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NONPHARMACEUTICAL AND PHARMACEUTICAL COVID-19 PREDICTION MODELS

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ABSTRACT

Global tourism and leisure came to hurt due to the Covid-19 pandemic. The ways we lived our lives was automatically truncated due to the fear of the virus of unknown etiology. We started adjusting to new lifestyle. Community life came to hurt due to lockdown to curtail the spread of the virus. Various forms of non-pharmaceutical approaches (NPA) or intervention (NPI) was adopted in the absence of vaccine. As time progresses different vaccine became available (Pharmaceutical approach {PA)) was discovered to mitigate the spread of the virus. To reassure the safety of people, different levels of social distancing values in meters was applied due to the fear that the virus was airborne. This study tends to investigate whether onset data from the NPA and PA interventions could be used to predict the probability of infection thereby bringing the spread of the virus to a hurt. The analysis based on these prediction models revealed that both the NPA and the PA are very effective in mitigating and hurting the spread of the virus. The PA prediction model revealed that as more people are vaccinated with time, the probability of infection reduces drastically thereby increasing the probability of social mingling. Therefore, we concluded that these data independent prediction models are useful to predict the likely outcome of infection of the disease of unknown etiology based on the onset data.

Keywords: Non-pharmaceutical approaches, Pharmaceutical approach, Covid-19, Prediction models

INTRODUCTION

Extensive literature exists in Covid-19 related research especially during the onset when vaccines and Covid-19 mutations were not categorized. Many reviews on Covid-19 etiology have been reported. The variation of the epicenter of Covid-19 for earlydays of the outbreak was extensively reviewed (Ahad et al., 2020).Prior to recent medical advancement on Covid-19 infection prevention was the famous non-pharmaceutical approach (NPA) of social distancing, lockdown, facemask, and handwashing(Ferguson et al., 2020). The NPA was a conventional tool to mitigate the spread of the virus. With the efforts of world leaders cum the world health organization (WHO) vaccine regime started flying in from different continent to curb the infection rate, this activated the pharmaceutical regime which also led to the discovery of different variants of the Covid-19 virus. In recent times, the pharmaceutical approach (PA) has gained more focus than the NPA.

The outbreak of Covid-19 altered prediction accuracy of many predictive models due to several factors associated to the pandemic and neglect of early warning signs. Demography, religion, and social gathering played significant role in the spread of Covid 19 as such infection rate was continentally inclined. Some factors that led to the inaccurate prediction of traditional prediction models are income, test capacity, unknow etiology of the virus, obesity, non-communicable disease (ND), poverty, and social poverty. Conventionally, prediction models could be designed for short and long-term depending on the origin and the objective of the problem(Santosh, 2020b) From the onset of the outbreak in December 2019 in Wuhan, different prediction models were applied to predict the likely number of daily infection and death cases. Traditional prediction model actually hovers around different variables in the face of uncertainty to predict correctly unfortunately, during the outbreak of the virus such variables were unknown to large community of scientist. As such model based on the NPA were developed to mitigate the effect of the pandemic. Many of the model during the epic of pandemic was based on the social distancing values measured in meters(m) or feet with 1.5meter or 2meters generally implemented followed by lockdown(F. Z. Okwonu, Ahad, Apanapudor, & Arunaye, 2021; F. Z. Okwonu, Ahad, Apanapudor, Arunaye, et al., 2021; F. Z. Okwonu et al., 2020) The implementation of the various version of the NPA actually mitigated rapid spread of the virus globally.

Prediction models often help various agencies to understand the situation of interest, aid in plaining and resource allocation. During the pandemic, artificial intelligence and machine learning predictive models(Long & Ehrenfeld, 2020; Santosh, 2020a)(el Asnaoui et al., 2021; Wang & Tang, 2020)were rolled out to help health workers and various government agencies to study the pattern of spread and infection rate of the virus to enable the agencies fashion out possible plans and solutions. Various models has been adduced for the purpose of predicting the Covid-19 etiology, say Agent based models, SEIR/SIR and Curve fitting models/extrapolation(Santosh, 2020b) CHIME Covid-19 hospital impact model(https://www.nodehealth.org/covid-resource/covid-19-hospital-impact-model-for-epidemics-chime/, 2021),Severe Covid-19 model and mapping tools(Branas et al., 2020), Confirmed and forecasted cased data model(Santosh, 2020b). Prediction model based on data mining and machine learning was used to study the spread pattern of the virus(Hirschprung & Hajaj, 2021). Variants of SIR and SEIR exist for Covid-19 modeling(Calafiore et al., 2020; W. Ma et al., 2004; Y. Ma et al., 2020; Mohammed et al., 2020). These models investigated the infection rate, discharged and death rate for different period ranging from three weeks to three months.

