

An agent-based model to assess coronavirus disease 19 spread and health systems burden

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ABSTRACT

The present pandemic has tremendously raised the health systems' burden around the globe. It is important to understand the transmission dynamics of the infection and impose localized strategies across different geographies to curtail the spread of the infection. The present study was designed to assess the transmission dynamics and the health systems' burden of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) using an agent-based modeling (ABM) approach. The study used a synthetic population with 31,738,240 agents representing 90.67 percent of the overall population of Telangana, India. The effects of imposing and lifting lockdowns, non-pharmaceutical interventions, and the role of immunity were analyzed. The distribution of people in different health states was measured separately for each district of Telangana. The spread dramatically increased and reached a peak soon after the lockdowns were relaxed. It was evident that is the protection offered is higher when a higher proportion of the population is exposed to the interventions. ABMs help to analyze grassroots details compared to compartmental models. Risk estimates provide insights on the proportion of the population protected by the adoption of one or more of the control measures, which is of practical significance for policymaking.

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1. INTRODUCTION

The first case of coronavirus disease (COVID-19) in India was reported on January 30, 2020, post which "public health emergency of international concern" was declared by the World Health Organization (WHO) considering the impact it could create globally [1]. The epidemic has spread across 221 countries with 228,946,779 reported cases and 4,700,214 mortalities globally as of September 19, 2021 [2]. In India, total infections reported are 1,73,06,420 with 28,07,388 active cases, 1,42,96,703 recoveries and 1,95,118 deaths, till April 25, 2021 [3]. The influx of infections has bothered the countries with a denser population [1]. Several factors such as gender, pollution level, viral load, comorbidities, and others also govern the intensity and duration of infection [4]. A larger proportion of the infected people remaining asymptomatic has further raised serious concerns as they are indistinguishable and act as the potential

sources of transmitting the infection [4], [5]. The healthcare fraternity, researchers, and policymakers from several domains have been trying hard to curtail the transmission of the infection completely [6]. Simulation studies in the past have been successful in addressing issues like preparing evacuation plans for airborne infections [7], devising vaccination strategies for influenza [8], smallpox [9], containing measles [10], and tuberculosis [11]. Agent-based models (ABM) have supported various application areas such as dynamics of transmission [12], tracking contacts [13], scheduling time and geography dependent contacts [12], [14], planning non-pharmaceutical interventions (NPI) [14], [15] such as enforcing lockdowns [12], [13], using face masks, and adopting social distancing [14], and shielding the susceptible population [14], [16].

In India, most researches have employed a compartmental approach based on the susceptible (S), infective (I), and recovered (R) model with modifications such as susceptible (S), exposed (E), infective (I), and recovered (R) (SEIR) [17], susceptible (S), hospitalized or quarantined (H), symptomatic (I), purely asymptomatic (P), exposed (E), recovered (R) and deceased (D) (SIPHERD) [18], and analytical models [19]. Simulations are used to study the real-life systems' behavior in its existing state and upon implementing modifications without associated risks and investment of time and cost [20], [21]. However, the accuracy is subject to authenticity of data, constraints, and assumptions [21]. Complex and dynamic problems could be effectively addressed using simulations [22]. ABM, discrete event simulation (DES), and system dynamics (SD) are three broad classifications of simulations. ABMs entitles the users to define agent-level details [22], [23] and are capable of reporting details of individual agents while DES and SD provide only collective measures [24]. Each agent in the population can be simulated based on different conditions and can be made to perform different actions. A bottom-up approach is employed by ABM wherein the behavior of each agent contributes to the behavior of the system. Each agent holds a specified state at any instant of the simulation [23]. Technological advancements have improved the capability of systems to handle complex models [22].

2. RESEARCH METHOD

From the literature, it was evident that most of the studies to assess the transmission dynamics of infectious diseases employ compartmental models, which fail to incorporate agent-level details. Hence, the present study aims to provide an ABM-based simulation to estimate the spread of COVID-19 by developing a disease model and simulating it using Python. Such simulation studies based on synthetic populations could be helpful for the policymakers and healthcare systems to equip themselves based on the estimates. The present study simulates agents of the synthetic population that represent 90.67% (n=35,003,674) of the overall population of a state. The parameters such as age and geographic information system (GIS) coordinates have been mapped to each individual in the population to ensure exact representation of the state. The incorporation of such agent-level details would help in effectively devising policies locally. Analyzing the NPIs and risk estimates have practical significance in terms of policymaking and governance. In accordance with the Swiss cheese model, the combined effect of multiple interventions on curtailing the spread of infection has been analyzed. Hospitals have been benefited from this approach of setting up multiple defense strategies [25], [26].

