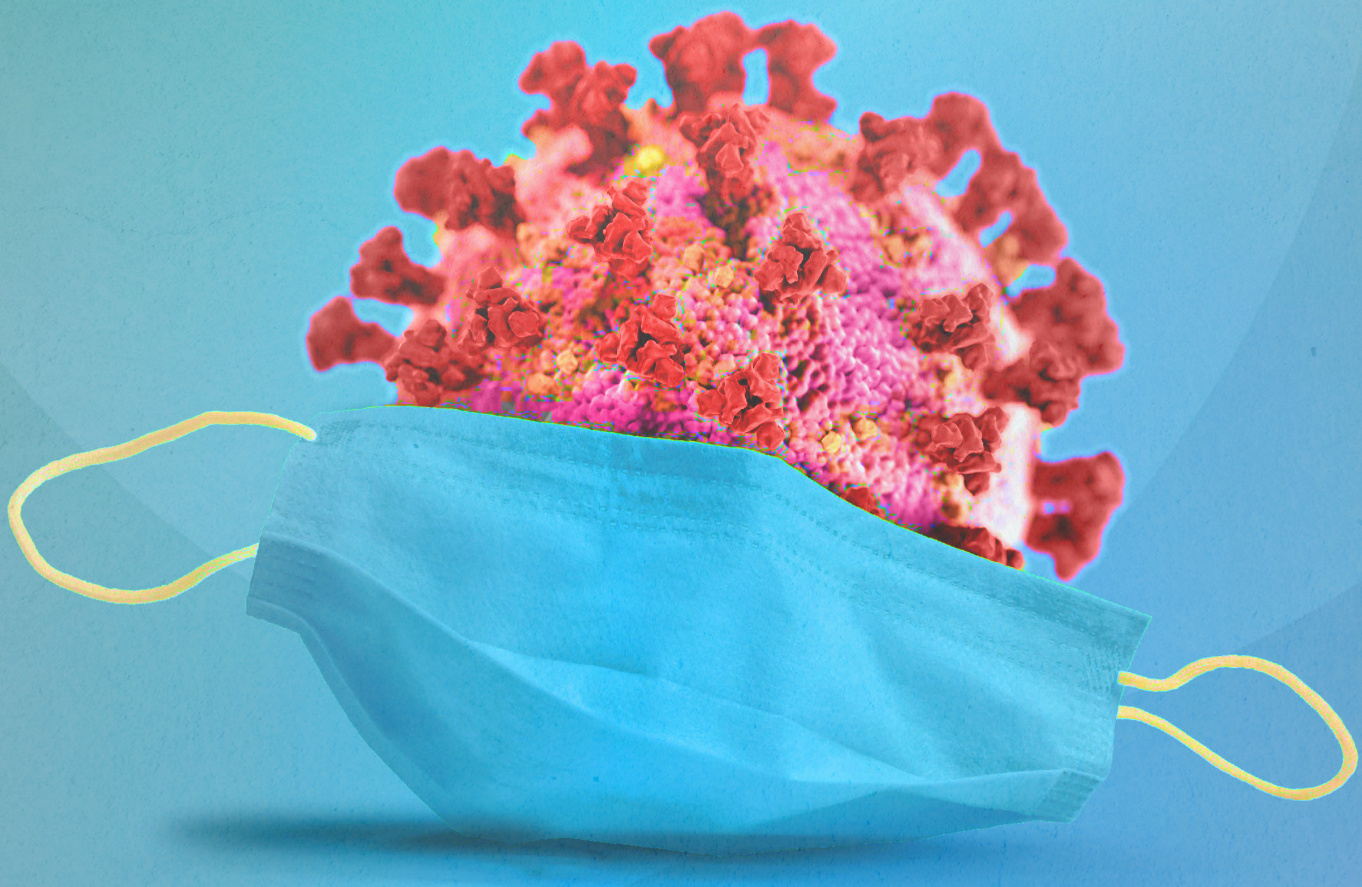
لين Lean

وزارة الصحة
Ministry of Health

NHCC
المركز الوطني الصحي للقيادة والتحكم
NATIONAL HEALTH COMMAND CENTER

Simulation Approach:

MEASURING THE IMPACT OF NON-PHARMACEUTICAL INTERVENTIONS ON THE SPREADING OF COVID-19 IN SAUDI ARABIA



October 2021

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EXECUTIVE SUMMARY

COVID-19 was reported in December 2019, in China. The WHO declared COVID-19 as an international public health emergency on January 30 and a pandemic on March 11, 2020. A strategic preparedness and response plan to slow and stop transmission, provide optimized medical care, and minimize the virus's effect on healthcare systems were put in place by countries globally (non-pharmaceutical intervention (NPIs).

This paper aims to estimate the impact of the implemented NPIs in Saudi Arabia during the pandemic. As a collaboration effort between National Health Command Center (NHCC) and Lean Business services, a novel hybrid simulation model using agent-based modeling (ABM) and system dynamics (SD) was built and validated using COVID-19 reported cases from Saudi Arabia between the period from March 2nd to July 1st, 2020. The validation process used reverse engineering on a weekly basis to project the active and total cases in Saudi Arabia.

Model projection of total and active cases:		Observed total and active cases:
3.6M and 1.4M	VS	**198k and 58k**

Without any NPIs, KSA will have 18 COVID-19 cases for each documented case at the end of the study period, and with a 63% change in the Ro for the study period.

