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Original article

Trends on modern family planning methods in Abuja, Nigeria (2010 - 2021)

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Abstract

Background: Using data from the Family Health Clinic in Abuja, Nigeria, this study explores deeply into family planning practices and forecasting models.

Methods: Monthly data on modern family planning methods from 2010 to 2021 were analyzed using time series techniques. The Autoregressive Integrated Moving Average (ARIMA) model was used to estimate and generate forecasts.

Results: Significant disparities in the use of current family planning methods were discovered. Notably, male condoms had different usage habits, as seen by their high standard deviation (624.66). Female condoms had the highest coefficient of variation (CV) (90.44%), suggesting the most relative variation. Skewness and kurtosis measurements revealed unique usage patterns, with injectables and intrauterine contraceptive devices (IUCD) having right-skewed, heavy-tailed distributions. In contrast, female condoms and implants were negatively skewed and light-tailed distributions. The study found that the exclusive use of male condoms outperformed all female family health care methods, albeit at a declining rate with seasonal changes. The ARIMA(1,0,2)x(2,1,2)12 model proved to be the best accurate forecasting model, as evidenced by statistically significant P-values, the lowest RMSE, MAE, MAPE, AIC, HQC, and SBIC values, and a negative MPE, implying exact forecasts with relative simplicity.

Conclusion: These findings have important implications for family planning programs and healthcare decisions in Abuja, Nigeria.

Keywords: Family Health, Forecasting, Random Work Model, ARIMA Model, Contraceptive Prevalence Rate, Nigeria

Introduction

According to the Nigeria Demographic and Health Survey (NDHS), the country has one of the world's highest rates of maternal mortality and morbidity, with an estimated 512 deaths per 100,000 live births. Despite the availability of modern family planning methods, Nigeria's contraceptive prevalence rate (CPR) remains low, with only 17% of married women utilizing any type of modern contraception, according to Fadeyibi (2). This low utilization of family planning services adds to the country's high rates of unplanned pregnancies and unsafe abortions, exacerbating already high maternal death and morbidity rates.

Furthermore, the use of contemporary family planning methods differs by location in Nigeria. While some states have made tremendous strides toward increasing the use of family planning services, others continue to have low utilization rates. This gap in the use of family planning services in Nigeria is cause for worry and necessitates a more in-

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depth examination of the factors underlying these differences (2, 3).

As a result, the purpose of this study is to investigate the trends in modern family planning methods in Nigeria between 2010 and 2021, utilizing the Family Health Clinic in Abuja as a case study. The project aims to model and forecast family planning methods in Nigeria, as well as make recommendations on how to enhance availability and use of these methods in the country.

Review of Related Literature

Ahmed (4) conducted a global investigation on the effectiveness of modern family planning strategies in preventing maternal mortality. The authors utilize statistical models to estimate the number of maternal deaths prevented by contraception in various nations. The findings emphasize the importance of current family planning approaches in lowering maternal mortality and improving reproductive health outcomes. By quantifying the benefits of contraception, the study contributes to the expanding body of evidence supporting the importance of accessible and comprehensive family planning services for women's health around the world.

Mulatu (5) investigated the effects of unintended pregnancies on maternal and child health outcomes. By discussing the role of modern family planning methods in mitigating these consequences, the study emphasizes the potential for improved reproductive health through informed contraceptive choices. The complete analysis emphasizes the importance of promoting modern family planning methods as a key component of improving maternal and child well-being.

Another study by Ali (6) examines contraceptive dropout and provides insight into the problems associated with maintaining contraceptive use. By identifying factors that influence the discontinuance of modern family planning methods in underdeveloped countries, this study tackles essential issues of contraceptive adoption and maintenance. The findings add to our understanding of how method-related concerns, counseling, and service quality influence contraceptive usage, providing strategies for ensuring the ongoing use of modern family planning techniques.

Sedgh (7) conducted a study on intended and unintended pregnancies, which provides a comprehensive assessment of global reproductive health trends. The study highlights the importance of modern family planning methods in preventing unintended pregnancies. The findings highlight the need of addressing unmet needs and raising awareness about modern family planning alternatives to guarantee that individuals and couples make informed reproductive decisions.

Hutchinson's (8) study focuses on Nigeria, investigating the attitudes and misconceptions about family planning methods among various demographic groups. By diving into the intricacies of knowledge and attitudes, the study emphasizes the importance of focused educational programs to refute myths and promote acceptance of modern family planning technologies. The findings help us understand how sociocultural influences influence contraceptive decision-making and usage habits.

Willcox (9) conducted another study in Uganda to explore barriers to long-acting reversible contraception (LARC) adoption during the postpartum period. By investigating LARC uptake problems, the study sheds light on how to improve access, awareness, and acceptance of modern family planning technologies during the important postpartum period. The findings contribute to conversations about improving family planning service delivery and meeting the unique requirements of postpartum women.

Shattuck (10) also conducted a Malawi inquiry at men's roles in encouraging family planning through the Malawi Male Motivator Project. The project investigates novel tactics for increasing the use of modern family planning approaches by including males in family planning discussions. The study contributes to conversations about holistic methods to family planning promotion by acknowledging men's participation as a potential catalyst for informed decision-making and better reproductive health outcomes.

