



COMPARATIVE ANALYSIS OF STATISTICAL MODELS FOR EPILEPSY INCIDENCE

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ABSTRACT

Purpose: The paper aims to identify the best-fit trajectory model among selected model candidates on the epilepsy dataset, emphasising time and demographic factors.

Design/Methods/Approach: The study employed secondary monthly count data from the District Health Information Management System-2 (DHIMS-2) of the Ghana Health Service. The data was analysed using zero-inflated Poisson (ZIP) regression, zero-inflated negative binomial (ZINB) regression, and geometric regression (GR) models. These models were evaluated based on their goodness-of-fit to the dataset.

Findings: The geometric regression (GR) model emerged as the best-fit model compared to the ZIP and ZINB models. The results revealed that epilepsy incidence in the Saboba District is sex-dependent, with a significant p-value of 0.0369. Furthermore, the study found that epilepsy prevalence is relatively lower in younger children (0-9 years) and older adults (60-70+ years).



Participants within the economically active age group (18-59 years) were found to be at the highest risk. Moreover, the year 2015 recorded the highest epilepsy incidence, while 2013 had the lowest.

Research Limitation: The study solely used a dataset from the Saboba District, Ghana. As a result, its conclusion may not be broadly applicable.

Practical implications: The study provides crucial information for healthcare policymakers to develop targeted interventions for epilepsy. It emphasizes the need to protect the rights of people living with Epilepsy (PLWE), integrate risk factors into outreach programs, and improve access to healthcare services. These findings can help health systems incorporate better treatment and care strategies for high-risk populations.

Social implications: The study highlights the significant social impact of epilepsy, particularly on the economically active population. It stresses the importance of addressing the stigma and discrimination faced by PLWE through public education and awareness campaigns.

Originality /value: This study uses advanced statistical models to offer a vigorous methodological lens for analysing epilepsy data, thus supporting future research and policy development in mental health and epilepsy management in Ghana and beyond.

Keywords: *Epilepsy. demographic. geometric distribution. poisson distribution. zero-inflated poisson*

INTRODUCTION

Despite numerous scientific attempts to eradicate epilepsy, a plethora of scholarly and anecdotal evidence indicates that the prevalence of epilepsy remains high globally. The primary reasons for these trajectories are the socioeconomic and cultural effects of the disease (Beghi et al., 2018; Beghi et al., 2019; Gupta et al., 2021; Srober, 2018; Bastaki et al., 2024). According to earlier research, 50 million individuals worldwide receive an epilepsy diagnosis each year, with a higher-than-average death rate (Deegbe et al., 2021). For example, between 1999 and 2017, the death rate from epilepsy increased by 98.8% in the United States (Degiorgio et al., 2021). According to additional empirical data, developed economies typically diagnose 49 out of every 100,000 people with epilepsy annually.

It is estimated that 80% of people with epilepsy (PLWE) reside in emerging and transitioning nations where poverty is widespread (WHO, 2019; WHO, 2022; Bauer, 2024). The increasing trend of epilepsy is also linked to a higher risk of endemic illnesses such as malaria, greater frequency of injuries from traffic accidents, and injuries from childbirth. Other reasons are inadequate preventive health programs and inadequate medical infrastructure.



It may be argued that, after a few decades, experts still disagree on the best way to define epilepsy. This is mainly because medical professionals' perceptions of epilepsy as a medical idiosyncrasy have changed throughout time, leading to differing conclusions. In this context, many authors (Kaculini et al., 2021; Strober, 2018; Gupta et al., 2021; Issa et al., 2023; Younes et al., 2024; Singh et al., 2024) have established epilepsy as a prime entity or stand-alone condition within a larger spectrum of convulsive or neurological disorders. As a medical term, "epilepsy" refers to a condition causing recurring epileptic seizures or the person experiencing the seizures themselves. Accordingly, the majority of the early definitions of the term "epilepsy" emphasised the occurrence of convulsions that caused a loss of consciousness (Eadie & Bladin, 2010; Chan et al., 2023; Ryvlin et al., 2023; Herron & Kilpatrick, 2023).

It is possible to trace the historical development of epilepsy back to inscriptions and epigraphs of Akkadian provenance from 4,000 years ago (Beghi et al., 2019; Kaculini et al., 2021; Blank & Jette, 2023; Magiorkinis, 2014). Every year, approximately 10 million individuals in Africa suffer from epilepsy. Sub-Saharan Africa (SSA) had the highest prevalence rate. The sub-regions poverty and weak medical support networks are the main causes (Deegbe, 2021; Deegbe, 2019). The long duration of epilepsy and the devastation it unleashes on humanity have drawn the interest of scholars. Given this context, several academic publications have recently emerged to deepen conversations around epilepsy (Chen et al., 2012; Degiorgio et al., 2020; Shah et al., 2023; Xiao & Pan, 2023; Kim et al., 2024)

While earlier research indicated that epilepsy prevalence is comparatively higher in developing nations, there is evidence to imply that a lot of this research was carried out in the West. Because industrialised and developing nations have different socioeconomic conditions, it is practically impossible to generalise the results of these investigations (Mesraoua, 2020; Chen et al., 2012; Cui et al., 2022; D'Souza et al., 2023; Fiest et al., 2022). As a result, "there is a paucity" of information on epilepsy and a considerable gap in neurological literature.

Furthermore, many recent studies on epilepsy have primarily concentrated on coping strategies, causes, beliefs, social isolation, management, and stigma associated with PLWE (Adeloye et al., 2012; Sottie et al. 2018; and Mhlari & Sodi, 2017; Kim & Lee, 2023; Bauer & Chen, 2024). It was never the goal of any of these studies to statistically predict the incidence of epilepsy in Africa to support effective decision-making on the treatment and elimination of the condition. Based on strong statistical counting methods, including negative binomial regression, zero-inflated Poisson regression, and geometric regression models, the current study aims to fill this "void" by modelling the course of epilepsy cases.



The remaining sections of our study are structured as follows: Ghana's epilepsy landscape, review of relevant resources, material and methods, results, conclusion, implications, limitations, and recommendations.

REVIEW OF RELATED MATERIALS

Overview of Epilepsy

Classified as a persistent, non-contagious neurological condition, epilepsy is typically characterised by uncontrollably frequent and repeated seizures. The entire body or a portion of it experiences a brief episode of reflexive, spontaneous movement. Typically, epilepsy results in the loss of consciousness combined with involuntary bowel or bladder movements (Sugandha et al., 2021; Srober, 2018; Herron & Kilpatrick, 2023; Shah et al., 2023; Cui et al., 2022; Ngugi et al., 2023). According to earlier research, these seizures may occur spontaneously because of strong electrical discharges from the brain cells. Regardless of demographic background, epilepsy can affect anybody. Epilepsy-related fatalities frequently result from burns, falls, drowning, and extended seizures (WHO, 2019; Puteikis et al., 2021; Puteikis, 2021;).

