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Understanding Childhood Obesity in London: A Multi-Factor Analysis of Key Determinants

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Abstract: Nowadays, childhood obesity has become an increasingly significant public health challenge, particularly in developed urban environments. In order to have a better understanding of this heated topic, this study investigates the obesity rate of children in London by analyzing its spatial and temporal trends. Besides, the research uses multiple linear regression to examine the possible socioeconomic driving factors of childhood obesity, including poverty rates, sports participation, crime rates, and the number of looked-after children (LAC). The findings reveal that the obesity rate of year 6 (ages 10-11) children showed an upward trend from 2008 to 2018, and eastern London boroughs had a relatively high childhood obesity rate during this period. As for the driving factors, poverty rates have the strongest correlation with the childhood obesity rate, followed by sports participation rates, while crime rates and LAC rates show weaker associations. The results highlight the need for targeted public health interventions addressing socioeconomic disparities and promoting physical activity to reduce childhood obesity in high-risk areas, particularly in eastern London boroughs.

Keywords: Childhood obesity, Multiple linear regression, Driving factors, London

1. Introduction

Since 1980, the global obesity rate has continued to rise, with obesity rates doubling in over 70 countries [1]. Essentially, obesity is the abnormal accumulation of excess fat [2]. It is a chronic condition and a risk factor for other chronic conditions in many other organ systems, which is associated with increased morbidity and mortality [3-4]. Actually, obesity is currently ranked as the fifth most common leading cause of death globally [5]. Sin and Sutherland [6] found that obesity could potentially increase the risk of asthma; Gardiner *et al.* [7] concluded that the higher the obesity rate in a country, the higher the COVID-19 mortality rate. Obesity can begin early in life during the preschool years, and once established, obesity is extremely difficult to reverse. Nowadays, childhood obesity has emerged as a significant public health challenge, with far-reaching implications for physical health, psychological well-being, and societal costs. Childhood obesity has reached epidemic levels in developed countries [8]. It could significantly impact children’s health [9]. Almost all researchers agree that prevention could be the key strategy for controlling the current epidemic of obesity [8]. Therefore, it is imperative to study the causes of childhood obesity so that countermeasures can be taken to decrease the obesity rate. This study focuses on childhood obesity rates in London, examining the temporal trends and spatial patterns across boroughs. By using data including poverty rates, sports participation rates, crime rates, and the number of looked-after children

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(LAC), this research aims to identify the possible contributing factors of childhood obesity. The study seeks to uncover relationships between these factors and obesity rates, providing a comprehensive perspective on the issue.

2. Literature review

The body of research on childhood obesity causes is strong since the relationship between obesity and mental health has been studied for several decades [10]. For example, Cole [11] explored the early causes of childhood obesity, with a particular focus on how fetal and infant growth patterns affect future obesity risk; Zilanawala *et al.* [12] used multiple regression analysis to investigate the relationship between ethnicity and obesity while controlling for the influence of socioeconomic and cultural factors; Hoffman *et al.* [13] focused on early-life undernutrition; an official report from the Scottish Government [14] emphasized the importance of improving diet quality and increasing physical activity; Kırmızıbekmez *et al.* [15] highlighted the significance of early screening for MC4R variants in obesity diagnosis; Ells *et al.* [9] concluded that the prevalence of severe obesity varied significantly by geography, ethnicity, and socioeconomic status, etc. However, there are still unanswered questions about how these factors interact and change over time and space in urban environments. There is space for localized observations and recommendations because little research has explicitly examined the influence of specific socioeconomic factors in London, like poverty, sports participation, crime, and LAC.

3. Research questions

While some previous studies have explored the possible contributing factors of childhood obesity, relatively limited research focuses on the specific dynamics within London, particularly regarding spatial and temporal variations and the impacts of different socioeconomic variables on childhood obesity rates. This study aims to address the following key questions:

a) What significant spatial and temporal patterns can be observed in childhood obesity rates across different boroughs and time periods in London?
b) Which socioeconomic factors may impact childhood obesity rates, and what is the degree of influence of these factors?
c) Do the effects of these factors vary across different times?

By addressing these questions, this research seeks to enhance understanding of childhood obesity in London, identify the key driving factors behind its development, and provide scientific evidence to support the formulation of more targeted public health policies.

