from 1990 to 2021. However, in our study, we focused exclusively on the data for the year 2021. We assumed that the relationships between these indexes were not time-dependent (although we would verify this assumption later, during the data pre-processing phase). Therefore, we restructured the data set to organize the years and indexes into separate columns. This restructuring allowed us to simplify future queries of the data. Within this dataset, we now have 43 unique attributes covering a period from 1990 to 2021 and representing 195 countries worldwide. As a final step, we made a selection of the attributes, keeping only those that we felt were relevant to our analysis.

2.2. Indicis List

The obtained data frame has the following attributes, divided into macro-categories based on the topic. The first group indicates the country, the reference year, and the continent of belonging (a column added by us):

- *Country*: considered country.
- *Edition*: reference year.
- *Continent*: Continent of belonging (column added by us).

The second group is the Human Development Index along with the values required for its calculation. Recall that the *HDI* is calculated as the geometric mean of 4 indices, which are considered key areas for human parading, namely income education and health. The mean is then normalized to fall within a range between 0 and 1. Accordingly, our columns are:

- *hdi*: human development index.
- *le*: life expectancy at birth.
- *eys*: expected Years of schooling .
- *mys*: mean years of schooling.
- *gnipc*: gross national income per capita.

The third macro-category is reserved for the Gender Development Index. The *GDI* follows a similar philosophy to the *HDI* because the same key areas are considered for calculation. Our dataset has the columns Human Development Index between men and women is shown for each country, along with the respective calculation indices. These indices are also broken down for men and women for the subsequent calculation of the

HDI for men and women, which is used to calculate the disparity between the two genders. The result is the Gender Development Index, which is a number between 0 and 1. A value of 1 indicates complete gender equality, while a value below 1 indicates gender inequality in the context of human development:

- *hdi_m & hdi_f*: human development index for males and females.
- *le_m & le_f*: life expectancy at birth for males and females.
- *eys_m & eys_f*: expected Years of schooling for males and females.
- *mys_m & mys_f*: mean years of schooling for males and females.
- *gni_pc_m & gni_pc_f*: gross national income per capita (males - females).

The fourth macro-category is related to the Inequality-adjusted Human Development Index, where, unlike the *HDI*, it takes into account inequalities within a country in each of the three dimensions of *HDI*. It evaluates not only health, education, and income but also how these are distributed fairly within society. The *IHDI* is a value between 0 and 1. A value of 1 represents complete equality among the population, while a value less than 1 indicates the presence of inequalities in the context of human development:

- *ihdi*: inequality-adjusted HDI.
- *coef_ineq*: coefficient of human inequality (geometric mean of the three ineq).
- *loss*: loss of HDI due to inequality.
- *ineq_le*: differenze nell'aspettativa di vita.
- *ineq_edu*: differenze nell'istruzione.
- *ineq_inc*: differenze nel reddito.

The fifth macro-category pertains to the Gender Inequality Index. This indicator measures gender inequality in various countries around the world, doing so in the key dimensions of health, education, and economic participation. The *GII* is a value between 0, representing complete gender equality, and 1:

- *gii*: gender inequality index.
- *mmr*: maternal mortality ratio (deaths per 100,000 live births).
- *abr*: adolescent birth ratio (births per 1,000 women ages 15-19).
- *se_m & se_f*: population with at least some secondary education (male and female).
- *pr_m & pr_f*: percentage of share of seats in parliament (male and female).
- *lfpr_m & lfpr_f*: percentage of labour force partecipation rate. Who are employed or looking for work, both males and females (ages 15 and older).

The final macro-category is related to the Planetary Pressure-Adjusted HDI. It is an experimental index that adjusts the *HDI* for planetary pressures in the Anthropocene. The *PHDI* discounts the *HDI* for planetary pressures to reflect a concern for intergenerational inequality, similar to the Inequality-adjusted *HDI* adjustment, which is motivated by a concern for intragenerational inequality. The *PHDI* is computed as the product of the *HDI* and (1 – index of planetary pressures), where (1 – index of planetary pressures) can be seen as an adjustment factor:

- *phdi*: planetary pressure-pdjusted HDI.
- *diff_hdi_phdi*: Difference from HDI value (%).
- *co2_prod*: CO2 emissions per capita (tonnes).
- *mf*: material footprint per capita (tonnes).

2.3. Treatment of Null Values

Unfortunately, the data contains a significant number of null values, ranging from a few units to as many as 40 in the *PHDI* category. In fact we would lost most of the indicators with this method. To avoid losing too many rows through removal, we employed an iterative imputation technique to estimate the missing values using the IterativeImputer provided by the Python library scikit-learn.

