Impact of Comorbidity on Mortality rate among Patients with COVID-19

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Abstract

COVID-19, a coronavirus disease 2019, is an ongoing pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first case in Kenya was identified on March 13, 2020, with the pandemic increasing to about 237,000 confirmed cases and 4,746 deaths by end of August 2021. The deaths among COVID-19 patients are closely related with their pre-existing conditions (comorbidities) [3] that may include hypertension, diabetes, cancers, chronic respiratory diseases among others [2]. We developed a deterministic SEIR model to predict the COVID-19 pandemic in Kenya. An SEIR compartmental model was developed to predict the daily new cases, severe, critically ill, and death cases of COVID-19. The model had 8 compartments containing sub-populations of: Susceptible, Exposed, Symptomatic Infectious, Asymptomatic Infectious, Hospitalized, Intensive Care Unit, Deaths and Recovered. The model equations were then solved to obtain the number of cases that would be infected on a daily basis beginning March 14th to July 2021. The average time difference between the peaks of wave 1 to wave 3 was observed to be about 130 days. At the peaks of the three waves, there were 485, 578 and 455 new patients with a comorbid condition in wave 1, 2 and 3 respectively. These represents 43percent of the total new cases notified with COVID-19. During the peaks of the three waves, a total of 37, 46, and 32 patients developed severe disease meaning they would require hospitalization. A total of 14, 18 and 12 patients then would develop critical illness and therefore, would require intensive care unit (ICU) services [1]. From our study results, at the peak of wave 1 to 3, there were 3, 4 and 3 deaths respectively of patients with comorbidities. These represents a 23percent mortality rate of the deaths due to COVID-19 for patients who had other comorbidities. The mortality rate represents a 10-fold times of the overall population. The findings of this study are key in developing informed mitigation strategies to ensure that the pandemic is contained and inform the preparedness of policy makers and health care workers. Further, populations with comorbidities require special interventions to ensure prevention of transmission and aversion of deaths for those who acquire the disease.

Introduction

The novel coronavirus 2019 is a constituent of a group of corona viruses revealed in 1968 by an eight-member group of virologists. The emergent coronavirus in 2019 was first called ‘2019-novel coronavirus’ (2019-nCov) by the Word Health Organization (World Health Organization, 2020) on 22th January 2020. Later, WHO christened the disease caused by the virus as ‘COVID-19’. The spread of the virus is said to have originated from an animal to human ([1]). Later, through human-to-human transmission, the disease was spread to most of the countries globally with 194,080,019 confirmed cases and 4,162,304 deaths as at 26th July 2021.

The clinical symptoms include; fever, cough, gastro-intestinal infections and difficulty in breathing ([2],[3]). This led to development of global standard precautionary elements for acute respiratory diseases (ARDs) namely; hand hygiene; use of personal protective equipment (PPE) to avoid contact with the patient’s body fluids and non-intact skin; respiratory hygiene and cough etiquette;

waste management; and cleaning and disinfection of the environment and equipment among other [3].

Since the first case in Kenya was reported on 13th March 2020, various public health interventions which include social distancing measures, wearing of protective masks, curfews, closure of schools, isolation, quarantine and cessation of movement were instituted. A total of 197,959 cases has since been notified and 3872 deaths by 26th July 2021. One of the major challenges that Countries are facing in controlling the disease is the mutation of the corona-virus that has led to multiple waves of the pandemic in most of the affected Countries. According to WHO, the variant of concern at the moment is the Delta variant which is more transmissible.

A study done in China by [4] found out that there was a great effect of the interventions implemented in reversing the transmission of new infections. Kenya Continues to implement the non-pharmaceutical measures and in addition rolling out the vaccination to its citizens. Despite all the efforts being made, the number of cases continue to increase and so far, 3 waves of the pandemic have already been observed. The most transmissible variant; delta was first detected in Kisumu County in the Western Kenya. This variant has since spread to various counties in the country that include, Nairobi, Mombasa, Nakuru, Siaya, Homabay, Kiambu, Machakos among others.

Given the dynamics of this pandemic, countries have to keep monitoring and tracking the disease status to ensure control interventions are put in place up front. Disease modeling has been cited as one of the strategic tools in understanding the disease patterns and evaluating the impact of various control measures ([5], [6]).

Further to the use of mathematical models to predicting the future of COVID19 transmission, a study by Thompson referred them to be of utmost importance in determining the undefined impact of ”re-opening economies” decisions ([6], [?]) as reported by Kiarie et.al (Preprint,2021). A number of mathematical modeling studies have been done so far in different Countries. Most of them have used global parameters to model the disease progression ([7], [8]).

The objective of this study was to model the progression of COVID-19 cases in Kenya. An SEIR deterministic model was developed by first using the available data to estimate the model parameters, and secondly modeling the pandemic using the local parameters. This will be useful in informing planning of resources, preparedness of health facilities and creating awareness on the future curves, daily infections and peak times.

