



OBESITY AND ITS IMPACT ON METABOLIC HEALTH: PATTERNS, DETERMINANTS, AND ASSOCIATED COMORBIDITIES

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Abstract

Obesity is an emerging population health issue that is linked to poor metabolic health consequences and heightened risk of obesity-related comorbidities. This paper has analyzed patterns of obesity, determinants and metabolic health risk indicators using the Estimation of Obesity Levels Based On Eating Habits and Physical Condition dataset on the UCI Machine learning Repository. A quantitative cross-sectional research design was applied on the basis of secondary data of 2,111 participants at Mexico, Peru and Colombia. The outcome variable was the level of obesity which was categorised into seven groups whereas the independent variables were classified into demographic, anthropometric, dietary, behavioural, lifestyle and family-history variables. The distribution of obesity and the determinants were evaluated using descriptive statistics, comparative analysis, chi-square tests and binary logistic regression. The findings indicated that 46.57% of the respondents were obese. The progress of BMI and body weight in obesity categories confirmed the existence of a strong anthropometry pattern. Family history with overweight was identified as the strongest predictor of obesity and frequent consumption of high-caloric foods, food consumption between meals, passive transportation, alcohol use, and low calorie-consumption monitoring were also found to be important indicators of obesity-related risk factors. Protective associations were observed between physical activity and monitoring calories. Metabolic health and comorbidity implications were determined by the severity of obesity and lifestyle related risk factors. The results indicate that there is a need to have integrated obesity prevention strategies that emphasize on the regulation of the dietary intake, active living, awareness on the prevention of obesity at the family level, and behavioural self-monitoring.

Keywords: Obesity, metabolic health, BMI, lifestyle determinants, comorbidity risk.

1. Introduction

Obesity has emerged among the biggest community health issues across the globe. No longer is it thought to be a condition merely of excessive body weight, but rather, it is a complex metabolic disorder that is influenced by biological, behavioural, dietary, environmental and lifestyle-related factors. The growing prevalence in obesity has been attributed to the alterations in food consumption patterns, lack of physical activity, sedentary behaviour, urbanization, and increased consumption of

foods of high energy content. According to Bluher (2019), obesity is a multifactorial disease, which includes genetic predisposition, dysfunction of adipose tissue, neuroendocrine, and environmental factors. In the same manner, Heymsfield and Wadden (2017) clarify that obesity is a relapsing and chronic disease, which has significant physiological and metabolic outcomes.

Obesity has become a global burden which has been gaining momentum over the past decades. According to Chooi, Ding, and Magkos (2019), obesity has spread across nations, demographics, and socioeconomic groups, and is thus a significant population health issue. Hruby and Hu (2015) also stressed the fact that obesity is a significant issue in terms of its contribution to health-related, economic, and social burdens. The results of the GBD 2015 Obesity Collaborators (2017) further demonstrated that overweight and obesity are linked with a higher morbidity and mortality in 195 countries. Such results show that obesity is not an individual lifestyle problem, but a worldwide health problem which needs to be systematically researched on its patterns, determinants, and health related outcomes.

The body mass index has been extensively utilized to categorize the status of weight and approximate the weight burden of obesity at population level. Though the BMI does not directly translate to the fat distribution and metabolic dysfunction, it is still a significant parameter used to determine the pattern of obesity. According to the NCD Risk Factor Collaboration (2016) there is a long-term rise of adult BMI in most countries, which is indicative of major changes in diet, physical activity, and lifestyle structures. Yet, the problem of obesity cannot be explained only by means of BMI since people with the same BMI level may vary in terms of metabolic risk due to their family history, eating habits, physical activity, sedentary behaviour, and other aspects of their lifestyle.

