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MODELLING THE EFFECTIVENESS OF COVID-19 INTERVENTION MEASURES FOR DIFFERENT DEMOGRAPHIES

BY

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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ABSTRACT

The study aims to discuss on how differences in timing and duration of implementation of an intervention measure would affect the results from intervention. It also seeks to find how effectiveness of an intervention would differ if put in different countries with different demographic characteristics. A Susceptible- Infected- Recovered (SIR) model is developed to provide a theoretical framework for the study. The model uses the SIR model but accounts for different demographics and how intervention (school closure) affects the rate at which individuals move form susceptible to infected. Using data of confirmed cases of different countries and the interventions put in place, the study deduces the importance of timing and duration in implementation of an intervention. The study deduces that for an intervention to be greatly effective considerations must be done on the timing and duration of the intervention. Demography of a region should be considered when picking out an intervention.

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1.0 INTRODUCTION

1.1 Background

Pandemics are diseases that affect a large population and is spread over multiple countries. They can cause significant economic, social, and political disruption. In the 21st century, there have been six pandemics preceding Covid-19. This comes in a span of 20 years. 'Studies have shown that this can be attributed to the increase in global travel and integration, urbanization, and greater exploitation of the natural environment' (Jones et al 2008, Morse 1995).

SARS virus was identified with its first patient from Guangdong Province in China in November 2002. According to WHO, it affected 26 countries and had a total of 8437 cases by 11th July 2003. In 2012, Middle East Respiratory Syndrome (MERS) was identified with the first case in Saudi Arabia with about 35% of the total cases dying. It has affected 27 countries. Ebola outbreaks have been seen in West Africa with 2014-2016 being the worst.

Late November 2019 would see the birth of Covid-19 with the first case in Wuhan, China. It was not until late January that the virus took a turn for the worse. As of 2nd February, 2021, there have been 213 countries affected, more than 84,588,500 million reported cases, and 1,835,788 deaths.

Pandemics although do not occur on regularly, although tend to be increasing in frequency due to global networking, often leave much damage with huge death tolls. The 1918 flu led to about 50 million deaths. The spread of a pandemic is driven by how quickly it is bound to spread and where it arises from. African countries tend to be more prone to high spread due to lack of measures, high poverty levels, and underdeveloped health care systems.

These pandemics lead to economic disruptions. Due to the Covid-19 threat, most governments have implemented social distancing and lockdowns. As of the 2nd week of May 2020, the oil prices were negative. Due to lockdown, there is no traveling that has affected the tourism industry, which accounts for 10.4% of the total Gross Domestic Product (GDP) worldwide as of 2019. America has decided to print out more money to pay for the $1,200 checks Americans are bound to get to finance them. But this is possible because the American dollar is not tied to gold or other assets and currencies. This cannot be said for other countries. But printing out money would lead to an influx of money in the economy, hence weakening the dollar.

During the lockdown, most companies and learning institutions have moved towards online platforms such as Zoom and Skype. This has given a boost to online service providers and companies are now moving digital. Studies have shown that after pandemics there has been economic growth. After the

1918 flu industrial economies were no longer bound by Malthusian constraints. (Elizabeth Brainerd, Brandeis University) American cities that suffered worse from the disease grew faster afterward. Pandemics should be contained to prevent rampant spread. This would mitigate against risks it is associated with. By modelling the spread of Covid-19, would allow for better insight into the economic, social, and political disruptions that may come along with it. Countries would also prepare themselves accordingly.

1.2 Problem statement

The occurrence of pandemics and the extent of its effect has increased in the 21st century. This has led to research on disease modelling and appropriate interventions.

In recent years there has been more interest in disease modelling and with the Ebola outbreak more on pandemics. Covid-19 has led to numerous predictive models being established and more insights into deep learning. One of the earliest models was the Kermack-McKendrick model (1927) that introduced the concept stochastic of infection and recovery by dividing the population into three states: Susceptible, Infectious and Recovered (SIR). This has seen many SIR models some of which involve partial differential equations and other statistics. (Fokas, Dikaios & Kastis, 2020) uses the Ricatti equation for predictive modelling of Covid-19.

To reduce impact of a pandemic, Governments need to come up with intervention measures. The process of achieving the most appropriate and effective measures may be riddled with losses and failures. To minimize this, there may be a need to understand the region's demography.

1.3 Research objectives

The study aims to discuss the following:

1. Fitting the SIR model
2. To determine the effect of timing and duration of an intervention in case there is a pandemic.
3. To determine how effectiveness of school closure on different demographic characteristics.

1.4 Research questions

1. Does timing and duration of an intervention affect its effectiveness?
2. Does school closure effect differ with different demographic characteristics?

1.5 Significance of the research

The research will be beneficial to governments, health committees, and pandemic committees by getting insight into how a pandemic would spread to put appropriate measures in place to assist in curb the disease before massive damage occurs.

It would be beneficial to the government by giving insight to appropriate suppression measures to be put in place in case of an outbreak, and mitigation measures in the early stages of an outbreak or whether to put both measures in place. For health committees, it would give an insight on how to prepare for health-related concerns as on how the pandemic is expected to spread. Pandemic committees would be better prepared for the extent of the outbreak. The study aims to be beneficial to other researchers.

