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The impact of non-pharmaceutical interventions on the spread of COVID-19 in Saudi Arabia: Simulation approach

Ahmad Alhomaid [a,1], Abdullah H. Alzeer [a,1], Fahad Alsaawi [a], Abdulaziz Aljandal [a], Rami Al-Jafar [a,b,*], Marwan Albalawi [c], Dana Alotaibi [a], Raghad Alabdullatif [a], Razan AlGhassab [a], Dalia M. Mominkhan [d], Muaddi Alharbi [d], Ahmad A. Alghamdi [d], Maryam Almoklif [d], Mohammed K. Alabdulaali [e]

[a] *Data Services Sector, Lean Business Services, Riyadh, Saudi Arabia*
[b] *School of Public Health, Imperial College London, London, UK*
[c] *Department of Digital Health, Lean Business Services, Riyadh, Saudi Arabia*
[d] *National Health Command Center, Ministry of Health, Riyadh, Saudi Arabia*
[e] *Ministry of Health, Riyadh, Saudi Arabia*

A R T I C L E I N F O

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A B S T R A C T

Objectives: This paper aims to measure the impact of the implemented nonpharmaceutical interventions (NPIs) in the Kingdom of Saudi Arabia (KSA) during the pandemic using simulation modeling.
Methods: To measure the impact of NPI, a hybrid agent-based and system dynamics simulation model was built and validated. Data were collected prospectively on a weekly basis. The core epidemiological model is based on a complex Susceptible-Exposed-Infectious-Recovered and Dead model of epidemic dynamics. Reverse engineering was performed on a weekly basis throughout the study period as a mean for model validation which reported on four outcomes: total cases, active cases, ICU cases, and deaths cases. To measure the impact of each NPI, the observed values of active and total cases were captured and compared to the projected values of active and total cases from the simulation. To measure the impact of each NPI, the study period was divided into rounds of incubation periods (cycles of 14 days each). The behavioral change of the spread of the disease was interpreted as the impact of NPIs that occurred at the beginning of the cycle. The behavioral change was measured by the change in the initial reproduction rate (R_0).
Results: After 18 weeks of the reverse engineering process, the model achieved a 0.4 % difference in total cases for prediction at the end of the study period. The results estimated that NPIs led to 64 % change in The R_0. Our breakdown analysis of the impact of each NPI indicates that banning going to schools had the greatest impact on the infection reproduction rate (24 %).
Conclusion: We used hybrid simulation modeling to measure the impact of NPIs taken by the KSA government. The finding further supports the notion that early NPIs adoption can effectively limit the spread of COVID-19. It also supports using simulation for building mathematical modeling for epidemiological scenarios.

1. 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) (WHO, 2020a). In December 2019, China reported a cluster of pneumonia cases in patients associated with the Huanan Seafood Wholesale Market in Wuhan, Hubei Province.

* Corresponding author.
E-mail addresses: a.alhomaid@lean.sa (A. Alhomaid), A.Alzeer@lean.sa (A.H. Alzeer), f.alsaawi@lean.sa (F. Alsaawi), A.aljandal@lean.sa (A. Aljandal), r.aljafar@lean.sa (R. Al-Jafar), M.Albalawi@lean.sa (M. Albalawi), d.alotaibi@lean.sa (D. Alotaibi), R.alabdullatif@lean.sa (R. Alabdullatif), r.alghassab@lean.sa (R. AlGhassab), dmmominkhan@moh.gov.sa (D.M. Mominkhan), alghamdi29@moh.gov.sa (A.A. Alghamdi), Maryam.Almaklf@health.sa (M. Almoklif), MAL-Abdul-Aali@moh.gov.sa (M.K. Alabdulaali).

[1] Abdullah Alzeer and Ahmad Alhomaid contributed equally to this paper.

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On January 7, 2020, the Chinese government confirmed that the incidence was because of a novel coronavirus (COVID-19) (Holshue et al., 2020). The virus spread from China to other countries in the following months, prompting the World Health Organization (WHO) to declare COVID-19 a public health emergency of international concern on January 30 and a pandemic on March 11 (WHO, 2020b).

In response to the COVID-19 spread, Kingdom of Saudi Arabia (KSA) declared a ban on going to school 7 days after the reporting of the first case on March 2nd, 2019. Other nonpharmaceutical interventions (NPIs) were applied to limit the spread of COVID-19 such as suspending domestic and international flights (Arab_News, 2020; Nasrallah, 2020), entry for visiting pilgrims (BBC, 2020), and major sport and social events (SAFF, 2020), along with many other interventions (Table 1).