2.4. Data Exploration analysis

At this stage of exploratory analysis, our main goal is to discover correlations between indices to gain valuable insights for deeper analysis. It is essential to always keep in mind the diverse socio-cultural context that characterizes our planet. This helps us avoid the risk of being conditioned by the Western perspective, which often dominates the way we see the world. However, it is important to note that we expect to find fairly uniform trends among the variables. Differences in socio-cultural contexts may influence the analysis to a greater extent in so-called "gender indicators" than in general inequalities or pollution issues. This means that despite cultural diversity, we may observe similar trends when examining broader or environmental issues. This approach allows us to look beyond our predefined perspectives and gain a richer understanding of global dynamics. The diversity of our world is an asset, and by exploring correlations among indices, we can discover surprising connections that help us develop a more comprehensive and inclusive view of human well-being.

2.4.1. GDI

Often, when we look at a country's Human Development Index, we are presented with an average view of the nation's well-being. But this view can conceal a much more complex reality. Two countries might seemingly share the same average *HDI* value, but beneath the surface lie deep inequalities in levels of human development among the people who live there. The *HDI* is a useful tool that considers various aspects of human development and tries to highlight some of the inequalities that exist. However, it is important to note that it fails to capture all inequalities of opportunity between men and women. These gender inequalities can emerge clearly in crucial areas such as health care, nutrition, and access to health care. Too often, these inequalities result in higher mortality rates among women than men. To specifically address these gender inequalities, the Gender Development Index was developed. The *GDI* focuses on the differences between men and women in human development, clearly and unambiguously highlighting the substantial differences in quality of life between the sexes. However, despite the crucial importance of considering gender inequality in our analysis, the *GDI* may fail to fully represent it. Correlations between the *GDI* and the various *GDI*-related indices give us an interesting perspective. While the correlations between *HDI* and its gender-related versions show expected values, equal to 1, the correlation between *HDI* and *GDI* is 0.62. This suggests a connection between the two, but not so strong as to indicate a direct relationship. This correlation can be explained by the fact that both indices are based on similar measures. If human development levels rise, so does the average *GDI*, since the *GDI* is calculated by taking into account the separate *HDI*s of the genders. But the link is more complex than it seems at first glance. For a conclusive assessment, it is best to conduct more in-depth analyses.

Figure 1 shows this concept: all indicators, already present in the *HDI* but in a split version

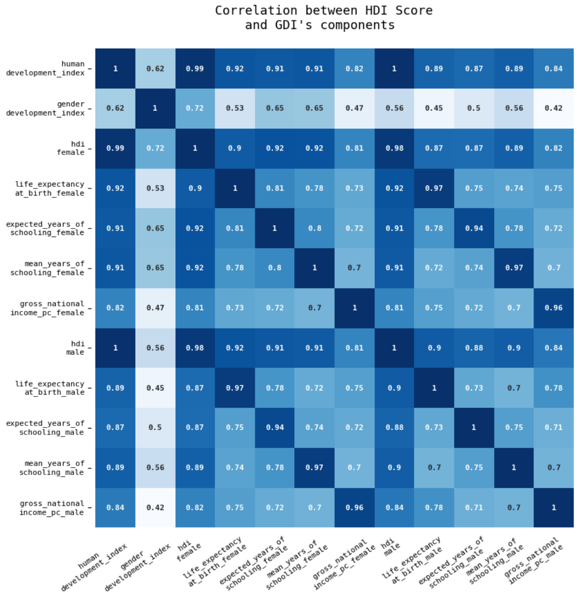

Figure 1

have a great correlation with the *HDI* as the information they carry is the same.

2.4.2. IHDI

The inequality-adjusted Human Development Index is a key step forward in the analysis of inequality in human development. For a long time, the Human Development Index has focused primarily on a country's average performance, largely neglecting internal inequalities. However there is a technical limitation to keep in mind: the *HDI* cannot assess inequality within each of the three dimensions of the index in detail, nor can it adequately adjust them to the socioeconomic context of a specific country. This limitation becomes evident when we consider developing or economically disadvantaged countries. In these contexts, differences in how indicators are interpreted can distort the overall picture. Take, for example, life expectancy, which in such countries may have a bimodal distribution. This means that many deaths occur in the early years of life, followed by a gradual decline in mortality until old age. The second "mode" of life expectancy usually approaches around age 50. This bimodal distribution can lead to a reduction in average life expectancy, offering a distorted view of the situation. However, it should be emphasized that the *IHDI* is a widely recognized and used index. These limitations should not be misunderstood as errors in its design, but rather as technical challenges related to its application in different contexts. What is important is that the *IHDI* represents a significant step forward in the analysis of inequalities in human well-being.