2.0 LITERATURE REVIEW

2.1 Introduction

Due to the reduction in the intervals between pandemics occurrences and the increase in their effects either economically or physically there has been a need for better forecasting methods. This section will review the different types of pandemic models. It starts with the SIR model that has become the basis for most of the models after. Secondly, a look into other recent models. Then interventions that have been put in place to curb the spread of a pandemic. Finally, the section will review socio-economic factors and their effect on outbreaks.

2.2 Review of SIR model

In 1925 McKendrick published a journal on the applications of mathematics to medical problems. The journal makes its first assumption that the human body or its cells are moving in all sorts of dimensions, hence can be reviewed by systems that study kinetics. By allocating compartments or cells to a human body with the first cell indicating his current condition and arrows indicating the probability of moving to the next cell, then if the arrows progressively become larger(smaller) there is an increase in susceptibility(immunity).

McKendrick and Kermack (1926) came up with the approach that in a population (N) where there is one infected person, individuals can go through three states: from susceptible (S), to infected (I), and recovered (R). Where S is the number of individuals at time t that can be infected, I is the number of individuals at time t that are infected and can transmit, and R is the number of individuals at time t that have become immune or dead.

The model combines compartments or deterministic approach with stochastic elements. The deterministic aspect of the model is the categorization of the population into S, I, and R. The stochastic aspect comes in when differentiation is done to obtain how S, I, and R change with respect with time. The following are the ODEs:

- $\frac{dS}{dt} = -aSI$; the coefficient is negative because S becomes smaller with increase in I
- $\frac{dI}{dt} = aSI - bR$; the infection coefficient is negative since recovery in an infected implies that infected population reduces by one infected. Change in I with respect to t is dependent on values of both S and I.
- $\frac{dR}{dt} = bI$; every loss from the infected population is gained in the recovered population through immunization or death.

- $N = S(t) + I(t) + R(t)$

The model assumes that N is fixed, no incubation period of the disease, infection is likely to occur if the disease is still there, and the population is homogeneous with no age, or social structure.

In simpler terms R=N-S, that is recovered(susceptible) is equal to the population less susceptible(recovered). By use of logarithms the equation $Ro = \frac{aN}{b}, Ro > 1$ is obtained, where the initial infected population, lo is small as compared to N. This implies that the disease would have non-negligible effects if Ro < 1, that is secondary infections from one infect would be very few so epidemic will die down. Parameter aN can be read as the numbers of infects per unit time via one infected individual while $\frac{1}{b}$ is the average infectious period bring about that Ro is the average number of secondary cases due to one infected person at the beginning of the epidemic.

The graph representing $\frac{dR}{dt}$ is similar to an exponential curve. If the plotted using lognormal figures a linear graph is obtained that can be used for forecasting.

2.3 Review of previous studies

Fokas et al (2020) built a predictive model for the value N(t) using the Ricatti equation that is specified by a time independent equation and a constant parameter N_f. The study comes up with a model that can give the upper bound and lower bound of $N(t)$ which can be done by birational and rational models, respectively. The rational model gave a better lower bound as compared to the logistics model.

Lixiang Li et al. (2020) modelled the transmission of the pandemic using Gaussian distribution. The distribution is used to estimate Ro, the number of secondary cases from one infected individual, starting with one infect infecting one susceptible then gradually increasing. But the rate at which Ro increases is affected by the -measures put in place in the area. It also makes assumptions that during the incubation period one is unaware and hence transmits without knowledge. The distribution also considers the period before recovery into account.

According to Fast, Gonzalez and Natasha (2015) "The spread of a disease and social response are simulated under several different intervention strategies". The study uses the Monte Carlo simulation to estimate the total number of infections and respective social response strategies. This is done by simulating the costs of intervention, social response, and the disease if summing them would give the cost of an outbreak. Simulations were done by AnaLytic Anxiety Response Model (ALARM) and a stochastic model. Simulations determined the most cost-effective social distancing strategy. The results were that depending on the type of intervention and perception of the risk different approaches should be taken.

2.4 Interventions with pandemics.

Interventions can be either pharmaceutical or non- pharmaceutical. Pharmaceutical interventions include vaccines, lifestyle habits, and disinfecting. Non-pharmaceutical interventions include social distancing, the closing of borders, and quarantines. The values of infected persons differ from one place to another. The control measures put in place vary by implementation date, type of intervention and, to what extent is the government intervening. Recent pandemics and epidemics have a lower number of deaths and infected as compared to when strategies were more primitive.

Non-pharmaceutical interventions aim to contact rates. Two strategies are mitigation that aims to slow down the spread of the disease and suppression that aim to reverse the growth of the disease by getting Ro<1 (Ferguson N.M. 2020). In the absence of any interventions, the paper found that the disease would reach a peak after three months and time would slightly vary between the USA and Great Britain due to their different demography. To get R_o to below 1 or close to, there would be a need for a combination of different interventions, most likely quarantine, social distancing, and closure of learning institutions. A feasible solution would-be a short-term mitigation policy that would reduce deaths by up to 50%.

Kucharski A.J et al (2020) combined a stochastic transmission model with datasets from Wuhan to determine the early dynamics of transmission. There was an estimated transmission decline of 50% after travel restrictions were placed.

To decide on the type of intervention consideration of the time of implementation and extent of damage done by the disease is important. Even the best policies may fall short in the case of implementation at the wrong time.

