FACTORS ASSOCIATED WITH STUNTING AMONG UNDER-FIVE YEAR OLD CHILDREN IN KENYA: A MULTILEVEL LOGISTIC REGRESSION APPROACH

EDITH AMONDI OLUOKO
PHONE NO. 0726 754749
EMAIL: amondiedith25@gmail.com

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DECLARATION

In submission of this thesis, I **Edith Amondi Oluoko** do certify that the work is original and has not been presented elsewhere in partial fulfilment for a degree. Having understood the rules of plagiarism and penalties that come with violation of rules, I declare that I am the original author of this work and other authors' work have been properly acknowledged.

Signature: .   Date: **7th Nov 2021**

SUPERVISORS

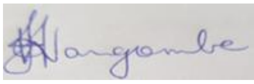
This research project has been submitted with approval from the University of Nairobi supervisors'

1. Signature:  Date: 8th November 2021

   Dr. Joseph Mung'atu

   Senior Lecturer

   Jomo Kenyatta University of Agriculture and Technology

2. Signature:  Date: 8th November 2021

   Ms. Ann Wang'ombe

   Senior Lecturer

   University of Nairobi, School Mathematics

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LIST OF ABBREVIATIONS

AAR	Annual Average Rate of Reduction
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DHS	Demographic and Health Survey
EA	Enumeration Area
GDP	Gross Domestic Product
GEE	Generalized Estimating Equations
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Models
HAZ	Height for Age Z score
ICC	Intercluster Correlation Coefficient
KDHS	Kenya Demographic and Health Survey
KNH/UON ERC	Kenyatta National Hospital/ University of Nairobi Ethics Review Committee
MLR	Multilevel Logistic Regression
MOR	Median Odds Ratio
NASSEP V	Fifth National Sample Survey and Evaluation Program
OLR	Ordinary Logistic Regression
RILR	Random Intercept Logistic Regression
SAS	Statistical Analysis Software
SDG	Sustainable Development Goals
SPSS	Statistical Package for Social Sciences
SSA	Sub Saharan Africa
UNICEF	United Nations Children’s Fund

WHO	World Health Organization

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DEFINATION OF OPERATIONAL TERMS

Anthropometric Measurements- quantitative measurements of the body these include; height, weight and age.

Birth Order – the length of time (months) between the birth that preceded the birth of the child in question. In case of multiple under five children in one household, for each child it refers to the length of time between the births of child who preceded the one whose measurements are being recorded.

Birth Weight – refers the child's weight recorded at birth in kilograms

Malnutrition- lack of proper nutrition; having insufficient or excessive nutrients in the body as a result of lack of sufficient or failure of the body to utilize the nutrients adequately.

Residence – in this context it refers to stratification of counties into either rural or urban types of respondents permanent dwelling places.

Stunting – A child whose height for age Z-score is below minus two standard deviations (2SD) from the median of the WHO reference population are considered stunted (short for their age) implying chronic malnutrition. Stunting reflects deprivation of adequate nutrition over a long time and is affected by recurrent infections and chronic illnesses.

Safe sources of drinking water: include piped water into the house, yard, or plot; a public standpipe/tap or borehole; a protected spring water or protected well; bottled water; and rainwater. Lack of easy access to an improved water source may limit the quantity of suitable drinking water that is available to a household as well as increase the risk of illness (Kenya National Bureau of Statistics, 2014).

Unsafe sources of drinking water: increase the spread of waterborne disease and the burden of service delivery through increased demand for health care; these sources include unprotected wells or springs, water delivered by tanker trucks, and surface water(Kenya National Bureau of Statistics, 2014)

ABSTRACT

Background: Stunting remains a global public health problem affecting millions of children. Stunting refers to growth retardation because of food deprivation or recurrent infections that tend to put a child at higher risk of illness or death. Stunting not only affects the health of individual in childhood but also has long term effects including; elevated risk of nutrition-related chronic diseases, low intellectual quotient, loss of productivity, and consequently poverty. Whereas significant efforts have been made towards reducing stunting in children under five, the rate of reduction remains slow in developing countries. Prevention of stunting in under five-year old children requires a multi-sectoral approach with a clear understanding of how certain factors play in different contexts. Most researchers in the past have studied stunting using the ordinary logistic regression even though most of the data used is complex survey data that may exhibit clustering in observations requiring the use of multilevel logistic regression to account for clustering.

Study Objective: To determine factors associated with stunting among under five children in Kenya using the most suitable regression model

Methodology: The study was a cross-sectional study design to examine factors associated with stunting among children under- five years in Kenya. The study used historical survey data from Kenya National Bureau of Statistics. The Kenya Demographic and Health Survey 2015 historical data was used. The study will use a total sample size of 18,582 which was collected from across the country using multi-stage sampling technique. Data was collected using household questionnaires and the nutrition status of children was recorded by measuring the height and weight of children 0-59 months. The ordinary logistic and multi-level logistic regression models which takes care of inter-correlation were fitted to select the best model for assessing factors associated with stunting. The Akaike Information Criterion (AIC) and Bayesian Information Criterion were used to select the best regression model.

Results: The study had a total sample of 18,582 children aged 0-59 years. The estimates obtained using the ordinary logistic regression and the multilevel had negligible variation. Regression results revealed that the chances of stunting increased with age, with highest rate among children aged 24-35 months relative to those aged between 0-5 months (OR =7.02, 95%CI (5.37-9.18)). Female children were found to have lower odds of stunting relative to male children (OR =0.665, 95%CI (0.61-0.73), p-value=0.000). Children whose birth weight was average or above average were found to have lower odds of stunting than those born underweight (OR =0.43, 95%CI (0.34-0.55). The preceding birth interval of less than 24 months increased the chances of a child being stunted compared to first birth (OR=1.54, 95%CI (1.29-1.84), p-value=0.000). Other factors found to have strong association with stunting include; mothers BMI, sanitation and wealth quintiles.

Conclusion: Findings in this study provide information on the use of multilevel logistic regression and the ordinary logistic regression in modelling stunting among children using complex survey data. Regardless, of the model used, relevant authorities and stakeholders involved in nutrition health policy formulation and implementation processes should design programs that are need specific and address the root causes of stunting such as empowerment to improve households' living standards.

1. CHAPTER ONE

INTRODUCTION

1.1. Study Background

Undernutrition in children remains a global health challenge affecting millions of children across the globe. Undernutrition not only impacts the health, growth, and wellbeing of a child but also may result in irreversible long term negative impacts on health and social wellbeing during adulthood (Guide, 2012). Stunting is a key indicator used to measure undernutrition in children aged five years and below. According to WHO, stunting refers to growth retardation as a result of food deprivation or recurrent infections that tend to put a child at higher risk of illness or death (Guide, 2012). A child whose height relative to age is less than minus two standard deviations from the WHO child's growth standard reference median is classified as stunted. Stunting has been cited as a significant cause of morbidity during the early stages of life. The long term consequences of stunting include; elevated risk of nutrition-related chronic diseases, low intellectual quotient, loss of productivity, and consequently poverty (Dewey, 2016), among others. Additionally, Black et al. (2008) assert that stunted children tend to gain weight rapidly after the age of two, which increases the risk of childhood obesity.

Global efforts to address undernutrition in children aged five years and below have been made; however, challenges persist. Even though the prevalence of stunting has been decreasing globally, it remains high in most low and middle-income countries. Data from UNICEF show that the incidence of stunting had reduced globally from 32.5% in the year 2000 to 21.9% by 2018. Currently, stunting affects approximately 149 million children globally, which is a significant decline from the estimated 198.2 million in the year 2000 (Unicef/ WHO/The World Bank, 2019). The rate of decline in most middle and low-income countries has been slow despite many interventions having been put in place. According to the KDHS 2015 survey, the prevalence of under-five stunting was estimated at 26%.

