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ANALYSIS OF VARIANCE AND COVARIANCE IN WEIGHT DISCREPANCIES BASED ON FEEDING PRACTICES OF INFANTS IN BOLORI II, MAIDUGURI BORNO STATE

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Abstract

This study investigated the relationship between infant feeding practices and weight gain in infants aged 0–6 months. A total of 69 infants were recruited for the study, and their feeding practices were categorized into three groups: exclusive breastfeeding, complementary breastfeeding, and predominant breastfeeding.

The results of the analysis of covariance (ANCOVA) showed a significant difference in the mean weight gain between the three feeding practice groups after controlling for infant age and sex. Specifically, infants who were exclusively breastfed had higher mean weight gain compared with those who received complementary or predominant breastfeeding.

The study'’sfindings have implications for health care professionals and parents in promoting optimal infant feeding practices that support healthy weight gain and overall growth and development.

1. INTRODUCTION

Infant feeding practice plays a critical role in child development. It is an important factor in determining the growth and development of a child. Poor feeding practices can adversely impact the health and nutritional status of children, which in turn has direct consequences for their mental and physical development, especially in the critical window from birth to 2 years of age.

Feeding practices during infancy are critical for the growth, development and health of a child during the first two years of life and are of importance for the early prevention of chronic degenerative diseases (WHO, 1979). Progress in improving infant and young child feeding practices in the developing world has been remarkably slow (Ruel, 2003) due to several factors. It is estimated that among children living in the 42 countries with 90% of global child deaths, a package of effective nutrition interventions could save 25% of childhood deaths each year (Jones *et al*., 2003)

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In infancy, no gift is more precious than breastfeeding; yet barely one in three infants is exclusively breastfed during the first 6 months of life. In Nigeria, over 50% of infants are given complementary foods before 6 months of age, and these foods are often of poor nutritional value—mostly inadequate in terms of energy, protein and micronutrients such as iron, zinc, iodine and vitamin A (Federal Ministry of Health [FMH] 2005). International consensus indicates that complementing breast milk even with water during the first six months of a child`s life is unnecessary and may increase the risk of diarrhea as extra solids and liquids are often contaminated (Martines *et al*., 1992). Providing other liquid or food in addition to breast milk during the first six months could potentially be harmful, i.e., risk of infection and poorer stimulation of breast milk production and should only be done if medical reasons exist (De Pee *et al*., 2003).

2. Infant feeding

Human milk was the only successful infant food until the advent of scientific pediatrics, the invention of electric refrigeration, and the development of formulas containing the major nutrients in concentrations similar to human milk. Improvements such as modification of protein by heat or lactic acid to improve digestibility and development of dextrin-maltose as an energy source had a large impact on the quality of the formulas. Direct advertising of new products and formulas to physicians probably influenced the use of the formulas. Infants apparently thrive on artificial formulas, but the current formulas represent only a stage in the journey to optimal nutrition for infants. Better analyses of the composition of human milk are likely to lead to an improved understanding of the infant's nutritional requirements and thus to better feeding practices (Palmquist et al, 2019). Before the 20th century, breastfeeding was the main way of feeding babies. If for any reason the natural mother could not breastfeed, a wet nurse was used. Attempts were made in the 15th century Europe to use cow or goat milk, but these attempts were not successful. In the 18th century, flour or cereal mixed with broth was introduced as a substitute for breastfeeding, but this did not have a favorable outcome either. Commercial infant formulas appeared on the market in the mid-19th century, but their use did not become widespread until after World War II.

3. Breastfeeding

Breastfeeding has many health benefits for both the mother and infant. Breast milk contains all the nutrients an infanneedsed in the first 6 months of life. Breastfeeding protects against diarrhea and common childhood illnesses such as pneumonia and may also have long-term health benefits for the mother and child, such as reducing the risk of overweight and obesity in childhood and adolescence. UNICEF and WHO recommend that children be exclusively breastfed (no other liquid, solid food, or plain water) during the first six months of life, since breast milk contains all the nutrients needed. Apart from being nutritionally inadequate, substitutes, such as formula, other kinds of milk, and/or porridge, can be contaminated, exposing infants to the risk of illness, thus increasing their risk of mortality. Introducing substitutes before the age of 6 months can also discourage breastfeeding, which, for many reasons, should be continued up to 2 years of age. According to the Lancet, an exclusively breastfed child is 14 times less likely to die in the first six months than a non-breastfed child, and breastfeeding drastically reduces deaths from acute respiratory infection (ARI) and diarrhea, two major child killers[0]. Despite the importance of breast milk, overall, only 28% of infants under six months of age were exclusively breastfed, a percentage consistent with the 2014 NNHS findings of 25% but far below the recommended WHO/UNICEF level of 50%. The NNHS 2014 findings also showed that the proportion of children exclusively breastfed sharply decreases with age from birth to the second third month and toward the sixth month of life. This finding is also consistent with NDHS 2013, which indicates that half of all Nigerian infants do not exclusively breastfeed, not even for a month.

Benefits of Breastfeeding in Infants

Scientific research, such as the studies summarized in 2the 2007review for the U.S Agency for Health care Research and Quality and a 2007 review for the WHO, presented the following benefits of breastfeeding to Infants:

i. Greater Immunity: During breastfeeding, antibodies are passed to the baby. This is one of the important features of colostrum. The breastmilk contains several anti-infective factors such as bile salt-stimulated lipase (protecting against amebic infections), lactoferrin (which binds to iron and inhibits the growth of intestinal bacteria) and immunoglobulin (a protection against microorganisms).

ii. Fewer infection: In a 1993 University of Texas Medical study, a longer period of breastfeeding was associated with a shorter duration of some middle ear infections (otitis media with effusion) in the first 2 years of life.

iii. Reduced Sudden Infant Death Syndrome: breastfed babies have better arousal from sleep at 2-3 months. This coincides with the peak incidence of sudden infant death syndrome. A study conducted at the University of Munster found that breastfeeding halved the risk of sudden infant death syndrome in children up to the age of 1.

iv. Less diabetes: infants exclusively breastfed have a lower chance of developing diabetes mellitus type 1 than peers with a shorter duration of breastfeeding and an earlier exposure to cow milk and solid foods. Breastfeeding also appears to protect against mellitus type 2, at least in part due to its effects on the child's weight.

v. Less Childhood Obesity: Breastfeeding appears to reduce the risk of extreme obesity in children. The protective effect of breastfeeding against obesity is consistent though small across many studies, and appears to increase with the duration of breastfeeding. A study has also shown that infants who are bottle-fed in early infancy are more likely to empty the bottle or cup in late infancy than those who are breastfed. Breastfeeding, regardless of the type of milk, is distinct from feeding at the breast in its effect on infants. According to the study, this may be due to one of three possible factors, including that when bottle feeding, parents may encourage infants to finish the content of the bottle, whereas when breastfeeding, an infant naturally develops self-regulation of milk intake. A study in Today's pediatric association showed that solid food given too early to formular-fed babies before 4 months old will make them 6 times as likely to become obese by age 3. It did not happen if the babies were given solid foods with breastfeeding.