Strong relationships are found between obesity and problems in metabolic health and obesity-related comorbidities. Overweight adiposity is a risk factor in insulin resistance, persistent inflammation, dyslipidaemia, hypertension, and cardiovascular risks. According to Fruh (2017), one of the key risk factors that increase the likelihood of a number of complications is obesity. The close association between obesity and cardiovascular disease was also mentioned by Kachur et al. (2017), who also emphasized the connection between obesity and hypertension, as well as the linkage between obesity and coronary artery disease and heart failure. Thus, obesity needs to be studied as not only an anthropometric disease, but also as an indication of a greater risk of metabolic disease.

Metabolic syndrome can be considered as one of the most significant health issues of obesity. It comprises a group of risk factors which include abdominal obesity, abnormal glucose regulation, dyslipidaemia and high blood pressure. According to Bovolini et al. (2021), metabolic syndrome is caused by insulin resistance, malfunction of adipose tissues, inflammation, and lifestyle-related exposures. Even if some data sets do not include direct clinical measures (glucose, cholesterol, triglycerides, blood pressure) the degree of obesity, the body mass index, the diet, physical inactivity, sedentary lifestyle, smoking, alcohol consumption, and passive transport can still give useful indicators of metabolic health risk.

The central theme of the development and progression of obesity is lifestyle behaviours. The high-caloric foods, unregulated eating behaviours, lack of physical activities, sedentary behaviours and passive transportation can all predispose the likelihood of weight gain and obesity. Conversely, exercise plays a protective effect on metabolic well-being. Battista et al. (2021) discovered that exercise enhances cardiometabolic outcomes in adults with overweight or obesity, especially regarding blood pressure, insulin resistance, intrahepatic fat. These findings substantiate the necessity to investigate the problem of obesity using the integrated framework consisting of dietary, behavioural, physical and lifestyle-related factors.

The family history is a significant determinant of the risk of obesity. It can be genetic predisposition, as well as similarity in the household dietary habits, cultural practice and common lifestyle behaviours. Thus in the study of obesity both inheritable and modifiable factors should be taken into account. The current study with the title of Obesity and Its Impact on Metabolic Health: Patterns, Determinants, and Associated Comorbidities uses secondary data on eating habits, physical condition, lifestyle behaviours, family history as well as obesity classification. Because the data does not encompass direct clinical measures of comorbidity such as diabetes, hypertension, cholesterol,

glucose or blood pressure, metabolic health and comorbidities are perceived based on the risk markers that are related to obesity, such as BMI, severity of obesity, physical inactivity, dietary behaviour, sedentary lifestyle, smoking, alcohol consumption and passive transportation. The aim of the research is:

1. To assess the distribution and burden of obesity levels among participants.
2. To analyze anthropometric, dietary, lifestyle, behavioural, and family-history determinants associated with obesity status.
3. To evaluate obesity-related metabolic health and comorbidity risk indicators using BMI, obesity severity, physical activity, calorie monitoring, alcohol use, and transportation mode.

2. Methodology

2.1 Research Design

The research design employed in this study was a quantitative cross-sectional research design to investigate the patterns of obesity, lifestyle determinants, and the indicators of metabolic health risks that were associated with obesity. The research design was suitable since the study involved secondary participant-level data that was collected at one point in time. Analysis aimed at the distribution of obesity levels and the correlation between these levels and demographic, anthropometric, dietary, behavioural and lifestyle factors. As the data was both observational and cross-sectional it was interpreted as an association and not a causal relationship.

2.2 Data Source and Study Sample

The research was conducted using the secondary data source called Estimation of Obesity Levels Based On Eating Habits and Physical Condition, which is located on the UCI Machine Learning Repository (Estimation of Obesity Levels Based On Eating Habits and Physical Condition [Dataset], 2019). The dataset has information on people of Mexico, Peru and Colombia and includes variables about eating behaviour, physical state, lifestyle behaviour, family history of overweight and classification of obesity. The data set had 2,111 observations and 17 variables. Following data screening, the duplicates of records were eliminated, and all records of the valid participants were incorporated in the final analysis.