4. Data

The raw data used in this research are listed in Table 1, including their period and data sources. During the data preprocessing, this research calculated the crime rate (per 1000 people) of each borough in London, and the rest of the data could be used directly in this research. Due to data availability, this study focused on analyzing data from three years: 2008, 2012, and 2016.

Table 1: Raw data and data sources

Raw data	Period	Data source
Childhood obesity rate	2006-2019	Prevalence of Childhood Obesity, Borough, Ward and MSOA - London Datastore
Children’s poverty rate	2006-2016	Children in Poverty, Borough and Ward - London Datastore

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Table 1: (continued).

Sports participation rate	2006-2016	Sports Participation Rates, Borough - London Datastore
Recorded crime	2010-2024	MPS Recorded Crime: Geographic Breakdown - London Datastore
Children looked after (LAC)	2005-2019	Children Looked After, Borough – London Datastore
Statistical GIS Boundary for London	/	Statistical GIS Boundary Files for London - London Datastore

5. Methodology

5.1. The calculation of crime rate

The recorded crime data includes the number of crime incidents of each crime type of each month of each borough in London. To calculate the crime rate of each borough in a specific year, this study used Equation 1:

$$Crime\ rate\ (per\ 1000\ people) = \frac{Total\ number\ of\ crime\ incidents}{Population} \times 1000 \tag{1}$$

5.2. Multiple linear regression

This study used a multiple linear regression model to explore the impact of each factor on childhood obesity rates. The model can be represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \epsilon \tag{2}$$

In this research, there are four different factors, so the model is adapted as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_3 x_3 + \beta_4 x_4 + \epsilon \tag{3}$$

Where y is the obesity rate, x_1 to x_4 represents the four factors: children's poverty rate, sports participation rate, crime rate (per 1000 people), and children looked after (per 10000 children). β_0 is the intercept, β_1 to β_4 represents the coefficient of each factor, and ϵ is the error term.

6. Results

6.1. Children's obesity rate

With emphasis on children in the "reception" (ages 4-5) and "year 6" (ages 10-11) phases, Figure 1 shows the trends in the average childhood obesity rates of London boroughs between 2008 and 2018. While the obesity rate for "reception" is trending downward, the "year 6" rate is trending upward. And the p-values indicate that both trends are statistically significant.