Identifying the actual cause of stunting is not straight forward. According to Heinn & Hoa (2009), this cannot be achieved by simply regressing the proxy determinants against the outcome. According to the authors, some of the behavioural factors that affect nutrition are likely to be correlated with unobserved determinants of nutrition such as health knowledge and hence most authors have dwelled on distal determinants of malnutrition (Buisman et al., 2019). Studies in the past have examined a wide range of factors that influence stunting ranging from maternal health, socio-demographic, socio-economic, environmental, cultural practises and health related factors (Geberselassie, Abebe, Melsew, Mutuku, & Wassie, 2018). Some of the factors that have stood out to have association with stunting include; mothers level of education, mother's age, poor feeding practices, poor sanitation, infection, child sex, age, and wealth index (Geberselassie et al., 2018).

Prevention of stunting in under-five children requires a multi-sectoral approach with a clear understanding of how certain factors play in different contexts. Even though recent studies show that the prevalence of stunting is reducing, the rate of reduction is slow in most middle and low-income countries for SDG goal two of ending any form of malnutrition by the year 2030 to be realized. Most studies in the past have relied on ordinary logistic regression to understand the relationship between demographic, socio-economic, health factors, and the nutrition outcome, stunting. One of the critical assumptions of OLR is the independence of observations. This is not always the case with most household surveys. In real practice, children are always nested in families, families nested in communities, and communities nested in regions. If the assumptions for OLR are violated, the accuracy of the estimated coefficients is affected. In this paper, we explore the use of the generalized linear mixed model (GLMM), which takes into account the effect of the cluster and higher-level effects.

1.2. Problem Statement

Numerous studies have been done in the past in effort to understand the determinants of stunting among children aged five years and below. From the studies that have been conducted, sex, age, maternal level of education and maternal health are some of the key factors that have been identified to determine a child's nutrition status (stunting). In most cases, the data on study variables assessed are usually collected using multistage cluster sampling and therefore the normal logistic regression model may fail to capture clustering of observations in the event that clustering is not adequately factored in sampling. Failure to address clustering in complex survey data at either sampling stage or analysis can result to misleading information about the relationship between the outcome and the predictor/ independent variables.

1.1. Justification

In Kenya, the prevalence of stunting has been declining nationally, however, in some counties the prevalence still remains very high relative to the national prevalence of 26% estimated in 2014/2015 Kenya Demographic Household Survey. Many of the factors that influence stunting are linked to household or community level factors. The knowledge of how different factors that influence stunting in children play out in different levels is key in designing interventions programs that are tailored to meet specific need at the lowest level. The past studies have modelled factors associated with stunting without accounting for inter-class correlation and higher levels in data, a common phenomenon with household based survey data.

This study intends to model factors that influence stunting in children under five years using the most appropriate model between OLR and GLMM which takes into account the intercluster correlation and higher levels in the data. This study will give insight into factors associated with stunting and help fill research gap and could be used to influence nutritional health policies on prevention of stunting in under five children. Moreover, the study will add useful knowledge on statistical models best suited for studying stunting and could form basis for further research in this area.

1.2. Study Questions

1. Is there a difference between the use of Ordinary Logistic and the Multilevel Logistic Modelling of stunting among children under the age of five years old?
2. What are the socio-demographic and socio-economic factors that affect stunting using the appropriate model?

1.3. Broad Objective

To determine factors associated with stunting among under five children in Kenya using the most suitable regression model

1.3.1. Specific Objective

1. To model stunting among under-five year old children in Kenya using the Ordinary Logistic Model and Multilevel Logistic Model
2. To determine factors associated with stunting among under five children in Kenya based on the most appropriate logistic model

2. CHAPTER TWO

LITERATURE REVIEW

2.1. Current State of Stunting

Whereas the world is on course to end any form of malnutrition by 2030 (SDG), globally, stunting remains a public health problem affecting many children living in middle and low-income countries. The global report on the burden of malnutrition developed by UNICEF showed that in 2018, the prevalence of stunting globally was 22.2%, with approximately 150.8 million children affected (Unicef/ WHO/The World Bank, 2019). The prevalence of stunting has been slowly but steadily declining over the years, with a drop from 32.2% in the year 2000 to 22.2% by the year 2017 (Unicef/ WHO/The World Bank, 2019). The decline can be attributed to a number of efforts that have been made towards eradicating stunting. The fall has been at an annual average rate of reduction (AAR) of 2.3%, which is less than AAR of 3.9%, which is recommended by WHO to be able to eradicate stunting by 2030. In the year 2000, the number of stunted children was 198.4 million globally, and this has declined to 150.8 million. According to Kharas, Mcarthur, and Rasmussen (2018), only 44% of countries worldwide are achieving the SDG target of eradicating stunting by 2030.

The prevalence of stunting remains very high in southern Asia and Africa regions, with prevalence above 30% (WHO, 2018). Africa also registered a significant decline in the prevalence of stunting from 38% in the year 2000 to 30% in 2018 (WHO, 2018). Despite the decrease in the prevalence, the number of stunted children was reported to be increasing in Africa. Reports show that the number of stunted children in Africa increased from 50.3 million in the year 2000 to 58.8 million by the year 2018. In Eastern Africa, the prevalence of stunting declined from 45.8% in the year 2000 to 35.2% in 2018. Kenya has also made progress towards eradication of stunting in children under five. A situational report by UNICEF shows that the prevalence of stunting declined from 35% in the year 2009 to 26% in recent years. The decline in the prevalence of stunting can be attributed to combined efforts towards addressing the issue such as; scaling up of high impact nutrition interventions, community based programming and increase in GDP among others (UNICEF, 2017). A lot still needs to be done for Kenya to realize the SDG target of ending stunting by 2030. Development of effective intervention strategies to combat stunting is key to achieving targets.

2.2. Prevention of Stunting

By definition, stunting entails linear retardation of growth due to prolonged lack of adequate nutrient uptake. This leads to failure to meet bodily nutrient needs. Such poor nutrient uptake can also emanate from poor diet, substandard childcare practices, poverty, and recurrent illnesses that interfere with the utilization of nutrients. The permanent damage of the brain at the earliest stages of life as a result of insufficient nutrient uptake has been documented by scholars such as Iannotti, (2019), (*Nutrition and Brain Dev - Policy Implications.Pdf*, n.d.), Kapil & Bhavna (2002) and Cunnane & Crawford (2014).

Other studies such as Black et al. (2014) associate stunting with morbidity and mortality, delayed development, low intellectual capacity, and poor performance in school (Black et al., 2013). Hence, there is compelling evidence that the prevention of stunting in children goes beyond proper nutrition alone. The interventions must address other factors that lead to stunting. This necessitates the use of diversified models that capture solutions to each of these problems. A study conducted in West Africa by Agbadi et al. (2017) revealed that children aged between 6 and 11 months hardly access a diverse diet due to insufficient food and low levels of literacy (Agbadi, Urke, & Mittelmark, 2017). This supports the argument that communal and household factors are critical to the improvement of child nutrition (Goudet, Bogin, Madise, & Griffiths, 2019).

2.3. Child Factors

As stated earlier, the developing countries depict the highest level of stunted growth. It is vital to note that this is a substantial health and social problem. Notably, stunted children fail to meet the expected physical and mental development, and populations that have a high percentage of stunted children have a low likelihood of attaining optimal levels of intellectual and physical growth and development, as observed (Prendergast & Humphrey, 2014).This means that the probability of such children achieving the expected rates of productivity is lower than their non-stunted peers. The risk factors for stunting that are associated with the child can be present before and after birth.