The stigma associated with the disease is still relatively high worldwide, even though PLWE can be cured to resume a regular life in society with the right medication therapy and coping methods. PLWE were forbidden from offering any sacrifice in the early centuries when the stigma against them first emerged. The PLWE continue to experience substantial discrimination in a variety of ways in the 21st century. In Africa, socioeconomic discrimination and other culturally degrading acts are frequent experiences of PLEW, especially when it comes to issues about marriage, work, and health insurance (Ghanean, 2013; WHO, 2019; WHO, 2022).

Burden of Epilepsy, symptoms, causes and treatment

PLWE experience a wide range of seizures. It primarily depends on the disruption of brain cell sources and the underlying dissemination mechanisms. Loss of awareness, movement issues, feelings (including vision, hearing, and taste), and moody tendencies are the temporal symptoms of epilepsy. According to the WHO (2019), PLWE has a higher prevalence of psychological disorders, including anxiety and depression, as well as a higher incidence of physical issues, such as fractures and bruising from seizure-related accidents (Gupta et al., 2021; Stroder, 2018; Mesraoua, 2020; Lauren, 2018; Issa et al., 2023; Kim et al., 2024; Xiao & Pan, 2023).

According to the WHO, in 2019, 50% of all epilepsy cases have unidentified or unexplained causes. However, there are other categories of epilepsy causes, including metabolic, infectious,

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genetic, structural, immunological, and unknown causes. Congenital abnormalities (genetic conditions resulting in brain malformations), prenatal or perinatal brain damage (such as oxygen loss or trauma during birth and low birth weight), and strokes that limit oxygen flow to the brain are the most common causes of epilepsy in the literature. The remaining conditions include brain tumours, serious head injuries, and infections such as meningitis, encephalitis, or neurocysticercosis (Gupta, 2021; Kaculini, 2021; Freidel et al., 2024).

Medical professionals can administer suitable and focused medications to treat and manage epilepsy (Baskati et al., 2013; Younes et al., 2024; D'Souza et al., 2023; Baskati et al., 2024). Surgery is another option for managing (treating) this condition. In the 19th century, Heyman performed the first effective surgical surgery for epileptic patients with brain abscesses. Epileptic patients have undergone some successful surgical treatments worldwide (Magiorkinis et al., 2014). Nonetheless, some scholars, including Deeghe (2021) and Aziato et al. (2019), posit that epilepsy is a "spiritual disease," and as such, some patients seek treatment from faith-based organizations and "traditional healers."

2.3 Antimicrobial resistance in Epilepsy treatment

Similar to other medical illnesses, antimicrobial resistance continues to develop in the treatment of epilepsy. This implies that different world regions have different approaches to managing epilepsy. This is mainly because drugs and diagnostic tools are readily available. It has been determined that antiepileptic medications, or AEDs, are the cornerstone of epilepsy treatment. However, these medications are unable to control the seizures in one-third of epilepsy cases. The high rate at which patients have comorbidities and psychosocial disorders ultimately leads to medication hesitation (Mesraoua, 2020; Fiest et al., 2022; Strzelczyk et al., 2023; Thijs et al., 2023). In comparative terms, antibiotic resistance in the treatment of epilepsy is a significant public health concern, according to empirical data. Therefore, medical professionals advise that prompt treatment with appropriate AEDs is essential for lowering the risk of epilepsy (Mesraoua, 2020; Chan et al., 2022).

Demographic characteristics as risk factors of Epilepsy

The majority of earlier studies have examined how epilepsy affects different age groups. However, the results of these studies are inconsistent. Different study timeframes, geographic boundaries, data sources, quality, and study rigour could all contribute to this (Sroder, 2018; Chen et al., 2012; Issa et al., 2023; Kim & Lee, 2023).

The effectiveness of epilepsy control programs can be affected by "gender-related dynamics in decision-making, treatment-seeking behaviour, resource allocation, and financial authority within



households.” Therefore, some studies have examined the distribution of epilepsy cases by sex. Some of these studies were done by Chen et al. (2012) and Strober (2018), who found that men are more prone to epilepsy than women. Magiorkinis et al., (2014) espouse that males become more susceptible whenever the prevalence rate of lifetime epilepsy is at its greatest (i.e., between the ages of 20 and 39 years). However, females are more vulnerable during the second peak (50–59 years).

Prevention of Epilepsy

According to the WHO (2019) “preventing head trauma is the best way to prevent post-traumatic epilepsy.” Furthermore, disorders of the central nervous system are the leading causes of epilepsy in various tropical areas. Therefore, strenuous efforts to eradicate parasitic growth in these areas may be one of the best ways to significantly lower the incidence of epilepsy (Degiorgio et al., 2020; Chen et al., 2012; Mesraoua, 2020). Practical methods to lower cardiovascular risk factors are also recommended as a preventative measure against stroke-induced epilepsy. These include determined attempts to give up smoking, abstaining from excessive alcohol consumption, and preventing obesity and high blood pressure (Adeloye et al., 2017; Adeloye et al., 2012). Studies have also demonstrated that temperature management methods can effectively limit childhood epilepsy by using prescription medications to reduce body temperature (WHO, 2019; Mhlari & Sodi, 2017; Adeloye et al., 2012).

Socio-economic Burden of Epilepsy

According to previous research, epilepsy accounts for 0.5% of the global disease burden. This was based on the total years of life lost due to mortality and prolonged illness. Thus, it has been determined that epilepsy, in significant margins, affects a country's socioeconomic standing negatively through early mortality, social stigma, and a loss in productivity (Kaculini et al., 2021; Chen et al., 2012). The degree, severity, prognosis, and reaction of individuals to therapy significantly impact the financial burden of epilepsy. Victims’ families suffer greatly from self-financing medical care and lost work hours.

It is imperative to recognise that the stigma and discrimination associated with epilepsy vary across national borders. These problems are thought to be "often more difficult to overcome than the seizures themselves. Stated differently, the PLWE are disproportionately subjected to discrimination and unjust treatment. This suggests that the "stigma of the disease can discourage people from seeking treatment for symptoms to avoid... identified with the disease" WHO (2019).



Context of the study: The Landscape of Epilepsy in Ghana

According to estimates from the WHO (2019), 1% of Ghana's population suffered from epilepsy in 2016. In light of this, the Ghana Ministry of Health and the WHO 2012 jointly launched the first-ever campaign to combat epilepsy. This was a five-year project within the framework of: "improving the identification and management of people with convulsive forms of epilepsy in the existing primary health care system and developing a model of epilepsy care at the community level" (Sottie, 2018). There were fifty-five hospitals and clinics involved in this project. Five primary sub-themes were used in the project. These were: "the development of a mechanism for delivering epilepsy care among the populace, training of health care workers and volunteers, raising awareness and education among communities, engaging traditional and faith healers and lastly, strengthening the monitoring mechanism of epilepsy."