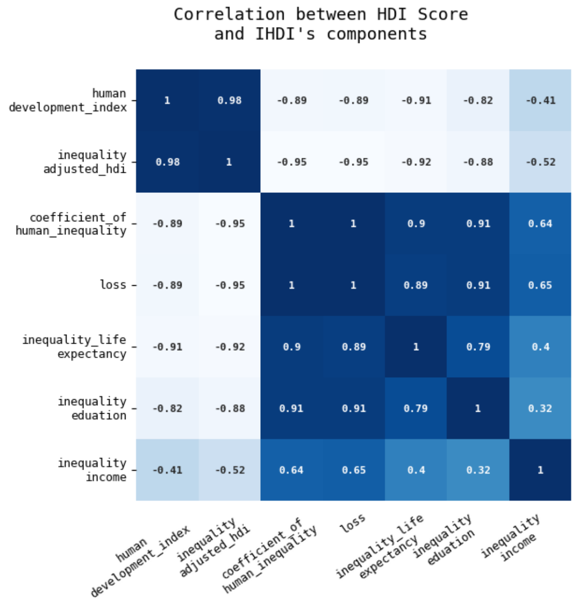

Figure 2

Looking at the correlations between the *HDI* and *IHDI* indices in Figure 2, some interesting points emerge. It can be seen immediately that all variables are strongly correlated with the *HDI* but in a negative sense. This means that the higher the *HDI* of a country, the lower the inequality. In addition, it appears that the inequality indices have broadly similar behaviour in the case of both, although the latter seems to have a slightly stronger correlation. This suggests that the two indices follow similar trends, but the *IHDI* provides additional depth in information, making it an even more valuable tool in the analysis of inequality in human development.

2.4.3. GII

The Gender Inequality Index is an indicator that focuses on entirely different aspects compared to those examined previously. Its uniqueness lies in its emphasis on critical issues related to women's education, economic and political participation, and specific aspects of their health. What makes the *GII* truly distinctive is that none of the other gender disparity measures includes an indicator related to reproductive health, a matter of great relevance to the choices women can make in their lives. If girls and women are systematically denied their freedoms and opportunities, this contradicts the principles of human development. The *GII* has been specifically designed to highlight to what extent the realization of human development potential in a country is hindered by gender inequality. It provides a robust empirical foundation for analyzing policies and supporting efforts to promote gender equality. The issue of adolescent fertility raises important questions about young women's access to contraceptives and sex education, which are essential for making informed decisions about their lives. This index allows us to combine issues where women's roles are assessed about men's with issues where there is no male equivalent, namely reproductive health. In comparison to the Gender Development Index, the latter is often criticized for resembling the Human Development Index too closely, highlighting limitations in effectively detecting gender inequalities. Both share the issue of being largely influenced by a nation's Gross Domestic Product at the expense of other critical indicators. In practice, the *GDI* is sometimes interpreted as the portion of GDP lost due to gender inequalities.

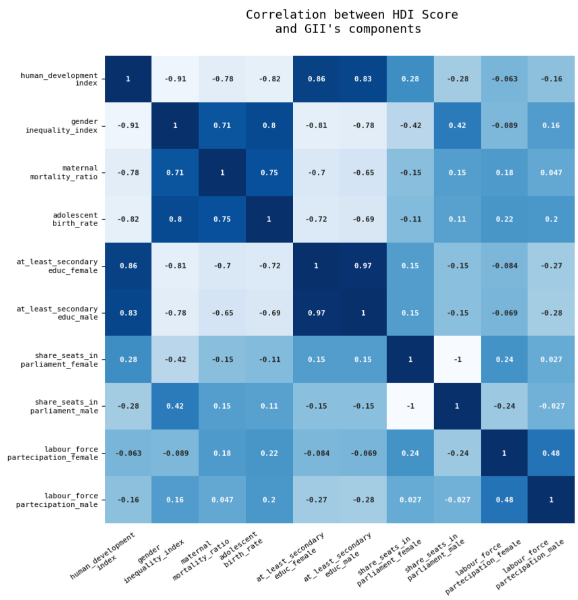

Figure 3

As we can see from Figure 3, there is a strong correlation between *HDI* and *GII*, like many other variables. However, it appears that the columns related to the share of seats in parliament and the labour force have a much less significant influence on the index. Further analysis is definitely needed to clarify these diverse correlations.

2.4.4. PHDI

In recent years, the concept of sustainable development has gained increasing importance due to the growing awareness of our planet's limited resources and the need to preserve our environment. The "Triple Bottom Line" is a key concept that emphasizes the importance of evaluating success not only in financial terms but also in terms of social and environmental impact. This approach promotes corporate sustainability and social responsibility.