Breakdown Analysis Of The Impact Of Each NPI (Rt)

24%
Ban on Going to School

4%
Partial Lockdown From 7pm to 6am

16%
24 Hours Lockdown

2%
Ban on Shopping, Gatherings and Going to Government Workplaces

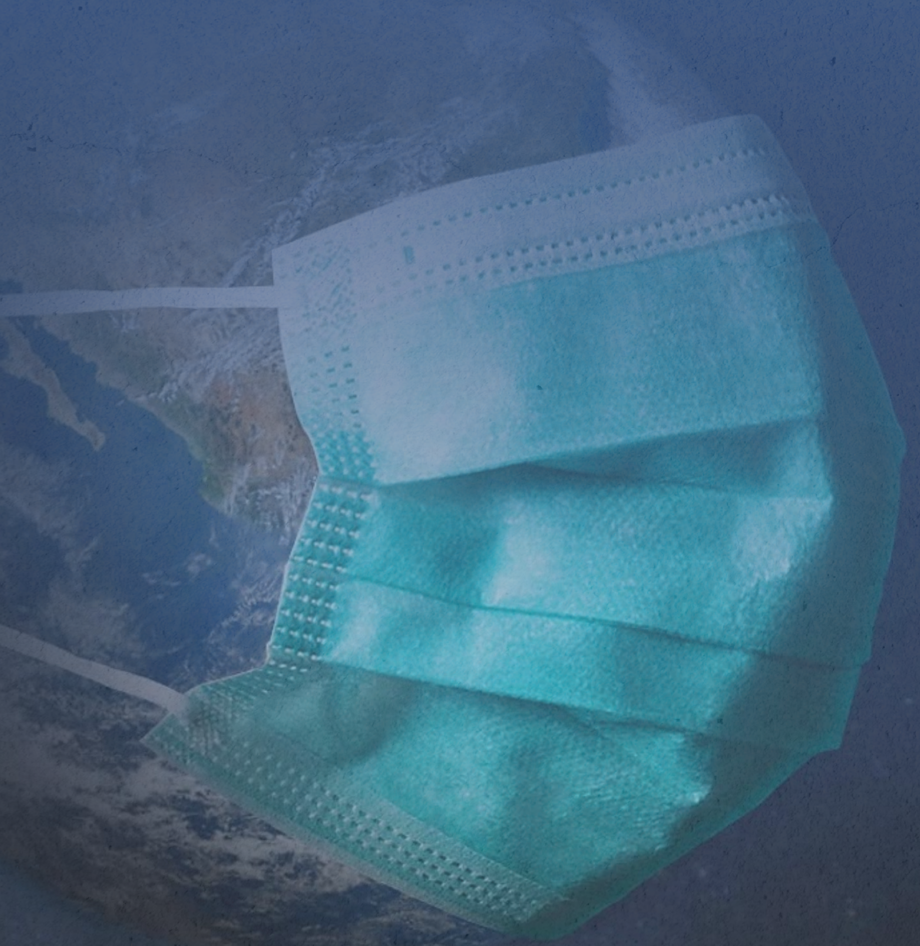
15%
Ban on International Travel

0.3%
Lockdown Extension

Our hybrid model can be used for healthcare planning other than the infectious-diseases context. An example of this is capacity planning for healthcare services and devices such as ICUs and ventilators. Finally, we showed that choosing the right paradigms of simulation can be a strong, practical decision support tool that can be further used in other fields outside the healthcare sector.

INTRODUCTION

Coronaviruses are a family of viruses that can cause a wide range of diseases and symptoms, from the common cold to more serious diseases, such as the Middle East respiratory syndrome (MERS-CoV) and severe acute respiratory syndrome (SARS-CoV) (1). In December 2019, China reported a cluster of pneumonia cases in patients associated with the Huanan Seafood Wholesale Market in Wuhan, Hubei Province. On January 7, 2020, the Chinese government confirmed that the incidence was because of a novel coronavirus (COVID-19) (2). The virus spread from China to other countries in the following months, and in response to the COVID-19 pandemic, the WHO issued a strategic preparedness and response plan to slow and stop coronavirus transmission, provide optimized care for infected patients, and minimize the virus's effect on healthcare systems (3). Moreover, countries have begun implementing drastic measures to control the situation. Limiting movement within their borders and restricting international visits are some of the measures that have been applied in different forms across the affected countries (4, 5).



World Health Organization

declared COVID-19 a public health emergency of international concern on January 30 and a pandemic on March 11

The government of the Kingdom of Saudi Arabia (KSA) has taken several nonpharmaceutical interventions (NPIs) toward limiting the spread of the coronavirus. The local authorities suspended domestic and international flights (6, 7), entry for visiting pilgrims (8), and major sport and social events (9), along with many other decisions. Figure 1 lists all NPIs taken by local authorities in KSA during the study period.

Figure 1: NPIs taken by local authorities in KSA

Despite growing evidence of the effectiveness of NPIs at minimizing the spread of COVID-19 (10, 11), the unintended economic and social consequences of these NPIs hinder stakeholders from implementing them in their communities for a prolonged period (12-14). As such, several simulation/mathematical approaches have been implemented to support decision-making by evaluating the impact of an individual or a set of NPIs (15-18). Despite many of these models adopting the suspected–exposed–infected–recovered (SEIR) epidemiological model, these simulation approaches intrinsically vary in performance accuracy and resilience. For instance, the system dynamics (SD) approach is a top–down information feedback method that uses causal loops and stock-flow modeling. It is well-developed for visualizing, analyzing, and understanding complex dynamic feedback. The method's essence is the feedback structures with high order, multiloops, and nonlinearity (19). The advantage of this approach includes its ability to simulate large events with relatively low computational power. However, the drawback of this approach is its inability to simulate events at the micro level, such as simulating each behavior separately at the individual level.

In contrast, agent-based modeling (ABM) is a bottom–up computational modeling approach. In this approach, discrete agents that interact autonomously in a simulated space represent individual entities in a complex adaptive system to produce emergent and nonintuitive outcomes at the population level. The interactions or communications among the agents are made according to a set of predefined rules. The rules governing an individual agent's behavior influence the outcomes/predictions of ABM (19). The advantage of this approach is its ability to build high representation for each discreet agent in the scenario. However, a large amount of computational power and more time are required for each iteration due to the complexity of the model, making it less ideal in agile situations.

This study builds and validates the results of a Saudi-based hybrid COVID-19 simulation model. The validated model will be used to estimate the impact of the implemented NPIs in Saudi Arabia during the pandemic. This research is a collaborative effort between NHCC and Lean Business Services to utilize simulation technology in healthcare system. The results will help in future decision-making in Saudi Arabia and other culturally similar countries in the region.

METHODS

The Mathematical Model

In this study, ABM is used to simulate the behavior at the individual level and SD is used to simulate the behavior at the population level. ABM can simulate the behavior at the granular level, whereas SD can manage large information at the aggregate level. Combining these two techniques can increase the model flexibility to accommodate various scenarios (20, 21).