Rabiu's (11) investigation of contraceptive effectiveness dives into the complexities of numerous family planning methods, including current alternatives. The study contributes to a better understanding of the impact and promise of modern family planning methods in reducing unwanted pregnancies by investigating method-related aspects and user behaviors. These findings increase understanding of the benefits and drawbacks of various approaches, assisting individuals, healthcare providers, and policymakers in making informed decisions about family planning.

Mulatu (12) conducted a comprehensive review in 2020 on the relationship between sexual and reproductive health and general well-being. The authors emphasized the importance of current family planning technologies in preventing unplanned births and lowering maternal mortality, highlighting the need of informed reproductive decision-making. The study demonstrates the relevance of incorporating current family planning alternatives into a broader health promotion framework, emphasizing the potential to enhance lives and contribute to sustainable development.

Ayad's (13) study in Rwanda provides insights into the trends and causes of unmet family planning needs. The study examines data from the Rwanda Demographic and Health Surveys to identify factors that contribute to the disparity between intended family size and contraceptive use (14). The findings contribute to a better knowledge of the specific constraints and dynamics that influence the uptake of modern family planning technologies, informing strategies for addressing unmet need and improving reproductive health outcomes.

Methodology

The secondary data used in this study was gathered from the data/research department of the Family Health Clinic in Abuja. The data set includes monthly records on current family planning methods from 2010 to 2021.

The ARIMA Model

Time series analysis is understanding the underlying context of data points by using models to forecast future values based on past data. This study mentions various time series models, including MA (Moving Average), AR (AutoRegressive), ARIMA (AutoRegressive Integrated Moving Average), as well as GARCH, TARCH, EGARCH, FIGARCH, and CGARCH models. However, the primary focus of the study in question centers on MA, AR, ARMA, and ARIMA models.

ARIMA is an acronym for Auto-Regressive Integrated Moving Average. This is a known time series model, which could be defined algebraically as:

$$Y_t = \mu + \alpha_1 y_{t-1} + \ldots + \alpha_p y_{p-1} + e_t - \delta_1 e t_{-1} + \delta_q e_{t-1} \quad \text{Equation 1}$$

at time $t = 1, \ldots, n$, where e_{t-j} $(j=0,1,\ldots ,q)$ are the lagged forecast errors. Usually, the $p + q+1$ unknown parameters $\mu,\ \alpha_j \ldots,\alpha_p$ *and* $\alpha_i \ldots,\alpha_q$ are determined by minimizing the squared residuals (15).

The ARIMA approach predicts the dependent variable yt in the first part of the right-hand side of equation 1 above based on its values at previous time periods. This constitutes the autoregressive (AR) part in equation 1 above. In the second part, the dependent variable y_t also depends on the values of the residuals at earlier time periods, which may be regarded as prior random alarms. This is the moving average (MA) part of equation 1.

In addition to the AR and MA parameters, ARIMA models may also include a constant. The interpretation of a statistically significant constant is determined on the model used.. Two indicative situations are:

i. There are no autoregressive parameters in the series. In this scenario, the constant's predicted value equals the series' mean.

ii. The situation of autoregressive parameters in the series. In such a case, the constant represents the intercept. If the series is different, then the constant represents the mean or intercept of the differenced series. For the non-seasonal scenario, the simple ARIMA (p, d,q) model is used with p the number of autoregressive terms, d the number of non-seasonal differences, and q the number of lagged forecast errors in the prediction equation. However, climatic data usually contains seasonal variations. Thus, it is more apt to incorporate the full Seasonal Auto Regressive Integrated Moving Average (SARIMA) model:

$$\text{SARIMA}(p\ d\ q)(\ P\ D\ Q\ )_S \quad \text{Equation 2}$$

with P the order of the seasonal AR-model; D the order of the seasonal differencing and Q the order of the seasonal MA-model. The subscript s represents the number of periods in the season. Mathematically, the general form of the model represented in equation 2 above can be written in the backshift notation (B) as:

$$\alpha_{AR}(B) \quad \alpha_{SAR}(B^s)(1-B^s)^d(1-B^s)^D \quad y_t = \delta_{MA}(B)\delta_{SAM}(B^s)e_t \quad \text{Equation 3}$$

where α_{AR} is the non-seasonal AR parameter, δ_{MA} the non-seasonal MA parameter, α_{SAR}, the seasonal AR parameter, and δ_{SAM} the seasonal MA parameter.

The Stationarity condition

Stationarity is an important condition for ARIMA models. In practice, the mean and variance should be constant as a function of time before performing the analysis. Otherwise, past effects would accumulate and the values of successive y_t 's would approach infinity making the process non-stationary. For a first order non-stationarity, the observations with ARIMA models should be sieved first by differencing the observations d times, using $\Delta^d y_t$ instead of y_t as the time series to obtain stationary data. This is usually done with the transformation:

$$\Delta y_t = y_t - y_{t-1} \quad \text{Equation 4}$$

The operations of equation 4 will result to the values $d = 0,1,2,\ldots$ for the non-seasonal part and values $D=0,1,2,\ldots$ for the seasonal part and this serves as an indicative guide in eliminating the first order non stationarity in the model identification process.

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It should be noted that in the case of second order non-stationarity, a simple transformation (such as the log transformation) may be a desirable operation to execute when found.