Furthermore, we believe it is essential to introduce a "green index" that can effectively measure the quality of life in developing countries, especially in Asia, where rapid economic growth and increased access to education are being experienced. Even China, in 2004, adopted the concept of "Green GDP" in an attempt to balance economic growth with environmental protection. This green index is crucial for a more comprehensive assessment of well-being, considering both economic and environmental aspects, and contributing to sustainable growth in these regions.

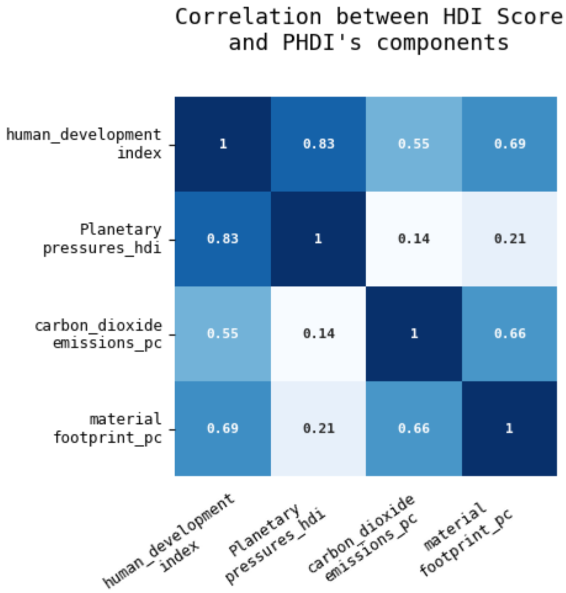

Figure 4

From the correlation matrix in Figure 4, it is noticeable that there is a relationship between the two indices; however, the correlations between *HDI* and CO2 emissions per capita are lower than expected. Several variables need to be taken into account, including the green path that more developed countries have recently chosen to pursue. This may have harmed data representation, particularly with this method. Further in-depth analysis will require plotting a scatterplot to examine the relationship between the two variables, which may not be linear.

3. PCA and Regression

3.1. Principal Component Analysis

Principal component analysis is a statistical technique that aims to reduce the number of columns in a data set. Prior analysis independent of the handling of outliers and missing values is required before it can be carried out. Principal component analysis is used in situations where there are many interrelated variables while losing as little information as possible, as in our case. Therefore, we decided to take advantage of this technique to more easily handle a complex situation with many initial indices. As a first pass, we perform a correlation matrix to check which covariates are moderately correlated with the *HDI*.

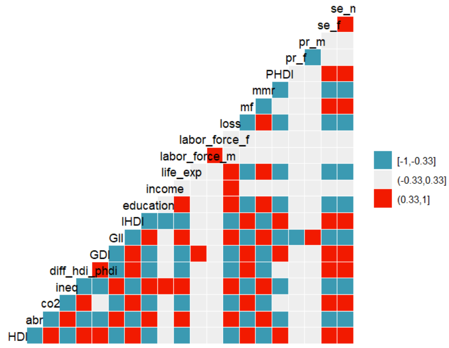

Figure 5

Since the study of principal components is based on the pooled variance among the variables, it makes sense to include in the model only those variables that are found to be correlated with each other, so we only detect the one with a correlation index greater than 0.3 in absolute value. The graph in Figure 1 depicts the various correlations, note that the ones with a value less than 0.3 were put at 0 to highlight their low correlation.

The variables incriminated *inequality income* and both male and female *labor force* and *share parliament*. Hence PCA suggests that pink quotas, both male and female empowerment, and economic inequality do not significantly influence *HDI*. As with all analyses based on variance, single outliers can affect the results; to control for any extreme points, we applied the z-score technique. Z score, also called standard score, is used to scale the features in a data set for machine learning model training. It can also be used to detect outliers. In this one, we will first see how to compute Z-scores and then use it to detect outliers. To perform a principal component analysis, it is advisable to have at least 5-10 statistical units for each column to be included. After removing outliers, we have 178 rows for 17 variables slightly exceeding the threshold of 170 observations. However, the small number of rows limited to the number of countries in the world should be taken into account. Applying PCA with the R software, we obtain the following table showing the explained variance for each principal component. We see that already with only the first component, we get 98% of the explained variance.

The following chart shows the main loads for each component for each index.