First, fetal growth restriction and childhood nutrition, multiple births, and infection. Concerning the growth of the fetus, preterm births (parturition before the 37^{th} week of gestation), and fetal growth restriction (birth weight below the 10^{th} percentile for the term gestation) are the leading causes of stunting among children. Fetal growth restriction (FGR) contributes to 25% of the stunting cases (Danaei et al., 2016). Fetuses that do not receive sufficient food for more than the transient period cannot regain the momentum of growth despite the subsequent supplementary feeding. Given this, an increase in the length-for-age by one point at birth leads to a substantial decline of the risk of stunting between the first and second years of life (Prendergast & Humphrey, 2014). In light of this, the likelihood of stunting among multiple births (twins, triplets, quadruplets, and so forth) is higher than those born as singletons. This is because numerous births are associated with low birth weight, cerebral palsy, and congenital disabilities. To predict the probability of stunting, physicians use the measurement of length at birth.

The other child-linked factors that are associated with stunting are sex, age, nutritional status, and infections. Concerning the sex of the child, Derso et al. (2017) allege that baby boys have a higher likelihood of falling sick and dying under the same conditions than their female counterparts, especially when born early (Derso et al., 2017). This is because the rate of male infant growth is higher than that of females; hence, when malnourished, they are more likely to be stunted. It follows that the probability of male children becoming stunted is twice as high as those of females if they are undernourished when they are infants. Besides, the stunting occurs earlier in boys than girls. Additionally, stunting increases with age. According to Marriot et al. (2012), at six months, only 14% of the children are at risk of stunting. On the other hand, 46% of the stunting is likely to occur between 18 and 23 months (Marriott et al., 2012). This implies that the stunting incidences between 18 and 24 months are twice as high as that of 12 months.

Diarrhea and other diseases that exacerbate chronic malnutrition cause an upsurge in the rate of stunting. To minimize the risks of infections and nutrition issues is exclusive breastfeeding in the first six months of life. According to Grote et al. (2016), half and one-third of the energy requirement for babies at one year of birth and two years, respectively, is obtained from breastfeeding (Grote et al., 2016). The rest of the energy requirement must be supplied by complementary feeding with energy-dense foods. Failing to breastfeed children during the first six months, and discontinuing it before the child reaches two years increases the risk of stunting. Infections, including HIV and infant diarrhea, harm the growth potential of the child (Prendergast & Humphrey, 2014). Likewise, lack of minerals at infancy is also responsible for stunting among newly-born babies. Therefore, the sex of the child (male or female), age, length, and weight are the key variables of interest in the exploration of child stunting.

2.4. Maternal Factors

The key maternal factors that promote stunting among children are malnutrition, malaria, teenage pregnancy, and short intervals between births. In particular, stunting is widespread among children born by mothers whose body mass index is lower than 18.5 (Prendergast & Humphrey, 2014). Secondly, children born by mothers whose height is less than 160 centimeters and those with anemia are likely to be stunted compared to children from taller and non-anemic mothers (*Nutrition and Brain Dev - Policy Implications.Pdf*, n.d.). Mothers with such issues are expected to deliver children with low birth weight and infants with a length that is less than the 5^{th} percentile. Besides, the level of education and social status of the mother can influence stunting among children.

As indicated earlier, poor weaning and dietary practices promote stunting in children. Mothers with a high level of education have a higher understanding of proper nutrition and hygiene for the infant as it grows up, including adequate breastfeeding before weaning. Hence, they are more likely to prevent exposure to different kinds of infections and diarrheas diseases than their less educated peers (Vijayalakshmi & Susheela,D., 2015). Further, women from wealthier families have a higher capability of controlling stunting among their children because they can adhere to proper dietary intake at the critical age of the child, according to the World Health Organization (2013). The key maternal variables of interest are the health, weight, height age of conceiving, and birth intervals.

2.5. Environmental/Community factors

The surroundings in which the child grows play a critical role in the likelihood of being stunted. According to Prendergast & Humphrey (2014), an example of the environmental aspects which influence stunted growth among children is societal rate of literacy and poverty. Education is critical to understanding the importance of nutritional health for mothers and newborns. A society that is well educated and endowed with adequate resources can easily overcome the common health challenges that lead to stunted growth among the newborns and infants. By contrast, communities that are deficient of proper education and poorer find it challenging to overcome such problems. As an illustration, poor sanitation, which is linked to the unavailability of freshwater and facilities for toileting. Likewise, unhygienic food handling is common among less educated societies. The resultant ailments associated with low education and lack of resources such as diarrhea drain nutrients from the body of the child and cause stunting. Given this, currently, improper sanitation across the world is associated with 7 million diarrhea and 6 million stunting incidences.

As stated earlier, children that cannot access sufficient and balanced diet have higher odds of becoming stunted. This implies that the food insecurity, which is common among developing countries, is the other environmental cause of stunting. The available statistics indicate that the probability of stunting among children born in low-income families is three times higher than those found in the middle and upper-income brackets. The impact of food insecurity is amplified by family size and reduced access to healthcare services. Prendergast & Humphrey (2014) contend that when the family is large and poor, stunting is inevitable because the parents cannot afford sufficient food to meet the nutritional needs of every child. Besides, poverty limits the access to medical attention when necessary. It follows that the reduced access to healthy food, fresh drinking water, and low levels of education among parents and poor access to healthcare reinforce stunted growth in some societies. Today, the environment is the second leading cause of stunting in sub-Saharan Africa, South and South-East Asia, and Pacific regions (Danaei et al., 2016). Therefore, when looking into the environmental factors of stunting, the critical variables of interest are the residence of the children (urban or rural), the education, and the economic status of the parent (s).

2.6. Application of Generalized Linear Mixed Models in Modelling Stunting

Statistical models for clustered data should account for clustering in data at each level, otherwise the estimates may be biased thus resulting to misleading inferences. Clustered data arise from data recorded from multiple items within clusters or groupings. Examples of such data include; complex surveys, panel studies (with multiple times points within an observation) and family studies among others. In this study, complex survey data will be used to answer the study questions. Considering the fact that the sampling design in primary survey was multi-stage cluster survey, there is an expected level of clustering in the data and therefore the need to take into account clustering while modelling. There are different approaches of handling clustered data when using regression models, and these include; introduction of random effects and introduction of fixed effects in the model among others. Regression models that have additional random effects to the main effects to account for clustering in data are referred to as the mixed effects models. Mixed effects regression models for clustered data are commonly used approach in handling clustered data. In mixed effects regression model, introduction of random effects in the regression models allow models for clustered data to account for variability in the outcome around its mean by allowing variation across both levels of units (Fitzmaurice, n.d.). In an example of a two level mixed effects logistic model with random effects, a larger variation in the second level random effects relative to the first level variability, the higher degree of correlation/ clustering. The advantage of using random effects model in mixed effects regression analyses is that it requires fewer assumptions.

In regression analyses, model selection is key statistical aspect that enables researcher to choose a more parsimonious model from sets of models to better understanding of subject under study. According to Posada & Buckley (2004), a perfect model does not exist and all models are wrong. However, the authors assert that model selection should be seen as a way of approximating reality rather than identifying. There are a number of approaches used to select a model/ models over others and these include; Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and likelihood ratio tests (LRT) among others. In this study, the focus will be on BIC and AIC for model selection.

The BIC gives an approximation to the log maximum likelihood of a model, thus the difference between two estimates of the BIC may provide good approximation of the natural log of the Bayes factor (Posada & Buckley, 2004).The BIC is appropriate for models fit under the framework of maximum likelihood estimation. The BIC is considered to be consistent in model selection and with large sample sizes, it is guaranteed to select the best model if it's among the set of models subject to selection (Vrieze, 2012) .The model with the smallest BIC among a set of models is considered to be the best model. The BIC is computed as follows;

$$BIC = -2l + k\log(n)$$

Where; k is the number of estimated parameters in the model, n is the sample size and l is the log likelihood of the model.

