DOI: 10.52131/pjhss.2024.v12i3.2423

Pakistan Journal of Humanities and Social Sciences

Volume 12, Number 03, 2024, Pages 2429-2438
Journal Homepage:
https://journals.internationalrasd.org/index.php/pjhss

Relating Environmental Changes on Human Health – A Global Clustering Analysis

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ARTICLE INFO

Article History:
Received: May 14, 2024
Revised: August 15, 2024
Accepted: August 15, 2024
Available Online: August 16, 2024

Keywords:
Environmental Changes
Human Health
Green Environment

Funding:
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Green Environment is a dream of the modern world but there are several direct and indirect environmental factors affecting our health. For this purpose, this study is efficiently highlighted key environmental indicators, those are caused to increase or decrease human obesity (globesity) in global prospective. This study plays a key role by collecting several global databases of 183 countries based on the availability data from the World Health Organization, World Development Indicators by World Bank and other sources. This study has used principal axis factoring (PAF), correlations, advanced visualizations and global clustering. The results show that global environment index has indirect relationship with globesity. The results also shown that low human developed countries have low effect of obesity, but very high human developed countries have high level of globesity. This is concluded that if environment index is increasing then human obesity at high risk and sown at high levels of correlation in global prospective at all HDI countries.

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1. Introduction

Environmental challenges, such as pollution, urbanization, and changes in agricultural practices, have contributed to the growing human health crisis, including the rise in obesity. Modern lifestyles, marked by processed food consumption, sedentary behavior, and exposure to environmental toxins, are significantly influencing global obesity rates. According to the World Health Organization (WHO), obesity has nearly tripled since 1975, with over 4 million deaths attributed to obesity-related complications annually. Environmental factors like food deserts, where access to nutritious food is limited, and pollution, which disrupts metabolic functions, further exacerbate this issue. This interaction between environmental degradation and obesity highlights how critical it is to adopt sustainable practices not just for the planet but also for human health. A cleaner, more balanced environment can promote healthier lifestyles and mitigate the risks associated with obesity. Obesity is characterized by an abnormal or excessive fat accumulation, which can compromise an individual's health. Since fat storage occurs throughout the body, it is not possible to quantify it directly. As such, physical weight alone is not enough to make an evaluation. Instead, several different measures are used to assess obesity and overweight status, including skinfold thickness, bioimpedance, waist circumference, body mass index (BMI), waist and hip ratio (Swinburn et al., 2019). Obesity has become a major health issue in recent time periods throughout the world that occurs due to a chronic imbalance between increased energy intake and reduced energy burnout (Kipping, Jago, & Lawlor, 2008). WHO estimates indicate that more than 1.9 billion adults aged 18 years and older are overweight, with over 650 million adults being classified as obese. Obesity cannot be solely attributed to the genetic background because external factors like environment, sedentary lifestyle, economics and culture have highly influenced it (Hruby et al., 2016).

Various environmental factors such as high food consumption, high caloric beverages, and less physical activity are driving factors for an increasing obesity trend. The increase in global urbanization can hugely influence urban lifestyles like less physical activity, increase in junk food consumption, and sedentary behavior leading towards an energy imbalance (De Bont et al., 2021). It has been demonstrated that an increase in air pollution levels, road traffic and traffic noise is directly linked with obesity (Christensen, Hjortebjerg, Raaschou-Nielsen, Ketzel, Sørensen, & Sørensen, 2016; De Bont et al., 2019; Jerrett et al., 2010) while open green spaces, more diversified land areas and walking areas contribute to a protective role against the obesity (Feng, Glass, Curriero, Stewart, & Schwartz, 2010; Frank, Sallis, Conway, Chapman, Saelens, & Bachman, 2006). Air pollution contains various contaminants that may obstruct the normal molecular mechanisms and pathways, causing to an increase in obesity and its related pathogenesis (Frank et al., 2006). Similarly, an increase in noise levels have been associated with stress hormones and disturbed sleeping patterns, increasing the risk of overweight (Münzel et al., 2016; Nielsen, Danielsen, & Sørensen, 2011). Understanding the associations between urban behavior and lifestyle with behavioral patterns affected by body weight is important. For instance, an increase in fast food consumption and decreased physical was seen in children and adults living in air polluted environments (Chen et al., 2019; Wang et al., 2021). Contrarily, residents living in green space exposure results in increased levels of physical activity and an improved sleep quality (Luo et al., 2020; Shin, Parab, An, & Grigsby-Toussaint, 2020).

