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Mathematical modeling of awareness-driven interventions for gender-based violence control in a closed population

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Abstract

Gender-based violence (GBV) remains a critical global health issue with profound social, economic, and psychological implications. Despite concerted efforts to address this challenge, traditional intervention approaches often fall short of effectively mitigating its prevalence. In recent years, there has been growing recognition of the potential impact of awareness-based interventions in addressing various social and health crises. This paper introduces a modeling framework to explore the efficacy of awareness-based interventions in influencing the dynamics of the GBV epidemic within a closed population. A detailed sensitivity analysis, utilizing a normalized sensitivity index method, reveals that the violence transfer rate between perpetrators and at-risk individuals, the rate of transfer between violence-affected and violence-non-reconciled individuals, and the recruitment rate of the at-risk population exert the greatest influence on GBV dynamics. Furthermore, simulations have demonstrated that awareness interventions can significantly reduce the number of perpetrators and violence-affected individuals in the population, while increasing the proportion of individuals free from GBV.

Introduction

Gender refers to the social, cultural, and psychological attributes, roles, behaviors, and identities that a society considers appropriate for individuals based on their perceived or assigned sex (Connell 2009). As a social construct, gender varies from society to society and can change over time. Gender-based violence (GBV) represents a pervasive and deeply entrenched public health issue that transcends geographical, cultural, and socioeconomic boundaries (Lorber 2018). Defined as any act of violence perpetrated against an individual based on their gender identity or perceived gender roles. GBV encompasses a wide spectrum of behaviors, including physical, sexual, psychological, and economic abuse (Russo and Pirlott 2006). Despite concerted efforts to address this epidemic, GBV continues to exact a significant toll on individuals, communities, and societies worldwide, manifesting in profound physical, psychological, emotional, verbal, social, and economic. These consequences affect survivors and perpetuate cycles of inequality and injustice (Garcia-Moreno et al. 2006). The reported incidence of GBV cases differ across the world, depending on the sociocultural context and level of development in each community. According to a survey conducted by the WHO from a year 2000 to 2018, in 161 countries, nearly 30% of the world's female population has been subjected to some form of GBV. Additionally, 27% of women aged 15–49 who have been in a relationship have experienced physical or sexual violence by their intimate partners. The prevalence estimates were 31% in the Eastern Mediterranean Region, 20% in the Western Pacific, 22% in high-income countries and Europe, 25% in the Region of the Americas, 33% in the WHO African Region, and 33% in the South-East Asia Region (Krahe 2016, WHO 2021).

Traditional approaches to GBV prevention and intervention have predominantly focused on legal reforms, law enforcement, and support services for survivors. While these efforts play a crucial role in addressing immediate needs and ensuring accountability, they often fall short in addressing the underlying drivers of GBV, including deeply ingrained social norms, attitudes, and behaviors that perpetuate violence (Jewkes, 2002). As such, there is a growing recognition of the need for comprehensive, multi-level interventions that target not only individual behaviors but also the broader social and cultural contexts in which GBV occurs (Dworkin et al. 2013, Fallik et al. 2020).

Awareness raising on gender violence includes a series of initiatives that are carried out in order to address gender violence in society. These may be done at individual level, in communities or even in institutions. They play a crucial role in addressing gender violence epidemics in the society by targeting various aspects of society, including individuals, communities, and institutions. These interventions involve educational programs and campaigns aimed at increasing understanding about the causes, consequences, and dynamics of GBV. By

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disseminating information and fostering critical reflection, these interventions empower individuals to recognize GBV, challenge harmful attitudes and behaviors that perpetuate gender violence, and support survivors. Researches have shown that education and awareness programs can lead to improved knowledge, attitudes, and behaviors related to GBV (Flood 2011; Michau et al. 2015). The motive is to focus on educating individuals about gender roles and stereotypes.

In recent years, awareness-based interventions have emerged as a promising approach to complement traditional strategies by challenging social norms, raising consciousness, and promoting attitudinal and behavioral change surrounding GBV (Fallik et al. 2020, Menon et al. 2020; Stabile et al. 2020). These interventions encompass a range of activities, including public awareness campaigns, community mobilization efforts, and educational initiatives aimed at fostering empathy, promoting gender equality, and challenging harmful stereotypes and beliefs (Racionero et al. 2021; Villardón-Gallego et al. 2023). By harnessing the power of information dissemination, storytelling, and community engagement, awareness-based interventions seek to shift societal norms and values towards non-violence and respect for gender equality.

While the potential of awareness-based interventions to influence GBV dynamics is increasingly recognized, there remains a paucity of empirical evidence and theoretical frameworks elucidating their mechanisms of action and impact. Consequently, there is a need for rigorous modeling approaches that can systematically evaluate the efficacy of these interventions in influencing the prevalence and persistence of GBV within populations. By simulating the complex interactions between individual behaviors, social networks, and intervention strategies, such models can provide valuable insights into the dynamics of GBV epidemics and inform the design and implementation of evidence-based prevention efforts.

Mathematical modeling has become increasingly recognized as a valuable tool for understanding the dynamics of GBV within various populations. This approach is particularly reminiscent of research conducted on disease transmission dynamics, where mathematical models have been extensively utilized to study the spread and control of infectious diseases. Similarly, in the realm of GBV, mathematical models offer a systematic framework for analyzing the complex interactions and factors contributing to the perpetuation of violence (Delgadillo-Aleman et al. 2019, Paul and Biswas 2023, Teklu and Terefe 2022, Terefe 2022, Wiley et al. 2016, Woo et al. 2011).

Delgadillo-Aleman et al. 2019, proposed and studied the system of differential equations of Intimate Partner Violence dynamics in a romantic couple. In the model, interactions between the intimate partners considered factors such as the self-esteem, self-regulation and man's need to oppress a woman.

Paul and Biswas 2023, proposed a linear mathematical model on the dynamics of violence caused by misinformation spread among people. The model has five classes including the internet user termed as the susceptible population, users having misinformation, users spreading misinformation, users intentionally spreading misinformation, and the skeptic population who initially needs to know the truth of information before sharing to the large population. Each of these populations is involved in the spread of the misinformation. In its general explanation, the model pointed out the general spreader class which involve people who share every information regardless on its authenticity source.

Shewafera and Terefe 2022 proposed a mathematical model to study the coexistence of violence and racism as a contagious disease in a community. The formulated model has eight classes each with distinct meaning and features to the rest of the classes. The sensitivity analysis of the model found that the transmission rates influence the coexistence of violence and racism in the community. Moreover, the study recommended to nations to formulate, apply and ensures the anti-violence and antiracism laws for reducing the problem.

Terefe 2022 formulated mathematical model to study the diffusion of violence in the population. The model had five distinct classes including susceptible, exposed class to violence, violence class negotiated, and the covered class. The result of the model revealed that violence in the population can decrease when the contact rate between the susceptible and the violent population is lowered.

Wiley et al. (2016) proposes a Susceptible–Transmitter–Victim Epidemic model, to explore the impact of violence interruption on the diffusion of violence in the population. Woo et al. (2011) investigated the diffusion model for web forums based on the Kermack and McKendrick model 1991 where the interactions of the susceptible, infected, and the recovery population were considered.

