Research Article

Global Stability of Pneumococcal Pneumonia with Awareness and Saturated Treatment

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Received 18 September 2019; Revised 31 December 2019; Accepted 9 January 2020; Published 13 February 2020

1. Introduction

Pneumonia is one of the severe forms of pneumococcal diseases caused by pneumococcus [1]. Pneumococcal pneumonia is preventable through vaccination, diagnostic testing, environmental control measures, and appropriate treatment [2]. However, treatment of pneumococcal pneumonia has become tricky due to antibiotic selection that increases resistance of Streptococcus pneumoniae to penicillin and the successive evolution of resistance to numerous classes of antibiotics [3]. Bacteria develop resistance against antibiotics, causing severe illness to an individual. Ultimately, it requires costly treatment to control and eradicate the disease [4]. The emergence of antimicrobial resistance threatens the successful treatment of pneumococcal infections [5]. Repeated and improper use of antibiotics is on an increase and identified as the main cause of the emerging resistance [6]. In the event of acute side effects, patients tend to discard their treatment, only to return to the hospital with persistent infections of a more virulent and resistant strain of the bacteria [7]. Antibiotic resistance is a major worldwide threat to the provision of safe and effective health care. To control antibiotic resistance, vaccines have been proposed as an essential intervention, complementing improvements in antibiotic stewardship and drug pipelines [8].

In treatment of pneumonia, microorganisms occasionally persevere, emerge or remerge despite the good clinical responses. Thus, recovered individuals may relapse and return to the infective class [9]. However, relapse may occur due to treatment failure with regard to elimination of an infecting causative agent. Recurrence of disease is a significant feature of some animal and human diseases; for
example, malaria, herpes, and tuberculosis [10]. Patients with HIV/AIDS commonly have a recurrence of pneumococcal bacteremia due to pre-existing drug resistance [11, 12]. Pneumococcal pneumonia patients infected with chronic diseases, such as HIV/AIDS, are more likely to relapse compared with individuals without chronic diseases [13].

Disease appropriate awareness in a population can control an infection effectively [14]. Enhanced levels of awareness, for instance, practice of better hygiene, voluntary quarantine, application of preventive medicine, or vaccination and avoidance of places containing large number of people, may reduce the spread and contraction of the disease [15]. Mass media awareness plays a vital role in changing behavior related to public health [16]. The spread of an infectious disease is reported by the media, such as television programs, newspapers, radio, or online social networks. Daily updates and reports about infections and mortality have a significant effect on the necessity of control of an epidemic [17]. Campaigns mainly focus on increasing an individual’s knowledge about disease transmission and control measures that may reduce the likelihood of being infected [18].

Despite the application of all control methods that have been advocated for, individuals in developing countries lack information on the transmission and control of pneumococcal pneumonia. Individuals continue to practice self-medication [19, 20], which leads to delays in the administration of adequate antimicrobial treatment, increase resistance to antibiotics, and appear to increase the risk for hospital mortality [21].

Mathematical models that describe the influence of media coverage to inform individuals regarding disease and control in a population have been generalized in the forms of SIS, SIRS, SEI, and SEIR [22–25]. Media coverage, private individual information, and appropriate treatment have proven to be among control measures undertaken by health institutions and the public to reduce the spread of most infectious diseases. Models of infections that include awareness have been studied widely; for instance, Saha and Roy [26] performed a comparative study between two systems with and without awareness in controlling HIV/AIDS. The study revealed that aware populations were less vulnerable to HIV infection than the unaware population. Roy et al. [27] studied the effect of awareness programs in controlling the disease HIV/AIDS and found out that increased awareness campaign during high infection is likely to delay the inception of infection among aware compared with unaware population.

In this paper, we propose and analyze a mathematical model for pneumococcal pneumonia disease with awareness about antibiotic resistance and saturated treatment. The aim of this study is to investigate the impact of awareness about antibiotic resistance and treatment on the incidence and control of pneumococcal pneumonia in the human population. We consider a model developed by [2] and extend it by introducing new compartments of susceptible and infective individuals. That is, we subdivide the compartment of susceptible into aware individuals and unaware individuals and the infectious into infected individuals receiving treatment and infected individuals resistant to first line treatment. A relapse of resistant individuals, a modified saturated treatment, and a reduced disease transmission rate with the effect of antibiotic resistance awareness through media are also added.

The remaining part of this paper is organized as follows. In Section 2, materials and methods of a mathematical model are presented. In Section 3, the basic reproduction number and local stability of the steady states of the model are presented. We present global stability of the steady states in Section 4 and give the numerical results, discussion, and conclusion in Section 5.

2. Materials and Methods

2.1. Model Description and Formulation. The total population under consideration is \( N(t) \), comprising four classes with the susceptible and infectious individuals, each partitioned into two. The susceptible class consists of the aware susceptible individuals \( S_a(t) \) who have had a chance to attend the available antibiotic resistance awareness programs and the unaware susceptible individuals \( S_u(t) \) who have never heard of the prevailing programs or have heard of the existing programs but have not responded. The infectious class consists of infected individuals receiving treatment \( I(t) \) and infected individuals but resistant to first line treatment \( R(t) \). It is assumed that, in a population, antibiotic resistance awareness is disseminated by private individuals and the media at rates \( \nu \) and \( m \), respectively. Furthermore, we assume that all classes are decreased by a natural mortality rate \( \mu \).