vi. Less Tendencies to Develop Allergic Disease (Atopy): In children who are at risk of developing allergic disease (defined as at least one parent or sibling have atopy), atopic syndrome can be prevented or delayed through exclusive breastfeeding for four months, although this benefit may not be present after four months of age. However, the key factor may be the age at which non-breast milk is introduced rather than the duration of breastfeeding. Atopic dermatitis, the most common form of eczema, can be reduced through exclusive breastfeeding beyond 12 weeks in individuals with a family history of atopy, but when breastfeeding beyond 12 weeks is combined with other foods, the incidence of eczema increases irrespective of the family history.

vii. Less Necrotizing Enter Colitis in Premature Infants: This is an acute inflammatory disease in the intestines of infants. Necrosis or death of the intestinal tissue may follow. It is mainly found in premature births. In one study of 926 preterm infants, NEC developed in 51 infants (5.5%). The death rate from necrotizing enter colitis was 26%. NEC was found to be six to ten a mixture of breast milk and formula, compared with exclusive breastfeeding. In infants born at more than 30 weeks, NEC was 20 times more common in infants fed exclusively on formula. A 2007 meta-analysis of four randomized controlled trials found a marginally statistically significant association between breastfeeding and a reduction in the risk of NEC.

4. Complementary Feeding

An appropriate and adequate start of complementary feeding at 6 months is critical for development. In many developing countries, children of these age groups do not receive timely, appropriate, and adequate feeding to grow to the optimum level. Adding food too soon takes the place of breast milk, which results in low nutrients and increases the risk of illness. Often the child does not receive appropriate nutrients, thus resulting in the restriction of growth and development. Feeding infants requires active care and stimulation where the caregivers should be responsive to the child clues for hunger and encourage the child to eat. Complementary feeding contributes to child growth and development as infants for 6 months to 18 months are especially vulnerable in developing malnutrition. According to UNICEF, a third of children younger than 5 years in developing countries have linear growth retardation or stunting. Stunting is a chronic malnutrition caused by poor nutrition and infection. Stunting is also associated with lethargy, a less positive effect, lower levels of play, and poor attention. Receiving food in addition to breast milk from 6 months onwards with the right amount and consistency will avert malnutrition and stunting-associated developmental delays (Pem, 2012).

5. Empirical Review/Review of previous Studies

Mathew et al. (2009) found that practices of exclusive breastfeeding in northwest were not in full compliance with the international recommendation. Only about half of the mothers that participated in the study practiced exclusive breastfeeding from birth up to the age of six months, but in addition to the breast milk, over three-quarters of them gave water, most of start giving water to their children at birth. The main question arising from these data is why are so many children given something before the initiation of breastfeeding? While some caregivers reasoned that it makes the child healthy and helps to reduce thirst, others simply said it was a tradition passed on to them by elders in their community. It was found that the majority of the children (51.5%) were given plain water, followed by those children given other things like cow butter (23.2%) before the initiation of breastfeeding. Over 50% of caregivers in Kaduna state bottle-feed their child at the 6th month with infant formula, while some in Kebbi state (31.58%) start as early as less than one month of age. Complementary foods were introduced to the majority of the children much earlier at the 3rd month than the 6th month recommended, contrary to the recommendation of the World Health Organization, that complementary feeding should be initiated on the 6th month (WHO, 1995). Studies in Malawi revealed that children who were given foods according to the timing set by the World Health Organization were found to be well-nourished as compared with children who were introduced to solids too early (Madise and Mpoma, 1997). The high proportions of mothers in North Western Nigeria who sustained breastfeeding/bottle feeding/complementary feeding during child`s illness indicate that the practice of withholding foods during an episode of illness was uncommon.

In their study, Shinn et al. aimed at assessing the changes in infant WHO growth indicators (weight-for-age, weight-for-length, and head circumference z-scores) from birth to 12 months of age as a function of feeding practices (FP) and (2) to describe the proportion of infants experiencing rapid weight gain (RWG; defined as change in weight-for-age z-score of ≥0.67 between birth and six months) among different FP. The modified Infant Feeding Practices Study II questionnaire was administered to 149 diverse caretakers/mothers of infants who were less than six months of age in a pediatric outpatient clinic. Growth as a function of FP was assessed using repeated measures ANOVA, while logistic regression was used to describe the correlates of RWG. The largest proportion of caretakers was African American (37%), 46% completed college, and 48% were enrolled in the Women, Infants, and Children (WIC) program. Regarding FP, 32% of infants were formula fed and 18% were breastfed, with the remaining being either mixed fed or complementary fed, with nearly 40% of infants demonstrating RWG. While changes in weight-for-age z-scores differed among FP across time ($p<0.05$), the observed patterns for head-circumference-for-age and weight-for-length z-scores did not. Various demographic correlates (caretaker race-ethnicity, education, and WIC enrollment) were associated with FP. Only the patterns of change in the weight-for-age z-scores at 9 and 12 months differed among FP (with breastfeeding being the lowest at both time points).

Griffiths et al (2009) found that Caucasian infants who received no breast milk were more likely to exhibit a faster rate of weight gain from birth to 3 years of age than those who received any breastmilk ($OR=0.06$, $p<0.05$, 95% CI (0.02 to 0.09)), regardless of duration and when adjusted for maternal social class, pregnancy BMI, parity, smoking during pregnancy, and 3-year height z-score. Weight gain was also inversely related to breastfeeding duration; infants breastfed for less than 4 months were more likely to have RWG when compared to those breastfed for 4 months or more. Again, these findings were based on a large sample of White infants, unlike the diverse sample in this study. Kramer et al. examined the effects of various FPs on growth through 12 months of age. Similar to those of the present study, they found that mixed feeding and formula (or other milk) led to higher weight-for-age z-scores from three to six months of age when compared with exclusive breastfeeding.

Iguacel et al. (2019), in their study to assess the associations between lactation practices (breast-fed vs formula-fed infants) during the introduction of complementary food period, applied Linear regression models to measure two hundred and three infants randomly selected from Spanish Primary Health Centers. The results of the study showed that Breast-fed infants had a lower change in z-score of weight, height and BMI from six to 12 months of age and these differences remained when adjusting for confounders such as sex, parental education and total food intake. They concluded that formula-fed infants during the complementary feeding period had a higher food intake and showed higher rates of rapid infant weight gain compared to breast-fed infants.

The Framingham Offspring study noted a relationship between breastfeeding and a lower BMI and higher high-density lipoprotein concentration in adults. A sibling difference model study noted that the breastfed sibling weighed 14 pounds less than the sibling fed commercial infant formula and was less likely to reach the BMI obesity threshold. The duration of breastfeeding also is inversely related to the risk of being overweight; each month of breastfeeding was associated with a 4% reduction in risk.

The interpretation of these data is confounded by the lack of a definition in many studies of whether human milk was given by breastfeeding or by bottle. This is of particular importance because breastfed infants self-regulate intake volume irrespective of maneuvers that increase the available milk volume, and the early programming of self-regulation, in turn, affects adult weight gain. This concept is further supported by the observations that infants who are fed by bottle, formula, or expressed breast milk will have increased bottle emptying, poorer self-regulation, and excessive weight gain in late infancy (older than 6 months) compared with infants who only nurse from the breast.