2.5 Socio-economic with pandemics

Pandemics leave a significant negative influence on the economy. After a pandemic with more than 100,000 deaths, there is a large contraction in the labor force, thus in the ratio of labor to capital. After a pandemic comes a decline in economic activities hence a need to borrow that leads to a debt that needs appropriate policies for its payment (Jorda Oscar, Singh S.R., Taylor A.M 2020). Oil prices had shot to negative in April 2020 and growth rates showed a decline. The economic impact of a pandemic is increasing as globalization is expanding.

The larger the susceptible population the easier it is to contact an infected person, hence the greater the value of R_o. Movement between different states or countries will affect the rate of transmission. According to Fan Changyu et al (2020), there is a correlation between the floating population in Wuhan and the number of infected in Wuhan.

Different infectious age influences the transmission trend. Age is important during the earlier states of transmission (Yang J., Chen Y. 2017). The younger and older population are more prone to infection. The young are more reckless while the older have a low immunity. Areas that have more of the young or older population like Great Britain are more prone to higher cases of Covid-19.

Most countries that are underdeveloped have poor health facilities and are have little to no preparedness in the case of an outbreak. An outbreak would require interventions and a decline in economic activities due to reduced labor force participation because of fear of infection (UNICEF 2020). This would require the countries to fund the intervention policies for effective results. To execute a lockdown there is a need to finance the informal sector worker and that there would be a need to revise financial policies such as tax.

2.6 Conclusion

This part of the study has looked into SIR models and other approaches to modelling of pandemics researches done on interventions and socio-economic factors with pandemics. However, most of the researches done have focused more on either socio-economic factors or interventions. Based on the above, the study will look into both socio-economic factors and interventions.

3.0 METHODOLOGY

3.1 Research design

This study will follow an inferential research design using quantitative data and qualitative data. Inferential research design allows for predictions on a parameter by use of sample data that can be later applied to a larger population. This study attempts to predict the spread of pandemics and how the results would differ in different areas due to variables, hence inferential research is most suitable.

3.2 Population and Sampling

The number of countries affected by the Covid-19 pandemic is slightly over 200. Different countries have different development achievements and varying environments. African countries belong to the developing economies hence low per capita income.

The study will look into three countries: Kenya, Canada, and South Korea. Kenya is a third world country implying that it is a developing country with a large population and a low GDP per capita. Canada and South Korea belong to developed countries. However, Canada has better welfare and abundant resources and a higher GDP per capita.

3.3 Data Collection

The data used will be secondary data. The main sources of the data will be from WHO, published journals, and country wise health reports. Data collected is Covid-19 reports, healthcare reports and demography of the country. The Covid-19 data will be from John Hopkins Research Centre, downloaded via Humanitarian Data Exchange.

The Covid-19 data will entail daily data of infected, recovered, and deaths by country. Data on mitigations implemented will be obtained from the respective governments and articles.

3.4 Data Analysis

The study uses both descriptive analysis and transmission dynamic modelling. Descriptive analysis is applied to get a correlation amongst the variables. Descriptive statistics will enable the obtainment of measures of central tendencies and variability. This is done by Python. The statistics will be presented in charts for better visualization. The graphical representation would enable easy identification of trends and changes.

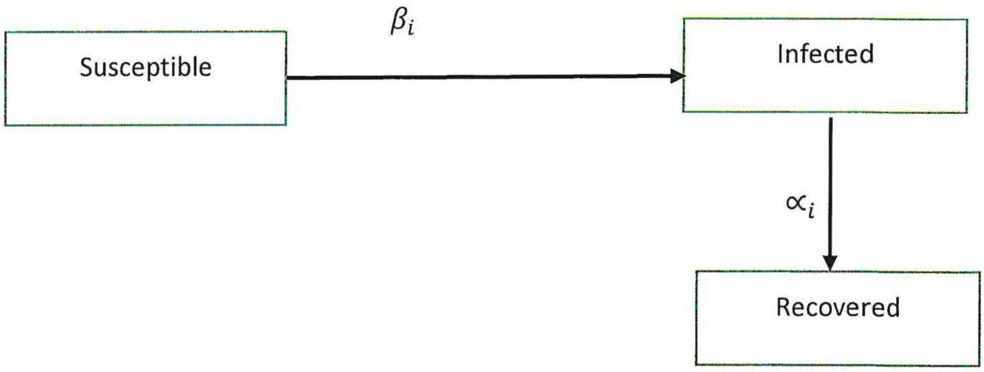
The study aims to predict the value of R_0. The study will be using transmission dynamic model since model will be accounting for non-pharmaceutical interventions and socio-economic factors.

Transmission dynamic models give insight to how a model behaves and responds to interventions (Ted & Peter, 2016).

The model adapted has the following assumptions:

- All infected individuals who recover develop an immunity.
- The population is closed.
- The population is divided into 5 age groups.

A graphical representation of the model:



The differential equations are:

- $\frac{dS}{dt} = -\beta_i S\left(\frac{I}{N}\right)$
- $\frac{dI}{dt} = \beta_i S\left(\frac{I}{N}\right) - \alpha_i I$
- $\frac{dR}{dt} = \alpha_i I$

Where the symbols represent the following:

- β_i Is the rate at which individuals in age group i move from susceptible to infected with (I/N) representing the demography concept.
- $\propto_i$ is rate at which an individual in age group i shifts from infected to recovered.