Ron and Chen (2021)have developed predictive models to predict the number of infected cases using previous data set(Hirschprung & Hajaj, 2021). Yakovyna and Shakhovvska (2021) developed a model to predict the death rate for three weeks in Sweden(Yakovyna & Shakhovska, 2021). Different predictive models have been advanced to predict the infection rate of Covid-19 globally(Al-Najjar & Al-Rousan, 2020; Ardabili et al., 2020; Basu & Campbell, 2020; Borovkov et al., 2022; Fanelli & Piazza, 2020; García-García et al., 2020; Hu et al., 2020; Ribeiro et al., 2020; Tuli et al., 2020; Wynants et al., 2020; Yang et al., 2020; Zhao et al., 2021; Zheng et al., 2020) These models often predict the rate of spread and death rate. In this paper, we focused on the effects of the NPA and PA to combat the spread of the Covid-19 pandemic. In this study, without details on the traditional modeling concept, we apply the data independent predictive model using the onset data to investigate the effects of NP cum vaccination if it reduces or increase the infection rate. The focus of this study is to determine if the NPA and the NP played vital role in hurting the spread of the Covid-19.

The rest of this article is organized as follow. Section 2 discuss the data independent predictive models followed by data collection in Section 3. Results and discussion is presented in Section 4 followed by conclusion in Section 5.

MATERIALS AND METHODS

The outbreak of Covid-19 and subsequent lockdown revealed the importance of free movement and social mingling. We intend to apply data independent prediction model based on onset data to determine the importance of NPA and PA interventions.

Data independent prediction model (DIPM)

Conventionally, prediction model requires exploiting the data set to infer more information regard the study interest. However, during the Covid-19 outbreak, such data set were not readily available for exploitation due to the unknown etiology of the disease. This era gave rise to other predictive models that rely sole on onset data to predict the likelihood of future outcome based on the causality information or data. Based onthis, the prediction model Equation (1)derived in (Ahmad & Okwonu, 2011; F. Z. Okwonu, Ahad, Apanapudor, & Arunaye, 2021) as Equation (6) is started as follows

$$k(\emptyset) = \rho e^{\rho t}. \quad (1)$$

Equation (1) is simply an NPA concept which was applied to predict the probability of spread of Covid-19 basedon the social distancing values. This model revealed that as the distancing values increases, the probability of infection decreases (John A. Rice, 2007; F. Z. , Okwonu et al., 2020; F. Z. Okwonu, Ahad, Apanapudor, & Arunaye, 2021). For the NP prediction model, we reformulate Equation (1)as follows

$$p_i = \omega\left[Ce^{-g(t)}\right] \quad (2)$$

Where C denotes tunning parameter for prediction control and e is the exponential. Then the following are defined

i. g denotes rate of change,
ii. t denotes the period under consideration
iii. ωonset value from Equation (1)
iv. $p_i, i = 1,2,3,\dots,n$ the predicted values

This model tends to predict the effect of vaccination on the spread of the Covid-19. It is expected that as vaccination was initiated globally, the likelihood that the probability of survival will be high as vaccination continues unabated. Equation (1) and Equation (2) are discrete predictive models because they utilize raw data,and theinput parameters are subject to tunning during training. The implication of these types of models is that they are dependent on a particular situation and can be tuned for another situation to be useful in that instance(Santosh, 2020b). The input parameters are subject to changes for different purposes and period.These models mimic the variation of input parameters for the CHIME Covid-19 hospital model for epidemic [2]

Data collection

In this study, are interested on the impacts of NPA (Equation (6)) (F. Z. Okwonu, Ahad, Apanapudor, & Arunaye, 2021) and PA via prediction analysis.Based on the DIPM concept, the input parameter values for Equation (2) are

Table 1: Input Parameters for DIPM E

DIPM Parameter	DIPM parameter values
α	1.05
β	0.15(SH)
γ	0.13(SH(K)
e	2.718282
δ	0.00015
n	5

Based on the study in [6] and in Table 1, we assumed that 15 out of every 100 people during the peak of the Covid 19 outbreak may be infected for the queuing group (SH) while 13 people out of every 100 people seated (SH(K)) in a social gathering is assumed to be infected. However, the parameters in Table 1 are subject to changes based on the study interest. Variation of input parameter values is the species of DIPM techniques. We note that the prediction constant (α) is the tuning value to control the accuracy of the model. This implies that the duration of investigation is designed to satisfy $\sum_{i=n}^{n} p_i(\alpha) = 1$, where $i = 1,2,3,\dots,n$ is the period $(i)$of study. Therefore, i and α determine the values of p_i. This is to say that as i increases the value of α is user controlled.