Due to the adoption NPIs across different countries, a growing assessment of the effectiveness of NPIs at minimizing the spread of COVID-19 is populating the literature (Chan et al., 2021; Haug et al., 2020; Liu et al., 2020; Snoeijer et al., 2021; Yang et al., 2021). Some studies have measured the impact of NPIs indirectly, such as measuring the effect of NPIs on population mobility during COVID-19 using mobility data from Google and Apple (Ružić Gorenjec et al., 2021; Snoeijer et al., 2021), while other studies used more direct approach by measuring the impact of NPIs on the spread of COVID-19 using the change in reproduction number (R_0) literature (Liu et al., 2020). Despite the method used, there is a general notion (not census) across studies that closure of public places (Haug et al., 2020; Hunter et al., 2020; Liu et al., 2020; Wibbens et al., 2020) and limiting mobility (Dreher et al., 2021; Esra et al., 2020; Olney et al., 2021) were among the most effective NPIs in controlling the spread of the virus. In a systematic review conducted on 34 studies assessed the NPIs effectiveness on the context of COVID-19, the study found school closures, workplace closure and venue bans were the most effective NPIs among the studies identified. While limiting movement such as lockdown and travel restriction had an intermediate impact on studies' outcomes (Mendez-Brito et al., 2021). However, these findings did not go unchallenged, Fukumoto, et al (2021) has conducted a study to measure the causal effect of school closure on the spread of COVID-19 by matching each municipality with open schools to a municipality with closed schools (Fukumoto et al., 2021). The study found no evidence that school closure can lead to less spread of COVID-19 (Fukumoto et al., 2021). The variation in the effectiveness of an NPI might be affected by several factors, such as how early the NPI was taken (Chaudhry et al., 2020; Koh et al., 2020) and the number and types of concurrent implementation of NPIs (Bo et al., 2021; Islam et al., 2020).

Despite the debate over the positive impact of the NPIs on the spread of COVID-19, the negative economic and social consequences of these NPIs might hinder stakeholders from implementing them in their communities for a prolonged period (Barrot et al., 2020; Koren & Pető, 2020; Thunström et al., 2020). Education, wellbeing, and global economy are all example of affected aspects in life (Co-operation & Development, 2020; Pfefferbaum & North, 2020; Snoeijer et al., 2021). These consequences can be more prominent in economies dependent on oil (UN_in_KSA, 2020). As it was described in the United Nation's diagnostic paper: KSA was hit with a "dual impact", from socioeconomic perspective, due to the low oil prices and COVID-19 pandemic which led the government to spend over 7 % of its gross domestic product to ease the socioeconomic impact of COVID-19 (UN_in_KSA, 2020).

Table 1
Nonpharmaceutical interventions (NPIs) made by the Saudi Arabian government from March 2 to July 1, 2020.

Start	End/Measured until	NPI
23/01/2020	July 1, 2020	Media campaigns
8/03/2020	July 1, 2020	Ban going to schools
9/03/2020	July 1, 2020	Umrah hold for all
15/03/2020	28/5/2020	Ban on shopping, gatherings, and going to governmental workplaces
16/03/2020	31/6/2020	Isolation of Travelers/ Ban on international travel
17/03/2020	31/6/2020	Closed mosques
23/03/2020	30/3/2020	Partial lockdown from 3 pm to 7 pm
25/03/2020	30/3/2020	Lockdown extension from 7 pm to 6 am
30/03/2020	28/5/2020	Start of 24-h lockdown in some cities

1.1. Literature review on simulation modeling for COVID-19

Since the start of the pandemic, several simulation/mathematical approaches have been implemented to evaluate the impact of the NPIs in limiting the spread of the Covid-19 pandemic to support decision-making. Agent-based model (ABM) is a popular method captures the epidemic spreading. Various ABM have been increasingly utilized to investigate the spreading dynamics of COVID-19 and to measure the impact of the different NPIs in limiting the spread of the pandemic (Aleta et al., 2020; Alzu'bi et al., 2021; Bouchnita & Jebrane, 2020; Carcione et al., 2020; Ding et al., 2018; Ferguson et al., 2020; Kaffai & Heiberger, 2021; Lai et al., 2020; Naimark et al., 2021; Ogden et al., 2020; Wilder et al., 2020; Yang et al., 2020).