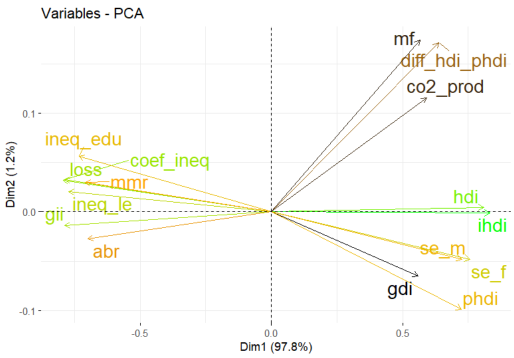

Figure 6

The gradient shows how much the individual variables contribute to the component loadings. We can see that there are strong distinctions between the columns, as *IHDI* and *HDI* go hand in hand; this is not surprising given that *IHDI* is a weighted *HDI*. *GII* also seems to have a strong connection with *HDI*, although opposite. Both explain much of the variance in principal component 1 and little in principal component 2; moreover, the fact that they have opposite directions indicates that as inequality increases there is a decrease in *HDI*, as we expected. *GDI* and *PHDI* seem to be the least *HDI*-like indices because of the larger secondary principal component, however, it must be taken into account that the second component explains only 1.2% of the total variance, so it is more opportune to focus more on the x-axis. According to this interpretation, the indices are more similar and have similar behavior. It is noteworthy that the indices used to construct the *PHDI*, *CO2 production*, and *material footprint*, have a secondary principal component of the opposite sign. We explained this according to the behavior of the *PHDI* itself. This has a range between 0 and the value of the *HDI*; it decreases the more the "planetary pressure" increases. This graph shows the quality of the representation of rows/columns from the results of PCA.

The index that contributes the least to the principal components is the *GDI*, while the *GII* and *IHDI* are among the top contributors. The advantage is that the *GII* has components that convey different information from those provided by the *HDI*, so we consider it among the top candidates for creating a new index that synthesizes both pieces of information. Turning to the individual components, we see that the variables related to the environment are in the same quadrant as the

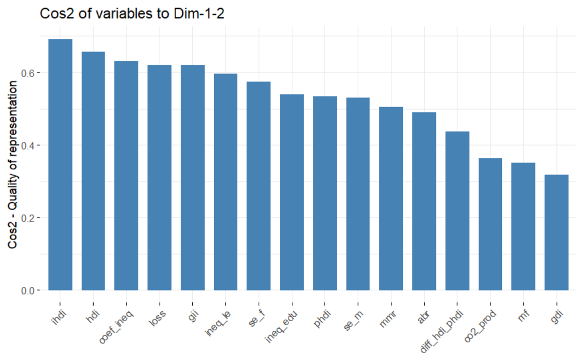

Figure 7

HDI but with a more prominent secondary principal component. They also contribute less to the quality of the representation. From the graph, the most "promising" variables appear to be those related to the *GII* and, therefore, to gender and economic inequality. These variables provide a higher explained variance with a negative sign, so as they increase, the *HDI* will decrease.

3.2. Multiple Linear Regression

The purpose of this regression is not to be able to predict the trend of the data but rather to try to approximate the trend of the *HDI* using the other indices and study THE output thus identifying the most significant covariates. To facilitate the analysis, we divided the indices into main categories. Each of these categories consists of a "main index" and other indices used in its processing. This approach allows us to make a preliminary selection, with a view to a subsequent regression that will include all the chosen covariates. These categories are GDI, IHDI, GII, and PHDI.

3.2.1. GDI

For the category related to the GDI, we discarded all variables except the *GDI* itself because they carried the same information as the *HDI*, only divided by males and females. This led to very high correlations between the covariates, which leads to nonsignificant regressions.

As can be seen from the scatterplot we can see that *HDI* and *GDI* seem to have some relationship, although there seems to be quite a lot of variance. Two outliers are present, which turn out to be Yemen and Afghanistan. The correlation is 0.61. Removing the outliers the regression defined the *GDI* covariate as significant, having a very small t-test p-value, but with an R-squared of 0.41.

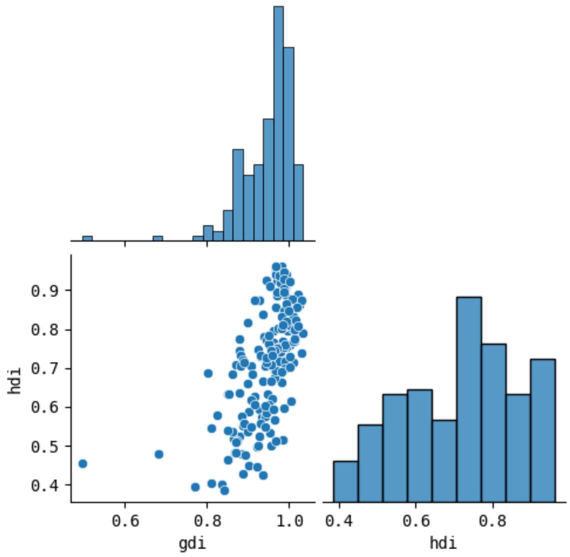

Figure 8

3.2.2. IHDI

For the *IHDI* category, we limited ourselves to performing a scatterplot with a correlation matrix; this is because the data showed quite clear behavior right away. In the figure 9 we can show the high relation between the two variables. All covariates seem to have a relationship with *HDI*, except income inequality. This surprised us since the inequality of education and life expectancy show a higher correlation.