Epidemiological Model

The Core Epidemiological Model

The simulation is based on a complex SEIR and dead (SEIR+D) model of epidemic dynamics, which is a five-state/stock nonlinear SD model for simulating the spread of infection between agents using multiple parameters (22-24). In the proposed model, the infectious state is divided into four stocks: mild, mild isolated, severe, and severe isolated (Figure 2). To account for infectious travelers, a flow of mild infectious travelers' rate is linked to the mild stock to simulate the infection coming from outside the system (country/region).

Additional Epidemiological Models

As mentioned earlier, the core of the epidemiological model is a SEIR+D model. Multiple models are built on top of it to reassemble the complex behaviors that affect the spread of the disease. As such, some of these models cover the behavior of the contact rate, such as in an airplane, for which an agent-based model is built. Another example of these simulations is to simulate student behavior in a calssroom.

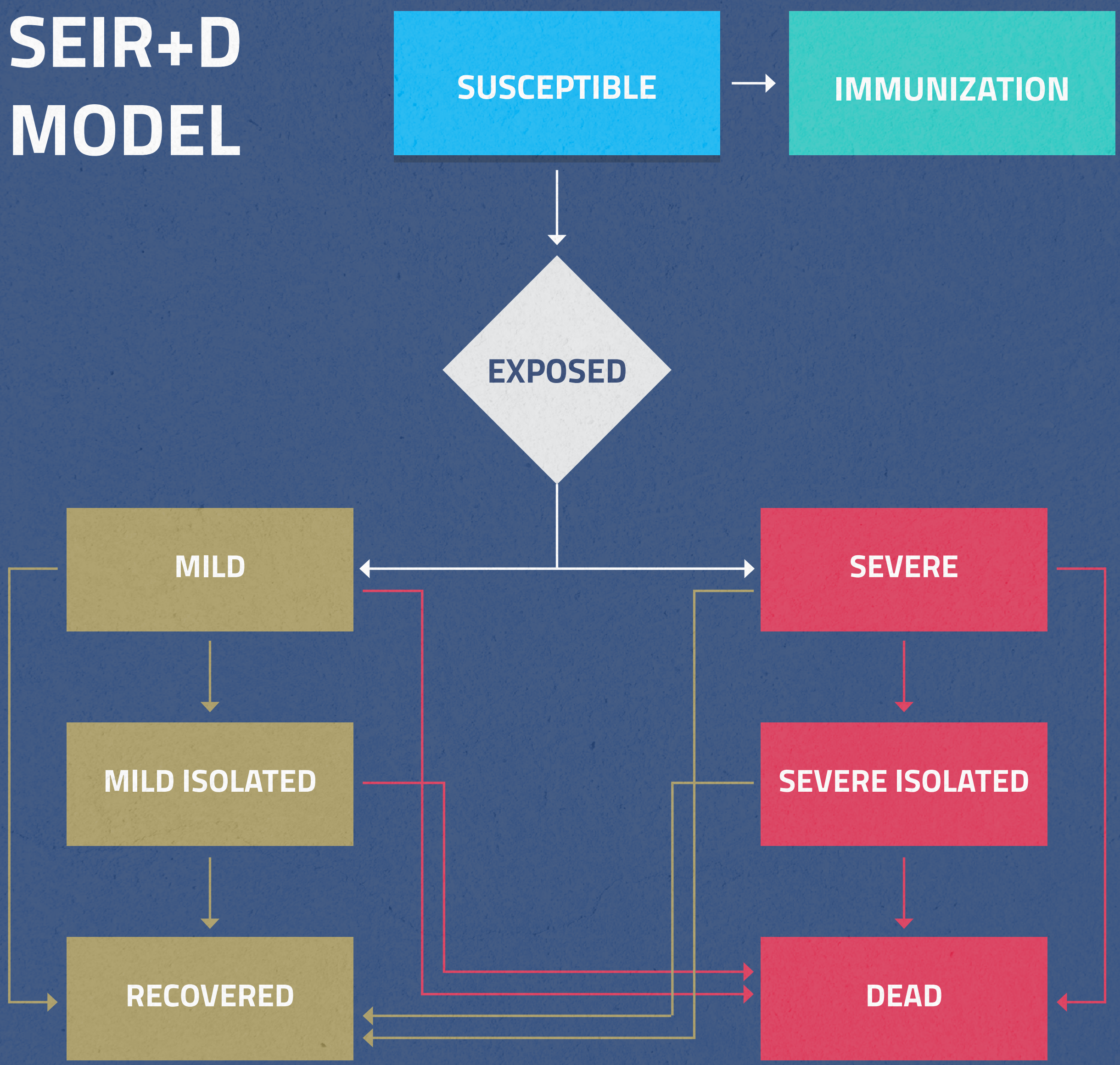


Figure 2: SEIR+D Model

On day 0, the entire population is assumed to be susceptible. On day one, i.e., March 2, 2020, an infectious individual is introduced into the system as a traveler. Susceptible individuals will become exposed based on the exposed rate flow, which depends on the contact rate, infectivity, number of nonisolated infections, and the proportion of susceptible population to total population. Both infectivity and contact rate comprise multiple parameters. After the incubation period, an exposed person becomes infectious. Based on the severity proportion among the community, some infections will be mild while others will be severe. In both cases, some of the infected individuals are isolated (either mildly isolated or severely isolated).

After the average illness duration, an infected person would either recover or die, both of which are assumed to be immune to the disease. The incubation period and the average illness are calculated dynamically based on severity and demographics.

This model is duplicated into multiple models as 20 hyper arrays, simulating the 20 health directorates of KSA.

The separate models can interact with each other based on the actual national travel schedule before the local travel ban (25). There is also an array for eight age distribution groups, which mainly differ in terms of the severity proportion and mortality rate. For instance, older age groups have a higher mortality rate than younger age groups.

Overview of Mathematical Formula

In this model we will be using differential equations to simulate the rate of change of flows with respect to time.