Main text

Methods

To describe the transmission and spread of COVID-19, eight (8) disease states compartmental model is used. The total population N(t) at any time t is sub divided into compartments (S) containing the susceptible individuals, (E) the exposed who are presumed to be in the incubation stage of the disease, after exposure some of the individuals will develop the disease without symptoms (A), others will develop the disease and show symptoms (M). The infected will then be hospitalized (H) and it’s assumed that some will move to critical illness (C). Some of the critically ill will die due to severity of the disease (D). The individuals that recover from either asymptomatic disease, symptomatic disease, hospitalization or critical illness will be denoted by (R). Where;

$$N(t) = S(t) + E(t) + A(t) + M(t) + H(t) + C(t) + D(t) + R(t) \quad (1)$$

The transmission model is illustrated in the flow diagram labeled Figure 1.

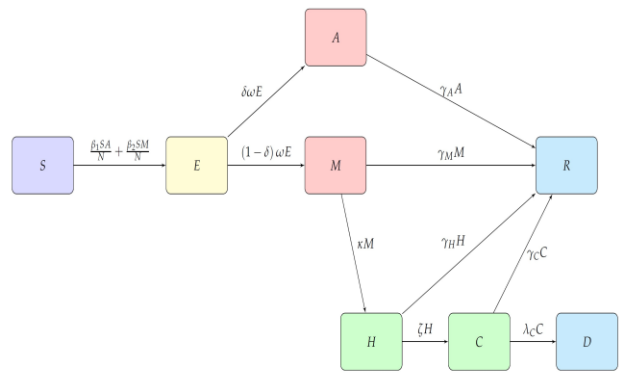

Figure 1 SEIR model of COVID-19 transmission

The COVID-19 transmission model parameters are defined in the table 1.

Table 1 Description of model parameters.

Parameter description	Symbol	Value
Rate of transmission from S to E due to contact with I_A	β_1	0.151
Rate of transmission from S to E due to contact with I_M	β_2	0.436
Proportion of symptomatic infectious people	δ	0.803
Progression rate from E to either I_A or I_S	ω	0.15
Recovery rate of the asymptomatic infected individuals	γ_A	0.9495
Recovery rate of the symptomatic infected individuals	γ_M	0.4996
Recovery rate of the hospitalized individuals	γ_H	0.5003
Recovery rate of the critically ill individuals	γ_C	0.55
Rate of movement from hospitalization to critical illness condition	ζ	0.4994
Hospitalization rate of the symptomatic infected individuals	k	0.02598
Death rate of the critically ill due to the virus	λ_c	0.4999

The parameters listed in the table above were estimated from the data reported up to 26th July 2021.

The ordinary differential equations of the transmission model are therefore formulated as follows.

$$\begin{cases} \frac{dS}{dt} = -(\frac{\beta_1 SA}{N} + \frac{\beta_2 SM}{N}) \\ \frac{dE}{dt} = \left(\frac{\beta_1 A}{N} + \frac{\beta_2 M}{N}\right) S - \omega E \\ \frac{dA}{dt} = \delta\omega E - \gamma_A A \\ \frac{dM}{dt} = (1-\delta)\,\omega E - (\gamma_M + k)\, M \\ \frac{dH}{dt} = kM - (\zeta + \gamma_H)\, H \\ \frac{dC}{dt} = \zeta H - (\gamma_C + \lambda_C)\, C \\ \frac{dD}{dt} = \lambda_C C \\ \frac{dR}{dt} = \gamma_A A + \gamma_M M + \gamma_H H + \gamma_C C \end{cases} \qquad (2)$$

where the initial conditions are;

$S(0) \geq 0, E(0) \geq 0, A(0) \geq 0, M(0) \geq 0, H(0) \geq 0$ (3)

The susceptible transition to latent phase of the disease at a rate β. Movement from latency to either asymptomatic or symptomatic infected happen at a rate of ω. The infected then progress to hospitalization at a rate k and either move to the critically ill compartment at a rate ζ or to recovery at a rate γ. The critically ill cases could either recover or die at a rate of γ and λ respectively. The recovery rate of the asymptomatic cases is defined by γ. The main aim of social distancing interventions is to minimize the rate at which the infectious individuals come into contact with the susceptible population

In this work, the parameters were estimated using the least squares method. Where $y = (y_1, y_2,\ldots,y_N)$ and σ_2 is the estimated measurement error which is calculated as the mean square error (MSE = RSS \ (N − p)). RSS is the residual sum of squares; N represents the number of measurements and p the number of parameters in the model.

