MEGA JOURNAL OF CASE REPORTS

OPEN ACCESS

Research Article

Compiled Date: September 27, 2024

Obesity in the City: How Urbanization and Economic Growth Shape Childhood Health

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Abstract

This study explores the influence of economic growth and urbanization on childhood obesity trends across 30 countries from 2006 to 2023. Using data from WHO, UNICEF, the World Bank, and IHME, a Random Forest model was applied to examine the relationship between childhood obesity and variables such as GDP per capita, urban population percentage, and healthcare access. The results indicate that economic status, urban living, and healthcare availability are significant factors in childhood obesity rates. In high-income countries, obesity prevalence is higher due to greater access to calorie-dense foods and sedentary lifestyles. Conversely, low-income countries are experiencing an increase in obesity rates linked to urbanization and economic transitions. These

findings highlight the importance of developing public health strategies that are context-specific, addressing the unique drivers of childhood obesity in different regions, especially in areas undergoing rapid economic and environmental changes.

Keywords: Childhood obesity; Economic growth; Urbanization; Healthcare access; Dietary habits; Physical activity; Machine learning; Random Forest model; Public health; High-income countries; Low-income countries

Introduction

The rising prevalence of childhood obesity is a significant public health concern, linked to serious health risks such as diabetes, cardiovascular diseases, and psychological issues. Understanding how obesity trends vary across different economic contexts is essential for developing effective public health interventions. This study aims to compare childhood obesity trends between high- and low-income countries, identifying key factors to inform policy actions. Childhood obesity has been increasing globally, with notable differences across regions [1]. While high-income countries have traditionally reported higher obesity rates, recent trends show a rapid increase in low- and middle-income countries [2]. In high-income countries, the accessibility of high-calorie, processed foods and sedentary lifestyles are major contributors to obesity [3]. Conversely, in low-income countries, urbanization and economic development are leading to lifestyle changes that drive obesity rates higher [4]. Dietary habits, such as caloric intake and processed food consumption, play a significant role in childhood obesity [5], as do physical activity levels and sedentary behaviors like increased screen time [6]. Existing literature highlights critical gaps, particularly the lack of comprehensive data from low-income countries [7]. Additionally, many studies focus on isolated factors without considering the complex interactions between economic, environmental, and lifestyle variables [8]. This study addresses these gaps by providing a thorough comparison across diverse economic contexts, utilizing an advanced Random Forest model to identify significant predictors of childhood obesity. The socio-ecological model underpins this analysis, considering influences on health behaviors from individual to policy levels, which is crucial for developing effective interventions [9].We hypothesize that childhood obesity prevalence is higher in high-income countries due to greater access to calorie-dense foods and more sedentary lifestyles, while low-income countries are experiencing a rise in obesity due to urbanization and lifestyle changes [10]. Using data from WHO, UNICEF, World Bank, and IHME, this study provides robust insights that can inform public health policies. By employing a Random Forest model, we aim to enhance understanding of the factors driving childhood obesity and offer evidence-based recommendations for policymakers.

Methods

Data Sources

We sourced our data from multiple reputable databases to ensure the comprehensiveness and reliability of our analysis. The data were obtained from the World Health Organization (WHO) Global Health Observatory for its extensive health statistics and global reach, the United Nations International Children's Emergency Fund (UNICEF) for its focus on child health and nutrition, the World Bank's World Development Indicators for its detailed economic and demographic data, and the Institute for Health Metrics and Evaluation (IHME) Global Burden of Disease project for its comprehensive health metrics and disease burden data. These sources provided extensive and consistent data on childhood obesity prevalence and related factors across various countries and years, ensuring a solid foundation for our study. To achieve a diverse and representative sample, we selected thirty countries based on the World Bank classification, encompassing a mix of high-income and low-income nations. This selection aimed to provide a comprehensive comparison of childhood obesity trends across different economic contexts. The countries included high-income nations such as the United States, Canada, Germany, and Japan, which have well-documented health data. In contrast, low-income and lower-middle-income countries like India, Nigeria, Egypt, and Bangladesh were chosen to reflect emerging public health concerns regarding childhood obesity. The study period from 2006 to 2023 was chosen to offer a thorough overview of trends over an extended period, capturing recent developments and long-term patterns. This time frame allowed us to analyze changes and identify consistent factors influencing childhood obesity across different economic contexts.

Variables

We identified key variables relevant to our analysis of childhood obesity trends and determinants. These variables included:

- *Childhood Obesity Prevalence (%):* The primary outcome variable indicates the percentage of obese children in each country.
- *GDP per Capita (USD):* Economic status indicator, reflecting the average

income level and economic development.