2.1. Research design

An ABM approach is employed to assess the outbreak of COVID-19 and its burden on health systems using Telangana state's synthetic population as shown in Table 1. The code for simulation was developed in python, an object-oriented programming (OOP) language using PyCharm, an integrated development environment. The model was simulated for 365 days for various lockdown strictness as per the Indian scenario [27], [28]. The main functionalities of the code involve creating agents, defining contact networks, developing a disease model, devising interventions, and simulating. Transparency of code, assumptions, variables, and scope of the study are retained throughout in adherence with the ethical good practices in modeling and the International Society for Pharmacoeconomics and Outcomes Research (ISPOR-SMDM) modeling good research practices [29]–[31].

2.2. Agent creation

The main idea to employ an ABM was to represent the population of a state by defining the actual attributes to each of them. Data of 31,738,270 people were taken from the 2011 census of India to generate the synthetic population of Telangana. Unique identifiers for person and household, district codes, and geocoordinates were mapped to the agents. During the data cleansing process, 30 invalid entries were eliminated to obtain 35,003,674 valid records that represent 90.67% of the state's population as shown in Table 1 [32], [33].

Table 1. Model parameters

Parameters	<5	5-59	>59	References
Number of contacts per day		Supplementary [28]		[34], [35]
Probability of getting infected through contact (%)	i) closer circle: (3 to 10); ii) other contacts: (1 to 5)			[34]
Proportion of people remaining asymptomatic		0.8		[36], [37]
Average incubation period (in days)		5		[23], [38]
Average treatment duration (in days)		14		[38]
Proportion of hospitalized cases in ICU		0.11		[39], [40]
Treatment duration in ICU (in days)		Triangular (7, 8, 9)		[38], [40]
Proportion of people moving from ICU to critical illness (Ventilator)		0.88		[40]
Treatment duration in ventilator state (in days)		Triangular (5, 7, 12)		[38]
Time between symptom arrival and admission (in days)		3		[41]
Proportion of people who die		As per Indian statistics		[3]
Risk difference for use of control measures (percentage)		i) Mask: 10.2; ii) Distancing: 14.3		[42]

2.3. Contact network

The spread of infection is majorly governed by transmission rates and contact networks. The rate of transmission was varied from 3 to 10% and 1 to 5% for external contacts and household contacts respectively [34]. Contact rates for the present study were assumed to be density-dependent to be varied rationally across districts [15]. The probability with which any two agents meet was assumed to be inversely proportional to the distance between them. Kumar *et al.* [34] conducted a study in Ballabgarh, India to define contact rates for close-contact infections. This was used in integration with the density-dependent contact rate assumption to determine the contact distributions for all the districts. A multiplication factor (ratio of population density of the district under consideration to that of Ballabgarh) was used to find the proportionate corresponding contact rates for each district [15], [34]. Input analyzer tool of arena that helps to fit datasets into various distributions with corresponding errors was utilized to derive the distributions for contact rates of each district [43].

2.4. Disease model

Disease models depict the progression of any disease through various states that govern the behavior of agents. Each agent exists in one of the states at any point in time which changes based on the conditions presented in the statechart as shown in Figure 1. State chart indicates the state of existence of agents in the simulation.

