NOUN Journal of Physical and Life Sciences
Volume 2(1): 67-83, JUNE, 2018
ISSN: 2645-2480
www.njpls.nou.edu.ng; njpls@noun.edu.ng

EVALUATION OF MATERNAL FACTORS ON INFANT'S BIRTH SIZE USING CANONICAL CORRELATION ANALYSIS IN OSOGBO, OSUN STATE

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ABSTRACT

The size of an infant at birth is a major factor in determining its survival, physical and mental growth. Maternal factors also go a long way in predicting the eventual birth weight of an infant. This study investigated the association between birth measurements and maternal factors in predicting the birth size of infants in Osogbo, Osun State using canonical correlation analysis (CCA). Five dependent variables were considered from the infant (weight, head circumference, chest circumference, length and mid-upper arm circumference) and five independent variables from the mother (living standard index, preterm delivery, age at enrollment, parity, early pregnancy and number of Antenatal care visits) as well as sex of the infant. Data on mother and infants were collected from our lady of Fatimah hospital, Jaleyemi, Osogbo, Osun State. The result revealed that more than 75% of the infants were born large with 50% of the infants were females. Mean maternal age was 30 ± 6.3 years. More than half of the women were nulliparous (51.5 %) and their mean parity was 1.72 ± 0.85. Most of the women were educated but almost half of them fall into the category with low living standard index (47%). The first canonical correlation was 0.22, which signifies a low correlation between the five birth size variables and maternal factors. Loadings of the birth size measurements revealed that length of the baby (0.69) contributed most to the first canonical function, followed by Head Circumference (0.35), MUAC (0.24), Chest Circumference (0.10) and weight (0.07). Our findings in this study suggest CCA to be a better method for assessing the effects of the maternal factors on infant size at birth than usual multivariate techniques like multiple linear regression.

Keywords: Canonical correlation, multivariate, regression, circumference, survival

INTRODUCTION

Birth size is one of the important predictors of a child's mental development, future physical growth, and survival. It is in fact, one of the major risk factors for child morbidity and mortality (Ballot *et al*., 2010; Lawn et al., 2005; Onubogu *et al*., 2017). As reported by the World Health Organization (WHO), low birth weight (LBW) is defined as an infant birth weight of less than 2,500 g (WHO, 2011). Children in this category are considered to have a greater risk of neonatal, post-neonatal death, and morbidity (Dahlui *et al*., 2016). An association has been previously reported between infants with LBW as well as early and late morbid conditions. (Richards *et al*., 2001), psychological disorders and coronary heart disease (Eriksson *et al*., 1999).

The effect of low birth weight on infant mortality is not only additive but also interactive. The magnitude of the contribution of low birth weight to infant mortality is higher in developing countries given that the survival of such infants is dependent on environmental sanitation, effective post-natal nutrition and rehabilitation, and the availability of medical care. Low birth weight is a public health problem all over the world and is connected with a lot of health challenges and even deaths (Isiugo-Abanihe and Oke, 2011).

The study of the relationship between birth size and some maternal factors is on the increase among maternal and health researcher. (Kabir *et al.*, 2014). Research has shown that socio-economic factor is a great determinant of the nutritional status of the mother and that women that come from wealthy homes usually have better access to healthy foods during pregnancy and better antenatal care (ANC) visits. However, women from poor backgrounds are more prone to having children with low birth weight due to lack of good nutrition (Leal *et al*., 2006; Silva *et al.*, 2012).

Studies have shown that women of advanced maternal age (ages 35 and above at the time of delivery) tend to have larger babies compared to younger women. Low birth weight (less than 2500 grams) and very low birth weight (less than 1500 grams) deliveries are more common among under-aged mothers (Fall *et al*., 2015). However, women between the ages 18 and 35 are more probable to conceive healthy children because they are in their prime of child bearing years. The occurrence of low birth weight is higher among mothers under the age of 18 or above the age of 35. Women in these two age groups are faced with the challenge of not being able to sustain pregnancy due to the size of their uterus (Neggers *et al*., 1995).

Foetal growth is usually evaluated using birth weight. However, the use of other measurements like the head and length, arm and chest circumferences may be very important in the prediction of long-term health and development results (Neggers *et al*., 1995). Research on the health effects of different exposures, observational epidemiological studies often involve data that include a set of exposure and outcome variables. Statistical approaches like multiple linear regression usually employed to measure the level of association between these sets of variables have the challenge of multicollinearity and multiple testing. Some authors have analyzed birth size and other maternal, social and environmental variables (Neggers *et al*., 1995) using multiple linear regression despite its limitations. Since CCA is very useful in assessing the correlation between two composite variables also known as canonical variates, one representing a set of exposure variables and the other a set of outcome variables (Sherry and Henson, 2005; Thompson, 1991), it may therefore be an appropriate method to assess the effect of maternal factors on infant's size at birth.