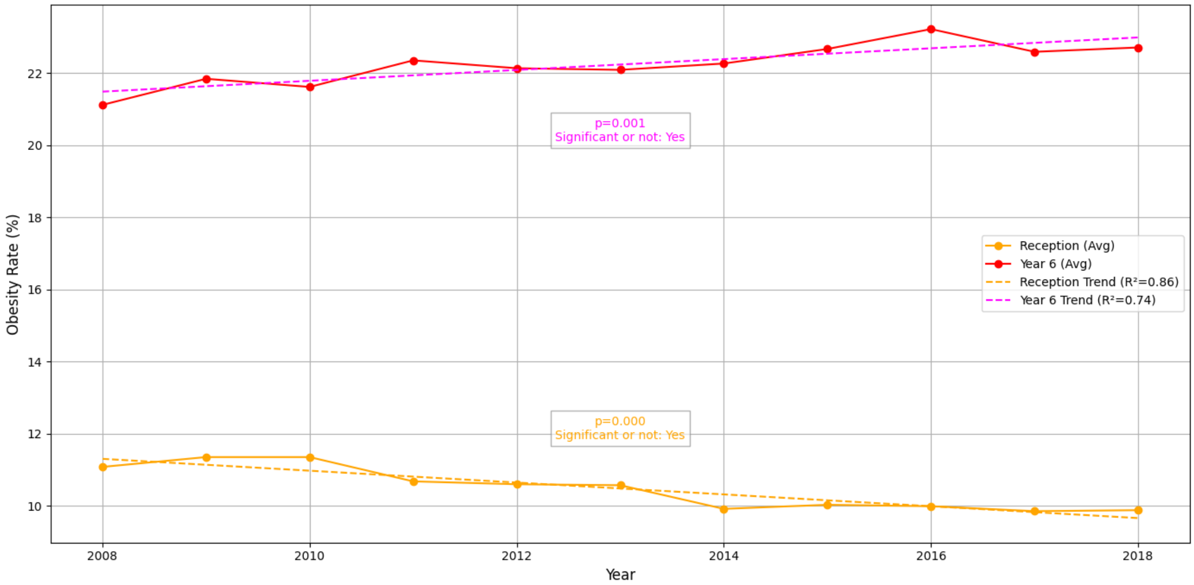

Figure 1: Obesity rate of reception and year 6 children

Figure 2 shows clear spatial patterns of childhood obesity rates for children in reception and year 6 across the boroughs of London. The central and northeastern boroughs initially had the highest obesity rates for children in reception, but these areas gradually improved, with fewer boroughs having high rates by 2016–2017. On the other hand, year 6 students continue to have high obesity rates, with the highest rates moving from the central and northeastern regions to the southeastern boroughs by 2016–2017. This draws attention to a widening geographic gap that is especially noticeable in eastern London, where year 6 obesity rates are still startlingly high when compared to children in reception.

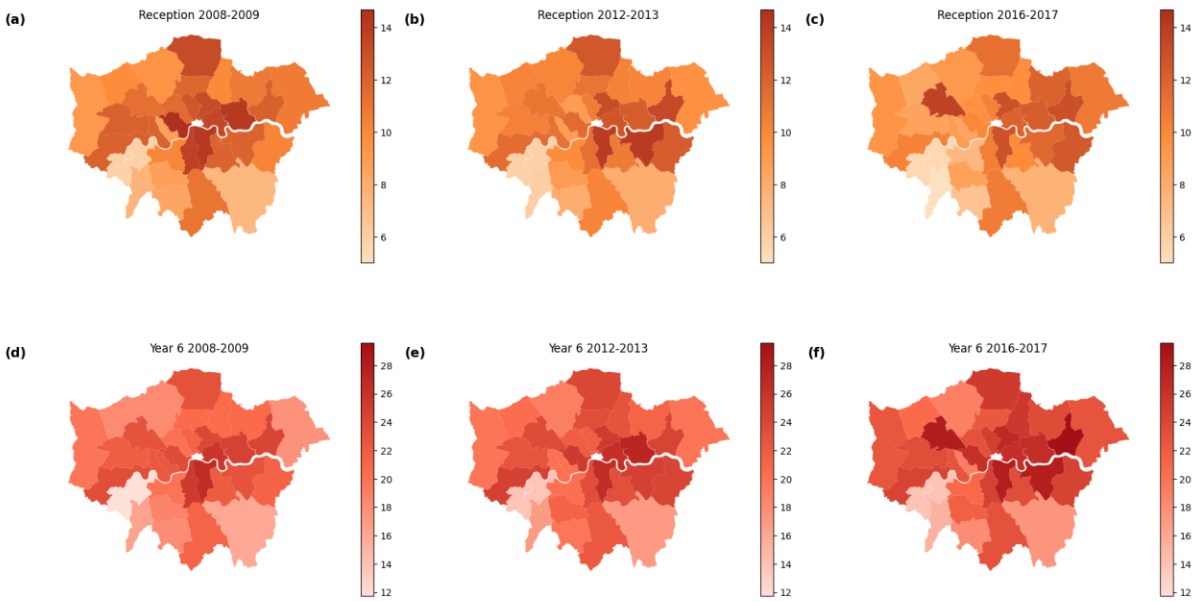

Figure 2: Spatial and temporal patterns of children's obesity rate (%) in London

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6.2. Possible driving factors

Section 6.1 notices that the obesity of year 6 children increased rapidly, so it is essential to explore the possible driving factors. Figure 3 examines the connections between year 6 obesity rates in 2008, 2012, and 2016 and different socioeconomic and demographic characteristics.

Obesity rates and child poverty rates are strongly positively correlated, as shown in Figure 3(a). R^2 represents the proportion of variance in the dependent variable that is explained by the independent variable. A higher R^2 value indicates that the regression model explains a greater proportion of the variance in the dependent variable. The greater slope of the 2016 regression line indicates that obesity rates are consistently higher in regions with higher child poverty, and this association seems to get stronger over time. According to the R^2 values, variations in obesity rates are highly explained by poverty rates. Figure 3(b) illustrates the connection between childhood obesity and adult inactivity rates (no sport rate). Although there is a positive link, it is not as strong as it would be in poverty. This suggests that although the explanatory power of this factor is relatively limited, areas with more excellent childhood obesity rates may also have higher rates of adult inactivity. The association between obesity and crime rates for 2012 and 2016 is examined in Figure 3(c). Regression lines are less steep, though, and the R^2 values are modest, suggesting that crime rates alone have little effect on childhood obesity. Figure 3(d) investigates the connection between obesity trends and the number of Looked After Children (LAC). All three years show a continuous positive correlation, with higher rates of childhood obesity being correlated with higher rates of LAC. The slopes and R^2 values grow with time, suggesting this link gets more potent. According to the research, although the relationship is not strong enough, areas with a large LAC population may experience systemic issues that raise obesity rates.