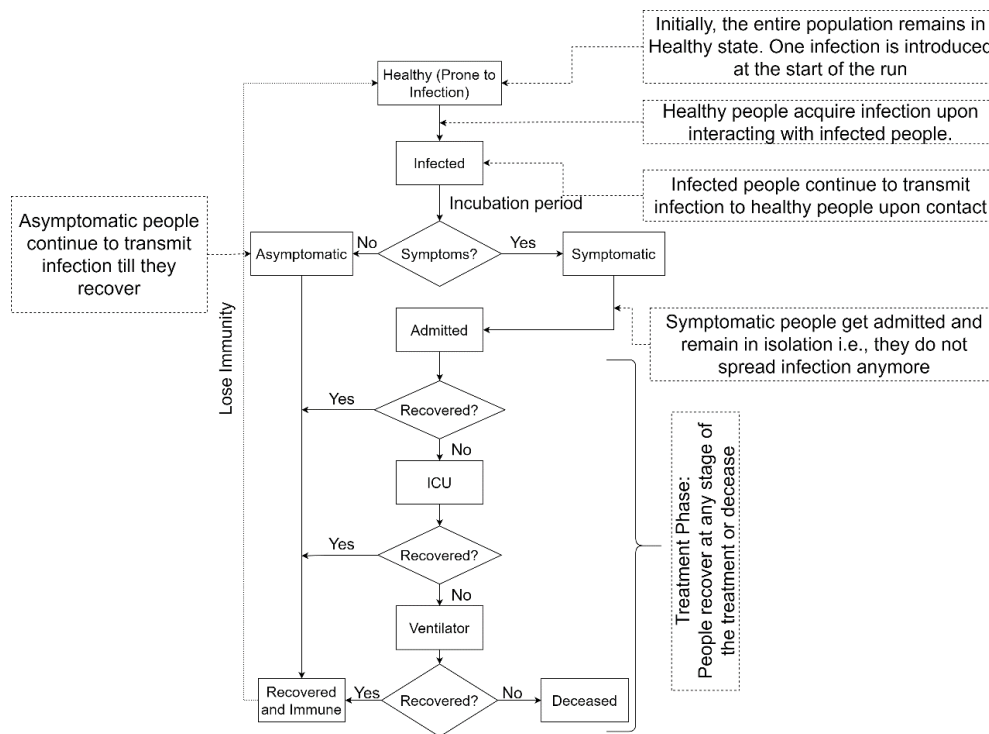


Figure 1. Statechart

At any instant, each agent can exist in one of the states mentioned in the statechart. These are governed by the actions that are defined for each agent during the simulation. The interaction of agents drives the transmission of infection from an infected to a healthy agent. Post transmission of infection, agents turn to be either asymptomatic or symptomatic. The latter undergo treatment after the incubation period while the former are untraceable and are not admitted for treatment. However, they spread the infection till recovery. Symptomatic agents further traverse along three states admitted, intensive care unit (ICU) and ventilator during which they either recover or decrease. The conditions that govern the progression across states with the period of existence in each state are shown in Table 1.

2.5. Model initialization

Various variables that were used to develop the model were obtained from secondary sources including those from the models of infectious disease agent study (MIDAS) [44]. Spatial resolution cannot be attributed as the paths of agents are not considered rather the geo-coordinates are only taken into account. A time step of one day was considered for the simulation.

2.6. Model simulation

The Python code was simulated for the six scenarios defined in Table 2 to compare the effects of various NPIs [45]. The variations in strictness of lockdowns were taken care of by altering the contacts of agents at different locations such as home, schools, and work, depending on the place and age. The contacts outside the home were reduced in accordance with the stringency of lockdowns.