The aim of this study therefore, is to investigate the association between factors that affect birth size and maternal factors using Canonical Correlation Analysis and Multiple Linear Regression and to pinpoint the very important variables in the relationship and the significant interactions between the variables.

MATERIALS AND METHODS

The data for this study were collected from 200 hundred women that had successful delivery at private hospital in Osogbo, Osun State. Our team visited the hospital and obtained information from the women during post-natal visits and also from the hospital records. The consent of the women was sought before being interviewed. They were interviewed about their household socioeconomic conditions, education, demographic characteristics, previous pregnancy history. A living standard index (LSI) was constructed from the household socio-economic variables and was used as the main socio-economic variable. The number of antenatal visits and care during labour and delivery and condition of the infant were also recorded.

Data on the infants that included Birth size measurements (length, weight, head and chest circumferences, mid-upper arm circumference (MUAC)), delivery status and sex were collected. Infants that were born preterm, that is, less than 37 weeks of gestation was another characteristic that was included in the analysis. The maternal characteristics included in this study were: Age at enrollment at the hospital, parity, level of education, LSI and number of ANC visits.

Canonical correlation analysis (CCA) was carried out on the data collected from the study for the dependent and independent variables. Statistical analysis was carried out using SAS 9.3 software and SPSS software version 20.0. The results from the CCA were used to explain the relationship between the different maternal factors affecting birth size of an infant.

Canonical Correlation Analysis (CCA)

Canonical Correlation Analysis

When two variables X and Y that are linearly related and there is an increase in one of the variables and it is accompanied by an increase or a decrease in the other variables, then the variables are said to be correlated. Canonical correlation analysis is a method for exploring the relationship between two multivariate sets or variates (vectors) all measured on the same individual. Canonical correlation analysis is also called “set correlation” which determines a set of canonical variables, orthogonal linear combination of the variable with each set that best explains the variability within and between the sets. Hence, canonical correlation analysis

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(CCA) finds two bases, one for each variable that are optimal with respect to correlations and at the same time, it finds the two bases in which the correlation matrix between the variable is diagonal and the correlations on the diagonal are maximized and the dimensionality of the set of new bases is equal to or less than the smallest dimensionality of the two variables.

Canonical is the statistical term for analyzing latent variables (which are not directly observed) that represent multiple variables (which are directly observed). CCA is the analysis of multiple independent (X) and multiple independent (Y) correlation. The Canonical Correlation Coefficient measures of the degree of association between two Canonical Variates. A Canonical Variate (CV) is defined as the weighted sum of the variables in the analysis. CCA is the preferred choice of analysis in analyzing the degree of association between two constructs.
For multiple X and Y the canonical correlation analysis constructs two variates

$$CV_{x1} = a_1x_1 + a_2\,x_2 + a_3x_3 + \cdots + a_nx_n$$

and

$$CV_{y1} = b_1y_1 + b_2\,y_2 + b_3y_3 + \cdots + b_my_m$$

The canonical weights $a_1\ \ldots a_n$ and $b_1\ \ldots b_m$ are chosen so that they maximize the correlation between the canonical variates CV_{X1} and CV_{Y1}. A pair of canonical variates is called a *canonical root***.** This step is repeated for the *residuals* to generate additional duplets of canonical variates until the cut-off value = min (n,m) is reached; for example, in this study, we calculated the canonical correlation between five variables on birth size and six variables on maternal socio-demographic factors that could affect the infant size at birth. So, we would extract five pairs of canonical variates or five canonical roots since five is the minimum of the two set of variables (http://www.statisticssolutions.com/canonical-correlation/).

A very important advantage of canonical correlations over ordinary correlations is there are invariance with respect to affine transformations of the variables (Borga, 2001). This is a vital difference between the two analyses which depends greatly on the basis of the description of the variables.

CCA was developed by (Hotelling, 1936), he extends a linear combinations that capture correlations between two multivariate variable or data sets, although CCA which is being used as a standard tool in statistical analysis has been used in different field such as economics, medical studies, meteorology and even in class. It is surprisingly unknown in the fields of learning and signal processing.