There has always been a significant treatment gap for epilepsy in Ghana. The state of affairs in developing nations is reflected in this. The percentage of the population that needs treatment for epilepsy but has not gotten it is known as the epilepsy treatment gap, according to the WHO. Previous research has shown that the active treatment gap for epilepsy is more than 75% in low-income nations such as Ghana. However, the median gap for active epilepsy treatment has been reported to be >50% in middle-income nations and <10% in high-income countries. According to Di Giorgio et al. (2020), there are several reasons why treatment gaps for epilepsy vary widely between economic blocs. These include low priority given to epilepsy care and attention, inadequate healthcare systems for the condition, a shortage of skilled and committed staff, poverty, stigma, and misunderstandings.

According to the health facilities across Ghana, epilepsy is one of the five most challenging medical conditions to treat. Specification at the nation's specialist neurological healthcare facilities, epilepsy is considered one of the primary reasons for referral cases. The seriousness of the situation prompted the WHO to conduct an extensive analysis of Ghana's mental health ecosystem (Deegbe et al., 2019). As one of Ghana's leading referral hospitals, the Korle Bu Teaching Hospital claims to serve more than 1600 PLWEs annually, on average (Ajdei et al., 2011).

In 2013, the Ministry of Health released official figures showing that epilepsy continues to be the most common neuropsychiatric disorder in both rural and district mental health. The nation lacks the necessary resources to treat PLWE and other neurological disorders. According to Ae-Ngibise (2015), the prevalence rate of epilepsy in Ghana is 10.1 per 1000 people or 1% of the population. Moreover, Deegbe (2021) indicated that the leading causes of active convulsive epilepsy in Ghana



are parasitic infection, family history, and perinatal problems). The study further espoused that 85% of PLWEs in Ghana are not receiving any medicine.

MATERIAL AND METHODS

The authors obtained a secondary dataset from the District Health Information Management System-2 (DHIMS-2) of the Saboba District in northern Ghana. The dataset covered epilepsy cases in both inpatients and outpatients between January 2012 and December 2019. The year range of the dataset was due to data availability and completeness. IBM SPSS version 24 and NCSS were used to analyse the dataset. Specifically, model diagnostic tests, including the Akaike Information Criterion (AIC) likelihood ratio test and other best-fit techniques for count data, were compared (Kamo et al., 2013). Because all the count models in the study had the same number of unknown parameters and there was no compelling reason to select one over the other, the likelihood ratio test was employed.

Poisson regression, negative binomial regression, zero-inflated Poisson regression, zero-inflated negative binomial regression, and geometric regression models were among the count models used in the study. Poisson regression is typically considered the fundamental regression model for count data. In the event of "overdispersion", the alternative model is the negative binomial regression (Goncalves et al., 2016). In contrast, zero-inflated models are used if overdispersion is caused by an excess of zeros in the dataset. Drawing on NCSS (2014) and Wang and Yang (2012), the authors included the zero-inflated Poisson regression, zero-inflated negative binomial regression and geometric regression models in the study.

Zero-inflated Poisson (ZIP) regression

For count data that exhibits "overdispersion" and excess zeros, zero-inflated Poisson (ZIP) regression is utilised. The distribution of the dataset used in this study calls for a combination of logit and Poisson distributions. The non-negative integers 0, 1, 2, 3, and so forth are the potential values of Y. Assuming that there are two possible outcomes for every observation, counts, including zeros, are produced using a Poisson model if Case 1 occurs. When Case 2 occurs, the counts are zero. Suppose also that Case 1 occurs with probability π and Case 2 occurs with probability $1 - \pi$. According to Mendoza et al. (2016), the probability distribution of the ZIP random variable y_i can be written as:



$$\Pr (y_i=j) = \begin{cases} \pi_i + (1 - \pi_i) \exp(-\mu_i) & \text{if } j = 0 \\ (1 - \pi_i) \frac{\mu_i^{y_i} \exp(-\mu_i)}{y_i!} & \text{if } j > 0 \end{cases} \quad (1)$$

In the following definition, π_i represents the logistic connection function. The Poisson component can include an exposure period of t and a set of k regressor variables (x). The formula that connects these amounts is:

$$\mu_i = \exp(\ln(t_i) + \beta_1\beta_{1i} + \beta_2\beta_{2i} + \dots + \beta_k\beta_{ki}) \quad (2)$$

Mostly, $x_1 \equiv 1$, and β_1 is the *intercept*. The regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ are unknown parameters estimated from a data set. Their estimates are denoted as b_1, b_2, \dots, b_k .

The logistic link function π_i is therefore given as:

$$\pi_i = \frac{\lambda_i}{1 + \lambda_i} \quad (3)$$

where:

$$\lambda_i = \exp(t_i) + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \dots + \gamma_m z_{mi} \quad (4)$$

This logistic component includes an exposure time t and a set of m regressor variables (the z 's).

However, the z 's and the x 's may or may not include terms in common.

Maximum likelihood estimation

The Maximum Likelihood method was used to estimate the regression coefficients. Hilbe (2014) states that the logarithm of the likelihood function can be determined by:

$$L = L1 + L2 - L3 \quad (5)$$

where:

$$L1 = \sum_{\{i:y_i=0\}} \ln[\lambda_i + \exp(-\mu_i)] \quad (6)$$

$$L2 = \sum_{\{i:y_i>0\}} \{y_i \ln(\mu_i) - \mu_i - \ln(y_i)\} \quad (7)$$

$$L3 = \sum_{i=1}^n \ln(1 + \lambda_i) \quad (8)$$

The gradient of L above is given by:

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$$\frac{\partial L}{\partial \beta_r} = \sum_{\{i:y_i=0\}} \left[\frac{-x_{ir}\mu_i}{\lambda_i \exp(\mu_i) + 1} \right] + \sum_{\{i:y_i>0\}} [y_i - \mu_i] x_{ir}, \quad r = 1, 2, \dots, k \quad (9)$$

$$\frac{\partial L}{\partial y_r} = \sum_{\{i:y_i=0\}} \left[\frac{z_{ir}\lambda_i \exp(\mu_i)}{\lambda_i \exp(\mu_i) + 1} \right] - \sum_{i=1}^n \left[\frac{\lambda_i}{1 + \lambda_i} \right] z_{ir}, \quad r = 1, 2, \dots, m \quad (10)$$