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 (Homer and Hirsch, 2006). 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 (Flaxman et al., 2020). 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, 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. The advantage of this approach is its ability to build high representation for each discreet agent in the scenario. Nonetheless, ABMs have several drawbacks and limitations in terms of ycomputational power and simulation time (Tracy et al., 2018). The large number of the independent individuals and the complexity of the models to disease spread in cities leads to the simulation time issue where they require a long time.

Despite the several simulation/mathematical approaches that have been implemented to evaluate the impact of the NPIs measures, only a few studies have used a hybrid simulation conducted to this point, especially to quantify the impact of NPIs measures in limiting the spread of the pandemic of Covid-19.

So far, two studies assessed the impact of the NPIs in KSA. Bisanzio et al conducted a study to evaluate the effect of NPIs on the spread of Covid-19 (Bisanzio et al., 2022). However, this study only considered the main measures, namely physical distancing, mask-wearing, and contact tracing and overlooked other measures, such as mosques closure and Umrah hold. Another study deployed a SEIR-type model of COVID-19 transmission to assess the effect of the NPIs in KSA and considered most measures applied during the pandemic (Perez-Saez et al., 2022). However, none have evaluated the impact of each NPI separately and their contribution to the overall impact. Thus, this paper aims to estimate the impact of the implemented NPIs collectively and how much each has contributed to the overall impact on the spread of COVID-19 in KSA during the early months of the pandemic using a hybrid simulation model.

2. Methods

2.1. Methods overview

To measure the impact of NPI, a hybrid simulation model was built and validated. To this end, data were collected prospectively on weekly basis between the period weekly between March 2 and July 1, 2020. The mathematical model is based on ABM to simulate the behavior at the individual level and SD is used to simulate the behavior at the population level- the ABM fed information on individuals' behaviour, specifically mobility, into the SD. The core epidemiological model is based on a complex SEIR and dead (SEIRD) model of epidemic dynamics. To simulate the behavior of the infection in KSA, a set of multiple hyperparameters was added to the model and categorized into clinical, behavior, population, health resources. 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, deaths cases. Finally, to measure the impact of each NPI, we divided the study period into rounds of incubation periods (14 days each). 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). For further details see (Appendix A).

2.2. The mathematical model

This study proposed a hybrid simulation modeling that overcomes the limitations of the SD and the ABM to show a good compromise between the flexibility to accommodate various scenarios and the complexity of the model related to the computational power. For that reason, the model utilized ABM to simulate the behavior at the granular level whereas SD was utilized to manage large information at the aggregate level, where combining these two techniques increase the flexibility of the model to accommodate various scenarios (Sewall et al., 2011; Swinerd & McNaught, 2012).

We utilized SD to simulate the behavior at the population level, in particular the day-to-day interactions and the spread behavior of the disease on each region. At this level, we don't have specific attributes for the individuals, but we have attributes for each region such as policies, number of cases, number of active cases, and number of mortalities. Nonetheless, to represent certain scenarios in the individual level, ABM is needed to capture the attributes of the individuals. Thus, ABM was utilized to simulate behavior at the individual level, in particular traveling from city to another, performing hajj, and inside a classroom, where we have specific attributes for the individuals such as infection status, immunization status, age, flight information, comorbidities, body mass index, and polymerase chain reaction test. (Fig. 1) in Appendix A shows the utilization of ABM and SD.

The hybrid model (ABM + SD) enabled us to validate results performance for each run. Consequently, that enabled us to change the parameters based on the reverse engineer until either an acceptable percentage difference or saturation is reached.

2.3. The core epidemiological model

The simulation is based on a complex SEIRD model of epidemic dynamics, which is a five-state/stock nonlinear SD model for simulating the spread of infection between agents using multiple parameters (Campillo-Funollet et al., 2020; Krivorot'ko et al., 2020; Signes-Pont et al., 2021). In the proposed model, the infectious state is divided into four stocks: mild, mild isolated, severe, and severe isolated (Fig. 2) in Appendix A. 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).

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 non-isolated 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 (flighttrader24, 2020). 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.