Furthermore, a considerable proportion of work has been done on non-linear extensions of CCA, including neutral network based variant, (Bach and Jordan, 2002). Most works in the generative approach retain the linear nature of CCA, but provide inference methods more robust than the classical linear algebraic solution and more importantly, the approach leads to the basic principles of hierarchical modeling. Hence, CCA seeks a part of linear transformation for each of the set of variables such that when the set of variables are transformed, the corresponding coordinates are maximized.

Multiple Linear Regression

Multiple linear regression (MLR), is used when the value of a variable based on two or more other variables is to be estimated. The variable to be predicted is called the dependent variable (or sometimes, the outcome, target or criterion variable). The variables used to predict the value of the dependent variables are called the independent or explanatory variables.

Multiple Linear Regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable X is associated with a dependent variable Y.

The model for multiple linear regression, given *n* observations, is

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + E_j$$

The values fitted by the equation $b_0 + b_i + \ldots\ldots + b_p X_{ip}$ are denoted by Ÿ and the residuals e_i are equal to $Y_i - Y$ the difference between the observed and fitted values. Hence the sum of the residual is equal to zero.

These two statistical methodologies were applied on data from mother and infants that could affect the size of a child at birth. It is widely believed that birth weight is strongly associated with mortality and morbidity in infancy and early childhood (McCormick, 1985; Medicine, 2001). However, foetal growth is largely a function of the nutrients intake of the mother before and during gestation as well as the capacity of the placenta to supply the needed nutrients in adequate quantities to the foetus (Thame *et al.*, 1997).

Relationship between canonical correlation analysis (CCA) and multiple regression analysis (MLR)

Canonical correlation analysis and multiple linear regression serve almost similar purposes, since multiple linear regression is an extension of simple linear regression and it is used to predict the value of a variable based on the value of two or more other variables i.e. the dependent variable and the independent variable. On the other hand Canonical Correlation is an additional procedure for assessing the relationship between variables. Specifically, its analysis allows one to investigate the relationship between two sets of variables. Hence multiple regression allows one to assess the relationship between a dependent variable and a set of independent variables and canonical correlation analysis is useful for exploring the relationships between a set of categorical variables (Matin et al., 2008).

RESULTS AND DISCUSSION

Most of the infants involved in this study were born big. Most of them were born weighing more than 2.5kg, MUAC greater than 10cm, HC greater than 33cm, CC greater than 30cm. More than 70% were moderate preterm according to WHO definition which says that infants born less than 28 weeks are extremely preterm; 28 to 32 weeks are very preterm and those born 32 to 37 weeks were moderate to late preterm.

More than 50% of the infants were females. Mean maternal age was 30 ± 6.3 years. More than half of the women were nulliparous (51.5 %) and their mean parity was 1.72 ± 0.85. Most of the women were educated but almost half of them fall into the category with low living standard index (47%). The descriptive statistics for the study is presented in table 1.

Table 1: Descriptive statistics for birth size and maternal factors from Osogbo in 2014-2015, n = 200.

Variables	Mean (SD)	Median (IQR)
Birth size within 72 hours of birth		
Weight (kg)	3.09 (0.40)	3.05 (2.9, 3.3)
Length (cm)	48.81 (4.21)	49.00 (47, 52)
MUAC (cm)	10.52 (1.85)	11.00 (10, 11)
HC (cm)	33.76 (2.60)	34 (32, 35)
CC (cm)	33.29 (2.11)	33 (32, 34)
Maternal Socio-Demographic Factors		
Parity	1.72 (0.85)	1.00 (1, 2)
Age at enrollment (years)	29.55 (6.27)	29.00 (25, 33)
LSI	1.84 (0.87)	2.00 (1, 3)
No of ANC visit	10.02 (4.51)	10.00 (7, 12)
Preterm delivery[1]	0.76 (0.43)	1.00 (1, 1)
Infant sex	0.69 (0.47)	1.00 (0, 1)

ANC: Antenatal Care; CC: Chest Circumference; HC: Head Circumference; MUAC: Mid-Upper Arm Circumference; LSI: Living Standard Index.

[1]For any delivery that occurred before 37 weeks of gestation

The Pearson's correlation coefficient between maternal factors and infant's size at birth were presented in table 2. All the maternal factors except infant sex were negatively correlated with MUAC. Only preterm delivery and length of the infant showed significant association, there was no significant correlation between the other maternal factors and birth size measurements.