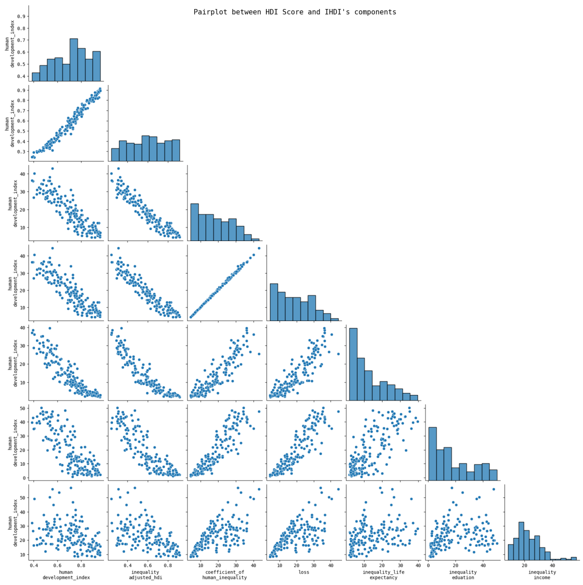

Figure 9

3.2.3. GII

The management of the category was more complex. The variable *mmr* has a logarithmic distribution, while the variable *pr_m* was excluded because it redundantly duplicated *pr_f*. From both the partial correlation matrix and the scatterplot, it was found that the covariates *pr_f* and *lfpr* showed no significant relationship with the human development indicator. To improve the correlation of the maternal mortality ratio with the *HDI*, we applied a linear transformation. Next, we performed a linear regression analysis and selected the most significant covariates using the Vif and step functions in R. The Vif function calculates the variance inflation factor, while the step function implements a stepwise algorithm to minimize the Akaike Information Criterion (AIC). The application of the step function resulted in the removal of the variables mentioned above since they did not contribute significantly to the model.

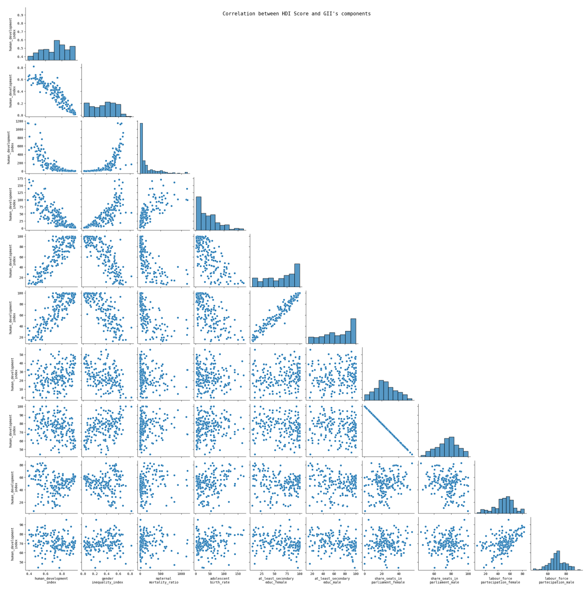

Figure 10

3.2.4. PHDI

We see that all the indices used to construct the *PHDI* have a logarithmic relationship with *HDI*, leading us to another linearization. The regression was applied only to the variables *co2_prod* and *mf* for obvious reasons. Both covariates have a very low t-test p-value but R-squared is equal to 0.43.

3.2.5. Final Regression

The final model was computed using the covariates considered most appropriate, we had to remove the a priori loss as it was complementary to *coef_ineq*.

We noted that the *GDI* has the highest p-value among all the indices, suggesting its limited pre-

```
Call:
lm(formula = DS1$DS.hdi ~ ., data = DS1)

Residuals:
      Min        1Q    Median        3Q       Max
-0.113066 -0.024541  0.001684  0.027213  0.086525

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         0.7171189  0.0931075   7.702 8.30e-13 ***
DS.gdi              0.0583219  0.0889831   0.655 0.513021
DS.coef_ineq        0.0002685  0.0009975   0.269 0.788070
DS.gii             -0.1475215  0.0475949  -3.100 0.002246 **
`DS.log(mmr)`      -0.0197616  0.0052121  -3.791 0.000204 ***
DS.abr              0.0001234  0.0001605   0.769 0.442909
DS.se_f             0.0009835  0.0002751   3.576 0.000447 ***
`DS.log(co2_prod)`  0.0200213  0.0039065   5.125 7.55e-07 ***
`DS.log(mf)`        0.0137102  0.0045771   2.995 0.003123 **
DS.ineq_edu         0.0006829  0.0006053   1.128 0.260737
DS.ineq_le         -0.0041903  0.0008879  -4.720 4.70e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04053 on 182 degrees of freedom
Multiple R-squared:  0.9295,    Adjusted R-squared:  0.9256
F-statistic: 239.8 on 10 and 182 DF,  p-value: < 2.2e-16
```