Thus, the second derivative can be expressed as

$$\frac{\partial^2 L}{\partial \beta_r \partial \beta_s} = \sum_{\{i:y_i=0\}} \frac{x_{ir}x_{is} \mu_i \exp[(\mu_i - 1)\lambda_i \exp(\mu_i) - 1]}{[\lambda_i \exp(\mu_i) + 1]^2} - \sum_{\{i:y_i>0\}} \mu_i x_{ir} x_{is}, \quad r, s = 1, 2, \dots, k \quad (11)$$

$$\frac{\partial^2 L}{\partial y_r \partial y_s} = \sum_{\{i:y_i=0\}} \frac{z_{ir}z_{is}\lambda_i \exp(\mu_i)}{[\lambda_i \exp(\mu_i) + 1]^2} - \sum_{i=1}^n \frac{z_{ir}z_{is}\lambda_i}{(\lambda_i + 1)^2}, \quad r, s = 1, 2, \dots, m \quad (12)$$

$$\frac{\partial^2 L}{\partial \beta_r \partial y_s} = \sum_{\{i:y_i=0\}} \frac{x_{ir}z_{is}\lambda_i \mu_i \exp(\mu_i)}{[\lambda_i \exp(\mu_i) + 1]^2} \quad r = 1, 2, \dots, k; s = 1, 2, \dots, m \quad (13)$$

Zero-inflated negative binomial regression model (ZINB)

Suppose that for each observation, there are only two possible cases. If Case 1 occurs, the count is zero. However, if Case 2 occurs, counts (including zeros) are generated according to the negative binomial model. Suppose that Case 1 occurs with probability π and Case 2 occurs with probability $1 - \pi$. Therefore, the probability distribution of the ZINB random variable y_i can be written as:

$$\Pr (y_i = j) = \begin{cases} \pi i + (1 - \pi i) g(y_i = 0) & \text{if } j = 0 \\ (1 - \pi i) g(y_i) & \text{if } j > 0 \end{cases} \quad (14)$$

where πi is the logistic link function defined below and $g(y_i)$ is the negative binomial distribution given by:

$$g(y_i) = \Pr (Y=y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i+1)} \left(\frac{1}{1 + \alpha\mu_i} \right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i} \right) \quad (15)$$

$$\mu_i = \exp(\ln(t_i) + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) \quad (16)$$



As stated above, $x_1 \equiv 1$, and thus, β_1 is interpreted as the *intercept*. The regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ are unknown parameters estimated from a data set. Their estimates are denoted as b_1, b_2, \dots, b_k .

Thus, the logistic link function π_i is given by:

$$\pi_i = \frac{\lambda_i}{1 + \lambda_i},$$

Where:

$$\lambda_i = \exp(\ln(t_i) + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \dots + \gamma_m z_{mi}) \tag{17}$$

The logistic component includes exposure time t and a set of m regressor variables (z). It should be noted that z and x may or may not include common terms.

Geometric regression (GR)

The dispersion parameter in GR is fixed at 1, making it a particular instance of negative binomial regression. In the case of the GR, the dependent variable (Y) is an observed count that complies with the geometric distribution, which is one of the main distinctions between the two. The non-negative integers 0, 1, 2, 3, and so forth are the possible values of Y . According to Hilbe (2014), GR is essentially a generalisation of Poisson regression (PR) with a less stringent "assumption that the variance is equal to the mean as advanced in the Poisson model." This generalisation of PR entails a gamma noise variable with a mean of 1 and ν as a scale parameter. Thus, the Poisson-gamma mixture (negative binomial) distribution can be denoted by:

$$\Pr(Y=y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i+1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i} \tag{18}$$

where:

$$\mu_i = t_i \mu_i \tag{19}$$

$$\alpha = \frac{1}{\nu} \tag{20}$$

The parameter μ represents the average frequency of y (number of epilepsy cases) for each exposure unit. The exposure can be in population size, volume, area, time, or space. The authors represented the exposure for a specific observation using the symbol t_i because exposure is frequently defined as the duration of time. Additionally, parameter μ can be seen as the probability of the event happening again within a given exposure period, t . If the dispersion parameter α is set



to 1, the outcome is GR. In GR, given the exposure period t and a collection of k regressor variables, the x 's, are used to obtain the mean of y through the following:

$$\mu_i = \exp(\ln(t_i) + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) \quad (21)$$

Mostly, $x_1 = 1$. In these circumstances, β_1 is the *intercept*. The regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ are the parameters estimated from a given dataset. Their estimates are denoted as b_1, b_2, \dots, b_k . Concerning this notation, the fundamental GR model for observation i is expressed as:

$$\Pr(Y=y_i|\mu_i) = \frac{\Gamma(y_i + 1)}{\Gamma(y_i + 1) (1 + \mu_i)} \left(\frac{1}{1 + \mu_i}\right)^1 \left(\frac{\mu_i}{1 + \mu_i}\right)^{y_i} \quad (22)$$

Akaike information criterion (AIC)

The Akaike Information Criterion (AIC) is a frequently used fit statistic that can be calculated mathematically as follows:

$$AIC = 2k - 2\ln(L) \quad (23)$$

Where k is the number of estimated parameters in the model

L = the maximum likelihood

$\ln(L)$ = natural logarithm of the likelihood

RESULTS AND DISCUSSION

The Akaike Information Criterion (AIC) and likelihood ratio tests were used to determine which model best fit the study data.

Exploratory data analysis

The fundamental presumption of Poisson regression, or "mean-variance equality," is violated, as shown in Figure 1. In particular, a μ of 1.13 as against the σ^2 of 4.18. Furthermore, there is proof that the violation was most likely caused by the excess zero in the dataset. This clarifies the authors' choice of zero-inflated models from other contending models.

Table 1 presents the goodness-of-fit (AIC (1)) results for the ZIP, ZINB, and GR models. It clearly shows that, compared to the ZIP and ZINB regression models, the GR model best fits the epilepsy data. This is because AIC (1) seems smaller than ZIP and ZINB.

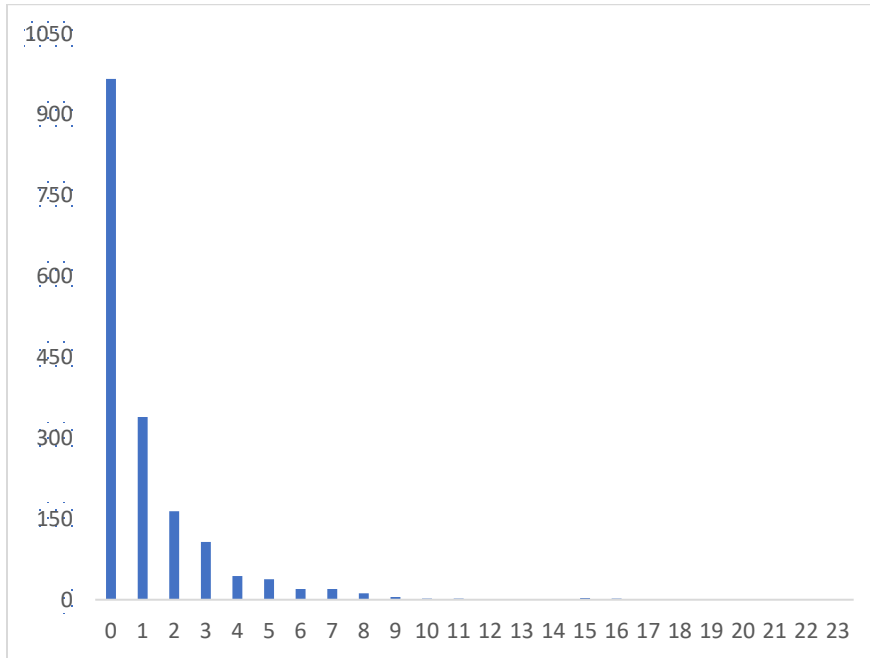


Figure 1: Epilepsy cases in Saboba district

Thus, the GR model appears to be more robust in modeling the incidence of epilepsy than the other models.