Let

P be the total population,

$S(t)$ be the number of susciptible in time t, $S(t) \geq 0$

$E(t)$ be the number of exposed in time t, $E(t) \geq 0$

$M(t)$ be the number of mild in time t, $M(t) \geq 0$

$MI(t)$ be the number of mild isolated in time t, $MI(t) \geq 0$

$V(t)$ be the number of severe in time t, $V(t) \geq 0$

$VI(t)$ be the number of severe isolated in time t, $VI(t) \geq 0$

$R(t)$ be the number of recovered in time t, $R(t) \geq 0$

$D(t)$ be the number of dead in time t, $D(t) \geq 0$

Then,

$P = S(t) + E(t) + MI(t) + MI(t) + V(t) + VI(t) + R(t) + D(t)$

$$dS/dt = -\alpha SI/P$$

$$dE/dt = \alpha SI/P - \varepsilon E$$

$$dM/dt = (1-s)*(\varepsilon E - \beta I - \mu I)$$

$$dMI/dt = (-\beta I - \mu I) - [(1-s)*(\varepsilon E - \beta I - \mu I)]$$

$$dV/dt = s*(\varepsilon E - \beta I - \mu I)$$

$$dVI/dt = (-\beta I - \mu I) - [s*(\varepsilon E - \beta I - \mu I)]$$

$$dR/dt = \beta I$$

$$dD/dt = \mu I$$

$$dS/dt + dE/dt + dM/dt + dMI/dt + dV/dt + dVI/dt + dR/dt + dD/dt = 0,$$

where α is the contagion parameter ($\alpha > 0$), β is the recovery rate ($\beta > 0$), μ is the fatality rate ($\mu > 0$), and ε is the incubation parameter ($\varepsilon > 0$).

PATHWAYS

To maximize the model's accuracy to simulate the behavior of the infection in KSA, a set of multiple hyperparameters was added to the model. The addition of the parameters was based on subject matter experts' opinion from NHCC, data availability and as well as benchmark from other similar world experiences. Each hyperparameter has initial values but can be changed with time via actions and rules. Actions are events that happened in KSA that affected one or more hyperparameters used in the model. Rules are triggers that can affect one or more hyperparameters used in the model. The hyperparameters are divided into four categories (Clinical, Behavior, Population, Healthcare Resource).

Parameters and Categories Used in The Model

Clinical parameters are related to the behavior of the disease itself, such as:

- Asymptomatic rate
- Average illness duration
- Average incubation time
- Comorbidity rate
- Rate of PPEs
- Infection case
- Mild days to isolation
- Severe average illness duration
- Severe days to isolation
- Severe proportion
- Mild average illness Duration
- Initial infectivity
- Death rate
- Isolation beds rate
- Death rate of patients with comorbidities
- Hospitalization rate
- Ventilation rate

Behavior parameters are related to the behavior of the population, such as:

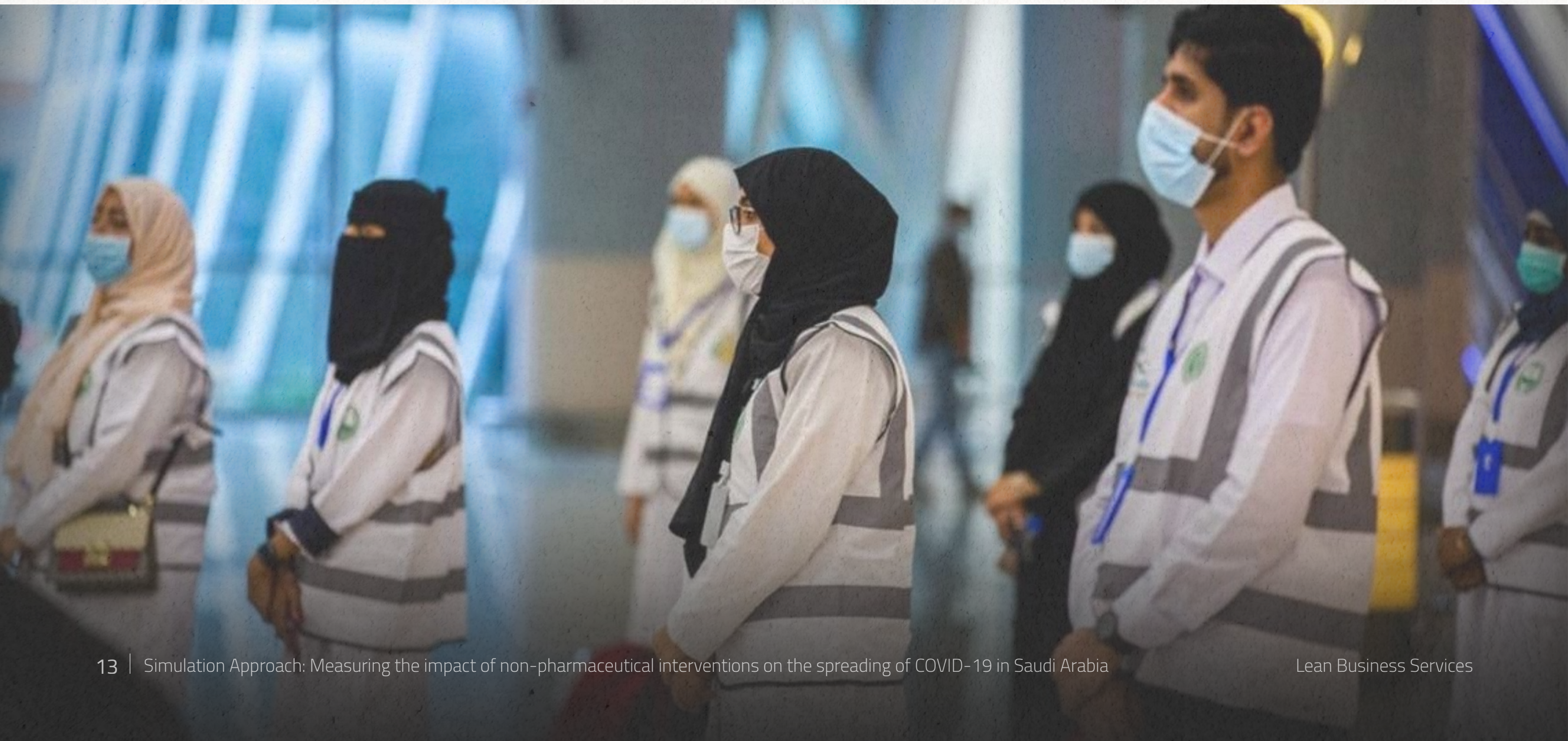
- Non-Governmental workplace
- Governmental workplace
- Infectious travelers
- Initial hand hygiene behavior
- Media campaigns
- Mobility
- Lockdown
- Schools
- Reopening of schools
- Shopping
- Reopening of workplaces
- Swab rate
- Initial contact rate infectious