The differences in demography are accounted for when the study assumes that N is equivalent to the country's population. The intervention measures the study will take into consideration is the closure of schools as it would affect the different age groups differently. However, the measure was put in place at different periods in the various countries.

The differences in demography are accounted for when the study assumes that N is equivalent to the country's population. The intervention measure the study will take into consideration is the closure of schools as it would affect the different age groups differently. Similarly, the measure was put in place at different periods in the various countries. Interventions will seek to reduce the amount of people who become infected. That is reduce the rate at which susceptible become infected, represented by β_i.

For an outbreak to die down R_o should be less than or equal to 1. The population that is not susceptible should be given by $R_o(1-p)$ for an epidemic to die down. Where p is the proportion of the population that is immune, hence $p = 1 - 1/R_o$. This can be done by decreasing the rate of transmission while the rate of recovery increases, that is, $\frac{dS}{dt} < \frac{dI}{dt} < \frac{dR}{dt}$. Interventions decrease the number of individuals susceptible hence if there is a decrease in infected during the effect of an intervention measure then the measure is effective. The extent to which the measure is effective is dependent on the change in number of infected individuals. If $\beta_i > 0$ then for the age group i there is a positive impact on the number of infections. Therefore, to reduce $R_o, \beta_i < 0, and \propto_i > 0$. For births and deaths in the population, it would be better if $\mu \leq b$.

4.0 RESULTS AND ANALYSIS

4.1 Data

Covid-19 data was obtained from John Hopkins Research Centre. The data entailed the number of confirmed cases, recovered cases and deaths per reported country. The study uses the data from Canada, Kenya and South Korea. Canada and South Korea have a similar population distribution, however, they both have different timings and durations of placing intervention measures. Kenya has a different population distribution to both Canada and South Korea, but put interventions in a manner that leans more towards South Korea.

The interventions data are obtained from respective country's media and government. While the socio-economic factor is obtained from the website index mundi. Information that was obtained in regards to interventions includes dates and duration of implementation of the measures. The measure used in this study is closure of learning institutions. For the aspect of investigating the demographic factors, data on the population distribution and population density are used.

4.2 Data presentation

From Figure 1, South Korea was the first to report a case among the three countries however it has the least total number of cases whereas Canada has the most cases although their first reported case was later.

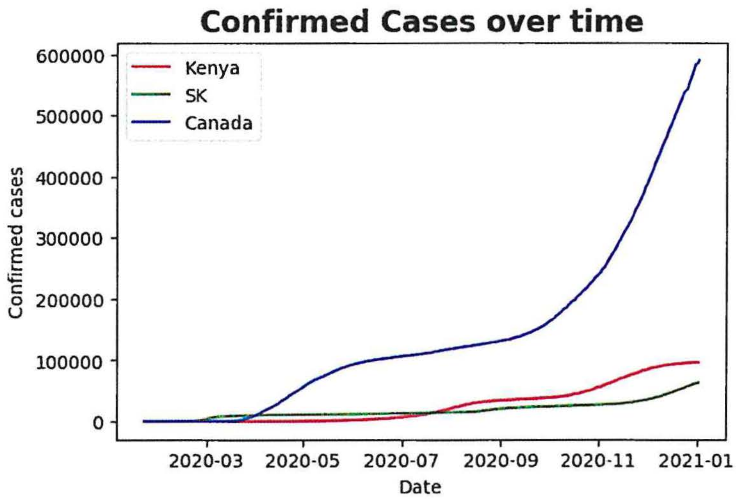
Canada had a spike in cases between May and June. In the month of May, Canada reopened schools and while restrictions are lifted in several states. There was a decrease in the rate of increase in the infected around August as the government puts in measures such as introduction of smartphone app that warns when nearing a positively tested Covid-19 individual, travel bans on individuals with temperatures above 38^0C.

South Korea had a lockdown imposed on all military bases late February and closed the churches mid-March. Introduced quarantine on April 1st 2020. South Korea controlled the pandemic at the onset leading to fewer confirmed cases. This is done by testing and contact trace measures. They trace bank cards and mobile phones to identify who to test.

Kenya had travel restrictions that started in March and ceased in August. Schools were closed on March and reopened on January, 2021.

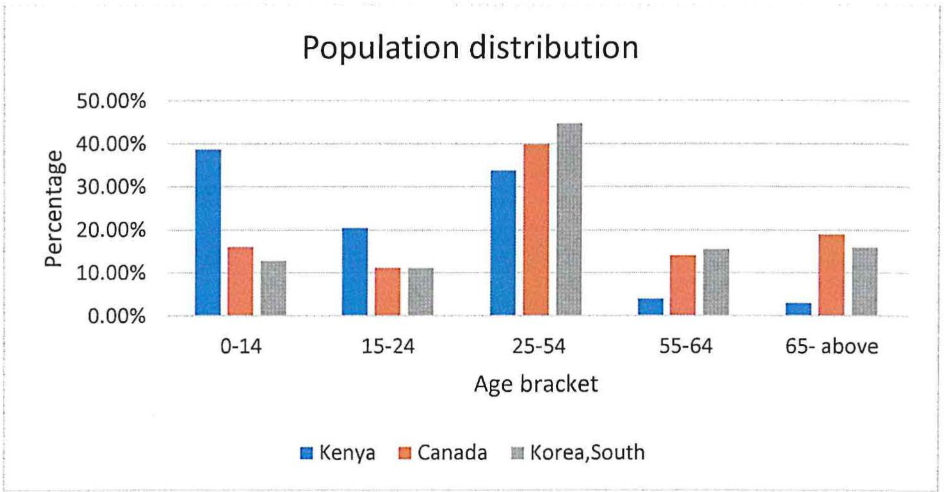
South Korea effected intervention measures at the onset of the pandemic and the measures were often for a long duration. On the other hand, Canada delayed in placing measures and were lifted after short durations. Kenya put in place measures later than South Korea however the measures were not lifted as early as those in Canada. This implies that timing and duration of effect of the intervention measure dictates the effectiveness of the measure. Early timing and longer duration of measure being in effect is the most effective.