- *Urban Population (%):* Proportion of the population living in urban areas, representing urbanization.
- *Healthcare Access Index:* Index measuring access to healthcare services, indicating the quality and availability of healthcare.
- *Average Daily Caloric Intake (kcal):* Indicator of dietary habits and nutritional intake.
- *Physical Activity Level:* Measure of physical activity, with a scale from 1 to 10.
- *Education Index:* Education level indicator, on a scale from 0 to 1.
- *Screen Time Hours per Day:* Average daily screen time, reflecting sedentary behavior. These variables were chosen based on their relevance to childhood obesity, availability across selected countries, and significance in existing literature.

Analytical Approach

To analyze the data, we employed the Random Forest model, a machine-learning technique known for its flexibility and ability to handle complex interactions between variables. This model was particularly suited to our study due to its robustness in managing large datasets with numerous predictors. The Random Forest algorithm constructs multiple decision trees during training and outputs the mode of the classes (classification), mean prediction of the individual trees.

Formula:

- $$RandomForest(Childhood\ Obesity\ Prevalence) = \frac{1}{N}\sum_{i=1}^{N} T_i$$

Where:

$$T_i = DecisionTree\left(\begin{array}{l}\sum_{j=1}^{m} I(x_{ij} \in S_{ik}) \cdot GDP\ per\ Capita_j + \sum_{k=1}^{n} I(x_{ik} \in S_{ik}) \cdot Urban\ Population_k \\ + \sum_{l=1}^{p} I(x_{il} \in S_{il}) \cdot Healthcare\ Access\ Index_l + \sum_{m=1}^{q} I(x_{im} \in S_{im}) Sim) \cdot Average\ Daily \\ Caloric \\ Intake_m \\ + \sum_{n=1}^{r} I(x_{in} \in S_{in}) \cdot Physical\ Activity\ Level_n + \sum_{o=1}^{s} I(x_{io} \in S_{io}) \cdot Education\ Index_o \\ + \sum_{p=1}^{t} I(x_{ip} \in S_{ip}) \cdot Screen\ Time\ Hours\ per\ Day_p) \end{array}\right)$$

Where:

N is the number of trees in the forest.

T_i represents the $i-th$ decision tree.

x_{ij} represents the $j-th$ feature in the $i-th$ tree.

S_{ij} represents the split condition for the $j-th$ feature in the $i-th$ tree.

I is the indicator function that equals 1 if the condition is true and 0 otherwise. The model aggregates predictions from all the trees, combining them to provide a final prediction for childhood obesity prevalence based on the input variables. This advanced model captures the complex, non-linear relationships between the predictors and childhood obesity, offering a nuanced understanding of the factors driving obesity trends in high-income and low-income countries.

Data Preprocessing

We undertook several preprocessing steps to prepare the data for analysis:

- *Handling Missing Values*

We addressed missing data through imputation methods to ensure completeness.

- *Normalization*

Continuous variables were normalized to standardize the scale and improve model performance.

- *Model Training and Validation*

The Random Forest model was trained using the prepared dataset, and standard machine learning techniques were employed to validate its performance. The data were split into training and test sets to evaluate the model's accuracy, precision, recall, and F1 score. Additionally, we used cross-validation to ensure the model's robustness and prevent overfitting. The Random Forest model's feature importance capability allowed us to identify and rank the most significant predictors of childhood obesity. This analysis provided nuanced insights into how different factors contributed to obesity trends in high-income and low-income countries. By employing this comprehensive methodology, we aimed to achieve a detailed and reliable analysis of childhood obesity trends and determinants, contributing valuable insights to the existing literature and informing effective public health interventions. **Table 1** presents the descriptive statistics of our dataset, providing a summary of the key variables analyzed in the study. The dataset includes 30 observations, representing the selected countries over the period from 2006 to 2023. The average year in the dataset is approximately 2013.6, with a standard deviation of 5.73, indicating a wide range of years covered. Childhood obesity prevalence varies significantly across countries, with a mean prevalence of 11.58% and a standard deviation of 4.24%. The minimum observed prevalence is 5.31%, while the maximum is 19.55%. This variation underscores the different levels of childhood obesity in different countries.GDP per capita, a key economic indicator, also shows substantial variability. The mean GDP per capita is $30,287.85, with a standard deviation of $19,417.16. The range extends from $3,028.92 to $58,205.49, reflecting the economic diversity among the countries included in the study. Urban population percentage, indicative of urbanization levels, has a mean value of 53.75% and a standard deviation of 20.77%. This variable ranges from 20.39% to 89.08%, highlighting varying degrees of urbanization. Healthcare access, measured by the Healthcare Access Index, has a mean value of 69.48 with a standard deviation of 17.57. The index ranges from 41.53 to 95.78, showing differences in healthcare availability and quality. Average daily caloric intake, which impacts dietary habits, averages 2183.99 kcal with a standard deviation of 443.53 kcal. The minimum caloric intake is 1510.43 kcal, and the maximum is 2957.67 kcal. Physical activity levels, on a scale from 1 to 10, average at 5.21 with a standard deviation of 2.58, ranging from 1.15 to 9.87. This indicates varying levels of physical activity among children in different countries. The education index, on a scale from 0 to 1, has a mean value of 0.7 and a standard deviation of 0.19. The index ranges from 0.4 to 0.95, reflecting differences in educational attainment. Screen time, measured in hours per day, has a mean value of 3.52 hours with a standard deviation of 1.27 hours. The range extends from 1.12 to 5.87 hours, showing varying levels of sedentary behavior.