Moreover, mathematical models become useful on studying the effects of mass media as one among control measures on the dynamics of infectious diseases (Chatterjee and Ganguly 2022, Goswami et al. 2024, Liu and Cui 2008, Misra et al. 2024, Xia et al. 2019). Motivated with the work of Teklu 2022, and Terefe 2022, this work aims to present a mathematical framework for analyzing the effects of awareness-based intervention on GBV epidemic. Drawing on principles from epidemiology, behavioral psychology, and social network theory, the model seeks to elucidate the pathways through which awareness initiatives can lead to meaningful reductions in GBV prevalence. Through computational simulations and sensitivity analyses, the model enables the exploration of various intervention scenarios and their potential impact on shifting social norms and behaviors surrounding GBV.

In the subsequent sections, we will delineate the conceptual underpinnings of the modeling framework, describe its key components and variables, and present findings from simulated intervention scenarios. By examining of the role of awareness-based interventions in influencing GBV dynamics, this study aims to contribute to the effectiveness of GBV prevention strategies and ultimately advance efforts to create a world free from gender violence.

The GBV Model Framework

This section presents the human social groups with interactions that lead to gender violence epidemic. The formulation of the model is based on the following assumptions;

(i) The population is socially and environmentally constructed, that means, gender violence doesn't occur in isolation but is deeply intertwined with broader societal dynamics (Mootz et al. 2017, Wen et al. 2020)
(ii) In the closed population, interactions occur only within the defined group, with no migration or external influences such as government interventions, media campaigns, or economic changes, affecting the system beyond natural births and deaths. Thus, GBV dynamics evolve solely through internal interactions.
(iii) GBV is generated and fostered among individuals within closed populations (Heise 1998).
(iv) Gender-based awareness programme can help in reducing the gender violence behavior among individuals in a closed population (Abramsky et al. 2014).

In this model, the total human population $N(t)$ is divided into six sub-populations: the at-risk individuals abbreviated by$A(t)$, the exposed to violence individual $E(t)$, violence-infected individuals $V(t)$, violence reconciled individuals $V_R(t)$, violence non-reconcile $V_N(t)$ and the perpetrator individuals $P(t)$. Therefore,

$$N(t) = P(t) + A(t) + E(t) + V(t) + V_R(t) + V_N(t). \tag{1}$$

The at-risk population $A(t)$ refers to individuals who have not yet involved or infected with GBV at any time t. The population exposed to violence, denoted as $E(t)$, comprises with individuals who are closely associated with the environment or individuals exhibiting GBV behaviors. The individuals exposed to violence are not capable of transmitting GBV. The population of violence-infected individuals, denoted as $V(t)$, refers to a group of individuals subjected to GBV, causing to them physical, emotional, or both types of suffering. The perpetrator population, denoted as $P(t)$, are individuals who engage in habits such as physical or sexual abuse, emotional abuse or coercion against others based on gender. The violence-reconciled group $V_R(t)$ refers to individuals reconciled from violence through shared experiences. The violence non-reconciled group $V_N(t)$ are individuals who do not want reconciliation after being treated differently based on their gender. The perpetrator population is recruited at the rate $\rho\alpha V_N(t)$ from the non-reconciled violence-affected individuals and reduced by individual's natural death rate $\mu P(t)$. These rates of transfer into and out of the perpetrator population lead to the following linear equation,

$$\frac{dP(t)}{dt} = \rho\alpha V_N(t) - \mu P(t) \tag{2}$$

The at-risk population is recruited at the natural birth rate π and reduced by violence habits at a rate denoted by λ, where $\lambda = \beta P(t)A(t)$. Here, the symbol β represents violence habits based on gender transferred to at-risk individuals by perpetrators and violence non-reconciled individuals, respectively. Additionally, the at-risk population increases through individuals transitioning from violence-reconciled individuals at a rate of $\tau V_R(t)$ and from violence non-reconciled individuals at a rate of $\rho(1-\alpha)V_N(t)$. Following the work of (Cui et al. 2008; Goswami et al. 2024; Liu et al. 2008), an exponential media function $e^{-mV(t)}$ where $m$is a cumulative GBV reports from different media educative programmes is introduced into the model as the GBV cumulative media reports covered from different sources intending to overcome the problem of GBV on the population. These processes, along with its natural death rate, lead to the following changes of the at-risk population.

$$\frac{dA(t)}{dt} = \pi + \tau V_R(t) + \rho(1-\alpha)V_N(t) - e^{-mV(t)}\beta P(t) + \mu A(t) \tag{3}$$

The exposed to violence population is resulted from the interaction between the perpetrators and the at-risk individuals. After some latency period, the exposed to violence population is formed at rate λ and reduces at the incubation and natural death rate $(\mu + \sigma)E(t)$, respectively. The exposed to violence population change at time t is given by the equation

$$\frac{dE(t)}{dt} = e^{-mV(t)}\beta P(t)A(t) - (\mu + \sigma)E(t) \tag{4}$$

and consequently, the rate of change of violence population is represented by equation (5) as follows;

$$\frac{d\boldsymbol{V(t)}}{d\boldsymbol{t}} = \boldsymbol{\sigma E(t) - (\psi + \mu)V(t)} \tag{5}$$

As time goes on, the population of the violence-infected individuals divides into two populations, the violence-reconciled population and violence non-reconciled population. The violence-reconciled population is increased at the rate $\psi(1-\varepsilon)V(t)$ and reduced at the rate $(\tau + \mu)V_R(t)$ where εrepresents the probability of an individual becoming non-reconciled. The rate of change of the violence-reconciled population at any time t is given by the equation (6) as follows

$$\frac{dV_R(t)}{dt} = \psi(1-\varepsilon)V(t) - (\tau + \mu)V_R(t) \tag{6}$$

The violence non-reconciled population is increased at the rate $\varepsilon\psi V(t)$ and reduced at the rate $(\rho + \mu)V_N(t)$. The rate of change of this population is therefore given as;

$$\frac{dV_N(t)}{dt} = \varepsilon\psi V(t) - (\rho + \mu)V_N(t) \tag{7}$$

The state variables and parameter descriptions are found in Table 1.

Table 1: Parameter descriptions of the model system (8)

Symbol	Description	Value (per day)	Source
π	Natural birth rate of human in the population	$0.001-0.06$	Liana and Chuma 2023, Tchoumi et al. 2024
λ	The force of violence behavior in the population	$1/100$	Assumed
β	Violence transfer rate between A and P	$1/100$	Assumed
σ	Incubation rate of violence in human	$1/365$	Assumed
τ	Loss of protection to V_R individuals	$1/30$	Assumed
ρ	Probability of V_N becoming Perpetrator	$[0,1]$	Assumed
α	The rate of transfer of V_N becoming Perpetrator	$1/(10\times 365)$	Assumed
ψ	Violence transfer rate from V to V_N	$1/30$	Ali and Kitula 2024
ε	Probability of V becoming V_N	$[0,1]$	Assumed
μ	Natural death rate of human in the population	$1/(65\times 365)$	Chuma and Ngailo 2024, Osman et al. 2020
m	Cumulative media reports based on GBV	$1/10$	Ali and Kitula 2024

Descriptions of the schematic diagram in Figure 1 leads to the following system of linear differential equation;

$$\frac{dP(t)}{dt}=\rho\alpha V_N(t)-\mu P(t)$$
$$\frac{dA(t)}{dt}=\pi+\tau V_R(t)+\rho(1-\alpha)V_N(t)-\left(e^{-mV(t)}\beta P(t)+\mu\right)A(t)$$
$$\frac{dE(t)}{dt}=e^{-mV(t)}\beta P(t)A(t)-(\mu+\sigma)E(t)$$
$$\frac{dV(t)}{dt}=\sigma E(t)-(\psi+\mu)V(t)$$
$$\frac{dV_R(t)}{dt}=\psi(1-\varepsilon)V(t)-(\tau+\mu)V_R(t)$$
$$\frac{dV_N(t)}{dt}=\varepsilon\psi V(t)-(\rho+\mu)V_N(t) \tag{8}$$

With initial conditions $P(0)=P(0)>0, A(0)>0, E(0)>0\ V>0, V_R(0)>0, V_N(0)>0$.