Figure 1 Confirmed cases in Canada, South Korea and Kenya



This study takes into account that the total population is divided into five age brackets as shown in the Figure 2. From the figure, Kenya has a higher population below 24 years and a lower population above 24 years compared to South Korea and Canada. However South Korea has a slightly larger population than Canada within the age bracket 25 and 54 years.

Figure 2 Population distribution over the age brackets in Canada, Kenya and South Korea



4.3 Fitting the model

The study considers one intervention measure: schools closing. Model fitting is done to look if the data is in line with the model and its assumption. Kenya has the best fit to the model while South Korea has the worst fit to the model.

The age bracket 0-14 and 15-24 are students. Among the three countries Kenya fits the model best since the percentage population in the age bracket is the twice as large as that of Canada and South Korea. Therefore, the measure would be more effective in Kenya. However, for age bracket 0-14 Canada is a better fit compared to South Korea due to its percentage population in the age bracket being significantly larger than South Korea. This is shown by Figure 3 to Figure 9.

The ages above 25 years mainly consists of non-students. From Figure 10 and Figure 17, excluding Figure 15, it can be deduced that the model is not a good fit for the particular data sets. When schools close, it reduces the possibility of non-students being secondary cases where students are the primary cases. Therefore, the impact of the measure is on the minimal side.

Kenya's percentage population above 65 years is five times lower than South Korea's percentage population and six time lower than Canada's percentage population within the same age bracket. Thus, with or without intervention measures put to cater for the population, the number of cases would not vary by much. The age bracket has little to no impact on the intervention measures put in place. Therefore, the data fits the model as shown on Figure 15.

From this it can be seen given the intervention measure, the population can be grouped in a new manner. The closure of schools divides the population into two major groups. The students whom the measure affects greatly and non-students who are with or without the measure are not that greatly affected.

