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Assessing the Impact of Proximate and Non-Proximate Determinants of Fertility in Namibia: A Structural Equation Modelling Approach

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ABSTRACT

Fertility rate has been declining over the years in Namibia, and a number of studies have been conducted to investigate how socio-economic and physiological factors influenced fertility decline. This study was aimed at modelling the direct and indirect effects of socio-economic, socio-demographic and health attributes on fertility, as well as the proximate and non-proximate determinants of fertility using the Structural Equation Modelling (SEM) technique and the data from the 2013 Namibia Demographic Health Survey. To be precise, the confirmatory factor analysis part of the SEM technique was used to test the theorized model of the proximate and non-proximate determinants of fertility, while the factor modelling part was used to measure the effects that these two constructs of fertility determinants had on fertility. Results from this study showed that the proximate determinants had a direct negative impact $\beta =$ -0.023) on the number of children ever born, while there was a (significant) positive effect $\beta =$ 0.053) between the non-proximate determinants and the number of children ever born. In addition, age at first birth had a (significant) positive effect on the number of children ever born by Namibian women while the effect of contraceptive use was found to have a minor effect. Moreover, women who had their first birth at the beginning of their reproductive period were more likely to have more children born to them, while women who had their first marriage at younger ages were more likely to have more children. It is therefore recommended that there is a need to promote contraceptive use among Namibian women to further reduce fertility, especially among women from poor households as the cost of rising children has become high as the year progresses. Additionally, there is also a need to promote and strengthen the education of young females in order to increase their age at first birth and at first marriage in Namibia.

1. Introduction

Globally, the Total Fertility Rate (TFR) has declined from 2.58 children per woman to 2.47 children per woman between 2010 and 2019 respectively (UN-DESA, 2019). A similar trend was also observed in Sub-Saharan Africa with the TFR dropping from 5.40 children per woman to 4.72 children per woman during the same period (UN-DESA, 2019). In Namibia, the TFR dropped from 5.4 children per woman in 1992 to 3.6 children per woman in 2013, and it was projected in 2011 to still have a linear decline to 2.4 children per woman by 2041 (NSA, 2014b, p. 2). Additionally, the TFR varied between the urban and rural areas and across regions in Namibia. To this effect, it was found that fertility was lower in the urban areas with 3.2 children per woman compared to the rural areas with 4.9 children per woman (NSA, 2014a). With respect to regions, a low TFR was recorded for the Khomas (3.0), Oshana (3.2) and Erongo (3.2) regions, whereas the Kunene (5.3), Ohangwena (4.9) and Omaheke (4.7) regions recorded a high TFR (NSA, 2014a). Moreover, fertility (levels) differs among women due to socio-economic factors such as educational attainment, wealth status and occupation.

NSA (2014a) reported that education attainment, occupation, and wealth status were closely related to fertility, in that as the years of education rises, the TFR varied from 5.7 children per woman among women with no education to 3 children among women with secondary and tertiary education. In addition, women who were widowed recorded a lower TFR of 4.2 children per woman, followed by women who were divorced/separated and never married with a TFR of 3.9 and 3.1 children respectively, while women who were in consensual unions and married women with certificate/traditionally recorded a TFR of 6.3 and 6.0 children respectively (NSA, 2014a). By economic activities, women who were homemakers had a high TFR (5.9) compared to unemployed women (5.13), employed women (4.01) and those who were students (1.98) (NSA, 2014a).

Over the year, most studies done on fertility in Namibia and other parts of the world found that recent fertility decline was attributed to factors such as increment in the costs of rising children, mother's educational attainment, household's wealth, years at first marriage and first birth, contraception use, abortion and induced abortion, postponement of first birth, employment status, postponement of marriages, changing marriage patterns, and postpartum infecundability (Chola & Michelo, 2016; Indongo & Pazvakawambwa, 2012; Islam et al., 2016; Johnson, Abderrahim, & Rutstein, 2011; Majumder & Ram, 2015; Palamuleni, 2017; Shinyemba, 2014). In addition to the foresaid factors, the Human Immunodeficiency Virus/Acquired Immunodeficiency Syndrome (HIV/AIDS) was found to have a moderate influence on fertility decline in some countries in recent years (Fortson, 2009; Johnson et al., 2011; Milly Marston et al., 2017; Marston, Zaba, & Eaton, 2017). However, the implication of HIV/AIDS on fertility in Namibia has not yet been sufficiently quantified. A study done in Namibia by Palamuleni (2017) concluded that the presence of HIV/AIDS might have changed the attitudes and behaviour of individuals regarding pre-marital sexual intercourse, having multiple sexual partners and postponement of marriages. His argument concurs with that of Johnson et al. (2011) who claimed that women fertility preferences were changing due to the Human Immunodeficiency Virus (HIV) pandemic as women who are HIV positive were more likely to use contraceptives to avoid infecting and/or re-infection from their partners, thereby reducing their risk of falling pregnant.

