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ANALYSING THE IMPACT OF AGE, WEALTH, MOTHER'S EDUCATION, AREA OF RESIDENCE, AND GENDER ON CHILD WEIGHT: A REGRESSION APPROACH

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Abstract

The purpose of this article is to analyse the impact of age, wealth, mother's education, area of residence, and gender all together on child weight using multiple linear regression model. Previous studies have examined the effects of these factors on child weight singly or in pairs but not all together. The various factors affecting child weight that contribute to the broader issues of malnutrition and obesity need to be examined. This study addresses this issue with the aim of identifying the most significant predictors of healthy child weight. The data were collected from a secondary source for a sample size of 760 children aged 0-59 months. The data were analysed using multiple linear regression with SPSS software. The correlation coefficient (0.861) between the observed and predicted values of the dependent variable (child weight) suggests a strong positive correlation. 74.2 per cent of the variability in child weight is explained by the predictors in this model, indicating a good fit. The model also explains 74 per cent of the variance, suggesting a robust fit. Age, gender, wealth, and mother's education are significant predictors of child weight, whilst area of residence is not statistically significant, though location-specific strategies may still be beneficial for child health outcomes. Based on the findings of this study, public health programs should prioritise age-appropriate nutrition, gender-sensitive interventions, and enhanced maternal education to improve child weight outcomes.

Key terms: Child health, child weight, health interventions, multiple regression, socioeconomic factors.

1.0 INTRODUCTION

The unequal distribution of resources, healthcare, and education often leads to disparities in child health outcomes, including weight. There was a need to examine how various factors, particularly age, wealth, mother's education, area of residence, and gender, affect child weight, contributing to the broader issues of malnutrition and obesity. This study addressed this issue by analysing these variables through a regression approach, aiming to identify the strongest predictors of healthy child weight.

Child weight is a key indicator of health, reflecting not only physical well-being but also potential disparities in access to nutrition and healthcare. Factors like age serve as a key indicator of proper growth and development during critical stages of life. In early childhood (0–5 years), weight is a marker of nutritional adequacy and health; insufficient weight gain during this period may indicate malnutrition or underlying health conditions that could impair physical and cognitive development. Child weight is intricately linked to family wealth, influencing both under nutrition and obesity. Family wealth determines access to resources such as nutritious food, healthcare, and education, which significantly impact a child's growth and weight status.

Maternal education is a strong predictor of child health, including weight status. Educated mothers are more likely to make informed decisions regarding nutrition, healthcare, and lifestyle that promote healthy growth and weight management. Interventions aimed at improving maternal education can, therefore, play an important role in addressing issues like childhood malnutrition, obesity, and related long-term health problems.

The area of residence plays a significant role in shaping a child's weight due to varying access to food, healthcare, physical activity opportunities, and socioeconomic factors. Urban areas may present a higher risk for obesity due to the availability of unhealthy food and sedentary lifestyles, while rural areas may contribute to under nutrition due to limited access to diverse and nutritious foods. Addressing disparities in child weight based on geographic location requires targeted interventions that improve food security, healthcare access, and opportunities for physical activity in both urban and rural settings.

Gender plays an important role in determining child weight through a combination of biological, social, and cultural factors. While boys and girls experience different growth patterns, nutritional needs, and challenges, gender-specific interventions can help address issues like obesity, under nutrition, and overall growth. Understanding these gender differences is key to developing tailored public health strategies that promote healthy weight and well-being in children.

The complex relationships between these socioeconomic and demographic variables and child weight are essential for designing effective public health interventions aimed at addressing childhood malnutrition and obesity. Many researchers have investigated the problem of child weight by considering predictor variables individually or in pairs, but none have examined all relevant factors together. This study has developed a predictive regression model to estimate child weight based on age, gender, wealth, maternal education, and area of residence.

Weight-related health challenges in children remain significant public health concerns, influenced by various socioeconomic and demographic factors. This study investigates how age, wealth, maternal education, areaof residence, and gender contribute to disparities in weight outcomes. By analysing these relationships, the

research provides valuable insights into the key determinants of healthy weight, allowing policymakers to develop more focused and effective interventions to support child health and nutrition.

