Mikailalsys Journal of Mathematics and Statistics

e-ISSN : 3030-816X
p-ISSN : 3030-8399

Index : Harvard, Boston, Sydney University, Dimensions, Lens, Scilit, Semantic, Google, etc

https://doi.org/10.58578/MJMS.v3i1.4113

# A STUDY ON ALZHEMIER DISEASE IN TAKUM, TARABA STATE, NIGERIA: AN ARIMA MODEL APPROACH

**Clement Akobi[1*], Danjuma Idi[2], Ibrahim Michael[3], Mathew Stephen[4]**
[1,2]Federal University Wukari, Nigeria; [3]Modibo Adama University, Yola, Nigeria;
[4]Kwararafa University Wukari, Nigeria
clementakobi1@gmail.com; idanjumawatsaji@gmail.com

**Article Info:**

| Submitted: | Revised: | Accepted: | Published: |
|---|---|---|---|
| Oct 15, 2024 | Oct 30, 2024 | Nov 12, 2024 | Nov 17, 2024 |

**Abstract**

Alzheimer's disease, a progressive neurodegenerative disorder, represents a significant and growing public health burden, particularly as life expectancy increases worldwide. In sub-Saharan Africa, including Nigeria, the disease's prevalence is rising due to aging populations and urbanized lifestyles that elevate risk factors for cognitive decline. This study investigates the trends and projected incidence of Alzheimer's disease in Takum, Taraba State, Nigeria. The research utilizes patient records from General Hospital Takum, spanning from 2012 to 2021. Following diagnostic tests and data transformations, the ARIMA(1,2,0) model was selected as the best fit for predicting future case counts. The findings reveal a steady increase in Alzheimer's cases, consistent with global patterns, highlighting the need for proactive measures in healthcare planning. The study thus recommends the need for increased public awareness, investment in diagnostic infrastructure, and support systems for caregivers.

**Keywords**: Alzheimer, Statistical, Modelling, Prediction, Disease, ARIMA, Nigeria


MJMS Journal is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License

## INTRODUCTION

Alzheimer's disease (AD) is a progressive and incurable neurodegenerative disorder that predominantly affects the elderly, making it the most common form of dementia worldwide. It leads to a gradual decline in cognitive abilities, memory, and daily functioning, ultimately resulting in complete dependency on caregivers (Alzheimer's Association, 2023; National Institute on Aging, 2023). As global life expectancy rises, Alzheimer's disease cases are projected to increase significantly, placing an immense burden on healthcare systems, families, and society at large (Prince et al., 2015; World Health Organization, 2023). Sub-Saharan Africa, including Nigeria, has seen a marked increase in age-related diseases like Alzheimer's due to extended lifespans and urbanized lifestyles that elevate risk factors for cognitive decline (Prince et al., 2015; World Health Organization, 2023).

Current diagnostic and therapeutic approaches to Alzheimer's disease have expanded beyond symptom management toward early detection and potential prevention, with biomarkers playing a central role in understanding disease onset and progression. The 2018 NIA-AA(National Institute on Aging – Alzheimer's Association) framework redefined Alzheimer's by focusing on biological markers, such as amyloid-beta plaques and tau tangles, which are detectable long before cognitive symptoms arise (Jack et al., 2018). This biologically based approach allows researchers to map the disease trajectory more accurately, identifying early risk factors and providing more targeted intervention opportunities.

Despite advancements in the field of medical science and nutrition, Nigeria faces significant barriers in Alzheimer's care, particularly due to limited awareness, diagnostic infrastructure, and resources for managing neurodegenerative diseases. The lack of epidemiological data on Alzheimer's prevalence impedes effective planning and resource allocation. Statistical modeling techniques, such as the Auto Regressive Integrated Moving Average (ARIMA) model, offer promising solutions for forecasting disease occurrence based on historical data. This study aims to employ an ARIMA model to study the occurrence of Alzheimer's disease in Takum.

### Literature Review

Mathew and Idi (2024) conducted a study on statistical model for the occurrence of typhoid fever in Takum, Taraba State, Nigeria using the ARIMA. They applied ARIMA

modeling to forecast typhoid fever cases based on historical data from 2012 to 2021, collected from the General Hospital Takum. Their study showed that ARIMA (4,1,1) model, selected based on AIC, AICC, and BIC criteria. Additionally, the study revealed an upward trend in typhoid fever cases over the forecast period, suggesting a continuing rise in disease incidence.