The role of environmental factors in exerting an effect through the entire development process, that leads to an increase in obesity has been well documented (Nicolaïdis, 2008). Youngsters with no access or limited access to recreational facilities increase the chance of obesity by 68%. Similarly, the "screen-watching habit" contributes to an increase of 5% to 15% in body weight. Global environmental changes will impact future health and the incidence of obesity. For instance, increased ambient temperature can alter glucose metabolism by decreasing the activity of brown adipose tissue. The current global prevalence of glucose intolerance and other metabolic abnormalities that favour the occurrence of obesity is partly caused by rising global temperatures (Blauw et al., 2017). An interesting study showed a direct relationship between obesity and seasonal affective disorders. An increase in carbohydrate rich food intake during November-December months with the shortest number of daylight hours was seen in patients with atypical form of depression (Wurtman & Wurtman, 2015). Since stoutness is affected by hereditarily communicated changes tweaked by climate and way of life hazard factors, comprehend the genomic component that permits these associations. It was shown that increased BMI communicates with ecological openings and utilizes the DNA methylation epigenetic component (Nicolaidis, 2019). Approaches for manageable weight control plans are explicit and explicit. They can bring about simultaneous decreases in natural, and well-being changes universally and, in many locales, especially in top-level salary and center pay nations. However, they can likewise build assets for use in low-pay nations when diets are enhanced. A general well-being system zeroed in on further developing energy equilibrium and dietary changes towards overwhelmingly plant-based eating regimens, following proof that smart dieting is an appropriate method for practical weight control plans. Refreshing public dietary rules to mirror the most recent proof on smart dieting can, without anyone else, be significant for further developing well-being and lessening ecological effects and can supplement more extensive and more express models of manageability (Springmann et al., 2017). The main objective of this research is to find the constructs of the global Environment index with respect to global human obesity.

2. Methodology

This study has used all related global databases to collect data. Several global variables have been collected from 2008 to 2019 including 183 countries based on the availability data. The most famous database is World Development indicators by the World Bank. This research article has used a lot of big datasets. Several variables have been collected from World Bank sources. The second database uses World Health Organization statistics, which consist of many datasets for the public. There are thousands of databases available in unique styles, formats, contexts, and layouts. The current study has used several valid and reliable databases for research because these are highly cited sources and well known and recognized international platforms. All the databases have explained in Table 2 which were available in different layouts, patterns, styles, formats, and structures, but few were available on request.

2.1. Exclusion and Inclusion Criteria of Countries

Initially, a total of 183 countries were selected based on the availability of global secondary databases related to our topic and research theme. Overall, 12 years of data were collected from 2008 to 2019 for this purpose. There were many datasets available but excluded due to missing data, irrelevancy with the topic, not validity, unreliable and sufficient information. The following software like MS. Excel, R language, STATA and SPSS (Statistics) were used for data analyses. In this study, 183 countries data have been used and removed 43 countries with a lot of reasons like missing observations and availability of data. The following countries are not being used in this study: Angola, Belize, Bahamas, Belarus, Antigua & Barbuda, Brunei Darussalam, Guinea, Eritrea, Dem. Rep., Andorra, Cape Verde, Grenada, Congo, Arab Rep., Barbados, Cote d'lvoire, Fiji, Dominica, Papua New Guinea, Cuba, Maldives, Congo, Djibouti, Egypt, Islamic Rep., Guyana, Equatorial Eswatini, Seychelles, Micronesia, Gambia, Saint Vinend and the Grenadines, Guinea Bissau, Iran, Somoa, Kiribati, Syria, timor, Marshall Island, Palau, Russia, Saint Cucia, Sao Tome and Principe, Solomon Island Korea Rep., Tonga and Vanuatu.