2.3 Study Variables

The outcome variable was the level of obesity measured by the use of the NObeyesdad which grouped the participants into seven categories that included insufficient weight to obesity type III. These were retained to be analyzed descriptively, and a regression analysis was done where a binary classification was used: obesity type I, II, and III were coded as obese and the rest as non-obese. The independent variables were age, gender, height, weight, BMI, family history, dietary habits, water intake, alcohol use, smoking, calorie monitoring, physical activity, time of technology-use, and mode of transportation. Because there were no measures of clinical comorbidity, metabolic health was measured using obesity-related lifestyle and risk factors.

2.4 Data Processing and Cleaning

The data were filtered to remove any missing data, duplicated records, inconsistent category names, and unrealistic anthropometric data. Continuous variables like age, height, weight, vegetable intake, frequency of main meals, amount of daily water, frequency of physical activities, and time of use of technology were validated with correct range. Reviewing of coding consistency was done on categorical variables.

Body mass index was computed as the weight in kilograms/height in metres squared. Another anthropometric measure calculated was used to support the interpretation of the severity of obesity, the risk of metabolic health and the risk of comorbidity associated with obesity. The original seven-category obesity variable was used to analyze the data descriptively and comparatively, and a binary obesity-status variable was created to analyze the data regressively.

2.5 Data Analysis

Participant characteristics and distribution by level of obesity were summarized using descriptive statistics. Categorical variables frequencies and percentages were calculated, whereas continuous variables means and standard deviations were calculated. Obesity trends were studied in terms of the seven categories of obesity, and the BMI compared across the groups to determine consistency between the computed anthropometric status and the obesity category.

The relationships between the level of obesity and the categorical determinants were tested using the chi-square tests. Comparison of continuous variables across obesity groups was done by use of analysis of variance or where necessary use of non-parametric tests. Lastly, to determine the key predictors of obesity status, the binary logistic regression was employed. The variables that were used as predictors were demographic, anthropometric, dietary, behavioural, lifestyle, and family-history variables. This method of analysis made it possible to evaluate the patterns of obesity, its determinants, and metabolic health and comorbidity risks indicators in the context of the available data.

3. Results

3.1 Data Screening and Sample Characteristics

The initial data has 2,111 observations, 17 variables. The screening provided no cases of missing cases; nevertheless, 24 duplicates were eliminated, and the final sample of the analysis consisted of 2,087 participants. As Table 1 shows, the mean age of subjects was 24.35 years old, with the mean BMI having a value of 29.77 kg/m², which implies that the sample was concentrated mostly within the range of overweight and obesity.

Table 1. Descriptive characteristics of the study sample

Variable	Mean	SD	Minimum	Maximum
Age	24.35	6.37	14.00	61.00
Height	1.70	0.09	1.45	1.98
Weight	86.86	26.19	39.00	173.00
BMI	29.77	8.02	13.00	50.81
Vegetable consumption	2.42	0.53	1.00	3.00
Number of main meals	2.70	0.76	1.00	4.00
Water intake	2.00	0.61	1.00	3.00
Physical activity	1.01	0.85	0.00	3.00
Technology-use time	0.66	0.61	0.00	2.00

3.2 Distribution of Obesity Levels

The distribution of the sample according to the level of obesity revealed that the sample was not too unbalanced in terms of the distribution across the seven categories. Table 2 reveals that the highest category was Obesity Type I with a total of 351 participants, Obesity Type III with 324 participants and Obesity Type II with 297 participants. A combination of the type I, II, and III of obesity established a number of 972 participants who represented 46.57 percent of the cleansed sample as obese. This means that there is a significant obesity burden among the individuals in the study. The figure 1 shows the average BMI trend among the obesity categories.