In Namibia, fertility decline can be attributed to several factors that had both direct and indirect effects, with each factors affecting fertility differently. Although there are number of studies done in Namibia documenting fertility decline and factors contributing to the trend (Indongo & Pazvakawambwa, 2012; Palamuleni, 2017; Shemeikka, Notkola, & Siiskonen, 2005; Shinyemba, 2014), no studies have been done (in Namibia) to assess the impact that socio-economic, socio-demographic and health attributes might have on fertility. Hence, the effect that these attributes have on fertility remains unknown, and presently lawmakers and researchers cannot quantify the enormity of these attributes on fertility. Therefore, the aim of the study was to examine and model the direct, indirect and joint effects of socio-economic, socio-demographic and health attributes on fertility for Namibian women, using the Structural Equation Modelling (SEM) approach.

2. Methods

2.1. Data and Sample

The data used in this study was obtained from the 2013 Namibia Demographic Health Survey (NDHS) carried out by the Ministry of Health and Social Services (MoHSS). This survey was designed to provide demographic, socio-economic and health information necessary for policy making, planning, monitoring and evaluation of national health and population programme in Namibia. For the NDHS, 9,176 women in the reproductive age group of 15 to 49 years were interviewed. For this study, the number of Children Ever Born (CEB) per woman was used as a proxy of fertility (for the women). The independent variables of this study (which were the socio-economic, socio-demographic and health attributes of the women) were classified into the indirect cause (age, place of residence, level of education, working status, exposure to mass media, fertility preferences, health care during pregnancy and wealth index), and the direct cause (contraceptive use, age at first marriage, age at first birth, duration of breastfeeding and age at first sexual intercourse). The choice of attributes used was derived from reviewed literature. These variables were further classified as proximate and non-proximate determinants of fertility. Table 1 shows the list of variables used in this study as well as their codenames.

2.2 Statistical Analysis

Structural Equation Modelling (SEM) is a complex statistical modelling technique that attempts to describe the structural relationships between observed and unobserved variables, with a basic goal of providing a quantitative test of a theoretical model hypothesized by a researcher (Sánchez, Budtz-Jørgensen, Ryan, & Hu, 2005). To be precise, SEM is a combination of the Confirmatory Factor Analysis (CFA) and multiple regression analysis (often termed the factor modelling) approaches.

Table 1 List of variables used and their codenames

Variable codename	Variable
V012	Respodents current age
V025	Type of place of residence
V130	Religion
V106	Educational Attainment
V157	Fequency of reading Rewspapers
V158	Fequency of listening to the Radio
V159	Frequency of watching Television
V190	Wealth Index
V201	Total Children Ever Born
V212	Age at first birth
V312	Current contarceptive method
V404	Breastfeeding
V501	Marital status
V511	Age at first cohabitation
V525	Age at first sex
V602	Fertility preference
V714	Working status

It works by combining the CFA and factor modelling approaches to analyze the structural relationship between the observed (manifest) variables and unobserved (latent) variables. CFA enables a researcher to confirm or reject the defined theorized model, which state that there is a relationship between the observed (manifest) and their underlying latent (unobserved) variables (Hair, Black, Babin, & Anderson, 2009). CFA forms part of SEMs, as the techinique uses standardized regression scores to relate unobserved variables to observed variables using using path diagrams. There are three steps involved during the CFA model building. The first step deal with the estimation of the (theorized) model parameters, while the second step deals with the identification of parameters in the model. The third stage assesses how well the estimated model predicts the covariance matrix of the manifest variables (Schumacker & Lomax, 2010; Shinyemba, Nickanor, & Kazembe, 2019). The CFA model can be summarized as follows. First, the observed variables $x's$ are collected into a vector x for each individual subject, with x_i denoting the observable variable i, for $i = 1,2, \dots, m$. That is,

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix}$$

Secondly, the vector of variables x is assumed to be a random vector sampled from a population with a mean vector μ, where μ is defined as