Assuming all new recruitments (through birth and immigrants) to be unaware, it is further assumed that aware susceptible individuals transfer to unaware susceptible class due to loss of memory or social factors. The unaware susceptible class is increased through a constant recruitment \( B \), and fading of information by aware susceptible individuals is at a rate \( c \). The infection is spread through the interaction of infected and susceptible individuals. We consider a reduced incidence rate of the form \( g(I) = (\beta I - \beta_1(mI/m + I)) \), where \( m > 0 \) is the effect of media coverage on the contact transmission [28], \( \beta > 0 \) is the maximal effective contact rate before awareness, and \( \beta_1 > 0 \) is the maximal reduced effective contact rate due to media alert in the presence of infective individuals. The transmission term has been considered because in real life, every individual will take precaution to protect themselves from infections as soon as infected individuals with antibiotic resistant bacteria have been identified/reported in a wholly susceptible population which will reduce the disease spread [22]. Due to the fact that the coverage report about antibiotic resistance against existing treatment does not prevent spread of disease completely, we assume \( \beta \geq \beta_1 > 0 \). The unaware susceptible individuals transfer to the aware class after receiving information through private individuals at a rate \( \nu \).

Transmission of the infection is assumed to be governed by the bilinear incidence term \( \beta_2 S_a I \) with \( \beta_2 > 0 \)
being the contact rate between aware individuals and infected individuals. The infected class is increased through the relapse of resistant individuals at a rate $\gamma_i$. It is assumed that infected individuals upon receiving the first line of treatment tend not to complete the prescribed medication and develop resistant bacteria that may require costly treatment to be eliminated. A saturated treatment is considered because there exist delays in administering treatment by infected individuals, and the medical resources may be limited. Suppose that infected individuals are immediately treated with first line of treatment at a rate $\phi$, and a fraction of infected individuals respond to treatment and recover from the pneumonia. Thus, we obtain the system of nonlinear ordinary differential equations:

$$\begin{align*}
\dot{S}_u &= B + \xi S_u - g(I) S_u - v I S_u - \mu S_u - (g(I) + v I - \mu) S_u, \\
\dot{S}_a &= v I S_u + (1 - p) \Phi T(I) - (\beta_2 I + \xi + \mu) S_a, \\
\dot{I} &= g(I) S_u + \beta_2 S_a I + \gamma_1 R - \Phi T(I) - (\mu + \delta_1) I, \\
\dot{R} &= p \Phi T(I) - (\gamma_1 + \mu) R,
\end{align*}$$

where $T(I) = I/1 + \tau I$ and $g(I) = (\beta I - \beta_1 (m I/m + I))$, with initial conditions $S_u(0) = S_a(0) = 0$, $S_a(0) = S_u(0) \geq 0$, $I(0) = I_0 \geq 0$, $R(0) = R_0 \geq 0$. Since model (1) describes human populations, all state variables and parameters are assumed positive for all $t \geq 0$.

### 2.2. Positivity of Solution Trajectories in Model (1)

**Lemma 1.** Solutions of model (1) with initial conditions $S_u(0) = S_a(0) \geq 0$, $S_a(0) = S_u(0) \geq 0$, $I(0) = I_0 \geq 0$ and $R(0) = R_0 \geq 0$ are always nonnegative for all $t \geq 0$.

**Proof.** Suppose $S_u(t), S_a(t), I(t), R(t)$ are solutions to model (1); then, from the first equation of model (1), we have

$$\frac{dS_u}{dt} = B + \xi S_u - g(I) S_u - v I S_u - \mu S_u - (g(I) + v I - \mu) S_u.$$  

By using the technique of separation of variables, we have

$$S_u(t) \geq S_u(0) \exp \left( - \left( \mu t + \int_0^t (g(I(\theta)) + v I(\theta)) d\theta \right) \right) \geq 0.$$  

Therefore, the solution of $S_u(t)$ in equation (3) is non–negative for all $t \geq 0$. Applying the same technique to the remaining variables of model (1), we get

$$S_u(t) \geq S_u(0) \exp \left( - (\xi + \mu) \int_0^t \beta_2 I(\theta) d\theta \right) \geq 0,$$

$$I(t) = I_0 \exp \left( - (\mu + \delta_1) t \right) \geq 0,$$

$$R(t) \geq R_0 \exp \left( - (\gamma_1 + \mu) t \right) \geq 0.$$  

Therefore, all solutions of $S_u(t), I(t)$ and $R(t)$ in equations (4)–(6) are nonnegative for all times $t \geq 0$. This completes the proof. □

### 2.3. Invariant Region

Here, we obtain a region in which the solution of model (1) is bounded. For this model, the total population is $N = S_u + S_a + I + R$, such that the rate of change of the total population is

$$\frac{dN}{dt} = B - \mu N - \delta I,$$

$$\frac{dN}{dt} \leq B - \mu N.$$  

Equation (8) corresponds to instances of no pneumococcal pneumonia-related death. Therefore, we obtain

$$N \leq N_0 e^{-\mu t} + \frac{B}{\mu} \left( 1 - e^{-\mu t} \right),$$

where $N_0 = S_u(0) + S_a(0) + I_0 + R_0$.

Thus, from equation (9), we have

$$N(t) \leq \max \left( N_0, \frac{B}{\mu} \right).$$

Then, $0 \leq S_u + S_a + I + R \leq B/\mu$. This implies that the region $D = \{(S_u, S_a, I, R) \in \mathbb{R}^4_+: S_u + S_a + I + R = N \leq B/\mu\}$, which implies $N(t)$ is bounded and so are $S_u, S_a, I$, and $R$.