The canonical correlation, eigenvalue and the proportion of the sum of the eigenvalues represented by a given eigenvalue are presented in table 3. The Pearson correlations of the pairs of canonical variates were listed as canonical correlations in table 3. The CCA result was restricted to 5 functions because the dependent set of variables had the minimum number of variables between the two sets. The first pair of variates which is a linear combination of the birth size measurements and a linear combination of the maternal factors has a correlation coefficient of 0.22. This value represents the highest possible correlation between any linear combination of the maternal factors and any linear combination of the birth size measurements. The second pair has a correlation coefficient of 0.18, the third has 0.13, and the last two had very low correlation coefficients.

Canonical loadings and cross loadings of the dependent and independent variables for the first canonical function are presented in table 4. These loadings suggested that the most important predictor of birth size was the number of antenatal care visit (-0.73), followed by age of the mother at enrollment (-0.58), preterm delivery (0.38), Sex of the infant (0.35), parity (-0.16) and living standard index (0.06). Loadings of the birth size measurements revealed that length of the baby (0.69) contributed most to the first canonical function, followed by Head Circumference (0.35), MUAC (0.24), Chest Circumference (0.10) and weight (0.07). This suggested that the length of the infant, head circumference and mid upper arm circumference were strongly negatively associated with the number of antenatal care visits, age of the mother at enrollment and parity but positively correlated with preterm delivery, sex of the infant and living standard index respectively.

The Canonical Redundancy Analysis of the Standardized Variance of the Infant Size Measurements explained by their Canonical Variables and the Canonical Variables of the Maternal Factors were reported in table 5. These values showed that neither of the first pair of canonical variables was a good overall predictor of the opposite set of variables given that the proportion of variance explained were 0.1331 and 0.0063.

Results on Regression Analysis of maternal factors on birth size were presented in table 6. It was discovered that none of the variables had significant effect on the birth size indicator variables. This result was contrary to the findings of (Kabir *et al*., 2014) where all factors were significant predictors of infant size at birth. This could also be as a result of the difference in the study design and location.

Table 2: Pairwise Pearson's correlation coefficient, r (p-value) between the indicators of birth size and maternal socio-demographic factors from Osogbo, Osun State between 2014 and 2015, n= 200.

	Birth size				
Maternal Factors	**Weight (cm)**	**Length (cm)**	**MUAC (cm)**	**HC (cm)**	**CC (cm)**
Age a enrollment	0.0213	-0.0187	-0.1129	-0.0470	-0.0108
Parity	0.0513	0.0394	-0.0618	-0.0083	0.0398
LSI	0.0171	0.0285	-0.0686	0.0938	-0.0566
No. of ANC visi	0.0265	-0.1051	-0.0278	-0.0330	-0.0154
Preterm delivery	0.0223	0.1418*	-0.0829	0.0022	0.0205
Infant se: (F=1,M=0)	0.0583	0.0436	0.0746	0.0203	0.0254

ANC: Antenatal Care; CC: Chest Circumference; HC: Head Circumference; MUAC: Mid-Upper Arm Circumference; LSI: Living Standard Index.
*p < 0.05

Table 3: Canonical Correlation Analysis of birth size and maternal socio-demographic factors from Osogbo, Osun State between 2014 and 2015, n= 200.

Canonical Variates	Canonical Correlation	Eigenvalue	Proportion	Cumulative
Variate – 1	0.2176	0.0497	0.4466	0.4466
Variate – 2	0.1826	0.0345	0.3101	0.7567
Variate – 3	0.1338	0.0182	0.1639	0.9206
Variate – 4	0.0884	0.0079	0.0708	0.9914
Variate – 5	0.0309	0.0010	0.0086	1.0000

Table 4: Canonical loadings and cross loadings for the first canonical function of the birth size measurements and maternal factors from Osogbo, Osun State between 2014 and 2015, n=200

Variables	Loadings	Cross loadings
Independent variables		
Age	-0.58	-0.13
Parity	-0.16	-0.04
LSI	0.06	0.01
No. of ANC visit	-0.73	-0.16
Preterm delivery	0.38	0.08
Infant sex (F=1,M=0)	0.35	0.07
Dependent variables		
Weight (kg)	0.07	0.01
Length (cm)	0.69	0.15
MUAC (cm)	0.24	0.05
HC (cm)	0.35	0.08
CC (cm)	0.10	0.02

ANC: Antenatal Care; CC: Chest Circumference; HC: Head Circumference; MUAC: Mid-Upper Arm Circumference; LSI: Living Standard Index.