Table 2. Risk estimations

Duration (days)	Scenario	Number of people infected		Relative Risk (95% CI)	Attributable Risk (AR) (95% CI)	PAR	PAR %
		Unexposed	Exposed				
0 to 104	MD100I90	2554	69371	NA	NA		
	MD75I90	21310	31228	0.48 (0.471, 0.506)	-0.001 (-0.0014, -0.00137)	-0.001	-
	MD50I90	20348	14235	0.70 (0.678, 0.721)	-0.0004(-0.00042, -0.00038)	-0.0002	-
	MD100I180	2100	33437	NA	NA		
	MD75I180	32016	55428	0.58 (0.563, 0.591)	-0.0017(-0.00174, -0.00166)	-0.0013	-
	MD50I180	19685	12586	0.64 (0.617, 0.662)	-0.0004(-0.00042, -0.00038)	-0.0002	-
105 to 204	MD100I90	0	6547839	NA	NA		
	MD75I90	1938398	4330703	0.74 (0.743, 0.746)	-0.0624(-0.0627, -0.0621)	-0.0468	-
	MD50I90	3266488	2541571	0.78 (0.777, 0.78)	-0.0457 (-0.046, -0.0454)	-0.0228	-
	MD100I180	0	5668435	NA	NA		
	MD75I180	1693952	3907223	0.77 (0.767, 0.77)	-0.0493 (-0.0496, -0.049)	-0.037	-
	MD50I180	3382489	2782060	0.82 (0.821, 0.824)	-0.0378 (-0.0385, -0.0375)	-0.0189	-
205 to 304	MD100I90	0	5999937	NA	NA		
	MD75I90	1841228	4716186	0.85 (0.852, 0.855)	-0.034 (-0.0342, -0.0336)	-0.0254	-
	MD50I90	3332683	2445789	0.73 (0.732, 0.735)	-0.056 (-0.0562, -0.0556)	-0.0279	-
	MD100I180	0	1171268	NA	NA		
	MD75I180	427366	1008006	0.79 (0.783, 0.79)	-0.011 (-0.0117, -0.0113)	-0.0086	-
	MD50I180	544102	297366	0.54 (0.542, 0.551)	-0.015 (-0.0156, -0.0154)	-0.0078	-
							29.42

3. RESULTS AND DISCUSSION

The effects of various NPIs such as lockdowns with varied stringency, adoption of social distancing, and use of face masks along with the impact of immunity on the spread of infection was observed over 365 days by simulation of six scenarios. The six scenarios would be referred to as MD100I90, MD75I90, MD50I90, MD100I180, MD75I180, and MD50I180 in subsequent sections. The numbers after 'MD' and 'I' indicate the proportion of the population exposed to control measures and immunity period (days) post-recovery respectively. Time-series graphs representing the number of people in asymptomatic and symptomatic states from the overall population are presented in Figure 2. The supplementary file contains time series data of individual districts.

Figure 2 reveals that the spread of infection has risen sharply after the lifting of lockdowns. The reason for subsequent spikes in Figure 2(a) as compared to Figure 2(b) and also in Figure 2(c) as compared to Figure 2(d) is due to the loss of immunity in Figures 2(a) and 2(c) after 90 days of recovery. Lockdowns prove to be the most effective control measure as the variation in terms of infections reduced relatively lesser even though a higher proportion of the population adopt social distancing and mask. However, there is a decline in the peaks of graphs in scenarios with a larger population exposed to interventions.