### 2.4. Existence and Uniqueness of the Steady States

From model (1), equating the right hand side to zero, Proposition 1 shall represent the existence and uniqueness of the endemic steady state.
Table 1: Description of parameters.

| Parameter | Description | Value/day⁻¹ | Ref |
|-----------|-------------|-------------|-----|
| A         | Recruitment by birth/immigration | 5           | Assd |
| β         | Maximal effective contact rate before antibiotic resistance awareness | 0.0417      | [32] |
| α         | Maximal reduced effective contact rate due to media alerts | 0.0046      | Assd |
| β₂       | Contact rate of aware susceptible to infective individuals | 0.000007498 | Assd |
| γ         | Rate of relapse encountered in administering treatment | 0.00145     | Assd |
| μ         | Natural mortality rate | 2.0 × 10⁻⁴  | [2]  |
| m         | Efficiency of awareness through media coverage | 0.5         | Assd |
| δ         | Excess death due to pneumococcal pneumonia | 0.1         | [33, 34] |
| ξ         | Loss of information about disease by aware susceptible individuals | 0.3         | [15] |
| Φ         | Recovery rate due to treatment | 0.9         | [35] |
|τ         | Rate of delay to receive appropriate treatment | 0.2703      | Assd |
| p         | Probability of acquiring resistance during treatment | 0.0–0.03    | [30] |
| ν         | Rate at which unaware susceptible individuals become aware of antibiotic resistance | 0.0029      | Assd |

Table 2: Description of state variables.

| Variable | Description |
|----------|-------------|
| S₀(t)    | Unaware individuals |
| S₁(t)    | Aware individuals |
| I(t)     | Infected individuals receiving treatment |
| R(t)     | Infected individuals but resistant to first line of treatment |
| N(t)     | Total population (N(t) = S₀(t) + S₁(t) + I(t) + R(t)) |

Figure 1: A transition diagram showing the dynamics of pneumococcal pneumonia.

**Proposition 1.** If conditions \((γ_1 + μ)(μ + δ) > Φ(γ_1(p - 1) - μ), B > I^∗, \((vI^∗ + μ)(β_2I^∗ + ξ + μ) > vI^∗(β_2I^∗ + ξ), \) and \((Φ + μ + δ_2)(γ_1 + μ) > pΦγ_1\) hold, then model (1) will admit a unique endemic steady state, \(E^∗ = (S₀^∗, S₁^∗, I^∗, R^∗)\) if \(R₀ > 1\).

**Proof.** Suppose \(E^∗ = (S₀^∗, S₁^∗, I^∗, R^∗)\) is a steady state of model (1) satisfying the following system.

\[
\begin{align*}
B + ξS₀^∗ & - (g(I^∗) + νI^∗ + μ)S₀^∗ = 0, \\
vI^∗S₀^∗ & + (1 - p)ΦT(I^∗) - (β_2I^∗ + ξ + μ)S₀^∗ = 0, \\
g(I^∗)S₀^∗ & + β_2S₀^∗I^∗ + γ_1R^∗ - ΦT(I^∗) - (μ + δ_2)I^∗ = 0, \\
pΦT(I^∗) & - (γ_1 + μ)R^∗ = 0.
\end{align*}
\]

From equation (11) it follows that if we let \(I^∗ = R^∗ = 0\), then we have the disease-free steady state \(E_0^∗ = (S₀^0, S₁^0, I^0, R^0) = ((ξ + μ)/ν, (Bν - μξ - μ^2)/νμ, 0, 0)\) that exists for all epidemiological parameter values.

On the other hand, if \(I^∗ ≠ 0, R^∗ ≠ 0\), then we have the endemic steady state \(E^∗ = (S₀^∗, S₁^∗, I^∗, R^∗)\), where

\[
\begin{align*}
S₀^∗ & = \frac{(1 + τI^∗)^2(β_2I^∗ + ξ + μ)(B - I^∗d) + (β_2I^∗ + ξ)(1 - p)ΦI^∗}{K(1 + τI^*)}, \\
S₁^∗ & = \frac{nu^∗(1 + τI^∗)^2(B - I^∗d) + (1 - p)ΦI^∗(υI^∗ + μ)}{K(1 + τI^*)}, \\
R^∗ & = \frac{pΦI^∗}{(γ + μ)(1 + τI^∗)}, \\
I^∗ & = I^∗ - \frac{-r_0 + \sqrt{(r_0^2 - 4r_3r_0)}}{2r_3},
\end{align*}
\]

with

\[
\begin{align*}
r_0 & = m(β - β_1)S₀^∗ + m\left(\frac{y_1Φp}{γ_1 + μ} + Φ\right) - (μ + δ_1), \\
r_1 & = (β + τm(β - β_1))S₀^∗ + τ(β - β_1)m + \frac{γ_1pΦ}{γ_1 + μ} \\
& + φ - (μ + δ_1)(1 + τm), \\
r_2 & = τ(βS₀^∗ - (μ + δ_1)), \\
d & = (γ_1 + μ)((γ_1 + μ)(μ + δ_1) - Φ(γ_1(p - 1) - μ)), \\
K & = (υI^∗ + μ)(β_2I^∗ + ξ + μ) - υI^∗(β_2I^∗ + ξ).
\end{align*}
\]
Therefore, there exists a unique endemic steady state \( E^* \), provided conditions \((\gamma_1 + \mu)(\mu + \delta_1) > \Phi(\gamma_1 (p - 1) - \mu), B > I^* d, (vI^* + \mu) (\beta_2 I^* + \xi + \mu) > vI^* (\beta_2 I^* + \xi)\), \( r_1 < 0 \), \( r_2 > 0 \), and \( r_0 < 0 \) hold. This completes the proof.  

