

Tracking of Death Case So Flassa Feverout Breakinnig Eriausinga Modifiedewma Control Chart

Alabi Oluwapelumi¹, Olarinde Olawumi B², Kayode Olarewaju J³, Omotoso Saliu A⁴, Adeolu Abel⁵

Department of Mathematics and Statistics, Rufus Giwa Polytechnic, Owo, Ondo State, Nigeria

DOI: <https://doi.org/10.51244/IJRSI.2026.1315PH00172>

Received: 18 November 2025; Accepted: 18 November 2025; Published: 15 September 2026

ABSTRACT

Lassa fever remains a recurrent and endemic public health threat in Nigeria, with mortality that is often seasonal, over-dispersed, and difficult to monitor using classical, threshold-based surveillance methods. This study applied a Modified Exponentially Weighted Moving Average (MEWMA) control chart, developed by Khan et al. (2017), to monitor weekly Lassa fever deaths in Nigeria using surveillance data obtained from the Nigeria Centre for Disease Control (NCDC) covering January 2021 to September 2025 (244 weeks). In-control process parameters were estimated from a baseline period, and the MEWMA statistic was constructed using the smoothing parameter $\lambda = 0.2$, control chart coefficient $L = 2.793$, $k = \lambda/2$, and a nominal in-control Average Run Length (ARL₀) of 370. Descriptive analysis showed that weekly deaths were approximately normally distributed, with no marked skewness or extreme outliers, while a time plot revealed natural fluctuations without an immediately obvious pattern. The Modified EWMA chart, however, detected several statistically significant out-of-control signals, most prominently in 2024, indicating periods when Lassa fever deaths rose above the expected baseline. Similar, less pronounced signals were observed in 2021, 2022, 2023, and early 2025, suggesting a recurring seasonal or periodic outbreak pattern. These findings demonstrate that the Modified EWMA chart is a sensitive and practical early-warning tool for Lassa fever mortality surveillance in Nigeria, and its adoption by public health authorities could support more timely outbreak response.

Keywords: Lassa fever; Modified EWM A control chart; Statistical process control; Average Run Length; Diseases surveillance; Nigeria

INTRODUCTION

Lassa fever has been recognized as an endemic threat in several West African countries since the Lassa virus was first discovered in Lassa town, Borno State, Nigeria, in 1969. The principal host of the Lassa virus is the multimammate rat (*Mastomys natalensis*), an asymptomatic carrier that excretes the virus in its urine and faeces. Human infection typically occurs through contact with contaminated surfaces, consumption of food contaminated with rodent excreta, or direct contact with the rodents themselves. Human-to-human transmission, through contact with the blood or other bodily fluids of an infected person, is also commonly observed. Consequently, the virus has spread rapidly to virtually all parts of Nigeria. In 2025, 21 of the 36 states (including the Federal Capital Territory) recorded at least one confirmed case, with Ondo, Taraba, Edo, Bauchi, and Ebonyi states recording the highest numbers of cases. Specifically, 172 confirmed deaths were recorded (NCDC, 2025), with Ondo and Taraba states recording the highest numbers of deaths (37 and 36, respectively). The spread and distribution of confirmed death cases across the states of Nigeria are represented in the map in Figure 1.