Akaike Information Criterion (AIC) is another approach to model selection. The AIC is an asymptotically unbiased estimator of expected relative information quantity (Posada & Buckley, 2004) which represents the information lost when a model is used to approximate another model (Posada & Buckley, 2004). The AIC is designed to estimate predictive accuracy of competing models (Vrieze, 2012). The AIC for a given model is given by its maximum log-likelihood (l) and the number of estimated parameters (k);

$$AIC = -2l + 2k$$

Like the BIC, the model with the smallest AIC among a set of model is considered the best model. The AIC is constructed under the assumption that; all data sets are drawn from the same underlying process, the sample size is large enough to allow for approximation of its asymptotic properties and that with a large ample size the parameter estimates follows multivariate normal distribution. Notably, the BIC unlike the AIC penalizes model complexity more heavily which implies complex models will have high score making them less likely to be selected. In this study, both the BIC and the AIC of the three models will be computed and comparison made to identify the most appropriate model (model with the least AIC or BIC values depending on model complexity and assumptions of BIC and AIC).

The Intra-Cluster Correlation coefficient (ICC) is a measure of the degree of similarity of observations in clustered data. There are different methods of computing the ICC, all these basically compare the variation within the clusters to variation between the clusters. The ICC is given by;

$$ICC\ or\ \rho = \frac{Between\ cluster\ variation}{(Within\ cluster\ variability\ + Between\ cluster\ variation)}$$

The ICC value ranges from 0 to 1 with a higher value signifying high levels of similarity of individuals' observations within clusters. The ICC will be computed for the higher level regression models to evaluate the degree of similarity within clusters.

Generalized linear mixed models (GLMM) are extension of generalized linear models (GLM) which are commonly used to model clustered or hierarchal data with a dichotomous outcome. The use of generalized linear mixed model has been on the rise in public health research. One of the most recent review of the application of GLMM in modelling stunting was a study by Akter, Bhowmik, Das, & Hasan, (2019). In this study, the authors modelled the correlates of stunting using different regression models; Ordinary Logistic Regression (OLR), Generalized Estimating Equation (GEE) and GLMM with intent to compare and identify the best model for modelling correlates of stunting. From the three models fitted, the authors observed that some variables were not significantly associated with stunting using OLR but were significantly associated with stunting using the Random Intercept Logistic Regression (RILR) which is a special case of GLMM (Akter et al., 2019). A comparison of the models using the AIC revealed that the RILR model was the best in modelling correlates of stunting (Akter et al., 2019). Another study by Sultana et al. (2019) used GLMM to model the correlates of stunting in Bangladesh. In this study, the authors considered three models from the GLMM family to study the factors associated with stunting. The first model was a two level GLMM considering division as second level hierarchical factor, the second considered residential status as second level hierarchical factor while the third model was a three level GLMM considering residential status as third level and division as the second level hierarchical factors (Sultana et al., 2019). This study revealed that the three level model with residence as the third and division as the second model respectively was the best model based on the AIC and BIC having the least value of each among the set models (Sultana et al., 2019). Results from the study were consistent with other studies; child age, sex, birth interval, mother level of education, and wealth quintile were found to be strongly associated with stunting. Kim, Mejía-Guevara, Corsi, Aguayo, & Subramanian, (2017) conducted a study to highlight the relative importance of 13 correlates of child stunting in South Asia. The study was a cross-sectional study with data from four countries namely; Bangladesh, India, Nepal and Pakistan. In this study, country was considered fixed effects in the regression model (Kim et al., 2017). The results from this study showed that mothers' BMI, mothers' level of education and wealth quintiles were significantly associated with stunting in all the four countries among other variables (Kim et al., 2017). Akombi et al., (2017) recently examined stunting and severe stunting in Nigeria using multilevel analysis. A generalized linear latent and mixed model (GLLMM) was employed to determine factors significantly associated with stunting. In this study, the authors modelled factors associated with stunting among children under five using a five staged conceptual modelling technique (Akombi et al., 2017). A manual stepwise backward elimination technique was used to retain only variables that were significantly associated with the outcome variable. In the second stage, the socio demographic variables were added and so on. Lastly, the environmental factors were added by retaining the p values at each stage. The community level factors; residence and geopolitical zones, socio demographic factors; wealth quintile, mothers' level of education and environmental factors - source of drinking water - were found to be significantly associated with stunting. Proximate determinants; mothers' age and BMI and delivery factors were found to be associated with stunting (Akombi et al., 2017). Child factors; sex, birth order and size at birth all remained significantly associated with stunting in the parsimonious model.

3. CHAPTER THREE

METHODOLOGY

3.1. Introduction

This section presents the study context, describes the design, and elaborates the data sets that will be used in the study alongside the sampling strategy employed. The section also gives a detailed description of variables of interest, data management and the analysis methodologies with a focus on comparison of regression models, the OLR and multilevel logistic regression (MLR) to study factors associated with stunting.

3.1. Study Area

The study is based on past KDHS 2014 data which was a nationally representative sample drawn across the country and therefore the study area is Kenya. The country is divided into 47 counties which are stratified by urban or rural except for Nairobi and Mombasa counties. From each county, representative sample of households were drawn.

3.2. Study Design

The study used secondary data from the Kenya Demographic and Health Survey (KDHS) 2014 which is a nationally representative survey conducted by the Kenya National Bureau of Statistics (KNBS). The study adopted an analytical cross-sectional study design to look into the factors that are associated with stunting among children under the age of five years in Kenya.

The secondary data used in this study was collected from a representative sample of households across all the 47 counties by teams of trained staff in the primary study. The household questionnaire was administered to collect information on characteristics of the households, household members' information and to record height and weight of children under the age of five and women aged 15-49 years old. Trained field staff collected data on nutritional status of children aged 0-59 months by measuring the height and weight.

3.3. Study Population

The study target population comprised children aged between 0-59 months old who were living in Kenya at the time of the primary survey. Anthropometric measurements were taken from each child living in the preselected households for interviews. A representative sample of children aged between 0-59 months was obtained from the population across counties in Kenya.

3.3.1. Inclusion Criteria

All children under the age of five whose caretakers were interviewed, and anthropometric measurements taken during the time of survey

3.3.2. Exclusion Criteria

Children whose anthropometric measurements were not recorded during the time of the KDHS 2014 survey were excluded from this study.

3.4. Sampling Method

The study used the KDHS 2014 data which was drawn using multi-stage sampling. The sample for the KDHS 2014 was drawn from the Fifth National Survey and Evaluation Program (NASSEP V) master sampling frame. This sampling frame contains a total of 5,360 clusters divided into four equal sub samples which were drawn from 96,251 enumeration areas (EAs) in 2009 Kenya Population and Housing Census using stratified probability sampling proportional to size sampling methodology. KDHS 2014 used two sub samples of the NASSEP

V sampling frame. In the NASSEP V frame, each of the counties were stratified into urban and rural except for Mombasa and Nairobi counties resulting into a total of 92 sampling strata.

The KDHS was designed to provide representative estimates for most survey indicators at the national, urban areas, rural areas, and regional for selected indicators at county level. The sample for the KDHS 2014 was designed to include 40,300 households from a total of 1,612 clusters spread across the country with a total of 617 and 995 clusters in urban and rural areas respectively.

A two staged sampling design was used to independently select samples in each sampling strata. The primary sampling unit was the enumeration areas. A total of 1,612 enumeration areas were selected with equal probability from the NASSEP V frame. For the second stage sampling, the household listing served as a sampling frame in which 25 households were selected from each cluster. Data was collected from the preselected households without replacement using structured questionnaires.

3.5. Sample Size Determination

The study used all the data for under five children in the KDHS 2014/2015 which had a total of 18,582 children who were present in the sampled households during the time of survey.

The final sample size formula for the DHS survey was given by;

$$n = \mathrm{Deft}^2 \times \frac{(1/P - 1)}{\alpha^2} \Big/ (R_i \times R_h \times d)$$

Where;

n is the sample size in households;

Deft is the design effect (a measure of variability in estimation of parameters of interest resulting from the sample design relative to estimates that would have been gotten from the sample size obtained by simple random sampling. The DHS program specifies that a default value of 1.5 should be used if deft is not specified);

P is the estimated proportion;

α is the desired relative standard error;

R_i is the individual response rate;

R_h is the *household gross response rate*; and

d is the number of eligible individuals per household

3.6. Study Variables

The variables in this study include;

3.6.1. Dependent variable

The dependent variable is stunting (HAZ) which is classified using the WHO 2006 standards based on the anthropometric measurements developed by UNICEF.