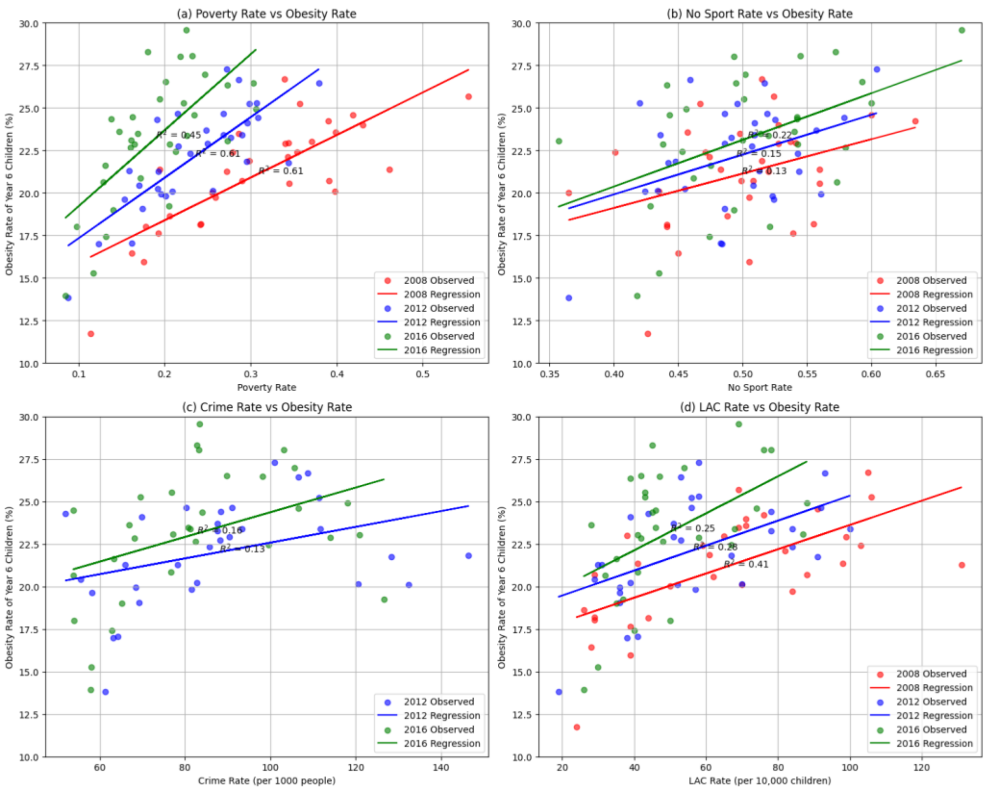

Figure 3: Possible driving factors of children's obesity rate

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6.3. The weight of each contributing factor

Due to the lack of crime rate data in 2008, this section uses the data from 2012 and 2016 to conduct multiple linear regression analyses. After conducting VIF and multicollinearity tests, the correlation matrixes of the four variables are constructed, as seen in Figure 4.

Figures 4(a) and 4(b) display the correlations for 2012 and 2016, respectively. Crime and poverty rates continuously correlate positively in both years (0.55 in 2012 and 0.73 in 2016). Furthermore, a positive association exists between poverty and LAC rates (0.68 in 2012, 0.50 in 2016). On the other hand, there aren't many significant associations between no sport rate and other variables in either year.