Applying the ARIMA Technique

So far, the preceding focused on the Box and Jenkins technique with its benchmark model application procedure consisting of three primary steps:
a) Identification
b) Estimation and
c) Forecasting or diagnostic checking.
During the identification stage, the determination of tentative values of the *p*,*d*, *q* and the *P*,*D*,*Q* sets was used through the linear least squares method. In the identification stage, a stationary or a weakly stationary situation is obtained by differencing and transformation of the data if needed. Then, the ACF and the PACF plots are used to suggest possible models by determining the orders *p* and *q* in the Seasonal ARIMA(*p, d, q,*)(*P, D, Q,*)*S* model. The goodness of the best models could be evaluated using the Mean Square Error (Residuals) MSE or using the Akaike Information Criterion AIC (16, 17).

Autocorrelation and partial autocorrelation

Autocorrelation and Partial autocorrelation are the time series techniques to measure the linear relationship between lagged values of the time series. The higher the deviation of these coefficients from zero, indicates more dependency of the series at a specific time with its lag values (18, 19). Correlograms (Plot of Autocorrelation functions (ACF) & Partial autocorrelation functions (PACF)) graphically indicate magnitude of dependency of the series on past values (15).

Forecasting Evaluation

Forecasting Evaluation Criteria Numerous error measures are available for forecast evaluation; thus, this study evaluates the forecasting ability of state space and Box-Jenkins type models by means of three different loss functions. The root mean squared error (RMSE), mean absolute error (MAE), and Theil's U statistic are defined as follows:

$$\boldsymbol{RMSE} = \sqrt{\boldsymbol{MSE}} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\mathrm{A}_t - \mathrm{F}_t)^2} \quad \text{Equation 5}$$

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{t=1}^{n}|(\mathrm{A}_t - \mathrm{F}_t)^2| \quad \text{Equation 6}$$

$$Ut = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(\mathrm{A}_t - \mathrm{F}_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(\mathrm{A}_t - A_{t-1})^2}} \quad \text{Equation 7}$$

where A_t is the actual value in time t, and F_t is the forecast value in time t. Theil's U statistic compares the accuracy of forecasts for different models. The overall perform of the estimating methods were accessed using the average of the three loss functions, that is $Average = (RMSE + MAE + Ut)/3$, the method with the minimum Average is the best.

Results

The data includes monthly records of the family planning methods requested by visitors from January 2010 to December 2021. The clinic offers oral contraceptives, injectable contraceptives, intrauterine devices (IUDs), implants, and condoms.
Table 1 shows descriptive statistics for monthly family planning methods requested by visitors to Family Health Clinic (FHC), Abuja based on sex. Males' monthly family planning visits appear to be higher on average and more variable than female visits. The distribution of visits in the female is more skewed to the right, whereas the male is more evenly distributed.
Table 2 shows descriptive statistics for the various family planning methods used at the FHC facility in Abuja. Table 2 also gives information on the demand distribution and variability of various family planning methods in FHC Abuja. Among the methods described, male condoms are in the most demand. Injectables have the least variability among the approaches, while female condoms have the most. Male condoms have the greatest range, indicating a more widespread dispersion of demand. These statistics shed light on the demand and distribution of various family planning methods in FHC, Abuja, with differences in average demand, variability, skewness, and kurtosis between the methods. It is critical for resource planning and understanding the prevalence and variability of each contraceptive method.

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Table 1. Descriptive Statistics of Monthly Family Planning Visits in FHC, Abuja, Nigeria

	Females Contraceptives	***Males Contraceptives***
Number of Family Planning Methods	57566	154993
Average	399.76	1076.34
Standard deviation	122.98	624.66
Coeff. of variation	30.76%	58.04%
Minimum	118	207
Maximum	879	2980
Range	761	2773
Stnd. Skewness	7.32	3.43
Stnd. Kurtosis	7.35	-0.12

FHC = Family Health Clinic

Table 2. Descriptive Statistics of Family Planning Methods used in FHC, Abuja, Nigeria

Family Planning Methods demanded	***Male condom***	***Female condom***	***Injectables***	***Oral pill***	***IUCD***	***Implants***
Number	154993	7261	20958	14531	7539	7277
Average	1076.34	50.42	145.54	100.91	52.35	50.53
Standard deviation	624.66	45.60	71.96	32.62	20.30	16.80
Coeff. of variation	58.04%	90.45%	49.45%	32.32%	38.77%	33.24%
Minimum	207	0	51	14	0	0
Maximum	2980	219	414	179	127	89
Range	2773	219	363	165	127	89
Stnd. skewness	3.43	6.31	11.25	0.38	4.76	-2.34
Stnd. kurtosis	-0.12	4.83	12.91	-0.38	6.28	1.06