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_m \end{pmatrix}$$

Here, the unobserved common factors f_i are collected in a vector f as follows:

$$f = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{pmatrix}$$

On the other hand, the factor modelling part of the SEM is a series of multiple regressions, which are predicting each of the observable variables x_i from the values of the unobserved common factors f_i. The regression coefficients are obtained as follows:

$$\begin{gathered} X_1 = \mu_1 + l_{11}f_1 + l_{12}f_2 + \cdots + l_{1m}f_m + \varepsilon_1 \\ X_2 = \mu_2 + l_{21}f_1 + l_{22}f_2 + \cdots + l_{2m}f_m + \varepsilon_2 \\ \vdots \\ X_p = \mu_p + l_{p1}f_1 + l_{p2}f_2 + \cdots + l_{pm}f_m + \varepsilon_p \end{gathered}$$

where μ_i to μ_p are the intercept terms of the regression equation and ε_1 to ε_p are the error terms. The regression coefficients l_{ij}, for $i = 1,2, \dots, p$ and $j = 1,2, \dots, m$ are referred to as the factor loadings, which can be written in a matrix form as:

$$L = \begin{pmatrix} l_{11} & l_{12} & . & . & . & l_{1m} \\ l_{21} & l_{22} & . & . & . & l_{2m} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ l_{p1} & l_{p2} & . & . & . & l_{pm} \end{pmatrix}$$

The error terms can also be collected into a vector ε as follows:

$$\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdot \\ \cdot \\ \varepsilon_p \end{pmatrix}$$

Here, the error terms (ε_i) are often referred to as the specific factors of variable *i*. Thus, the regression coefficients in the factor modelling can be written in matrix notation as

$$X = \mu + \mathrm{Lf} + \varepsilon$$

In this study, the SEM was fitted to identify the underlying structural relationship between the indirect and direct determinants of fertility as well as their joint effect. To be precise, the CFA part of the SEM was used to test the theorized model of the proximate and non-proximate determinants of fertility as per Bongaarts (1978) classification, while the factor modelling part was used to assess the relationship between these two constructs of fertility determinants and afterwards model their effects on fertility.

The R software was used to perform the data analyses of this part, with the R packages 'lavaan', 'semTools' and 'semPlots' were used to fit the SEM.

3. Results

Table 2 shows the output obtained from the basic descriptive analysis of all the women considered in the 2013 NDHS. It can be observed that the sexual debut for the women was at the early age of 10 years. The youngest woman gave birth to her first child at the age of 12 years, while the eldest woman gave birth to her first child at the age of 42. The highest numbers of CEB by a woman was 13 children as shown in Table 2. Furthermore, the average age of women in the NDHS was 29.11 years, whereas the average age at first birth was 20.37 years, which meant that most women had their first child birth before they reached the age of 21 years. Moreover, from Table 2, it can be observed that most women started cohabiting at the age of 23.12 years on average, although the average age at first sex was found to be 18.19 years. On average, a Namibian woman had 2.80 children, which implies that each woman had at least 2 children born to her as shown in Table 2.

Table 2 Descriptive analysis of respondents' background

Variables	Minimum	Maximum	Mean
Age of respondents	15	49	29.11
Age at first birth	12	42	20.37
Age at first Cohabitation	10	48	23.12
Age at first Sex	10	46	18.19
Total Child Ever Born	0	13	2.80

3.1 Model Evaluation

Several fit indices can be used to evaluate the appropriateness of the CFA models. The most common fit index used to assess the goodness of fit is the Chi-Square (χ^2) test, where χ^2 value > 200 indicates a good fit for the model. However, Schumacker & Lomax (2010), Brown (2006) and Jöreskog (1969) found the Chi-Square (χ^2) test to be sensitive to sample size effect. Alternatively, the Root Mean Square Error Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) indices can be used to assess the validity of a fitted CFA model. The values of the RMSEA, SRMR, CFI and TLI indices ranges for 0 to 1, with 1 indicating an unacceptable fit (Hu & Bentler, 1999). In this study, a model was regarded as good fit if the RMSEA value ≤ 0.09, the SRMR value ≤0.08, the CFI value ≥ 0.9 and the TLI value ≥ 0.9.