3.6.2. Independent Variable

The independent variables for the OLR and multilevel logistic regression models are; age of child, sex, weight at birth, preceding birth interval, mothers' level of education, mothers' BMI, mothers' age, wealth quintile, improved sanitation, source of drinking water, residence and region.

Factors

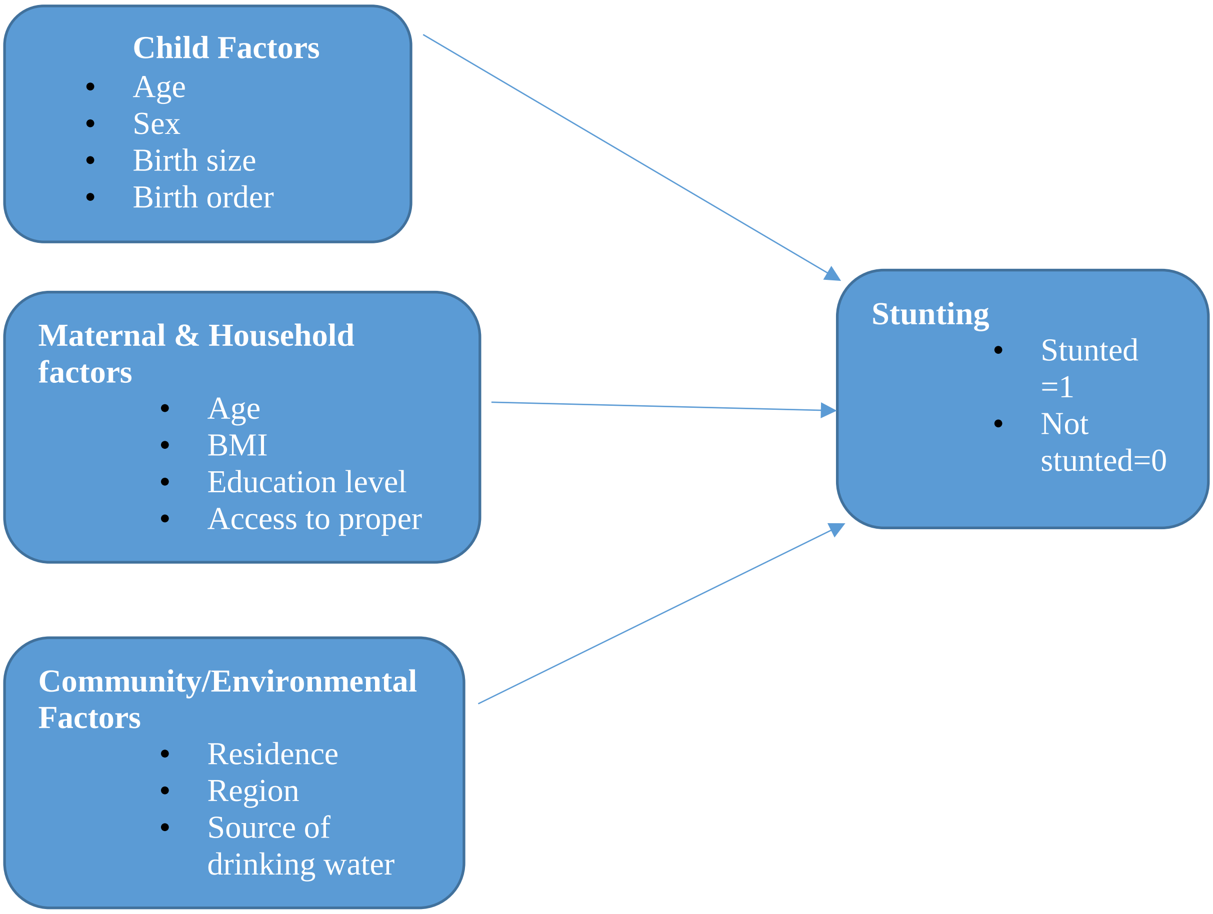

Figure 1 Conceptual Framework

The conceptual framework demonstrates various variables and their associated elements under exploration. The study theorizes that each of the variables works alone or in combination to bring about stunted growth in children. The first independent variable is child-linked factors. The elements that are under these variables include the child's age, sex, birth weight, and order of birth. The study posits that children that are increasingly younger are increasingly vulnerable if subjected to factors that trigger stunted growth, such as inadequate dietary intake.

Regarding gender, males are more prone to stunting than female children. Concerning the birth weight, children that do not meet the standard weight at birth, and those that are poorly spaced are more vulnerable to stunting and vice versa. The second variable encompasses the maternal factors, which comprises of the mother's age, body mass index, level of education, and access to proper sanitation facilities. The study adopts the idea that children born by teenagers and mothers with low BMI are prone to stunting. Additionally, more educated mothers are likely to observe proper diet to prevent stunting in their children relative to their less-educated counterparts. Also, mothers who can access sanitation facilities such as toiletries can curb stunting because they can control ailments that lead to diarrhoea and, consequently, loss of nutrients in their children. The last variable entails the surrounding or community factors, including the residence and sources of drinking water for the children. Here, the key elements that are in focus include the ability of parents to access a balanced diet for their children, freshwater, and sanitation. Here, this research theorizes rural residency and access to clean water as the key factors that promote stunted growth. Notably, this variable is closely linked with maternal factors since it incorporates access to facilities and resources.

3.7. Data Collection

The study used secondary data available in the DHS program website with permission from the relevant authorities. DHS data is obtained from the website by first registering as a user then making an official request for data detailing the purpose and analyses to be carried out. Upon approval, permission to download data is granted and data can be downloaded as zipped files in formats suitable to the user (STATA, flat files, SPSS and SAS). For this study, permission to use data was sought after research approval by the KNH/UON ERC. A form was filled on the DHS website online detailing the variables of interest and data downloaded as STATA data files. For this study, the KDHS 2014 data was screened for children aged between 0-59 months old whose height and weight were available.

3.8. Data Management and Analysis

Data was downloaded in STATA format. Data cleaning, coding and analysis was carried out using STATA version 15. Preliminary (exploratory) data analysis was used to summarize the data. These are presented using bar graphs and tables.

The OLR and multilevel logistic regression models (MLRM) were used to explore the association between stunting and independent variables included in the study. The AIC, BIC and ICC were used to decide which regression model best fitted the data (association between stunting and factors that affect stunting among children under five years). The odds ratios together with their corresponding p-values and confidence intervals will be reported for both models.

Regression models to be used;

Model 1; $ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots \dots \dots \dots .. \beta_k X_k$

Model 2; $ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots \dots \dots \dots .. \beta_k X_k + U_i$

Model 3; $ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots \dots \dots \dots .. \beta_k X_k + U_j$

Where;

p= probability that a child is stunted

U_i- Random effects at first level

U_j- Random effects at second level

β – Coefficients representing the effect of each independent variable on the dependent

X – Independent variables

3.9. Ethical Considerations

Considering that the data used in this study was secondary, the ethical issue that may have been associated with this study is breach of confidentiality. To ensure confidentiality, passwords were used to access data. Additionally, data for this study was used with exclusive permission from the relevant authorities (DHS Program and KNH/UON ERC) and the use of data was based on strict adherence to DHS Program data use policy. A waiver for individual consent was sought from the KNH-UoN ERC because the study was based on secondary data already available in the public domain.

3.10. Study Limitations

There were no major setbacks in sampling or data quality in this study considering data used was already available in the public domain and could be obtained easily upon request. However, failure to control for confounders and inclusion of other factors that are well known to be associated with stunting such us biological makeup, diseases and household food security may be limiting to the findings in this study.

