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ANALYZING HOW CHANGES IN THE HEALTH STATUS OF HEALTHCARE WORKERS AFFECTS EPIDEMIC OUTCOMES

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ABSTRACT

During a disease outbreak, healthcare professionals are essential to treat patients and prevent new cases. However, these healthcare professionals are themselves susceptible to contracting the disease. As more healthcare workers get infected, fewer are available to provide care for others, and the overall quality of care available to patients diminishes. This depletion of healthcare workers may contribute to the severity of the epidemic. To examine this decline in quality of care, we explicitly include a quality of care term in a differential equation-based SIRV model. We assume quality of care for a health force declines as the proportion of healthy healthcare workers declines. We analyze the resulting time series dynamics, cumulative cases and mortality during an outbreak. We assume that vaccination, recovery, and survival rates are impacted by the quality of care function. We compare 4 models: 1) a standard SIRV model, 2) an SIRV model with a separate class for healthcare workers, 3) an SIRV model where transitions are dependent on a quality of care function, and 4) an SIRV model with a separate class of healthcare workers and where transitions are dependent on a quality of care function. Quality of care is described by a function with two shape parameters: the loss impact parameter, which defines the negative impact on the quality of care arising from the loss of a single healthcare worker; and the redundancy parameter, which defines the number of healthcare workers that may be lost before collapse in the healthcare system.

By comparing these models, we show that explicitly modelling healthcare workers and accounting for declining quality of care changes our predictions of epidemic outcomes. Our results show an increase in the number of individuals who get infected in both models that consider the quality of care function, with a greater increase occurring when healthcare workers are considered separately from the general population. The models also project larger epidemic outcomes when the healthcare system is fragile. This occurs when the loss impact parameter is high (i.e. each lost healthcare worker has a relatively large negative impact on the quality of care) and the redundancy parameter is low (i.e. when there is little built-in redundancy in the healthcare system). These differences between the models show the importance of including quality of care in epidemic models that include management techniques. As more notable differences were seen when healthcare workers were considered separately, our full model (IV) can likely best be used to inform health policy that may differ for healthcare workers and the general population. This may help to improve the choice of management interventions considered to mitigate the effects of a future outbreak.

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Chapter 1

Introduction

In 2014, an Ebola epidemic ravaged western Africa. Over the course of this epidemic, healthcare access and quality became increasingly limited[1]. According to the World Health Organization (WHO), the weight of the Ebola burden caused the already limited healthcare systems of the affected countries to collapse[1,2] and many people were not able to receive the medical aid they needed[1,3]. Specifically, quality of care provided to patients declined dramatically as an unprecedented number of healthcare workers got infected[1,4]. For example, in the Kenema Hospital in Sierra Leone, deaths among healthcare workers, already in short supply, pushed the hospital to the verge of collapse, as the Ebola epidemic progressed[5]. Clinic closures, personal protective equipment shortages and overcrowding of hospitals in the midst of the epidemic resulted from a progressively limited health force[1]. The survival rates for individuals without healthcare access were dramatically lower than they were for individuals with healthcare access[3].

Each year dozens of potentially lethal outbreaks affect populations around the world. For example, annual epidemics of seasonal influenza kill thousands of people[6], and emergent strains of pandemic influenza (e.g. the 2009 H1N1 pandemic) may have even higher mortality burden[7]. Additionally, outbreaks sparked by translocated infectious diseases can have especially high burdens (cases and deaths) and overwhelm existing health systems in the locations where they emerge. Zika emerged in the Americas starting in Brazil in 2015 and was quickly declared a public health emergency by the WHO[8]. Dozens of other infectious diseases have recently caused lethal outbreaks, including cholera, Nipah virus, Rift Valley Fever, Yellow Fever, and measles[9]. As the primary source of care, healthcare workers are essential to providing care during such outbreaks. However, their exposure means they may also become victims of the outbreak, due to their frequent contact with infected individuals. Infection hinders their ability to provide care[10], either because policy forbids them to work, or because they are too sick to work effectively, or because they die. Access to healthcare is already a bottleneck for public health in many parts of the world[11]. As healthcare workers become infected during an outbreak, healthcare access perforce becomes limited as the system is overwhelmed, which causes the quality of care that can be offered to the average individual to decline.

Reduced quality of care may have several effects on epidemic outcomes. The absolute number of cases and disease-induced deaths could be impacted by a declining quality of care function, as healthcare workers are essential for providing vaccinations to prevent the disease from spreading and the necessary care to reduce cases and deaths. Treating patients may either reduce the duration during which the individual is infectious or reduce the probability that the patient dies from infection. At the population level, reduced healthcare thus likely translates into fewer administered doses of vaccine (if one exists), longer duration of infection, and increased case fatality ratios. Thus, not only does a decline in quality of care affect individual outcomes including duration of infection and likelihood of death, it poses problems for controlling the epidemic at a population scale, likely increasing the number of cases, the number of deaths, and the severity and duration of the outbreak.

Conventional epidemic models fail to take into consideration that epidemic rates may change over the course of the outbreak, and thus neglect the potential impact of a declining quality of care[12]. As a result, such models may underestimate epidemic burdens, especially when quality of care has the potential to decrease dramatically over the course of the epidemic. To assess the impact of a declining quality of care function, we develop four epidemiological models based on a compartmental differential equation model, where the classes of individuals are susceptible, S, infected, I, recovered, R, and vaccinated, V. Model I is an SIR-type[13] model with vaccination (SIRV). In model II, we extend model I to include healthcare workers as a separate sub-population. In model III, we instead extend model I to include a quality of care function, which depends on the proportion of uninfected individuals in the total population. Finally, in model IV, we combine models II and III to simultaneously model healthcare workers as a separate sub population and to include a quality of care function that now depends on the proportion of uninfected healthcare workers in the sub population of healthcare workers.

The decline in quality of care over the course of a general epidemic is difficult to characterize empirically and is likely context-specific. Thus, for the purposes of our models, and to maintain generality, we model the quality of care function with a sigmoidal function, as this function can incorporate both linear and exponential changes to the quality of care as the proportion of uninfected individuals or uninfected healthcare workers change. We here examine the effect of the specific parameterization of the quality of care function on epidemic burdens, specifically case counts and mortality, in terms of both the loss impact parameter, which quantifies how much quality of care declines if a single healthcare worker becomes infected, and the system redundancy, which quantifies how many healthcare workers can be lost before quality of care sees serious decline. We compare outcomes produce by our four models to assess the differences in predictions yielded by explicit consideration of healthcare as a dynamic resource. We show that the inclusion of the quality of care does matter and impacts epidemic outcomes, by showing conventional models may underestimate resulting case counts and mortality.

Chapter 2

Methods

We aim to investigate the direct impact of the loss of healthcare workers (HCWs) on outbreak outcomes. To this end, we developed four SIR-type models in order to account for the following four scenarios. In model I, we take HCWs to be some fraction of the general population (Fig. 1A). However, in some cases, HCWs may have higher infection rates, associated with more frequent contact with infected individuals[14], and may also be priority targets for interventions such as vaccines[3]. Therefore, in model II, we describe HCWs as a separate population (Fig. 1B). In model I and model II we do not account for the quality of care delivered by HCWs through an outbreak, which may affect recovery rates and likelihood of survival, thus these models provide a baseline representative of current modeling practice. Models III (Fig. 1C) and IV (Fig. 1D) are extensions of models I and II, respectively, in which we model quality of care as a function of infection prevalence. In the following we outline each of these models and discuss specifically how we model quality of care as a function of healthcare worker population, for models III and IV.