Table 1: Comparison of Likelihood ratio test AIC) for best-fit model

| LK Estimate/Best fit model Criterion | Zero-Inflated Regression Model Type | | |
|--------------------------------------|-------------------------------------|------------|------------|
| | ZIP | ZINB | GR |
| Log-likelihood | -2608.7117 | -2338.9707 | -2538.8798 |
| AIC (1) | 5237.4234 | 4699.9414 | 4203.8789 |

Source: Computation from DHIMS 2 database

Estimated Geometric Regression Models

The proposed models were modeled using GR estimates (Table 2), as follows:

Model 1: $\text{Log}(\text{counts_Epilepsy incident}) = \beta_0 + \beta_i \text{Year}, i = 1 \dots 8$

$$\Rightarrow \text{Log}(\text{counts_Epilepsy incident}) = \text{Log}(\mu) = -3.08080 + 0(2012) + 1.22432(2013) + 1.29760(2014) + 2.51227(2015) + 2.24627(2016) + 1.38801(2017) + 1.61748(2018) + 2.42905(2019)$$



Model 2: $\text{Log}(\text{counts_Epilepsy incident}) = \beta_0 + \beta_i \text{Gender} , i = 1 \dots, 2$

$\Rightarrow \text{Log}(\text{counts_Epilepsy}) = \text{Log}(\mu) = -3.08080 + 0(\text{female}) + 0.15761(\text{male})$

Model 3: $\text{Log}(\text{counts_Epilepsy incident}) = \beta_0 + \beta_i \text{Age group} , i = 1 \dots 9$

$\Rightarrow \text{Log}(\text{counts_Epilepsy incident}) = \text{Log}(\mu) = -3.08080 + 0.36494(0-4)\text{yrs} + 1.03856(5-9)\text{ yrs} + 1.50699(10-14)\text{ yrs} + 1.77331(15-19)\text{ yrs} + 1.85201(20-34)\text{ yrs} + 1.19726(35-49)\text{ yrs} + 0.02037(50-59)\text{ yrs} - 0.59771(60-69)\text{ yrs} + 0(70+)\text{ yrs}.$

Model 3 was inappropriate for forecasting the incidence of epilepsy using age grouping as an explanatory variable. This is based on closely examining the estimates from the three models in Table 2. In particular, the corresponding *p*-values of 0.0619 (Age= "0-4") and 0.9212 (Age= "50-59") indicate that it is statistically insignificant. This exceeded the 5% significance threshold. Therefore, models 1 and 2 are the most appropriate models.

Table 2: Estimated geometric regression coefficients

| 95.0% Independent Variable | Regression Coefficient b(i) | Standard Error Sb(i) | Z Value H0: $\beta=0$ | Two- Sided P-Value | Lower 95.0% Confidence limit | Upper Confidence limit |
|----------------------------------|-----------------------------------|----------------------------|--------------------------|--------------------------|------------------------------------|------------------------------|
| Intercept | -3.08080 | 0.27049 | -11.39 | 0.0000 | -3.61095 | -2.55064 |
| (Year=2013) | 1.22432 | 0.21857 | 5.60 | 0.0000 | 0.79594 | 1.65270 |
| (Year=2014) | 1.29760 | 0.21722 | 5.97 | 0.0000 | 0.87186 | 1.72335 |
| (Year=2015) | 2.51227 | 0.20378 | 12.33 | 0.0000 | 2.11288 | 2.91166 |
| (Year=2016) | 2.24627 | 0.20565 | 10.92 | 0.0000 | 1.84321 | 2.64933 |
| (Year=2017) | 1.38801 | 0.21567 | 6.44 | 0.0000 | 0.96530 | 1.81072 |
| (Year=2018) | 1.61748 | 0.21224 | 7.62 | 0.0000 | 1.20150 | 2.03345 |
| (Year=2019) | 2.42905 | 0.20431 | 11.89 | 0.0000 | 2.02861 | 2.82950 |
| (Month="Jan") | 0.13055 | 0.18719 | 0.70 | 0.4855 | -0.23634 | 0.49744 |
| (Month="Feb") | 0.01495 | 0.18975 | 0.08 | 0.9372 | -0.35696 | 0.38686 |
| (Month="Mar") | 0.05363 | 0.18887 | 0.28 | 0.7764 | -0.31655 | 0.42381 |
| (Month="May") | -0.21660 | 0.19559 | -1.11 | 0.2681 | -0.59994 | 0.16675 |
| (Month="Jun") | 0.42758 | 0.18152 | 2.36 | 0.0185 | 0.07180 | 0.78335 |
| (Month="Jul") | 0.43408 | 0.18141 | 2.39 | 0.0167 | 0.07852 | 0.78963 |
| (Month="Aug") | 0.87024 | 0.17509 | 4.97 | 0.0000 | 0.52707 | 1.21341 |
| (Month="Sept") | -0.43600 | 0.20210 | -2.16 | 0.0310 | -0.83211 | -0.03989 |
| (Month="Oct") | 0.11178 | 0.18759 | 0.60 | 0.5513 | -0.25589 | 0.47945 |
| (Month="Nov") | -0.00211 | 0.19015 | -0.01 | 0.9912 | -0.37480 | 0.37058 |
| (Month="Dec") | -0.03981 | 0.19105 | -0.21 | 0.8349 | -0.41425 | 0.33463 |
| (Sex="M") | 0.15761 | 0.07551 | 2.09 | 0.0369 | 0.00961 | 0.30561 |
| (Age="0-4") | 0.36494 | 0.19548 | 1.87 | 0.0619 | -0.01819 | 0.74806 |



| | | | | | | |
|---------------|----------|---------|-------|--------|----------|----------|
| (Age="5-9") | ,1.03856 | 0.18176 | 5.71 | 0.0000 | 0.68232 | 1.39480 |
| (Age="10-14") | 1.50699 | 0.17587 | 8.57 | 0.0000 | 1.16230 | 1.85168 |
| (Age="15-19") | 1.77331 | 0.17343 | 10.23 | 0.0000 | 1.43340 | 2.11322 |
| (Age="20-34") | 1.85201 | 0.17281 | 10.72 | 0.0000 | 1.51331 | 2.19071 |
| (Age="35-49") | 1.19726 | 0.17950 | 6.67 | 0.0000 | 0.84545 | 1.54906 |
| (Age="50-59") | 0.02037 | 0.20598 | 0.10 | 0.9212 | -0.38334 | 0.42407 |
| (Age="60-69") | -0.59771 | 0.23352 | -2.56 | 0.0105 | -1.05541 | -0.14001 |

Source: Computation from DHIMS 2 database

The exploratory research findings were further supported by the predicted parameters of epilepsy incidence, as shown in Table 3. Based on baseline data, the incidence of epilepsy in males was 0.15761 times higher than that in females. This represented “the multiplicative effect on the fitted value” (the mean of epilepsy diseases) or $e^{-0.15761} = 1.1707$.