Table 1: Variables Descriptions and Sources

Variables	Name of Variables	Factors
En1	Country-wise Forest Area cover (% of land area) (Source: World Development Indicators, by World Bank)	Environment-1
En2	Environmental Quality (CO2 Emissions) (Source: World Development Indicators, by World Bank)	Environment-2
En3	Vulnerability (Source: World Development Indicators, by World Bank)	Environment-3
En4	Share of global food emissions (Source: World Development Indicators, by World Bank)	Environment-4
Ob	Body Mass Index (BMI) country wise during 2008-2019 (Adult population %) (Source: WHO and Ourworldindata.org)	Obesity
levels	Global Human Development countries levels classifications (HDI) (Source: World Development Indicators, by World Bank)	HDI

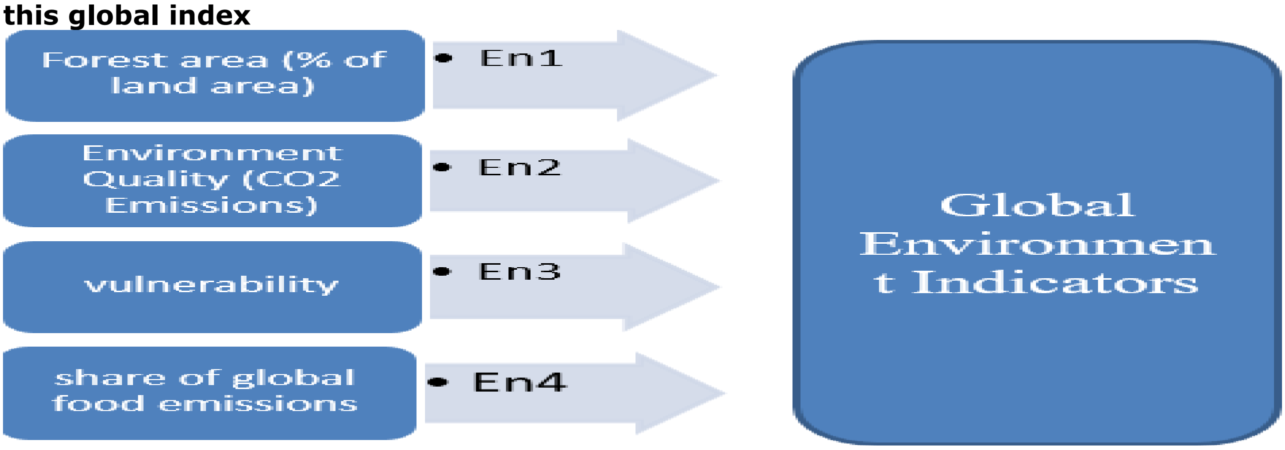
2.2. Principal Axis Factors

A method for obtaining components from the original correlation matrix by using the diagonally squared multiple correlation coefficients as initial estimates of communality. The diagonal's new communalities, which replace the previous communality estimates, are computed using these factor loadings. Iterations are performed until the user is satisfied with the communalities' modifications from one iteration to the next. The following libraries were used in r language during PAF analyzing data (library(ggplot2), library(psych) used for rotated factor analysis, library(visdat), library(polycor), library (GPArotation), library (corrplot) and library(qgraph)). Four worldwide indicators were used to work the global environment index including obesity (as BMI) and HDI Index.

2.3. Formation of Environment Index

Climate change is one of the significant threats ahead. Rapid environmental change has an immediate effect on human health and diet. These elements might contribute to the obesity problem. The environment index was created using the following international datasets (Figure 1).

Figure 1: Global Environment Index: Four international datasets were used for making this global index



