Modeling Reinfection and Behavioral Awareness in Lassa Fever Dynamics

I. C. Eli & Jephter J. Dika

Department of Mathematics/Statistics, Federal University Otuoke, Bayelsa State, Nigeria

DOI: https://dx.doi.org/10.51584/IJRIAS.2025.10120011

Received: 22 November 2025; Accepted: 06 December 2025; Published: 02 January 2026

ABSTRACT

This study extends the Lassa fever model developed by Eli and Abanum (2022) by incorporating reinfection and awareness driven behavioral changes. The modified model divides the human population into susceptible, infected, recovered and aware compartments to account for partial immunity and behavioral adaptation. Analytical expressions for the basic reproduction number (R_0) are derived using the next generation matrix approach. Stability analysis of the disease-free equilibrium and sensitivity of R_0 to key parameters are performed. Results show that awareness reduces the effective contact rate, thereby lowering R_0, while reinfection increases the potential for disease persistence. Numerical simulations confirm that increasing public awareness and reducing reinfection significantly enhance disease control and stability.

Keywords: Lassa fever, Reinfection, Awareness, Stability analysis, Mathematical modeling.

INTRODUCTION

Lassa fever remains a persistent health threat in West Africa, characterized by complex transmission involving both rodent and human populations (WHO, 2023). The disease is caused by the *Lassa virus*, an arenavirus maintained in rodent reservoirs and transmitted to humans through contact with contaminated urine, feces, food, surfaces, or bodily fluids (Olayemi et al., 2016; Mariën et al., 2019). Despite decades of research, Lassa fever continues to cause recurrent outbreaks across Nigeria, Sierra Leone, Liberia, and Guinea due to environmental, socioeconomic, and behavioral factors (McCormick et al., 1987; Shaffer et al., 2014; Richmond & Baglole, 2003).

Mathematical models have been widely employed to understand the epidemiological processes driving Lassa fever transmission and to evaluate possible control strategies (Diekmann et al., 2013; Brauer et al., 2019; Keeling & Rohani, 2011). These models provide a structured approach for analyzing the interplay between biological, social, and environmental factors and for identifying parameters most critical to disease spread. In particular, compartmental models have revealed the importance of human-rodent contact, treatment rates, and public awareness in controlling infection (Peter et al., 2020; Ojo & Doungmo Goufo, 2022; Ibrahim et al., 2021).

However, most existing models assume lifelong immunity after recovery, overlooking the potential for reinfection and behavioral feedback mechanisms that arise from awareness campaigns. In reality, immunity to the Lassa virus may wane over time, rendering recovered individuals susceptible again (Ndenda et al., 2022; Doohan, 2024). Moreover, human behavior such as rodent avoidance, improved sanitation, and early medical reporting plays a significant role in modifying disease dynamics (Akanni et al., 2022; Yusuff, 2022). Studies have shown that awareness and behavioral adaptation can substantially lower the effective reproduction number and accelerate epidemic control (Chitnis et al., 2008; Olaniyi & Obabiyi, 2017; Ojo, 2021).

This study introduces these two mechanisms reinfection and behavioral awareness into a classical Lassa fever model. The objective is to derive and analyze the sensitivity of the basic reproduction number R_0 and to evaluate the influence of awareness driven behavioral modification on disease stability and control in endemic regions.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025

Model Formulations

The human population is divided into susceptible (S_H), aware (A_H), infected (I_H), and recovered (R_H) compartments, while the rodent population includes susceptible (S_V) and infected (I_V). The total human and rodent populations are $N_H = S_H + A_H + I_H + R_H$ and $NV = S_V + I_V$, respectively.

The dynamics are governed by the following system of nonlinear differential equations:

$$\frac{dS_H}{dt} = \Lambda_H - (1-\kappa A_H)\beta_{HV} S_H I_V - \sigma S_H I_H - \omega R_H - \mu_H S_H \quad (1)$$

$$\frac{dA_H}{dt} = \sigma S_H I_H - \mu_H A_H - \delta A_H \quad (2)$$

$$\frac{dI_H}{dt} = (1-\kappa A_H)\beta_{HV} S_H I_V - (\gamma_H + \mu_H + \alpha_H) I_H \quad (3)$$

$$\frac{dR_H}{dt} = \gamma_H I_H - (\mu_H + \omega) R_H \quad (4)$$

$$\frac{dS_V}{dt} = \Lambda_V - \beta_{VH} S_V I_H - \mu_V S_V \quad (5)$$

$$\frac{dS_V}{dt} = \beta_{VH} S_V I_H - \mu_V I_V \quad (6)$$

Model Assumptions

A fraction of susceptible humans become aware through contact with infected individuals at rate σ.