Properties of the GBV Model

Given that the GBV model system (8) pertains to the human population, which cannot have negative values, it becomes necessary to show that all solutions of system (8) maintain positivity when subjected to initial conditions in a bounded region,

$\omega=(P,A,E,V,V_R,V_N)\in\Re^6_+.$

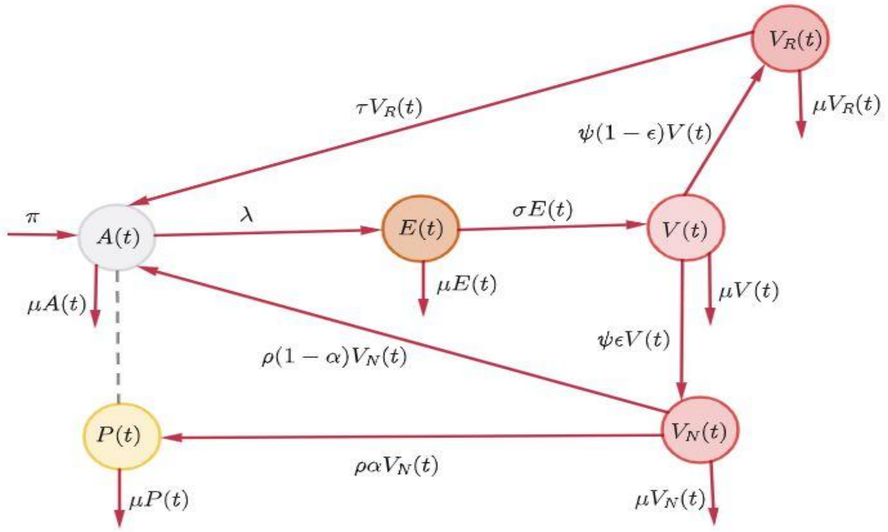

Figure 1: Schematic diagram of GBV in a closed population.

Boundedness of the solution

Theorem 1. *The region $\boldsymbol{\omega}$ of the model system (8) is bounded in the space $\mathfrak{R}_+^6$.*

Proof. Here, we need to show that the state variables of the model system (8) are positive for all t. Let $\Theta = sup\{t > 0; A(0) > 0, P(0) > 0, E(0) > 0, V(0) > 0, V_R(0) > 0, V_N(0) > 0\}$. From the GBV model system (8), the total population is

$$\frac{dN(t)}{dt} = \frac{dP(t)}{dt} + \frac{dA(t)}{dt} + \frac{dE(t)}{dt} + \frac{dV(t)}{dt} + \frac{dV_R(t)}{dt} + \frac{dV_N(t)}{dt}$$

$$\frac{dN(t)}{dt} = \pi - \mu N(t) \tag{9}$$

Integration of equation (9) leads to

$$N(t) = \frac{\pi}{\mu} + \left(N(0) - \frac{\pi}{\mu}\right)e^{-\mu t}. \tag{10}$$

As $t \to \infty, \lim_{t\to\infty} N(t) = \lim_{t\to\infty}\left(\frac{\pi}{\mu} + \left(N(0) - \frac{\pi}{\mu}\right)e^{-\mu t}\right) = \frac{\pi}{\mu} > 0$

Therefore, the solutions P, A, E, V, V_R and V_N of the GBV model system (8) are bounded above by $\frac{\pi}{\mu}$ that means, $0 \le N(t) \le \frac{\pi}{\mu}$. Hence, all the state variables of the GBV model system (8) are socially meaningful and enters the invariant region

$$\omega = \left\{(P, A, E, V, V_R, V_N) \in \mathfrak{R}_+^6 : P + A + E + V + V_R + V_N \le \frac{\pi}{\mu}\right\}.$$

Positivity of the solution

Here we show the positivity of the solution of the GBV of model system (8) using the method presented in (Abimbade et al. 2024; Goswami et al. 2024; Olaniyi et al. 2024). By considering the equations of model system (8), it follows that,

$$\left(\frac{dP}{dt}\right)_{P=0} = \rho\alpha V_N > 0, \left(\frac{dA}{dt}\right)_{A=0} = \pi + \tau V_R + \rho(1-\alpha)V_N > 0,$$

$$\left(\frac{d\boldsymbol{E}}{d\boldsymbol{t}}\right)_{\boldsymbol{E}=0} = \boldsymbol{e^{-mV}\beta PA > 0}, \left(\frac{d\boldsymbol{V}}{d\boldsymbol{t}}\right)_{\boldsymbol{V}=0} = \boldsymbol{\sigma E > 0},$$

$$\left(\frac{d\boldsymbol{V_R}}{d\boldsymbol{t}}\right)_{\boldsymbol{V_R}=0} = \boldsymbol{\psi(1-\varepsilon)V > 0}, \tag{11}$$

$$\left(\frac{d\boldsymbol{V_N}}{d\boldsymbol{t}}\right)_{\boldsymbol{V_N}=0\boldsymbol{\psi}} = \boldsymbol{\varepsilon V > 0}.$$

From equation (11), it is clearly shown that all solutions of the GBV model system (8) are positively bounded.

GBV-free equilibrium point I_0 and violence reproduction number R_0

The model system (8) has a unique GBV-free equilibrium point given as

$$\Im_0 = \left(0, \frac{\pi}{\mu}, 0, 0, 0\right).$$

Using the next generation matrix method (Almuqati and Allehiany 2023, Cui et al. 2008, Diekmann et al. 1990, Ndendya et al. 2024, Liana and Mary 2024, Singo et al. 2024), it follows that, the rate of new violence and rate of transfer in and out of compartments are respectively presented with the functions

$f = (0, \beta e^{-mV} PA, 0,0,0)$ and

$$v = \left(-\rho\alpha V_N + \mu P, (\sigma+\mu)E, -\sigma E + (\psi+\mu)V, -\frac{dV_R}{dt}, -\varepsilon\psi V + (\rho+\mu)V_N\right).$$

Partial derivatives of these rates evaluated at GBV-free equilibrium point leads to the following matrices

$$F = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ \frac{\pi\beta}{\mu} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad (12)$$

and

$$M = \begin{pmatrix} \mu & 0 & 0 & 0 & -\rho\alpha \\ 0 & \sigma+\mu & 0 & 0 & 0 \\ 0 & -\sigma & \psi+\mu & 0 & 0 \\ 0 & 0 & -\psi(1-\varepsilon) & \tau+\mu & 0 \\ 0 & 0 & -\varepsilon\psi & 0 & \rho+\mu \end{pmatrix} \quad (13)$$

Using the matrix (12) and the inverse of matrix (13), the eigenvalues of matrix FM^{-1} are

$$\left(0,0,0, \frac{\pi\beta\sigma\rho\alpha\psi\varepsilon}{\mu^2(\mu+\sigma)(\mu+\psi)(\mu+\rho)}\right)(\mu+\tau).$$

$$R_0 = max\left\{0,0,0, \frac{\pi\beta\sigma\rho\alpha\psi\varepsilon}{\mu^2(\mu+\sigma)(\mu+\psi)(\mu+\rho)(\mu+\tau)}\right\}. \quad (14)$$

Here, the violence reproduction number is dominant eigenvalue of matrix $\boldsymbol{FM^{-1}}$. Therefore, the basic reproduction number of the model system (8) is

$$\boldsymbol{R_0} = \frac{\boldsymbol{\pi\beta\sigma\rho\alpha\psi\varepsilon}}{\boldsymbol{\mu^2(\mu+\sigma)(\mu+\psi)(\mu+\rho)(\mu+\tau)}}$$

Stability Analysis of the equilibria of GBV Model

Under this section, the stability behavior of GBV model (8) as approaching for both GBV- free and GBV-present equilibrium points are studied.