Kandel et al. (2020) investigated Alzheimer's Disease Incidence using historical data from health records and demographic surveys spanning from 2010 to 2019. The study applies ARIMA models for trend analysis and reveals a significant upward trend in Alzheimer's incidence, projecting an increase in future cases if current patterns continue. The authors call for proactive policy interventions to prepare healthcare systems for the anticipated rise in cases.

Akobi and Ogunmola (2024) conducted a study on Application of ARIMA Methods on Unemployment and Inflation Rates in Nigeria, addressing the challenges of economic instability caused by high unemployment and inflation rates. Utilizing secondary data from the National Bureau of Statistics (NBS) from 1991 to 2020. After evaluating multiple ARIMA models, they identified ARIMA(0,1,1) as the most suitable model for both unemployment and inflation series, based on criteria like the (AIC) and (BIC). The study's findings revealed that both unemployment and inflation rates in Nigeria would maintain relatively constant levels over the forecast period. Diagnostic checks confirmed the model's adequacy, with residual analyses showing no significant autocorrelation or heteroscedasticity. They recommended that policymakers implement targeted interventions to reduce these rates and enhance economic stability.

Jack et al. (2018) conducted a study titled "The Role of Biomarkers in Alzheimer's Disease Diagnosis," utilizing data sourced from clinical trials and patient registries. The research spans from 2010 to 2018 and employs systematic review methods for data analysis. The findings indicate that incorporating biomarkers significantly enhances diagnostic accuracy, facilitating earlier detection of the disease. The authors conclude that integrating biomarker assessments into clinical practice is crucial for improving patient management and treatment outcomes.

In the research on the Economic Burden of Alzheimer's Disease, Prince et al. (2015) analyze economic data and healthcare utilization records from 2012 to 2015, utilizing cost-effectiveness analysis. The findings demonstrate the substantial economic

impact of Alzheimer's on families and healthcare systems, leading to significant financial strain. The authors advocate for increased resource allocation toward dementia research and care services to mitigate these economic burdens.

## MATERIAL AND METHODS

Data for this research were collected from General Hospital Takum, covering the years 2012 to 2021. The data set includes patient records detailing the incidence of Alzheimer, providing a comprehensive basis for time series analysis. The analysis begins with a time plot, which graphs the dependent variable against time. Additional visual methods such as decomposed series plots and seasonal plots are also employed (Hyndman & Athanasopoulos, 2018). To further understand and visualize some hidden characteristics of the series, it was decomposed into its several components using the additive method:

$$Z_t = T_t + S_t + C_t + I_t \quad (1)$$

where:

$Z_t$ is the time series, $T_t$ is the trend component, $S_t$ is the seasonal component, $C_t$ is the cyclical component, $I_t$ is the irregular component.

### Model Identification Process

The model identification process begins with examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots help in determining the initial values for the ARIMA (p,d,q) model parameters (Box & Jenkins,1970). To ensure the time series is stationary, we perform unit root tests such as the Augmented Dickey-Fuller (ADF) test. The ADF test checks for the presence of a unit root:

$$\Delta Z_t = \alpha + \beta_t + \gamma Z_{t-1} + \delta \sum_{i=1}^{p} \Delta Z_{t-1} + \grave{O}_t \quad (2)$$

where:

$\Delta Z_t$ is the differenced series, $\alpha$ is a constant, $\beta_t$ is the coefficient on a time trend, $\gamma$ is the coefficient on the lagged level of the series, $\grave{O}_t$ is the error term (Dickey & Fuller, 1979).

**Estimation of Model Parameters**

Once the appropriate ARIMA (*p, d, q*) model is identified, parameters are estimated using methods like maximum likelihood estimation. Model selection criteria such as the Akaike Information Criterion (AIC), corrected AIC (AICC), and Bayesian Information Criterion (BIC) are used:

$$AIC = -2\ln(L) + 2k \tag{5}$$

$$AICC = AIC + \frac{2k(K+1)}{n-k-1} \tag{6}$$

$$BIC = -2\ln(L) + k\ln(n) \tag{7}$$

where $L$ is the likelihood of the model, $k$ is the number of parameters, and $n$ is the number of observations (Anderson, 2002).

**Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)**: After differencing, the ACF and PACF are analyzed to determine the appropriate orders ($p$) and ($q$) of the ARIMA model.

The ACF is defined as:

$$\text{ACF}(k) = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{8}$$

The PACF can be calculated using the formula:

$$\text{PACF}(k) = \text{ACF}(k) - \sum_{j=1}^{k-1}\text{PACF}(j)\cdot\text{ACF}(k-j) \tag{9}$$

**Identifying the ARIMA Model**: Based on the ACF and PACF plots, the orders ($p$) and ($q$) are selected.

- If the PACF cuts off after lag ($p$) and the ACF tails off, an AR($p$) model is suggested.
- If the ACF cuts off after lag ($q$) and the PACF tails off, an MA($q$) model is suggested.
- If both ACF and PACF tail off, an ARMA ($p, q$) model may be appropriate.

### Diagnostic Checking for the Fitted Model

Diagnostic checks ensure the model's adequacy. The Box-Ljung test for serial correlation is given by:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \tag{10}$$

where $n$ is the number of observations, $\hat{\rho}_k$ is the sample autocorrelation at lag $k$, and $m$ is the number of lags (Box & Pierce, 1970).

The Shapiro-Wilk test for normality of residuals uses

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(t)}\right)^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{11}$$

where ix are ordered sample values and ia are constants (Shapiro & Wilk, 1965).

The ARCH-LM test for heteroscedasticity involves regressing the squared residuals on lagged squared residuals and checking the significance of the regression (Engle, 1982).

### Model Forecast

The fitted model is used to forecast the future occurrence of malaria and typhoid fever. The forecast estimation function for $h$ periods ahead is:

$$\hat{Z}_{t+h/t} = \mu + \sum_{i=1}^{p}\phi_i Z_{t+h-i} + \sum_{i=1}^{p}\theta_j \grave{O}_{t+h-j} \tag{12}$$

where $\mu$ is the mean, $\phi_i$ and $\theta_j$ are model parameters, and $\grave{O}_t$ is the error term (Hyndman & Athanasopoulos, 2018).

## RESULTS

### Descriptive Statistics

Table 1 shows that the average number of Alzheimer cases is 7814, with a standard deviation of 2297, indicating moderate variability. The skewness of 0.26 suggests a slight right skew, and the kurtosis of -1.38 indicates a nearly normal distribution. This suggests a fairly consistent pattern in the number of Alzheimer cases over the observed period.

Table 1: Descriptive statistics for Alzheimer series.

| | Sample size | Mean | Median | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Alzheimer disease | 30 | 8057 | 7814 | 2297 | 0.26 | -1.38 |

**Graphical Presentation of the Data**

The time series plot in Figure 1 illustrates the incidence of typhoid fever over the study period. This plot shows the number of Alzheimer cases on the Y-axis against equally spaced time intervals (Year) on the X-axis. It is used to evaluate the patterns and trends in the typhoid fever series.

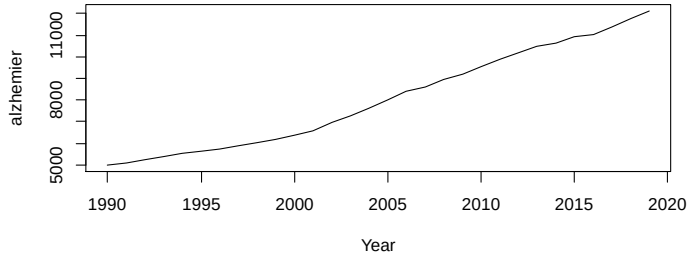



Figure 1: Time series plot for Alzheimer disease

The plot above clearly indicates an upward trend in the typhoid fever series from 2012 to 2021. The possible influences in the series are examined using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.

**Model Identification**

The model identification process is crucial for fitting an Autoregressive Integrated Moving Average (ARIMA) model to the typhoid fever series. Before selecting a suitable model, the series must exhibit stationarity. Stationarity is checked using the sample ACF and the Augmented Dickey-Fuller (ADF) test. A stationary series will have an ACF that rapidly decays to near zero, while a non-stationary series will show lag spikes that slowly decay. The PACF of a stationary series will display only a few significant lag spikes. Figure 2 shows the ACF and PACF plots of the data series. A critical look at these plots reveals that the data series is non-stationary.