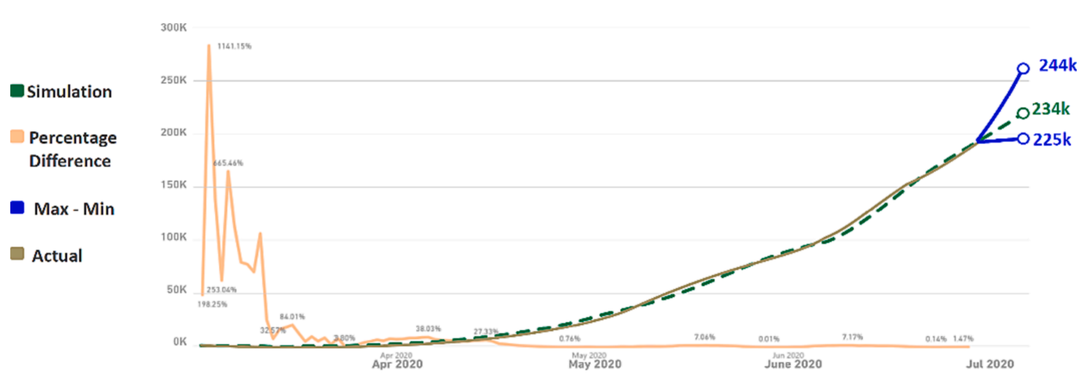

Fig. 1. Seven-day prediction performance against the observed numbers in KSA through the study period.

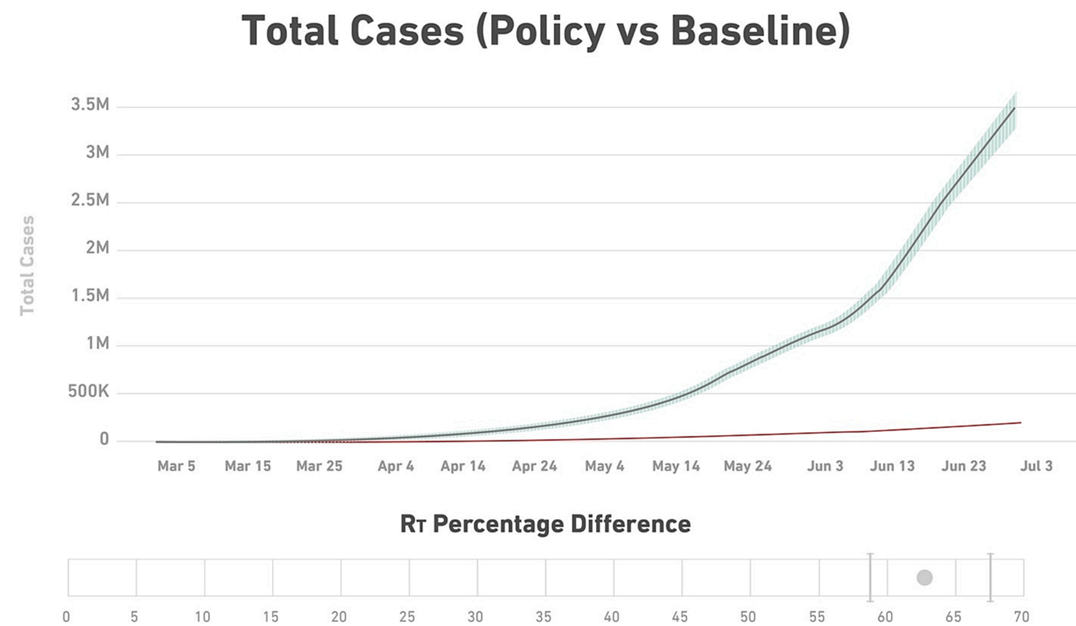

Fig. 2. The total impact of All NPIs on Total cases at the end of the study.

2.4. Additional epidemiological models

Multiple models are built on top of SEIRD model 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 ABM is built. Another example of these simulations is one to simulate national travel, whether by airplane, road trips, or trains.

2.5. R0 calculation

The behavioral change was measured by the change in the initial reproduction rate (R_0) (Jones, 2007).

$$R0 = \tau\hat{A}\cdot c\hat{A}\overline{\hat{A}}\cdot d$$

τ refers to the probability of infection due to infected and susceptible individuals contact; $c\hat{A}$ refers to contact between infected and susceptible average rate; d refers to infectiousness duration. The Ministry of Health provided data on these factors on a regular basis to be utilized in this project. R0 was estimated with and without the NPIs, for example, with and without mobility (lockdown).