The findings can inform government policies aimed at addressing weight disparities by focusing on the most critical influencing factors. Healthcare providers can use the results to prioritise interventions tailored to impactful socioeconomic and demographic variables. Insights into the role of maternal education can drive the creation of programs promoting maternal and child health while understanding the impact of residence enables the development of location-specific strategies for urban and rural populations.

The study examined children aged 0-59 months, analysing the influence of age, wealth, mother's education, area of residence (urban vs. rural), and gender on their weight. Using data from secondary sources, aregression model was developed that showed the relationships between these variables and child weight.

2.0 LITERATURE REVIEW

Previous research has highlighted socioeconomic status, parental education, and demographic variables as essential determinants of child health. Kobylińska et al. (2022) showed age and gender significantly affectchild weight patterns, with trends indicating increases in weight as children grow, though differences in these trends can often be seen between boys and girls. Studies commonly highlight that children and adolescents experience an increase in body mass with age, especially as they approach puberty, where distinct physiological changes also begin to reflect gender-related differences. Further, the study examined children aged 6-15 and found that both boys and girls showed comparable body composition before puberty, but differences became more pronounced after age 12, with boys typically having higher muscle mass and girls tending to carry more body fat, reflecting gender-specific growth patterns.

Miller et al. (2021) showed that wealth and maternal education are crucial factors in determining children's access to nutrition, healthcare, and early development resources. Higher maternal education is linked tobetter child health outcomes, as educated mothers are more likely to ensure access to healthcare, appropriate nutrition, and a stimulating environment, which together support early cognitive and socio-emotional development. Additionally, wealthier families are better positioned to invest in these resources, leading to reduced stress within the household and enabling parents to offer more responsive and nurturing caregiving environments.

Andriani (2021) described the relationship between birth weight and childhood obesity and, investigated the influence that residence and household wealth have on this relationship and concluded that effective prevention and intervention to childhood obesity as early as possible are imperative.

Currie et al. (2020) explored how social factors contribute to health disparities among children, emphasising the importance of socioeconomic factors and education levels in shaping health outcomes. They examined the pathways through which parental Socioeconomic Status (SES) influences child health, focusing on the implications for future educational and economic outcomes. They looked at various social determinants, including SES, and their impact on children's mental health outcomes, highlighting the role of education and economic resources.

Cheng et al. (2015) discussed the disparities in child health based on race, ethnicity, and socioeconomic status and how these factors interact to affect health and healthcare access. They showed disparities experienced

during childhood can result in a wide variety of health and healthcare outcomes, such as adult morbidity and mortality, demonstrate the need to investigate the impact of inequities across the life course. Bolton et al. (2014) showed that there was a significant interaction of weight status by gender, whereby overweight females had poorer health-related quality of life relative to healthy-weight females.

Case et al. (2002) showed that children from lower-income households with chronic health conditions have worse health than children from higher-income households. Further, they found that children's health is highly connected with long-run average household income and that the negative health impacts of lower permanent income build across children's lives.

Bradley and Corwyn (2002) discussed socioeconomic status as associated with a wide array of health, cognitive, and socioemotional outcomes in children, with effects beginning prior to birth and continuing into adulthood. They further showed that socioeconomic status influences child well-being through disparities in access to resources and responses to stress, operating across family and neighbourhood levels and moderated by children's traits, family dynamics, and external support systems.

This study contributes to the existing literature by examining how age, wealth, mother's education, area of residence, and gender influence child weight simultaneously within a single regression model.

3.0 METHODOLOGY

Multiple Linear Regression (MLR) is a powerful tool in statistical modelling used to analyse relationships between a dependent variable and several independent variables, helping to assess both the individual and collective influence of predictors. Multiple Linear Regression (MLR) was chosen as the methodology for modelling the relationship between multiple predictors: age, wealth, maternal education, gender and area of residence with child weight because it allows for the simultaneous analysis of the influence of several independent variables on a continuous dependent variable. This approach is particularly suitable since child weight, the dependent variable, is a continuous variable, making MLR an appropriate statistical method for understanding and predicting its variability based on the predictors. MLR enables the estimation of the unique contribution of each predictor variable to the dependent variable while controlling for the effects of the others. This is essential in complex systems where several factors may be interrelated.