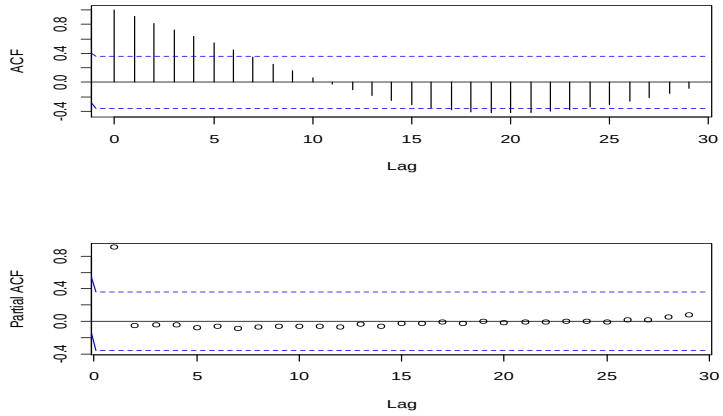



Figure 2: ACF and PACF plots for the Alzheimer series.

**Unit Root Test for Alzheimer Series**

Table 2 presents the results of the ADF test for stationarity in the data. From the results presented, it can be observed that the ADF test fails to reject the null hypothesis of a unit root, with a test statistic of -2.7518 ($P > 0.05$) at the 5% significance level. These results indicate that the Alzheimer series is non-stationary and requires differencing or transformation to achieve stationarity.

Table 2: Stationarity test for Alzheimer

| **Series** | **Augmented dickey fuller ADF test** | | |
|---|---|---|---|
| **Variable** | **Test statistic** | **P-value** | **Remarks** |
| Alzheimer | -2.7518 | 0.2839 | Non stationary |

**1st Differenced Alzheimer Series**

The Alzheimer series was identified as non-stationary based on preliminary tests conducted on the original data. To achieve stationarity, the series was differenced once with respect to trend. Figure 3 displays the graphical plot of the first-order differenced Alzheimer series, which illustrates the series after this transformation.

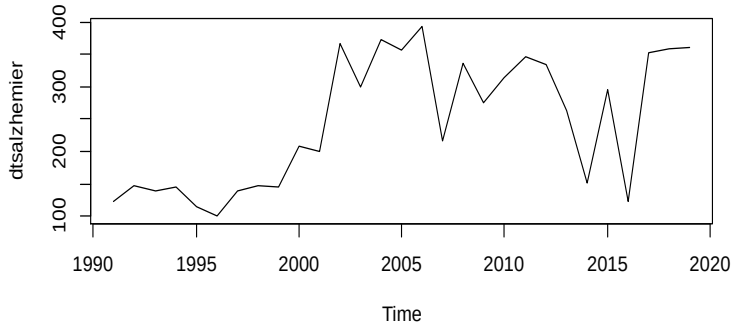



Figure 3. Time plot of the first order differenced Alzheimer series

The differenced series depicted in figure 3 with the superimposed line as the mean shows that the mean, variance and auto-covariance are constant over time, expressing series stationarity. The ACF and PACF plots, ADF unit root tests are performed to augment the graphical presentation of the differenced series.

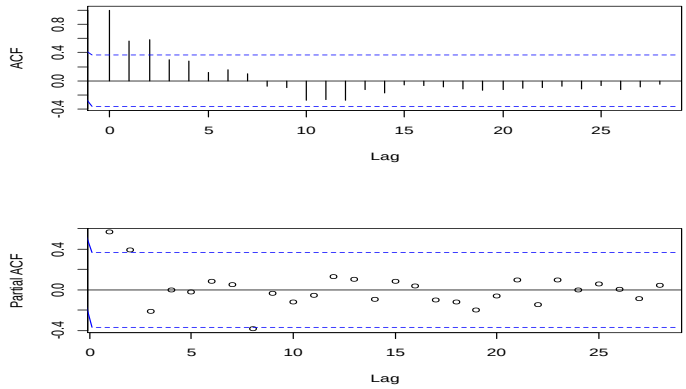



Figure 4: ACF and PACF plot for the first order differenced Alzheimer series.