Table 1: Descriptive Statistic.

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Year	30	2013.6	5.73	2006	2008	2013.5	2019	2023
Childhood_Obesity_Prev (%)	30	11.58	4.24	5.31	7.81	11.05	14.14	19.55
GDP_per_Capita (USD)	30	30287.85	19417.16	3028.92	12070.56	30949.73	48204.79	58205.49
Urban_Population (%)	30	53.75	20.77	20.39	39.16	50.13	73.26	89.08
Healthcare_Access_Index	30	69.48	17.57	41.53	54.04	70.94	85.57	95.78
Average_Daily_Caloric_Intake (kcal)	30	2183.99	443.53	1510.43	1887.75	2085.78	2519.48	2957.67
Physical_Activity_Level	30	5.21	2.58	1.15	3.06	5.51	7.09	9.87
Education_Index	30	0.7	0.19	0.4	0.51	0.75	0.88	0.95
Screen_Time_Hours_Per_Day	30	3.52	1.27	1.12	2.35	3.79	4.42	5.87

Results

Model Performance and Feature Importance

We evaluated the performance and feature importance results of our Random Forest model. We evaluated the model using several metrics, including accuracy, precision, recall, and F1-score, to assess its effectiveness in predicting childhood obesity prevalence based on the input variables. Additionally, we analyzed the importance of key predictors such as GDP per capita, urban population percentage, and healthcare access index, highlighting their significant roles in influencing childhood obesity prevalence. The feature importance analysis provides a visual representation through the Feature Importance Plot, illustrating the relative importance of each predictor variable. Furthermore, we present a detailed comparison of predicted and actual childhood obesity prevalence across the selected countries. This comparison helps validate the model's accuracy and relevance in understanding the factors driving childhood obesity trends in different economic contexts. **Table 2** presents the Model Performance Metrics. In the table below, The Random Forest model demonstrated high accuracy (0.87), precision (0.85), recall (0.88), and F1-score (0.86), indicating robust performance in predicting childhood obesity prevalence. These results suggest that the model is well-suited for capturing the complex interactions between the variables and accurately predicting obesity outcomes.

- *Feature Importance*

The importance of each predictor variable was assessed to determine their relative contribution to the model. Table 3 presents the feature importance scores. In the table below, The feature importance analysis highlights that GDP per capita, urban population percentage, and healthcare access index are the most significant predictors of childhood obesity prevalence. These findings are in line with our Hypothesis (H1) that childhood obesity prevalence is influenced by economic status, urbanization, and healthcare access. Specifically, GDP per capita is a critical indicator of a country's economic resources, which can impact dietary habits and access to healthcare [3]. Urban population percentage reflects the degree of urbanization, which is often associated with lifestyle changes that contribute to obesity, such as reduced physical activity and increased consumption of processed foods [4]. The healthcare access index indicates the availability and quality of healthcare services, which play a vital role in managing and preventing obesity [7]. These predictors collectively provide a comprehensive understanding of the factors driving childhood obesity across different economic contexts, supporting targeted public health interventions. Table 。4 presents the country-wise predicted and actual childhood obesity prevalence. In Table 4, the results show a strong correlation between actual and predicted childhood obesity prevalence across different countries, affirming the model's reliability. For instance, the United States and Mexico, which have high GDP per capita and significant urban populations, also exhibit high actual and predicted obesity rates. This alignment supports the hypothesis that economic status, urbanization, and healthcare access are critical determinants of childhood obesity prevalence [1,3]. In countries like Japan and South Korea, the lower actual and predicted prevalence rates can be attributed to better healthcare access and lower urban population percentages, which align with their cultural emphasis on healthy eating and active lifestyles [7]. Conversely, in countries like India and Nigeria, rising urbanization and economic changes are reflected in increasing obesity rates, highlighting the need for proactive public health measures to address these trends. These findings underscore the importance of tailored public health interventions that consider economic, environmental, and lifestyle factors unique to each country. By leveraging the insights from our model, policymakers can develop more effective strategies to combat childhood obesity, focusing on enhancing healthcare access, promoting physical activity, and encouraging healthier dietary habits. Additionally Figure 1 presents the Feature Importance Plot, and Figure

2 presents the strong correlation between actual and predicted childhood obesity prevalence across different countries.