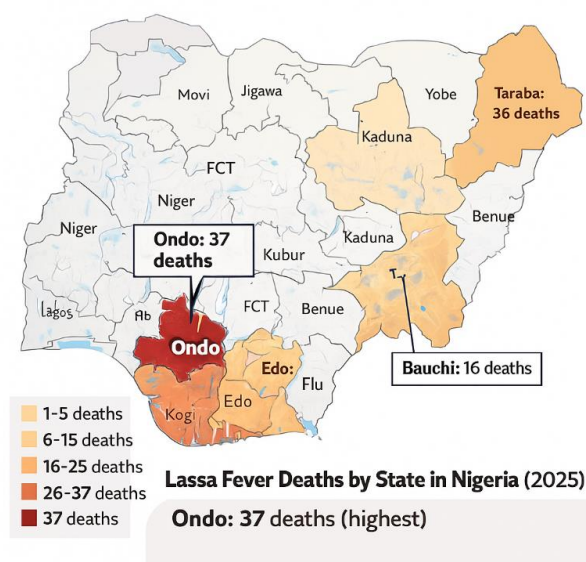


Figure1:DeathCasesduetoLassafeveracrosstheStates

TheexpandinggeographicaldistributionandtheconsistentlyhighCaseFatalityRatio(CFR)areimportantindicatorsof theendemicityofLassafeverandthecontinuingthreatitposestotheNigerianhealthsystem.Thediseaseislargelyseason al,withthehighestincidence duringthedryseason(NovembertoMarch),whenscarcenaturalfoodsourcesdriverodents, themainreservoir,toforageinhumansettlements(Musaetal.,2024).Duringthisperiod,healthsystemsandthegeneralp opulationneedtoremainhighlyvigilant.ThecasefatalityrateforLassafeverinNigeriaiscurrentlyreportedtorangebetw een13.5%and18.3%amongconfirmedcases,reflectingconstraintsinearlyresponsetotheillnessandinpublicawarene ss(OCHA,2024).

Given therecurrentnatureofLassafeveroutbreaksandtheassociateddeaths,continuousandreliablemonitoringofmort alityisessentialfortimelyinterventionandeffectiveepidemiccontrol.Classicalepidemiologicalsurveillancemethods oftenrelyondescriptivestatisticsandthreshold-basedalerts systems. Whileuseful,thesemethodsmayfailtodetectsubtlebutimportantchangesinmortalitytrends,partic ularlywhentheincreaseisgradual.Thislimitationhasmotivatedtheadoptionofstatisticalprocesscontrol(SPC)method s,whichprovidemoresensitivetoolsformonitoringpublichealthdataovertime.

Thecontrolchartisregardedasthemostimportantinstrumentinstatisticalprocesscontrol(SPC)andisnowwidelyuseda crossmanufacturing,service,andpublichealthsectors(Wuetal.,2010;Alfaro&Ortega,2011;Sarkar&Pal,1997;Shuet al.,2012;Rakitzis&Antzoulakos,2012).WalterA.Shewhartintroducedtheconceptofagraphicalsummaryofprocessi nformation tomonitorandsurveyproductionprocessesinthe1920s.Thisgraphicalsummary,knownasacontrolchart,e nsuresthatarandomprocessremainswithinanacceptablerangeratherthandriftingtoofarfromitsexpectedlevel.Monit oringchangeinareassuchassignalsegmentation,navigationsystemperformance,andqualitycontrolisimportantforpr eventinglosses.

Roberts(1959)introducedtheexponentiallyweightedmovingaverage(EWMA)controlchartasaneffectivealternativ etothetraditionalShewhartcontrolchartformonitoringsmallshiftsinprocessparameters(Yang,2013).TheEWMAco ntrolcharthasgainedconsiderablesignificanceoverthepastfewdecades.Numericalmethodsdevelopedbyqualitycont rolresearcherssuchasRobinsonandHo(1978),Crowder(1987),andLucasandSaccucci(1987)havemadethisscheme moreaccessibleinthequalitycontrolliterature.

TheEWMAtechniquewasmadesimpleandeasytoapplythroughthegraphicalmethodsestablishedbyRoberts(1959)a ndChantraine(1987).AccordingtoShuetal.(2014),theliteratureontherobustnessandeffectivenessoftheEWMAtech niqueindicatesthatitisoneofthemostvaluabletechniquesforidentifyingsmallandmoderateprocesschanges.

Inpublichealthapplications,severalstudieshaveadoptedEWMAcontrolchartstomonitor diseaseincidence,mortality ,andotherhealthindicators,owingtotheircapacityforearlyoutbreakdetection,particularlyforinfectiousdiseases(Wo odall,2006;Zhangetal.,2020).

Despite its benefits, the conventional EWMA control chart assumes normality, independence, and constant variance, as assumptions that are frequently not met in epidemiological count data such as Lassa fever deaths. Mortality data of this kind are generally skewed and overdispersed, and may exhibit seasonality or autocorrelation.