Population parameters are related to demographics, such a:

- Age distribution
- Immunization
- Student population
- Total population

Health Resources parameters are related to healthcare resources, such as:

- Availability rate of ICU beds
- Clinical staff
- Medication
- Number of critical beds
- Number of isolation beds
- Manpower
- Number of PPEs
- Number of swabs
- Number of total beds
- Number of ventilators



ANALYSIS

Model Validation Process And NPIs' Impact Measurement

The analysis comprises two main components: model validation using reverse engineering and measurement of the impact of NPIs. Here, we explain the two main components of the analysis.

The Mathematical Model

Several assumptions were made when devising the parameters on the basis of the data collected by our research group during the study and published papers (26). **To validate the model performance, reverse engineering was performed weekly between March 2 and July 1, 2020.** The data from infection numbers in KSA were used to compensate and explain the missing values via reverse engineering. **The model validation reported primarily on four outcomes:**

TOTAL CASES	ACTIVE CASES	ICU CASES	DEATH CASES
number of infectious cases (including recovered, mortality, and active infectious cases) from day 0 to a specified day	number of active infectious cases on a specified day. Active Cases =Total cases – (Recovered + Mortality)	number of active infectious cases that were admitted to the ICU because of Covid-19 on a specified day	number of mortality cases because of COVID-19 from day 0 to a specified day

To validate the model percentage difference, all four outcomes are calculated. The model simulates the value of each outcome for seven days. After each of these periods has passed, the actual values are compared to the simulated values as a percentage difference as follows: (Simulation – Actual)/Actual. If the percentage difference is deemed large, the parameters are edited. This process is iterative until either an acceptable percentage difference or saturation is reached.

Impact of nonpharmaceutical interventions

The model consists of continuous rounds of incubation periods. In the first cycle, the model simulates the baseline cycle of transmitting the disease without adding any NPI. The observed values of active and total cases are captured and compared to the projected values of active and total cases from the simulation. The behavioral change of the spread of the disease is interpreted as the impact of NPIs that occurred at the beginning of the cycle (where the numbers are captured and compared).

THE BEHAVIORAL CHANGE IS MEASURED BY THE CHANGE IN R_0 (R_t).

The R_t is applied for each NPI on the same day that intervention occurred. If multiple NPIs occurred on the same time, they will be treated as one NPI (combined impact).

The impact of the following NPIs was measured individually

Ban on going to school

Ban on international travel

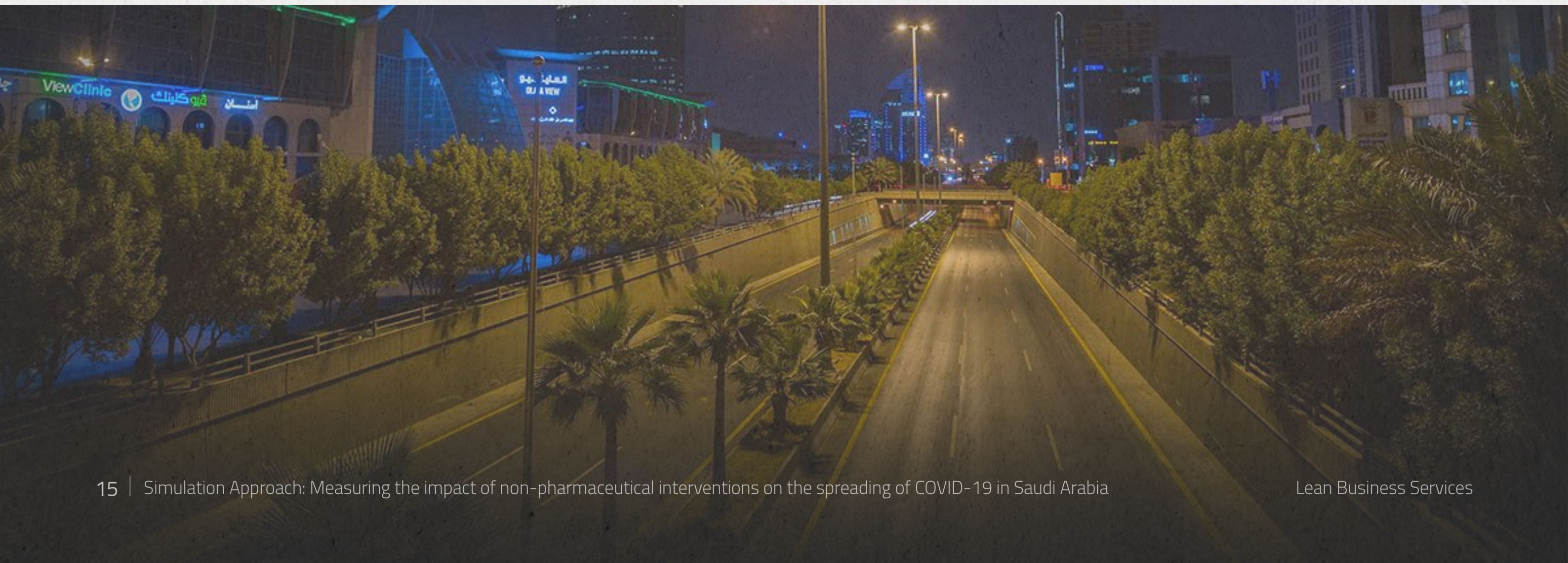
Ban on going to all workplaces

- Partial lockdown from 7pm to 6am
- Lockdown extension
- 24 hours lockdown.

The impact of the following NPIs was measured as a combined impact

Ban on shopping, gatherings and going to governmental workplaces

In order to compare the impact of the NPIs, we will report the impact for the first 14 days after the implementation of the NPI as well as at the end of the study period.