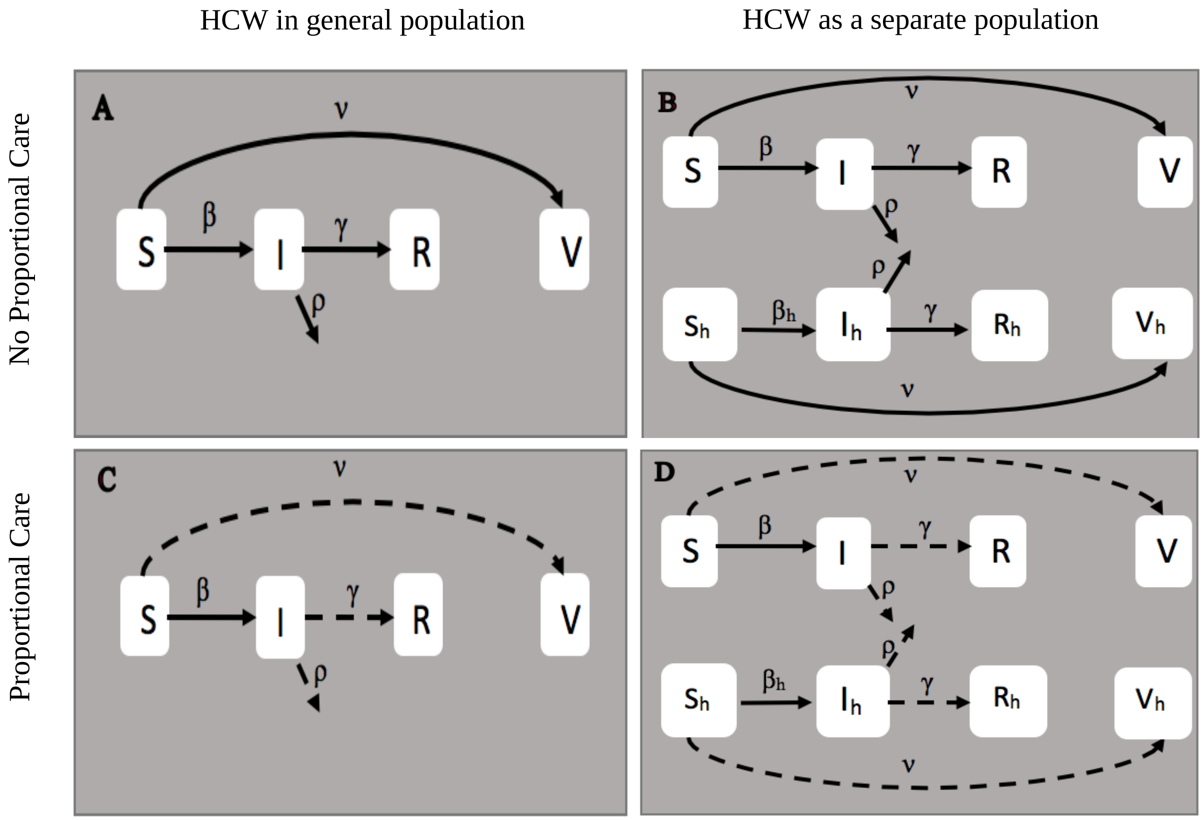


Figure 1: Model schematic comparison of the four distinct compartmental models that are used.

β (Beta) is the rate of transmission, γ (gamma) is the recovery rate, ρ (survival parameter) is the probability of survival, and v (vaccination rate) is the rate of a fully effective vaccine. Rates for both systems in models II and IV are the same between both sets of individuals.

A: Illustration of Model I where healthcare workers are part of the general population

B: Illustration of Model II where the healthcare workers are a separate group from the rest of the population. The classes for healthcare workers are denoted with an h-subscript

C: Illustration of Model III where healthcare workers are part of the general population and the dotted lines are rates affected by a proportional quality of care function

D: Illustration of Model IV where the healthcare workers are a separate group from the rest of the population and the dotted lines are rates affected by a proportional quality of care function

For all models we apply the following parameterization. Susceptible individuals, S, are infected at a rate β. Infected individuals, I, may die with probability ρ or recover with probability 1-ρ, at recovery rate γ. We assume that once infected individuals have recovered, R, they are no longer susceptible. Further, we assume that vaccines grant lasting immunity to the disease as well, so the susceptible individuals, vaccinated at rate v, will remain in the vaccinated class, at least for the duration of the outbreak under consideration as vaccinated individuals, V. Model I is a SIR-type model with an additional vaccinated class, shown schematically in Fig. 1A. This model is described by the following system of differential equations:

$$\dot{S}(t) = -\frac{\beta\big(I(t)\big)}{N(t)}S(t) - \ vS(t) \qquad (Eq\ 1)$$

$$\dot{I}(t) = \frac{\beta\big(I(t)\big)}{N(t)}S(t) - \frac{\gamma I(t)}{(1-\rho)} \qquad (Eq\ 2)$$

$$\dot{R}(t) = \gamma I(t) \quad Eq(3)$$

$$\dot{V}(t) = vS(t) \quad Eq(4)$$

$$N(t) = S(t) + I(t) + R(t) + V(t) \quad Eq(5)$$

For each class of susceptible (S), infected (I), recovered (R) and vaccinated (V), individuals may enter and leave the classes at the rates seen in the equations. In model II, we extend model I to capture distinct dynamics between the general population and HCWs separately. In principle, due to the nature of work done by HCWs, such as frequent involvement with infected individuals, infection dynamics parameters may differ between HCWs and non-HCWs. Classes to account for the susceptible, infected, recovered and vaccinated population of HCWs have been added in addition to the previous four classes, which allows for them to possibly be parameterized differently compared to the rest of the population. Additionally, both HCWs and the general population may contribute to the transmission of infection. Classes related to the HCWs are denoted with a subscript, h. The system of differential equations for model II becomes:

$$\dot{S}(t) = -\frac{\beta\big(I(t) + I_h(t)\big)}{N(t)}S(t) - \ vS(t) \ \ (Eq7)$$

$$\dot{I}(t) = \frac{\beta\big(I(t) + I_h(t)\big)}{N(t)}S(t) - \frac{\gamma I(t)}{(1-\rho)} \ (Eq8)$$

$$\dot{R}(t) = \gamma I(t) \ (Eq9)$$

$$\dot{V}(t) = vS(t) \ (Eq10)$$

$$\dot{S}_h(t) = -\frac{\beta_h\big(I(t) + I_h(t)\big)}{N(t)}S_h(t) - \ vS_h(t) \ (Eq11)$$

$$\dot{I}_h(t) = \frac{\beta_h\big(I(t) + I_h(t)\big)}{N(t)} S_h(t) - \frac{\gamma I_h(t)}{(1-\rho)} \ \ (Eq12)$$

$$\dot{R}_h(t) = \gamma I_h(t)\ (Eq13)$$

$$\dot{V}_h(t) = v S_h(t)\ (Eq14)$$

$$N(t) = S(t) + I(t) + R(t) + V(t) + S_h(t) + I_h(t) + R_h(t) + V_h(t)\ \ (Eq15)$$

There is no prioritization of vaccination in our model parameterization and both population groups are vaccinated at the same rate in all variations of the model. We make the distinction between models I and II, which account for the HCW population as a separate population denoted by subscript *h*, in preparation for modeling quality of care delivered in the course of an outbreak, which will affect recovery rates and likelihood of survival. We will take the quality of care as a function of the fraction uninfected individuals in the population, extending model I, or uninfected fraction of HCWs, extending model II.

Quality of Care Function

Conventional models do not take a declining quality of care provided by HCWs into consideration. However, the quality of care given to infected individuals likely affects epidemic outcomes, since the care provided can, for example, improve recovery rates and reduce mortality. Here we describe how we model quality of care, as we are interested in understanding how the inclusion of quality of care impacts epidemic outcomes.

We model the quality of care, *Q(P(t))*, as a function of the proportion of HCWs, *P(t),* that are uninfected and able to provide care. We construe the two shape parameters associated with *Q(P(t))*, *k* and *m,* as describing loss impact (*k*) and the health system redundancy (*m*). We choose *Q(P(t))* to be a sigmoidal function, $1/\big(1 + e^{-k(P(t)-m)}\big)$, that is normalized to range from 0 to 1. This allows us to showcase healthcare systems working at levels from 0% to 100%.

$$Q(t) = Q\big(P(t)\big) = \frac{\dfrac{1}{1+e^{-k(P(t)-m)}} - \dfrac{1}{1+e^{km}}}{\dfrac{1}{1+e^{-k(1-m)}} - \dfrac{1}{1+e^{km}}}. \qquad (Eq\ 16)$$

When all HCWs are infected (*P(t)=0*), the healthcare system can provide no care (*Q(P)=0*) and is said to be operating at 0%, while if no HCWs are infected (*P(t)*=1), the quality of care that the health system can provide is its best (*Q(P)=1*) and is operating at its full capacity of 100%. We choose a sigmoidal function because of the range of dynamics it captures via the shape parameters, *m* and *k*. Examples of the quality of care function, for a few shape parameterizations, are provided in Figure 2.