4. CHAPTER FOUR

RESULTS

4.1. Descriptive Summary of Study Variables

Table 1 below gives summary statistics of study variables. A total of 18,582 children aged between 0-59 months were included in the study of whom 9173 (49.4%) were female and 9409 (50.6%) were male.

Table 1: Summary Statistics of Study Variables

Characteristics	Total (%)	Not Stunted (%)	Stunted (%)
Age Group			
<6 months	1713 (9.2)	1567 (91.5)	146 (8.5)
6-11 months	2007 (10.8)	1783 (88.8)	224 (11.2)
12-23 months	3881 (20.9)	2898 (74.7)	983 (25.3)
24-35 months	3781 (20.3)	2328 (61.6)	1453 (38.4)
36-47 months	3814 (20.5)	2473 (64.8)	1341 (35.2)
48-59 months	3386 (18.2)	2341 (69.1)	1045 (30.9)
Child Sex			
Male	9409 (50.6)	6494 (69.0)	2915 (31.0)
Female	9173 (49.4)	6896 (75.2)	2277 (24.8)
Preceding birth interval			
First birth	4109 (22.1)	3143 (76.5)	966 (23.5)
<24 months	2679 (14.4)	1742 (65.0)	937 (35.0)
24-47 months	7463 (40.2)	5176 (69.4)	2287 (30.6)
>=48 months	4296 (23.1)	3309 (77.0)	987 (23.0)
Birth Weight			
Below average	384 (4.00)	231 (60.2)	153 (39.8)
Average and above	8571 (96.0)	6230 (72.7)	2341 (27.3)
Mothers' Age			
<=24 years	5235 (28.2)	3823 (73.0)	1412 (27.0)
25-34 years	9441 (50.8)	6800 (72.0)	2641 (28.0)

Characteristics	Total (%)	Not Stunted (%)	Stunted (%)
>=35 years	3906 (21)	2767 (70.8)	1139 (29.2)
Mothers' BMI			
Underweight	1083 (12.1)	735 (67.9)	348 (32.1)
Normal	5562 (62.2)	3902 (70.2)	1660 (29.8)
Overweight	1665 (18.6)	1291 (77.5)	374 (22.5)
Obese	634 (7.1)	525 (82.8)	109 (17.2)
Level of Education			
No education	4060 (21.8)	2826 (69.6)	1234 (30.4)
Primary	9834 (52.9)	6767 (68.8)	3067 (31.2)
Secondary	3534 (19.0)	2800 (79.2)	734 (20.8)
Higher	1154 (6.2)	997 (86.4)	157 (13.6)
Sanitation			
Unimproved	15031 (80.9)	10593 (70.5)	4438 (29.5)
Improved sanitation	3546 (19.1)	2793 (78.8)	753 (21.2)
Source of drinking water			
Unsafe water	7422 (39.9)	5020 (67.6)	2402 (32.4)
Safe water	11153 (60.0)	8367 (75.0)	2786 (25.0)
Wealth Quintile			
Poorest	6434 (34.6)	4190 (65.1)	2244 (34.9)
Poorer	3936 (21.2)	2699 (68.6)	1237 (31.4)
Middle	3120 (16.8)	2316 (74.2)	804 (25.8)
Richer	2714 (14.6)	2132 (78.6)	582 (21.4)
Richest	2378 (12.8)	2053 (86.3)	325 (13.7)
Residence			
Urban	5836 (31.4)	4548 (77.9)	1288 (22.1)
Rural	12746 (68.6)	8842 (69.4)	3904 (30.6)
Region			
Coast	2330 (12.5)	1607 (69.0)	723 (31.0)
North eastern	1362 (7.3)	1013 (74.4)	349 (25.6)
Eastern	2770 (14.9)	2000 (72.2)	770 (27.8)
Central	1281 (6.9)	1014 (79.2)	267 (20.8)

Characteristics	Total (%)	Not Stunted (%)	Stunted (%)
Rift valley	6105 (32.9)	4223 (69.2)	1882 (30.8)
Western	1766 (9.5)	1299 (73.6)	467 (26.4)
Nyanza	2537 (13.7)	1888 (74.4)	649 (25.6)
Nairobi	431 (2.3)	346 (80.3)	85 (19.7)

A significant proportion of children aged 25-35 months and 36-47 months were found to be stunted by 38.4% and 35.2% respectively. Among the children included in the study, 2% were born below the average birth size of whom a proportion 39.8% were found to be stunted. Majority of the mothers were aged between 25-34 years at the time of birth constituting 50.8% of the total sample. About 22% of the mothers did not have formal education while majority (52.9%) had completed primary level of education and 19% completed secondary level. Most mothers were found to have normal BMI (62.2%) while 18.6% were overweight and 7% obese. Majority of the respondents were from households without improved sanitation (80.9%). Sixty eight percent of the respondents were from the rural areas while 31.4% were from the urban dwelling. Results showed that stunting differed significantly by residence and region. Majority of children found to be stunted were from rural setting (30.6%). Among the five regions, most children included in the study were from Rift Valley and Eastern regions constituting 32.9% and 14.9% to the total sample respectively. Coast province had the highest proportion of stunted children (31%) followed by Rift Valley region (30.8%). Figure 1 below gives a summary of stunting by region.

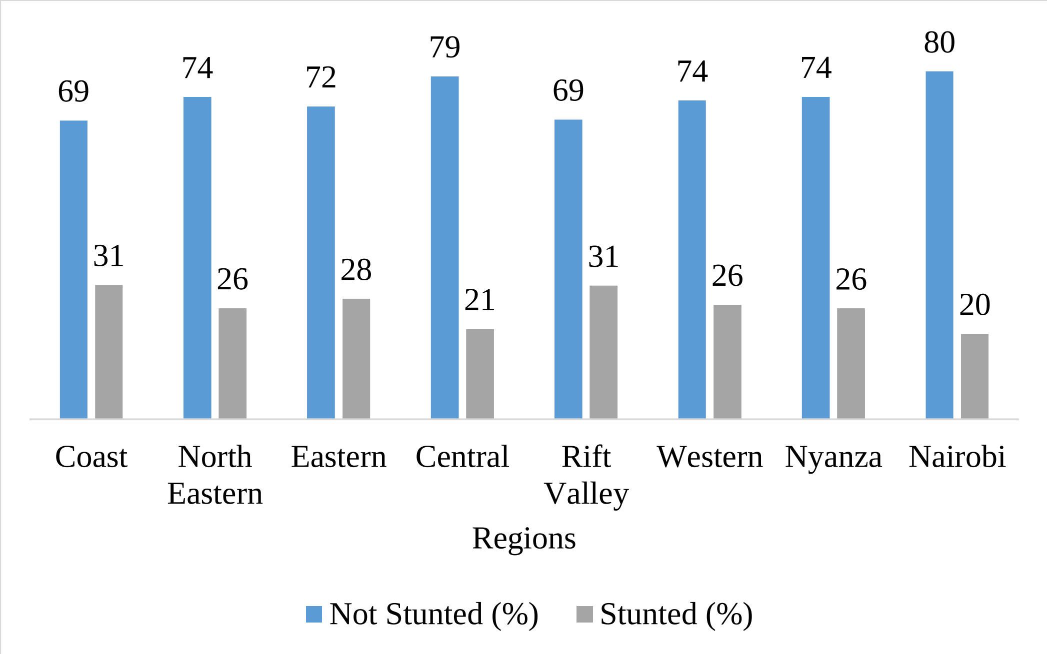

Figure 2: Prevalence of Stunting by Region

4.2. Generalized Regression Models

Table 2 presents results from one ordinary logistic regression (OLR) and two multilevel generalized liner regression models (MGLM) from binomial family of distribution with logit link to stunting (nutrition status of children aged 0-59 months). From the results model III of the MGLR model was the best model going by the Akaike Information Criterion (AIC), Interclass Correlation Coefficient (ICC) and the Bayesian Information Criterion (BIC). Model III had the least AIC (9587.72) and the least BIC of (9772.14) relative to model II of the MGLR. Comparing the second model of the multilevel generalized linear model with results obtained from the OLR model, the estimates for the factors associated with stunting do not differ greatly however, the MGLM gave more precise estimates with narrower confidence intervals for some estimates.