To overcome these shortcomings, a number of modified EWMA control charts have been proposed in the literature. Stein et al. (2000) reported that risk-adjusted, modified control charts are highly sensitive and have lower false-alarm rates than traditional charts when monitoring rare events such as mortality. Similarly, Zhou and Guan (2018) established that Poisson-based EWMA charts are better suited to disease-count data than conventional normal-based EWMA charts. Modified EWMA charts have also been applied to monitor Ebola, COVID-19, and malaria deaths in the context of infectious diseases surveillance. For instance, Brookmeyer and Stroup (2004) highlighted statistical surveillance techniques for identifying abnormal mortality trends during an epidemic, and their work favours the application of adaptive and modified EWMA charts for real-time mortality monitoring.

Nevertheless, the literature specifically addressing the use of modified EWMA control charts to monitor Lassa fever mortality remains limited, particularly in Nigeria. This gap highlights the need for empirical research applying improved SP C techniques to Lassa fever deaths, with a view to improving public health responses to outbreaks.

This study therefore adopted the Modified EWMA (MEWMA) control chart introduced by Khan et al. (2017) to monitor upward shifts in Lassa fever deaths using data from the Nigeria Centre for Disease Control (NCDC). Previous studies have shown that EWMA charts are more efficient at detecting disease outbreaks than conventional techniques. MEWMA charts are more sensitive than Shewhart charts to small and gradual changes in disease prevalence, which commonly occur at the onset of infectious disease outbreaks. MEWMA charts also offer broader monitoring capability and greater tolerance to temporary variation than standard EWMA charts (Khan et al., 2017), making them well suited to weekly surveillance data that may contain irregularities in reporting.

Specifically, this study aims to: (i) examine the descriptive and distributional characteristics of weekly Lassa fever deaths in Nigeria; (ii) construct a Modified EWMA control chart to monitor upward shifts in Lassa fever mortality; and (iii) evaluate the performance of the chart using the Average Run Length (ARL) criterion.

METHODOLOGY

2.1 Research Design

The study utilised a statistical process monitoring framework to assess mortality trends caused by Lassa fever in Nigeria, based on a Modified Exponentially Weighted Moving Average (MEWMA) control chart. The Modified EWMA chart proposed by Khan et al. (2017) was adopted because of its improved sensitivity to the small and persistent changes that are characteristic of diseases surveillance and mortality data.

Here, X_t denotes the number of reported deaths at time t , extracted from the Nigeria Centre for Disease Control (NCDC) website. All reported deaths from January 2021 to September 2025 were retrieved from <https://ncdc.gov.ng/diseases/sitreps>, where $t = 1, 2, \dots, T$. An initial historical period, over which the mortality process was assumed to be stable, was identified and used as the baseline (in-control) period from which the process parameters were estimated.

2.2 Estimation of In-Control Parameters

The in-control mean and standard deviation of the mortality level, denoted μ_0 and σ , were estimated from the baseline data of size n as:

$$\mu_0 = \frac{1}{n} \sum_{i=1}^n X_i, \quad i=1, 2, \dots, n, \quad \sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \mu_0)^2}$$

Since Lassa fever mortality data frequently exhibit low and discrete counts, a Poisson assumption was considered appropriate, under which the variance is approximately equal to the mean ($\sigma^2 \approx \mu_0$); otherwise, the Poisson model may not be suitable. The observed data were therefore reassessed to determine the distribution they follow.

2.3 Modified EWMA (MEWMA) Control Chart

The Modified EWMA (MEWMA) chart was introduced by Khan et al. (2017). If X_t represents the number of Lassa fever deaths per week, the MEWMA statistic is defined as:

$$Z_t = (1 - \lambda)Z_{t-1} + \lambda X_t + k(X_t - X_{t-1}) \quad (1)$$

where k is a constant and $0 < \lambda \leq 1$ is a smoothing parameter. The initial value Z_0 is the process target, so that $Z_0 = \mu_0$, although the average of the preliminary data may sometimes be used as the starting value, i.e. $Z_0 = \bar{X}$. The MEWMA chart depends on two constants, λ and k , where a small value of λ leads to quicker detection of small shifts. The MEWMA statistic can be regarded as a weighted average of all past and recent observations, making it insensitive to the normality assumption; it is therefore well suited for use with individual observations (Montgomery, 2019). The MEWMA chart is an extension of existing control charts, reducing to the EWMA chart of Roberts (1959) and the modified EWMA chart of Patel and Divecha (2011) when $k = 0$ and $k = 1$, respectively.