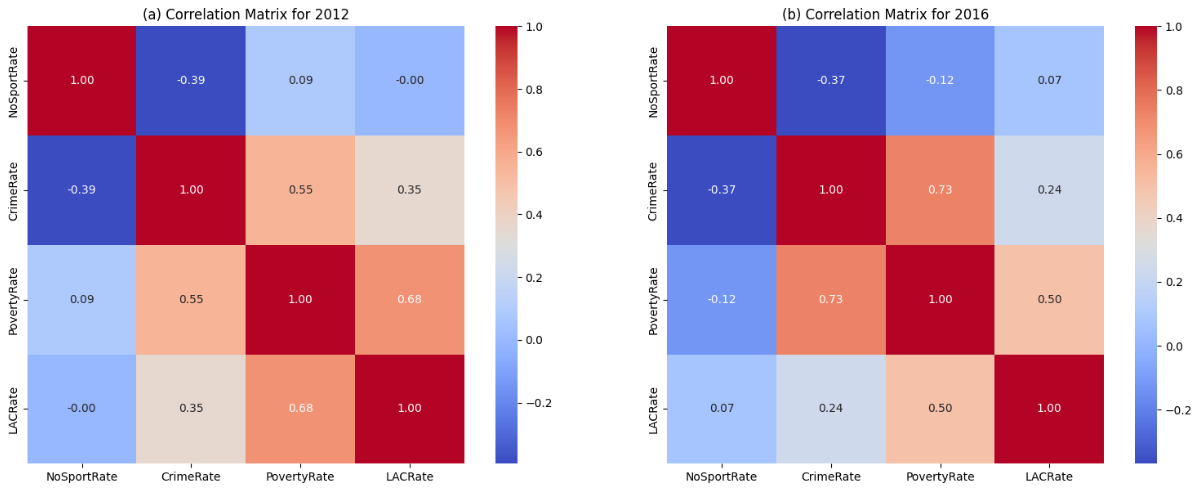

Figure 4: Correlation matrixes of four variables (2012, 2016)

Table 2 shows the findings of linear regression studies for 2016 and 2012, emphasizing the connections between the obesity rate and the four factors. With significant coefficients and p-values below 0.05, the no sport and poverty rates show notable effects in both years (e.g., 34.65 and 36.57 in 2016, 24.04 and 28.23 in 2012, respectively). In contrast, the higher p-values for the crime rate and LAC rate indicate that they have little influence and are not statistically significant. The confidence intervals show more uncertainty for variables with more significant coefficients, especially the poverty rate. The findings highlight the persistent significance of the poverty and no sport rates in predicting the obesity rate in both years.

Table 2: The results of multiple linear regression

Year	Variable	Coefficient	Std Err	t-value	P-Value	CI Lower	CI Upper
2016	const	-4.5991	3.3820	-1.3599	0.1851	-11.5383	2.3402
2016	No sport rate	34.6543	5.7449	6.0322	0.0000	22.8667	46.4419
2016	crime rate	0.0230	0.0186	1.2357	0.2272	-0.0152	0.0611
2016	poverty rate	36.5719	10.0198	3.6500	0.0011	16.0131	57.1308
2016	LAC rate	0.0289	0.0232	1.2465	0.2233	-0.0187	0.0764
2012	const	2.0363	3.6938	0.5513	0.5860	-5.5427	9.6153
2012	no sport rate	24.0430	7.1464	3.3644	0.0023	9.3798	38.7061
2012	crime rate	0.0123	0.0106	1.1605	0.2560	-0.0095	0.0341
2012	poverty rate	28.2317	7.5654	3.7317	0.0009	12.7089	43.7545
2012	LAC rate	0.0073	0.0191	0.3798	0.7070	-0.0319	0.0465

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The residual diagnostics for the multiple linear regression models from 2012 and 2016 are shown in Figure 5. The residuals are dispersed randomly about the zero line in the residuals vs. fitted plots for both years, demonstrating that the assumptions of linearity and homoscedasticity are satisfied. Although a small amount of skewness indicates tiny departures from normalcy, the residual histograms are generally centered around zero. With only slight variations seen at the tails, the Q-Q plots demonstrate that the residuals closely resemble the theoretical normal distribution. With very minor deviations from normalcy, the diagnostic plots indicate that the regression models for both years generally meet the requirements of linear regression.