The predictors include both continuous variables and categorical variables. MLR can accommodate this combination effectively by incorporating dummy coding for categorical variables. The method provides coefficients that quantify the strength and direction that is positive or negative of the relationship between each predictor and child weight, offering interpretable results. The assumptions of MLR, such as linearity, independence, homoscedasticity, and normality of residuals, are generally reasonable for this type of analysis and can be tested to ensure validity. MLR is a widely used and well-understood statistical technique, making it appropriate for studies aiming to inform policies or interventions in a generalisable manner.

This methodology ensures a comprehensive analysis of how demographic, socioeconomic, and biological factors collectively influence child weight, providing insights critical for targeted health interventions.

Data Collection

The data were collected from secondary sources of children aged 0-59 Months. Detailed information on demographics (age, gender), socioeconomic status (wealth, mother's education, area of residence), and health measurements (child weight) were investigated. Wealth was assessed using an asset-based index and expressed in quintiles, mother's education was classified as have (have not) and area of residence categorised as urban (rural).

Variable Specification

Dependent Variable: Child weight (kg)

Independent Variables:

Age: Continuous variable measured in months

Wealth: Continuous variable based on household asset index

Mother's Education: Categorical variable (have, have not)

Gender: Binary variable (male = 1, female = 0)

Area: Binary variable (urban = 1, rural = 0)

Statistical Analysis

The data were analysed using multiple linear regression using SPSS software to evaluate the effect of each predictor on child weight. Before running the regression, we conducted exploratory data analysis (EDA) to summarise the data and identify any correlations. Diagnostic tests were performed to confirm that regression assumptions (linearity, independence, homoscedasticity, and normality of residuals) were met.

The regression model is specified as follows:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + e$$

Where:

Y_i is the child weight

β_0 is the intercept

$X_i's$ are the predictor variables

$\beta_i's$ are the coefficients of the predictor variables and

e is the error term $for\ i = 1, 2, 3, 4, 5$

4.0 RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 shows the summary statistics for child weight, age, wealth index, mother's education level, gender and area of residence for a sample size of 760 children aged between 0 to 59 months.

Table 1: Summary Statistics for Child Weight, Age, Wealth Index, Mother's Education Level, Gender and Area of Residence

	Mean	Std. Deviation	N
Child's weight (kilograms)	11.57	3.359	760
Age (months)	29.10	16.867	760
Sex	.50	.500	760
Mother's education	.38	.486	760
Area	.45	.498	760
Wealth index quintile	2.01	1.379	760

The Durbin-Watson (1.819) in Table 2 shows independence in the observed values, which are favourable. The partial regression plots indicate that there is a linear relationship between child weight and age, gender, mother's education, area of residence and wealth, as shown in Table 3 (Fig 3a – Fig 3e). Fig 3f in Table 3 shows that the data exhibits homoscedasticity, which means that the variances remain similar, constant and elliptical.

Table 4 gives tolerance for each independent variable to be greater than 0.1 and variance inflation factor to be less than 10, indicating that there is no multicollinearity among the independent variables; thus, each independent variable contributes to the variance explained in the dependent variable. Using casewise diagnostics, no significant outliers were found. The histogram with superimposed normal curve and thenormal p-p plot in Table 5 indicate that the residuals of the regression line are approximately normally distributed.