Using model III, results indicated that the odds of stunting among children increased with age with highest OR in the age bracket of 24-35 months (OR =7.02, 95%CI (5.37-9.18), p-value=0.000) and the age bracket 36-47 months (OR=6.46, 95%CI (4.93-8.46), p-value=0.000) after adjusting for the other variables in the model. Child's sex was found to be significantly associated with stunting. Female children were found to have lower odds of stunting relative to male children (OR =0.665, 95%CI (0.61-0.73), p-value=0.000) after controlling for the other variables in the model. Children whose birth weight was average or above average were found to have lower odds of being stunted than children who had below average weight at birth (OR =0.43, 95%CI (0.34-0.55), p-value=0.000) having adjusted for the other variables. The preceding birth interval in months was also found to be statistically associated with stunting particularly, an interval of less than 24 months increased the chances of a child being stunted compared to first birth (OR=1.54, 95%CI (1.29-1.84), p-value=0.000) after controlling for other variables.

There was no association between mothers' age category and stunting among children aged five years and below. Mothers' nutritional status as measured by the BMI was found to have statistically significant association with stunting. Children with overweight and obese parents were found to have lower odds stunting compared to those whose mothers had normal BMI. The odds of stunting among children whose mothers' were overweight was 0.79 (95%CI (0.68-091), p-value=0.001) and those whose mothers were obese 0.67 (95%CI (0.53, 0.85), p-value=0.001).

The household factors included in the model were sanitation, source of drinking water and wealth quintiles. All these factors were found to have statistically significant association with stunting after adjusting for the effect of other variables in the model. Children from households with improved sanitation were found to have lower odds of being stunted compared to children from households with poor sanitation (OR= 0.81, 95%CI (0.71-0.94), p-value=0.005). Similarly, children from households with safe sources of drinking water had lower odds of being stunted compared to those from families whose source of drinking water was considered unsafe (OR=0.90, 95%CI (0.81-0.99), p-value=0.059) after adjusting for the other variables, however this association was weak. Results shows that wealth quintile had a strong association with stunting. The odds of stunting decreased up the wealth quintiles relative to the poorest wealth quintile. Children from poorer households had 22% lower odds of being stunted than children from the poorest households (OR=0.78, 95%CI (0.67-0.90), p-value=0.001). Children from the richest households had 62% lower chances of being stunted compared to children from the poorest families (OR=0.38, 95%CI (0.30-0.48), p-value=0.000).

Table 2: Odds Ratios for the Factors Associated with Stunting

	Model 1		**Model 2**		**Model 3**	
Factors	**Odds Ratio**	**P>z**	**Odds Ratio**	**P>z**	**Odds Ratio**	**P>z**
Age Group						
0-5 months (ref)	1.0		1.0		1.0	
6-11 months	1.26 (0.91, 1.75)	0.158	1.26 (0.91, 1.75)	0.158	1.26 (0.91, 1.74)	0.162
12-23 months	3.83 (2.93, 5.02)	0.000	3.83 (2.93, 5.02)	0.000	3.83 (2.93, 5.02)	0.000
24-35 months	7.02 (5.37, 9.18)	0.000	7.02 (5.37, 9.18)	0.000	7.03 (5.39, 9.22)	0.000
36-47 months	6.46 (4.93, 8.44)	0.000	6.46 (4.93, 8.44)	0.000	6.46 (4.94, 8.46)	0.000
48-59 months	4.82 (3.67, 6.34)	0.000	4.82 (3.67, 6.34)	0.000	4.84 (3.69, 6.38)	0.000
Sex						
Male (ref)	1.0		1.0		1.0	
Female	0.66 (0.60, 0.73)	0.000	0.66 (0.60, 0.73)	0.000	0.66 (0.60, 0.73)	0.000
Preceding Birth Interval						
First birth (ref)	1.0		1.0		1.0	
<24 months	1.51 (1.27, 1.81)	0.000	1.51 (1.27, 1.81)	0.000	1.54 (1.29, 1.84)	0.000
24-47 months	1.16 (0.99, 1.35)	0.065	1.16 (0.99, 1.35)	0.065	1.16 (1.00, 1.36)	0.054
>=48 months	0.90 (0.75, 1.08)	0.263	0.90 (0.75, 1.08)	0.263	0.90 (0.75, 1.08)	0.277
Birth Weight						
Below average	1.0		1.0		1.0	
Average and above	0.43 (0.34, 0.54)	0.000	0.43 (0.34, 0.54)	0.000	0.43 (0.34, 0.55)	0.000
Mothers' Age						
<=25 (ref)	1.0		1.0		1.0	
25-34	0.96 (0.83, 1.09)	0.508	0.96 (0.83, 1.09)	0.508	0.95 (0.83, 1.09)	0.513

Factors	Model 1		Model 2		Model 3	
	Odds Ratio	**P>z**	**Odds Ratio**	**P>z**	**Odds Ratio**	**P>z**
>=35	1.01 (0.85, 1.19)	0.944	1.01 (0.85, 1.19)	0.944	1.00 (0.85, 1.18)	0.978
Mothers' BMI						
Normal (ref)	1.0		1.0		1.0	
Underweight	1.05 (0.90, 1.22)	0.546	1.05 (0.90, 1.22)	0.546	1.03 (0.89, 1.20)	0.661
Overweight	0.78 (0.68, 0.90)	0.001	0.78 (0.68, 0.90)	0.001	0.79 (0.68, 0.91)	0.001
Obese	0.67 (0.53, 0.85)	0.001	0.67 (0.53, 0.85)	0.001	0.67 (0.53, 0.85)	0.001
Level of Education						
No education (ref)	1.0		1.0		1.0	
Primary	1.40 (1.22, 1.61)	0.000	1.40 (1.22, 1.61)	0.000	1.36 (1.17, 1.58)	0.000
Secondary	1.05 (0.87, 1.27)	0.599	1.05 (0.87, 1.27)	0.599	1.03 (0.84, 1.25)	0.780
Higher	1.09 (0.80, 1.48)	0.586	1.09 (0.80, 1.48)	0.586	1.05 (0.77, 1.44)	0.733
Sanitation						
Unimproved (ref)	1.0		1.0		1.0	
Improved	0.82 (0.71, 0.95)	0.006	0.82 (0.71, 0.95)	0.006	0.81 (0.71, 0.94)	0.005
Source of Drinking Water						
Unsafe (ref)	1.0		1.0		1.0	
Safe	0.90 (0.81, 1.00)	0.047	0.90 (0.81, 1.00)	0.047	0.90 (0.81, 1.00)	0.059
Wealth Quintiles						
Poorest (ref)	1.0		1.0		1.0	
Poorer	0.76 (0.66, 0.88)	0.000	0.76 (0.66, 0.88)	0.000	0.78 (0.67, 0.90)	0.001
Middle	0.63 (0.54, 0.74)	0.000	0.63 (0.54, 0.74)	0.000	0.64 (0.55, 0.76)	0.000
Richer	0.59 (0.49, 0.71)	0.000	0.59 (0.49, 0.71)	0.000	0.60 (0.50, 0.72)	0.000
Richest	0.38 (0.30, 0.48)	0.000	0.38 (0.30, 0.48)	0.000	0.38 (0.30, 0.48)	0.000
Random Effects Parameter Estimates						
Residence			0.00 (0)			
Region					0.11 (0.04, 0.27)	
AIC	**9589.19**		**9592.45**		**9587.72**	
BIC	**9774.52**		**9776.87**		**9772.14**	
ICC			**0.000**		**0.003**	

Note: *Model 1 is the ordinary logistic regression model, Model 2 is the multilevel logistic regression model with the residence (Urban/Rural) as the random effect, and Model 3 is the multilevel logistic regression model with the region (8 former provinces) as the random effect.*

5. CHAPTER FIVE

5.1. DISCUSSION

This study examined the factors associated with stunting among children aged 0-59 months in Kenya using the ordinary logistic regression and multilevel logistic regression approaches. Reliability of estimates obtained in regression models lies in the use of most appropriate statistical model, else estimates may be just mere numbers with no value when it comes to prediction of outcomes. This study suspected high clustering of observations within regions and residences, and fitted a multilevel logistic regression model to account for clustering. The study found out that observations within residences were independent and those within region exhibited a significant level of clustering. The main factors found to have significant association with stunting were; age of child, sex, size of child at birth, mothers' level of education, mothers' nutritional status, wealth quintiles and sanitation.