RESULTS

Model Validation Using Reverse Engineering

Between March 2 and July 1, 2020, the model was in an iterative process of training and retraining using reverse engineering. Figure 3 shows the seven-day-prediction performance against the observed numbers in KSA for the four reported outcomes.

* The initial model performance was poor and the percentage difference between the predicted and observed numbers was:

17.3%	8.2%	150%
Total Cases	Active Cases	COVID-19-Related Death Cases

** Note that initial ICU data were not available thus, no comparison could be established*

After 14 weeks of continuous reverse engineering, the percentage difference between the predicted and observed numbers became:

0.4%	3.2%	<0.1%	4.5%
Total Cases	Active Cases	ICU-Admitted Cases	COVID-19-Related Death Cases

Figure 3: Seven-day-prediction performance against the observed numbers in KSA through the study period

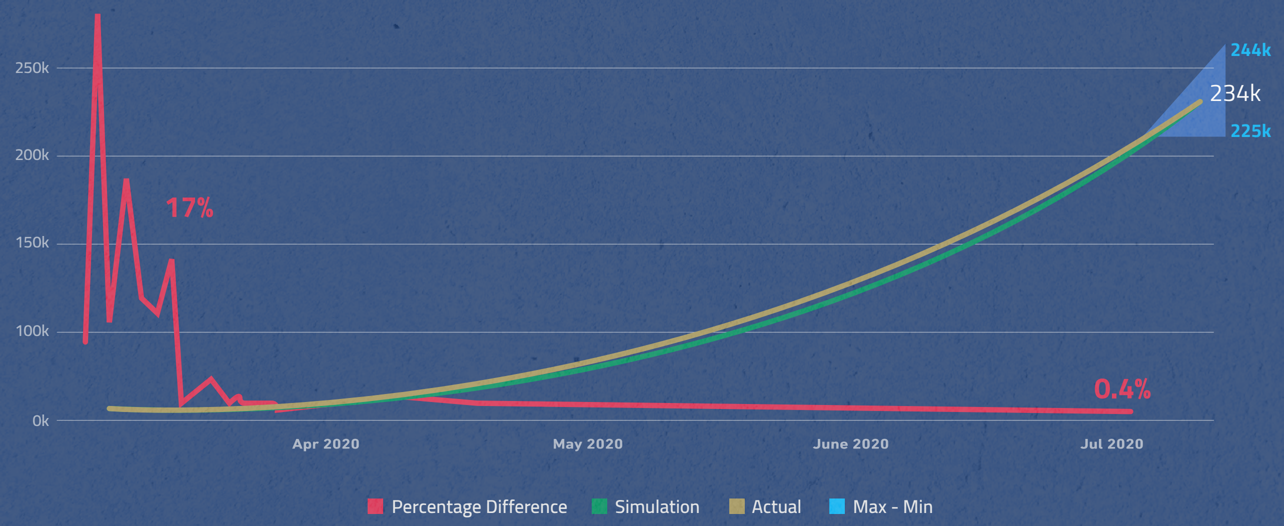


Table 1: Model's Performance at Week 4 And at the End of Week 18 of the Validation Period Across All Simulated Outcomes.

Week	Week 4			Week 18		
Outcome	Simulation	Actual	Percentage Difference	Simulation	Actual	Percentage Difference
Total cases	1056	900	17.3%	234k	235k	0.4%
Active cases	798	869	8.2%	61k	63k	3.2%
ICU	29	NA	-	2.2k	2.2k	<0.1%
Mortality	5	2	150%	2.1k	2.2k	4.5%

RESULTS

Impact of Nonpharmaceutical Interventions

Building The No-NPI Baseline

The validated model using reverse engineering was used to project the active and total cases in KSA (as if there were no NPIs) for the period between March 2nd and July 1st, 2020; the model projected results were then compared with the observed/reported active and total number of cases (Figure 4).

Figure 4: The Total Impact Of All NPIs On Total Cases At The End Of The Study

The model indicated that NPIs taken in Saudi Arabia lead to:

63%
Decrease in Ro

Thus, witout taking the NPIs, there would be an increase of cases:

From
198k
COVID-19 cases

To
3.6m
COVID-19 cases

This can be translated into:

18
COVID-19 cases

were prevented for each documented

1
positive COVID-19 case

Measuring the impact of each NPI

During the study period, we measured the impact of six NPIs (ban on going to schools, the combined impact of the ban on shopping, gatherings, and governmental workplaces, partial lockdown from 7pm to 6am, ban on international travel, lockdown extension, ban on going to all workplaces, and 24-h lockdown).