Figure 3 Model fit of SIR model to Kenya population age 0-14

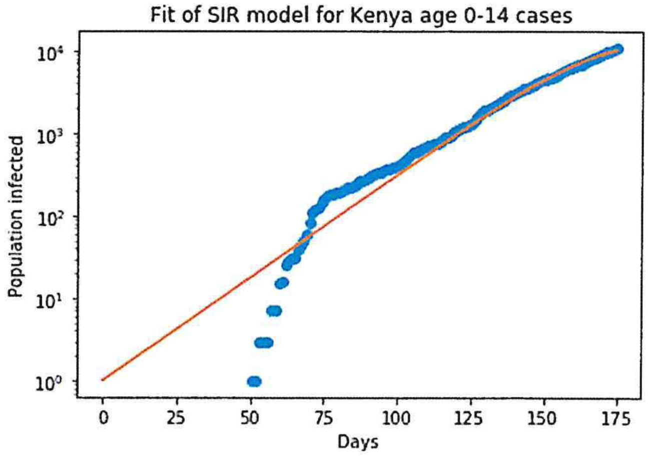


Figure 4 Model fit of SIR model to Canada population age 0-14

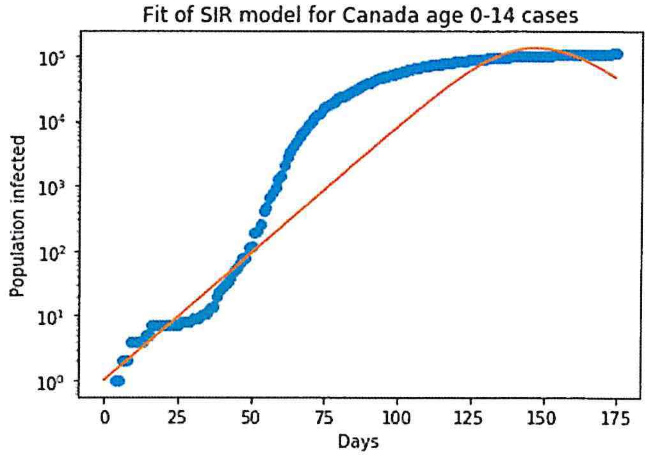


Figure 5 Model fit of SIR model to South Korea population age 0-14

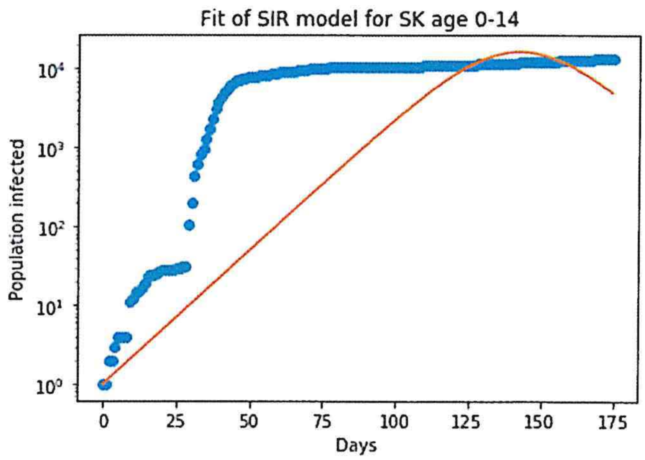


Figure 6 Model fit of SIR model to Kenya population age 15-24

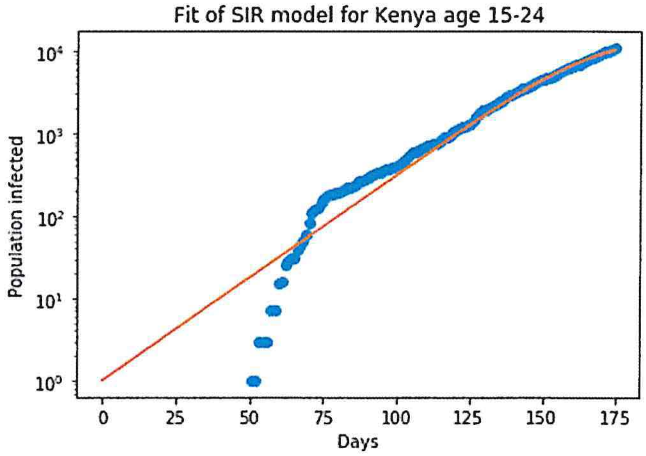


Figure 7 Model fit of SIR model to Canada population age 15-24

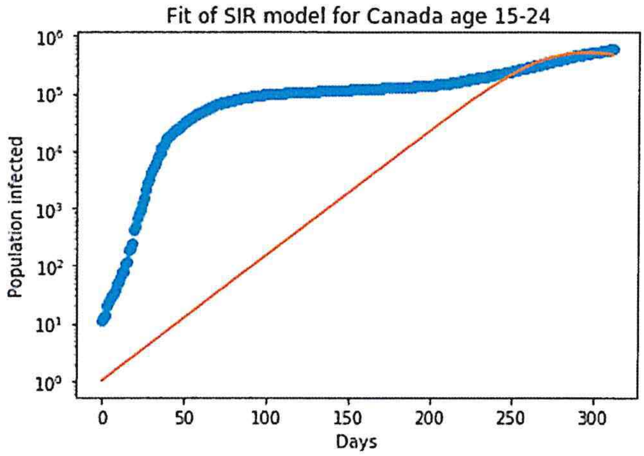


Figure 8 Model fit of SIR model to South Korea population age 15-24

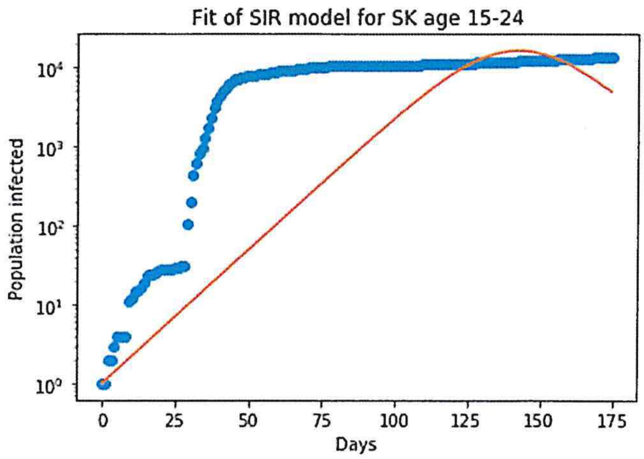


Figure 9 Model fit of SIR model to Kenya population age 25-54

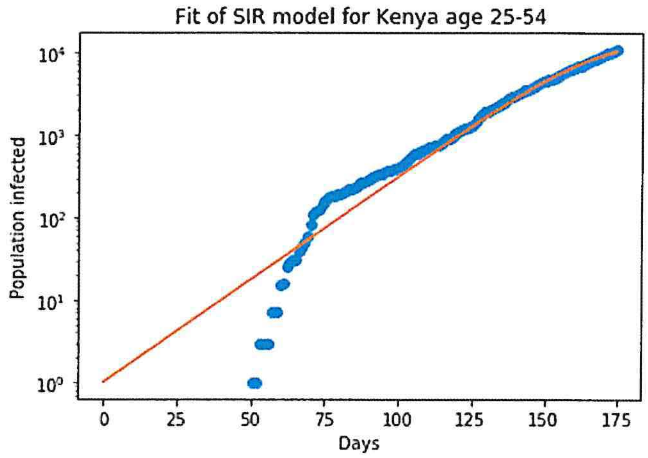


Figure 10 Model fit of SIR model to Canada population age 25-54

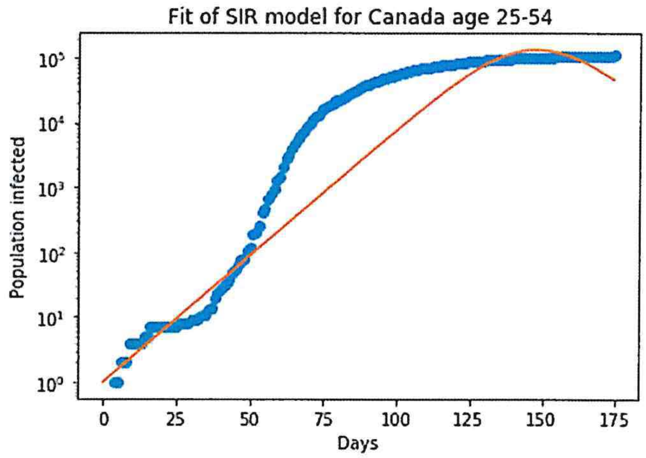


Figure 11 Model fit of SIR model to South Korea population age 25-54

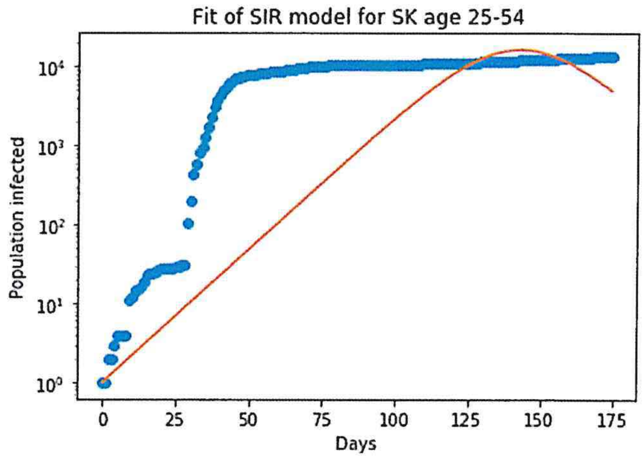


Figure 12 Model fit of SIR model to Kenya population age 55-64

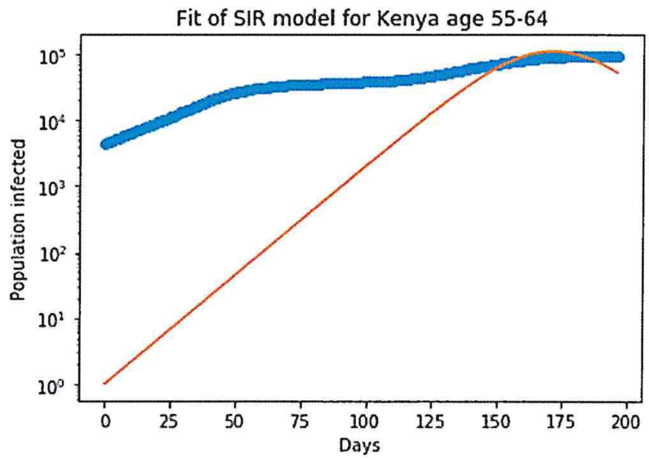


Figure 13 Model fit of SIR model to Canada population age 55-64

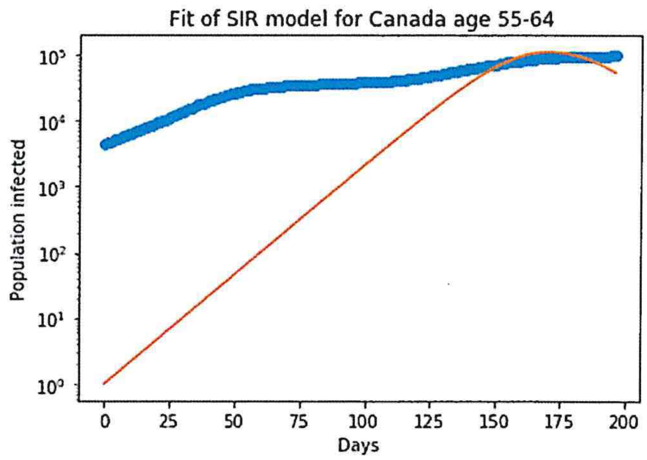


Figure 14 Model fit of SIR model to South Korea population age 55-64

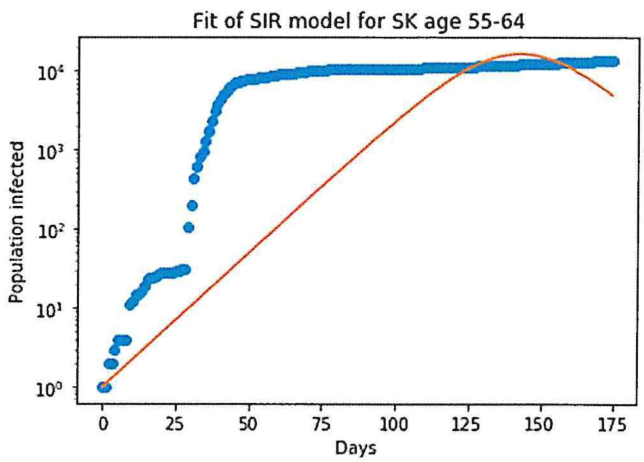


Figure 15 Model fit of SIR model to Kenya population age 65 and above

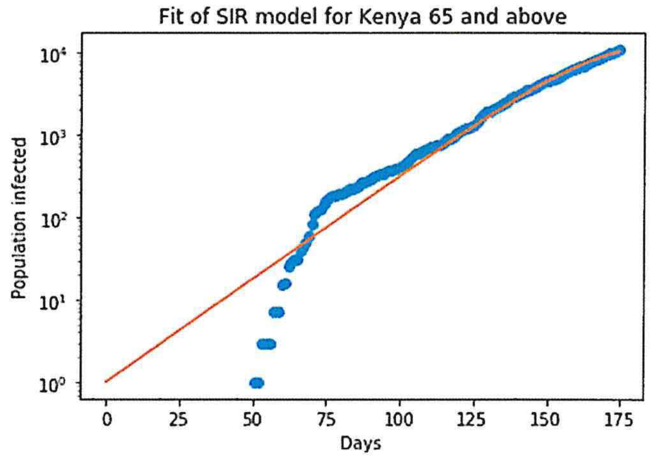


Figure 16 Model fit of SIR model to Canada population age 65 and above

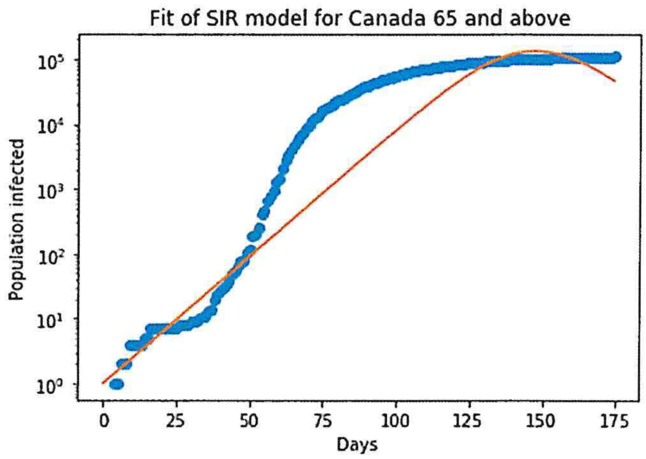