Results

The average time difference between the peaks of wave 1 to wave 3 was observed to be about 130 days. At the peaks of the three waves, there were 485, 578 and 455 new patients with a comorbid condition in wave 1, 2 and 3 respectively. These represents 43 percent of the total new cases notified with COVID-19. During the peaks of the three waves, a total of 37, 46, and 32 patients developed severe disease meaning they would require hospitalization. A total of 14, 18 and 12 patients then would develop critical illness and therefore, would require intensive care unit (ICU) services [1]. From our study results, at the peak of wave 1 to 3, there were 3, 4 and 3 deaths respectively of patients with comorbidities. These represents a 23 percent mortality rate of the deaths due to COVID-19 for patients who had other comorbidities. The mortality rate represents a 10-fold times of the overall population.

Pandemic Peak days and number of cases by Waves in Kenya										
	Wave	Wave 1			Wave 2			Wave 3		
		AC	WC	CC	AC	WC	CC	AC	WC	CC
New Cases	Day	122nd	122nd	122nd	221st	221st	221st	358th	358th	358th
	No of Cases	1128	485	19	1344	578	23	1057	455	18
Severe Cases	Day	129th	129th	129th	232nd	232nd	232nd	365th	365th	365th
	No of Cases	87	37	1	106	46	2	75	32	1
Critical Cases	Day	135th	135th	135th	236th	236th	236th	374th	374th	374th
	No of Cases	33	14	1	41	18	1	29	12	0
Deaths	Day	135th	135th	135th	236th	236th	236th	371st	371st	371st
	No of Cases	33	14	2	41	18	3	28	12	2

AC	All Cases
WC	With comorbidities
CC	Cancer cases

Table 2 Summary of Peak days and number of Cases.

Discussion

The model shows that the pandemic has persisted with 3 waves already experienced as at 26th July 2021. According to the peak days observed in the three waves, it takes about 120 days on average to get to the peak of each of the three waves of infections with over 1000 new cases reported daily. Withdrawal of social restriction measures and reopening of Countries' economies is a major risk to resurgence of new infections and at a higher rate of transmission. This could be associated to social behavior changes, more contact time at places of work, schools, in travels among other avenues. This study results are in agreement with those of ([9] [10]) whose findings were that the aggregate number of cases had an exponential growth with time when mitigative measures were stopped. Other studies like that done by [11] also indicated that re-opening economies and withdrawing interventions could result in a devastating state of the disease. Further,[12] found out that ignoring infection prevention control measures; social distancing, wearing masks, hand washing and travel controls would result to ravaging effects on the susceptible individuals.

With such effects of lifting mitigation measures, it is important to conduct continuous testing for COVID-19, put an emphasis on vaccination and use data to come up with real time parameters to predict future trends of the pandemic. This will ensure that new infections are isolated in real-time, well-informed policies are created, health systems are prepared as well as herd immunity against disease is attained.

References

1. Heymann, D.L., Shindo, N.: Covid-19: what is next for public health? The Lancet (2020)
2. Guo, Y.-R., Cao, Q.-D., Hong, Z.-S., Tan, Y.-Y., Chen, S.-D., Jin, H.-J., Tan, K.-S., Wang, D.-Y., Yan, Y.: The origin, transmission and clinical therapies on coronavirus disease 2019 (covid-19) outbreak–an update on the status. Military Medical Research (2020)
3. Organization, W.H.: Epidemic-prone and pandemic-prone acute respiratory diseases. summary guidance: Infection prevention & control in health-care facilities. World Health Organization and others (2007)

4. Leung, K., Wu, J.T., Liu, D., Leung, G.M.: First-wave covid-19 transmissibility and severity in china outside hubei after control measures, and second-wave scenario planning: a modelling impact assessment. The Lancet (2020)
5. Jewell, N.P., Lewnard, J.A., Jewell, B.: Predictive mathematical models of the covid-19 pandemic: Underlying principles and value of projections. Jama (2020)
6. Thompson, R.: Epidemiological models are important tools for guiding covid-19 interventions. BMC Medicine (2020)
7. Zareie, B., Roshani, A., Mansournia, M.A., Rasouli, M.A., Moradi, G.: A model for covid-19 prediction in iran based on china parameters. MedRxiv (2020)
8. Santosh, K.: Covid-19 prediction models and unexploited data. Journal of medical systems (2020)
9. Saez, M., Tobias, A., Varga, D., Barcel´o, M.A.: Effectiveness of the measures to flatten the epidemic curve of covid-19. the case of spain. Science of the Total Environment (2020)
10. Courtemanche, C.J., Garuccio, J., Le, A., Pinkston, J.C., Yelowitz, A.: Did social-distancing measures in kentucky help to flatten the covid-19 curve? uknowledge.uky.edu (2020)
11. Feng, Z., Damon-Feng, H., Zhao, H.: Sustaining social distancing policies to prevent a dangerous second peak of covid-19 outbreak. medRxiv (2020)
12. Mwalili, S., Kimanthi, M., Ojiambo, V., Gathungu, D., Mbogo, R.W.: Seir model for covid-19 dynamics incorporating the environment and social distancing. pprint (2020)