Painter et al. (2017), in their study of the effect of various self-monitoring behaviors on weight loss during a 6-month weight-loss intervention using de-identified data from the Retrofit weight-loss program, included all measures associated with self-monitoring behaviors involving weight measurements, dietary intake, and physical activity in a multiple regression analysis to predict weight loss during the intervention. Measures with a statistically significant contribution to predicting weight loss were identified. To determine the self-monitoring behaviors/measures that could be considered significant predictors of weight loss, three primary regression models were built. The first primary regression model assessed two weigh-in-related measures as predictors of weight loss. The second model included five activity-related measures as predictors of weight loss. The third primary regression model assessed four measures related to food logging as predictors of weight loss. All the significant predictors (ie, self-monitoring behaviors/measures) from the primary regression model were included in an overall regression model that considered all behaviors as predictors of weight loss. The significant predictors of the overall model were considered as the most important measures/behaviors for weight loss. Each significant self-monitoring measure was analyzed in depth to reveal the impact on outcomes during the intervention period to capture the significant association between high-level monitoring and higher outcome levels. For each behavior, one-way ANOVA tests were performed to determine the association between behavior frequency and weight loss and compare the behavior frequency of participants with different weight-loss levels.

Their results provided strong support for the use of self-monitoring in weight-management programs. Participants who complied more with body weight, physical activity, and food intake self-monitoring lost more weight than those who complied less. In a multiple regression equation, each category of self-monitoring contributed significantly to the prediction of weight loss. Furthermore, the independent analysis showed a significant association between each self-monitoring behavior and weight loss. Overall, the use of self-monitoring was found to have a high impact on weight management. They concluded that self-monitoring behaviors, such as self-weight-in, daily step counts, high-intensity activity, and persistent food logging, were significant predictors of weight change at 6 months. Specifically, weighing in three times or more per week, having a minimum of 60 highly active minutes per week, food logging for three days or more per week, and having a higher percentage of weeks with five or more food logs increased the participant's weight-loss success.

Postrach et al. (2013) analyzed possible associations between the intensity of KiloCoach (a web-based weight loss program) use and weight loss. Datasets of KiloCoach users (January 1, 2008 to December 31, 2011) who actively used the platform for 6 months were assigned to a retrospective analysis. Users (N=479) were 42.2% men, with a mean age of 44.0 years (SD 11.7), with a mean body mass index (BMI) of 31.7 kg/m2 (SD 3.2). Based on the weight loss achieved after 6 months, 3 success groups were generated. The unsuccessful group lost <5%, the moderate success group lost 5%-9.9%, and the high success group lost ≥10% of their baseline body weight. At baseline, the unsuccessful (n=261, 54.5%), moderate success (n=133, 27.8%), and high success (n=85, 17.8%) groups were similar in age, weight, BMI, and gender distribution.

After 6 months, the unsuccessful group lost 1.2% (SD 2.4), the moderate success group lost 7.4% (SD 1.5), and the high success group lost 14.2% (SD 3.8) of their initial weight (*P*<.001). Multivariate regression showed that early weight loss (weeks 3-4), the total number of dietary protocols, and the total number of weight entries were independent predictors for 6-month weight reduction (all *P*<.001) explaining 52% of the variance in weight reduction. Sensitivity analysis by the baseline carried forward method confirmed all independent predictors of 6-month weight loss and reduced the model fit by only 11%. The high success group lost weight faster and maintained weight loss more efficiently than the other groups (*P*<.001). Early weight loss was associated with weight maintenance after 1 and 2 years (both *P*<.001). Weight dynamics did not differ between men and women over 6 months when adjusted for baseline and usage parameters (*P*=.91). The percentage of male long-term users was unusually high (42.2%). The results suggested that early weight loss and close program adherence (ie, 5 dietary protocols per week and weekly entering of current weight), especially in the early phase of program usage, can improve the weight loss outcome.

Wang et al. (2022) examined the relationships between caregivers' concern about child weight and their non-responsive feeding practices. Data synthesis was performed using a semi-quantitative approach and a meta-analysis. Results: A total of 35 studies with 22,933 respondents were included in the review for semi-quantitative analyses. Thirty-four studies examined 52 associations between concern about child weight and restriction, with 40 statistically significant associations being observed. A total of 34 relationships between concern about child weight and pressure to eat were investigated, with 12 being statistically significant. The pooled regression coefficients (β) demonstrated that caregivers' concern about child overweight was positively associated with restriction (β = 0.22; 95%CI: 0.12, 0.31), negatively associated with use of food as a reward (β = −0.06; 95%CI: −0.11, −0.01), and not statistically associated with pressure to eat (β = −0.05; 95%CI: −0.13, 0.04). The pooled odds ratios (ORs) indicated that caregivers who were concerned about child overweight were found to use restrictive feeding more often (OR = 2.34; 95%CI: 1.69, 3.23), while less frequently adopting pressure to eat (OR = 0.76; 95%CI: 0.59, 0.98) compared with those without concerns. The results also showed that caregivers who were concerned about the child being underweight were more likely to force their children to eat (OR = 1.83; 95%CI: 1.44, 2.33) than those without concerns.

Abed et al. (2024) conducted the study to examine the relationship between mothers' feeding practices and child weight status under two years old. A descriptive correlational study design was carried out at Babylon Teaching Hospital for maternity and children and Al Nour Hospital, which was applied from December 2019 to the end of February 2020 as a period for data collection. The sample consisted of (150) mothers admitted with their infants in the pediatric wards. The study indicated that (76.7%) of mothers have bad feeding practices regarding child feeding, whereas (23.3%) have good feeding practices. In addition to other significant results, the study demonstrated a considerable positive relationship between the mode of feeding and a child's weight.

Yarnoff, (2013) examined the independent association of six different types of food (exclusive breastfeeding, non-exclusive breastfeeding, infant formula, milk liquids, non-milk liquids, and solid foods) with five measures of infant health (length, weight, diarrhea, fever, and cough). The study estimated associations with regression analysis, controlling for confounding factors with infant, mother, and household factors and community-year fixed effects. We used these estimates in a simulation model to quantify the burden of different combinations of food on infant health. The results show that for an infant younger than 6 months old, following current guidelines and exclusively breastfeeding instead of giving the infant solid foods may increase length by 0.75 cm and weight by 0.25 kg and decrease the prevalence of diarrhea, fever, and cough prevalence by 8, 12, and 11%, respectively. We found that the burden on infant health of some feeding practices is less than others. Although all other feeding practices are associated with worse health outcomes than exclusive breastfeeding, breastfeeding supplemented with liquids has a lower burden on infant health than solid foods, and infant formula has a lower burden than milk or non-milk liquids as measured by four of five health metrics. Providing specific quantified burden estimates of these practices can help inform public health policy related to infant feeding practices.

6. Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is a statistical technique that is used to check if the means of two or more groups are significantly different from each other. ANOVA checks the impact of one or more factors by comparing the means of different samples. It is an extension of the t-test statistic used to determine whether two means differ to the case where there are three or more means.