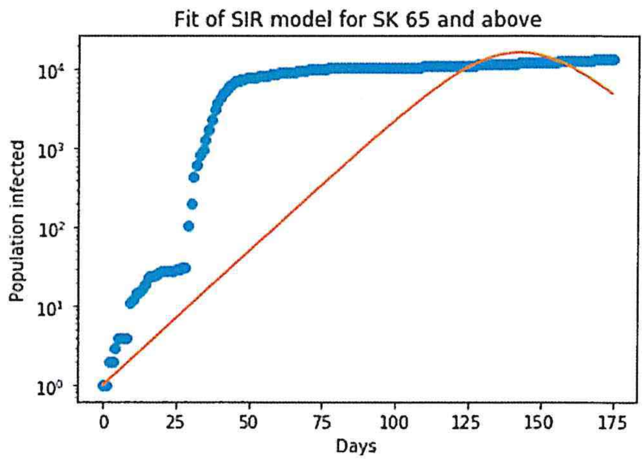


Figure 17 Model fit of SIR model to South Korea population age 65 and above



From Table 1 it can be seen that there is no scenario that gives a value of R_o that is less than one. This implies that placing school closure as the only intervention measure does not guarantee that the pandemic will be controlled. The larger the value of R_o, the harder it is to control the pandemic. For each age bracket and the total population, Kenya has the smallest value for R_o. This implies that closing schools produces a significant impact on a country or a region that has most of its population being students.

Table 1 Value of R_0 for Canada, Kenya, South Korea given school closure

Age Group	Kenya	Canada	South Korea
Total population	1.0224190245450075	1.0906764182970392	1.025786920108203
0-14	1.0224190245450075	1.2544983238392255	1.075029382009731
15-24	1.0508009304324903	1.8200061470477662	0.9720869590949425
25-54	1.0391516066301165	1.1501271506913409	1.039026734990315
55-64	1.1183867585428868	1.2446480147789531	1.067786857308168
65 and above	1.141198971847449	1.229777225918189	1.0667682647687236

5.0 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study aimed to determine the impact of interventions and varying demography among different areas. Mathematical models are effective in disease modelling. SIR model takes into account certain variations in the susceptible numbers due to the different interventions put in place. The study used the model to determine how closure of schools and varying demography would affect the transmissibility of the disease. The results showed that school closing would flatten out a curve for a population mainly consisting of school children illustrated by Kenya. Early non-pharmaceutical interventions would cause potential pandemic to flatten out. This is seen as both South Korea and Canada have a similar demography however Canada has higher confirmed cases compared to South Korea.

The duration and timing of an intervention measure would greatly affect its effectiveness. Although one intervention measure may not be able to completely control a pandemic, use of appropriate measure given a certain demography would lead to great results. Couple this with early timing and appropriate duration would bring out the most effect from the measure.

5.2 Recommendation

Pandemics are uncertain events that bring about huge disruptions. Therefore, adequate measures should be implemented on the onset of the outbreak to minimize the losses. By knowing the area's demography suitable measures could be put in place early and reduce the time and amount spent experimenting on the best fit solution for the region.

Pandemics often lead to other problems such as pressure on the healthcare systems and the economy. Thus, governments should build reserves that cater for such unexpected events and should be reviewing their healthcare systems regularly.

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