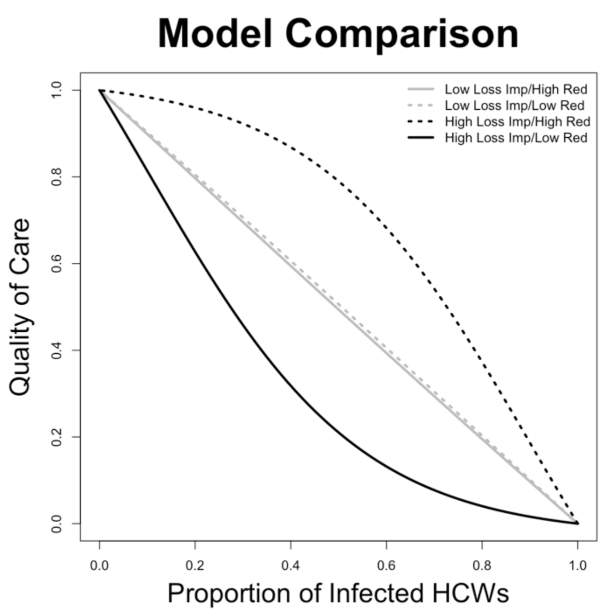


Figure 2: This figure illustrates a few shapes the quality of care function can be which depend on the value of the loss impact parameter and the redundancy parameter.

Additionally, each curve illustrates one sample quality of care function belonging to each quadrant in Fig. 4.

Mathematically, the loss impact parameter (*k*) is could be related to each healthcare worker's impact on the health force system. When this parameter is larger, a steeper decline is evident in the healthcare system for each healthcare worker that is infected, as seen in the black curves in Fig. 2 (see also Fig. S1 in the supplement). The health system redundancy parameter (*m*) accounts for the minimum health system provision, which is the minimum number of healthcare workers needed to provide adequate care. A higher health system redundancy parameter represents a healthcare system that is safeguarded compared to a lower redundancy parameter, as it is able to withstand the loss of more healthcare workers before it cannot provide adequate care, as shown in Fig. 2. When considered simultaneously, we find that the high redundancy parameter overall leads a stronger quality of care provided by the health force compared to systems with a low redundancy parameter. Collectively, these two shape parameters can represent a robust healthcare system (high loss impact *k*, high robustness *m*), a fragile system (high *k*, low *m*) and other combinations in between as seen in Figure 2. Due to the normalization of the quality of care function to bound the values between 0 and 1, this normalization leads to a counter-intuitive response to the loss impact parameter. While we would expect a higher loss impact parameter to pertain to a weaker health system, the normalization means that when *k* is high, there is little change in quality of care until some threshold, corresponding to *m*, is reached. We explore this further in the supplemental figures. Through these two shape parameters, the quality of care function *Q(t)* can describe multiple modes of decline. This flexibility is important as the function itself has no empirical estimate, and no supporting observations. As shown in Figure 4, we consider loss impact parameter values (*k*) between 0-5 and redundancy parameter values (*m*) between 0 and 1, and we test the sensitivity of epidemic outcomes as a function of *k* and m.

Since the quality of care *Q(P(t))* directly relates to the number of HCWs that are able to provide care, parameters describing the recovery rate and mortality risk for infected individuals, and population vaccination rate, may be modulated by the quality of care function. We assume that the decline in quality of care will affect all of these parameters simultaneously.

Models III & IV

We complement Models I and II with Models III and IV, which are distinguished by the inclusion of a quality of care function, which allows us to explore the different dynamics resulting from the inclusion of quality of care. Model III extends model I, and assumes that quality of care provided depends on the fraction of the prevalence of infection in the population. This is represented in the quality of care function, *Q(P(t))*, as $P(t) = \left(\frac{S+R+V}{S(0)+I(0)+R(0)+V(0)}\right)$, the fraction of uninfected individuals relative to the initial population.

As the quality of care function relates to the care that HCWs may provide, it will directly impact the rate at which the susceptible population is vaccinated, *v*. Further, the quality of care function affects the probability of dying as well as the rate at which individuals recover, as the stronger quality of care function suggests a higher likelihood of survival and recovery from the epidemic. Therefore, our extended model III differential equations are:

$$\dot{S}(t) = -\frac{\beta\big(I(t)\big)}{N(t)}S(t) - \ Q(P(t))vS(t) \qquad (Eq\ 17)$$

$$\dot{I}(t) = \frac{\beta\big(I(t)\big)}{N(t)}S(t) - \frac{\gamma I(t)Q(P(t))}{(1-\rho)Q(P(t))} \qquad (Eq\ 18)$$

$$\dot{R}(t) = Q(P(t))\gamma I(t) \quad Eq(19)$$

$$\dot{V}(t) = Q(P(t))vS(t) \quad Eq(20)$$

$$N(t) = S(t) + I(t) + R(t) + V(t) \quad Eq(21)$$

Healthcare workers are often subject to different dynamics, for example more frequent exposure to infected individuals or higher vaccination rates. To capture these differences in model IV, we extend model II to include a proportional quality of care function *Q(P(t))*; however, *Q(P(t))* is now driven by the proportion of uninfected healthcare workers. Thus for model IV, for *Q(P(t))*, P is given by the proportion of uninfected HCWs, $P(t) = \left(\frac{S_h+R_h+V_h}{S_h(0)+I_h(0)+R_h(0)+V_h(0)}\right)$, the fraction of uninfected HCWs relative to the initial HCW population. We extend the quality of care function to impact the same parameters in the same manner as in model III for the four additional healthcare worker classes. The extended system of differential equations for model IV is:

$$\dot{S}(t) = -\frac{\beta\big(I(t)+I_h(t)\big)}{N(t)}S(t) - \ Q(P(t))vS(t)\ (Eq\ 22)$$

$$\dot{I}(t) = \frac{\beta\big(I(t) + I_h(t)\big)}{N(t)} S(t) - \frac{\gamma I(t) Q(P(t))}{(1-\rho) Q(P(t))} \, (Eq\ 23)$$

$$\dot{R}(t) = Q(P(t))\gamma I(t) \ \ (Eq\ 24)$$

$$\dot{V}(t) = Q(P(t))\upsilon S(t) \ \ (Eq\ 25)$$

$$\dot{S}_h(t) = -\frac{\beta_h\big(I(t) + I_h(t)\big)}{N(t)} - \ Q(P(t))\upsilon S_h(t) \ (Eq\ 26)$$

$$\dot{I}_h(t) = \frac{\beta_h\big(I(t) + I_h(t)\big)}{N(t)} - \frac{\gamma Q(P(t)) I_h(t)}{(1-\rho) Q(P(t))} \ \ (Eq\ 27)$$

$$\dot{R}_h(t) = Q(P(t))\gamma I_h(t) \ \ (Eq\ 28)$$

$$\dot{V}_h(t) = Q(P(t))\upsilon S_h(t) \ (Eq\ 29)$$

$$N(t) = S(t) + I(t) + R(t) + V(t) + S_h(t) + I_h(t) + R_h(t) + V_h(t) \ \ (Eq\ 30)$$

In summary, we will discuss epidemic outcome predictions of four models, wherein we consider either HCWs as mixed in to the general population, or as a distinct population that may, in general, have its own dynamics, for example, a higher infection rate, associated with more frequent contact with infected individuals, along with epidemic dynamics neglecting or accounting for the impact of infection on quality of care (Figure 1). The equations in model III describe a system that gets overwhelmed as patient saturation increases in general, while the equations in model IV describe a system that is overwhelmed only when the saturation of healthcare workers increases. Comparing these four models will allow us to explicitly consider whether and to what extent the quality of care matters in epidemic models.