In one-way analysis of variance, we have k treatments or k different levels of a single factor for which we wish to test the equality of means.

Analysis of Covariance (ANCOVA) is an extension of ANOVA that controls for one or more additional variables, known as covariates, which may influence the outcome. These covariates are typically continuous variables that are related to the dependent variable.

Model for One-Way ANOVA

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}; \qquad (1)$$

Where;

$i = 1, 2, \ldots, k; \qquad j = 1, 2, \ldots, n.$

Y_{ij} is the j^{th} observation taken under the i^{th} treatment.

μ is the overall mean, which is constant for all treatments.

α_i is the effect of i^{th} treatment.

ε_{ij}; is the random error component associated with the response variable Y_{ij}.

Assumption of ANOVA

The following are the assumptions of the analysis of variance (ANOVA)

Normality: The residuals (errors) should be normally distributed. This can be checked using histograms, Q-Q plots, or normality tests (e.g., Shapiro-Wilk test).

Independence: Each observation should be independent of every other observation. This means that there should be no correlation between the residuals.

Homogeneity of Variances (Homoscedasticity): The variance of the residuals should be equal across all levels of the independent variable (i.e., equal variances in each group). This can be checked using Levene's test or Bartlett's test.

Random Sampling: The data should be randomly sampled from the population.

No significant Outliers: There should be no significant outliers in the data, as they can affect the results of the ANOVA.

Interval or Ratio Data: The dependent variable should be measured on an interval or ratio scale.

No Multicollinearity: The predictor variables should not be highly correlated with each other.

Assumption of ANCOVA

The following are the assumptions of the analysis of covariance (ANCOVA)

Normality: The residuals (errors) should be normally distributed.

Independence: Each observation should be independent of every other observation.

Homogeneity of Variances (Homoscedasticity): The variance of the residuals should be equal across all levels of the independent variable.

Linearity: There should be a linear relationship between the covariate and the dependent variable.

Homogeneity of Regression Slopes: The regression slopes between the covariate and the dependent variable should be equal across all levels of the independent variable.

No significant Outliers: There should be no significant outliers in the data.

Interval or Ratio Data: The dependent variable and covariate should be measured on an interval or ratio scale.

Random Sampling: The data should be randomly sampled from the population.

No Multicollinearity: The predictor variables and covariates should not be highly correlated with each other.

7. Confounding Factors

A confounding factor or a confounder is an extraneous variable whose presence affects the variables being studied so that the results do not reflect the actual relationship between the variables under study. According to Pourhoseingholi et al., (2012), "The aim of major epidemiological studies is to search for the causes of diseases, based on associations with various risk factors. There may also be other factors that are associated with the exposure and affect the risk of developing the disease and they will distort the observed association between the disease and exposure under study. A hypothetical example would be a study of the relationship between coffee drinking and lung cancer. If the person who entered the study as a coffee drinker was also more likely to be a cigarette smoker, and the study only measured coffee drinking but not smoking, the results may seem to show that coffee drinking increases the risk of lung cancer, which may not be true. However, if a confounding factor (in this example, smoking) is recognized, adjustments can be made in the study design or data analysis so that the effects of the confounder would be removed from the final results. Simpson's paradox is another classic example of confounding. Simpson's paradox refers to the reversal of the direction of an association when data from several groups are combined to form a single group.

The researchers therefore should account for these variables, either through experimental design and before the data gathering, or through statistical analysis after the data gathering process. In this case, the researchers are said to account for their effects to avoid a false positive (Type I) error (a false conclusion that the dependent variables are in a causal relationship with the independent variable). Thus, confounding is a major threat to the validity of inferences made about cause and effect (internal validity). There are various ways to modify a study design to actively exclude or control confounding variables, including randomization, restriction, and matching.

In randomization, the random assignment of study subjects to exposure categories to break any links between exposure and confounders. This reduces the potential for confounding by generating groups that are fairly comparable with respect to known and unknown confounding variables.

Restriction eliminates variation in the confounder (for example if an investigator only selects subjects of the same age or same sex then, the study will eliminate confounding by sex or age group). Matching, which involves the selection of a comparison group with respect to the distribution of one or more potential confounders. Matching is commonly used in case-control studies (for example, if age and sex are the matching variables, then a 45-year-old male case is matched to a male control with same age).

However, all these methods mentioned above are applicable at the time of study design and before the process of data gathering. When experimental designs are premature, impractical, or impossible, researchers must rely on statistical methods to adjust for potentially confounding effects."

8. Statistical Analysis to Eliminate Confounding Effects

Unlike selection or information bias, confounding is one type of bias that can be adjusted after data gathering using statistical models. To control for confounding in the analyses, investigators should measure the confounders in the study. Researchers usually do this by collecting data on all known, previously identified confounders. There are mostly two ways to deal with confounders in the analysis: Stratification and Multivariate methods.

i. Stratification

The basic objective of stratification is to fix the level of the confounders and produce groups within which the confounders do not differ. Then, evaluate the exposure-outcome association within each stratum of the confounder. Within each stratum, the confounder cannot be confounded because it does not vary across the exposure-outcome. After stratification, the Mantel-Haenszel (M-H) estimator can be used to provide an adjusted result according to the strata. If there is a difference between the crude result and the adjusted result (produced from strata), confounding is likely. However, in the case that the crude result does not differ from the adjusted result, then confounding is unlikely. Stratified analysis works best in the way that there are not a lot of strata and if only 1 or 2 confounders must be controlled. If the number of potential confounders or the level of their grouping is large, multivariate analysis offers the only solution.

ii Multivariate models

Multivariate models such as Logistics regression, linear regression, and analysis of covariance can handle large numbers of covariates (also confounders) simultaneously. For example, in a study to measure the relationship between body mass index and Dyspepsia, one could control for other covariates like age, sex, smoking, alcohol consumption, ethnicity, etc. in the same model.

Logistic regression: This is a statistical process that produces results that can be interpreted as an odds ratio, and it is easy to use by any statistical package. The special thing about logistic regression is that it can control for many confounders (if there is a large enough sample size). Thus, logistic regression is a mathematical model that can give an odds ratio that is controlled for multiple confounders. This odds ratio is known as the adjusted odds ratio because its value has been adjusted for the other covariates (including confounders).

Linear Regression: The linear regression analysis is another statistical model that can be used to examine the association between multiple covariates and a numeric outcome. This model can be employed as a multiple linear regression to see through confounding and isolate the relationship of interest. For example, in a research seeking the relationship between LDL cholesterol level and age, the multiple linear regression lets you answer the question, how does LDL level vary with age, after accounting for blood sugar and lipid (as the confounding factors)? In multiple linear regression (as mentioned for logistic regression), investigators can include many covariates at one time. The process of accounting for covariates is also called adjustment (similar to logistic regression model), and comparing the results of simple and multiple linear regressions can clarify the extent to which the confounders in the model distort the relationship between exposure and outcome.