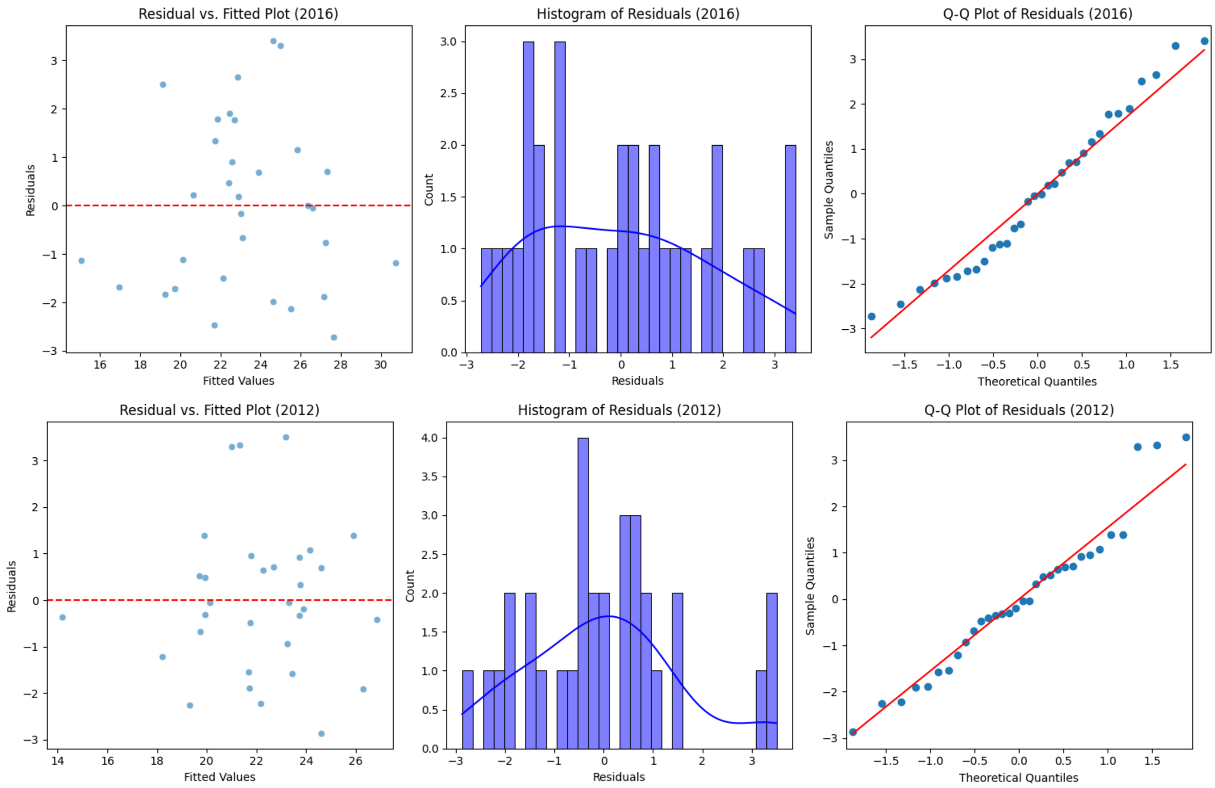

Figure 5: Residual diagnostics for the multiple linear regression models

7. Discussion

The results show distinct changes in London's childhood obesity rates over time and space, with notable differences between reception and year 6 students. While the persisting and rising rates among year 6 children show crucial areas requiring targeted interventions, the declining trend in reception obesity rates suggests some effectiveness with early intervention measures.

The multiple linear regression analysis findings shed important light on the variables affecting the prevalence of childhood obesity. Poverty rates showed the strongest positive correlation with obesity rates among the variables considered, which highlights the structural issues that low-income children confront. Also, a lack of physical activity options may make obesity risks worse. Indirectly measured by adult inactivity rates, sports participation rates seem to have an influence, though not as much as poverty rates. This implies that reducing socioeconomic disparities is still crucial, even when promoting physical exercise, which may help reduce obesity. Interestingly, the regression analysis showed weaker and statistically negligible relationships between obesity rates, crime rates, and the number of looked-after children. Nonetheless, the persistently positive relationship between obesity

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and LAC rates suggests possible systemic problems in regions with sizable LAC populations that may require more research.

8. Conclusions

This study examined the regional and temporal dynamics of London's children's obesity rates and the impact of different socioeconomic factors. The results, which show a complex interaction of variables, show that poverty rates are the most reliable indicator of obesity across many years. While adult inactivity and sports participation have a notable but lesser impact, crime and LAC rates demonstrate weaker associations. The result emphasizes the crucial role of poverty as a fundamental element of public health initiatives to lower childhood obesity. Targeted interventions could help children achieve healthier outcomes and close the observed geographic gaps, especially in high-risk areas like eastern London boroughs.

Limitations like data availability and omitting other potentially impacting factors (e.g., dietary habits or cultural norms) provide opportunities for future research. These results from this research may serve as the foundation for all-encompassing, just, and long-lasting policies to reduce childhood obesity in London.

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