Parameter Assumptions and Initial Conditions

The complete set of initial conditions and parameters are provided in Table 1. We assume that we have a basic reproduction ratio, R_0, of roughly 2.5, a mid-range value for a range of outbreak-prone diseases, such as Ebola[15], pandemic flu[16], SARS[17]. Further, we assume the probability of dying from disease is 0.2, another mid-range value between extremes of the same diseases: Ebola 0.7[18] and SARS

0.15[19]. We model disease dynamics assuming an initial population of 1000 individuals, while 2% of the population are healthcare workers in models III and IV, an intermediate value chosen from data provided by the WHO[20]. We assume that the outbreak is triggered by a single initial infected individual, and that this first case is in the general population, i.e., not an HCW.

Symbol	**Parameter**	**Baseline value [range]**	**Meaning**
υ	Vaccination rate	0.02 weeks^{-1}	Rate of vaccination
β	Transmission rate	5 weeks^{-1}	Rate of transmission
β_h	Transmission rate for HCW	5 weeks^{-1}	Rate of transmission
γ	Recovery rate	2 weeks^{-1}	Rate of recovery
ρ	Probability of Dying	0.2	Probability of dying once infected (see text) [18,19]
Q(t)	Quality of Care Function	[0,1]	Quality of Care function - HCW ratio
k	Loss impact parameter	4 [0-5]	Affects how steep sigmoid function is
m	Redundancy parameter	0.1 [0-1]	Affects midpoint of sigmoid function
N(0)	Population	1000	Starting total population
S(0)	Susceptible Gen Pop	979	Initial number of susceptible general group
I(0)	Infected Gen Pop	1	Initial number of infected general group
R(0)	Recovered Gen Pop	0	Initial number of recovered general group
V(0)	Vaccinated Gen Pop	0	Initial number of vaccinated general group
$S_h(0)$	Susceptible Med Pop	20	Initial number of susceptible HCWs (see text)
$I_h(0)$	Infected Med Pop	0	Initial number of infected HCWs
$R_h(0)$	Recovered Med Pop	0	Initial number of recovered HCWs
$V_h(0)$	Vaccinated Med Pop	0	Initial number of vaccinated HCWs

Table 1: Model IV Baseline Parameters and Initial Conditions

Chapter 3

Results

Underestimated Epidemic Outcomes (Cases & Deaths)

Of the four models we consider, models I, Eq(1-5) and II, Eq(7-15), represent conventional epidemic models with no explicit dependence on quality of care, while models III, Eq(17-21), and IV, Eq(22-30), represent the modified model which includes consideration of the quality of care. When both HCWs and the general population are assumed to have the same dynamics, i.e., have the same model parameters (Fig. 3A), models I and II - with no proportional quality of care - generate the same outcomes. The same is true for models III and IV, which include proportional quality of care, since disease dynamics are described by the same vaccination, recovery and mortality rates. Models that consider quality of care (models III and IV) generate different outcomes than models that do not (models I and II). Notably, the projected range of total cases increases when declining quality of care is included, as a lower quality of care function leads can lead to up to a 15% increase in infections for the baseline parameterization (Table 1) seen in Figure 3A.

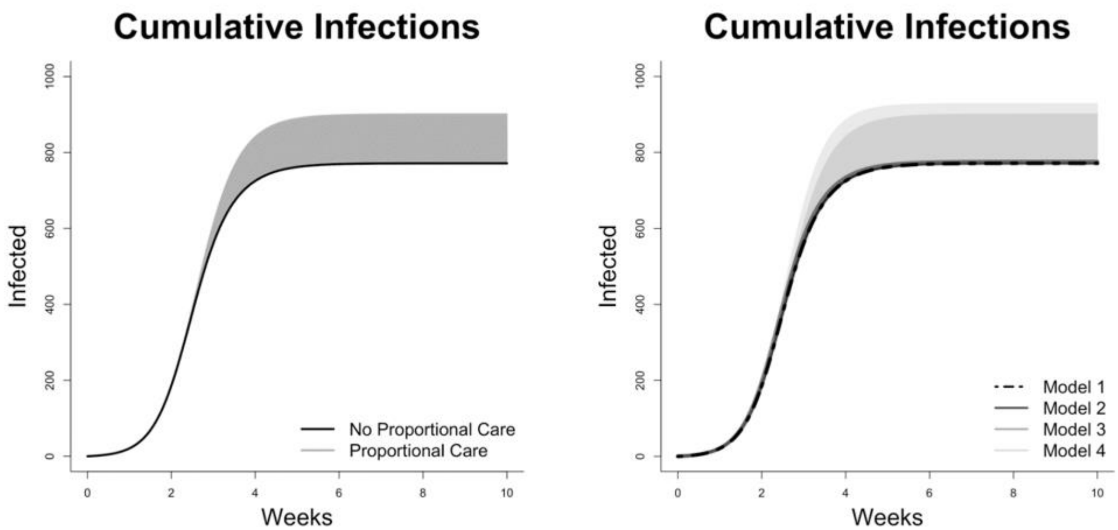


Figure 3: The number of cumulative infections for different models are shown below in two scenarios.

A: The cloud shows the range of cumulative infections that result for parameter combinations of the loss impact parameter and the redundancy parameter when a proportional quality of care function is included. Parameters for both population groups are the same.

B: The cloud shows the range of cumulative infections that result from parameter combinations of shape parameters when a proportional quality of care function is included. In this simulation, the transmission rate has been increased by 50% for healthcare workers only. All other parameter combinations for both groups are the same.

In Figure 3 we present a range of outcomes corresponding to a range of quality of care functions (that is, we considered a range of redundancy parameters and loss impact parameters in *Q(t))*. In Figure 3A, we present cumulative infections for models with no proportional care component, where we do not consider quality of care (black line), and cumulative infections for all parameterizations of the quality of care function we considered for models with proportional care (grey cloud). In Figure 3B, the light grey cloud (which is overlapped by the grey cloud down to the dotted black line), we present cumulative infections for all combinations of *k* and *m* of the quality of care function considered from model IV, while assuming infection rates are 50% higher for healthcare workers compared to the general population, achieved by assuming that the infection rate, β_h, is 150% greater for HCWs than for the general population. We also compare this to a result from model II where we make the same assumption (dark grey line in Figure 3B, nearly overlapped by the dotted black line). This illustrates scenarios where healthcare workers are at greater risk of infection due to increased contact amongst infected individuals, with the assumption that this increases their likelihood of getting infected. A higher infection rate, associated with increased exposure to infected individuals, may explain the scenario in which an unprecedented number of healthcare workers have been infected[1]. The choice of quality of care function, driven by the uninfected population or uninfected HCW saturation, results in a higher number of cumulative infections when healthcare workers have a higher infection rate. This corresponds to the light grey region of the cloud (Fig. 3B), while the grey region relates to the model where parameters are the same for each group of the population as they are modeled as one group. Regardless of the assumptions on infection dynamics in the healthcare worker population (model III vs model IV), it is apparent that the inclusion of quality of care has a substantial impact on the resulting epidemic outcomes as this showcases a range of total cases, instead of one singular outcome for each model.

The quality of care function shows a range of behaviors as it spans a concave to convex region which can be used to capture healthcare systems of varying strengths (Fig. 2). A high loss impact parameter and low redundancy parameter result in a quality of care that declines steeply after just a few healthcare workers are infected (solid black line Fig. 2). A high loss impact parameter and high redundancy parameter mean that quality of care declines gradually until many healthcare workers are infected, and then declines steeply (dotted black line Fig. 2). A low loss impact parameter gives quality of care that declines in an intermediate manner regardless of the redundancy parameter (solid and dotted grey lines Fig. 2).