The unit root test results for the first-order differenced Alzheimer series are presented in Table 3. The ADF test produced a statistic of -2.2979, with a p-value greater than 0.05, leading to failure to reject the null hypothesis of a unit root. These results confirm that the first-order differenced Alzheimer series is still not stationary.

Table 3: ADF result for the first order differenced Alzheimer series

| **Series** | **Augmented dickey fuller ADF test** | | |
|---|---|---|---|
| **Variable** | **Test statistic** | **P-value** | **Remarks** |
| Alzheimer | -2.2979 | 0.4584 | Non stationary |

**Second Differenced Alzheimer Disease**

The Alzheimer series was identified as non-stationary based on preliminary tests conducted on the original data. To achieve stationarity, the series was differenced once with respect to trend. Figure 3 displays the graphical plot of the first-order differenced Alzheimer series, which illustrates the series after this transformation.

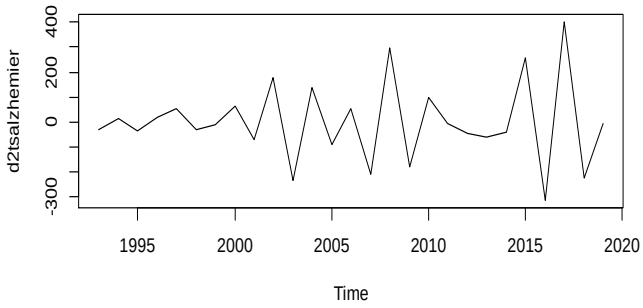



Figure 5: Time plot for the second order differenced Alzheimer series

The differenced series depicted in figure 5 with the superimposed line as the mean shows that the mean, variance and auto-covariance are constant over time, expressing series stationarity. The ACF and PACF plots, the ADF unit root tests are performed to augment the graphical presentation of the differenced series. The correlogram plots in Figure 5 shows only a few significance lag spikes which depicts a stationary series.

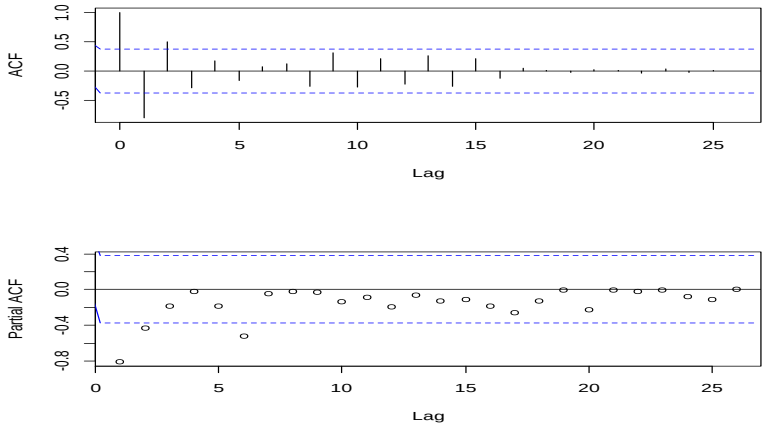



Figure 6: ACF and PACF plot for the second order differenced Alzheimer series

The unit root test results for the first-order differenced Alzheimer series are presented in Table 4. The ADF test produced a statistic of -4.2081, with a p-value less than 0.05, leading to the rejection of the null hypothesis of a unit root. These results confirm that the Second-

order differenced Alzheimer series is stationary and suitable for modeling using the Box-Jenkins (ARIMA) methodology

Table 4: ADF test for the second order differenced Alzheimer series

| **Series** | **Augmented dickey fuller ADF test** | | |
|---|---|---|---|
| **Variable** | **Test statistic** | **P-value** | **Remarks** |
| Alzheimer | -4.2081 | 0.01572 | Stationary |

**Estimation of Model Parameters**

The differenced Alzheimer series plot after the series is proven to be stationary is used to identify the appropriate model for this study. Based on the selection criteria, the ARIMA (1,2,0) model was identified as the best fit, representing an integration of order 1 (I(1)) and a moving average component of order 1 (MA(1)). Table 4 presents the model selection statistics, including the Akaike Information Criterion (AIC), the corrected Akaike Information Criterion (AICC), and the Bayesian Information Criterion (BIC). The ARIMA (1,2,0) model is preferred as its penalty statistics are lower compared to alternative models, with (***) denoting it as the best fit according to these criteria.