2.4 Control Limit of the Modified EWMA Chart

The mean and variance of the MEWMA statistic are given by:

$$E(Z_t) = \mu \text{ and } V(Z_t) = \left[\frac{\lambda + 2\lambda k + 2k^2}{(2 - \lambda)} \right] \frac{\sigma^2}{n} \quad (2)$$

The upper and lower control limits of the Modified EWMA chart are given by:

$$\begin{cases} UCL = \mu_0 + L\sigma \sqrt{\frac{\lambda + 2\lambda k + 2k^2}{n(2 - \lambda)}} \\ CL = \mu_0 \\ LCL = \mu_0 - L\sigma \sqrt{\frac{\lambda + 2\lambda k + 2k^2}{n(2 - \lambda)}} \end{cases} \quad (3)$$

where L is a control chart coefficient to be determined. The value of k may, in principle, be chosen independently of λ ; however, in this study, $k = -\lambda/2$ was used, as derived by Khan et al. (2017) to minimise the variance.

2.5 Choice of the Smoothing Parameter λ

The parameter λ determines the weight assigned to the current sample. Small values of λ provide greater smoothing and are suitable for monitoring rare occurrences. The values $\lambda = 0.20$ was examined, with $k = \lambda/2$ computed for each case; this enhances sensitivity to small shifts.

At a given time point t , the process is declared out of control if Z_t goes beyond the upper control limit or falls below the lower control limit. Since the focus of this study was on detecting an upward shift (increase) in deaths, emphasis was placed on upward signals, where $Z_t > UCL$.

2.6 Performance of the Control Chart

The most common way to assess the performance of a control chart is by evaluating how quickly it detects shifts in process quality; this is achieved by calculating the Average Run Length (ARL)—the average number of observations taken before an out-of-

control signal is triggered. In this study, the assessment criterion used was the ARL approximation of Khan et al. (2017), given as:

$$\rho_{out}^o = P(Z_t > UCL|\mu) + P(Z_t < LCL|\mu)$$

After simplification, out-of-control ARL given by

$$\rho_{out}^o = 1 - \phi\left(\frac{\mu + L\sigma\sqrt{\frac{(\lambda + 2\lambda k + 2k^2)}{n(2-\lambda)}} - \mu}{\sigma\sqrt{\frac{(\lambda + 2\lambda k + 2k^2)}{n(2-\lambda)}}}\right) + \phi\left(\frac{\mu - L\sigma\sqrt{\frac{(\lambda + 2\lambda k + 2k^2)}{n(2-\lambda)}} - \mu}{\sigma\sqrt{\frac{(\lambda + 2\lambda k + 2k^2)}{n(2-\lambda)}}}\right)$$

Where ϕ is the cumulative distribution function of the standard normal distribution.

$$\rho_{out}^o = 2(1 - \phi(L))$$

The ARL when the process is in control represented by ARL_0 is given as follows:

$$ARL_o = \frac{1}{\rho_{out}^o}$$

A control chart with the largest in-control ARL (ARL_0) and the smallest out-of-control ARL (ARL_1) is regarded as superior to the other charts considered. This is because memory-type charts, such as the MEWMA chart, are specifically designed to detect small and gradual shifts in the process variable.

RESULTS AND DISCUSSION

3.1 Descriptive Statistics

The histogram with superimposed normal curve for reported Lassa fever deaths is presented in Figure 2. It can be observed that most observations are concentrated around the central values, with relatively few observations at the lower and upper extremes. The bars closely follow the pattern of the normal curve, indicating that the data are approximately normally distributed.

The distribution appears fairly symmetric, with no indication of extreme skewness or outliers. Thus, the death-occurrence data satisfy the normality assumption required for many parametric statistical analyses. Similarly, the time plot in Figure 3 illustrates the reported Lassa fever deaths during the study period. The observations fluctuate over time, suggesting natural variation in the number of reported deaths. The plot also shows irregular peaks and dips, which may reflect seasonal or random fluctuations in death occurrence. However, these fluctuations alone do not reveal any persistent pattern or clearly indicate a sudden outbreak beyond the usual variation—

underscoring the need for a more sensitive monitoring tool such as the Modified EWMA chart applied in Section 3.2.