Shape Parameter Impacts on Case Counts and Deaths

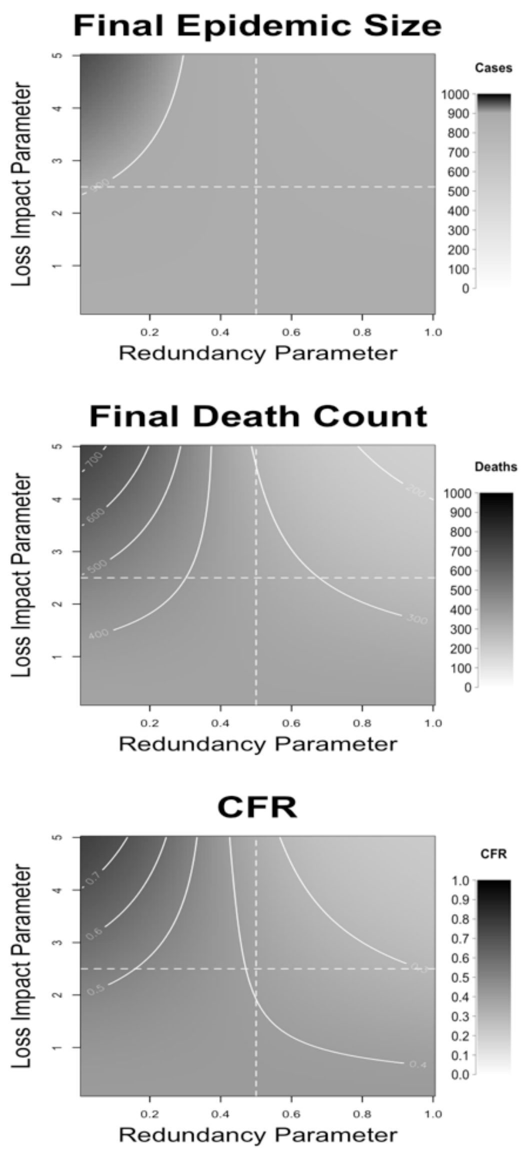


Figure 4: Each panel shows the epidemic burden resulting from each combination of the loss impact parameter and the redundancy parameters in the quality of care function.

Each panel is split into 4 quadrants representing choices of the quality of care function for model IV: The top left relates to a quality of care function with a high loss impact parameter and low redundancy parameter, the top right has a high loss impact parameter and high redundancy parameter, the bottom left has low loss impact and low redundancy while the bottom right has a low loss impact and high redundancy.

When compared to the sample quality of care functions included in the methods, each quadrant of the contour panels in figure 4 relates to one of the four sample quality of care functions – the upper right quadrant corresponds to the dotted black line in Figure 2, the lower right corresponds to the solid grey line in Figure 2, the lower left corresponds to the dotted grey line in Figure 2, and the upper left corresponds to the solid black line in Figure 2. We investigate the impact that quality of care parameters *k* and *m*, representing loss impact and redundancy respectively, have on epidemic burdens. A high loss parameter paired with a low redundancy parameter causes the most severe epidemic outcomes with respect to case counts and mortality, as this represents a weak health system that has a rapid decrease in quality of care as few healthcare workers are infected (solid black line in Figure 3, upper left corner in Figure 4). Conversely, the mildest epidemic outcomes all result from a combination of a high loss parameter along with a high redundancy parameter, as this represents a strong health system, due to the normalization process used (dotted black line in Figure 3, upper right corner in Figure 4). This is because there is a minimal decrease in quality of care until nearly all healthcare workers are infected, when there is a rapid decrease in quality of care. As that many healthcare workers are rarely infected, this means quality of care is rarely significantly reduced.

In Figure 4, we show the final epidemic size (Fig. 4A), mortality (Fig. 4B), and case fatality ratio (cfr) (Fig. 4C), predicted using model IV (assuming the transmission rate is the same between healthcare workers and the general population) for each combination of the two shape parameters in the quality of care function. Lighter regions indicate milder epidemic outcomes while darker regions indicate severe epidemic regions for each of the three panels on. The high loss impact suggests a large decline in performance of the healthcare system as an additional healthcare worker is infected. This paired with a low redundancy parameter means that the healthcare system is not well safeguarded, so a few infections amongst HCWs will cause the system to collapse. If this combination is representative of the current system, the system can mitigate epidemic burdens by either reducing the loss impact parameter or increasing redundancy in the system. It is important to note that the strongest system has both high loss parameter and high redundancy, so it would be better suited to focus improvement towards increasing redundancy, as due to the normalization process implemented to scale *Q(t)*, the high loss impact parameter results in little change until some threshold number, corresponding to *m*, of HCWs are infected. For the mildest predicted epidemic outcomes, while the high loss impact parameter remains, the high redundancy parameter suggests that the healthcare system is robust enough to withstand a large number of infections prior to rapid collapse once a very high proportion of HCWs are infected, which is indicative of a robust system.

Parameters Impacted by Infected HCWs

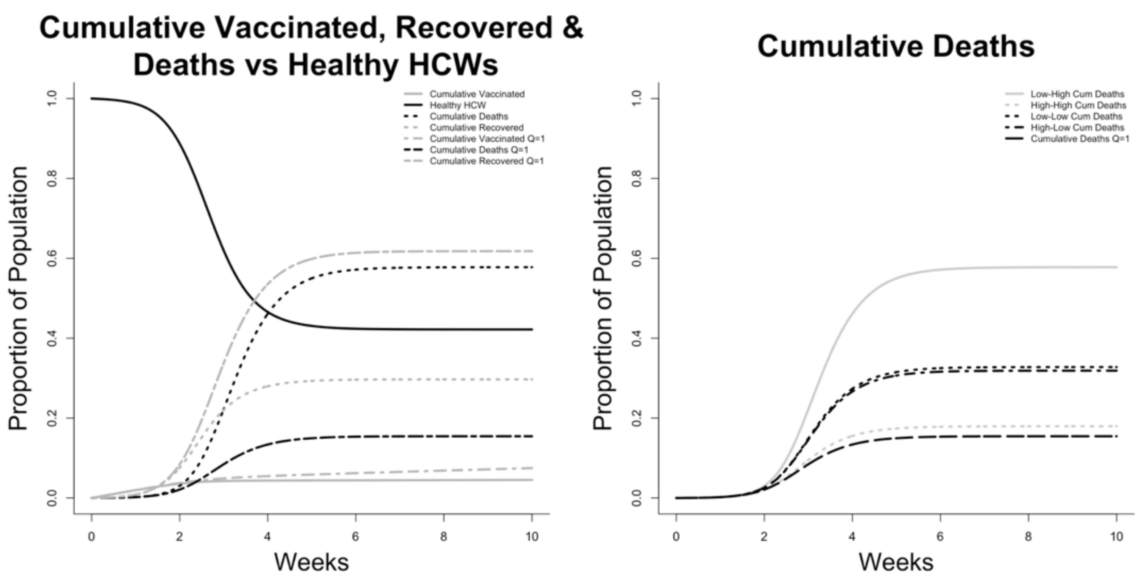


Figure 5: Impacts of the quality of care function are shown to relevant parameters as uninfected health care worker population declines.

A: Comparison between healthy healthcare worker ratio and the rates affected by the proportional quality of care function and rates when the Quality of Care Function is set to be maximal (1). Setting the quality of care function to 1 is the same as excluding it in the simulation. The model considered uses a quality of care function representing a weak healthcare system, ie high loss impact (k) and low redundancy parameter (m)

B: Cumulative deaths resulting from the simulation for the four sample sigmoidal quality of care functions from figure 3 are shown in addition to the amount of deaths resulting from having the quality of care 1, equivalent to models that do not consider it. This subfigure highlights the range of differences resulting from the shape of the quality of care function considered.

In Figure 5A, as the epidemic progresses, inclusion of the dynamic quality of care function clearly leads to drastic differences compared to the model excluding it. When decline in the quality of care is considered, the number of cumulative deaths increase by 274%, the number of vaccinations administered decreases by 40% and the number of individuals that recover decreases by 52%, using baseline parameters (Table 1). The quality of care used in Figure 5A, is one that is representative of a weak health force system with a high loss impact parameter and low redundancy parameter, which is the dotted black line seen in Figure 3. Figure 5B shows the impact inclusion of quality of care has on cumulative deaths for the four quality of care functions shown in Figure 3 and compares it to the resulting epidemic burdens when quality of care is not considered to be dynamic. While the increase in cumulative deaths that result from the inclusion of the quality of care function are not all as severe as seen in Figure 5A, the inclusion does further showcase the impact its consideration has on epidemic burdens.

Chapter 4

Discussion

Conventional epidemic models generally do not consider quality of care that changes as a disease outbreak proceeds, yet loss of healthcare workers and other impacts on quality of care could potentially radically affect disease dynamics, as it may have in the 2014 Ebola outbreak[1,21]. In this paper, we demonstrate that evolving quality of care impacts disease dynamics, and that inclusion of declining quality of care negatively impacts epidemic burdens.