Table 2: Shows Independence in the Observed Values

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.861[a]	.742	.740	1.712	.742	433.391	5	754	.000	1.819
a. Predictors: (Constant), Wealth index quintile, age (months), Sex, Mother's education, Area										
b. Dependent Variable: Child's weight (kilograms)										

Table 3

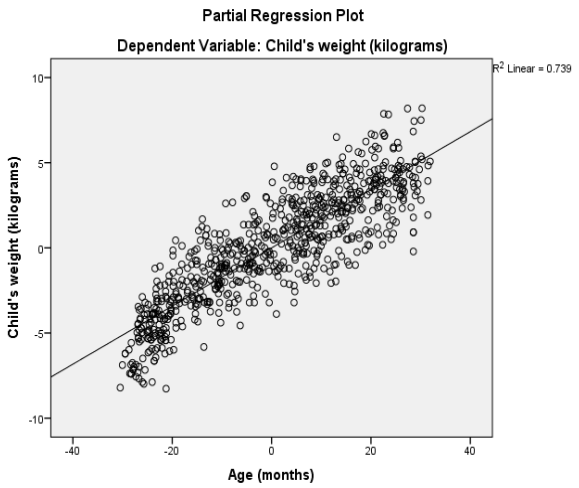


Fig 3a

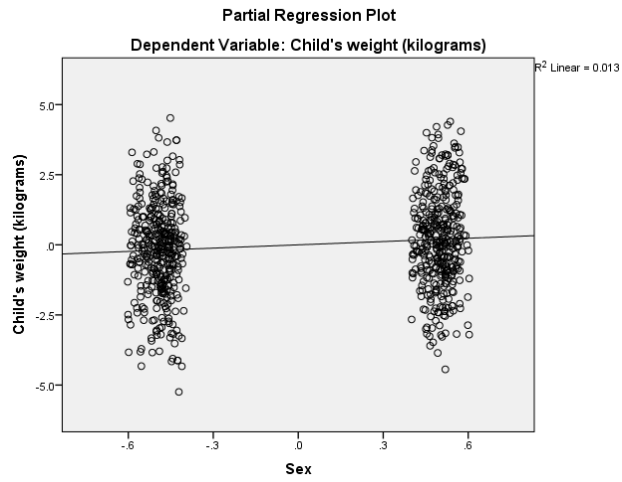


Fig 3b

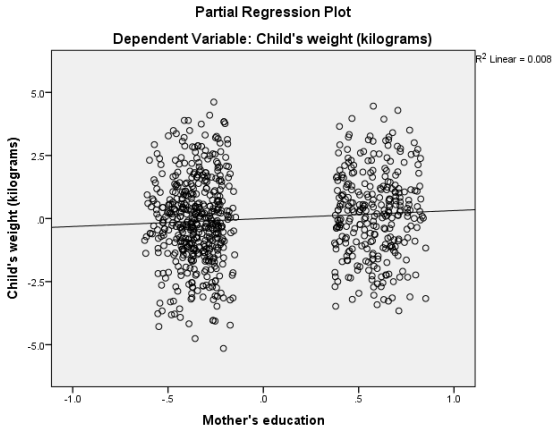


Fig 3c

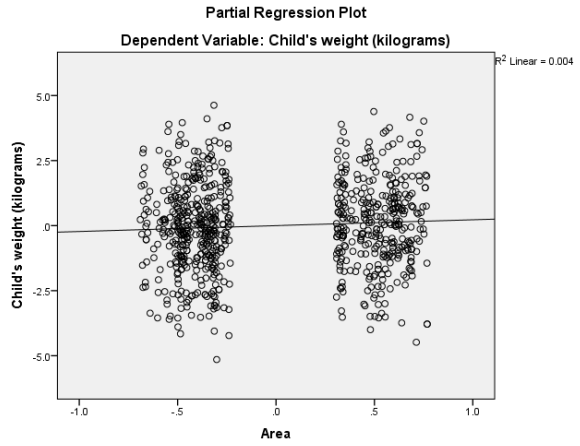


Fig 3d

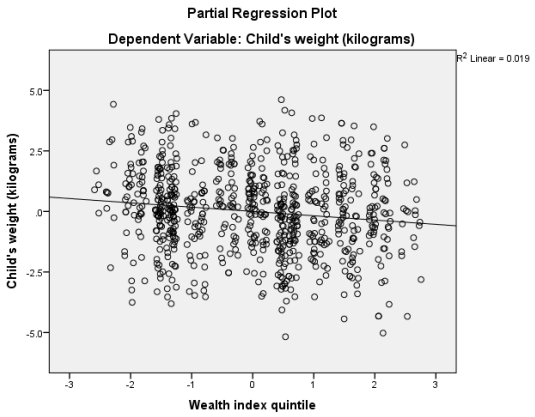


Fig 3e

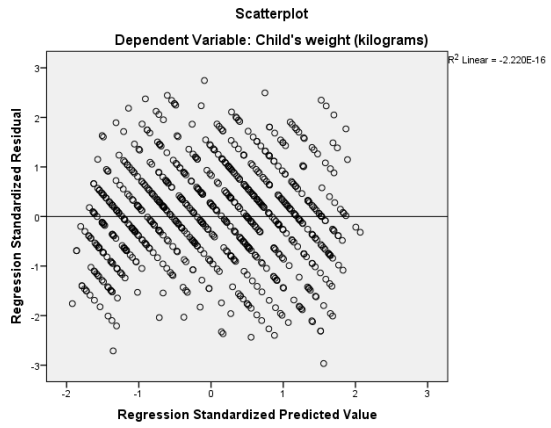
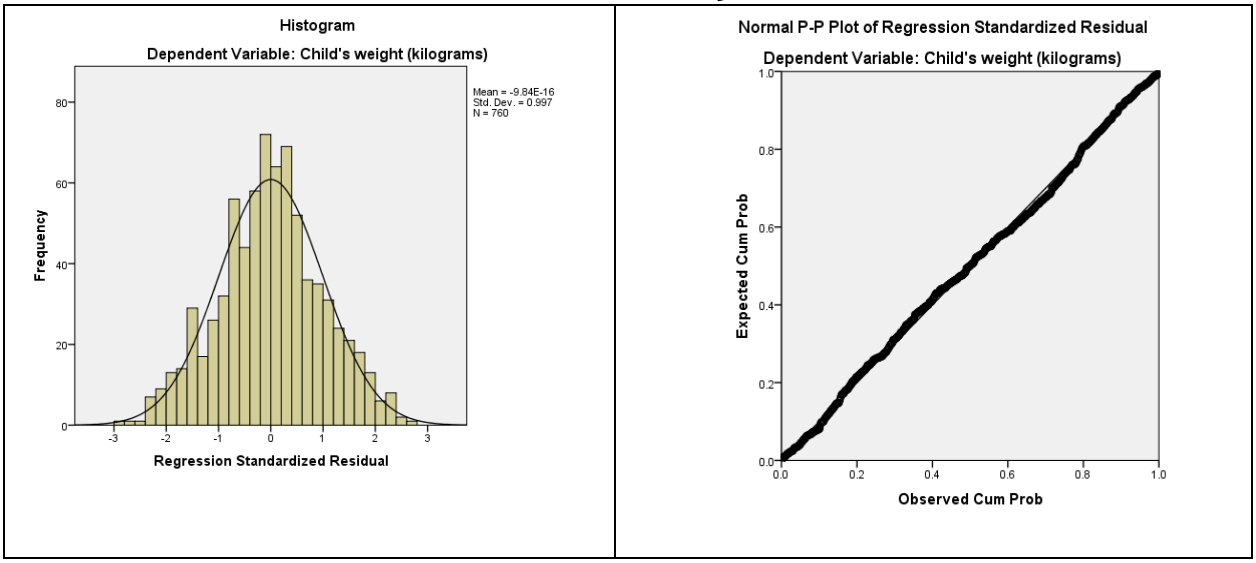


Fig 3f

Table 4

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
	(Constant)	6.543	.200		32.758	.000	6.151	6.935		
	Age (months)	.171	.004	.857	46.172	.000	.163	.178	.994	1.006
	Sex	.391	.125	.058	3.136	.002	.146	.636	.991	1.009
	Mother's education	.316	.132	.046	2.389	.017	.056	.575	.938	1.066
	Area	.226	.129	.033	1.747	.081	-.028	.479	.936	1.069
	Wealth index quintile	-.178	.047	-.073	-3.773	.000	-.270	-.085	.914	1.094
a. Dependent Variable: Child's weight (kilograms)										

Table 5



Regression Results

The correlation coefficient (0.861) between the observed and predicted values of the dependent variable(child weight) suggests a strong positive correlation. R-squared (0.742) represents the proportion of variance in the dependent variable explained by the independent variables. Here, 74.2 per cent of the variability in childweight is explained by the predictors in this model, indicating a good fit. The adjusted R^2 accounts for the number of predictors in the model, adjusting for potential over fitting. With an adjusted R^2 of 0.740, the model still explains around 74 per cent of the variance after considering the number of predictors, suggesting a robust fit. Standard Error of the Estimate (1.712) represents the average distance that the observed values fall from the regression line (See Table 2).