3. Results

3.1. Determination of Environment Index

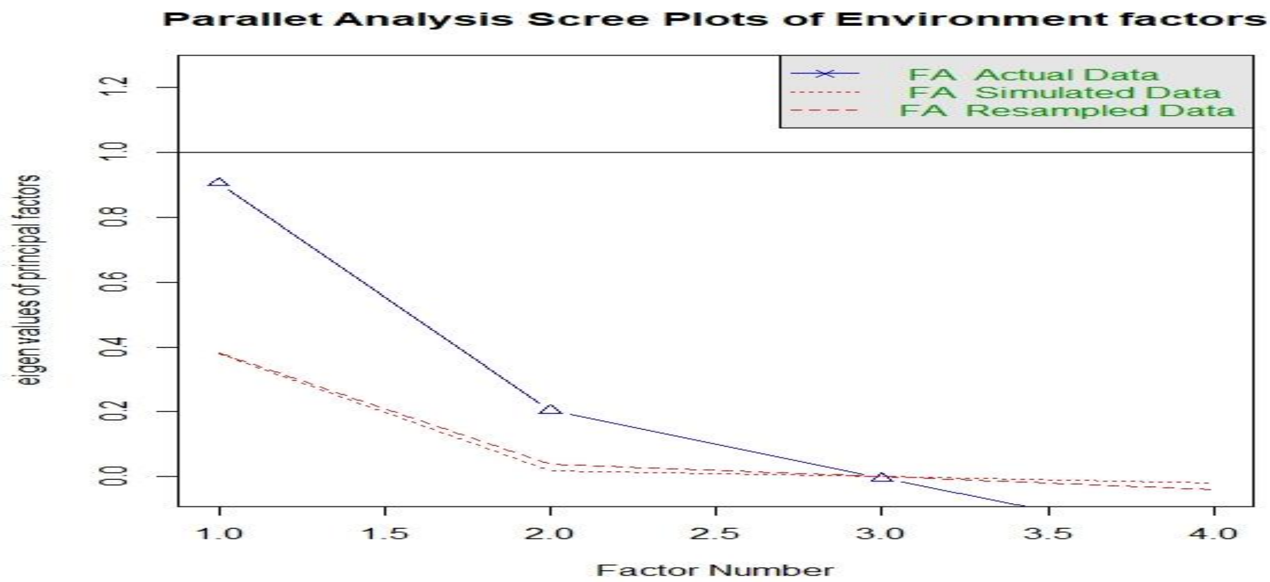
Climate change is one of the most imminent dangers. Our environment is rapidly changing, directly or indirectly affecting human health and diet. These factors may contribute to the aetiology of obesity (caused when extra calories are stored in the body as fat). Figure 1 shows that the following four global datasets were zed to create the environment index includes Forest area (En1), Environmental Quality (En2), vulnerability (En3) and share of global food emissions (En4). The important outcomes of factor analysis are shown (Table 2).

Table 2: Global Environment Index Results

Factors	Constructs	Barrett Test using Chi-Sq.	P value	RMSR
Environment Index	4	7.16887	0.000	0.08

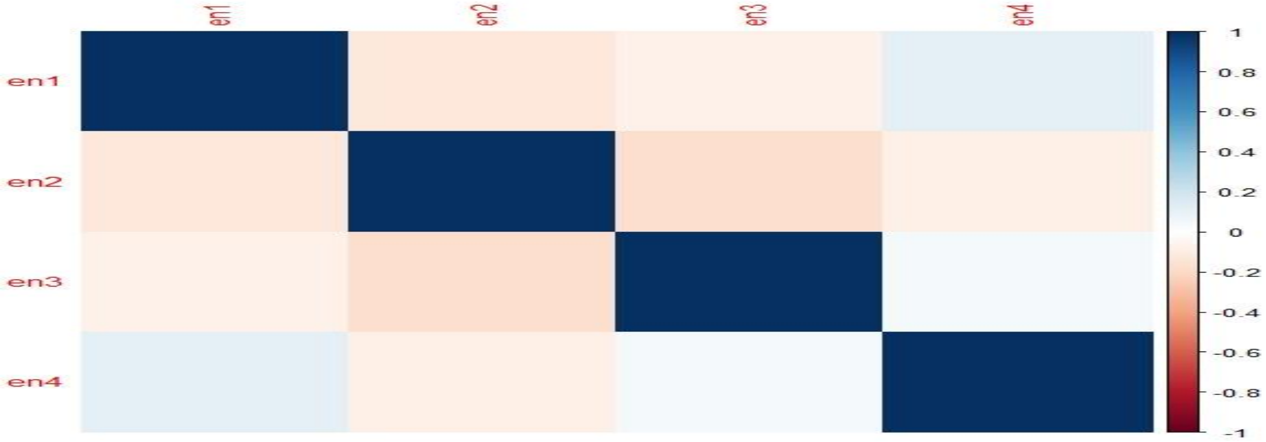
Table 2 shows that the values (chi-square and significant) through Bartlett's test are acceptable, the factor analysis results will likely be very informative. Consequently, the Root mean square of the residuals, and p-values indicate that the index is appropriate and usable (Wania et al., 2006). Using extraction communalities, the variance in each variable accounted for by the components of the factor solution is estimated. Small-valued variables do not connect well with the factor solution and should be eliminated from the following analysis due to low loadings. The scree plot supports utilizing all feasible components at line bends. The scree plot shows the eigenvalue against the number of components (Figure 2).