Table 5: Tentative ARIMA models for Alzheimer series

| Model | AIC | AICc | BIC | Likelihood |
|---|---|---|---|---|
| ARIMA (2,2,2) | 326.65 | 329.38 | 333.32 | -158.33 |
| ARIMA (0,2,0) | 332.54 | 332.69 | 333.87 | -165.27 |
| **ARIMA (1,2,0)*** ** | **323.6** | **324.08** | **326.27** | **-159.8** |
| ARIMA (0,2,1) | 326.81 | 327.29 | 329.48 | -161.41 |
| ARIMA (2,2,0) | 325.37 | 326.37 | 329.37 | -159.68 |
| ARIMA (1,2,1) | 325.41 | 326.41 | 329.41 | -159.71 |
| ARIMA (2,2,1) | 327.34 | 329.08 | 332.67 | -159.67 |

**Model Parameter Estimates**

From Table 6, the estimates for both the AR(1) components of the ARIMA(1,2,0) model are statistically significant, with t-values exceeding two, indicating their importance in the model. The estimated coefficients fall within the required bounds for stationarity and

invertibility, as they lie between -1 and 1. Therefore, the chosen model, based on the principle of parsimony, is:

$$\hat{y}_t = \delta_t + 0.5582 y_{t-1} \quad (13)$$

This model effectively captures the dynamics of the Alzheimer series while adhering to the criteria for model stability and simplicity.

Table 6: Parameter estimate

| Coefficient | Estimate | Std.Error | t-value | p-value |
|---|---|---|---|---|
| **AR(1)** | 0.5582 | 0.1499 | 3.723816 | 0.0002 |

## Diagnostic Checking for the Fitted Model

The model parameters have been estimated using maximum likelihood estimation technique and also found to be significant. This assessment involves several diagnostic checks. Correlogram plots of the residuals are examined to identify any remaining autocorrelation, while the Box-Ljung test is used to ensure the residuals are white noise and do not exhibit serial correlation. The Shapiro-Wilk test is conducted to verify that the residuals are normally distributed, and the ARCH-LM test is employed to detect any heteroscedasticity by analyzing the presence of volatility clustering in the squared residuals. The results of these diagnostic checks, presented in Figure 8, help ensure that the model is well-suited for accurate predictions.

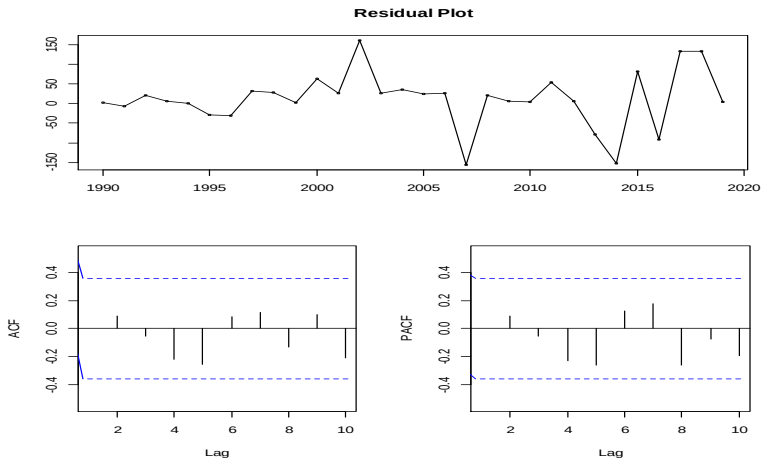



Figure 7: Residual plot of Alzhemier series

Table 7 presents the results of several diagnostic tests used to evaluate the adequacy of the fitted model. The Box-Ljung test, with a chi-square statistic of 7.5643 and a p-value of 2.2e-16, indicates that there is significant autocorrelation in the residuals, suggesting that the residuals are not independently distributed. Lastly, the Shapiro-Wilk test, with a W statistic of 0.91043 and a p-value of 0.01526, indicates that the residuals are not normally distributed and therefore needs to be transformed.