Table 2. Distribution of obesity categories

Obesity category	Frequency	Percentage
Insufficient weight	267	12.79%
Normal weight	282	13.51%
Overweight level I	276	13.22%
Overweight level II	290	13.90%
Obesity type I	351	16.82%
Obesity type II	297	14.23%

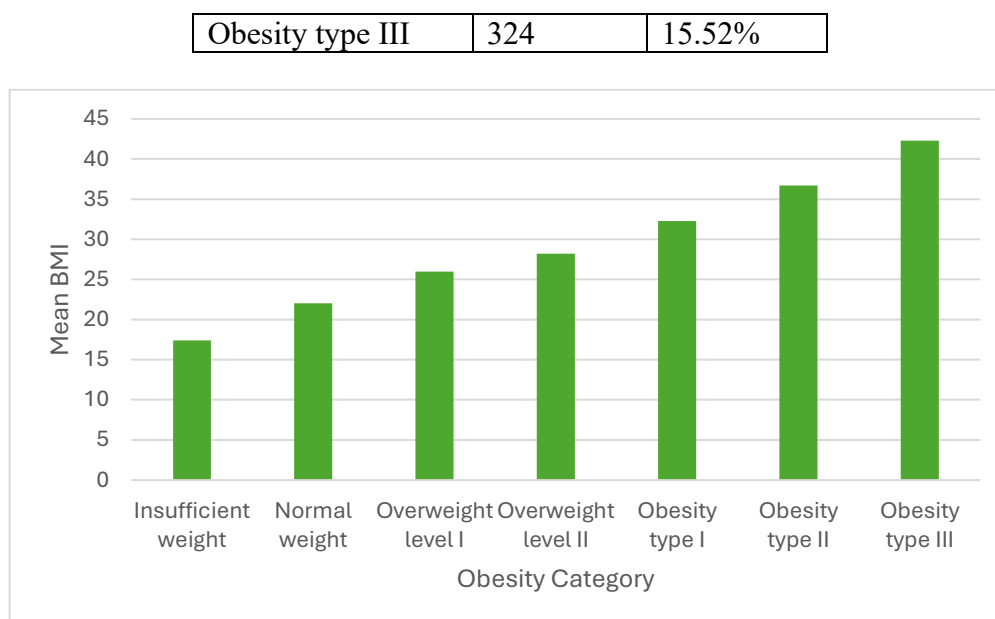


Figure 1. Mean BMI across obesity categories

3.3 Anthropometric Pattern and Metabolic Health Risk

An upward trend in BMI and body mass was observed among categories of obesity. Table 3 indicates that participants who were underweight in type III had a mean BMI of 17.39 kg/m², whereas obese participants in type III had a mean BMI of 42.27 kg/m². On the same note, mean weight rose to 120.94 kg in the obesity type III group as compared to 50.01 kg in the insufficient-weight group. This trend substantiates the fact that the obesity classification was highly aligned with calculated anthropometric status. Figure 2 also shows that there is an increase in BMI across the obesity categories, but this increase is greater at higher obesity levels. Figure 3 shows some of the continuous indicators that have been selected depending on the status of obesity.

Table 3. BMI, weight, age, and physical activity by obesity category

Obesity category	n	Mean BMI	Mean weight	Mean age	Mean physical activity
Insufficient weight	267	17.39	50.01	19.77	1.27
Normal weight	282	22.01	62.16	21.76	1.25
Overweight level I	276	25.96	74.48	23.54	1.06
Overweight level II	290	28.22	82.09	27.00	0.96
Obesity type I	351	32.26	92.87	25.88	0.99
Obesity type II	297	36.72	115.31	28.23	0.97
Obesity type III	324	42.27	120.94	23.50	0.66

3.4 Lifestyle, Dietary, and Behavioural Risk Indicators

The risk indicators lifestyle and behavioural risk factors differed between the participants who were obese and those who were not. Table 4 indicates that obese participants had the greatest family history of overweight, frequent intake of high-caloric foods, alcohol use, and passive transportation. Conversely, the monitoring of calorie-consumption was less in the case of obese participants. These results imply that hereditary risk and unhealthy dietary habits, insufficient self-monitoring and passive lifestyle behaviours were associated with obesity.