Local stability of the GBV-free equilibrium point of the model

Theorem 2. *The GBV-free equilibrium point I_0 of the model system (1) is locally asymptotically stable when $R_0 < 1$ and unstable otherwise.*

Proof. Consider the Jacobian matrix of the model system (8) evaluated at $\Im_0$.

$$J_{\Im_0} = \begin{pmatrix} -\mu & 0 & 0 & 0 & 0 & -\rho\alpha \\ 0 & -\mu & 0 & 0 & \tau & \rho(1-\varepsilon) \\ \frac{\pi\beta}{\mu} & 0 & -\sigma-\mu & 0 & 0 & 0 \\ 0 & 0 & \sigma & -\psi-\mu & 0 & 0 \\ 0 & 0 & -\varepsilon\psi & \psi(1-\varepsilon) & -\tau-\mu & 0 \\ 0 & 0 & 0 & \varepsilon\psi & 0 & -\rho-\mu \end{pmatrix} \quad (15)$$

Two eigenvalues of the Jacobian matrix (15) are $-\mu$ and $-(\tau+\mu)$. The reduced matrix is given as

$$J_{44} = \begin{pmatrix} -\mu & 0 & 0 & -\rho\alpha \\ \frac{\pi\beta}{\mu} & -\sigma-\mu & 0 & 0 \\ 0 & \sigma & -\psi-\mu & 0 \\ 0 & 0 & \varepsilon\psi & -\rho-\mu \end{pmatrix} \tag{16}$$

The remaining eigenvalues are the roots of polynomial (17) obtained from matrix (16) as follows,

$$A_0\lambda^4 + A_1\lambda^3 + A_2\lambda^2 + A_3\lambda + A_4 = 0$$

where

$$\begin{aligned} A_0 &= 1 \\ A_1 &= 4\mu + \psi + \rho + \sigma \\ A_2 &= 6\mu^2 + 3\mu(\psi+\rho+\sigma) + \psi\sigma + \rho\sigma + \psi\rho \\ A_3 &= 4\mu^3 + 3\mu^2(\psi+\rho+\sigma) + 2\mu(\psi\sigma+\rho\sigma+\psi\rho) + \psi\rho\sigma \\ A_4 &= \mu^4 + (\psi+\rho+\sigma)\mu^3 + ((\psi+\rho)\sigma+\psi\rho)\mu^2 - \frac{\pi\beta\sigma\rho\alpha\psi\varepsilon}{\mu} \end{aligned} \tag{17}$$

Using the Routh-Hurwitz criterion, the polynomial equation (17) will have negative real parts if the determinants of the Hurwitz; $\Delta_i > 0 (i = 1,2,3,4)$. Hurwitz matrices are

$$\Delta_1 = A_0 = 1$$

$$\Delta_2 = \begin{vmatrix} A_1 & 1 \\ A_3 & A_2 \end{vmatrix} = A_1A_2 - A_3 \tag{18}$$

$$\Delta_3 = \begin{vmatrix} A_1 & 1 & 0 \\ A_3 & A_2 & A_1 \\ 0 & A_4 & A_3 \end{vmatrix} = A_1A_2A_3 - A_1^2A_4 - A_3^2 \tag{19}$$

$$\Delta_4 = \begin{vmatrix} A_1 & 1 & 0 & 0 \\ A_3 & A_2 & A_1 & 1 \\ 0 & A_4 & A_3 & A_2 \\ 0 & 0 & 0 & A_4 \end{vmatrix} = A_1A_2A_3A_4 \tag{20}$$

Using the matrix values in (17), it is clear seen that $\boldsymbol{\Delta_1}, \boldsymbol{\Delta_2}$, and $\boldsymbol{\Delta_3} > \mathbf{0}$. The determinant, $\boldsymbol{\Delta_4}$ is would be positive only if $\boldsymbol{\mu^4 + (\psi+\rho+\sigma)\mu^3 + \big((\psi+\rho)\sigma+\psi\rho\big)\mu^2 > \frac{\pi\beta\sigma\rho\alpha\psi\varepsilon}{\mu}}$. This guarantees that the GBV-free equilibrium point is locally asymptotically stable, and hence, $\boldsymbol{R_0 < 1}$.

Socially, R_0 represents the average number of new perpetrators or incidents generated by a single existing perpetrator in a violence-free community. this result reveal that, the GBV-free equilibrium point is locally stable if and only if $R_0 < 1$, meaning that GBV cannot sustain transmission and will eventually die out. In this case, $R_0 = 0$ would mean an infectious individual produces zero secondary infections on average in a fully susceptible population. When $R_0 > 1$, the gender violence can spread, potentially causing an outbreak or epidemic.

Global stability of GBV-free equilibrium point

Theorem 3. *The GBV-free equilibrium point* $\Im_0$ *is locally asymptotically stable in* ω *of the model system (8) if* $R_0 < 1$.

Proof:

To prove theorem, we applied the approach used in Castillo-Chavez (2002) and Ndendya et al. (2024) for analyzing the global stability of the GBV-free equilibrium point of the system 8. Initially, the model system is split into two systems of the form

$$\frac{dB}{dt} = R(B,C)\frac{dC}{dt} = S(B,C), S(B,0) = 0 \tag{21}$$

where $B \in R^m$ *refers to GBV uninfected individuals and* $C \in R^n$ *refers to GBV infected individuals. Also,* $\Im_0 = (B^*,0)$ *represents the GBV-free equilibrium point of the model system (8). Moreover, the following conditions should hold:*

1. $\frac{dB}{dt} = R(B,0)$, $\Im_0$ *is globally asymptotically stable.*

2. $S(B,C) = TS - \hat{S}(B,C) \geq 0$, *for* $(B,C) \in \omega$,

where ω*is an invariant region and T=* $D_1 S(B^*;0)$ *is an* M *−matrix with non-negative off-diagonal elements.*

Proof. According to Olaniyi et al. 2024, $B = (A, V_R)$, then, for condition 1, we have

$$\frac{dR}{dt} = \begin{pmatrix} \pi + \tau V_R + \rho(1-\alpha)V_N - (e^{-mV}\beta P + \mu)A \\ \psi(1-\varepsilon)V - (\tau+\mu)V_R \end{pmatrix} \tag{22}$$

Equations (22) provide the solutions $A(t) = \frac{\pi}{\mu} + \left(A(0) - \frac{\pi}{\mu}\right)e^{-\mu t}$and $V_R = V_R(0)e^{-(\tau+\mu)t}$.