The multilevel model with residence (rural and urban) as the random effect produced results similar to the ordinary logistic regression. This implies that in the absence of clustering of observations, multilevel modelling is not necessary because it does not add any value to estimation and in that case estimates obtained using the ordinary logistic regression remain reliable. Results from this study indicated a small proportion of clustering of observations within regions and a multilevel model fitted with regions as the random effects. Estimates obtained using this model slightly deviated from the ones obtained using the ordinary logistic regression model. This indicates that with a large sample size, a small proportion of clustering of observations has very minimal effect on the estimates. The multilevel logistic model fitted with region as random effects was selected based on diagnostics discussed earlier.

Results from the multilevel logistic regression revealed that male children were more likely to be stunted than female children. This is consistent with results from other studies such as studies by Deso et al. (2017) and Marriot et al. (2012) who found out that the odds of stunting in male children was almost twice that in female children. Deso et al. (2017) asserted that the biological growth difference between the male and female children was the main underlying explanation to the observed differences. The ordinary logistic regression also gave consistent results with the multilevel model that accounts for clustering, however with a slight variation on the odds ratio estimate and 95% confidence interval.

Children with preceding birth interval of less than 24 months are at higher risk of stunting than first born children. Results showed that there was no significant difference between first born children and children born 48 or more months preceding previous birth with regard to probability of stunting. This may be attributed to competing attentive care to the young children in the household. These results are coherent with results Sultana et al. (2019) found out modelling stunting using multilevel logistic regression that controlled for clustering in divisions and residence. The results are also consistent with results obtained using the ordinary logistic regression.

Although past studies have shown that maternal nutritional status and level of education having strong association with stunting among children aged five years and below, this study produced contrary results to studies by Prendergast & Humphrey (2014) and Sultana et.al (2019). In this study, there was no association between mothers' BMI and stunting on the contrary, children born to overweight and obese mothers had lower chances of being stunted compared to those born of mothers with normal nutritional status. This study did not produce sufficient evidence that increasing mothers level of education reduces a child's chances of being stunted however, evidence showed that a child whose mother had primary level of education had reduced chances of being stunted compared to one whose mother had no education. Additionally, the study showed that there was no relationship between the nutritional status of a child (stunting) and mothers age. This is in contrary to studies that have been conducted in the past such as studies by Prendergast & Humphrey (2014), Sultana et.al (2019) and Akombi et.al (2017) who found out maternal age to be one of the predominant factors associated with stunting among children aged 0-59.

Household factors including; source of drinking water, sanitation and wealth quintiles were found to have strong association with stunting. Past studies have shown the same using both the multilevel logistic regression and the ordinary logistic regression. Prendergast & Humphrey (2014) results revealed that a child's home environment with regard to income or poverty are major drivers of stunting since poverty affects food security within a family. Several studies examining factors associated with stunting using the ordinary logistic regression have shown the association between stunting and sanitation, consistent with results for the multilevel logistic regression used in this study.

5.2. CONCLUSION & RECOMMENDATIONS

Conclusively, multilevel logistic regression model only adds value with regard to parameter estimates if level of clustering of observations is high. With a small percentage of clustering in data and a very large sample size, the parameter estimates obtained using the multilevel logistic regression and the ordinary logistic regression do not differ significantly. In well-designed multi-stage cluster surveys that adequately factors clustering in sampling, the ordinary logistic regression would still provide reliable estimates. Significant clustering was observed within regions and by taking into account clustering through introduction of random effects, estimates remained consistent with ones obtained using the ordinary logistic regression.

Child factors such as sex, age group and months preceding previous birth were found to be strongly associated with stunting. Similarly household factors; wealth quintiles, source of drinking water and sanitation are factors strongly associated with stunting. Government and other stakeholders involved in nutrition health policy formulation processes should design programs that are need specific and addresses the root causes of stunting such as empowerment to improve household living standards.

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APPENDICES

Appendix I: Anti- Plagiarism Report

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Appendix II: Ethical Approval Letter

UNIVERSITY OF NAIROBI
COLLEGE OF HEALTH SCIENCES
P O BOX 19676 Code 00202
Telegrams: varsity
Tel:(254-020) 2726300 Ext 44355

KNH-UON ERC
Email: uonknh_erc@uonbi.ac.ke
Website: http://www.erc.uonbi.ac.ke
Facebook: https://www.facebook.com/uonknh.erc
Twitter: @UONKNH_ERC https://twitter.com/UONKNH_ERC

KENYATTA NATIONAL HOSPITAL
P O BOX 20723 Code 00202
Tel: 726300-9
Fax: 725272
Telegrams: MEDSUP, Nairobi

Ref: KNH-ERC/A/400

12th November 2020

Edith Amondi Oluoko
Reg. No.W62/8571/2017
Institute of Tropical and Infectious Diseases(UNITID)
College of Health Sciences
University of Nairobi

APPROVED
12 NOV 2020
KNH/UoN-ERC

Dear Edith

RESEARCH PROPOSAL – FACTORS ASSOCIATED WITH STUNTING AMONG UNDER-FIVE YEAR OLD CHILDREN IN KENYA: A MULTILEVEL LOGISTIC REGRESSION APPROACH (P417/08/2020)

This is to inform you that the KNH- UoN Ethics & Research Committee (KNH- UoN ERC) has reviewed and **approved** your above research proposal. The approval period is 12th November 2020 – 11th November 2021.

This approval is subject to compliance with the following requirements:

a. Only approved documents (informed consents, study instruments, advertising materials etc) will be used.
b. All changes (amendments, deviations, violations etc.) are submitted for review and approval by KNH-UoN ERC before implementation.
c. Death and life threatening problems and serious adverse events (SAEs) or unexpected adverse events whether related or unrelated to the study must be reported to the KNH-UoN ERC within 72 hours of notification.
d. Any changes, anticipated or otherwise that may increase the risks or affect safety or welfare of study participants and others or affect the integrity of the research must be reported to KNH- UoN ERC within 72 hours.
e. Clearance for export of biological specimens must be obtained from KNH- UoN ERC for each batch of shipment.
f. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. (*Attach a comprehensive progress report to support the renewal*).
g. Submission of an *executive summary* report within 90 days upon completion of the study.
This information will form part of the data base that will be consulted in future when processing related research studies so as to minimize chances of study duplication and/ or plagiarism.

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For more details consult the KNH- UoN ERC website**http://www.erc.uonbi.ac.ke**

Yours sincerely,

PROF. M. L. CHINDIA
SECRETARY, KNH-UoN ERC

c.c. The Principal, College of Health Sciences, UoN
The Senior Director, CS, KNH
The Chairperson, KNH- UoN ERC
The Assistant Director, Health Information Dept, KNH
The Director, Institute of Tropical and Infectious Diseases(UNITID), UoN
Supervisors: Dr. Joseph Mung'atu, J.K.U.A.T
Ms. Ann Wang'ombe, School of Mathematics/UNITID, UoN