In this study, we intend to investigate the impact of vaccination in controlling the spread of Covid-19 virus. Previous study has shown that the NPA via social distancing has helped to mitigate the spread of the virus. At present, we also want to investigate whether vaccination would mitigate the infection rate thereby assuring the people that Covid-19 vaccination would stop the dissemination of the virus.

RESULTS AND DISCUSSION

The results in Table 2 (SH and SH(K)) were reported in Table 1in (Okwonu, Ahad, Apanapudor, & Arunaye, 2021) while Pred(SH) and Pred(SH(K)) values were generated using Equation (2). The output (SH and SH(K)) in Table 2 revealed that as more people observed the social distance rule, the probability of infection would decrease to an average of 0.0055 for both sitting and standing positions for $W = 5M$. Meanwhile, the people that would be on the safe net would increase to an average of 0.995 for both sitting and standing position provided they comply with the social distancing rule. This nonpharmaceutical approach was adopted during the outbreak of the virus in the absence of the pharmaceutical approach. Based on the proposed model (Equation (2)), the variable w denote months of vaccination instead of meters as was reported in (Okwonu, Ahad, Apanapudor, & Arunaye, 2021) . Therefore, the outputs (Pred (SH) and Pred (SH(K)) were derived using SH and SH(K) with W as the number of months. Hence, the implication of Pred (SH) and Pred (SH(K)) is that as more people are vaccinated due to the availability of vaccine with respect to time, the probability of infection decreases while the probability of people in the safe net increases. Figure 1 also captured the results reported in [6] and the proposed model (Equation (2)). Hence using social distancing concepts and vaccination based on time, both nonpharmaceutical and pharmaceutical approaches produce similar outcome. For instance, we observed that the probability of infection decreases from the 3rd months to the 5th months when vaccination started. Therefore, this model suggested that the more people are vaccinated the sooner the Covid-19 virus vanishes from the community. Therefore, both models suggest safety precautions for nonpharmaceutical and pharmaceutical approaches.

Table 2: comparative analysis of nonpharmaceutical and pharmaceutical models

W	SH	SH(K)	Pred(SH)	Pred(SH(K))
1.5	0.81	0.78	0.1574764	0.1364795
2	0.63	0.44	0.3149528	0.2729591
3	0.07	0.015	0.4724291	0.4094386
4	0.06	0.04	0.6299055	0.5459181
5	0.01	0.001	0.7873819	0.6823976

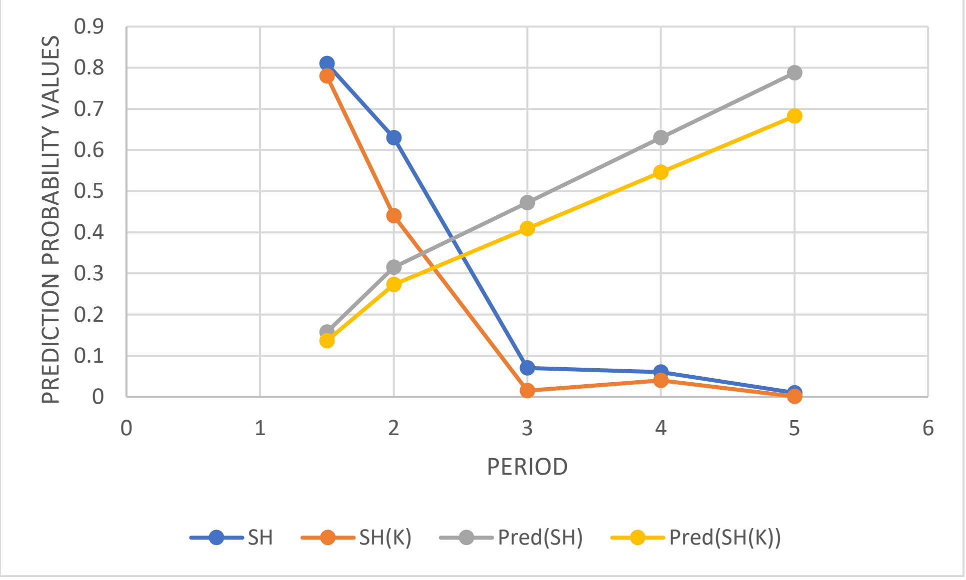

Figure 1: Comparative analysis of prediction models for nonpharmaceutical and pharmaceutical approaches

CONCLUSION

The application of the data independent predictive model based on the concept of onset data derived from the nonpharmaceutical approach (NPA) and pharmaceutical approach (PA) indicates that social distancing value and vaccination if adopted and implemented over a long period of time will drastically end the spread of the Covid-19 virus. This implies that global tourism and leisure sectors will be reactivated thereby promoting social mingling among friends and family members. If social distancing and vaccination policy is strictly adhered to, the global economic activities will be emancipated from the pandemic. Therefore, this study has revealed the importance of vaccination as a mechanism to end the pandemic.

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