As $t \to \infty$,we have $A(t) = \frac{\pi}{\mu}$ and $V_R(t) = V_R(0)$. Thus, I_0 is asymptotically stable satisfying condition 1. For condition 2, we have $C = (P, E, V, V_N)$, then,

$$\frac{dS}{dt} = \begin{pmatrix} \rho\alpha V_N - \mu P \\ e^{-mV}\beta PA - (\sigma+\mu)E \\ \sigma E - (\psi+\mu)V \\ \varepsilon\psi V - (\rho+\mu)V_N \end{pmatrix} \tag{23}$$

Thus

$$T = \frac{\partial S}{\partial C}(\Im_0) = \begin{pmatrix} -\mu & 0 & 0 & \rho\alpha \\ \frac{\pi}{\mu} & -\mu-\sigma & 0 & 0 \\ 0 & \sigma & \mu-\psi & 0 \\ 0 & 0 & \varepsilon\psi & -\mu-\rho \end{pmatrix}.$$

Moreover, condition 2 of the theorem leads to

$$\hat{S}(B,C) = TS - S(B,C) = \begin{pmatrix} 0 \\ \frac{\pi}{\mu} - \beta e^{-mV}PA \\ 0 \\ 0 \end{pmatrix} \tag{24}$$

Since $0 \leq A^* \leq \frac{\pi}{\mu}$, then equation (24) leads to $\hat{S}(B,C) \geq 0$which satisfy condition 2 of the theorem. Therefore, $I_0$of the GBV model system (8) is globally asymptotically stable, and hence Theorem 3 holds. Meaning that, no matter how many perpetrators or incidents of gender-based violence initially exist in the community, the system will always evolve over time toward the complete elimination of GBV, provided the key condition, $R_0 < 1$ holds.

GBV-present equilibrium point

The GBV-present equilibrium point of the system (8) refers to a stable state where the gender violence persists in a population at a steady level, neither growing exponentially nor dying out completely Brauer et al. 2019. Using the equations of model system (8), a set of the equilibrium point is

$$\Im_1 = (P^*, A^*, E^*, V^*, V_R^*, V_N^*)$$

where $P^* = \frac{\rho\alpha\varepsilon\psi}{\mu(\mu+\rho)}V^*$ $A^* = \frac{\pi}{\mu} + \left[\frac{\mu^2\sigma(\tau+\psi)(\mu+\tau) + \mu^2\sigma\psi\rho(1-\alpha)(1-\varepsilon)(\mu+\rho) + Q}{\mu^3\sigma(\mu+\rho)(\mu+\tau)}\right]V^*$,

$$E^* = \frac{(\mu+\psi)}{\sigma}V^*,$$

$$V^* = \frac{\mu\sigma(\mu+\tau)(\mu+\rho)A^* - \sigma\pi(\mu+\tau)(\mu+\rho)}{\tau\psi\sigma(1-\varepsilon)(\tau+\rho) + \varepsilon\rho\psi\sigma(1-\alpha)(\mu+\tau) + (\mu+\sigma)(\mu+\psi)(\mu+\rho)(\mu+\tau)} \tag{25}$$

$$V_R^* = \frac{\psi(1-\varepsilon)}{\mu+\tau}V^*,$$

$$V_N^* = \frac{\varepsilon\psi}{\mu+\rho}V^*$$

$Q = \mu^2(\mu+\rho)(\mu+\tau)(\mu+\sigma)(\mu+\psi)$,

Global stability of the Endemic equilibrium point

Theorem 4. *The GBV-present equilibrium point,* $\Im_1$ *of GBV model system (8) is asymptotically stable in* $\boldsymbol{\omega}$ *when* $\boldsymbol{R_0 > 1}$ *and unstable otherwise.*

Proof. Using the Lyapunov function as used in the work of studies (Goswami et al. 2024; Gutema et al. 2024; Olaniyi et al. 2024), we have

$$q = \frac{1}{2}\left[\left(P-P^*\right)+\left(A-A^*\right)+\left(E-E^*\right)+\left(V-V^*\right)+\left(V_R-V^*{}_R\right)+\left(V_N-V^*{}_N\right)\right]^2 \qquad (27)$$

Differentiating equation (26) with respect to the following

$$\frac{dq}{dt} = \left[\left(P-P^*\right)+\left(A-A^*\right)+\left(E-E^*\right)+\left(V-V^*\right)+\left(V_R-V^*{}_R\right)+\left(V_N-V^*{}_N\right)\right]\frac{dN}{dt} \qquad (28)$$

Combining the equation (9) and equation (28) leading to equation (29)

$$\frac{dq}{dt} = \left[\left(P+A+E+V+V_R+V_N\right)-\left(P^*+A^*+E^*+V^*+V^*{}_R+V^*{}_N\right)\right]\left(\pi-\mu N\right) \qquad (29)$$

$$\frac{dq}{dt} \leq \left[N-\frac{\pi}{\mu}\right](\pi-\mu N) \qquad (30)$$

Simplification of equation (30) gives the following inequality

$$\frac{dq}{dt} \leq -\frac{1}{\mu} \qquad (31)$$

Defining the relation in equation (31) it follows that $\frac{dq}{dt} < 0$and $\frac{dq}{dt} = 0$ if and only if

$$P-P^* = 0, E-E^* = 0, V-V^* = 0, V_R-V_R^* = 0, V_N-V_N^* = 0, \qquad (32)$$

respectively. Then, the invariant set

$$(P, A, E, V, V_R, V_N) \in \omega \subset \Re_+^6 : \frac{dq}{dt} \leq 0,$$

is the endemic equilibrium point of the system (8). Using the LaSalle invariant principle (Lasalle 1976), the endemic equilibrium point is globally asymptotically stable whenever $R_0 > 1$.

Bifurcation Analysis

Consider a general ODE system $\frac{dx}{dt} = f(x, \Phi), \rightleftarrows f: R^n \times R \rightarrow R^n$ and $f \in C^n(R^n \times R)$, (33)

where $x \in R^n$ represents the infected population, then is assumed that $\Im_0 = (B^*,0)$ is an equilibrium point of the system (32) , that is$f(0, \Phi) \equiv 0$, for all values of parameter Φ.

Theorem 5. (Castillo-Chaves and Song 2004)

Assume,

K: $H = D_x f(0,0) = \frac{\partial f_i}{\partial x_j}(0,0)$ *is a linearized matrix of system (32) arround the equilibrium point 0 with* Φ *evaluated at 0. Zero is a simple eigen values of* H *have negative real parts;*

P: *Matrix* H *has a non-negative right eigenvector* w *and a left eigenvector* v *corresponding to the zero eigenvalue. Suppose* f_k *is the* k^{th}*component of a vector field* f *and*

$$T = \sum_{k,i,j=1} v_k w_i w_j \frac{\partial^2 f_k}{\partial x_i \partial x_j}(0,0) \textit{and } \Upsilon = \sum_{k,i,j=1} v_k w_i \frac{\partial^2 f_k}{\partial x_i \partial \beta}(0,0).$$

The local dynamics of the system (32) around 0 are whole determined by the direction signs T *and* Υ *and hence,* he following conditions should hold;

i. If $T < 0, \Upsilon > 0$, A forward (supercritical) bifurcation occurs at $R_0 = 1$.The disease-free equilibrium is locally stable when $R_0 < 1$, and an endemic equilibrium appears for $R_0 > 1$.

ii. If $T > 0, \Upsilon > 0$, A backward bifurcation occurs at $R_0 = 1$.