If quality of care is considered to be static, this results in an underestimation of epidemic burdens. The magnitude of the impact declining quality of care on disease dynamics depends strongly on the way in which quality of care declines in response to the proportion of HCWs affected; a wide range of relatively mild to severe epidemic impacts may arise. Explicit consideration of healthcare worker dynamics (in contrast to assuming HCWs are well-mixed with the general population) also generally leads to more severe outcomes, suggesting that modeling them separately is necessary. We have shown that failing to include either of these aspects in epidemic models will cause one to underestimate, in some cases severely, epidemic burdens.

Knowing the empirical response of the healthcare system to loss of HCWs during the course of a serious outbreak would be ideal, but such trajectories are highly dependent on both context and pathogen. We avoid this issue by assuming that quality of care declines according to different, but plausible, functional forms. We specifically consider the loss impact (each healthcare worker's impact on the health system) and the level of built-in redundancy in the health system (the minimum number of health care workers required to provide adequate care); both are important, but redundancy dominates outcomes, as seen in Figure 3.

Models that explicitly incorporate dynamic quality of care may aid decision-making to control an epidemic. By anticipating the degree to which declining care quality might impact disease dynamics, control methods may be tailored to mitigate a healthcare system's redundancy and/or factors affecting loss impact, depending on the existing structure of the healthcare system. For example, the redundancy component of our quality of care scenarios did dominate outcomes and therefore is a likely initial target for improvements. This could be useful for management; for example, the level of effort put in to recruiting/training healthcare volunteers could be increased, which in turn would cause the system's redundancy to improve. It also may be beneficial to manage healthcare workers differently from the rest of the population to attempt to slow the decline in quality of care. Arguments are already made to prioritize healthcare workers for vaccination and/or other medical interventions as they are the primary source of care in epidemics[22] and often are faced with higher rates of infections compared to the general population[23]. Careful exploration of other dynamic quality of care scenarios may also lead to the identification of alternative management interventions. For example, information about quality of care decline may inform outside interventions, such as how many and when HCWs from NGOs are usefully to be deployed to assist in times of crisis, as seen in health care worker shortage during the Kenema Hospital collapse[5] (e.g. in terms of when system collapse is anticipated). This model is capable of distinguishing between these strategies, and thus is able to estimate the efficacy of a wider range of potential strategies.

Future Considerations

We used a sigmoidal function to describe quality of care; in the future we could consider other non-linear functional forms bounded between 0 and 1, for example the "Hill" function[24]. It is important to note that quality of care is likely context specific, due to the global heterogeneity in healthcare access; results may thus depend on local circumstances. Furthermore, the way in which the most complex models differentiate HCWs from the general population is deserving of further exploration; we did not fully consider how HCWs differ in infection risk and care received. As mentioned earlier, empirical data would be immensely informative, but difficult to obtain in advance. Nevertheless, with sufficient information it might even be possible to address multiple subclasses of HCWs (e.g. physicians, nurses, janitorial staff, midwives, volunteers) with different quality of care responses and different transmission dynamics based on their roles[25]. This would further allow us to explore various prioritization methods for healthcare workers to minimize impacts on quality of care provided[26].

The quality of care function might also be improved by including information on healthcare workers behavioral responses to the status of an epidemic. As an epidemic progresses further, the personal risk of working increases for healthcare workers. Behavioral avoidance of risk by HCWs, especially volunteer HCWs, may accelerate system collapse in extreme situations[21]. Applying game theoretic approaches may usefully address these tensions between personal and population-level benefits and costs/risks as HCW risk preferences may vary over the course of an epidemic[27,28]. Due to the severity and nature of the HIV outbreak in the 1980's, there were cases where healthcare workers felt overwhelmed, and in some cases avoided practicing, due to fears and burdens of the disease[29]. Accounting for behavioral or related tendencies which may impact healthcare worker participation in the work force is essential to consider their impacts to quality of care provided.

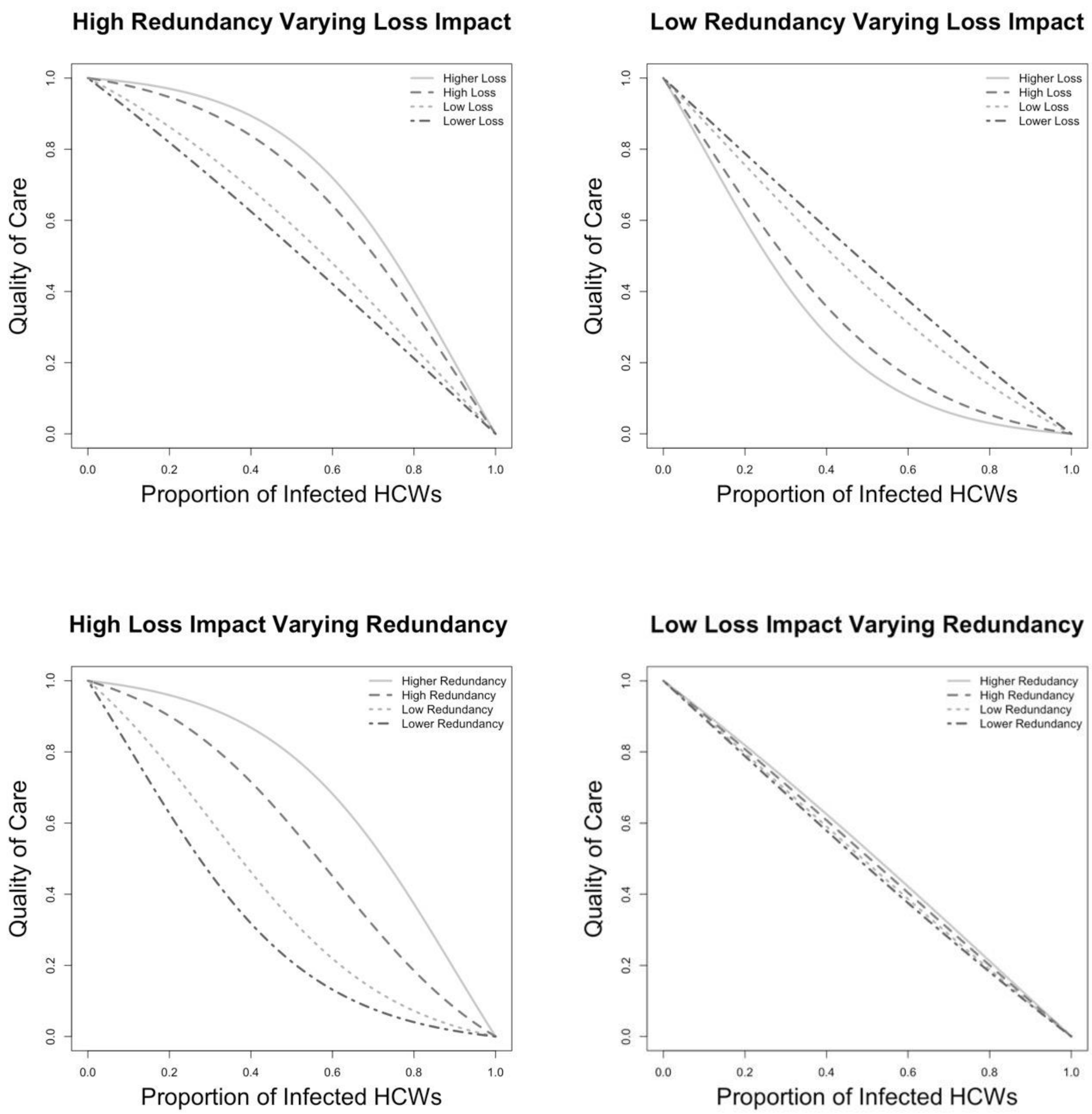
Our present work focuses on the healthcare system as it pertains to the management of one disease, but clearly there are ramifications for the quality of care provided for other public health issues. As healthcare declines, levels of care for other patients, affected by other issues, will also suffer[30]. For example, health seeking-behavior for malaria was impacted by concerns about Ebola[31,32]. In this case, the implications of failing to consider a declining quality of care function would be multiplied, and could be used to address a potential major gap in standard epidemiological modelling approaches.

Conclusion

We here demonstrate that consideration of the potential for declining quality of care affects epidemic outcomes, in some cases quite significantly. Addressing such declines in quality of care explicitly will allow epidemiologists to anticipate, plan for and mitigate changes in epidemic dynamics over the course of an epidemic. While much work remains to be done, addressing these critical issues offers significant potential public health benefits.