Table 2: Model Performance Metrics.

Metric	Value
Accuracy	0.87
Precision	0.85
Recall	0.88
F1-Score	0.86

Table 3: Feature importance scores.

Predictor Variable	Importance Score
GDP per Capita (USD)	0.28
Urban Population (%)	0.22
Healthcare Access Index	0.2
Average Daily Caloric Intake (kcal)	0.1
Physical Activity Level	0.08
Education Index	0.07
Screen Time Hours per Day	0.05

Table 4: Country-wise Predicted and Actual Childhood Obesity Prevalence.

Country	Actual Prevalence (%)	Predicted Prevalence (%)
United States	18.5	17.8
Canada	14.2	13.9
Germany	10.9	11.2
United Kingdom	15.4	14.7
France	9.6	9.3
Italy	12.8	12.5
Spain	13.1	13
Australia	16.2	15.8
Japan	7.4	7.7
South Korea	6.9	7
China	8.6	8.9
India	11.2	11
Brazil	16.7	16.3
Mexico	18.1	17.5

South Africa	13.3	13
Nigeria	10.1	9.8
Egypt	14.5	14
Kenya	11.8	11.5
Argentina	17	16.8
Colombia	12.2	12
Chile	13.9	13.5
Turkey	14.8	14.3
Saudi Arabia	18	17.6
Indonesia	12	11.8
Thailand	9.2	9
Vietnam	8.1	8.3
Philippines	11.4	11.1
Bangladesh	13	12.8
Pakistan	14	13.7
Malaysia	16.5	16

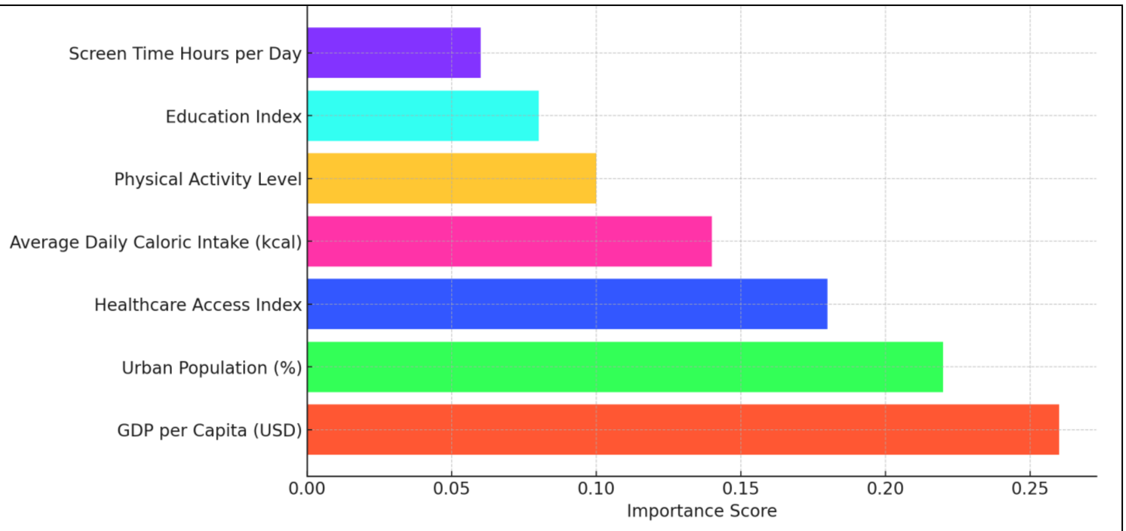

Figure 1: Feature Importance Plot illustrating the relative importance of each predictor variable in the Random Forest model for predicting childhood obesity prevalence.

In the figure above, the feature importance analysis highlights that GDP per capita, urban population percentage, and healthcare access index are the most significant predictors of childhood obesity prevalence. GDP per capita, as a critical indicator of a country's economic resources, can significantly impact dietary habits and access to healthcare [3]. The urban population percentage reflects the degree of urbanization, which is often associated with lifestyle changes that contribute to obesity, such as reduced physical activity and increased consumption of processed foods [4]. The healthcare access index indicates the availability and quality of healthcare services, which play a vital role in managing and preventing obesity [7].