Proof: from the Theorem,

The system (8) is reduced to retain only the infected compartment, $x = [P, E, V, V_R, V_N]^T$. The Jacobian matrix of the infected population, evaluated at the GBV-free equilibrium $\Im_0 = (B^*, 0)$, is therefore given as:

$$M = \begin{bmatrix} -\mu & 0 & 0 & 0 & \alpha\rho \\ \frac{\pi\beta}{\mu} & -\mu-\sigma & 0 & 0 & 0 \\ 0 & \sigma & -\mu-\psi & 0 & 0 \\ 0 & 0 & \psi(1-\tau) & -\mu-\tau & 0 \\ 0 & 0 & \varepsilon\psi & 0 & -\mu-\rho \end{bmatrix} \tag{34}$$

Let $w = [w_1, w_2, w_3, w_4, w_5]^{\rightleftarrows T}$ be the right eigenvector of the Jacobian matrix (34) at the bifurcation point $\beta = \beta_C$, satisfying $Mw = 0$. This leads to the following eigenvectors;

$w_1 = \dfrac{(\sigma+\mu)(\psi+\mu)}{\beta_C A^* \sigma}$, $w_2 = \dfrac{(\psi+\mu)}{\sigma}$, $w_3 = 1$, $w_4 = \frac{\psi(1-\varepsilon)}{\tau+\mu}$ and $\frac{\varepsilon\psi}{\rho+\mu}$. Again, let the left eigenvector $v = [v_1, v_2, v_3, v_4, v_5]^T$, satisfying $v^T M = 0$, $v^T w = 1$, leads to the following eigenvectors;

$$v_1 = \frac{-\alpha\pi\beta\rho\varepsilon\psi}{\mu(\mu+\rho)} v_3, v_3 = 1, v_4 = \frac{\psi(1-\tau)}{\mu+\tau} v_3, v_5 = \frac{\varepsilon\psi}{(\mu+\rho)} v_3.$$

Then, from the infected classes of the model, only the population E has quadratic numerality, so $f_2 = \beta B^* x_1 - \beta m B^* x_1 x_3 - (\sigma+\mu) x_2$. Hence the second derivative of f_2 contributes to

$\frac{\partial f_2}{\partial x_1 \partial x_3}(0, \Phi) = \frac{\partial f_2}{\partial x_3 \partial x_1}(0, \Phi) = -\beta m B^*$. Therefore, $T = v_2 w_1 w_3 (-2\beta m B^*) = -2\beta m B^* v_2 w_1 w_3$.

Again, $\Upsilon = \sum_{k=1}^{5} \sum_{i=1}^{5} v_k w_i \frac{\partial f}{\partial x_1 \partial \beta}(0,0)$, only equation E depends explicitly in β, that is,
$f_2 = \beta B^* x_1 - \beta m B^* x_1 x_3 - (\sigma+\mu) x_2$. So, $\frac{\partial^2 f_2}{\partial x_1 \partial \beta} = B^*, \frac{\partial^2 f_2}{\partial x_1 \partial \beta} = -m B^* x_3 \Rightarrow \frac{\partial^2 f_2}{\partial x_3 \partial \beta} = -m B^* x_1$.

At the GBV-free equilibrium point, only the first term survives, so $\Upsilon = v_2 w_2 B*$. Since all parameters of the system (8) are positive, we therefore conclude that $T < 0$and $\Upsilon > 0$, at this point, it is suffice to conclude that, the GBV-free equilibrium point of the model system (8) undergoes a forward bifurcation at $R_0 = 1$and is locally asymptotically stable when $R_0 < 1$. Therefore, preventive interventions such as education, law enforcement, and awareness campaigns are effective in completely eradicating the violence.

Sensitivity Analysis

In this subsection, we compute and study the behavior the of parameters of the basic re-production on the epidemic of GBV in the human population. The forward sensitivity index as used in (Duru et al. 2024, Liana and Chuma 2023, Nyerere and Liana 2024, Mgandu et al. 2025) is used to study the behavior of the parameters. The forward sensitivity index depending on parameter g is defined using the relation (32),

$$D_g^{R_0} = \frac{\partial R_0}{\partial g} \times \frac{g}{R_0} \tag{35}$$

Using parameter values in Table 1 and the basic reproduction number on equation (14), computations lead to the results presented on Figure 2. The positive sensitivity index means that an increase in the respective parameter leads to an increase in R_0 and vice-versa. In the computation, the analysis reveals that the parameters $\pi, \beta, \alpha$and ε are the most influential parameters of the basic reproduction number since each have a value of +1.00. The increase of these parameters increases also the value of the basic reproduction number and vice-versa. This observation implies that the GBV transmission rate βplays an important role on the dynamics of GBV in the population. The least influential parameters of the basic reproduction number are $\sigma, \rho,$ and ω. They have sensitivity index of +0.01515, +0.00842, and +0.135, respectively. On the other hand, the negative sensitivity index of a parameter indicates that an increase or decrease in a parameter value leads to a decrease or increase of the value of the basic reproduction number, respectively. In this case, the parameter$\tau$and μ influences the value of the basic reproduction number negatively. Their sensitivity index values are −0.998 and −2.016, respectively. The increase of these values ultimately lowers the value of the basic reproduction number, and its converse is also true. Figure 2 show variations of sensitivity index values of parameters of the basic reproduction number.

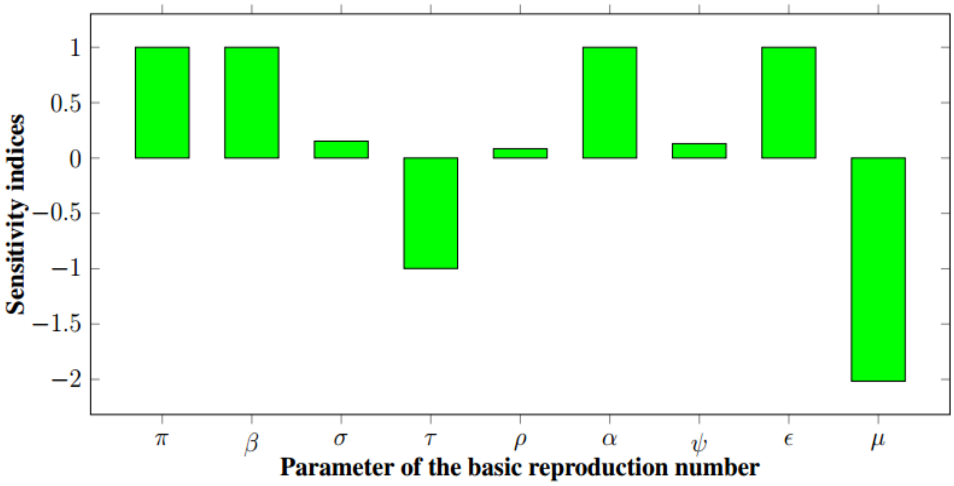

Figure 2: Sensitivity indices of parameters on the basic Reproduction number, R_0.