Table 4. Lifestyle and risk indicators by obesity status

Risk indicator	Non-obese	Obese
Family history with overweight	67.98%	99.18%
Frequent high-caloric food consumption	79.91%	98.05%

Food consumption between meals	96.86%	99.79%
Smoking	1.97%	2.26%
Calorie-consumption monitoring	8.34%	0.31%
Alcohol use	64.22%	75.62%
Passive transportation	94.80%	99.59%

3.5 Association Between Determinants and Obesity Status

The chi-square test was performed to analyze how the categorical determinants were related to the status of obesity. Table 5 reveals that family history with more than 50 percent overweight, food intake between meals, frequent consumption of high-caloric food, monitoring of calories intake, alcohol intake, mode of transportation were significantly linked with the obese state at $p < 0.001$. Among these variables, family history with overweight was the most associated variable with obesity status, followed by food consumption between meals, and high-caloric food consumption. The binary comparison of smoking and gender with obesity status did not show any significant association.

Table 5. Chi-square association between categorical variables and obesity status

Variable	Chi-square	df	p-value
Family history with overweight	348.03	1	<0.001
Food consumption between meals	264.06	3	<0.001
Frequent high-caloric food consumption	164.25	1	<0.001
Calorie-consumption monitoring	74.53	1	<0.001
Alcohol consumption	55.79	3	<0.001
Transportation mode	45.19	4	<0.001
Smoking	0.10	1	0.758
Gender	0.00	1	0.962

3.6 Predictors of Obesity Status

Binary logistic regression was conducted to determine key predictors of being obese. As Table 6 indicates, family history overweight was the best predictor of obesity. The odds of becoming obese were also increased by frequent consumption of high-caloric and food between meals. Exercise and monitoring of calorie consumption lowered the chances of obesity indicating protective measures. Other predictors that were not significant were smoking, gender, and the number of main meals.

Table 6. Logistic regression predictors of obesity status

Association direction	Main predictors	Adjusted OR range	p-value
Increased odds	Family history with overweight	43.10	<0.001
Increased odds	High-caloric food, passive transportation, food between meals	5.52–8.72	≤ 0.031
Increased odds	Vegetable consumption, alcohol use, water intake, age	1.04–2.27	≤ 0.007
Reduced odds	Calorie monitoring, physical activity, technology-use time	0.07–0.81	≤ 0.021
Not significant	Smoking, male gender, number of main meals	0.95–1.65	>0.05

4. Discussion

Obesity is a multifaceted issue in the area of public health that is influenced by biological, dietary, behavioural, lifestyle and environmental factors. The results indicated that there was a significant burden of obesity with almost half of the cleaned samples falling under obesity type I, II, or III. This trend can be linked to the broader data that obesity has emerged as an important health-related issue among populations. Smith and Smith (2016) indicated that the prevalence of obesity is on the rise and

it is linked to significant health and financial problems. On a similar note, Apovian (2016) defined obesity as a chronic disease, which involves a number of causes, comorbidities, and long-term health burdens.

The anthropometry results revealed a steady rise in BMI and body weight between the obesity categories. The participants in the insufficient-weight group had the lowest mean BMI and the participants in the obesity type III had the highest mean BMI. This confirms the fact that obesity categorization had a great degree of correspondence with the calculated BMI and weight. BMI is an effective population-level measure of the obesity classification and the prediction of the health risk. Nonetheless, BMI is not enough to comprehend obesity. Paczkowska-Abdulsalam and Kretowski (2021) stressed that obesity is a metabolically heterogeneous phenomenon, i.e. the fact that people with similar BMI values may differ in terms of metabolic health.

A family history including overweight became the most significant factor in determining the obesity status. The participants who reported a family history of being overweight had significantly higher odds of being obese, indicating that family, as well as, household and shared environmental factors, may have a very strong impact on the risk of obesity. This result confirms the opinion of Apovian (2016) that obesity is a product of the interaction of genetic, behavioural, environmental, and metabolic factors. The role of family history may be genetic predisposition, however, it may also reflect similarity in food habits, cultural dieting practices, lack of physical activity, and household lifestyle behaviour similarities.