Appendix A

Supplemental Figures



SF1: One shape parameter is fixed in each figure while the other is varied for low/high combinations of both, per the figure titles listed.

To bound the values of the quality of care function between 0 and 1, the function was normalized, which led to counterintuitive behavior in the high loss parameter in the quality of care function. It would be assumed that a higher loss impact per worker would lead to a worse quality of care function, but this is the opposite of what is observed, due to the fact that the redundancy parameter dominates outcomes as a result of the normalization process implemented. Cases to better understand the relationship between the two shape parameters, when one is fixed and the other is varied are explained below for the Supplemental Figure shown above.

For a fixed high redundancy parameter and varying the loss impact parameter, we observe that the higher loss impact parameter leads to the largest quality of care while a lower loss impact leads to the worst quality of care for a fixed redundancy parameter. For a fixed low redundancy parameter and varying the loss impact parameter, we see that a higher loss impact parameter now leads to the worst quality of care of the figure, while the lower loss impact now is the best quality of care. It should be noted that all of the resulting quality of care functions shown here are worse than those for the fixed high redundancy parameter.

When we have a fixed high loss impact parameter and varying the redundancy parameter, it can be seen that the quality of care provided decreases as the redundancy parameter worsens, i.e., the higher redundancy parameter led to the best quality of care for any HCW proportion compared to the lower redundancy parameter led to the worst quality of care for any HCW proportion. Additionally, for a fixed low loss impact parameter and varying the redundancy parameter, once again the best resultant quality of care function for any HCW proportion is induced by the higher redundancy parameter while the worst is caused by the lower redundancy parameter. It is important to note that the quality of care for the two highest redundancy parameter levels was stronger when the loss parameter was fixed to a high value, but for the lower redundancy parameter values, the higher quality of care functions belonged to cases where the loss parameter was fixed to a lower value.

The inclusion of the normalization parameter seems to contradict the assumption behind the loss impact parameter expected in the decline of the quality of care function. This has been showcased in the breakdown of the 4 scenarios shown in the supplemental figure. It also becomes apparent that with the inclusion of the normalization, the redundancy parameter care function will decline.

BIBLIOGRAPHY

1. WHO | Unprecedented number of medical staff infected with Ebola. (2015). *WHO*. Retrieved from http://www.who.int/mediacentre/news/Ebola/25-august-2014/en/
2. WHO | Ebola response: What needs to happen in 2015. (2015). *WHO*. Retrieved from http://www.who.int/csr/disease/Ebola/one-year-report/response-in-2015/en/
3. Satalkar, P., Elger, B. E., & Shaw, D. M. (2015). Prioritizing Healthcare Workers for Ebola Treatment: Treating Those at Greatest Risk to Confer Greatest Benefit. *Developing World Bioethics*, *15*(2), 59–67. https://doi.org/10.1111/dewb.12079
4. Jay Lewis. (2008). Healthcare worker shortage may be exacerbating HIV/AIDS epidemic. Retrieved September 6, 2018, from https://www.healio.com/infectious-disease/hiv-aids/news/print/infectious-disease-news/%7B05584fa7-2670-40ad-ac4f-367f58d469e0%7D/health-care-worker-shortage-may-be-exacerbating-hivaids-epidemic
5. Check Hayden, E. (2014). Infectious disease: Ebola's lost ward. *Nature*, *513*(7519), 474–477. https://doi.org/10.1038/513474a
6. CDC. (2018). Estimating Seasonal Influenza-Associated Deaths in the United States.
7. Dawood, F. S., Iuliano, A. D., Reed, C., Meltzer, M. I., Shay, D. K., Cheng, P.-Y., … Widdowson, M.-A. (2012). Estimated global mortality associated with the first 12 months of 2009 pandemic influenza A H1N1 virus circulation: a modelling study. *The Lancet Infectious Diseases*, *12*(9), 687–695. https://doi.org/10.1016/S1473-3099(12)70121-4
8. WHO | The history of Zika virus. (2016). *WHO*. Retrieved from http://www.who.int/emergencies/zika-virus/timeline/en/
9. WHO | 2018. (2018). *WHO*. Retrieved from http://www.who.int/csr/don/archive/year/2018/en/
10. WHO | Health worker Ebola infections in Guinea, Liberia and Sierra Leone. (2016). *WHO*. Retrieved from http://www.who.int/csr/resources/publications/Ebola/health-worker-infections/en/
11. WHO | New report shows that 400 million do not have access to essential health services. (2015). *WHO*. Retrieved from http://www.who.int/mediacentre/news/releases/2015/uhc-report/en/
12. Rivers, C. M., Lofgren, E. T., Marathe, M., Eubank, S., & Lewis, B. L. (2014). Modeling the impact of interventions on an epidemic of Ebola in Sierra Leone and Liberia. *PLoS Currents*, *6*. https://doi.org/10.1371/currents.outbreaks.4d41fe5d6c05e9df30ddce33c66d084c
13. Kermack, W. O., & McKendrick, A. G. (1991). Contributions to the mathematical theory of epidemics—I. *Bulletin of Mathematical Biology*, *53*(1–2), 33–55. https://doi.org/10.1016/S0092-8240(05)80040-0
14. Loeppke, R., Boldrighini, J., Bowe, J., Braun, B., Eggins, E., Eisenberg, B. S., … Yarbrough, M. (2017). Interaction of Healthcare Worker Health and Safety and Patient Health and Safety in the US Healthcare System: Recommendations From the 2016 Summit. https://doi.org/10.1097/JOM.0000000000001100

15. Althaus, C. L. (2014). Estimating the Reproduction Number of Ebola Virus (EBOV) During the 2014 Outbreak in West Africa. *PLoS Currents*. https://doi.org/10.1371/currents.outbreaks.91afb5e0f279e7f29e7056095255b288
16. Biggerstaff, M., Cauchemez, S., Reed, C., Gambhir, M., & Finelli, L. (2014). Estimates of the reproduction number for seasonal, pandemic, and zoonotic influenza: a systematic review of the literature. *BMC Infectious Diseases*, *14*, 480. https://doi.org/10.1186/1471-2334-14-480
17. Gryphon Scientific LLC. (n.d.). *Supplemental Information-Data Supporting MERS and SARS R0*. Retrieved from http://www.gryphonscientific.com/wp-content/uploads/2015/12/Supplemental-information-R0-of-CoV.pdf
18. Qureshi, A. I., Chughtai, M., Bah, E. I., Barry, M., Béavogui, K., Loua, T. O., & Malik, A. A. (2015). High survival rates and associated factors among Ebola virus disease patients hospitalized at donka national hospital, conakry, Guinea. *Journal of Vascular and Interventional Neurology*, *8*(1.5), S4–S11. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/25992182
19. WHO | Update 49 - SARS case fatality ratio, incubation period. (2015). *WHO*. Retrieved from http://www.who.int/csr/sars/archive/2003_05_07a/en/
20. WHO. (2006). *Health Workers: A Global Profile*. Retrieved from https://www.who.int/whr/2006/06_chap1_en.pdf
21. Forrester, J. D., Pillai, S. K., Beer, K. D., Neatherlin, J., Massaquoi, M., Nyenswah, T. G., … Centers for Disease Control and Prevention (CDC), K. De. (2014). Assessment of ebola virus disease, health care infrastructure, and preparedness - four counties,Southeastern Liberia, august 2014. *MMWR. Morbidity and Mortality Weekly Report*, *63*(40), 891–893. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/25299605
22. Polgreen, P. M., Tassier, T. L., Pemmaraju, S. V., & Segre, A. M. (2010). Prioritizing healthcare worker vaccinations on the basis of social network analysis. *Infection Control and Hospital Epidemiology*, *31*(9), 893–900. https://doi.org/10.1086/655466 (21)
23. Matanock, A., Arwady, M. A., Ayscue, P., Forrester, J. D., Gaddis, B., Hunter, J. C., … Centers for Disease Control and Prevention (CDC). (2014). Ebola virus disease cases among health care workers not working in Ebola treatment units--Liberia, June-August, 2014. *MMWR. Morbidity and Mortality Weekly Report*, *63*(46), 1077–1081. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/25412067
24. Santillán, M. (2008). On the Use of the Hill Functions in Mathematical Models of Gene Regulatory Networks. *Math. Model. Nat. Phenom*, *3*(2). https://doi.org/10.1051/mmnp:2008056 (22)
25. Kilmarx, P. H., Clarke, K. R., Dietz, P. M., Hamel, M. J., Husain, F., McFadden, J. D., … Centers for Disease Control and Prevention (CDC). (2014). Ebola virus disease in health care workers--Sierra Leone, 2014. *MMWR. Morbidity and Mortality Weekly Report*, *63*(49), 1168–1171. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/25503921
26. Jagger, J., Perry, J., Gomaa, A., & Phillips, E. K. (2008). The impact of U.S. policies to protect healthcare workers from blood borne pathogens: The critical role of safety-engineered devices. *Journal of Infection and Public Health*, *1*(2), 62–71. https://doi.org/10.1016/J.JIPH.2008.10.002