FHC = Family Health Clinic
IUCD = Intrauterine Contraceptive Device

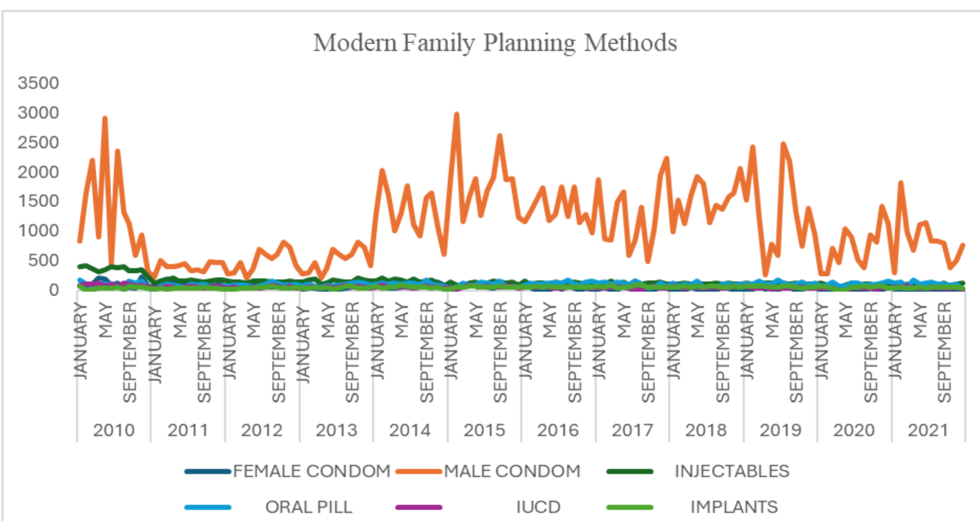

Figure 1. Time Series Plot of Family Planning Methods used

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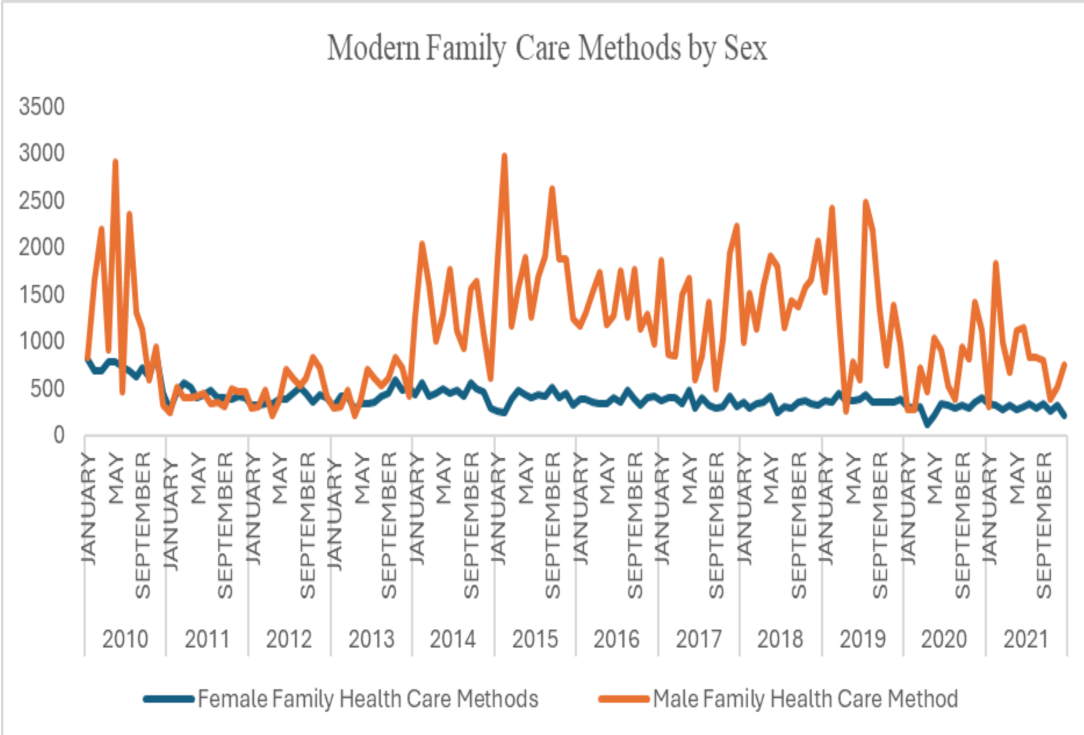

Figure 2. Modern Family Care Methods by Sex

Table 3. Unit Root Test

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-11.55	0.00
Test critical values:	1% level		-3.48	
	5% level		-2.88	
	10% level		-2.58	

Table 4. ARIMA Model Summary

Parameter	*Estimate*	*Stnd. Error*	*T*	*P-value*
AR(1)	0.93	0.06	16.18	0.00
MA(1)	0.56	0.11	5.26	0.00
MA(2)	0.11	0.10	1.10	0.27
SAR(1)	0.72	0.09	7.73	0.00
SAR(2)	-0.40	0.07	-5.55	0.00
SMA(1)	1.71	0.05	36.69	0.00
SMA(2)	-0.75	0.04	-17.57	0.00

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Statistic	*Estimation Period*
RMSE	469.94
MAE	371.06
MAPE	31.35
ME	-19.53
MPE	-12.48

RMSE: Root Mean Squared Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
ME: Mean Error
MPE: Mean Percentage Error
Back forecasting: yes