Strong relations were also found between dietary factors and the obesity status. The frequency of consumption of high-caloric food and intake between meals increased the probability of obesity, which means that diets with high caloric content, as well as the frequency of meals between them, could contribute to the excess consumption of caloric substances and the excess weight. Safaei et al. (2021) clarified that the development of obesity occurs through intersecting and interacting causes, which include the following: unhealthy eating habits, lifestyle behaviours, environmental exposures. This opinion is supported in the results because it appears that the classification of obesity was closely related to the eating behaviour.

The indicators of obesity related to lifestyle also indicated that behavioural and metabolic risk patterns were associated with obesity. Passive transportation and alcohol use were found to have increased odds of obesity whereas physical activity and monitoring of calorie consumption were found to have lower odds. These findings propose that low energy expenditure, sedentary mobility patterns and ineffective dietary self-monitoring can be contributing factors to the risk of obesity. Peiris, Van Namen, and O'Donoghue (2021) discovered that lifestyle intervention programs that entail education and exercise were more effective among adults with metabolic syndrome. Their results affirm the preventive effect of exercise and self-monitoring that has been found in this study. The fact that the relationship between physical activity and obesity was found to be negative further supports the significance of movement-based interventions in the prevention of obesity and improvement of the metabolic health risk.

The predictors of obesity status in the regression model were not significant predictors of obesity status because of smoking, gender or number of main meals. This shows that family history, dietary patterns, mode of transportation, alcohol consumption, physical exercise and calorie intake were strongly correlated with obesity in this dataset than these variables. Nevertheless, these non-significant findings cannot be construed to mean that smoking or gender do not relate to obesity, in general. Instead they imply that these factors did not independently predict the status of obesity after taking into consideration the other determinants in the model. Safaei et al. (2021) observed that predicting obesity relies on the interplay of several demographic, behavioural, and lifestyle factors, and the predictor may not have the same level of importance across populations and data sets.

The interpretation of metabolic health and related comorbidities used the risk indicators of obesity since the dataset did not include direct clinical measures, such as blood glucose, blood pressure, cholesterol, triglycerides, HbA1c, diabetes, or hypertension. This is a significant difference in that obesity is closely related to metabolic maladaptation, however, clinical comorbidities cannot be directly diagnosed without medical markers. As pointed out by Paczkowska-Abdulsalam and

Kretowski (2021), metabolic health in obesity is a complex biological process, encompassing insulin resistance, inflammation, and changes at the molecular level.

The results suggest a combination of numerous interacting determinants and not one single cause of obesity. The family history, high-calorie food intake, passive transportation, alcohol consumption, lack of physical activity, low calorie monitoring, BMI and the severity of obesity were found as significant factors in reflecting the metabolic health risk of obesity. These results are in line with past literature that has characterized obesity as a chronic and multifactorial condition that has metabolic and comorbidity implications.

5. Conclusion

Obesity can be defined as a complex health disorder that is determined by factors such as anthropometric, hereditary, dietary, behavioural and lifestyle-related factors. The results have shown that the severity of obesity was closely correlated with the rising BMI and the body weight and the severity of the obesity. This correlation also implies that categories of obesity may be useful indicators to identify patterns of risk in the context of missing clinical indicators. One of the interesting findings of the analysis is that the risk of obesity was influenced by inherited and modifiable determinants. Family history of overweight became the most powerful risk factor, which could be explained by the potential impact of genetic disposition, common diet, and family lifestyle patterns. Simultaneously, the significance of daily exposures of behaviour in the onset of obesity can be indicated by the high-caloric food intake, between-meal food intake, passive transportation, alcohol consumption, low physical activity, and limited calorie monitoring. The identified lifestyle and anthropometric trends suggest that there is a risk of metabolic health and comorbidity because the dataset did not include direct measures of diabetes, hypertension, glucose, cholesterol, and blood pressure. Hence, prevention of obesity must go beyond weight loss to include sustainable eating habits, physical activity, minimisation of sedentary behaviours and self-monitoring behaviours. The level of awareness at the family level is also significant, since the risk of being obese might be supported at the family and shared household level.

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