2.6. 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 $(t) \geq 0$
- MI (t) be the number of mild in time t, M $(t) \geq 0$
- M (t) be the number of mild isolated in time t, Se $(t) \geq 0$
- V (t) be the number of severe in time t, Se $(t) \geq 0$
- V $I(t)$ be the number of severe isolated in time t, I $(t) \geq 0$
- $R(t)$ be the number of recovered in time t, R $(t) \geq 0$
- $D(t)$be the number of dead in time t, $(t) \geq 0$

then,

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

$$\frac{dS}{dt} = -\frac{\alpha SI}{P}$$

$$\frac{dE}{dt} = \frac{\alpha SI}{P} - \Delta E$$

$$\frac{dM}{dt} = (1-s)^*(\Delta E - \beta I - \mu I)$$

$$\frac{dMI}{dt} = (-\beta I - \mu I) - [(1-s)^*(\Delta E - \beta I - \mu I)]$$

$$\frac{dV}{dt} = s^*(\Delta E - \beta I - \mu I)$$

$$\frac{dVI}{dt} = (-\beta I - \mu I) - [s^*(\Delta E - \beta I - \mu I)]$$

$$\frac{dR}{dt} = \beta I$$

$$\frac{dD}{dt} = \mu I$$

$$\frac{dS}{dt} + \frac{dE}{dt} + \frac{dI}{dt} + \frac{dR}{dt} + \frac{dD}{dt} = 0$$

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 ($\varepsilon > 0$).

2.7. Pathways

To maximize the model's accuracy to simulate the behavior of the infection in Saudi Arabia, a set of multiple hyperparameters were added to the model. The addition of the parameters was based on subject matter experts' opinion from the National Health Command Center (NHCC), data availability and as well as benchmark from other similar world experiences (Kiarie et al., 2022; Kraemer et al., 2020). 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 hyperparmeters 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 (Table 1) in Appendix A. Clinical parameters are related to the behavior of the disease itself, such as the incubation period, probability of disease transmission when there is contact, mortality rate based on demographics (i.e., age and comorbidities), and ICU proportion. Behavior parameters are related to the behavior of the population, such as contact rate, mobility, and international and national travel. Population parameters are related to demographics, such as the population, age distribution, comorbidity prevalence, and students' and schools' demographic statistics. Finally, healthcare resource parameters are related to healthcare resources, such as ventilators, ICU beds, and human resources.

2.8. Analysis

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.

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 (Roda et al., 2020). 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: number of infectious cases (including recovered, mortality, and active infectious cases) from day 0 to a specified day
- Active cases: number of active infectious cases on a specified day. Active Cases = Total cases − (Recovered + Mortality)
- ICU cases: number of active infectious cases that were admitted to the ICU because of Covid-19 on a specified day
- Death cases: 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.

The model used to assess the impact of the NPIs 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 infection reproduction rate (R_t) -the reproduction rate at any given time (t)- is applied for each NPI on the same day that intervention occurred. If multiple NPIs occurred at the same time, they will be treated as one NPI (combined impact). The impact of the following NPIs was measured individually:

Ban schools' physical attendance, lockdown from 7 pm to 6 am; the ban on international travel, lockdown extension from 7 pm to 6 am, the ban on going to all workplaces, and 24-h lockdown. The impact of the following NPIs was measured as a combined impact: the ban on shopping, gatherings, and 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.

3. Results

3.1. 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. Fig. 1 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 % for the total cases, 8.2 % for active cases, and 150 % COVID-19 related death cases. Note that initial ICU data was 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 % for the total cases, 3.2 % for active cases, <0.1 % ICU-admitted cases, and 4.5 % COVID-19 related death cases. The model's performance improved over time and reached optimal prediction, reflecting its effectiveness. During March 2020, the initial period of the model, the overall percentage difference across the four outcomes (total cases, active cases, ICU, mortality) peaked at 1141 %, and after iterative runs, it reached its optimal precision at a percentage difference of 0.14–1.5 % in Jul 2020. Table 2 demonstrates the model's performance at the beginning and end of the validation period across all simulated outcomes. In this validation process, we report on the results from the fourth week as our initial model performance reporting because the first weeks do not capture the full complexity of the model; instead, they mainly capture a part of the model where infected people come from outside the country. Still, the average decline in the percentage difference was large (41.6 %), reflecting the improvement acceleration.