Results

Different simulations were carried out using MATLAB's ODE45 solver to assess the dynamics of GBV epidemics and the potential impact of awareness interventions within the community. The constructed GBV model, which represents social connections across demographic classes, was used during these simulations. Awareness interventions were implemented in the simulation, targeting both the at-risk population and perpetrators within the social network. The initial values of the state variables and in a closed population were assumed to be 10, 1000, 500, 150, 240, and 300, respectively. As shown in Table 1, all parameter estimates are expressed in terms of days per year. The average life expectancy of human is taken to be 65 years, which corresponds to a mortality rate of approximately, $\mu = \frac{1}{65\times365}$ per day. The incubation period of violence in humans is assumed to be at least one year, so $\sigma = \frac{1}{365}$ per day, while an individual is assumed to be at risk of becoming a victim of violence if not protected for at least one month, which gives a rate $\tau = \frac{1}{30}$ per day. It is also assumed that one perpetrator can cause gender-based violence to up to 100 individuals, depending on the nature of the population; hence, $\beta = \frac{1}{100}$. Moreover, the model assumes that ten years are sufficient for an individual to become a perpetrator, giving a rate of $\rho = \frac{1}{10}$ per day. Due to sociocultural practices in some communities, certain gender-based violence cases are rarely reported publicly. Thus, the model assumes that only one out of ten media houses reports such cases per day, resulting in a rate of $m = \frac{1}{10}$ per day. Since η and α are probabilities, they are assumed to lie within the range [0,1].

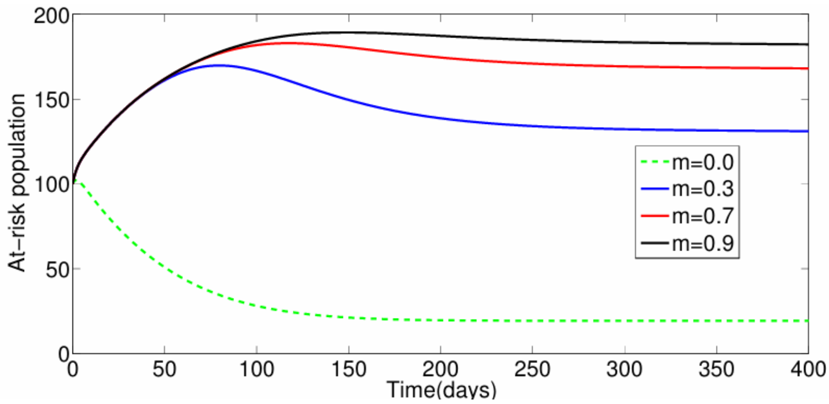

Figure 3: Influence of proportions of awareness interventions on the at-risk population of human for m(0.0,0.3,0.7,0.9) .

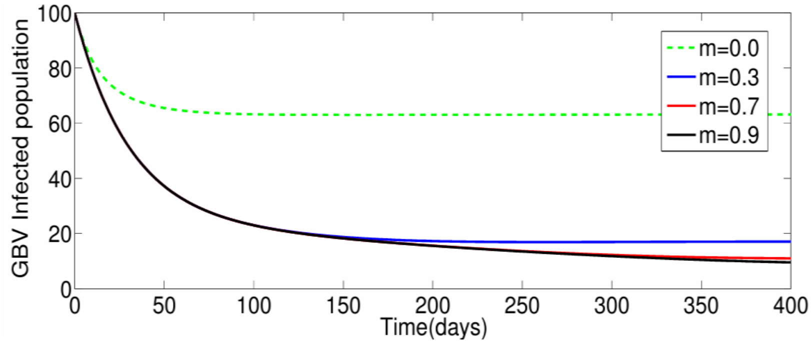

Figure 4: Influence of proportions of awareness interventions on the Perpetrators population for m(0.0,0.3,0.7,0.9).

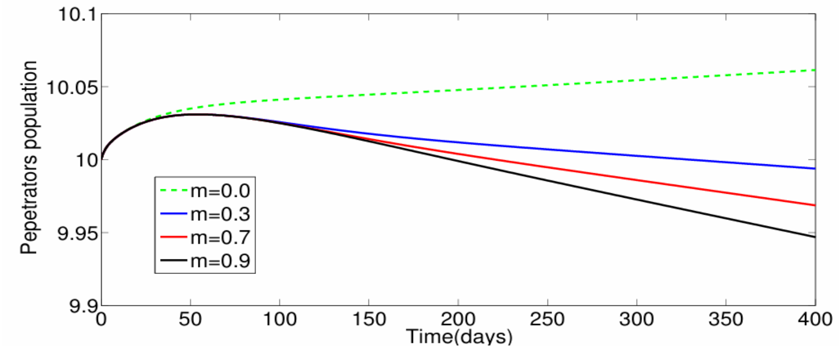

Figure 5: Influence of proportions of awareness interventions on the GBV Infected population $m = (0.0, 0.3, 0.7, 0.9)$.

The plot in Figure 3 shows the effect of awareness intervention on the at-risk population over time for different proportional values of media reports. The results show that the at-risk population increases over time for all values $(\boldsymbol{m = 0.0, m = 0.3, m = 0.9})$. This is because the awareness campaign is effective in reducing the number of people who joins the exposed to GBV population. The higher the awareness programs on GBV lowers much the violence transfer rate $(\boldsymbol{\beta})$ between the at-risk population and perpetrators. However, the at-risk population become lower for lower proportional values of $\boldsymbol{m}$ (see, e.g. $\boldsymbol{m = 0.0}$ and $\boldsymbol{m = 0.3}$). This is because when the awareness campaign is less effective, the contact rate between the at-risk individuals and perpetrators become higher and thus the number of people who become exposed to GBV become higher. Figure 4 shows the influence of proportions of awareness intervention on the population of GBV infected population. As it seen in the diagram, more GBV inflammations lower the number of GBV infected individuals. Figure 5 shows the influence of awareness interventions on the perpetrator population. The simulation was done on $\boldsymbol{m\ (0.0, 0.3, 0.7, 0.9)}$. The results show that the awareness interventions are effective in reducing the number of perpetrators in the population and hence lowers the contact rate with the at-risk population. The higher the awareness programme $(\boldsymbol{m})$, the more effective the awareness interventions. Figure 5 shows the influence of awareness interventions on the GBV infected population.

The simulation was done on $m(0.0, 0.3, 0.7, 0.9)$. The results show that the awareness interventions have a significant impact on the GBV infected population. The higher the value of m, the greater the impact of the interventions by reducing the number of infected individuals. For example, when $m = 0.9$, the number of GBV infected individuals is reduced compared to when $m = 0.0$.

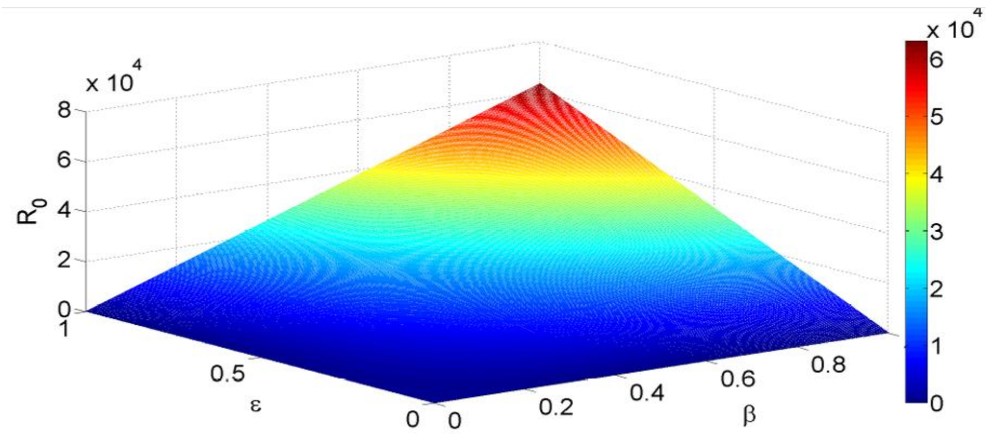

Figure 6: Influence of perpetrators-At risk population contact rate (β) and the probability of becoming violence non-

reconciled (ε) on the basic Reproduction number.