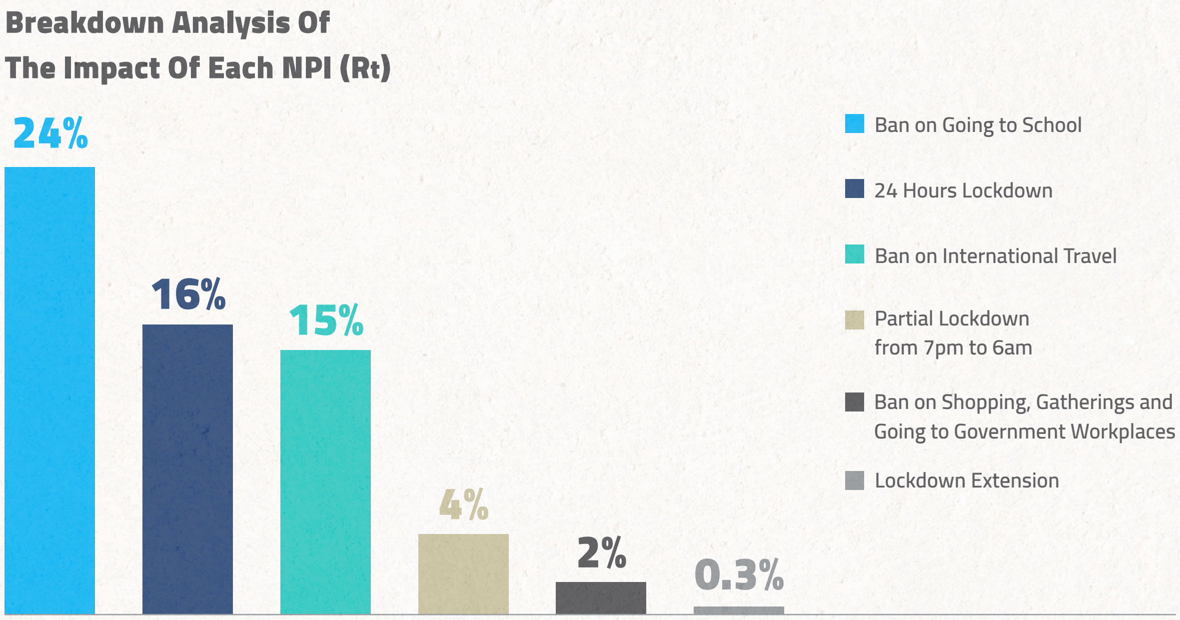


Figure 5 - Breakdown Analysis Of The Impact Of Each NP R_t

NPI	% R_t	% Lower Limit	% Upper limit
Ban going to Schools	24	19	28
Ban International Travel	16	11	20
Start of 24 hr Lockdown in Some Cities	15	11	20
Partial Lockdown from 7pm to 6am	4	0	9
Ban on Shopping, Gatherings, and Going to Government Workplaces	2	0	6
Lockdown Extension	0.3	0	5

Table 2: The Impact of each measured NPI based on the R_t

Additionally, for the purpose of standardizing the impact measure across all NPIs, we reported percentage difference of the four outcomes for each NPI at the end of day 14 from issuing the NPI (Table 4).

NPI	Total Cases	Mortality	Active Case	ICU
Ban going to Schools	36	36	39	39
Ban International Travel	19	19	20	20
Start of 24 hr Lockdown in Some Cities	15	15	18	18
Partial Lockdown from 7pm to 6am	5	5	6	6
Ban on Shopping, Gatherings, and Going to Government Workplaces	2	2	2	2
Lockdown Extension	2	2	2	2

Table 3: Percentage difference calculated as NPI post 14 days simulated outcomes – observed outcomes/ observed outcomes.

Finally, we visualized the simulated impact of each measured NPI on total cases at the end of the study period and compared it with the observed total cases (Page 21). We simulated what would occur if the only measured impact was not implemented while all other NPIs were in place.

1.2M
Ban on Going to School

304K
24 Hours Lockdown

238K
Ban on International Travel

271K
Partial Lockdown From 7pm to 6am

225K
Ban on Shopping, Gatherings and Going to Governmental Workplaces

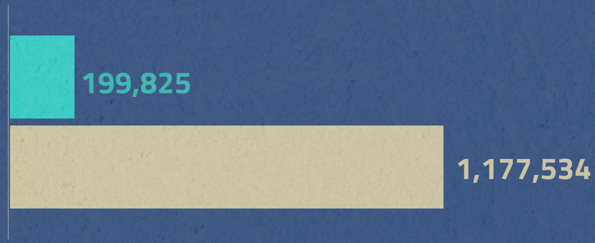
204K
Lockdown Extension

The Total impact Of Each Measured NPI On Total Cases At The End Of The Study

Total Cases: Baseline (Model Projection) **vs Policy** (Observed)

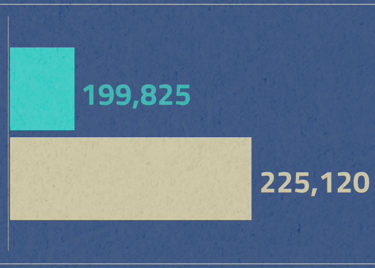
Ban on Going to School
08/03/2020

This policy affected the Rt rate by [20%-30%]



Ban Shopping, Gatherings and going to Governmental Workplace
16/03/2020

Activating this policy affected the Rt Rate by [0%-5%].

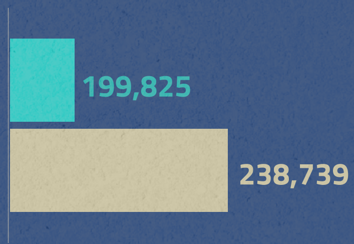


Partial Lockdown from 7pm to 6am
23/03/2020

Activating this policy has affected the Rt rate by [0%-9%]

Ban International Travel
15/03/2020

This policy affected the Rt rate by [10%-20%]

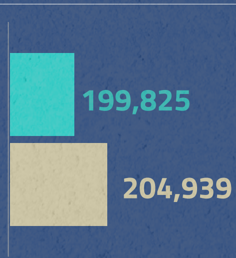


24 Hours Lockdown in Some Cities
30/03/2020

Activating this policy has affected the Rt by [10%-20%]

Lockdown Extension
26/03/2020

Since the previous graph shows no significant changes in the simulated scenario, activating this policy has affected the Rt by [0%-5%] only.



DISCUSSION

In this study, we built a simulation model for COVID-19 based on the context of dealing with the pandemic in KSA. The model was validated using 18 weeks of data using reverse engineering and achieved a 0.4% difference in total cases for prediction at the end of the study period. Moreover, the validated model was used to estimate the impact of implemented NPIs on the spread of COVID-19 in KSA. The model results indicate that without any NPIs, KSA will have 18 COVID-19 cases for each documented case at the end of the study period, with a 64% change in the R_0 for the study period. Our breakdown analysis of the impact of each NPI indicates that banning going to schools had the greatest impact on R_t (24%), followed by 24-h lockdown (16%) and ban on international travel (15%).

Impact Of NPIs Compared to Other Studies

A comparison of the overall impact of NPIs in KSA with that in other countries showed similar patterns. Flaxman et al. (2020) conducted a study to estimate the effect of NPIs on COVID-19 in 11 European countries and found that the estimates of R_t ranged from 0.44 to 0.82, with an average of 0.66, which is a change of 82% in the pre-interventional R_0 (29). In KSA, the reduction in R_0 was 63% from the pre-interventional R_0. Comparing the effectiveness of individual impact of NPIs in KSA with other countries,

Haug et al. (2020) conducted a study to rank the effectiveness of global COVID-19 government interventions; they collected data from 79 territories and reported the results from 46 most effective NPIs. Comparing their findings with ours, school banning came second (first in ours), whereas the travel ban came third (second in ours), and lockdown came sixth (first in ours) (10).