Change Statistics

R Square Change (0.742) translates as the amount of variance explained by the model. Since this is the only model tested, it is identical to R^2. The F statistic tests the overall significance of the model, with such a large F-value (433.391) and a Sig. F Change of 0.000, the model is statistically significant, indicating that at least one of the predictors is meaningfully associated with child weight.

Predictor Variables

Table 4 presents the estimated and standardised coefficients, standard errors, 95 per cent confidence level and p-values for each variable. Key findings include: Age has a positive association with child weight, as expected, due to natural growth and development (β_1 = 0.171 and p = 0.000). Gender has a statistically significant effect on child weight in this sample ($p < 0.05$). The parameter associated with gender shows a positive value β_2 = 0.391, which suggests that gender may be an important factor to consider when analysing child weight in this sample. Mothers' education has a statistically significant association with child weight (p = 0.17 less than 0.05) and a positive parameter (β_3 = 0.316), indicating that the more the mother gets educated, the higher the child's weight. The area has a positive parameter (β_4 = 0.226), indicating that the area correlates with higher child weight. A p-value of 0.081, which is greater than 0.05, indicates that the area did not have a statistically significant effect on child weight in this sample. A negative parameter (β_5 = - 0.178) shows that lower wealth

correlates with higher child weight. A p-value of 0.000, which is less than 0.05, indicates a statistically significant association with child weight.

Thus, the multiple linear regression model equation, predicting a dependent variable $\hat{Y}$ based on the several independent variables: Age, Sex, Mother's Education, and Wealth Index Quintile, is as follows;

$$\hat{Y} = 6.543 + 0.171\,(Age) + 0.391\,(Sex) + 0.316\,(Mother's\ education) - 0.178\,(Wealth\ index\ quintile)$$

Discussion

This study's analysis identifies age, gender, wealth and mother's education as significant predictors of child weight, aligning with existing literature that highlights the importance of socioeconomic resources and maternal education on child health outcomes. The Standardised Coefficients (Beta) provide a way to compare the relative impact of each predictor by standardising them on the same scale. Age (0.857) has the largest beta value, indicating it has the strongest effect on child weight relative to the other variables, whilst the wealth index quintile (-0.073) has a smaller beta value but is still statistically significant, showing a weaker inverse effect on child weight.

These findings underscore the importance of addressing socioeconomic inequalities and promoting maternal education as a means of improving childhood nutritional outcomes. Limitations of this study include its cross-sectional design, which limits causal inference, and the potential for unmeasured confounding factors. Future research could examine additional factors, such as dietary habits or health service access, and employ longitudinal methods for a deeper understanding.

5.0 CONCLUSION AND RECOMMENDATIONS

Conclusion: This study reveals that age, gender, household wealth and mother's education significantly influence child weight, emphasising the role of socioeconomic and educational interventions in public health strategies. The model identifies age as the most significant predictor of child weight, followed by sex and mother's education with smaller but significant effects. Wealth index quintile shows a weak but significant negative association, while area does not significantly predict child weight.

Recommendations: Public health programs which focus on age-appropriate nutritional support to ensure healthy growth patterns. Nutrition and activity programs that address gender variations effectively. Enhance educational opportunities for mothers, particularly about child nutrition and health, that can positively impact child weight outcomes. Programs targeting urban and rural settings that address the unique challenges faced in each area can be initiated. Policies that promote balanced nutrition and healthy practices across all economic strata should be made to address wealth disparities. Thus, by focusing on age, gender, wealth, maternal education, and area of residence, interventions can better support healthy weight development in children across different socioeconomic and demographic contexts.

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