Table 5: Canonical Redundancy Analysis of the Standardized Variance of the Infant Size Measurements explained by their Canonical Variables and the Canonical Variables of the Maternal Factors

Canonical Variable Number	**Infant Size Variables**	**Canonica**	**Canonical R-Square**	**Maternal Canonical**	**Factors Variables**
	Proportion	Cumulative Proportion		Proportion	Cumulative Proportion
1	0.1331	0.1331	0.0473	0.0063	0.0063
2	0.2258	0.3589	0.0333	0.0075	0.0138
3	0.1709	0.5298	0.0179	0.0031	0.0169
4	0.2663	0.7961	0.0078	0.0021	0.0190
5	0.2039	1.0000	0.0010	0.0002	0.0192

Table 6: Regression Analysis of maternal factors on birth size using canonical correlation

	Weight(Kg)	**Length (cm)**	**MUAC (cm)**	**CC (cm)**	**HC (cm)**
Predictors	Model	Model	Model	Model	Model
	β (P-value)	β (P-value)	β (P-value)	β (P-value)	β (P-value)
Age	-0.0011 (0.837)	-0.0165 (0.772)	-0.0304 (0.226)	-0.0109 (0.707)	-0.0262 (0.462)
Parity	0.0313 (0.422)	0.2952 (0.470)	-0.0144 (0.936)	0.1465 (0.481)	0.0758 (0.766)
No of ANC visit	0.0025 (0.701)	-0.0879 (0.201)	-0.0049 (0.872)	-0.0022 (0.949)	-0.0147 (0.732)
Preterm	0.0223 (0.738)	1.3551 (0.055)	-0.4241 (0.171)	0.0737 (0.836)	0.0328 (0.940)
LSI	0.0160 (0.638)	0.2947 (0.410)	-0.1078 (0.493)	-0.1189 (0.513)	0.3391 (0.130)
Female	0.0594 (0.349)	0.5117 (0.441)	0.2553 (0.383)	0.0774 (0.819)	0.2659 (0.521)

ANC: Antenatal Care; CC: Chest Circumference; HC: Head Circumference; MUAC: Mid-Upper Arm Circumference; LSI: Living Standard Index.

A canonical correlation analysis was carried out using five maternal factors and the sex of the infant as independent variable on five birth size measurements to evaluate the multivariate shared relationship between the two sets of variables.

The choice of using CCA was made because of its competence to concurrently model the effect of multiple independent variables on multiple dependent variables instead of separate linear regression modeling. Originally proposed by (Hotelling, 1935, 1936), canonical correlation analysis (CCA) which is a generalization of Karl Pearson's product moment correlation coefficient (Pearson, 1920).CCA is also a very useful data reduction technique that could precede MANOVA, MMR, and SEM (Dattalo, 2014).

Since CCA makes use of all the information from the variables in both the dependent and explanatory variable sets, it could offer a more effective method for the assessment of the effects of the maternal factors affecting infant size at birth rather than the usual traditional methods.

Since CCA begins with simultaneous consideration of the two sets of variables, the inefficiencies that are known with conventional multiple testing as well as type-1 error are reduced, thereby giving more credibility to its results. The use of latent variable approach used in CCA also helped to avoid multicollinearity (Liu *et al.*, 2009).

Our study revealed that infant size at birth in Osogbo did not have any significant association with the included maternal factors in our model. It is however suggested that further work may be carried out over a longer period of time and increased sample size.

CONCLUSION

This study revealed that CCA is a better method for measuring the most significant effect of the maternal factors on infant size at birth than the routine multivariate methods used for such cases. Preterm delivery showed a significant but moderate association with length of the infant.

REFERENCES

Bach, F.R., and Jordan, M.I. (2002). Kernel independent component analysis. *JMLR 3*, 1–48.

Ballot, D.E., Chirwa, T.F., and Cooper, P.A. (2010). Determinants of survival in very low birth weight neonates in a public sector hospital in Johannesburg. BMC Pediatr. *10*, 30.

Borga, M. (2001). Canonical Correlation - a tutorial.

Dahlui, M., Azahar, N., Oche, O.M., and Aziz, N.A. (2016). Risk factors for low birth weight in Nigeria: evidence from the 2013 Nigeria Demographic and Health Survey. *Glob. Health Action 9.*

Dattalo, P.C. (2014). A demonstration of canonical correlation analysis with orthogonal rotation to facilitate interpretation.