Estimated white noise variance = 266702. with 125 degrees of freedom

Estimated white noise standard deviation = 516.432

Number of iterations: 19

Table 5. Estimation Period

Model	*RMSE*	*MAE*	*MAPE*	*ME*	*MPE*	*AIC*	*HQC*	*SBIC*
(A)	621.26	428.35	31.31	-6.94	-8.14	13.02	13.11	13.24
(B)	623.59	428.15	31.22	-0.07	-7.58	13.04	13.14	13.29
(C)	669.38	532.81	44.85	-2.37	-21.59	13.18	13.28	13.43
(D)	671.73	532.31	44.74	-2.42	-21.53	13.20	13.31	13.47
(E)	655.61	496.83	41.25	-2.45	-19.83	13.17	13.28	13.45
(F)	686.45	525.82	40.08	133.06	-10.28	13.24	13.35	13.51
(G)	686.25	524.58	39.95	132.78	-10.26	13.24	13.35	13.51
(H)	574.93	416.72	30.98	-13.52	-9.80	12.88	12.98	13.12
(I)	526.39	386.83	29.76	-29.41	-12.10	12.70	12.80	12.95
(J)	545.73	407.08	30.84	-23.39	-9.15	12.77	12.87	13.02
(K)	532.54	389.48	29.37	-0.81	-8.70	12.74	12.84	13.00
(L)	562.05	425.02	32.50	-12.94	-7.35	12.83	12.93	13.08
(M)	500.59	386.71	30.24	38.19	-3.77	12.47	12.50	12.54
(N)	469.94	371.06	31.35	-19.53	-12.48	12.40	12.46	12.55
(O)	471.47	372.94	31.50	-19.22	-12.51	12.41	12.47	12.55
(P)	474.50	365.81	29.93	10.61	-8.72	12.42	12.48	12.57
(Q)	499.06	382.62	32.01	-23.70	-13.91	12.48	12.51	12.56
(R)	499.22	384.11	32.15	-22.88	-13.88	12.48	12.52	12.56

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Model	***RMSE***	***RUNS***	***RUNM***	***AUTO***	***MEAN***	***VAR***
(A)	621.26	OK	***	***	OK	OK
(B)	623.59	OK	***	***	OK	OK
(C)	669.38	OK	***	***	OK	*
(D)	671.73	OK	***	***	OK	*
(E)	655.61	OK	***	***	OK	**
(F)	686.45	OK	***	***	OK	OK
(G)	686.25	OK	***	***	OK	OK
(H)	574.93	*	OK	***	OK	OK
(I)	526.39	OK	OK	*	OK	OK
(J)	545.73	OK	*	*	OK	OK
(K)	532.54	OK	OK	*	OK	OK
(L)	562.05	OK	**	*	OK	OK
(M)	500.59	OK	OK	OK	*	*
(N)	469.94	OK	OK	OK	OK	*
(O)	471.47	OK	OK	OK	OK	*
(P)	474.50	OK	OK	OK	OK	*
(Q)	499.06	OK	OK	OK	OK	OK
(R)	499.22	OK	OK	OK	OK	OK

Models

(A) Random walk

(B) Random walk with drift = -6.86289

(C) Constant mean = 1478.47

(D) Linear trend = 1182.89 + 0.372981 t

(E) Quadratic trend = -63613.8 + 164.349 t + -0.103455 t^2

(F) Exponential trend = exp(6.59209 + 0.000769698 t)

(G) S-curve trend = exp(7.91394 + -562.602 /t)

(H) Simple moving average of 2 terms

(I) Simple exponential smoothing with alpha = 0.3198

(J) Brown's linear exp. smoothing with alpha = 0.1842

(K) Holt's linear exp. smoothing with alpha = 0.322 and beta = 0.0238

(L) Brown's quadratic exp. smoothing with alpha = 0.1385

(M) Winters' exp. smoothing with alpha = 0.3074, beta = 0.0587, gamma = 0.0712

(N) ARIMA(1,0,2)x(2,1,2)12

(O) ARIMA(2,0,1)x(2,1,2)12

(P) ARIMA(2,1,1)x(2,1,2)12

(Q) ARIMA(2,0,1)x(0,1,1)12

(R) ARIMA(1,0,2)x(0,1,1)12

RMSE = Root Mean Squared Error

RUNS = Test for excessive runs up and down

RUNM = Test for excessive runs above and below median

AUTO = Ljung-Box test for excessive autocorrelation

MEAN = Test for difference in mean 1st half to 2nd half

VAR = Test for difference in variance 1st half to 2nd half

OK = not significant (p >= 0.05)

* = marginally significant (0.01 < p <= 0.05)