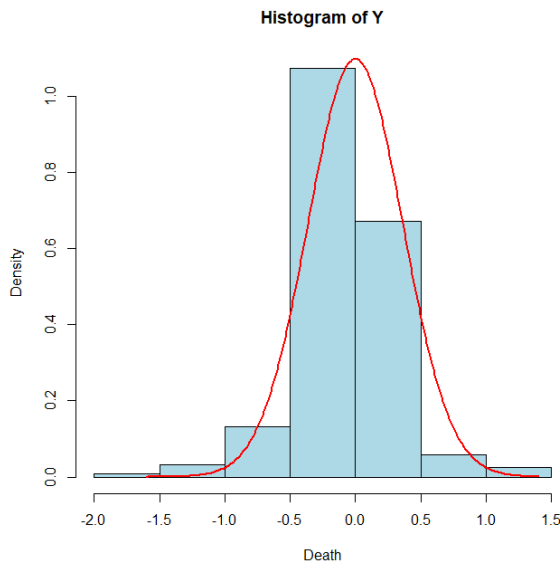


Figure2:HistogramandNormalCurveofDeathOccurrence due to Lassafever

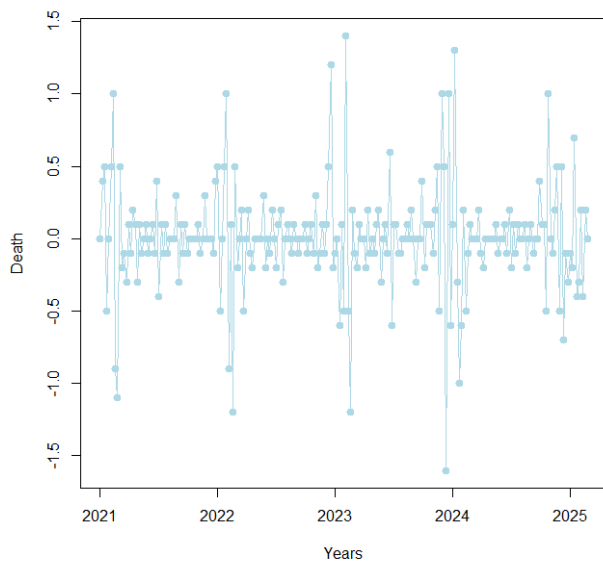


Figure3:TimePlotofDeathOccurrence due to Lassafever

Application of the Modified EWMA Control Chart

Historical data on Lassafever deaths were extracted from the NCDC website for a period of 244 weeks (January 2021 to September 2025) and were used to estimate the baseline death occurrence. A Modified EWMA chart was constructed by recursively smoothing the observed weekly number of deaths using the parameters recommended by Khan et al. (2017):

$\lambda = 0.2, L = 2.793, ARL_0 = 370$, and $k = \lambda/$

2. Using the estimated baseline parameters $\mu_0 = 3.43$ and $\sigma = 4.87$, the Modified EWMA upper control limit was computed as:

$$UCL = \mu_0 + L\sigma \sqrt{\frac{\lambda + 2\lambda k + 2k^2}{(2 - \lambda)}} = 3.43 + (2.793)(4.87) \sqrt{\frac{0.2 + 2(0.2)(0.1) + 2(0.1)^2}{(2 - 0.2)}} = 6.8$$

using the variance of the Modified EWMA statistic, allowing for early detection of small and steady changes in mortality. The Modified EWMA chart is presented in Figure 4. The chart shows that most observations are below the UCL and are cat

egorised as “in-control”, indicating that the observed death cases were generally stable during these periods and that their variation was due to common or natural causes. However, several observations plot above the UCL and are reclassified as “out-of-control” points, suggesting periods when Lassa fever deaths rose above the expected level.