3.2 Model fit: Validating constructs

Two models were fitted to validate the two constructs of fertility determinants and both models were found to be good fit model for the data using the model evaluation criterion discussed above. Even though all the fitted models were found to be good fit, upon inspecting variables contributing to the non-proximate determinants, it was found that the religion (V130) variable was not a significant (*p > 0.05*) predictor of this construct. This model was re-fitted, after the removal of the religion (V130) variable from the model. Comparing the Akaike Information Criterion (AIC) and the Expected Cross-Validated Index (ECVI) values for both the initial model (with religion included) and the re-fitted model (without religion included), the re-fitted model had a lower AIC and ECVI values compared to the initial model. According to Schreiber, Nora, Stage, Barlow, and King (2006), the model with the lowest AIC and ECVI values can be concluded to be a good model fit. Thus, the re-fitted model was selected as the approriate model to use for the non-proximate determinants.

3.3 Full model fitting: linking CEB to proximate and non-proximate determinants of fertility

Here, the full model fitting was done in two stages. In the first stage, the fitted model was assessed to see if the model fits the data well (Tables 3 & 4) and validated to see if all the manifest variables in the model were significant predictors of the study constructs (Table 5). In the second stage, the two constructs of fertility (proximate and non-proximate) were linked to the number of CEB, to capture their direct and indirect effects (Table 6).

Table 3 shows the overall goodness of fit model for the proximate and non-proximate determinants was satisfactory with χ^2_{88}=2,033.328 (>200), with a significant p-value (*p*<0.001) at a 5% significance level. The result also showed a RMSEA value of 0.082 (90% CI: 0.079, 0.085), and a SRMR value of 0.068, which are below the suggested cut-off value, indicating a good model fit. Additionaly, the GFI value of 0.917 (from Table 4) suggests that the model has a good fit. However, from Table 3, the CFI value of 0.830 and TLI value of 0.797 were below the cut-off value of at least 0.90 or 0.95, implying that the model has an unacceptable fit. Thus, using the model fit indices of Table 4, it can be concluded that the (re-fitted) model has a good fit.

Table 1 Baseline model and fit indices for proximate and non-proximate determinants of fertility

Number of observations	*n*= 9,176
Estimator	ML
Minimum fit test statistic	2033.328
Degree of freedom	88
P-value(Chi-square) <=0.05	<0.001***
User model versus baseline model	
Comperative Fit Index (CFI)	0.830
Tucker-Lewis index (TLI)	0.797
Root Mean Square Error of Approximation	
RMSEA	0.082
90% confidence interval	(0.079, 0.085)
P-value rmsea <=0.05	<0.001***
Standardized Root Mean Square Residual	
SRMR	0.068

**** Significant at a 5% significance level*

Table 4 Model fit indices of proximate and non-proximate (re-fitted model)

Index	Model Magnitude	Threshold of acceptance
Chi-Square	2,033.328	>200
RMSEA	0.082	<=0.06
SRMR	0.068	<=0.08
GFI	0.917	>0.90

Table 5 shows the result of the estimated model parameters. Since all the manifest variables had sigificant p-values at a 5% level of significance, as shown in Table 5, it can be concluded that all the manifest variables in the model were significant predictors of both non-proximate and proximate determinants. Furthermore, looking at the regression coefficient value for the non-proximate determinants in Table 5, it can be concluded that a significant direct (positive) effect exists between the non-proximate determinants and the number of CEB. To be precise, for every positive change in the non-proximate determinants the number of CEB would increase by 0.502 children. On the other hand, looking at the regression coefficient value for the proximate determinants, it can be concluded that the proximate determinants had a direct (negative) effect on the number of CEB to a Namibian woman. That is for every positive change in the proximate determinants, the number of CEB would reduce by 0.020 children as shown in Table 5.

Table 5 Parameter estimates for proximate and non-proximate determinants of fertility

Latent Variables	Estimates	Std.Err	P-value
Non-proximate =~			
V025	1.000		
V106	-1.387	0.049	<0.001***
V190	-3.986	0.106	<0.001***
V157	-1.824	0.057	<0.001***
V158	-0.848	0.049	<0.001***
V159	-2.273	0.066	<0.001***
V714	-0.699	0.032	<0.001***
V602	-0.152	0.065	0.021***
Proximate =~			
V212	1.000		
V312	17.988	4.902	<0.001***
V404	-0.236	0.076	0.002***
V501	-0.710	0.230	0.002***
V511	15.066	4.134	<0.001***
V525	12.208	3.323	<0.001***
Regression:			
Non-proximate ~ V201	0.052	0.003	<0.001***
Proximate~V201	-0.020	0.006	<0.001***