Figure 2: Scree plot of Environmental factors



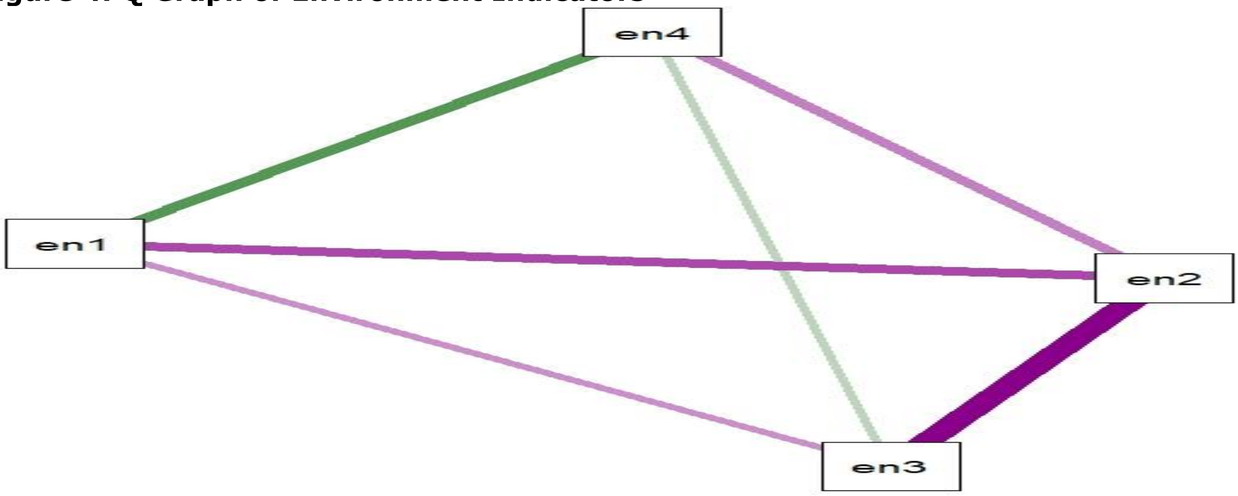
All environment-based indicators may be used to generate the global environment index. Four primary global environment indicators were extracted using the principal component analysis method. The component loading criterion of 0.3 was applied, so no component was eliminated due to low loading. The index is constructed using four global social indicators and exploratory factor analysis with primary axis factoring. The internal correlations of global environment indicators were examined against the global tendencies, significant impacts, and oscillations (Figure 3). Indicators of the global environment have direct and indirect within-correlations, but few indicators show week-to-week correlations. The colour with the highest correlations was the darkest blue, followed by the colour with the lowest correlations, which was the lightest blue. The colour with negative correlations was the darkest red, followed by the colour with weak but negative correlations, the colour with weak but negative correlations, and the colour with no correlation with white.

Figure 3: Correlation Plot of Global Environment Indicators



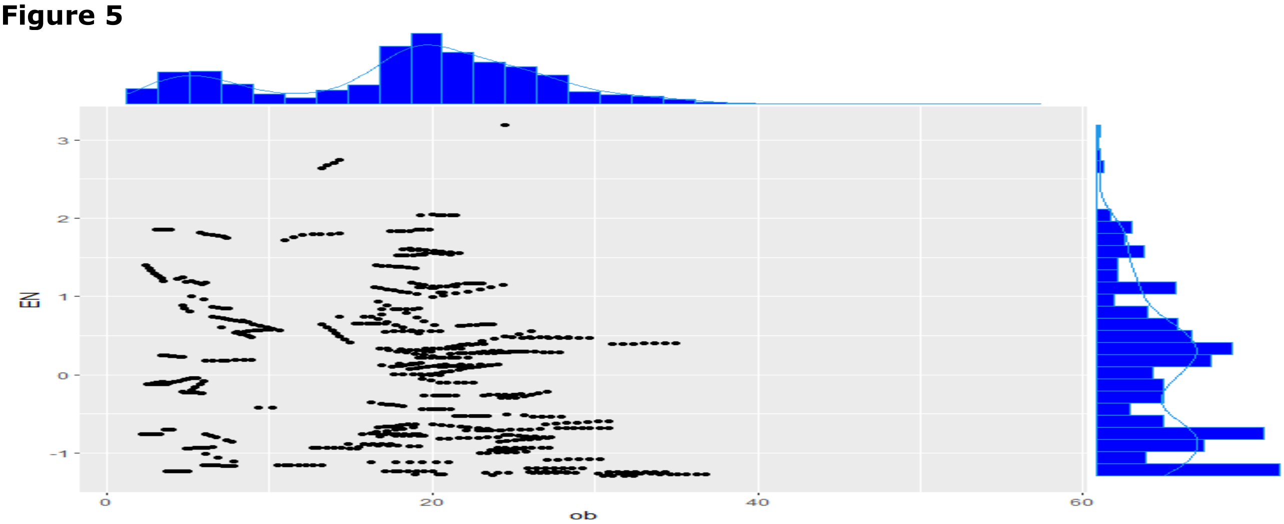
The connectedness in terms of the inner links between all environmental variables were shown in (Figure 4). The closest indicators have significant correlations, whereas the farthest ones have weak correlations. For indicators relating to the global environment, green reflects direct relationships while pink represents indirect relationships.