27. Coles, J., & Zhuang, J. (2011). Decisions in Disaster Recovery Operations: A Game Theoretic Perspective on Organization Cooperation. *Journal of Homeland Security and Emergency Management*, *8*(1). https://doi.org/10.2202/1547-7355.1772
28. Bauch, C. T., & Earn, D. J. D. (2004). *Vaccination and the theory of games*. Retrieved from www.pnas.orgcgidoi10.1073pnas.0403823101
29. Lin, C., Li, L., Wu, Z., Wu, S., & Jia, M. (2008). Occupational exposure to HIV among health care providers: a qualitative study in Yunnan, China. *Journal of the International Association of Physicians in AIDS Care (Chicago, Ill. : 2002)*, *7*(1), 35–41. https://doi.org/10.1177/1545109707302089
30. Tawfik, L., & Kinoti, S. N. (2006). *The impact of HIV/AIDS on the health workforce in developing countries*. Retrieved from http://www.who.int/hrh/documents/Impact_of_HIV.pdf
31. Parpia, A. S., Ndeffo-Mbah, M. L., Wenzel, N. S., & Galvani, A. P. (2016). Effects of Response to 2014-2015 Ebola Outbreak on Deaths from Malaria, HIV/AIDS, and Tuberculosis, West Africa. *Emerging Infectious Diseases*, *22*(3), 433–441. https://doi.org/10.3201/eid2203.150977
32. Takahashi, S., Metcalf, C. J. E., Ferrari, M. J., Moss, W. J., Truelove, S. A., Tatem, A. J., … Lessler, J. (2015). Reduced vaccination and the risk of measles and other childhood infections post-Ebola. *Science*, *347*(6227), 1240–1242. https://doi.org/10.1126/science.aaa3438

ACADEMIC VITA

Education

The Pennsylvania State University
Schreyer Honors College & Paterno Fellows Program
Majors: Mathematics (BS)-Systems Operations Option and Economics (BS)
Minor: Statistics

Research Experience

S.M.A.L.L. REU - Undergraduate Researcher Williams College *Summer 2018*

• One of 40 undergraduate researchers selected to participate in a summer of research.

• Worked under Dr. Julie Blackwood in small groups to study the impact of dispersal on the implementation of control to mitigate the spread of white nose syndrome in bats in a multi-hibernaculum setting.

• For a separate project, under a larger scope of Ecological Federalism, we explored optimal governance scenarios for disease management in two states with migration to determine where jurisdiction of control should optimally fall via a decision-making component as individual objectives may not be the same

• Manuscripts were written for both projects with the aim to publish in the upcoming year.

Shea Lab – Undergraduate Research Assistant The Pennsylvania State University

PI: Dr. Katriona Shea – Infectious Disease Lab *January 2016-Present*
Collaborating with Dr. Jessica M. Conway from the Math Dept.

Applied Mathematics REU - Pennsylvania State University *Summer 2016*

•Learned to use R to develop infectious disease models, which would be used in an independent project.

•Currently conducting an independent project analyzing how changes in the health status of health care workers impacts epidemic burdens.

•Spent a summer continuing this project work after being accepted into the Applied Mathematics REU at Penn State during the summer of 2016.

•Manuscript has been written with the intent to submit to Epidemics, and will also serve as my honors thesis.

Independent Study – Dr. Christopher Byrne The Pennsylvania State University

•Conducting a project related to a repeated prisoner's dilemma scenario *Sept 2018-Present*

•Through the use of differential equations, we are challenging assumptions made by an earlier Foster and Young paper, as we believe they do not have the correct basis of attraction in their model.

Conferences

Annual Biomedical Research Conference for Minority Students (ABRCMS) Phoenix, AZ

•Presented my independent project conducted in the Shea Lab as a poster presentation November 2017.

•Awarded a top presentation award in the category of Computational Biology.

All-In Conference The Pennsylvania State University

•I presented my work from the Shea lab as a representative of the Millennium Scholars Program to various faculty members from Penn State.

•This conference highlighted work that was done by individuals in STEM minority groups at Penn State University.

Working Papers

Analyzing how Changes in the Health Status of Healthcare Workers Impacts Epidemic Burdens

•Manuscript in progress with aim to submit by the end of 2018

Efficacy of control in a spatially dynamic model of White Nose Syndrome

•Manuscript in progress with aim to submit in 2019

Transboundary Disease Management Under Alternative Objectives

•Manuscript in progress with aim to submit in 2019

Work Experience

Lincoln Financial Group – Actuarial Intern in Life-Inforce Optimization Greensboro, NC

•Utilized VBA to reduce human error and time of processes from hours to minutes. *Summer 2017*

•Revised calculator with frasierization process to find Joint-Life policies suited for Enhanced Cash Surrender Value.

•Created a groundwork process for the development of new tracking database for IFO for thousands of entries.

•Adapted Retention Basis Calculator to work with new sets of policy data.

•Validated PLT Rates with current assumptions and summarized data in monthly workbooks.

•Passed P, FM & MFE actuarial exams and completed all VEE credits

Mehta Prep Academy – Mathematics/Economics Chair The Pennsylvania State University

•Led tutoring sessions for various math and economic classes weekly *January 2016-Present*

•Involved in company decisions as a board member of start-up

•Helped streamline process to reduce training time for new tutors as well as formally training tutors

•Our company aims to help students get through their entrance to major classes so they can succeed on their respective major paths.

Millennium Scholars Program – Peer Tutor The Pennsylvania State University
•Tutored fellow peers in the Millennium Scholars Program weekly. *January 2016-Present*

•Helped incoming freshman and sophomores learn the introductory math classes they struggled in to prepare them for their future work

Leadership and Extracurricular

Millennium Scholars Program – Cohort Council President (2017-2018)

•Highly selective program for high achieving STEM students pursuing higher education accompanied with a $15,000 per year scholarship for 4 years.

•Member of search committee for new director along with deans from the colleges associated with the program.

•Led and participated in science outreach days for cub scouts to teach and increase interest in science among young children through simple experiments.

•Mentor in the mentoring program to offer guidance and advice to underclassmen peers in the Millennium Scholars Program to ensure their future success.

Actuarial Science Club The Pennsylvania State University
•Attended professional workshops geared towards professional development and networking.

THON Dancer Relations Committee Member The Pennsylvania State University

•Assisted and motivated dancers as a volunteer for THON 2016, 2017 & 2018 *2016-Present*

Assistant Scoutmaster

•Supervised and was responsible for Boy Scouts in Troop 60 during outing *Aug 2015-Present*

Honors/Awards

Eagle Scout - August 2014

•Highest award attained in Boy Scouts of America

Schreyer Academic Excellence Award - August 2015

•Academic Merit Scholarship awarded to individuals admitted into the Schreyer Honors College at Pennsylvania State University - $4,500/year.

Pennsylvania State University Provost Award - August 2015

•Academic Merit Scholarship awarded to individuals based on merit upon admission into Pennsylvania State University - $4,000/year.

Pennsylvania State University Outstanding Student in Economics Award - October 2018

•Awarded to high achieving individuals in the major of economics at Pennsylvania State University - $2,000.

Skills - Advanced in R, Excel, Word & PowerPoint; Proficient in Python, Matlab, LaTeX & VBA; Novice in Access, SQL, STATA & SAS