**** Significant at 5% significance level*

Table 6 displays the results of the standardized factor loadings between the manifest variables and latent variables, with a graphical display shown in Figure 1. From Table 6, it can be observed that wealth index (V190) contributed the most towards the non-proximate determinants construct, with a factor loading of -0.880 and approximately 77.2% of explained variation in non-proximate determinants. Likewise, the fertility preference (V602) contributed the least towards the non-proximate determinants, with a factor loading of 0.040 and approximately 0.2% of explained variation in non-proximate determinants. On the other hand, it can be concluded that age at first birth (V212) and age at first sex (V525) contributed more towards the proximate determinants construct, with a factor loading of 0.820 and 0.720 respectively, and approximately 66.8% and 52.0% of explained variations in proximate determinants respectively as shown in Table 6. Moreover, it can be concluded that marital status (V501) and breastfeeding (V404) had the least contribution towards the proximate determinants construct, with both having a factor loading of -0.11, and 1.2% of explained variation in proximate determinants.

Table 6 Factor loadings for proximate and non-proximate determinants

	Standardized factor loadings	R-squared
Non-proximate determinants (*n*=9,176)		
V025	0.620	0.385
V106	-0.580	0.336
V157	-0.670	0.452
V158	-0.330	0.109
V159	-0.760	0.573
V190	-0.880	0.772
V714	-0.430	0.187
V602	0.040	0.002
Proximate determinants (*n*=9,176)		
V212	0.820	0.668
V312	0.070	0.005
V404	-0.110	0.012
V501	-0.110	0.012
V511	0.430	0.187
V525	0.720	0.520

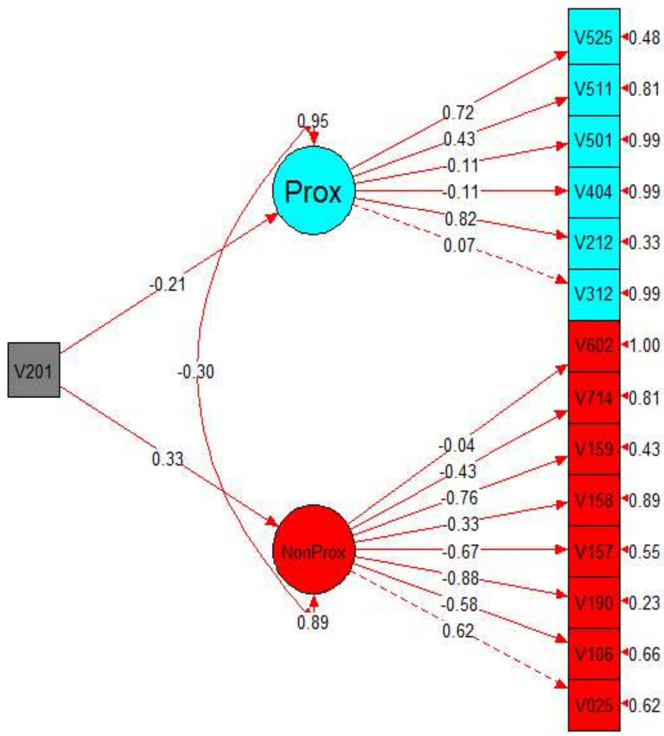

Figure 1 Proximate and non-proximate determinants of fertility factor model structure, where V201=Children Ever Born, Prox=Proximate, NonProx=non-proximate, with factor loadings (middle) and errors (end)

4. Discussions

The study objective was to model the relationship between proximate and non-proximate determinants of fertility using SEM approach. The identified latent constructs were validated using CFA and the analysis was concluded by linking the two constructs (proximate and non-proximate determinants) to the number of CEB, with the relationship between the variables depicted in a path diagram (Figure 1), a process that complete SEM.

The study findings revealed that most women in Namibia started to engage in sexual intercourse at an early age of 10 years old, and this might have increased their likelihood of bearing more children by the time they reach the end of the reproductive period. The study also found that, half of the women had their first union when they were age below 20 years, and this had a significant contribution to high fertility rate. The study further found that educational attainment, wealth index, exposure to media (newspaper, television and radio), employment status were significant predictors of fertility in Namibia.