Analysis of Covariance: The Analysis of Covariance (ANCOVA) is a type of Analysis of Variance (ANOVA) that is used to control for potential confounding variables. ANCOVA is a statistical linear model with a continuous outcome variable (quantitative, scaled) and two or more predictor variables where at least one is continuous (quantitative, scaled) and at least one is categorical (nominal, non-scaled). ANCOVA is a combination of ANOVA and linear regression. ANCOVA tests whether certain factors influence the outcome variable after removing the variance for which quantitative covariates (confounders) account. The inclusion of this analysis can increase the statistical power.

9. One-way Analysis of the Covariance

This is the aspect of ANCOVA that involves one independent variable with one or more covariates. It can be thought of as an extension of the one-way ANOVA to incorporate a covariate. Like the one-way ANOVA, the one-way ANCOVA is used to determine whether there are any significant differences between two or more independent groups on a dependent variable. However, while the ANOVA looks for differences in the group means, the ANCOVA looks for differences in the adjusted means (i.e., adjusted for the covariate).

According to Oladugba et al. (2014), There are two purposes for including covariates in the analysis.

i. To reduce within-group error: In the analysis of covariance, the effect of an experiment is assessed by comparing the amount of variability in the data that the experiment can explain against the variability that it cannot explain. If we can explain some of this unexplained variance in terms of other variables (covariates), we can reduce the error variance, allowing us to more accurately assess the effect of the experimental treatment.

ii. Elimination of confounds: In any experiment, there may be an unmeasured variable that confounds the result (i.e., variables that varies systematically with the experimental treatment). If any variables influence the dependent variable being measured, the ANCOVA is ideally suited to remove the bias of these variables. Once a possible confounding variable has been identified, it can be measured and entered the analysis as a covariate.

Model for one-factor analysis of covariance

In the case of a single factor experiment with one covariate and assuming that there is a linear relationship between the response and the covariates, the statistical model is given as follows:

$$y_{ij} = \mu + \alpha_i + \beta(x_{ij} - \bar{x}) + e_{ij} \qquad (2)$$

$i = 1, 2, \ldots, m$

$j = 1, 2, \ldots, n$

The terms in this model have the following meanings:

y_{ij} = j^{th} observation on the response variable taken under the i^{th} treatment or level of the single factor.

μ = overall true mean involving the specified treatment

α_i = the effect of the i^{th} treatment, $\sum_{i=1}^{m} \alpha_i = 0$
β = true common slope of the m regression lines. It is the linear coefficient indicating the dependency of y on x.
x_{ij} = covariate observed on the same sampling unit as y_{ij}
$\bar{x}$ = overall average of the covariate measurements.
e_{ij} random error component, e_{ij} is NID (0, σ^2).

Assumptions of the model for one-way ANCOVA

i. The regression lines have the same slope ($\beta_1 = \beta_2 = \ldots = \beta_m$)
ii. The relationship between x and y is linear
iii. The covariate is not affected by the treatment/independent variable
iv. The variance about the regression lines is equal.
v. The model also takes the usual assumptions of the ANOVA

10. Multiple Comparisons

Multiple comparisons Tests are performed when certain experimental conditions have a statistically significant mean difference or there is a specific aspect between the group means. A problem occurs if the error rate increases while multiple hypothesis tests are performed simultaneously. Consequently, in an MCT, it is necessary to control the error rate to an appropriate level. According to Sangseok L. (2018), The result of ANOVA does not provide detailed information regarding the differences among various combinations of groups. Therefore, researchers usually perform additional analysis to clarify the differences between particular pairs of experimental groups. If the null hypothesis (H_0) is rejected in the ANOVA for the three groups, the following cases are considered:

$$\mu_A \neq \mu_B \neq \mu_C \text{ or } \mu_A \neq \mu_B = \mu_C \text{ or } \mu_A = \mu_B \neq \mu_C \text{ or } \mu_A \neq \mu_C = \mu_B \qquad (3)$$

In which of these cases is the null hypothesis rejected? The only way to answer this question is to apply the 'multiple comparison test' (MCT), which is sometimes also called a 'post-hoc test'. There are several methods for performing MCT, such as the Tukey method, Newman-Keuls method, Bonferroni method, Dunnett method, and Scheffé's test. Most of the pairwise MCTs are based on balanced data. Therefore, when there are large differences in the number of samples, care should be taken when selecting multiple comparison procedures. LSD, Sidak, Bonferroni, and Dunnett using the t-statistic do not pose any problems, since there is no assumption that the number of samples in each group is the same.

The Bonferroni correction was used to limit the possibility of obtaining a statistically significant result when testing multiple hypotheses. It is needed because the more tests you run, the more likely you are to get a significant result. The correction lowers the area where you can reject the null hypothesis. In other words, it makes your p-value smaller.

11. Research Design

This research uses secondary source data. The data from a Smart- Nutrition and Retrospective Mortality Survey in Bolori II, Maiduguri Metropolitan Council (mmc) Borno State, Nigeria. The survey was conducted in December 2019, initiated by Première Urgence Internationale (PUI) who are interested in determining the magnitude and severity of malnutrition of the under-five children in Bolori-II, so as to enhance the nutritional and health status of the vulnerable children living in the communities. One of the objectives of the survey was to assess Infant and Young Child Feeding practices among the households with children 0-0-23 months of age in the specific population. Since the sample group for this study is of infants 0-6 months, data for children 0-6 months and the variables of interest were extracted from the survey data set.

12. Population, Sample and Sampling Techniques

The sample size used for this research was arrived at by filtering out the dataset for children six month and below from the primary data set of Infant and Young Child feeding Practice, which included variables for children 0-23 months. Therefore, the resulting sample size for children 0-6 months of age within the Bolori II ward was 69.

13. Methods of Data collection

The collection exercise was performed simultaneously in 30 randomly selected clusters in the 9 sub-wards of Bolori II, MMC. About 89% of the planned households were reached in the survey with the Anthropometric and IYCF survey for children 0-23 months achieved more than 90%. Data on variables such as age, sex, weight, and IYCF practices were collected during the survey. Two standardized questionnaires were coded in Kobo collect and formatted on an Android smartphone/tablet.

14. Technique for Data Analysis and Model Specification

To test whether the weight differed across feeding practices, we performed a one-way Analysis of Covariance (ANCOVA) with four variables:

i. Infant Weight as the dependent or response variable,
ii. Feeding Practice is an independent variable that has three categories (Exclusive Breastfeeding, Predominant Breastfeeding and Complimentary feeding) as the treatment,
iii. Infant Age as a covariate
iv. Infant Sex was also an independent variable as the second covariate.

Model specification

According to Montgomery (2013)

$$y_{ij} = \mu + \alpha_i + \beta(x_{ij} - \bar{x}) + \gamma(w_{ij} - \bar{w}) + e_{ij} \quad (4)$$

$i = 1, 2, \dots, m$

$j = 1, 2, \dots, n$

y_{ij} - j^{th} observation on the response variable (weight) taken under the i^{th} treatment (feeding practice) or level of the single factor.

μ - overall true mean involving the specified treatment

α_i - the effect of the i^{th} treatment, $\sum_{i=1}^{m} \alpha_i = 0$

β - true common slope of the three regression lines. It is the linear coefficient indicating the dependency of y on x.

x_{ij} - first covariate observed on the same sampling unit as y_{ij}

$\bar{x}$ - overall average of the first covariate measurements.