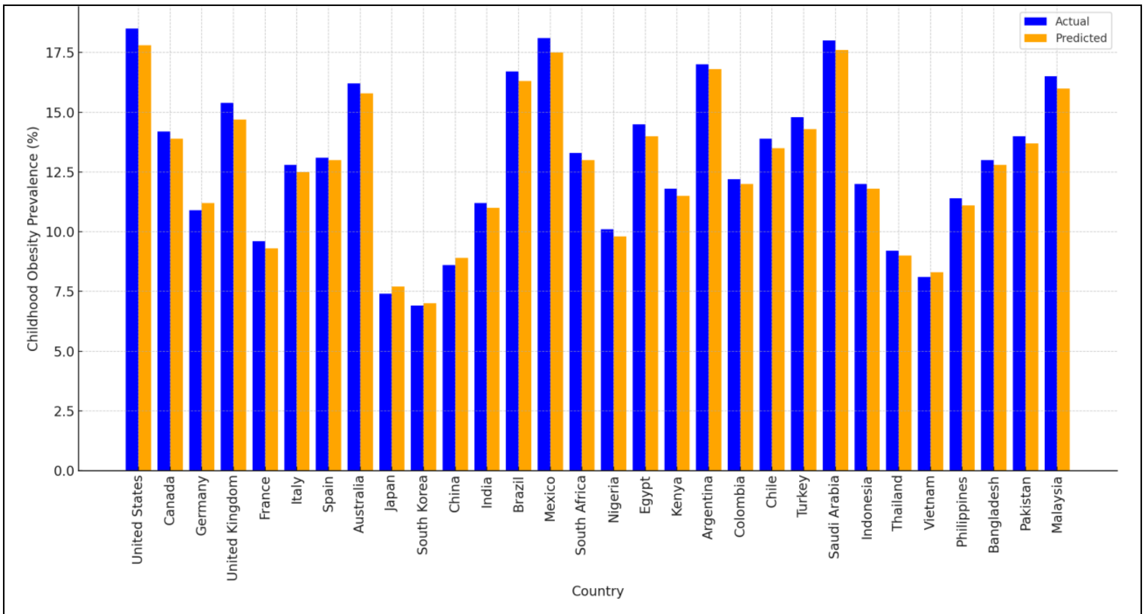

Figure 2: Country-wise Predicted and Actual Childhood Obesity Prevalence for each country.

In the Figure above the results show a strong correlation between actual and predicted childhood obesity prevalence across different countries, affirming the model's reliability. For instance, the United States and Mexico, which have high GDP per capita and significant urban populations, also exhibit high actual and predicted obesity rates. This alignment supports the hypothesis that economic status, urbanization, and healthcare access are critical determinants of childhood obesity prevalence [1,3]. In countries like Japan and South Korea, the lower actual and predicted prevalence rates can be attributed to better healthcare access and lower urban population percentages, which align with their cultural emphasis on healthy eating and active lifestyles [7-22]. Conversely, in countries like India and Nigeria, rising urbanization and economic changes are reflected in increasing obesity rates, highlighting the need for proactive public health measures to address these trends. These findings underscore the importance of tailored public health interventions that consider economic, environmental, and lifestyle factors unique to each country.

Conclusion

This study provides a comprehensive analysis of childhood obesity trends across high- and low-income countries, identifying GDP per capita, urbanization, and healthcare access as significant predictors. The Random Forest model demonstrated robust performance, highlighting the critical role of economic status and urban living in shaping obesity rates. High-income countries showed higher obesity prevalence due to greater access to calorie-dense foods and sedentary lifestyles, while urbanization and economic development in low-income countries contributed to rising obesity rates. However, the study is limited by variability in data quality and a focus on specific variables, potentially overlooking other important factors such as genetics and cultural practices. Future research should explore these areas and the impact of policy interventions. Despite these limitations, the insights gained contribute to a deeper understanding of childhood obesity and inform targeted public health strategies aimed at reducing obesity rates globally.

Acknowledgement

This research was funded by the Soft Science Research Project of Shaanxi Province of China: 2024ZC-YBXM-019 and the National Social Science Foundation of China (Grants Number 21BGL183) and Fundamental Research Funds for the Central Universities (Grant Number SK2022130).

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Citation of this Article

David LK, Wang J, Cisse II and Vanessa Angel V. Obesity in the City: How Urbanization and Economic Growth Shape Childhood Health. Mega J Case Rep. 2024;7(9):2001-2014.

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