Table 3: Estimation of rate ratio of epilepsy given time, sex and age groupings of epilepsy patients

| Independent Variable | Regression Coefficient b(i) | Rate Ratio Exp(b(i)) | Lower 95.0% Confidence Limit | Upper 95.0% Confidence Limit |
|----------------------|-----------------------------|----------------------|------------------------------|------------------------------|
| (Year=2013) | 1.22432 | 3.402 | 2.217 | 5.221 |
| (Year=2014) | 1.29760 | 3.661 | 2.391 | 5.603 |
| (Year=2015) | 2.51227 | 12.333 | 8.272 | 18.387 |
| (Year=2016) | 2.24627 | 9.452 | 6.317 | 14.145 |
| (Year=2017) | 1.38801 | 4.007 | 2.626 | 6.115 |
| (Year=2018) | 1.61748 | 5.040 | 3.325 | 7.640 |
| (Year=2019) | 2.42905 | 11.348 | 7.603 | 16.937 |
| (Month="Feb") | 0.13055 | 1.139 | 0.790 | 1.644 |
| (Month="Mar") | 0.01495 | 1.015 | 0.700 | 1.472 |
| (Month="Apr") | 0.05363 | 1.055 | 0.729 | 1.528 |
| (Month="May") | -0.21660 | 0.805 | 0.549 | 1.181 |
| (Month="Jun") | 0.42758 | 1.534 | 1.074 | 2.189 |
| (Month="Jul") | 0.43408 | 1.544 | 1.082 | 2.203 |
| (Month="Aug") | 0.87024 | 2.387 | 1.694 | 3.365 |
| (Month="Sept") | -0.43600 | 0.647 | 0.435 | 0.961 |



| | | | | |
|---------------|----------|-------|-------|-------|
| (Month="Oct") | 0.11178 | 1.118 | 0.774 | 1.615 |
| (Month="Nov") | -0.00211 | 0.998 | 0.687 | 1.449 |
| (Month="Dec") | -0.03981 | 0.961 | 0.661 | 1.397 |
| (Sex="M") | 0.15761 | 1.171 | 1.010 | 1.357 |
| (Age="0-4") | 0.36494 | 1.440 | 0.982 | 2.113 |
| (Age="5-9") | 1.03856 | 2.825 | 1.978 | 4.034 |
| (Age="10-14") | 1.50699 | 4.513 | 3.197 | 6.371 |
| (Age="15-19") | 1.77331 | 5.890 | 4.193 | 8.275 |
| (Age="20-34") | 1.85201 | 6.373 | 4.542 | 8.942 |
| (Age="35-49") | 1.19726 | 3.311 | 2.329 | 4.707 |
| (Age="50-59") | 0.02037 | 1.021 | 0.682 | 1.528 |
| (Age="60-69") | -0.59771 | 0.550 | 0.348 | 0.869 |

Source: Computation from DHIMS 2 database

Table 3 indicates that the effect, $\beta = 0.15761$, is positive. This suggests that as the number of individuals with epilepsy increases, so do the expected counts of the condition among males. Seventeen (17) percent of all epilepsy cases reported in the study area between 2012 and 2019 are represented by this. Based on the research data, it is sufficient to conclude that “men are more likely than women” to be affected by epilepsy in Saboba district. However, it also implies that “men are more likely than women” to report having epilepsy and seek medical assistance. Other researchers have reported similar results (Stroder, 2018; Chen et al., 2012; Kaculini et al., 2021).

Gender conventions, culture, poverty, and high rates of illiteracy are prevalent in the Saboba area. The employment of preventative measures, including early warning signs, epileptic symptoms, and high-quality health education in the district, must be given high priority. Ensuring efficient epilepsy control programs requires an “understanding of the gender-related dynamics of treatment-seeking behaviour, decision-making, resource allocation, and financial authority within families” (Chen et al., 2012).

The corresponding p-values of 0.0619 and 0.9212 for the age brackets “0-4” and “50-59” show that the prevalence of epilepsy was statistically insignificant at the 5% level for the two age groups. These values were 0.36494 and 0.02037 times greater than those of the other age subgroups of epilepsy patients. The effects (β) = $0.36494 = e^{-0.36494} = (1.4404)$ and $0.02037 = e^{-0.02037} = (1.0206)$ indicate that as the age group of epileptic patients increases, so do the predicted counts of epileptic incidence in terms of age groups (0-4) and (50-59) in the district. These made up about 14% and 2% of all cases of epilepsy that were recorded.



Similarly, the incidence of epilepsy in the district was found to be 1.03856, 1.50699, 1.77331, 1.85201, and 1.19726 times higher in the 5–9, 10–14, 15–19, 20–34, 35–49, and 60–69 age groups, respectively, than in the 70+ age group (baseline). The age group of 20–34 years had the highest p-value of 0.000, but all of these were statistically significant at the 5% level. Positive effects were observed in all age categories of epileptic patients (β). Based on this, the district's epilepsy incidence counts for the specified age groups would rise with every unit increase in the corresponding age groups.

Nonetheless, it was discovered that the 60–69 age group was -0.59771 times smaller than the other age groups. The results indicate that when the age group of epileptic patients continues to rise, the predicted counts of epileptic incidence in terms of age groups (60–69) in the district decline (β) = $-0.59771 = e^{-0.59771} = (0.5501)$. This represented 55% of all epileptic cases documented in the district during the study. Overall, the study, which used 70+ years as the base year for all reported cases, indicated a significant occurrence of epilepsy among the age categories (10–34). In addition, the incidence of epilepsy fell sharply in the 35–49 age group and continued to decline steadily until the age of 69 years, in line with Adeloje's 2012 result.

The findings of this study imply that “among younger children in the age bracket” (0–9 years) and the elderly (60–70+ years), the frequency of epilepsy is relatively mild or non-threatening. The economically active population in the research area is the most affected segment. This may be because the majority of these young people ignore health education about the causes of epilepsy (genetic or developmental disorders, brain injuries, alcohol, and stress), symptoms (partial seizures), and early warning signs (a strange or detached feeling, an odd smell or taste, and momentary confusion). The high prevalence of epilepsy in economically active age groups may have a negative impact on productivity as found in (Fadaie et al., 2020; Strzelczyk & Reese, 2016; Ayilara, 2010).