3.2. Impact of NPIs

The validated model using reverse engineering was used to project the active and total cases in KSA (as if there were no NPIs) between March 2 and July 1, 2020; the model results were then compared with the observed/reported active and total number of cases. The model projected the total and active cases to be 3.6 M and 1.4 M compared to the observed 198 K and 58 k total and active cases, with a change of 63 % in R_0 at the end of the study period. This can be translated into 18 COVID-19 cases for each documented case at the end of the study period. (Fig. 2) visualizes the total impact of All NPIs on total cases (No NPI baseline).

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; lockdown from 7 pm to 6 am; ban on international travel; lockdown extension from 7 pm to 6 am; ban on going to all workplaces; and 24-h lockdown). Our analysis of the R_t attributed to each NPI shows that the ban on going to school had the greatest R_t (24 %), followed by 24-h lockdown (16 %), ban on international travel (15 %), Lockdown extension from 7 pm to 6 am (4 %), Ban on shopping, gatherings, and going to government workplaces (2 %), then Partial lockdown from 3 pm to 7 pm (0.3 %) (Table 3).

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).

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 (Appendix B: Figures 3–8). We simulated what would occur if the only measured impact was not implemented while all other NPIs were in place. Our analysis to the impact of each measured NPI shows that without banning going to school the total cases would have been 1.2 M cases at the end of the study. The other NPIs showed the following results on total cases at the end of the study period: 24-h lockdown (304 K), ban on international travel (238 K), Partial lockdown from 3 pm to 7 pm (271 K), Ban on shopping, gatherings, and going to government workplaces (225 K), then Partial lockdown from 3

Table 2
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	234 k	235 k	0.4
Active cases	798	869	8.2	61 k	63 k	3.2
ICU	29	NA	–	2.2 k	2.2 k	<0.1
Mortality	5	2	150	2.1 k	2.2 k	4.5

Table 3
The Impact of each measured NPI based on the 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 3 pm to 7 pm	4	0	9
Ban on shopping, gatherings, and going to government workplaces	2	0	6
Lockdown extension from 7 pm to 6 am	0.3	0	5

Table 4
Percentage difference of four outcomes after 14 days for each measured NPI.

NPI	Percentage difference (%)* of four outcomes after 14 days			
	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 3 pm to 7 pm	5	5	6	6
Ban on shopping, gatherings, and going to government workplaces	2	2	2	2
Lockdown extension from 7 pm to 6 pm	2	2	2	2

* Percentage difference calculated as NPI post 14 days simulated outcomes – observed outcomes/ observed outcomes.

pm to 7 pm (204 K).

4. Discussion

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. The rapid decline in the percentage difference between simulated and observed outcomes reflected the model effectiveness. 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 effective reproduction number (R_t) 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 %).

4.1. 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 (Flaxman et al., 2020). 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) (Haug et al., 2020). 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.

4.2. 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.

4.3. 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.

5. Conclusion

We used hybrid simulation modeling to measure 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 24-h lockdown, ban on international travel, Lockdown extension from 7 pm to 6 am, Ban on shopping, gatherings, and going to government workplaces, then Partial lockdown from 3 pm to 7 pm. The finding further supports the notion of the early NPIs adoption can effectively limit the spread of COVID-19. It also supports using simulation for building mathematical modeling for epidemiological scenarios.

Summary Table:

What was already known on the topic	What this study added to our knowledge
Measuring the impact of NPIs was established in some parts of the world but NPIs impact were not measured in Saudi Arabia.	This study was the first effort to try identifying the impact of NPIs in Saudi Arabian cultural context.
No study compared the effectiveness of NPI on R0 in Saudi Arabia.	This study provide evidence on the effectiveness of several NPIs on changing R0 in Saudi Arabia.
No prior effort was conducted to build and validate a model to simulate COVID 19 behavior in Saudi Arabia.	This study built a hybrid model using system dynamics and Agent base modeling to simulate COVID 19 behavior in Saudi Arabia.

Ethics approval and consent to participate

The study was approved by Central Institutional Review Board at Ministry of Health, Saudi Arabia. with IRB number 20-209E. Email: GDRS-IRB@moh.gov.sa.

Availability of data and materials

The data that support the findings of this study are available from National Health Command Center, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the corresponding author upon reasonable request and with permission of Dr. Dalia M. Mominkhan, Email: dmmominkhan@moh.gov.sa.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsps.2023.101886.

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