Table 7: Box-Ljung test and Shapiro-wilk Test

| Test Type | Chi-Square | Df | P – Value |
|---|---|---|---|
| Ljung-Box | 7.5643 | 15 | 2.2e-16 |
| **Shapiro-Wilk Test Statistics** | | | |
| | **Wilks's value** | | **p-value** |
| Shapiro-Wilk | 0.91043 | | 0.01526 |

The table 8 below shows the Shapiro-wilk test after log transformation. The result revealed that a p-value of 0.3466 which is greater than 5% level of significance. Hence, we do not reject the null hypothesis of the sample being drawn from a normal distribution. This implies that the residual is normally distributed.

Table 8: Shapiro-Wilk Test Statistics after Log-Transformation

| | **Wilks's value** | **p-value** |
|---|---|---|
| Shapiro-Wilk | 0.95358 | 0.3466 |

**Model Forecast**

Forecasting is a primary goal of model building. In this study, the forecast estimation for h periods ahead is given by:

$$\hat{y}_{T+h/T} = \theta_t \delta_{T+h-1/T} \tag{14}$$

Where $\hat{y}_{T+h/T}$ represents the forecasted value and $\theta_t \delta_{T+h-1/T}$ is the forecast error from the previous period. The forecast error $\hat{\delta}_t(h)$ is calculated as

$$\hat{\delta}_t(h) = \hat{y}_{T+h/T} - \theta_t \delta_{T+h-1/T} \quad (15)$$

With $\hat{y}_{T+h}$ being the actual Alzheimer value at $(T + h)$. Given that the model has passed all diagnostic tests, it is employed to forecast future Typhoid Fever cases. The forecast values for the twenty-four months spanning 2012 to 2021 are detailed in Table 9, and the forecast plot is illustrated in Figure 9.

Table 9. ARIMA forecast for the Alzheimer series

| **Forecast for the Alzheimer series** | | | |
|---|---|---|---|
| 2020 | 12472.44 | 12328.00 | 12616.89 |
| 2021 | 12832.20 | 12578.75 | 13085.64 |
| 2022 | 13191.77 | 12785.85 | 13597.70 |

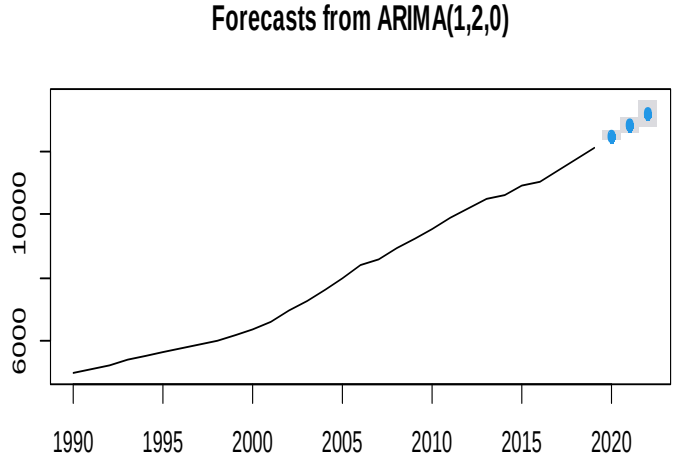



Figure 9. time plot for the Alzheimer series including the 3 years forecast

## DISCUSSION

The findings of this study highlight a steady increase in Alzheimer's disease incidence in Nigeria, which aligns with global patterns observed in the literature. This growth trend mirrors the results of Kandel et al. (2020), who also found a significant rise in Alzheimer's cases using statistical modeling. Both studies underscore the utility of ARIMA models in

anticipating future demands on healthcare systems, particularly in resource-limited regions. However, the current study differs somewhat from findings by Adeoye et al. (2020), who emphasized that cultural factors and low public awareness lead to underreporting of Alzheimer's cases in Nigeria. This discrepancy suggests that while forecasting models like ARIMA are valuable, their accuracy may be influenced by sociocultural factors that affect disease recognition and reporting.