Figure 11: model summary

dictive ability compared to the others. This could stem from the fact that the *GDI* incorporates information on gender inequality related to income, life expectancy, and education between the sexes. However, these aspects are partially addressed by other indices or are better represented by them. Covariates related to inequality, except that related to life expectancy, are found to be insignificant, including the variable adolescent birth rate which was surprising. Performing a visual analysis of the residuals, we observe that the less significant covariates exhibit clusters in their distribution, rather than widespread dispersion. No obvious signs of heteroskedasticity or distributions that follow a particular pattern, such as a quadratic shape, emerge. The Adjusted R-squared is equal to 0.9145 suggesting that we are on the right path. Next, we performed a selection of covariates using the stepwise approach to the model, removing those deemed less effective. By removing the variables related to coefficient inequality, *GDI*, the adolescent birth rate, and inequality education, we obtained results virtually similar to the previous model. Covariates considered most relevant include *GII*, logarithmic transformations of material footprint, maternal mortality ratio, and co2 production. *Ineq_edu* appears insignificant, probably because it provides information already included in *GII*, although initially suspected, was excluded along with its male counterpart. We also performed an analysis of influential points according to Cook's leverage and distance criteria, but no point was identified as being excluded. In addition, we verified that the residuals follow a normal distribution by a QQ plot, obtaining a positive result.

4. Final Consideration and Index Proposition

In our comprehensive exploration of the Human Development Index, we have encountered a series of noteworthy observations and challenges. To begin, our scrutiny of various indices has illuminated a fundamental truth – not all indices within the dataset bear equal significance. We've discerned a spectrum of correlations among these metrics, ranging from weaker associations to strong interdependencies. This divergence in the degree of correlation between indices has raised questions about the necessity and redundancy of some of the components used in the *HDI* computation.

As we delved deeper into the subject, we uncovered a shared sentiment among fellow researchers and analysts. They, too, had grappled with the same concerns and critiques. This alignment of perspectives led us to explore alternative approaches to measuring human development, and we arrived at a pivotal juncture inspired by the scholarly insights presented in the article titled "The Human Development Index: A Critical Review" by Cambridge's Professors Ambuj D Sagar and Adil Najam.

In light of the challenges posed by *HDI*, we have chosen to introduce and evaluate the Reformed Human Development Index (RHDI) as a viable alternative. *RHDI* introduces a more streamlined methodology, relying solely on two pivotal parameters:

- *Life expectancy at birth*: This fundamental metric provides a crucial glimpse into a nation's overall health and longevity.
- *Gross national income per capita*: This economic indicator is pivotal in assessing the standard of living and financial well-being of a nation's populace.

The crux of the criticism directed at *HDI*, as elucidated in the aforementioned article, revolves around the entanglement of education with economic factors. While *HDI* incorporates education-related indicators such as years of education and expected years of schooling, it remains heavily tethered to economic considerations. This intrinsic linkage can potentially lead to an overestimation of human development, thereby distorting the true landscape.

In our pursuit of a more accurate and holistic representation of human development, we have embarked on a path that dissociates *RHDI* from the confounding influence of education and focuses squarely on life expectancy and income. This strategic shift serves as a step toward a more unadulterated evaluation of human development, one that is less influenced by the intertwined economic aspect.

To illuminate the consequences of this recalibration, we propose a comparative analysis of the traditional *HDI* and the reformed *RHDI*. By assessing these two models side by side, we aim to shed light on the nuances and insights they offer into the multifaceted realm of human development. This exploration serves as a testament to the dynamic nature of the field, where constant evaluation and refinement are essential to capture the ever-evolving essence of human progress and well-being.

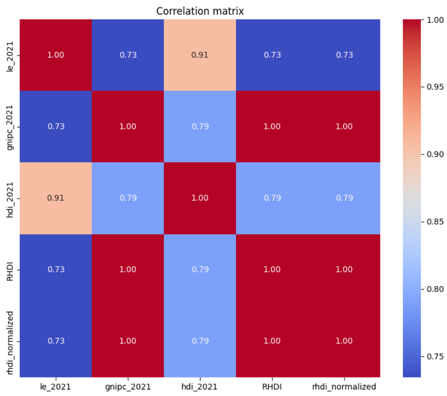

Figure 12

When examining the correlation matrix, we can observe that many of the indices utilized in the computation of both *HDI* and *RHDI* exhibit a notably high degree of correlation with one another. This suggests a strong interrelationship between several of the metrics used to quantify these indices, signifying their interdependence.