### 3. The Basic Reproductive Number and Stability of Steady States

The basic reproduction number, \( R_0 \), is computed for model (1) by the method introduced by Van den Driessche and Watmough [36] according to which \( R_0 = \rho(FV^{-1}) \), where \( \rho \) is the spectral radius of a matrix (the maximum eigenvalue obtained from the matrix). Let \( F \) and \( V \) be vectors representing new infections and remaining transfer terms, respectively.

\[
\begin{align*}
F &= \left( g(S_u, I) + \beta_2 S_u I \right), \\
V &= \left( \Phi T(I) + (\mu + \delta_1)I - \gamma_1 R \right) (\gamma_1 + \mu)R - p\Phi T(I).
\end{align*}
\]

(14)

\[
FV^{-1} = \begin{pmatrix}
\frac{((\beta - \beta_1)S_u^0 + \beta_2 S_u^0)}{(\Phi + \mu + \delta_1)(\gamma_1 + \mu) - p\gamma_1 \Phi} & \frac{((\beta - \beta_1)S_u^0 + \beta_2 S_u^0)\gamma_1}{(\Phi + \mu + \delta_1)(\gamma_1 + \mu) - p\gamma_1 \Phi} \\
0 & 0
\end{pmatrix}
\]

(16)

Therefore, making substitutions of \( S_u^0 \) and \( S_u^0 \), the basic reproduction number for model (1) is

\[
R_0 = \rho(FV^{-1}) = \frac{(\gamma_1 + \mu)((\beta - \beta_1)((\xi + \mu)/\nu) + (\beta_2 (B\nu - \mu \xi - \mu^2)/\mu \nu))}{(\Phi + \mu + \delta_1)(\gamma_1 + \mu) - p\gamma_1 \Phi}.
\]

(17)

#### 3.1. Local Stability Behavior of the Disease-Free Steady States

**Proposition 2.** If condition \( \Phi + \mu + \delta_1 > p\Phi \gamma_1 \) hold, then the disease-free steady state \( E_0^* \) is locally asymptotic if \( R_0 < 1 \) and unstable for \( R_0 > 1 \).

**Proof.** The Jacobian matrix of model (1) at \( E_0^* \) is given as

\[
J(E_0) = \begin{pmatrix}
-\mu & \xi & J_{13} & 0 \\
0 & -(\xi + \mu) & J_{23} & 0 \\
0 & 0 & J_{33} & \gamma_1 \\
0 & 0 & p\Phi & -\gamma_1 + \mu
\end{pmatrix},
\]

(18)

with

\[
J_{13} = \frac{(\beta - \beta_1)(\xi + \mu)}{\nu}, \quad J_{23} = \frac{(1 - p)\Phi + (\xi + \mu) - \beta_2 (B\nu - \mu \xi - \mu^2)}{\mu \nu}, \quad J_{33} = \frac{(\beta - \beta_1)(\xi + \mu) + (\beta_2 (B\nu - \mu \xi - \mu^2))}{\mu \nu} - (\Phi + \mu + \delta_1).
\]

(19)

The characteristic polynomial of the matrix in (18) is given by

\[
|J(E_0) - \lambda I| = \lambda^4 + m_3 \lambda^3 + m_2 \lambda^2 + m_1 \lambda + m_0 = 0,
\]

(20)

where \( m_3 = ((\beta_1 - \beta)(\xi + \mu)/\nu) + (4\mu + \varphi + \delta_1 + \gamma_1 + \xi) - (\beta_2 (B\nu - \mu \xi - \mu^2)/\mu \nu), m_2 = (\xi + \mu)((\beta_1 - \beta)(\xi + \mu)/\nu) -
\]
\[
(β_2 (Bv - μξ - μ^2)/μv) + (Φ + μ + δ_1) + (γ_1 + μ)) + μ((ξ + μ) + β_1 - (β_1 (ξ + μ))/μv) - (β_2 (Bv - μξ - μ^2)/μv) (Φ + μ + δ_1) + (γ_1 + μ)) ((β_1 - β_1 (ξ + μ))/μv) - (β_2 (Bv - μξ - μ^2)/μv) (Φ + μ + δ_1) - γ_1(ϕ_1 - μ(ξ + μ) (β_1 - β_1 (ξ + μ))/μv) - (β_2 (Bv - μξ - μ^2)/μv) + (Φ + μ + δ_1) + (γ_1 + μ)) ((β_1 - β_1 (ξ + μ))/μv) - (β_2 (Bv - μξ - μ^2)/μv) - (Φ + μ + δ_1)).
\]

Therefore, the characteristic roots determined from polynomial equation (20) are
\[
λ_1 = -μ,
\]
\[
λ_2 = -(ξ + μ),
\]
\[
λ_3 = \left(-\frac{f}{2} + \frac{(γ_1 + μ)}{2} \pm \sqrt{\left(\frac{f^2 + 2f(γ_1 + μ) + 4pγ_1Φ)}{2}\right)}\right),
\]
\[
λ_4 = \left(-\frac{f}{2} + \frac{(γ_1 + μ)}{2} - \sqrt{\left(\frac{f^2 + 2f(γ_1 + μ) + 4pγ_1Φ)}{2}\right)}\right),
\]
\[
(21)
\]
with
\[
f = \frac{(β_1 - β_1 (ξ + μ) + β_2 (Bv - μξ - μ^2)/μv) - (Φ + μ + δ_1)}{v}.
\]
\[
(22)
\]
Since all eigenvalues computed from polynomial equation (20) are negative, then we have \(f/2 + ((γ_1 + μ)/2) > \sqrt{(f^2 + 2f(γ_1 + μ) + 4pγ_1Φ)/2}\), implying that \((γ_1 + μ)/2) > (Φ + μ + δ_1) \text{ and } pγ_1Φ, 1 \text{; hence, if condition \(Φ + μ + δ_1 > pγ_1Φ, 1 \text{ holds, then } R_0 = (γ_1 + μ)/2) > (Φ + μ + δ_1) \text{ and } pγ_1Φ, 1 \text{, which implies } E_0 \text{ is locally asymptotically stable. Furthermore, if } R_0 > 1, \text{ then } λ_1 > 0, \text{ which implies } E_0 \text{ is unstable. This completes the proof.}
\]