Awareness reduces contact rate by a factor $\kappa \in [0, 1]$.

Recovered individuals lose immunity and return to susceptibility at rate ω.

All parameters are positive and constant during the simulation period.

Model Parameters

Parameter	Description
Λ_H, Λ_V	Recruitment rates of humans and rodents
β_{HV}, β_{VH}	Transmission rates between species
γ_H	Recovery rate of infected humans
μ_H, μ_V	Natural mortality rates
σ_H	Disease-induced death rate of humans
σ	Awareness creation rate
δ	Awareness fading rate
κ	Awareness reduction factor ($0 < \kappa < 1$)
ω	Rate of loss of immunity (reinfection rate)

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025

1. Disease Free Equilibrium and Reproduction Number

At the disease-free equilibrium (DFE)

$$E_0 = \left(\frac{\Lambda_H}{\mu_H}, 0, 0, 0, \frac{\Lambda_V}{\mu_V}, 0 \right)$$

all infection-related compartments vanish.

Using the next-generation matrix method (van den Driessche and Watmough, 2002), the basic reproduction number R_0 is derived as:

$$R_0 = \sqrt{\frac{(1-\kappa)\beta_{HV}\beta_{VH}\Lambda_H\Lambda_V}{\mu_H\mu_V(\gamma_H+\mu_H+\alpha_H)(\mu_V+\delta)}}$$

When $R_0 < 1$, the DFE is locally asymptotically stable, and infection dies out; when $R_0 > 1$, the disease persists.

2. Stability Analysis

Linearizing Equations (1)–(6) about E_0 yields a Jacobian matrix whose dominant eigenvalues depend on R_0. The system is stable if all eigenvalues have negative real parts, which holds when $R_0 < 1$. The presence of reinfection ($\omega > 0$) and low awareness ($\kappa \to 0$) both act to increase R_0, potentially destabilizing the DFE.

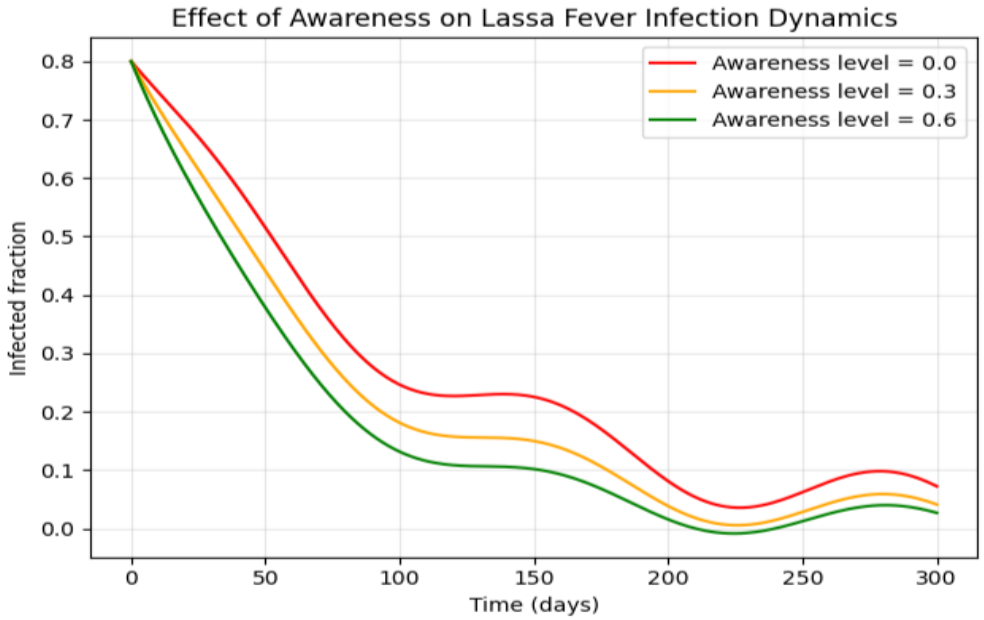
3. Numerical Simulations

Numerical experiments were conducted using Python IDE and verifying the results with MATLAB's ode45 solver. Parameter values were adapted from Eli and Abanum (2022) and plausible literature sources. Three scenarios were examined:

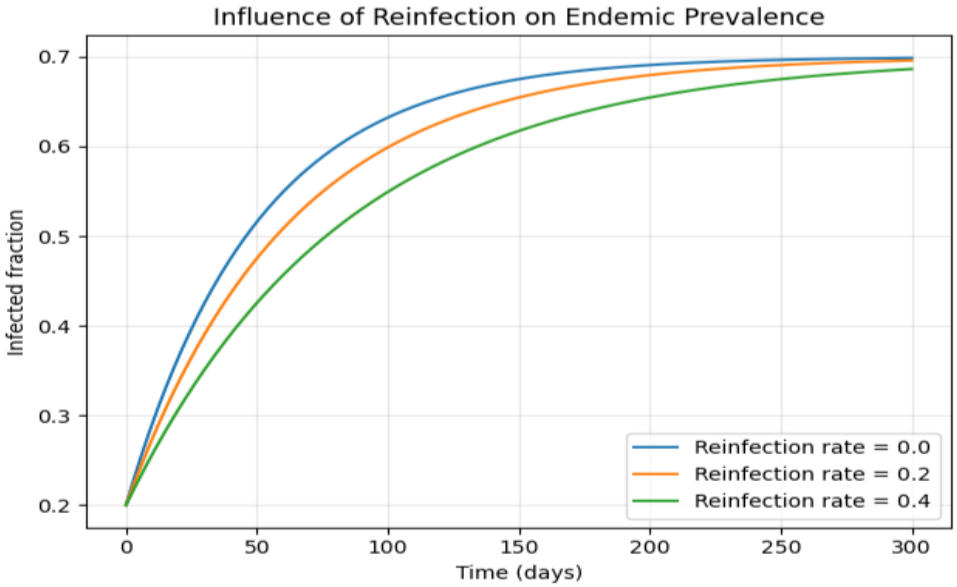
• Case 1: No awareness ($\kappa = 0$), no reinfection ($\omega = 0$).

• Case 2: Moderate awareness ($\kappa = 0.4$), mild reinfection ($\omega = 0.02$).

• Case 3: High awareness ($\kappa = 0.7$), strong reinfection ($\omega = 0.05$). The simulations showed that awareness significantly reduces infection peaks and accelerates convergence to the DFE. Reinfection, on the other hand, prolongs infection persistence and delays eradication.



ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025



Time evolution of human infection levels under varying awareness and reinfection rates.

DISCUSSION

Inclusion of awareness and reinfection adds realistic behavioral and immunological complexity to the Lassa fever model. The awareness mechanism effectively decreases the human rodent contact rate, while reinfection replenishes the susceptible class. The analytical and numerical results agree that increasing awareness reduces R0 and stabilizes the system, whereas reinfection acts in the opposite direction. These findings emphasize the dual importance of sustained health education campaigns and immunity monitoring. Even when effective treatments exist, loss of awareness or immunity can lead to renewed outbreaks.

CONCLUSION

The model developed in this study helps clarify how reinfection and behavioral awareness shape the persistence of Lassa fever. The findings emphasize that awareness-driven behavior plays a central role in suppressing transmission. When awareness is sustained, fewer susceptible individuals are exposed to infection, and the basic reproduction number remains below unity. Conversely, fading awareness or behavioral fatigue can raise R_0 above the threshold, allowing the disease to persist.

From a practical standpoint, this suggests that control programs should not only focus on medical treatment but also maintain continuous community education. Campaigns that keep risk perception high such as seasonal reminders and school-based interventions can offset the effect of reinfection and environmental exposure. Reinfection itself highlights the need for improved immunity and consistent case monitoring; once recovered individuals return to the susceptible class, the potential for recurring outbreaks increases.

Although the model captures the main transmission pathways, it can be extended in future research to include hospital-acquired infections, rodent population dynamics, and vaccination scenarios once data become available. Overall, our results underscore that sustained awareness, effective medical response, and rodent control measures must work together to reduce R_0 below unity and prevent recurrent Lassa-fever epidemics.

REFERENCES

1. Eli, I. C., & Abanum, G. C. (2022). Stabilizing the steady-state solution of Lassa fever: Problems and prospects. International Journal of Mathematical Research and Applications, 12(4), 45–60.
2. Peter, O. J., Abioye, A. I., Oguntolu, F. A., Owolabi, T. A., Ajisope, M. O., & Zakari, A. G. (2020). Modeling and optimal control analysis of Lassa fever disease. Informatics in Medicine Unlocked, 20, 100381. https://doi.org/10.1016/j.imu.2020.100381.