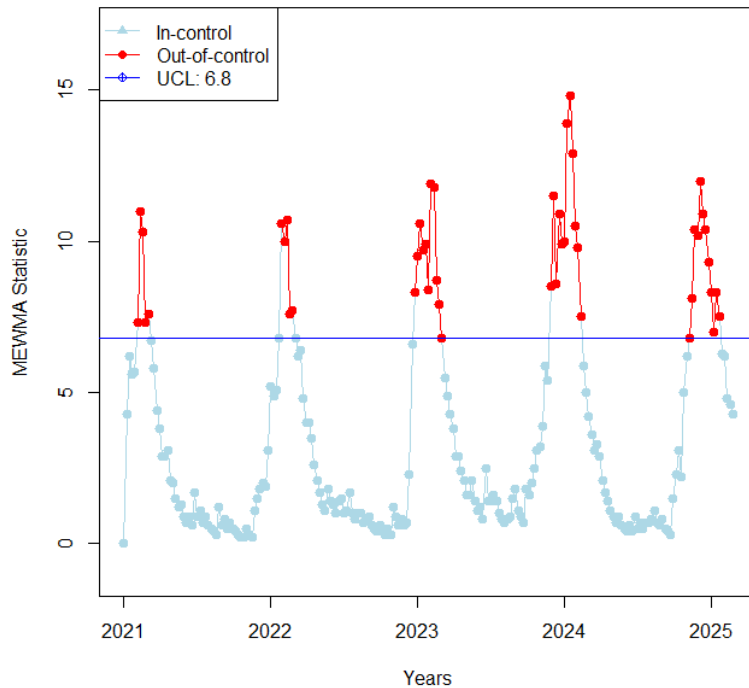


Figure 4: Modified EWMA Chart for Monitoring Death Prevalence due to Lassa fever

These out-of-control signals recur intermittently throughout the study period, with the highest peak occurring in 2024, suggesting that this year experienced the most severe increase in deaths. Similar, but less pronounced, peaks are also observed in 2021, 2022, 2023, and early 2025. The repeated pattern of these signals suggests that Lassa fever mortality displays a seasonal or periodic outbreak pattern rather than remaining constant throughout the year. The ability of the Modified EWMA chart to detect these increases demonstrates its effectiveness as a statistical tool for disease surveillance. The chart quickly detects abnormal increases in deaths, enabling public health authorities to implement timely interventions to reduce mortality.

CONCLUSION AND RECOMMENDATIONS

This study applied a Modified EWMA control chart to monitor weekly Lassa fever deaths in Nigeria using surveillance data obtained from the NCDC covering January 2021 to September 2025. The descriptive analysis showed that reported deaths were approximately normally distributed, with no marked skewness or extreme outliers, while the time plot revealed natural fluctuations without an immediately obvious outbreak pattern. However, the Modified EWMA chart, which is more sensitive to small and gradual shifts than conventional Shewhart-type charts, successfully identified several out-of-control periods, most notably in 2024, indicating episodes when Lassa fever deaths rose significantly above the expected baseline level.

These findings confirm that Lassa fever mortality in Nigeria follows a seasonal or periodic outbreak pattern, and that early, sensitive statistical surveillance tools such as the Modified EWMA chart can detect emerging increases in mortality before they escalate into wider crises. The chart therefore has practical value as a real-time early-warning tool for the NCDC and other public health stakeholders.

This study is limited by its reliance on secondary, reported death data, which may be subject to underreporting or delay in the typical of routine surveillance systems. Future work should validate these findings against independent field or laboratory-confirmed data where available.

Based on these findings, the following recommendations are made:

1. (i) The Nigeria Centre for Disease Control should consider incorporating Modified EWMA control charts into its routine weekly surveillance of Lassa fever and other infectious diseases, to complement existing threshold-based alert systems.
2. (ii) Given the seasonal pattern identified, public health authorities should intensify surveillance, rodent-control interventions, and public awareness campaigns, particularly ahead of and during the dry season (November to March).
3. (iii) Future studies should compare the performance of the Modified EWMA chart with other memory-type charts (e.g., CUSUM and generally weighted moving average charts) and extend the analysis to other infectious diseases and other regions of Nigeria.
4. (iv) Further research should explore the effect of overdispersion and autocorrelation in the mortality data by adopting count-data-specific control charts (e.g., Poisson EWMA or Negative Binomial EWMA charts).

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the Nigeria Centre for Disease Control (NCDC) for providing public access to the Lassa fever situation reports used in this study.

Conflict Of Interest

The authors declare that they have no conflict of interest.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

The data used in this study are publicly available on the Nigeria Centre for Disease Control website at <https://ncdc.gov.ng/diseases/sitreps>.