3.2. Local Stability of Endemic Steady State

Proposition 3. Suppose condition \((υI^* + μ)(β_2 I^* + ξ + μ) > υI^* (β_2 I^* + ξ + μ)\) holds; then, the endemic steady state \(E^*\) of model (1) is locally asymptotically stable in \(D\) for \(R_0 < 1\).

Proof. The variational matrix at \(E^*\) is given by
\[
J(E^*) = \begin{pmatrix}
    a & ξ & c & 0 \\
    υI^* & e & f & 0 \\
    g & β_2 I^* & h & γ_1 \\
    0 & 0 & l & -(γ_1 + μ)
\end{pmatrix},
\]
\[
(23)
\]
where \(a = -((β_1 - (β_1 mI^*/m + I^*)) + υI^* + μ), f = -((p - 1) - \Phi - υS^* + β_2 S^* + e = -(β_1 I^* + ξ + μ) + c = ((β_2 mI^*/m + I^*)) + v)S^*, g = (β_1 I^* - (β_1 mI^*/m + I^*))S^*, l = pθ(1 + rI^*)^2, h = β_2 S^* + (β - β_1 mI^*/(m + I^*)) S^* - Φ/(1 + rI^*)^2 - (Φ + μ + δ_1)).
\]

The characteristic equation associated to the variational matrix (23) is given by
\[
|J(E^*) - λI| = λ^4 + b_3λ^3 + b_2λ^2 + b_1λ + b_0 = 0,
\]
\[
(24)
\]
with \(b_3 = -(a + e + h - (γ_1 + μ)), b_2 = h(a + e) - (γ_1 + μ) (h + a) + e(a - (γ_1 + μ)) - (β_1 I^* + ξυI^* + γ_1 I + c g), b_1 = -β_1 I^* (a - (γ_1 + μ)) + (a + e)(γ_1 I + h(γ_1 + μ)) + (h - (γ_1 + μ))(ξυI^* - ae) - (ξυI^* - ae)(γ_1 I + h(γ_1 + μ)).
\]

Evaluating the coefficients of polynomial equation (24) using parameter values in Table 1, we have
\[
b_3 = 2531.7, \quad b_2 = 10981, \quad b_1 = 3545.26, \quad b_0 = 2215.745.
\]
Thus, polynomial equation (24) becomes
\[
λ^4 + 2531.7λ^3 + 10981λ^2 + 3545.26λ + 2215.745 = 0.
\]
\[
(25)
\]
Using polynomial function in MATLAB, the eigenvalues obtained are
\[
λ_1 = -0.7792,
\]
\[
λ_2 = -248.64,
\]
\[
λ_3 = -1.789 - 2.868i,
\]
\[
λ_4 = -1.789 + 2.86i.
\]

Since \(Re(λ_1) < 0\), the endemic steady state is locally asymptotically stable. This ends the proof.

4. Global Stability of Steady State

In this section, we deal with the global stability of steady states of model (1) using Lyapunov functionals with LaSalle’s invariant principle. Since it is often hard to construct appropriate Lyapunov functionals especially in epidemiological models with nonlinear and bilinear incidence rates, existing techniques for constructing Lyapunov functionals have been improved, see [37]. We propose the combination of quadratic and linear Lyapunov forms in the construction of Lyapunov function to prove a theorem for global stability of disease-free steady state of the form:
\[
U(x_1, x_2, x_3, x_4) = c \sum_{i=1}^{2} \frac{1}{x_i} (x_i - x_i^*)^2 + \sum_{i=3}^{4} (x_i - x_i^*),
\]
\[
(27)
\]
where \(c\) is a positive constant, \(\sum_{i=1}^{2} (1/2x_i^*) (x_i - x_i^*)^2\) represents a class containing susceptible population, and \(\sum_{i=3}^{4} (x_i - x_i^*)\) represents the remaining classes. The Goh–Lotka–Volterra Logarithmic of the form
\[
V(x_1, x_2, x_3, x_4) = c \sum_{i=1}^{n} (x_i - x_i^* - x_i^* \ln \frac{x_i}{x_i^*})
\]
\[
(28)
\]
is used to prove the theorem on global stability of the endemic steady state.
4.1. Global Stability of the Disease-Free Steady State

**Theorem 1.** By Proposition 2, if the disease-free steady state $E_0^*$ of model (1) is asymptotically stable, then $E_0^*$ is globally asymptotically stable in $D$.