It was also noted that education had a negative effect on the number of CEB. This maybe due to Namibian women with high level of educational attainment being more likely to have access to better family planning services, and more likely to (choose to) have few(er) children as a result of their contraceptive use and late marriage (postponement of marriage owing to the numbers of years spent in school). This finding is similar to those of Islam et al. (2016), who pointed out that educated women who lived in mid-town areas had fewer children than their uneducated counterparts.

In this study it was found that religion was not a significant predictor of fertility in Namibia. This finding is similar to those of Shinyemba (2014) who concluded that religion was not a significant predictor of fertility among adolescents in Namibia. The data sets used in these two studies were 6 years apart, thus, suggesting that religion still does not play a significant role in reducing fertility.

Exposure to mass media (newspaper, radio and television) was found to have a strong negative effect on the number of CEB to a Namibia woman. This means that women who were exposed to mass media were more likely to have few children compared to those who do not have access to mass media. This is because mass media communication provides a wide variety of information on sexual and reproductive health rights of both women and men, that covers contraceptive use, danger of sexually transmitted disease, violence against woman and girls amongst other. Exposure to mass media also teach women about child spacing and the cost of raising more children. However, Shinyemba (2014) found that exposure to mass media among adolescents had a positive impact on the number of children born by adolescents. This could be attributed to that fact that adolescent girls who watch TV and listen to the radio were more likely get exposed to sexual content broadcasted in the mass media which then triggers their sexual activities, even though contraceptive use among adolescents is known to be very low, consequently resulting in the girls engaging in unprotected sexual acts which most often leads to unplanned pregnancies.

Furthermore, the study showed that among the variables on the proximate determinants construct, age at first birth and age at first sex had the greatest positive effect on fertility. This means that, women who have had first sex at younger ages or a first birth at younger ages were more probable to have more children born, compared to women who had sexual debut at older ages or those that started childbearing at older ages. These findings were similar to those of Motsima and Malela-Majika (2016) who found age at first sexual intercourse to be a significant predictor of fertility outcomes in Lesotho. Similarly, Heywood, Patrick, Smith, and Pitts (2015) also found age at sexual debut to be related to the number of children born by women in the US.

It was also found that contraceptive use had minor negative effect on fertility. Palamuleni (2017) explained that it could be due to stagnant use of contraceptives from 2006. In Zambia, Chola and Michelo (2016) also found contraceptive use to have had a slight influence on fertility decline. However, issues contributing to unprogressively contraceptive use were beyond the scope of this study.

The study also found breastfeeding to have had a minor significant negative impact on the number of children. Suggesting that women who breastfeed were more likely to have fewer children compared to women who did not breastfeed, because breastfeeding increases postpartum infecundability. This finding concurs with those of Alene and Worku (2009) who also found prolonged breastfeeding to be the most important proximate determinants of fertility reduction in Ethiopia.

Moreover, this study showed that the proximate (direct) determinants had a negative significant impact on the number of children, suggesting that for every positive change in proximate determinants the number of children born were more likely to decline. Conversely, Alene and Worku (2009) and Hinde (2014) reported that proximate determinants played a major role in reducing fertility. On the other hand, the non-proximate (indirect) determinants were found to have a significant positive effect on the number of children born, implying that for every positive change in non-proximate determinants, the number of children were more likely to increase.

5. Conclusion

In conclusion the groupings of the socio-economic, socio-demographic and health attributes of fertility differed from the Bongaarts classification of proximate and no-proximate determinants of fertility. The study found that, proximate determinants of fertility had played an important role in the reduction of fertility in Namibia over the years. On the other hand, non-proximate determinants had played as significant role on the increase of fertility.

However, the findings of this study are based on the 2013 NDHS data that was collected about 9 years ago, the results might not reflect the current fertility performance of the population. Also, this study only focused on women fertility, which could have been of a great importance if men fertility were studies together with the women fertility and observe how fertility pattern has changed among men over time. In addition, studying male fertility can help policy makers to formulate policies geared to control male fertility.

The study recomends that there is a need to educate and promote the use contraceptives and prolong breastfeeding among the poor to further reduce fertility, especially among women from poor families as the cost of rising children has become high as the year progresses. Promotion of girl child education also need to strengthened especially in rural areas in order to increase the age at first marriage and first birth. Additionally, it is recommend that further studies be done to investigate factors that caused stagnation in contraceptive use between 2006 and 2013 in Namibia. Further investigation should also focus on evaluating the effect of HIV/AIDS pandemic on fertility in Namibia.

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