In the course of the study, it was discovered that the prevalence of epilepsy was statistically significant at the 5% level (p-value = 0.0000). By taking into account the entire years of the study, the effects of epilepsy (β) remained positive or more than zero. This indicates that over the years, the district may expect to report an increasing amount of epilepsy. However, the analysis showed a more considerable increase in the projected counts in 2015, 2019, and 2016. This translated into effects (β) of 12.3329, 11.3481, and 9.4524, respectively.

In 2015, the epilepsy density was very high. Using 2012 as the baseline year for comparison, 2019 and 2016 were also observed to experience a high rate of epilepsy. The lowest incidence of epilepsy was reported in 2013. It appears that, as the years moved on, the district's epilepsy trend assumed an upward dimension starting in 2017. Numerous causes, including a lack of knowledge



about the disease, may be responsible for this tendency. The district's top epilepsy caregivers were not accessible until the latter half of 2017, consistent with (Teferi et al., 2020; Khan & Mughal, 2018).

Estimation of Epilepsy rates

The rate ratio of epilepsy incidence was assessed within the years, months, sex, and demographic age groups of the study. By accounting for study time, this was meant to gauge the incidence of epilepsy.

Table 4: Rate ratio of epilepsy occurrence given years

| (year) | Regression Coefficient{b(i)} | Rate Ratio = e ^{b(i)} |
|--------|------------------------------|--------------------------------|
| (2013) | 1.22432 | 3.402 |
| (2014) | 1.29760 | 3.661 |
| (2015) | 2.51227 | 12.333 |
| (2016) | 2.24627 | 9.452 |
| (2017) | 1.38801 | 4.007 |
| (2018) | 1.61748 | 5.040 |
| (2019) | 2.42905 | 11.348 |

Source: Computation from DHIMS 2 database

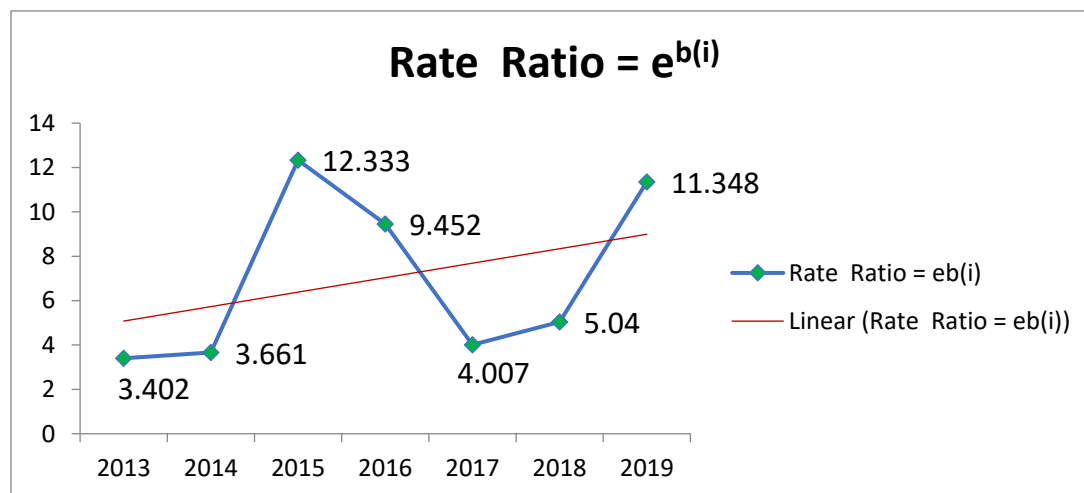


Figure 2: Rate ratio of epilepsy



Table 4 shows that, using 2012 as the base year for comparison, the district's epilepsy rate was high in 2015, followed by 2019 and 2016. The lowest incidence of epilepsy was reported in 2013. However, as Figure 2 shows, the number of epilepsy cases moved steadily after 2017.

Furthermore, using January as the base month for comparison, Table 5 shows that the incidence density of epilepsy was highly high in June, July, and August. This also implies that August peaked epilepsy cases during the study period. Figure 3 illustrates the significant decline from September to December.

The annual flooding in certain sections of northern Ghana, primarily in September and October, may cause this pattern. Many of the roads that connect the district remained unusable during flooding periods. Consequently, outreach initiatives in public spaces and schools cannot be done as earlier espoused by Magano and Kandjimi (2015); Davis et al., (2020)

Table 5: Monthly rate ratio of epilepsy occurrence

| (Month) | Regression Coefficient{b(i)} | Rate Ratio = e^{b(i)} |
|----------------|-------------------------------------|--------------------------------------|
| February | 0.13055 | 1.139 |
| March | 0.01495 | 1.015 |
| April | 0.05363 | 1.055 |
| May | -0.2166 | 0.805 |
| June | 0.42758 | 1.534 |
| July | 0.43408 | 1.544 |
| August | 0.87024 | 2.387 |
| September | -0.43600 | 0.647 |
| October | 0.11178 | 1.118 |
| November | -0.00211 | 0.998 |
| December | -0.03981 | 0.961 |

Source: Computation from DHIMS 2

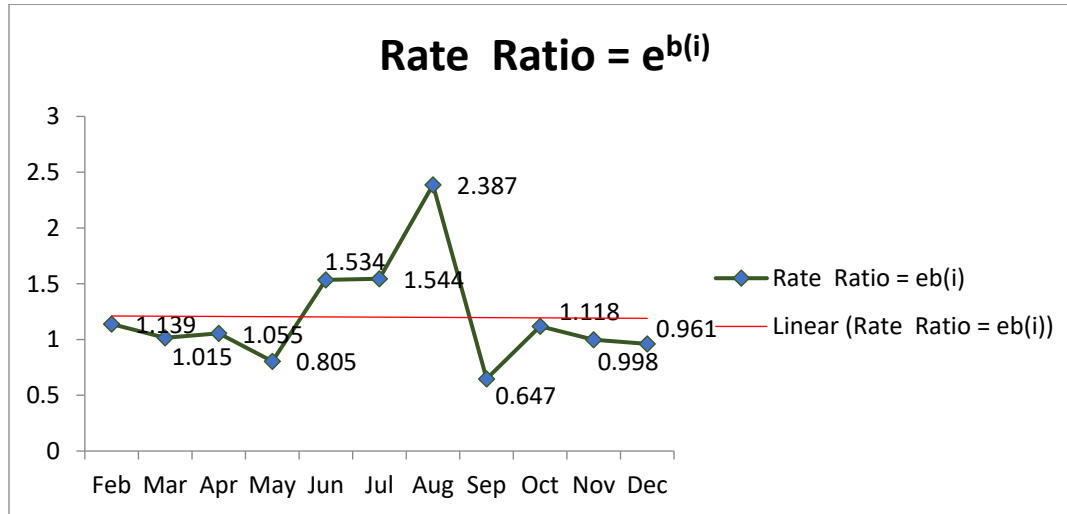


Figure 3: Rate ratio of epilepsy given months of incidence

Using a base year of ≥ 70 years, Table 6 illustrates the significant incidence of epilepsy in the age period of 10-34. Additionally, the age range of 35-49 years significantly declined. This was followed by a steady decline that persisted until age 69 (Figure 4).