**Proof.** Consider $U: D \longrightarrow \mathbb{R}$ that is defined by

$$U(S_u, S_a, I, R) = c\left(\frac{1}{2S_u^0}(S_u - S_u^0)^2 + \frac{1}{2S_a^0}(S_a - S_a^0)^2 + (I - I_0)\right)$$

$$+ c(R - R^0),$$

with $c = 1$. We find the derivative of the positive semidefinite function with respect to time along with the solution of model system (1) to get

$$\frac{dU}{dt} = \frac{S_u - S_u^0}{S_u^0} + \frac{S_a - S_a^0}{S_a^0} + I + R,$$

$$\frac{dU}{dt} = uS_u I\left(\frac{S_u - S_u^0}{S_u^0} + \xi S_u \left(\frac{S_u^0}{S_u} - \frac{S_u}{S_a} \right) + \frac{\phi I}{1 + \tau I} (1 - p)\right)$$

$$\cdot \left(2 + \frac{S_u}{S_u^0}\right) + \beta(S_u I + \frac{\beta I}{m + I}) + \left(\frac{\beta I}{m + I}\right)$$

$$\cdot \left(2 - \frac{S_u}{S_u^0}\right) + \frac{S_a}{S_u} I \left(1 - \frac{S_u^0}{S_u} + \frac{S_a^0}{S_u} \right) + \frac{S_a}{S_u} I + I + R$$

$$- (\delta I + \gamma I),$$

$$\frac{dU}{dt} \leq \beta S_a I\left(2 - \frac{S_a}{S_a^0}\right) + \frac{S_a}{S_u} I \left(1 - \frac{S_u^0}{S_u} + \frac{S_a^0}{S_u} \right) + \left(\frac{\beta I}{m + I}\right)$$

$$\cdot \left(2 - \frac{S_a}{S_a^0}\right) I - \mu (I + R) - (\delta I + \gamma I).$$

**Lemma 2.** Let $a_1, a_2, \ldots, a_m$ be positive numbers. The arithmetic mean $\bar{a} = (a_1 + a_2 + \cdots + a_m)/m$ is greater or equal to the geometric mean $\sqrt[m]{a_1 \times a_2 \times \cdots \times a_m}$, that is, $\bar{a} \geq \sqrt[m]{a}$. Applying Lemma 2 to equation (30), we have

$$\frac{dU}{dt} \leq \beta S_a I\left(2 - \frac{S_a}{S_a^0}\right) + \frac{S_a}{S_u} I \left(1 - \frac{S_u^0}{S_u} + \frac{S_a^0}{S_u} \right) + \left(\frac{\beta I}{m + I}\right)$$

$$\cdot \left(2 - \frac{S_a}{S_a^0}\right) I - \mu (I + R) - (\delta I + \gamma I).$$

(31)

Thus, due to local stability of $E_0$ or $E_1$, then $dU/dt \leq 0$ for all $(S_u, S_a, I, R) \in D$. However, the strict equality $dU/dt = 0$ is valid for $S_u = S_u^0, S_a = S_a^0, I = 0$ and $R = 0$. Then, the largest invariant set $\{(S_u, S_a, I, R) \in D: dU/dt = 0\}$ is reduced to the disease-free steady state $E_0^*$. Therefore, by LaSalle’s Invariance Principle [38], $E_0^*$ is an attractive point that is globally asymptotically stable in $D$. This ends the proof.

4.2. Global Stability of the Endemic Steady State

**Theorem 2.** If by Proposition 3, the unique endemic equilibrium of model (1) is asymptotically stable, then $E^*$ is globally asymptotically stable in the interior of $D$.

**Proof.** The Lyapunov function is defined as

$$W(S_u, S_a, I, R) = c_1 \left(\frac{S_u - S_u^* - S_a^*}{S_u^0} + S_u - S_u^*\ln \frac{S_u}{S_u^0} + S_a - S_a^*\ln \frac{S_a}{S_a^0}\right)$$

$$+ c_2 \left(I - I^* - I^*\ln \frac{I}{I^*} + R - R^* - R^*\ln \frac{R}{R^*}\right),$$

(32)

with

$$c_1 = 1, c_2 = R_0 = (\gamma_1 + \mu)/(\Phi + \delta_1) \cdot (C_1 + C_2 - p\Phi\gamma_1),$$

Function $W$ in (32) is defined, continuous, and positive definite for all $S_u, S_a, I, R > 0$. Thus, the function $W(S_u, S_a, I, R)$ takes the value $W(S_u, S_a, I, R) = 0$ at the steady state $E^*$, and the minimum value of $W(S_u, S_a, I, R)$ occurs at the endemic steady state $E^*$. We compute the derivative of $W$ along the solution trajectories of model (1) as

$$W = S_u \left(1 - \frac{S_u^0}{S_u}\right) + S_a \left(1 - \frac{S_a^0}{S_a}\right) + c_2 \left(I - I^*\right) + R \left(1 - R^*/R\right)$$

$$= B \left(1 - \frac{S_u^*}{S_u}\right) + \xi S_a^* \left(1 - \frac{S_a^0}{S_a}\right) + \theta I S_u^* \left(1 - \frac{S_u^0}{S_u}\right)$$

$$+ (1 - p)\phi T(I^*) \left(1 - \frac{S_u^0}{S_u}\right) + \beta I S_a^* \left(1 - \frac{S_a^0}{S_a}\right)$$

$$+ \xi S_u^* \left(1 - \frac{S_u^0}{S_u}\right) + \mu S_a^* \left(1 - \frac{S_a^0}{S_a}\right) + c_2 \left(g(I)\right) S_u^* \left(1 - I^*/I\right)$$

$$+ \beta S_a^* \left(1 - I^*/I\right) + \gamma R^* \left(1 - I^*/I\right) + \phi T(I^*) \left(1 - R^*/R\right)$$

$$+ (\mu + \delta_1) I^* \left(1 - I^*/I\right) + \phi T(I^*) \left(1 - R^*/R\right)$$

$$+ (\gamma_1 + \mu) R^* \left(1 - R^*/R\right).$$

(33)