Figure 4: Q Graph of Environment Indicators



The multi-objective and multi-dimensional visualizations illustrate the relationship between global obesity and global environment according to global HDI levels (Figures 4, 5 and 6). The following picture illustrates density plots with internal data variation for countries with low, moderate, high, and very high human development levels. The subsequent diagram also included scatter plots and trends for all four variables of HDI levels. Overall, the correlation between global environment index and globesity is favorable and direct.

Figure 5



Worldwide globesity is decreasing at low HDI level, high HDI level, and very high HDI levels due to rising national environmental standards. Figure 6 shows that there is a negative relationship between global environment index and globesity, which has shown an indirect relationship in countries with low, medium, high, and very high HDI levels but a highly significant correlation in countries with very high HDI levels. The correlation between worldwide human obesity and the global environment index in nations with low human development is minor, negative, and indirect, with a value of -0.183, indicating that globesity is declining in countries with low HDI level. The correlation between worldwide human obesity and the global environment index at a high degree of HDI is significant, negative, and indirect, with a value of -0.199. The correlation between globesity and the global environment index at a medium level of HDI level is significant, negative, and indirect, with a value of -0.257. The correlation between globesity and global environment at very high human development level is vital, negative, and indirect, with a value of -0.506, indicating that global human obesity is declining in countries with a more environmentally conscious culture. All the environmental factors (Forest area (En1), Environmental Quality (En2), vulnerability (En3) and share of global food emissions (En4)) are correlated with globesity.

Figure 6: Density Plots, Correlations, Trends and Clustering, of Global Environment and globesity by HDI