** = significant (0.001 < p <= 0.01)

*** = highly significant (p <= 0.001)

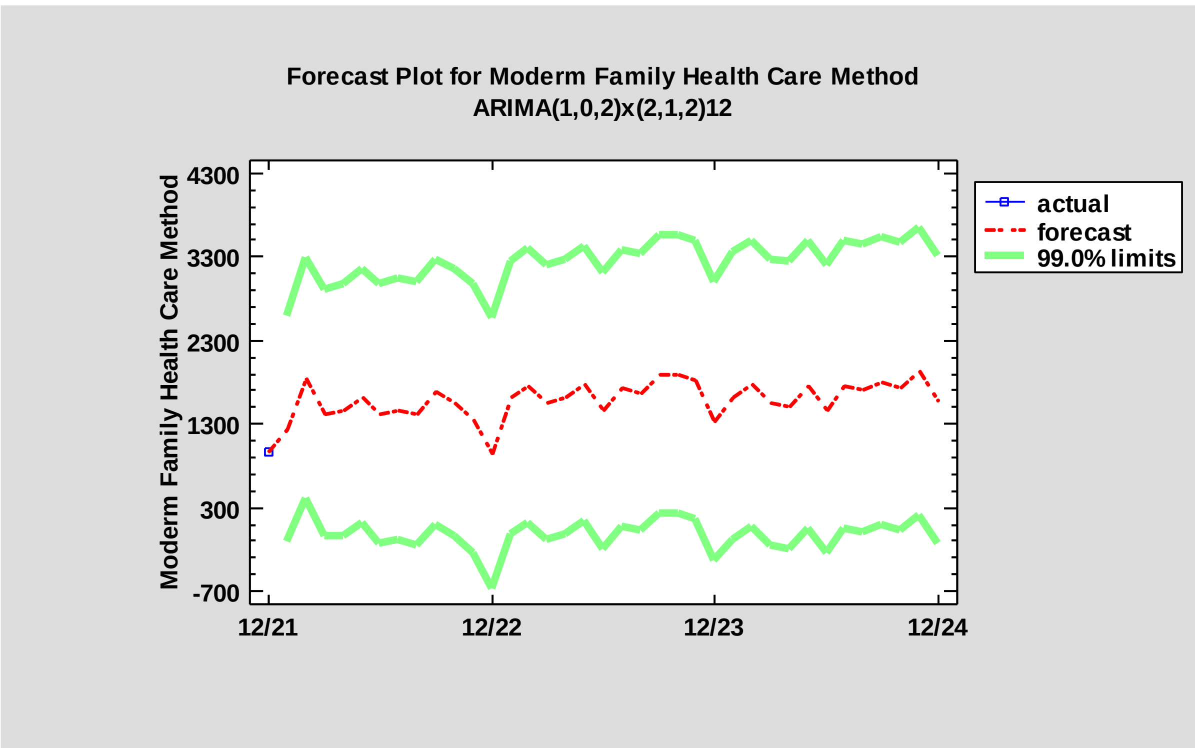

Figure 3. Forecast Plot of Monthly Family Planning Visits

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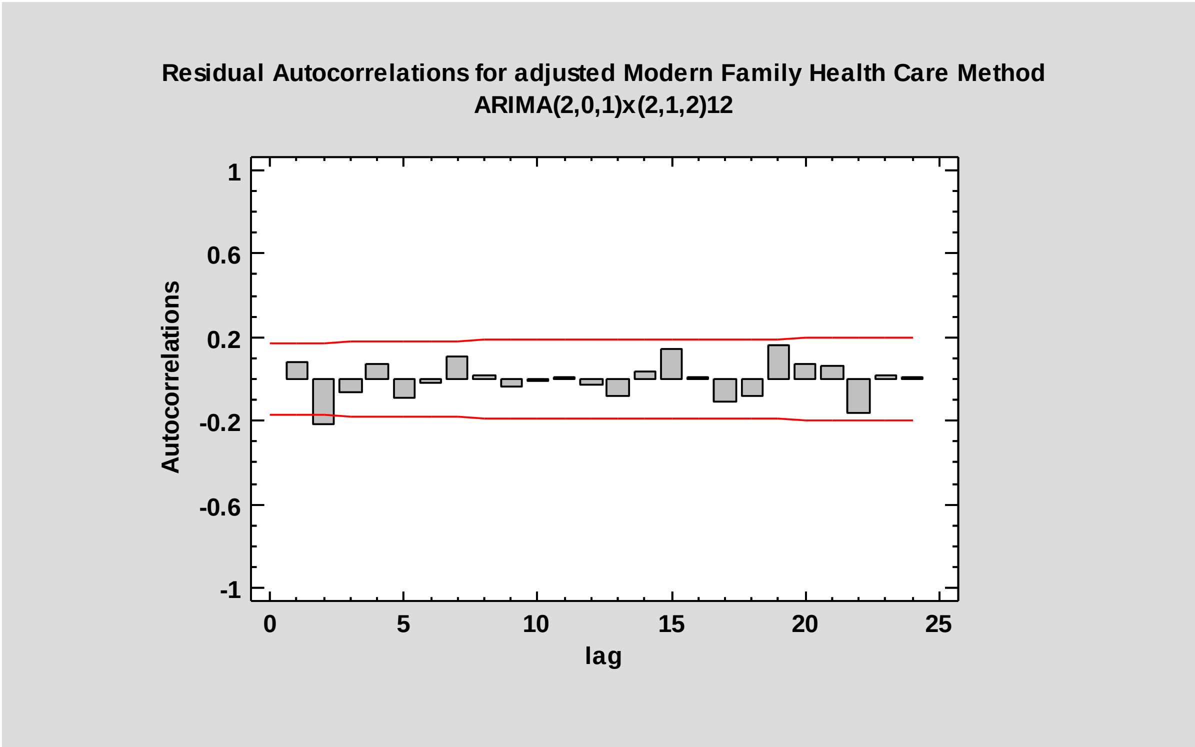