Since $(S_u^*, S_a^*, I^*, R^*)$ is an endemic steady state of model (1), we have

$$B = g(I^*) S_u^* + i I S_a^* + \mu S_a^* - \xi S_u^*,$$

(34)

and making a substitution of $B$ in equation (33) and collecting like terms, we get
\[ W = I^* S_a^\prime \left( v \left( 1 - \frac{S_a^\prime}{S_a} \right) + c_2 \left( \beta - \frac{\beta_i m}{m + I^*} \right) \right) - \mu \left( \frac{S_a}{S_a} - \frac{S_a^\prime}{S_a} \right) \]
\[ + c_1 I^* \left( \left( 1 - \frac{I^*}{I} \right) + R^\prime \left( 1 - \frac{R^\prime}{R} \right) \right) + \Phi T(I^*) \rho \frac{S_a^\prime}{S_a} \]
\[ \cdot \left( 1 - c_2 R^\prime \frac{S_a}{S_a^\prime} \right) + \Phi T(I^*) \left( 1 - \frac{S_a^\prime}{S_a} \right) p c_2 \Phi T(I^*) \]
\[ - \Phi T(I^*) c_2 \left( 1 - \frac{I^*}{I} \right) - \delta_1 c_2 I^* \left( 1 - \frac{I^*}{I} \right) + \frac{\beta_i S_a^\prime}{S_a} \]
\[ \cdot \left( 1 - \frac{S_a}{S_a^\prime} \frac{I^*}{I} \right). \]

\[ W \leq v \left( 1 - \frac{S_a^\prime}{S_a} \right) I^* S_a^\prime + R_0 I^* \left( 1 - \frac{I^*}{I} \right) + R^\prime \left( 1 - \frac{R^\prime}{R} \right) \]
\[ + \frac{R_0 \gamma_1 R^\prime}{R} \left( 1 - \frac{R^\prime}{R} \right) \left( I^* \right) + \frac{\beta_i S_a^\prime}{S_a} \left( 1 - \frac{S_a^\prime}{S_a} \right) \frac{I^*}{I} \]
\[ + \Phi T(I^*) \left( 1 - \frac{S_a^\prime}{S_a} \right) \]

Hence, since the arithmetic mean exceeds the geometric mean, we have
\[ \left( 1 - \frac{S_a^\prime}{S_a} \right) \leq 0, \]
\[ \left( 1 - \frac{R^\prime}{R} \right) \leq 0, \]
\[ \left( 1 - \frac{I^*}{I} \right) \leq 0. \]

Table 3: Sensitivity index (S. I) of \( R_0 \) w.r.t. the parameters.

| Code | Parameter | S. I. |
|------|-----------|-------|
| 1    | \( \beta \) | +1.07189 |
| 2    | \( \beta_1 \) | -0.11824 |
| 3    | \( \beta_2 \) | +0.04635 |
| 4    | \( \rho \) | +0.00079 |
| 5    | \( \xi \) | +0.95282 |
| 6    | \( \nu \) | -0.95345 |
| 7    | \( \delta_1 \) | -0.13570 |
| 8    | \( \mu \) | -0.04621 |
| 9    | \( \delta_1 \) | -0.10006 |
| 10   | \( \Phi \) | -0.89974 |
| 11   | \( \gamma_1 \) | +0.79958 |

4.3. Sensitivity Analysis. In this section, model parameters are varied with respect to the basic reproduction number, \( R_0 \), of model (1). Carrying out a sensitivity analysis of the model parameters will help us identify and verify model epidemiological parameters that most affect the basic reproduction number. Furthermore, values obtained for sensitivity indices indicate epidemiological parameters to be targeted for intervention purposes. We derive the sensitivity index using partial rank correlation coefficients (PRCC) of the basic reproductive number with respect to the parameters [39]. The normalized forward sensitivity index technique is used to obtain the index of \( R_0 \) with respect to the parameters (Table 1). Hence, \( \Delta_{\beta_i} = (\partial R_0/\partial q) \times (q/R_0) \), where \( R_0 \) is a variable and \( q \) is a differentiable parameter.

Since the availability of the literature and data especially on antibiotic resistance awareness of pneumococcal pneumonia is lacking, the qualitative predictions of our model (1) is dependent on estimating some of the epidemiological parameter values in Table 1.

From Table 3, the positive sign of sensitivity index of the basic reproduction number with respect to the model parameters indicates that an increase (or decrease) in the value of each parameter in such a category will lead to an increase (or decrease) in the basic reproduction number of the disease. On the other hand, the negative sign of sensitivity index of the control reproduction number with respect to the model epidemiological parameters implies that, an increase (or decrease) in the value of the epidemiological parameter shall give rise to a corresponding decrease (or increase) in the control reproduction number. For instance, in Figure 2, the sensitivity \( \Delta_{\beta_i} = 1 \) means that, when the loss of information about disease by aware susceptible individuals \( [\xi(5)] \) is increased (or decreased) by 10%, it leads to increases or decreases of \( R_0 \) by 10%.
From Figure 2, it can be seen that the basic reproduction number is positively sensitive to the maximal effective contact rate before antibiotic resistance awareness \( (\beta_1) \), loss of information about disease by aware susceptible individuals \( (\xi) \), and rate of relapse encountered in administering treatment \( (\gamma_1) \) and negatively sensitive to \( \nu \), recovery rate due to treatment \( (\Phi) \). Thus, with sensitivity analysis, one is able to get appropriate information on epidemiological parameters that can be targeted for intervention strategies that would help in preventing and controlling the transmission of pneumococcal pneumonia.