REFERENCES

1. Alfaro, J.-L., & Ortega, J.-F. (2011). Robust Hotelling's T^2 control charts under non-normality: The case of t -Student distribution. *Journal of Statistical Computation and Simulation*, 82(10), 1437–1447.
2. Brookmeyer, R., & Stroup, D. F. (Eds.). (2004). *Monitoring the health of populations: Statistical principles and methods for public health surveillance*. Oxford University Press.
3. Chantraine, P. M. R. (1987). Geometric moving average charts in a manufacturing environment. In *Proceedings of the 31st Annual Fall Technical Conference*, Atlantic City, NJ.
4. Crowder, S. V. (1987). A simple method for studying run length distributions of exponentially weighted moving average charts. *Technometrics*, 29(4), 401–407.
5. Dong, Y., Hedayat, A. S., & Sinha, B. K. (2008). Surveillance strategies for detecting change point in incidence rate based on exponentially weighted moving average methods. *Journal of the American Statistical Association*, 103(482), 843–853.
6. Khan, N., Aslam, M., & Jun, C. H. (2017). Design of a control chart using a modified EWMA statistic. *Quality and Reliability Engineering International*, 33(5), 1095–1104.

7. Lucas, J.M., & Saccucci, M.S. (1987). Exponentially weighted moving average control schemes: Properties and enhancements (Faculty Working Paper No. 87-5). Drexel University.
8. Mohammed, M.A., Worthington, P., & Woodall, W.H. (2008). Plotting basic control charts: Tutorial notes for the healthcare practitioners. *Quality and Safety in Health Care*, 17(2), 137–145.
9. Montgomery, D.C. (2019). *Introduction to statistical quality control* (8th ed.). John Wiley & Sons.
10. Musa, S.S., et al. (2024). [Please supply the full reference for this source cited in-text—journal, volume, and page numbers were not provided in the original manuscript.]
11. Nigeria Centre for Disease Control (NCDC). (2025). Lassa fever situation report, 2025. Retrieved from <https://ncdc.gov.ng/diseases/sitreps>
12. Patel, A.K., & Divecha, J. (2011). Modified exponentially weighted moving average (EWMA) control chart for analytical process data. *Journal of Chemical Engineering and Materials Science*, 2(1), 12–20.
13. Rakitzis, A.C., & Antzoulakos, D.L. (2012). Control charts with switching and sensitizing run rules for monitoring process variation. *Journal of Statistical Computation and Simulation*, 84(1), 37–56.
14. Roberts, S.W. (1959). Control chart tests based on geometric moving averages. *Technometrics*, 1(3), 239–250.
15. Robinson, P.B., & Ho, T.Y. (1978). Average run lengths of geometric moving average charts by numerical methods. *Technometrics*, 20(1), 85–93.
16. Sarkar, A., & Pal, S. (1997). Process control and evaluation in the presence of a systematic assignable cause. *Quality Engineering*, 10(2), 383–388.
17. Shu, L., Huang, W., & Jiang, W. (2014). A novel gradient approach for optimal design and sensitivity analysis of EWMA control charts. *Naval Research Logistics (NRL)*, 61(3), 223–237.
18. Shu, L., Jiang, W., & Wu, S. (2012). Computation of the run-length percentiles of CUSUM control charts under changes in variance. *Journal of Statistical Computation and Simulation*, 83(7), 1238–1251.
19. Steiner, S.H., Cook, R.J., Farewell, V.T., & Treasure, T. (2000). Monitoring surgical performance using risk-adjusted cumulative sum charts. *Biostatistics*, 1(4), 441–452.
20. United Nations Office for the Coordination of Humanitarian Affairs (OCHA). (2024). Nigeria: Lassa fever epidemic situation update. Retrieved from <https://reliefweb.int>
21. Woodall, W.H. (2006). The use of control charts in health-care and public-health surveillance. *Journal of Quality Technology*, 38(2), 89–104.
22. Wu, Z., Jiao, J., Yang, M., Liu, Y., & Wang, Z. (2010). A combined synthetic & X chart for monitoring the process mean. *International Journal of Production Research*, 48(24), 7423–7436.
23. Yang, S-F. (2013). Using a new VSIEWMA average loss control chart to monitor changes in the difference between the process mean and target and/or the process variability. *Applied Mathematical Modelling*, 37(24), 7973–7982.