γ - the linear coefficient indicating the dependency of y on w.

w_{ij} - second covariate observed on the same sampling unit as y_{ij}

$\bar{w}$ - overall average of the second covariate measurements.

e_{ij} - random error component, e_{ij} is NID $(0, \sigma^2$

One-Way ANCOVA Table with One Covariate

Regression Source	df	Sum of the Squares x xy y			Adjusted Sum of the Squares	df'	Mean Square MS	F Ratio
Treatment	m 1	α_{xx}	α_{xy}	α_{yy}				$\frac{MS_{\alpha(y)}}{MS_E}$
Error	m (n – 1)	E_{xx}	E_{xy}	E_{yy}	$SS'_{E(y)}$	m(n-1)-1	$MS_{E(y)} = \frac{SS'_{E(y)}}{m(n-1)-1}$	
Total	mn-1	T_{xx}	T_{xy}	T_{yy}	$SS'_{T(y)}$	mn-2		
Adjusted Treatment					$SS'_{\alpha(y)}$	m-1	$MS_{E(y)} = \frac{SS'_{\alpha(y)}}{m-1}$	

Test Statistics $F_{AT} = \frac{MS_{\alpha(y)}}{MS_E} \approx F_{(m-1,m(n-1)-1}$

Before analyzing covariance, we first run some statistical tests to check if our data meet the assumptions of ANCOVA. The normality of the error will be tested using the Shapiro-Wilk test. Then, the Levene's test to test for homogeneity of error variances. We will perform an ANOVA to Test that the covariates are independent of the treatment. Lastly, we will test that all the regression lines have a common slope, β by carrying out an ANCOVA model including both the independent variable, the covariate, and the independent variable × covariate (interaction term). If the interaction term is statistically significant, then the assumption is violated; otherwise, there is no interaction.

After testing for the assumptions of ANCOVA and performing the actual ANCOVA analysis, and if the main ANCOVA is significant, A post hoc test with Bonferroni correction is then carried out to see which feeding practices differ. The order by which the feeding practice affects infant weight is also determined by comparing their adjusted mean weight. The adjusted mean can be found by the formula:

$$\text{Adj } \bar{y}_{i.} = \bar{y}_{i.} - b\,(\bar{x}_{i.} - \bar{x}_{..}) \quad (25)$$

Where Adj $\bar{y}_{i.}$ is the adjusted mean of group i on the dependent variable,

$\bar{y}_{i.}$ is the mean of group i on the dependent variable,

where b is the common slope, $\bar{x}_{i.}$ is the mean of group i on the covariate,

$\bar{x}_{..}$ is the grand mean of the covariate, that is, the mean of the covariate over all groups.

All statistical analyses were conducted using IBM SPSS Statistics for Windows, with a p-value of < 0.05 as the level of significance.

15. Justification of the Method

This study employs ANCOVA to examine the relationship between feeding practices and infant weight while controlling for relevant covariates, ensuring a more precise and accurate comparison of group means. By statistically adjusting for the effects of confounding variables, ANCOVA reduces error variance, increases statistical power, and enhances the external validity of the findings. This approach allows for the examination of adjusted group means, providing a more nuanced understanding of the relationship between feeding practices and infant weight, while accounting for individual differences and complex relationships. Therefore, ANCOVA is an appropriate statistical technique for this study, enabling the identification of significant differences between feeding practice groups while controlling for covariates.

16. Data Presentation

The test, analysis and interpretation for this study was carried out using the following variables:

Response/Dependent Variable: Infant Weight measured on a continuous scale.

Independent Variable: Infant feeding practice was a categorical variable with three groups, namely, complementary, exclusive and dominant.

Covariates or Confounding Variables: Infant Age with interval 0-6 months and Infant Sex a categorical factor coded as Female = 0 and Male =1.

Below is a summary of the data used for the analysis.

Table 4.1.1 Summary of the Infant Feeding Practice

	Frequency	Percentage	Valid percentage	Cumulative percentage
Complementary	10	14.5	14.5	14.5
Exclusive	39	56.5	56.5	71.0
Predominant	20	29.0	29.0	100.0
Total	69	100.0	100.0	

Table 4.1.1 shows the summary of the feeding practice categories. We can see that 14.5% of the infants practice complementary breastfeeding, 56.5% are exclusively breastfed and 29% practice predominant breastfeeding. Also, there were no missing values for any category and all the 69 infants were captured in the analysis.

Table 4.1.2 Summary of the Infant Sex

		Number	Percentage	Valid percentage	Cumulative percentage
	Female	40	58.0	58.0	58.0
Valid	Male	29	42.0	42.0	100.0
	Total	69	100.0	100.0	

In table 4.1.2, we have the number and percentage of the male and female captured. With 40 females and 29 males, the proportion looks fine, but we would be concerned if one group had very few cases. We also see that there are no missing values in both groups.

Table 4.1.3 Summary of Infant Age

	Frequency	Percentage	Valid percentage	Cumulative percentage
0	10	14.5	14.5	14.5
1	6	8.7	8.7	23.2
2	13	18.8	18.8	42.0
3	10	14.5	14.5	56.5
4	15	21.7	21.7	78.3
5	9	13.0	13.0	91.3
6	6	8.7	8.7	100.0
Total	69	100.0	100.0	

Table 4.1.3 shows a summary of the number of infants at ages 0, 1, 2, 3…6 months used in our analysis. We see that there are no missing values, and all the 69 infants were captured in the analysis.

17. Data Analysis and Results

For an Analysis of Covariance to be valid, we first perform the following tests to verify the assumptions of an ANCOVA model.

i. **Test for Normality:** Here we verify for normality using Shapiro-Wilk tests, first to test the overall model fit and second to test the within-group normality at $\alpha = 0.05$.

Hypothesis:

H_0: the sample is normally distributed

H_1: the sample is not normally distributed

Decision rule:

Reject H_0 if the P-value < α; otherwise, do not reject H_0.

Table 4.2.1 Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Infant Weight	.089	69	.200*	.984	69	.510

*. This is the lower bound of the true significance.

a. Lilliefors Significance Correction

From table 4.2.1 above, we can see a Shapiro-Wilk P-value of 0.510 > 0.05, which is not statistically significant; hence, we fail to reject H_0 and assume that the dependent variable Infant weight is normally distributed.

Table 4.2.2 Test of Normality for Infant Feeding Practice Groups

Infant Feeding Practices		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Complementary	Infant Weight	.241	10	.104	.914	10	.306
Exclusive	Infant Weight	.086	39	.200*	.982	39	.760
Predominant	Infant Weight	.178	20	.097	.939	20	.231

*. This is the lower bound of the true significance.

a. Lilliefors Significance Correction

From table 4.2.2 above, we can see the Shapiro-Wilk P-value of 0.306, 0.760, and 0.231 for the complementary, exclusive, and dominant infant feeding practices, respectively, which are all greater than 0.05 (not statistically significant); hence, we assume that the infant weights in each of the feeding practice groups are normally distributed.

ii. **Test of Homogeneity of Error Variances:** Levene's test for equality of variance was performed to test the null hypothesis that the error variance of the dependent variable Infant weight is equal across the groups. Table 4.2.3 below shows the result of the Leven test for the homogeneity of the error variance.