Figure 4. Residual Autocorrelation for adjusted Modern Family Health Care Method

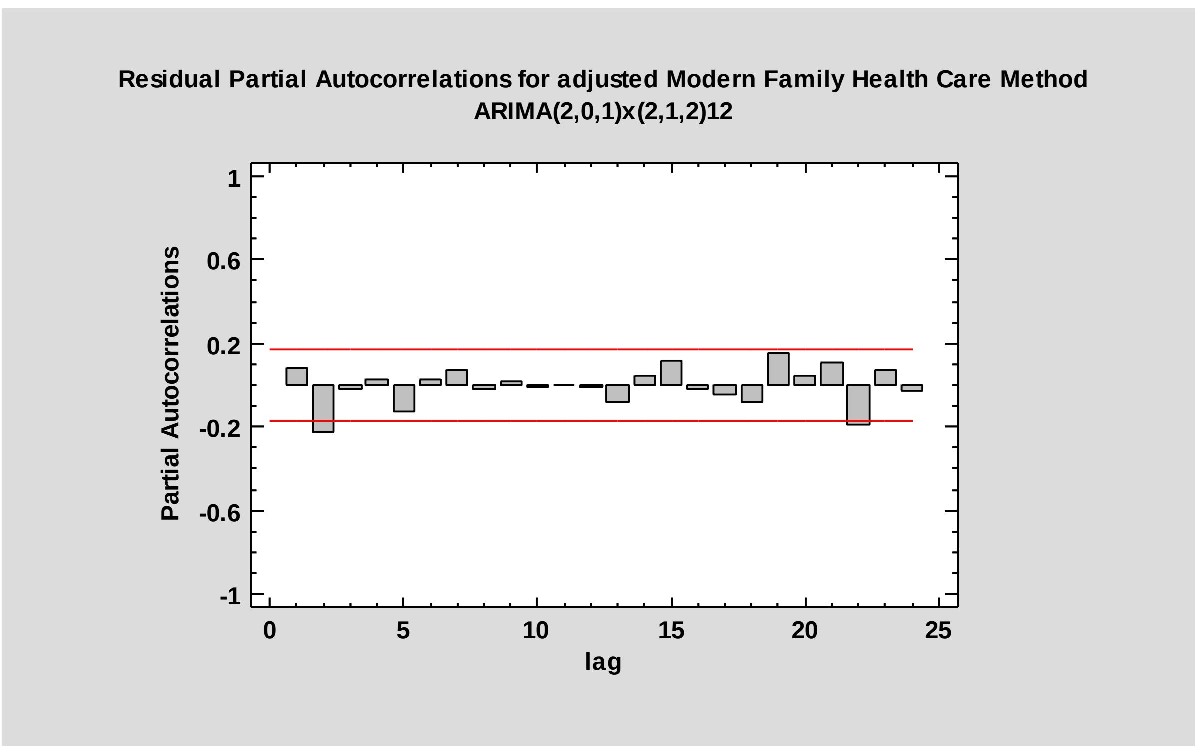

Figure 5. Residual Partial Autocorrelations for Adjusted Modern Family Health Care Method

Time Series Visualization

To display the time series data, we showed the number of contraceptives used each month during the research. Figure 1 shows the generated time series plot. The time series plot in Figure 1 shows a clear downward trend in the number of family planning visits over time, with some seasonal variability. This is cause for concern.
Figure 2 depicts a plot of modern family techniques by sex. The storyline combines all the current family methods employed by females in the Family Health Care Clinic in Abuja and dubbed it the "Female Family Health Care Method," followed using solely condoms as a family planning tool for males dubbed the "Male Family Health Care Method" and recorded over the course of the study. The plots reveal that male condom use outweighs all other female family health care techniques used during the study period. The plot demonstrates a decreasing tendency over the course of the research, with some seasonal variance.

Time Series Modeling

To model the time series data, we employed the Autoregressive Integrated Moving Average (ARIMA) model (20, 21). We initially tested the stationarity of the time series data using the Augmented Dickey-Fuller (ADF) test, as shown in Table 3. The ADF test determined that the time series data is stationary at first difference, with a p-value of 0.0000.
We then proceeded to determine the best ARIMA model for the data. The resulting model was an ARIMA(1,0,1)(2,1,2)12 model, which is shown in table 4.
Table 4 summarizes the statistical significance of the terms applied in the model. *AR(1), MA(1), MA(2), SAR(1), SAR(2), SMA(1), SMA(2)* are the estimated coefficients of the model. They represent the weights assigned to lagged values of the time series and the moving average terms. For example, the *AR(1)* coefficient is estimated as 0.931349, indicating a strong positive auto-regressive effect at lag 1. The P-values associated with each coefficient help assess their statistical significance. In this case, all the coefficients are statistically significant because their p-values are very close to zero ($p < 0.05$), except for *MA(2)*, which is not statistically significant ($p = 0.271812$). The ARIMA model has been estimated with various autoregressive and moving average terms. The coefficients are statistically significant, except for *MA(2)*. The model's accuracy is assessed using *RMSE*, *MAE*, and *MAPE*, with some indication of negative bias in predictions.