5. Numerical Simulation and Discussion

This section deals with the numerical simulation results of model (1) that are carried out in MATLAB’s standard solver for ODEs, the inbuilt function ode45. The epidemiological parameters chosen for the purpose of simulation are given in Table 1. The importance of \( R_0 \) is well demonstrated in all simulations.

From Figure 3(a), the unaware and aware populations approach disease-free steady state with unaware individuals maintaining a high number compared with the aware individuals. The basic reproduction number is less than
unity $R_0 = 0.3323 < 1$; thus, the disease-free steady state is stable. The stability of the disease-free steady state means that pneumococcus bacteria can be completely eliminated from the population with no more cases of pneumococcal pneumonia reported. Figure 3(b), shows that, if $R_0 = 1.9258 > 1$, the disease-free steady state is unstable, implying that if one infected individual is introduced in a wholly susceptible population, infected cases would rise and more unaware individuals are at a risk of contracting pneumococcus bacteria. This would require control strategies to reduce the transmission of the disease at the earliest time possible. Considering the main results, Proposition 4.2, and Theorem 2, the endemic steady state is locally asymptotically stable since $\text{Re}(\lambda_i) < 0$ and globally stable if $R_0 > 1$.

Figure 4, shows global stability of all solution trajectories to an endemic steady state $E^*$. This implies that pneumococcal pneumonia will continue to propagate in the population with more infected individuals compared with other states. Thus, the disease would persist in the population.

Figure 5, shows a unique endemic steady state attained in the long run with more aware individuals in the population. This implies that the pneumococcus bacteria could be controlled with appropriate techniques of awareness.

Figure 5: Time series global stability of the endemic steady state with initial state variables $S^*_u = 300$, $S^*_a = 200$, $I^* = 10$, $R^* = 10$. Parameter values $\xi = 0.003$, $m = 0.2$, $p = 0.02$, $\tau = 0.027$, and $\Phi = 0.6$; the remaining parameter values are specified in Table 1.

Figure 6: (a) Effect of varying the rate at which unaware susceptibles become aware of antibiotic resistance in treating the disease on the control reproduction number, with parameter value $\xi = 0.02$, and other parameter values remain as in Table 1. (b) The effect of varying loss of information about disease by aware susceptibles on the reproduction number and recovery rate, with the rest of parameter values unchanged as in Table 1.
programs, hence reducing the risk of acquiring the pneumococcal pneumonia infections in a population.

Figure 6(a), shows an exponential decay, that is, the family of curves switches due to the variation of private awareness from an increasing rate of growth to a decreasing rate, evidently suggesting the eradication of pneumococcus bacteria because of the presence of antibiotic resistance awareness and treatment.

Figure 6(b), shows effect of loss of information about antibiotic resistance awareness. An increase in the loss of information implies an increase in numbers of infected individuals and the basic reproduction number is high; however, due to the presence of treatment, the disease is always eradicated from the population. On the other hand, reducing the loss of information implies that more individuals are aware of the transmission and are able to take control measures of the disease and reduce its spread.

6. Conclusion

In this paper, the pneumococcal pneumonia model in the presence of awareness and saturated treatment is constructed. The threshold number (basic reproduction number, $R_0$) for pneumococcal pneumonia prevalence, the conditions for existence, and uniqueness of the equilibria are found.

The result of Proposition 2 indicates that if $R_0 \leq 1$, the disease-free steady state $E^*_0$ is locally asymptotically stable. Biologically, this means that pneumococcus bacteria cannot successfully invade the susceptible population and, thus, can easily be wiped out as time increases. This suggests that pneumococcal pneumonia can be controlled by ensuring $R_0$ is below unity. If $R_0 > 1$, then the disease-free steady state $E^*_0$ is unstable, implying that the disease could manifest in the population and more cases might arise causing an epidemic.

The quadratic-linear and Goh–voltera Lyapunov functional approaches are used to prove the global stabilities of the disease-free and endemic steady states, respectively. We found out that the endemic steady state is globally steady if $R_0 > 1$. Thus, pneumococcal disease would persist in a population regarding consciousness of people.

To control pneumococcal pneumonia, the results show that the family of decaying curves could help in providing mechanisms to design awareness strategies for containing pneumococcal pneumonia. The threshold parameter $R_0$ could be reduced to less than unity if antibiotic resistance awareness and treatment are implemented simultaneously to ensure eradication of pneumococcus bacteria; thus, spread of pneumococcus pneumonia in the population will die out.

Therefore, the model described, formulated, and analyzed and the findings presented in this work may help in controlling pneumococcal pneumonia through awareness. Awareness changes the trend of disease transmission and decreases the rate of infection within a human population.

6.1. Future Directions. To further understand the dynamics and control of the disease, it is paramount for researchers to extend the model by performing an optimization problem that helps in minimizing the total number of infected persons, maximizes the number of susceptible individuals, and reduces costs related to treatment of the disease.

Data Availability

The data supporting this mathematical model are from earlier published articles, and they have been suitably cited as references in this paper. Parameter values taken from published articles are cited in Table 1 of this paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to extend special thanks to Prof. Livingstone Luboobi, visiting professor, Institute of Mathematical Sciences, Strathmore University, and the referees for the useful comments that helped them improve the quality of this manuscript. This work was supported by Pan African University for Basic Sciences, Technology and Innovation, Nairobi, Kenya.

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