To note, the small gathering cancellation- which came first in rank among the measured NPIs in the referenced paper- was not included in our analysis. However, considering the social norms of KSA, this measure may show a significant impact as well.

Beyond COVID-19

This is one of a few studies internationally (and the first nationally) to adopt a hybrid simulation modeling to mimic epidemiological behavior. The model proposed herein can be used beyond the current COVID-19 pandemic and serves as a base for other epidemiological simulations in KSA and other countries. We implemented a hybrid simulation model to simulate various aspects of the Saudi culture during COVID-19; this model can be used for healthcare planning in contexts other than infectious diseases as well. An example of this is capacity planning for healthcare services and devices such as ICUs and ventilators. Finally, we showed that choosing the right paradigms of simulation can be a strong, practical decision support tool that can be further used in fields outside the healthcare sector.

Limitations

The data used in the proposed model were imported from a single country; thus, generalizing the results from the current model to other countries might result in less-than-optimal performance. We encapsulated the model into a simple graphical interface that allows users to manually adjust the default values for the model pathways and actions. Another limitation of our model is that there is a possibility of noise while capturing the impact of NPIs. This is challenging to prove because many NPIs were implemented only once during the study period. However, we accounted for this by defining multiple NPIs as one and measuring the cumulative impact. Future efforts should include measuring the long-term impact of NPIs on several occasions or compare data from several countries with an assumed similar cultural behavior to determine the impact from multiple resources. Finally, this model was based on documented cases; thus, changing the documentation/reporting process in the future might require further reverse engineering to the model.

CONCLUSION

In this study, we used hybrid simulation modeling to estimate the impact of NPIs taken by the KSA government. **The proposed model shows that COVID-19 cases will increase 18-fold in KSA if NPIs were not implemented.** Our breakdown analysis of the impact of each NPI indicates that the **ban on going to school had the greatest R_t**, followed by ban on international travel, 24-h lockdown, partial lockdown from 7pm to 6am, ban on shopping, gatherings, and going to government workplaces, then Lockdown extension.

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Acknowledgment

This white paper is a collaborative efforts of the Lean Business Services & the National Health Command Center (NHCC). The NHCC, has set its vision and mission to become a global reference in utilizing real-time healthcare data and to foster successful collaborative partnerships with stakeholders nationally and international. In addition, the NHCC aim to strengthen the health system, improve performance, spearhead technology and innovation, and to support growth and research. The collaboration with the NHCC, was instrumental in supporting Lean efforts through out this exercise. The NHCC, has fully supported Lean efforts throughout the pandemic and was the source of the data which Lean used to feed in the model. Lean would like to thank all participants from the NHCC especially those involved in the review of this paper, and those who have dedicated numerous hours of their time of this work to collect and update data of various dashboards. Finally, a special Thanks to Dr. Mohammed K. Al-Abdulaali, the Assistant of the Minister, MoH and Dr. Dhalia M. Khan.

Disclaimer

The effect of the newly developed model was measured without controlling of, or modeling the effects of the whole NHCC interventions and Tabuad app as COVID-19 control measures.

CONTRIBUTORS

Mohammed Alabdulaali, MD.

Assistant of the Minister, Ministry of Health
abdul-aali@moh.gov.sa

Hani Jokhdar, MD.

Deputy minister for Public Health, Ministry of Health
hjokhdar@moh.gov.sa

Talal Altuwaijri, MD.

Deputy Minister for Planning and Transformation Vision Realization Office Leader, Ministry of Health
taaltuwijri@moh.gov.sa

Abdullah Algwizani, MD.

Chief Executive Officer, Public Health Authority
argwizani@cdc.gov.sa

Dalia Mominkhan, MD.

CEO of the NHCC, Ministry of Health
dmmominkhan@moh.gov.sa

Maram Alotaiby, Ph.D.

General Supervisor for Laboratory Services, Transfusion Medicine and Medical Forensic Services, Ministry of Health
alotaibyma@moh.gov.sa

Waleed AlBahli, B.S.

General Manager, National Health Information Centre
w.albahli@shc.gov.sa

Haleema Alserehi, MD.

General Director, Communicable Diseases Department, Ministry of Health
halserehi@moh.gov.sa

Anas Khan, MBBS, SBEM, MHA

Global Center for Mass Gatherings Medicine, Ministry of Health
khanaa@moh.gov.sa

Muaddi Alharbi, Ph.D.

Advisor to the Assistant of the Minister, Ministry of Health
muaddi.alharbi@gmail.com

Maryam Almoklif, MD.

NHCC Strategic Advisor, Ministry of Health
mukalf@moh.gov.sa

Ahmad Alghamdi, B.S.

NHCC Analytics Team, Ministry of Health
aalghamdi29@moh.gov.sa

Nasser Abutaleb, B.S.

IT Consultant for Medical Referral Center, Ministry of Health
n3535082@kfshrc.edu.sa

Sarah Alqahtani, B.S.

Director of Studies and Consultation Office, Ministry of Health
qahtanisl@moh.gov.sa

Fahad Alsaawi, MS.

Chief Data Officer, Lean Business Services
f.alsaawi@lean.sa

Marwan Albalawi, MS.

Director, Department of Digital Health, Lean Business Services
m.albalawi@lean.sa

Abdullah Alzeer, Ph.D.

Research and Development Manager, Lean Business Services
a.alzeer@lean.sa

Ahmad Alhomaid, MS.

Senior Machine Learning Lead, Lean Business Services
a.alhomaid@lean.sa

Abdulaziz Aljandal, B.S.

Machine Learning Lead, Lean Business Services
a.aljandal.@lean.sa

Dana Alotaibi, B.S.

Data Analyst, Lean Business Services
danaturkiif@gmail.com

Abeer Alsouly, B.S.

Business Development Lead, Lean Business Services
abeeralsouly@gmail.com

Turki Albakran, B.S.

Business Analyst, Lean Business Services
t.albakran@lean.sa

Mohammad Hamad, B.S.

Senior Graphic Designer Lead, Lean Business Services
m.hamad@lean.sa

Lean's Business Services would like to express their sincere gratitude to The Ministry of Heath for all their valuable and continuous contributions and support.

www.lean.sa info@lean.sa +966114866818 lean-sa LeanSaudi

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