Table 4.2.3 Levene's Test of the Equality of Error Variances

Dependent Variable: Infant Weight

F	df1	df2	Sig.
.228	2	66	.797

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Sex + Age + Feeding

From table 4.2.3, the test indicates that we have not violated the homogeneity of the error variances assumption, since the difference in the error variances between groups indicates that the error variances are the same across the response categories with a significant value of 0.797 > 0.05.

iii. **Test that the Covariates are independent of the Treatment:** An Analysis of variance is used to check that age and the sex (covariates) are not affected by the Infant Feeding Practices (treatment). We want to see if age and sex are different across the IFPs. Tables 4.2.4 and 4.2.5 give the results of the test that the covariates are independent of Infant feeding practice.

Table 4.2.4 Tests of Between-Subjects Effects

Dependent Variable: Infant Age

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	6.521[a]	2	3.260	.955	.390	.028
Intercept	499.647	1	499.647	146.402	.000	.689
Feeding	6.521	2	3.260	.955	.390	.028
Error	225.247	66	3.413			
Total	829.000	69				
Corrected Total	231.768	68				

a. R Squared = .028 (Adjusted R Squared = -.001)

In table 4.2.4 above, we are interested in the significance value of the treatment Feeding which is 0.390 which is not significant so there is no statistically significant difference between the three feeding practice groups as measured by the dependent variable Age.

Table 4.2.5 Tests of Between-Subjects Effects

Dependent Variable: Sex:

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	.172[a]	2	.086	.341	.712	.010
Intercept	8.007	1	8.007	31.759	.000	.325
Feeding	.172	2	.086	.341	.712	.010
Error	16.640	66	.252			
Total	29.000	69				
Corrected Total	16.812	68				

a. R Squared = .010 (Adjusted R Squared = -.020)

From table 4.2.5 we have a significance value for Feeding as 0.712, which is not statistically significant; hence, no significant difference in sex was observed between the feeding practice groups.

iv. **Test for Homogeneity of Regression slopes:** Here we test the validity of the assumption that the regression lines have a common slope. The equality of the slope is demonstrated when there is no interaction between the covariates and the independent variable. To check if the covariates significantly interact with the independent variable, we ran an ANCOVA model including both the independent variable, the covariate, and the independent variable × covariate (feeding practice × age) term. If the interaction term is statistically significant, then the assumption is violated; otherwise, we conclude that there is no interaction, and the slope is approximately equal.

Table 4.2.6 Tests of Between-Subjects Effects (Dependent Variable: Infant Weight)

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	64.352[a]	5	12.870	29.600	.000	.701
Intercept	192.586	1	192.586	442.913	.000	.875
Feeding	.129	2	.065	.149	.862	.005
Age	34.396	1	34.396	79.103	.000	.557
Feeding * Age	2.667	2	1.334	3.067	.054	.089
Error	27.393	63	.435			
Total	2168.010	69				
Corrected Total	91.746	68				

a. R Squared = .701 (Adjusted R Squared = .678)

From table 4.2.6 we have a significance value for the interaction term Feeding * Age as 0.054, which is not statistically significant. Therefore, we can conclude that there is no interaction between feeding practice and age, and thus have an equal regression slope.

Table 4.2.7 Tests of Between-Subjects Effects (Dependent Variable: Infant Weight)

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	5.760[a]	5	1.152	.844	.524	.063
Intercept	949.722	1	949.722	695.846	.000	.917
Feeding	.828	2	.414	.303	.739	.010
Sex	.182	1	.182	.134	.716	.002
Feeding * Sex	4.190	2	2.095	1.535	.223	.046
Error	85.985	63	1.365			
Total	2168.010	69				
Corrected Total	91.746	68				

a. R Squared = .063 (Adjusted R Squared = -.012)

From table 4.2.7 we have significance value for the interaction term Feeding * Sex as 0.223, which is not statistically significant. Therefore, we can conclude that there is no interaction between feeding practice and sex.

4.2.2 Analysis of the Covariance

Here the age and sex variables are held constant and the effect of feeding on infant weight is analyzed, resulting in the ANCOVA table below.

Table 4.2.8 ANCOVA Tests of Between-Subjects Effects

Dependent Variable: Infant Weight

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	63.910[a]	4	15.978	36.736	.000	.697	146.944	1.000
Intercept	172.955	1	172.955	397.662	.000	.861	397.662	1.000
Sex	2.225	1	2.225	5.116	.027	.074	5.116	.606
Age	62.340	1	62.340	143.334	.000	.691	143.334	1.000
Feeding	4.527	2	2.264	5.204	.008	.140	10.409	.813
Error	27.835	64	.435					
Total	2168.010	69						
Corrected Total	91.746	68						

a. R Squared = .697 (Adjusted R Squared = .678)

b. Computed using alpha = .05

Looking at the significance (p-values) on table 4.2.8, we notice that for our treatment, which is feeding, we have a statistically significant variability with $p = 0.008 < 0.05$, after accounting for the difference in sex and age of the infants. The variable Feeding explains 14% of the variability in the infant weights, while the entire ANCOVA model explains 68% (Adjusted R Squared = 0.678) of the variability in infant weight.

4.2.3 Post Hoc Test (Multiple Comparison Test)

Since the ANCOVA test revealed that there is a significant difference in the mean effects of the feeding practices on infant weight, we now proceed to determine which of the feeding practices differ.

Table 4.2.9 Pairwise Comparisons

Dependent Variable: Infant Weight

(I) Infant Feeding Practice	(J) Infant Feeding Practice	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
Complementary	Exclusive	-.683*	.238	.016	-1.268	-.099
	Predominant	-.285	.258	.816	-.919	.348
Exclusive	Complementary	.683*	.238	.016	.099	1.268
	Predominant	.398	.182	.098	-.050	.845
Predominant	Complementary	.285	.258	.816	-.348	.919
	Exclusive	-.398	.182	.098	-.845	.050

Based on the estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Looking at table 4.2.9, we can see that the p-value of Exclusive vs. Complementary is less than the alpha level selected ($\alpha = 0.05$). This means that the exclusive and complementary groups have less than a 5% chance of belonging to the same population. Whereas for Exclusive vs Predominant and Complementary vs Predominant are much greater than the significance level.