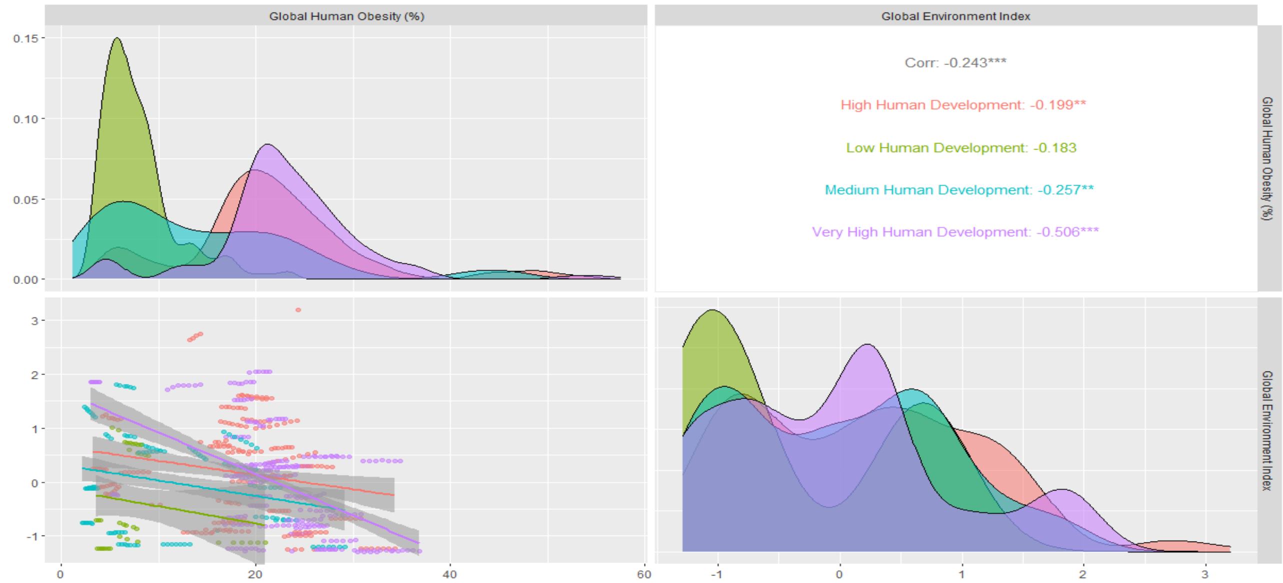


Figure 7: Global Clusters of Global globesity with Global environment Index through HDI

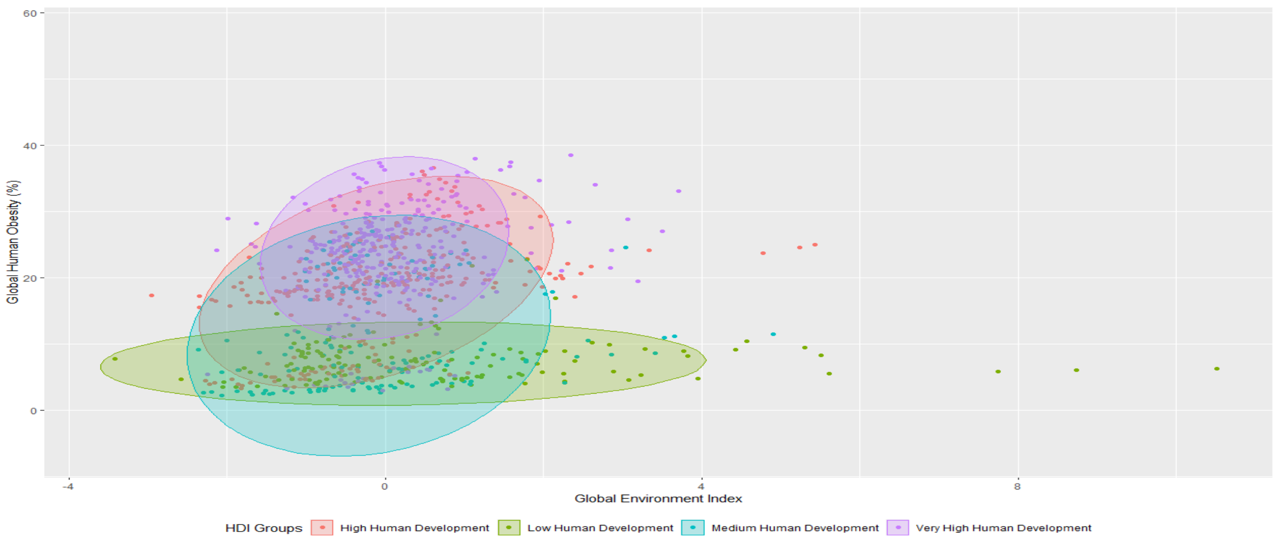


Figure 7 illustrates global clusters of the globesity and global environment index for four tiers of countries in relation to HDI levels. There have been four quadratics employed. In the first phase, countries with low human development have low environment and moderate obesity; in the second phase, countries with medium human development have moderate obesity and a moderate global environment. Third, a high worldwide environment with a high global obesity rate in countries with a high and very high global environment and a very high global obesity rate. This visualization demonstrates that countries with a very high level of HDI level have the highest level of environmental conditions and the highest level of human obesity, while countries with a low level of human development have a very low level of environmental conditions and a low level of globesity. It means that very high HDI countries have more obesity cases instead of low human developed countries.