Eriksson, J.G., Forsén, T., Tuomilehto, J., Winter, P.D., Osmond, C., and Barker, D.J. (1999). Catch-up growth in childhood and death from coronary heart disease: longitudinal study. *BMJ 318*, 427–431.

Fall, C.H.D., Sachdev, H.S., Osmond, C., Restrepo-Mendez, M.C., Victora, C., Martorell, R., Stein, A.D., Sinha, S., Tandon, N., Adair, L., et al. (2015). Association between maternal age at childbirth and child and adult outcomes in the offspring: a prospective study in five low-income and middle-income countries (COHORTS collaboration). *Lancet*

Glob. Health 3, e366–e377.

Hotelling, H. (1935). The most predictable criterion. *J. Educ. Psychol. 26*, 139–142.

Hotelling, H. (1936). Relations between two sets of variates. *Biom*. 28 321-377 *28*, 321–377.

Isiugo-Abanihe, U., and Oke, O. (2011). Maternal and environmental factors influencing infant birth weight in Ibadan, Nigeria. *Afr. Popul. Stud. 25*.

Kabir, A., Merrill, R.D., Shamim, A.A., Klemn, R.D.W., Labrique, A.B., Christian, P., Jr, K.P.W., and Nasser, M. (2014). Canonical Correlation Analysis of Infant's Size at Birth and Maternal Factors: A Study in Rural Northwest Bangladesh. PLOS ONE *9*, e94243.

Lawn, J.E., Cousens, S., Zupan, J., and Lancet Neonatal Survival Steering Team (2005). 4 million neonatal deaths: when? Where? Why? Lancet Lond. Engl. *365*, 891–900.

Leal, M., Gama, Sgn., and Cunha, Cb. (2006). Consequences of sociodemographic inequalities on birth weight. *Rev. Sau ´de Pu ´blica 40*, 466–473.

Liu, J., Drane, W., Liu, X., and Wu, T. (2009). Examination of the relationships between environmental exposures to volatile organic compounds and biochemical liver tests: application of canonical correlation analysis. *Environ. Res. 109*, 193–199.

Matin, A., Azimul, S.K., Matiur, A.K.M., Shamianaz, S., Shabnam, J.H., and Islam, T. (2008). Maternal Socioeconomic and Nutritional Determinants of Low Birth Weight in Urban area of Bangladesh. *J. Dhaka Med. Coll. 17*, 83–87.

McCormick, M.C. (1985). The contribution of low birth weight to infant mortality and childhood morbidity. *N. Engl. J. Med. 312*, 82–90.

Medicine, I. of (2001). Nutrition During Pregnancy: Part I: Weight Gain, Part II: Nutrient Supplements.

Neggers, Y., Goldenberg, R., Cliver, S., Hoffman, H., and Cutter, G. (1995). The relationship between maternal and neonatal anthropometric measurements in term newborns. Obstet. Gynecol. *85*, 192–196.

Onubogu, C.U., Egbuonu, I., Ugochukwu, E.F., Nwabueze, A.S., and Ugochukwu, O. (2017). The influence of maternal anthropometric characteristics on the birth size of term singleton South-East Nigerian newborn infants. *Niger. J. Clin. Pract. 20*, 852.

Pearson, K. (1920). Notes on the history of correlation. *Biometrika 13*, 25–45.

Richards, M., Hardy, R., Kuh, D., and Wadsworth, M.E. (2001). Birth weight and cognitive function in the British 1946 birth cohort: longitudinal population based study. BMJ *322*, 199–203.

Sherry, A., and Henson, R. (2005). Conducting and Interpreting Canonical Correlation Analysis in Personality Research: A User-Friendly Primer. *J. Pers. Assess. 84*, 37–48.

Silva, L., van Rossem, L., Jansen, P., Hokken-Koelega, A., and Moll, H. (2012). Children of Low Socioeconomic Status Show Accelerated Linear Growth in Early Childhood; Results from the Generation R Study. PloS One *7*.

Thame, M., Wilks, McFarlane-Anderson, N., Bennett, F., and Forrester, T.

(1997). Relationship between maternal nutritional status and infant's weight and body proportions at birth. *Eur. J. Clin. Nutr. 51*, 134–138.

Thompson, B. (1991). A primer on the logic and use of canonical correlation analysis. Meas. *Eval. Couns. Dev. 24*, 80–95.

WHO (2011). World health statistics 2011. (20 Avenue Appia, 1211 Geneva 27, Switzerland: WHO Press, World Health Organization).