Table 4.2.10 Estimated marginal means

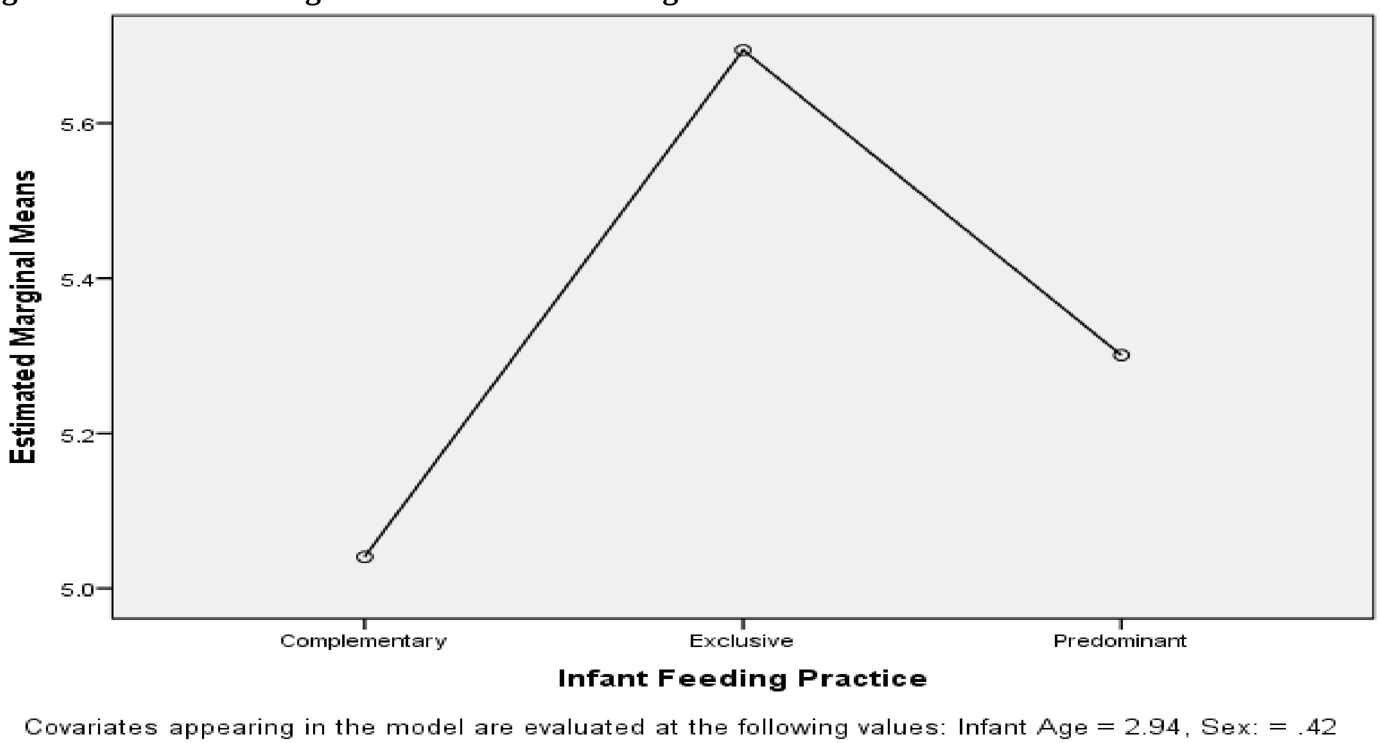
Dependent Variable: Infant Weight

Infant Feeding Practice	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Complementary	5.017[a]	.211	4.595	5.439
Exclusive	5.700[a]	.106	5.488	5.912
Predominant	5.302[a]	.148	5.007	5.597

a. Covariates appearing in the model were evaluated at the following values: Sex: = .42, Infant Age = 2.94.

Table 4.2.10 gives the adjusted values of the group means. Looking at the value of the means, it shows that holding the covariates; sex and age constant at their means, complementary feeding practice has the lowest mean weight (5.017kg) and exclusive has the highest adjusted mean at 5.700kg.

Fig 4.2.1 Estimated Marginal Means of Infant Weight



From Fig 4.2.1 we have a line graph, showing that complementary has the lowest estimated marginal mean, predominant with a higher value and exclusive having the highest estimated marginal mean.

18. Discussion of the Findings

An ANCOVA was conducted to compare the effect of three infant feeding practices (IFP) on infant weight whilst controlling for the sex and age of the infants. The data were tested to check for the assumptions of ANCOVA and the assumptions were met. After adjustment for sex and age, there was a statistically significant difference in the mean weight between the IFP categories, with $p = 0.008 < 0.05$, which led to the rejection of the null hypothesis of equal mean. Therefore, a test that compares the adjusted means was necessary. A post hoc test was performed with a Bonferroni adjustment to determine the order by which the mean weights differed. The test showed there was a significant difference between Exclusive breastfeeding and Complementary breastfeeding ($p = 0.16$). Comparing the estimated marginal means showed that Exclusive breast feeding had the highest weight with adjusted mean = 5.700kg, compared to Predominant (adjusted mean = 5.302kg) and Complementary (adjusted mean = 5.017kg).

19. Summary

The data sets used in this study were collected from a Smart- Nutrition and Retrospective Mortality Survey in Bolori II, Maiduguri Metropolitan Council (mmc) Borno State, Nigeria. The survey was conducted in December 2019, initiated by Première Urgence Internationale (PUI). The data for children 0-6 months and the variables of interest were extracted from the survey dataset. The IBM SPSS Statistics 21 and Microsoft Excel were employed in the collation and analysis of the data in this study.

The objectives of this study were to:

i. To Test for significant differences in weight across the three feeding practices by performing an Analysis of Covariance (ANCOVA).

Based on the SPSS result on table 4.2.2 we see that there is a significant difference in the Infant weights across the three feeding practices after controlling for the effect of sex and age.

ii. To test for significant interaction:

From our analysis, we discovered that the p-value of Exclusive vs. Complementary is less than the alpha level selected ($\alpha = 0.05$). Hence, have a significant difference.

iii. To determine which of the feeding practices is most effective on infant weight.

From the estimated means, we realized that Exclusive breast feeding has the highest mean weight value and so we concluded that Exclusive breastfeeding is the most effective.

20. Conclusion

Results from this study shows that each of the three-feeding practice have different effects on the weight of infants below 6 months. Exclusive breastfeeding with the highest estimated marginal mean weight had the greatest positive effect on infant weight, followed by dominant breastfeeding, while complementary breastfeeding had the lowest effect. Hence, we can conclude that infants that are exclusively breastfed tend to weigh higher than babies who were introduced to water, formular and other liquid substances before the age of six months. However, there are other factors like weight at birth, education level of caregiver, and immunization that might influence the weight of infant and were not included in this research. Nonetheless with the available variables, this study validates the UNICEF and WHO recommendations that children be exclusively breastfed during the first six months of life for better growth and development.

21. Recommendations

i. Mothers and caregivers should endeavor to practice exclusive breastfeeding on infants between 0 and 6 months for improved weight, which brings about healthy living.
ii. Intensified efforts should be made by the government and relevant agencies to promote best feeding practices for mothers of children 0-6 months with a focus on the benefits and duration of exclusive breastfeeding.

22. Limitations of the Study

The findings of this study are limited by the non-availability of specific data required to achieve the optimal result for the study. While Infant age and sex were controlled for in our statistical models, other potential confounding factors including infant birth weight, caretaker education, feeding frequency, immunization, health condition, etc. we're not available and therefore were not controlled for. Second, we have a small sample size due to the insurgence in Borno State, causing migration of the targeted population from the survey location. Therefore, the small sample size of this research limits the generalization of the findings from this study.

23. Suggestions for further study

i. A cohort study is suggested to determine in the most effective feeding practice other weight the gain of infants at intervals through the first 6 months of life.

ii. Further research is needed with larger diverse samples to verify the observations presented in this study.

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