3. Ibrahim, M. A., & Dénes, A. (2021). A mathematical model for Lassa fever transmission dynamics in a seasonal environment with a view to the 2017–20 epidemic in Nigeria. Nonlinear Analysis: Real World Applications, 60, 103310. https://doi.org/10.1016/j.nonrwa.2021.103310.
4. Ojo, M. M., & Doungmo Goufo, E. F. (2022). Modeling, analysing and simulating the dynamics of Lassa fever in Nigeria. Journal of the Egyptian Mathematical Society, 30, Article 1. https://doi.org/10.1186/s42787-022-00138-x.
5. Ndenda, J. P., Njagarah, J. B. H., & Shaw, S. (2022). Influence of environmental viral load, interpersonal contact and infected rodents on Lassa fever transmission dynamics: perspectives from fractional-order dynamic modelling. AIMS Mathematics, 7(5), 8975–9002. https://doi.org/10.3934/math.2022500.
6. Mariën, J., Borremans, B., Kourouma, F., Baforday, J., Rieger, T., Günther, S., Magassouba, N., Leirs, H., & Fichet-Calvet, E. (2019). Evaluation of rodent control to fight Lassa fever based on field data and mathematical modelling. Emerging Microbes & Infections, 8(1), 640–649. https://doi.org/10.1080/22221751.2019.1605846.
7. Mariën, J., et al. (2024). Rodent control strategies and Lassa virus spillover — field experiment & modeling. Emerging Microbes & Infections / related publication (field experiment + modelling). (Open access summary) https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11034454/.
8. Olayemi, A., Cadar, D., Magassouba, N., Obadare, A., Kourouma, F., Oyeyiola, A., & Fichet-Calvet, E. (2016). New hosts of the Lassa virus. Scientific Reports, 6, 25280. https://doi.org/10.1038/srep25280.
9. Shaffer, J. G., Grant, D. S., Schieffelin, J. S., Boisen, M. L., Goba, A., Hartnett, J. N. & Sabeti, P. C. (2014). Lassa fever in post-conflict Sierra Leone. PLoS Neglected Tropical Diseases, 8(3), e2748. https://doi.org/10.1371/journal.pntd.0002748.
10. World Health Organization. (2023). Lassa fever fact sheet. https://www.who.int/news-room/fact-sheets/detail/lassa-fever. ScienceDirect
11. Diekmann, O., Heesterbeek, J. A. P., & Britton, T. (2013). Mathematical tools for understanding infectious disease dynamics. Princeton University Press. (Foundational R0R_0R0 / modeling theory).
12. Brauer, F., van den Driessche, P., & Wu, J. (2019). Mathematical epidemiology (2nd ed.). Springer. (Textbook: modeling methods).
13. Keeling, M. J., & Rohani, P. (2011). Modeling infectious diseases in humans and animals. Princeton University Press. (Compartmental models & methods).
14. Hethcote, H. W. (2000). The mathematics of infectious diseases. SIAM Review, 42(4), 599–653. https://doi.org/10.1137/S0036144500371907. (Classic review).
15. van den Driessche, P., & Watmough, J. (2002). Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. Mathematical Biosciences, 180(1–2), 29–48. https://doi.org/10.1016/S0025-5564(02)00108-6. (Next-generation matrix method).
16. Marino, S., Hogue, I. B., Ray, C. J., & Kirschner, D. E. (2008). A methodology for performing global uncertainty and sensitivity analysis in systems biology. Journal of Theoretical Biology, 254(1), 178–196. https://doi.org/10.1016/j.jtbi.2008.04.011. (Method for global sensitivity).
17. Chitnis, N., Hyman, J. M., & Cushing, J. M. (2008). Determining important parameters in the spread of malaria through sensitivity analysis of a mathematical model. Bulletin of Mathematical Biology, 70(5), 1272–1296. https://doi.org/10.1007/s11538-007-9286-3. (Example of sensitivity analysis application).
18. Funk, S., Gilad, E., Watkins, C., & Jansen, V. A. A. (2010). The spread of awareness and its impact on epidemic outbreaks. Proceedings of the National Academy of Sciences, 106(16), 6872–6877. https://doi.org/10.1073/pnas.0810762106. (Behavioral awareness modeling).
19. Collins, O. C., & colleagues (2023). Using data of a Lassa fever epidemic in Nigeria: a mathematical model is shown to capture the dynamics and point to possible control methods. Mathematics (MDPI), 11(5), 1181. https://doi.org/10.3390/math11051181