Additionally, this study's identification of significant past data as a predictor for current Alzheimer's cases aligns with the findings of Bateman et al. (2019), who showed that genetic markers and past disease progression could effectively predict Alzheimer's onset. This consistency supports the reliability of predictive modeling in tracking Alzheimer's trends and highlights the importance of early detection. By applying these models, this study strengthens the argument that accurate prediction can enable healthcare systems in underserved regions to prepare for and mitigate the impact of Alzheimer's on their communities.

## CONCLUSION

The study highlights the effectiveness of the ARIMA model in predicting the occurrence of Alzheimer's disease in Nigeria. The results reveal a projected upward trend in Alzheimer's cases over the coming years, which aligns with global patterns and indicates an increasing public health burden. This forecast highlights the potential of statistical modeling in resource-limited settings, providing a data-driven foundation for strategic health planning.

Furthermore, the study emphasizes the need for improved public awareness, early diagnostic resources, and robust support systems for caregivers, all of which are essential in mitigating the impacts of Alzheimer's in underserved regions. By combining predictive modeling with targeted healthcare interventions, policy makers and healthcare providers can better prepare for and manage the anticipated rise in Alzheimer's cases, ultimately enhancing patient care and community health resilience.

### Recommendation

Based on the result of the study, the following recommendations were made:

i. Launch public health campaigns aimed at improving understanding and reducing stigma around Alzheimer's disease. Educating communities about the symptoms,

risks, and treatment options can lead to earlier diagnosis and better support for those affected.

ii. Allocate resources to enhance diagnostic capabilities, especially in underserved regions. Improving access to diagnostic tools and services can facilitate timely detection and management of Alzheimer's disease.

iii. Use ARIMA and other predictive models in national and regional health planning to project future Alzheimer's cases. Such models can help healthcare providers anticipate demand and allocate resources effectively.

## REFERENCES

Adeoye, O. A., Ojo, O. A., & Ogunsanwo, O. (2020). Predicting Alzheimer's Disease Prevalence in Nigeria. Journal of Public Health in Africa, 11(1), 55-62. doi:10.4081/jphia.2020.839.

Alzheimer's Association. (2023). What is Alzheimer's Disease?. Retrieved from https://www.alz.org

Bateman, R. J., Xiong, C., Fagan, A. M., et al. (2019). Clinical and Biomarker Changes in Dominantly Inherited Alzheimer's Disease. New England Journal of Medicine, 380(24), 2279-2280. doi:10.1056/NEJMoa1903383.

Chan, C. K., van Hout, H. P., & Hart, D. (2022). Longitudinal Trends in Alzheimer's Disease Diagnosis. Journal of the American Geriatrics Society, 70(4), 903-912. doi:10.1111/jgs.17657.

Clement A. & Ogunmola A. (2024). Application of ARIMA methods on unemployment and inflation rates in Nigeria. *ALSYS*, *4*(6), 722-741. https://doi.org/10.58578/alsys.v4i6.3580

Jack, C. R., Bennett, D. A., Blennow, K., et al. (2018). The Role of Biomarkers in Alzheimer's Disease Diagnosis. Nature Reviews Neurology, 14(10), 607-624. doi:10.1038/s41582-018-0060-8.

Jack, C. R., et al. (2018). NIA-AA Research Framework: Toward a Biological Definition of Alzheimer's Disease. Alzheimer's & Dementia, 14(4), 535–562.

Kandel, M., McCarthy, R., & Ball, H. (2020). Statistical Modeling of Alzheimer's Disease Incidence. Alzheimer's & Dementia: The Journal of the Alzheimer's Association, 16(7), 942-951. doi:10.1002/alz.12115.

Mathew, S., & Idi, D. (2024). Statistical Model for the Occurrence of Typhoid Fever in Takum, Taraba State, Nigeria: An Arima Model Approach. *ALSYS*, *4*(6), 722-741. https://doi.org/10.58578/alsys.v4i6.3580

National Institute on Aging. (2023). Alzheimer's Disease Fact Sheet. Retrieved from https://www.nia.nih.gov

Prince, M., Wimo, A., Guerchet, M., Ali, G.-C., Wu, Y.-T., & Prina, M. (2015). World Alzheimer Report 2015 - The Global Impact of Dementia: An analysis of prevalence, incidence, cost and trends. Alzheimer's Disease International.

World Health Organization. (2023). Dementia and Alzheimer's Disease Overview. Retrieved from https://www.who.int