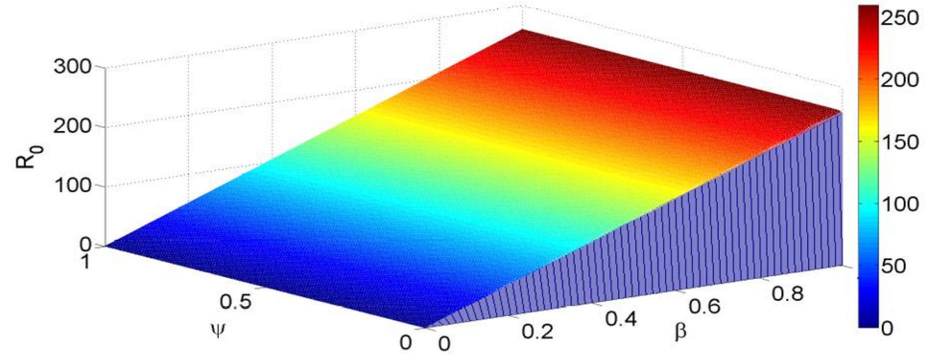

Figure 7: Influence of violence transfer rate (ψ) and perpetrator-At-risk contact rate (β) on the basic Reproduction number.

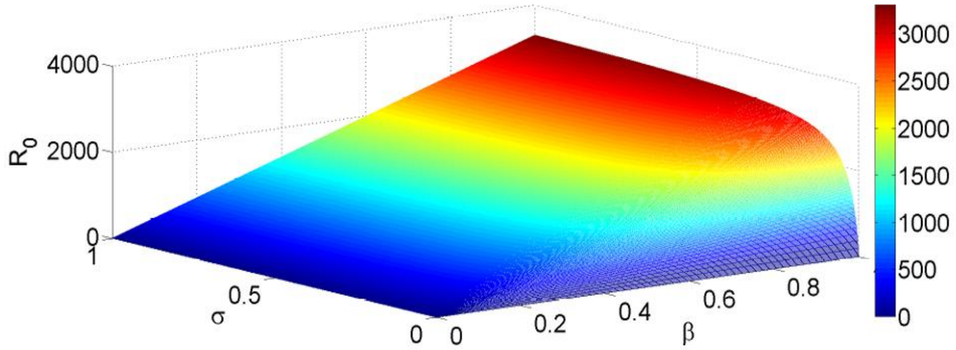

Figure 8: Influence of incubation period of violence in human (σ) and perpetrator-At-risk contact rate (β) on the basic Reproduction number.

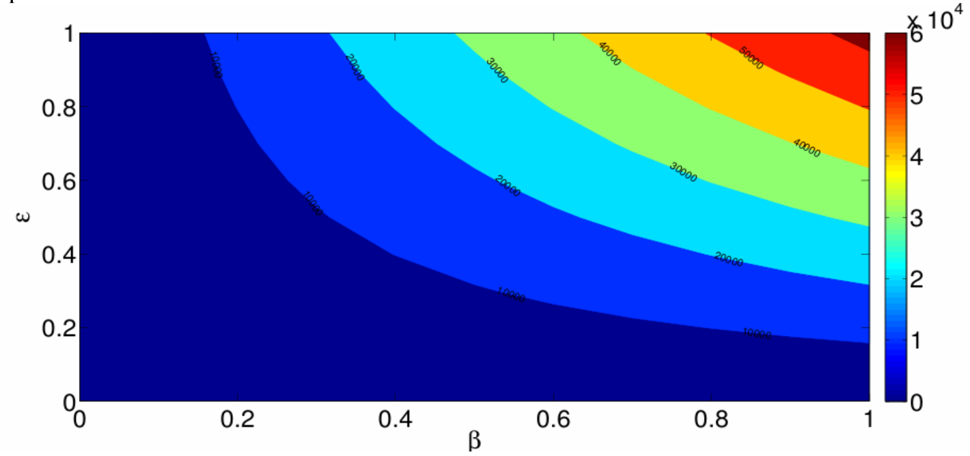

Figure 9: Contour plot of ε, β and R_0.

Figure 6 to Figure 8 represent the influence $\beta, \varepsilon, \sigma$, and ψ on the basic reproduction number, respectively. The simulations reveal that, all of the parameters have shown positive responses on the basic reproduction number. These results are similar to the simulation on the sensitivity analysis of the model parameters as shown in Figure 2. The increase in values of these parameters lead to the increase of the basic reproduction number and vice-versa. Comparatively, β and ε seems to have the greater influence on R_0 than σ and ψ. Moreover, the contour map presented on Figure 9 cements the positive influence of ε and β on R_0. Both parameters increase the value of R_0 and decrease it as they decrease.

Discussion

The analysis of the proposed GBV model revealed that enhancing public awareness and counseling efforts substantially reduces the prevalence of gender-based violence. The basic reproduction number, R_0, emerged as a key threshold parameter: when it is less than one, GBV gradually dies out, whereas values greater than one indicate persistence of violent behavior within the population. Sensitivity analysis further showed that awareness creation, counseling effectiveness, and rehabilitation rates strongly influence R_0, underscoring the importance of sustained community education and targeted intervention programs. Numerical simulations supported these findings by demonstrating that higher awareness levels decrease the number of violent individuals while increasing the proportion of individuals resistant to violent tendencies. These results are consistent with earlier studies emphasizing the critical role of education and prevention initiatives in mitigating GBV. Although the model assumes a closed and homogeneously mixed population, it provides important theoretical insights into how awareness campaigns and rehabilitation programs can contribute to long-term violence reduction. Future research may extend this work by incorporating heterogeneous population structures and external influences such as media engagement and law enforcement strategies.

Conclusion

A mathematical model of the dynamics of gender-based violence (GBV) with awareness-driven interventions in a closed population has been developed and analyzed. The GBV-free and GBV-present equilibrium points were found to be locally and globally asymptotically stable. Similar to findings in previous studies (e.g., Divya et al, 2024; Nyabadza, 2017), the model demonstrates that GBV can exhibit epidemic-like dynamics, where perpetrators normalize violence and contribute to its spread. A key finding is that the contact rate between perpetrators and the at-risk population significantly influences the propagation of GBV. The results also highlight the potential impact of awareness interventions in reducing GBV, with effectiveness depending on contextual factors and community participation. However, the model has limitations and does not fully capture the complexities of real-world GBV dynamics, such as resource constraints, cultural barriers, and political resistance. Future research should aim to integrate these factors into more comprehensive models. In conclusion, this study emphasizes the importance of proactive, community-driven strategies to combat GBV and promote gender equality through well-informed, network-aware interventions.

Data availability

Data were gathered from various sources in the literature and cited in the manuscript, while others were assumed based on the epidemiological aspects of GBV in a closed population.

Conflict of Interests

No conflicts of interest declared by the authors.

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