However, when we specifically focus our attention on the comparison between *RHDI* and *HDI*, we notice that the degree of correlation between these two particular indices is not as pronounced or strong in comparison to their correlations with the other metrics. This intriguing observation underscores the uniqueness and distinctiveness of *RHDI* as an alternative index, highlighting its potential to provide a different perspective on human development that is not as closely tied to the correlated factors as the traditional *HDI*.

As evident from the graphical representations, *RHDI* illuminates a significant shift in the positions of certain countries, both in a positive and negative direction. This observation underscores the validity of our earlier assumption, namely, that education, while undeniably a fundamental indicator, remains intimately intertwined with economic factors. This entanglement can potentially introduce an element of bias and reduce the overall reliability of the index.

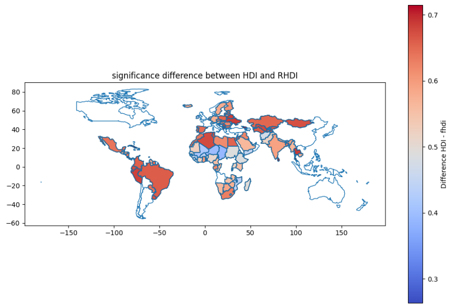

Figure 13

By opting to exclude education as a factor in our *RHDI* calculation, we embark on a path toward a more unadulterated assessment of the countries under consideration. This strategic adjustment enables us to form a more accurate and insightful perspective on these nations, one that is less influenced by the intertwined economic aspect. It represents a meaningful departure from the traditional *HDI* and provides a more nuanced lens through which we can evaluate and understand the diverse dynamics of human development across different regions.

For this reason, we have decided to take into account a crucial study to enhance our analysis. We chose to recalculate the *HDI*, excluding factors related to education and instead incorporating essential indicators such as CO2 emissions and ecological footprint. This approach allows us to consider the environmental health of the country in question, thereby supporting the initial criticism regarding the validity of *RHDI* for developing nations.

The result of this new calculation is an innovative index that integrates four key variables. But it doesn't stop there: to obtain a comprehensive picture, we have combined this new index with the *GII*, thus creating a definitive indicator. This approach enables us to represent the human development situation of a country more accurately. We now consider not only economic and health aspects but also gender disparities, reproductive health, and the environmental situation.

This expanded methodology not only makes our analysis more comprehensive but also makes the landscape of human progress more engaging and current. We are looking beyond traditional boundaries to provide a complete and detailed view of a nation's well-being.

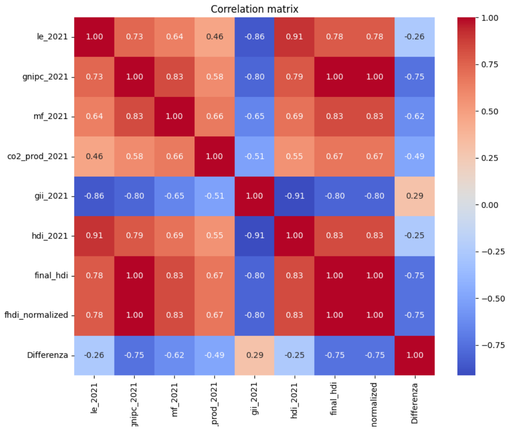

Figure 14

Fig. 10 shows the correlations between the new index and the old one. As we can see, the "final HDI" reflects the behaviour previously supposed. It rises with HDI and its components while decreasing with the rise of the GII.

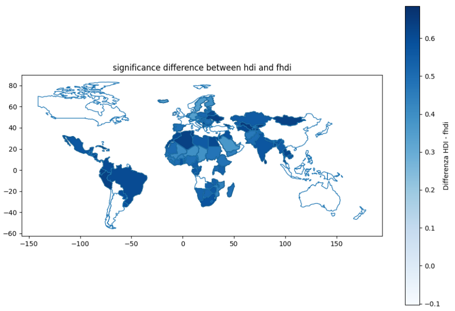

Figure 15

Behold the choropleth map, a representation of the contrast between our groundbreaking index and the traditional Human Development Index (HDI) across the globe. What unfolds before us is a striking revelation, especially in the context of developing nations like Brazil and Mexico. These are countries that bear the weight of their significant global footprint in terms of pollution and struggle with persistent challenges in women's rights. India and various Arab nations echo this concerning trend. As we cast our gaze towards Eastern Europe and Central Asia, the map unveils another dimension of disparities. The disparities in development and well-being across these regions are not just noticeable; they are glaring. It's as if the map itself is whispering tales of inequality and beckoning us to address these critical issues on a global scale.