Table 6: Rate ratio of occurrence of epilepsy given age groupings

| (Age Group) | Regression Coefficient{ $b(i)$ } | Rate Ratio = $e^{b(i)}$ |
|---------------|----------------------------------|-------------------------|
| (0 -4) years | 0.36494 | 1.440 |
| (5-9) years | 1.03856 | 2.825 |
| (10-14) years | 1.50699 | 4.513 |
| (15-19) years | 1.77331 | 5.890 |
| (20-34) years | 1.85201 | 6.373 |
| (35-49) years | 0.02037 | 1.021 |
| (50-59) years | 0.02037 | 1.021 |
| (60-69) years | -0.59771 | 0.550 |

Source: Computation from DHIMS 2 database

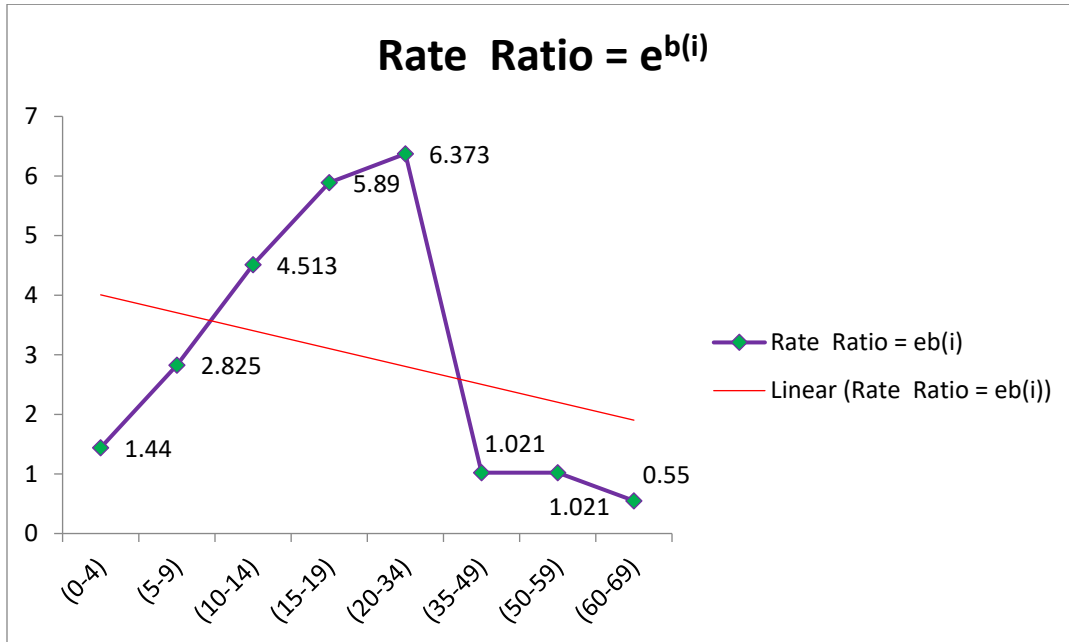


Figure 4: Rate ratio of epilepsy given demographic age grouping

CONCLUSION

The study aimed to determine the best-suited model for epilepsy cases in Ghana. The data for this study were obtained from the DHIMS 2 database. This led to the comparison of three models: geometric regression, zero-inflated binomial regression, and zero-inflated Poisson models. Given the demographic age groups, sex, and time (monthly and yearly), the geometric regression model was better. The Akaike Information Criterion (AIC), a well-known statistical goodness-of-fit model assessment and selection criterion, was used to determine the best-fit model. The best-fit model was also employed to model the parameters (age groups, sex, and time) and investigate the incidence rate ratio of epilepsy among patients with epilepsy experience.

The geometric regression (GR) model's AIC of 4203.88 demonstrated its superiority over the remaining model options, including the zero-inflated Poisson and zero-inflated negative binomial regression models. Additionally, according to the study's findings, Models 1 and 2 were the most robust models for predicting the occurrence of epilepsy during the study period. Using demographic age grouping as an explanatory variable, Model 3 did not show to be suitable for predicting the occurrence of epilepsy. This outcome can be attributed to its statistical significance.

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A trend of sex-dependency was discovered in the infectious rate ratio of epilepsy incidence from 2012 to 2019. Specifically, the p-value of 0.0369 was below the significance level of 0.05. Nevertheless, using 70+ as the base year for all reported cases, it was discovered that the rate ratio of epilepsy was notably high among the demographic age groups (10–34). This finding indicates that among younger children in the demographic age group (0–9) and the elderly (60–70+ years), the infectious risk of epilepsy is relatively low. The results of this study clearly show that people in the economically engaged category were at the highest risk. The study also showed that, in 2015, the epilepsy incidence density was very high. In contrast, the lowest number of epilepsy incidents was reported in 2013. However, the number of epilepsy cases began to increase again in 2017.

Theoretical Implication

This study contributes to the existing knowledge on predictive modelling of epidemiological datasets in the context of epilepsy. By identifying the GR model as the best fit among other candidates, this study underscores the importance of selecting appropriate statistical models within the framework of the goodness-of-fit criterion. This underpins the theoretical support for applying model selection techniques in health data analysis in the face of over-dispersed or zero-inflated datasets. Furthermore, this study underscores the relevance of demographic factors, such as age and sex, in shaping the trajectory of epilepsy. This, in effect, provides sufficient evidence for theories related to health disparities and the impact of sociodemographic variables in epidemiological studies.

Practical Implication

Identifying the economically active age group as the most at-risk demographic can inform targeted resource allocation, health intervention, and awareness campaigns. This will trigger effective planning and policy development in the health system, particularly in managing epilepsy. Second, the findings of the study regarding the incidence of sex-dependent epilepsy highlight the essence of gender-specific healthcare strategies. Policymakers can use these insights to integrate epilepsy education into healthcare outreach, embark on robust early detection programs, and bridge treatment gaps by training dedicated healthcare workers to serve high-risk populations better. Moreover, this study proposes a data-driven approach to understand epilepsy trends holistically. This is indispensable for shaping public health policies that are expected to reduce the incidence of epilepsy.



Limitation and Direction for Future Studies

The use of secondary data from DHIMS-2 is one of the weaknesses of this study. There could be reporting errors. Therefore, future studies should incorporate primary data collection techniques, such as patient surveys or clinical evaluations, to supplement secondary data. Furthermore, only Saboba district was included in the study. As a result, the study's conclusion is not as broadly applicable. Expanding this study to cover multiple districts (or regions) would provide a solid understanding of the incidence of epilepsy. Lastly, future research could examine the impact of genetic or environmental factors on the prevalence of epilepsy.

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