4. Discussion

Globesity is one of the main public health concerns globally in all sectors. According to the IMF report, the latest income growth projections between 2019 to 2024 would result in an increase of obesity at an average annual rate of 2.47% across studied regions. It has become a major concern due to various other diseases being associated with it, which lead to a high mortality rate. It is important to identify risk factors associated with unhealthy nutrition in countries undergoing socioeconomic changes that lead to an increase in obesity. The patterns of obesity and overweight are less common across the globe. In European nations, 11–20% of the population is fat, and 32–45% of the population is overweight. The high rates have been observed of overweight and obesity in Eastern European nations, including Slovenia, Hungary, the Czech Republic, and Lithuania. Variations in living standards and sedentary lifestyles might be the probable factors for these changes of overweight and obesity (Blundell et al., 2017; Jeffery & French, 1996). Currently, this epidemic is most prevalent in urban in the prevalence areas due to an increase in industrialization, yet an increase (Prentice, 2006). A review has highlighted the significant association between objectively measured built environment including residential density, street connectivity, and greenery access to destinations (Papas, Alberg, Ewing, Helzlsouer, Gary, & Klassen, 2007). This indicates that features are more predominant in very high and high HDI countries and less common in low HDI countries, hence justifying our results shown above. According to studies, being overweight was linked to the belief that commercial establishments like shops, stores, and markets were close to households. This can be attributed to a more dominant characteristic of highly humanely developed countries that results in people living in these areas having a more sedentary lifestyle (Alexander, Bergman, Hagströmer, & Sjöström, 2006; Sallis et al., 2009). Alternatively, when people thought of nearby rather than far-off destinations, they were more likely to participate in physical activity, especially walking for transportation. According to the Developmental Origins of Health and Illness (DOHaD) theory, excessive weight gain is also observed in newborns, and the environment has long been thought to be a critical factor in the development of obesity and cardio-metabolic illness in humans (Andriessen, Schrauwen, & Hoeks, 2021). For instance, low birth weight from undernutrition during pregnancy is associated with a higher risk of obesity, CVD, and T2D in later life (Barker, 2007).

The results from our study have demonstrated countries with a high and very high human development (HDI) levels have the highest levels of environmental conditions and the highest level of human obesity, which support the hypothesis that industrialization leads to more polluted environment that contributes indirectly to changing the metabolic process and increasing the overweight patterns. Growing concerns are being expressed about children's exposure to pollution and rising obesity rates in developing nations, particularly China. According to epidemiological data, air pollution raises the likelihood of childhood obesity (An, Ji, Yan, & Guan, 2018; Dong et al., 2014; Michalaki et al., 2018; Wei et al., 2016). Another macro-environmental moderator is the shifting of ' 'country's economy from an agricultural driven state to a more industrialized one that results in an associated move into more processed and junk diets connected to a higher prevalence of obesity in its population (Canella et al., 2014). The rationale is that countries with low human development index have traditionally lower food consumption due to their low incomes and higher energy expenditures in daily routines, hence a lower BMI and obesity rate. However, with increasing incomes, increasing streamlining process, mechanization and automation of agriculture system, constant reduction in agricultural areas and shifting towards a more urban lifestyle have been witnessing a reduction in energy expenditure and increased number of obese people in their societies (Prentice, 2006). An examination of more than 1100 individuals showed a link between women's higher BMI and longer workweeks

(Kim et al., 2016). The odds ratios (with a 95% confidence range ranging from 1.05 to 5.57) for obesity and extended work hours was 2.42. According to the study, long workdays may shorten sleep duration, increasing the risk of obesity. One of study was conducted in Hong Kong which included over 4700 participants and roughly equal numbers of male and female subjects (approximately 49% male and 51% female), revealed a significant correlation between longer work hours, shorter sleep duration, and higher body mass index (Ko et al., 2007).

5. Conclusion

In conclusion, global environmental factors are closely liked by global human obesity (globesity). This study has concluded that high and very high human developed countries have more obesity concerns. On the other hand, low-human developed countries have less human obesity concerns. It is very important to gain a thorough understanding of the relationship between obesity prevalence and the environment, given the severe health and economic costs of obesity, the obvious significance of economic development, and the rapidly changing environmental factors that are present at both the micro and macro level. Our study provides previously unexplored insights into the pattern and strength of the environment-obesity relationship as well as the roles of macro-environmental moderators by creating a global environment index from four different datasets in terms of different human development index countries. When taken as a whole, we firmly feel that our research adds fresh and significant insights to the current knowledge of the connection between environmental factors and the prevalence of obesity.

5.1. Limitations

This study needs to be addressed by using other environmental factors and add more years as well as use advanced modelling to generalized in further research. This study has concluded that globesity and global environmental factors are well connected with several reasons. Doors are open for further study in this area.

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