Forecasting

Figure 3 represents the anticipated values for the Modern Family Health Care Method. The graphic also shows 99.0% prediction boundaries for the forecasts. These boundaries indicate where the genuine value of the Modern Family Health Care Method is most likely to be with 99.0% certainty in the future.
We utilized the ARIMA model to forecast the number of family planning methods used in FHC Abuja. Figure 4 shows the resulting forecast plot.

Model Comparison

Table 5 compares the outcomes of fitting various models to the data. Based on the metrics provided, it appears that Model (N), which is an ARIMA(1,0,2)x(2,1,2)12 model, performs the best during the estimation period, as it has the lowest RMSE, MAE, MAPE, and AIC, HQC, and SBIC values, as well as a negative MPE, indicating that it provides the most accurate predictions and is less complex than the other models.
Figure 4 displays the estimated autocorrelations of the residuals at different delays. The lag k autocorrelation coefficient computes the correlation between the residuals at time t and time t-k. Also given are 99.0% probability bound around zero. If the probability bound for a given latency do not include the predicted coefficient, then there is a statistically significant connection at that lag at the 99.0% level. In this scenario, none of the 24 autocorrelation coefficients are statistically significant, indicating that the time series could be fully random.
Figure 5 shows the estimated partial autocorrelations of the residuals at different delays. The lag k partial autocorrelation coefficient calculates the correlation between the residuals at time t and time t+k, after accounting for correlations at all lower lags. It can be used to determine the order of the autoregressive models required to suit the data. Also given are 99.0% probability bound around zero. If the probability bound for a given latency do not include the predicted coefficient, then there is a statistically significant connection at that lag at the 99.0% level. At a confidence level of 99.0%, none of the 24 partial autocorrelation coefficients are statistically significant.

Discussion

Our detailed examination of family planning methods and forecasting models at the Family Health Care Clinic in Abuja, Nigeria, provided useful information

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for healthcare professionals, policymakers, and family planning program managers. Table 4 has a full summary of the use of various family planning strategies. These statistics provide insights into the distribution, central tendency, and variability of usage data. Notably, the statistics show that different approaches have large variances in utilization trends. For example, male condoms exhibit a wide range of usage habits, as evidenced by their relatively large standard deviation. This shows that the quantity of male condoms used varies dramatically over time. Conversely, female condoms have the largest coefficient of variation (CV), indicating significant relative variance among the approaches. These differences can be attributable to accessibility, awareness, and personal preferences.

Furthermore, the skewness and kurtosis metrics provide more information about the distributional features of the data. Injectables and intrauterine contraceptive devices (IUCD) have right-skewed distributions, indicating that their use is concentrated at lower levels with a lengthy tail on the right side. Female condoms and implants, on the other hand, are negatively skewed, indicating that they are used more frequently at higher values. Moreover, injectables and IUCD have strong positive kurtosis, indicating heavy-tailed distributions, but oral pills have slightly negative kurtosis, reflecting a lighter-tailed distribution. These findings can help family planning programs understand the dynamics of method utilization, allowing them to tailor their efforts more effectively.

The visual representation of family planning method usage by gender (Figure 4) shows that males exclusively use condoms, which surpasses other female family health care approaches. This discovery demonstrates gender-related tendencies in family planning, with a strong dependence on male contraception techniques. The falling trend during the research period, combined with seasonal changes, emphasizes the importance of continued monitoring and targeted interventions to encourage family planning strategies for both genders.

The ARIMA modeling results add another degree of insight by stressing the prediction ability of different models. Model (N), specifically the ARIMA(1,0,2)x(2,1,2)12 model, performs well throughout the estimation period. It has the lowest RMSE, MAE, and MAPE, indicating higher predictive accuracy. Furthermore, it has a negative Mean Percentage Error (MPE), indicating a modest underestimating of the data on average. Model (N) also has the lowest Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQC), and Schwarz Bayesian Information Criterion (SBIC) scores, indicating a reasonable balance between goodness of fit and model complexity.

These findings collectively indicate that Model (N) is the best option for estimating family planning technique usage at the Family Health Care Clinic in Abuja. Its precision and simplicity make it an invaluable resource for healthcare decision-makers and family planning program managers. However, it is critical to recognize that model performance might vary depending on the context and the data's unique properties.

Conclusion

In conclusion, our comprehensive investigation of family planning methods and forecasting models at the Family Health Care Clinic in Abuja, Nigeria, yielded excellent findings with practical applications. The study of family planning strategies indicated significant variation in utilization patterns, with certain approaches exhibiting large fluctuations and unusual distributional characteristics. This information is useful in adapting family planning services to the community's different tastes and requirements. Furthermore, our examination of gender-specific usage trends revealed a strong dependence on male contraceptive options, particularly condoms. The observed diminishing trend with seasonal changes emphasizes the significance of ongoing monitoring and tailored actions to promote family planning among men and women.

On the modeling front, the ARIMA (Autoregressive Integrated Moving Average) analysis revealed that the ARIMA(1,0,2)x(2,1,2)12 model (Model N) was the most accurate in forecasting family planning technique utilization over the estimation period. This model surpassed others in terms of predicted accuracy, boasting reduced error metrics and superior information criteria. Model N's capacity to generate precise predictions while being relatively simple has major implications for healthcare decision-makers and program managers. These findings provide vital information for improving family planning services and policies in Abuja, Nigeria.

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