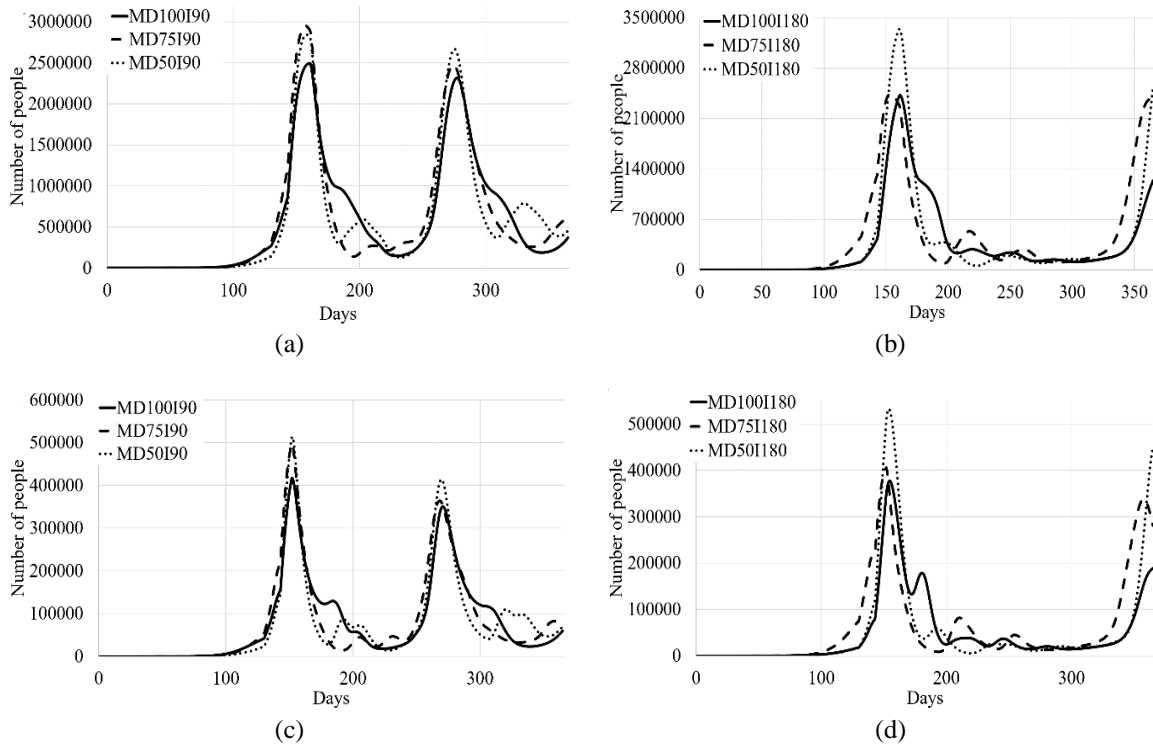


Figure 2. Time trend of infections (a) number of asymptomatic people (90 days immunity), (b) number of asymptomatic people (180 days immunity), (c) number of symptomatic people (90 days immunity), and (d) number of symptomatic people (180 days immunity)

The possibilities of subsequent peaks are higher in the absence of vaccination, as observed in Figure 3. These graphs could improve the preparedness of the healthcare systems and shed light on the capacity required to treat the admitted infections as shown in Figures 3(a) and 3(b), make arrangements for ICU as shown in Figures 3(c) and 3(d), and ventilators as shown in Figures 3(e) and 3(f). The secondary infections are observed as people start to lose their immunity over time. There is a spike in the number of deceased people post-lockdown with subsequent peaks in accordance with the trend of infections. Prolonged immunity provides an additional time window for planning the capacity and vaccination policies. Figure 4 shows a similar pattern with some temporal offset governed by the duration of existence in the preceding states. The second spike in cumulative infections is earlier in case of Figure 4(a) as compared to that of Figure 4(b) due to shorter immunity. Proportionate spikes are seen in Figures 4(c) and (d) indicating recovery post infections. Despite the high recovery rate, untraceable asymptomatic people pose a major challenge for curtailing the spread as they are highly untraceable to be isolated.

The risk estimates as shown in Table 2 reveal the level of protection offered through various interventions. The interpretation of these estimates are: i) relative risk (RR) is the probability of an event occurring to exposed vs unexposed groups; ii) attributable risk (AR) indicates the excess risk due to a risk factor. A negative value indicates protection offered; iii) population attributable risk (PAR) indicates the percentage of cases in the total population that can be attributed to the risk factor; and iv) PAR% is the proportion of the incidence of disease in the population due to exposure. The first period of 104 days indicates the period after which the first recovered person would lose immunity. Successively, these parameters are calculated for further time intervals to analyze how they vary for different lockdown and intervention scenarios. The RR being lesser than 1 denotes that the exposure offers protection rather than risk

[46]. Lifting of lockdowns is the reason for the increase in RR over time indicating the reduction in the protection offered. Owing to the higher protection imparted by the exposure, MD75I90 has a lower RR and PAR values than MD50I90 in the first two timeframes as a higher proportion of the population are exposed in the former scenario. The fact that higher protection is offered during stricter lockdowns is evident from and PAR%. The lifting of lockdowns on the 143rd day as shown in Table 3 has accelerated the transmission which has caused the values to peak drastically. The scenarios corresponding to 100 percent exposure i.e., the entire population follows control measures, have the least peak values.

The research by the center for disease dynamics, economics and policy (CDDEP) and Princeton University complements the present study as it provides information on the estimated state-wise surge in India to help the healthcare fraternity to equip themselves [47]. Considering some other parameters such as clustering in contact networks, especially in the context of the spread of infections would provide improved results. The inclusion of movement patterns along with GIS would enhance the accuracy of estimates. Using wearable devices would offer real-time tracking of COVID-19 patients [48]. The structure of communication networks could be studied deeper to establish contact networks [49], [50]. Detailed analyses on dynamics of population and contact patterns have a strong scope to understand the spread of infections better.

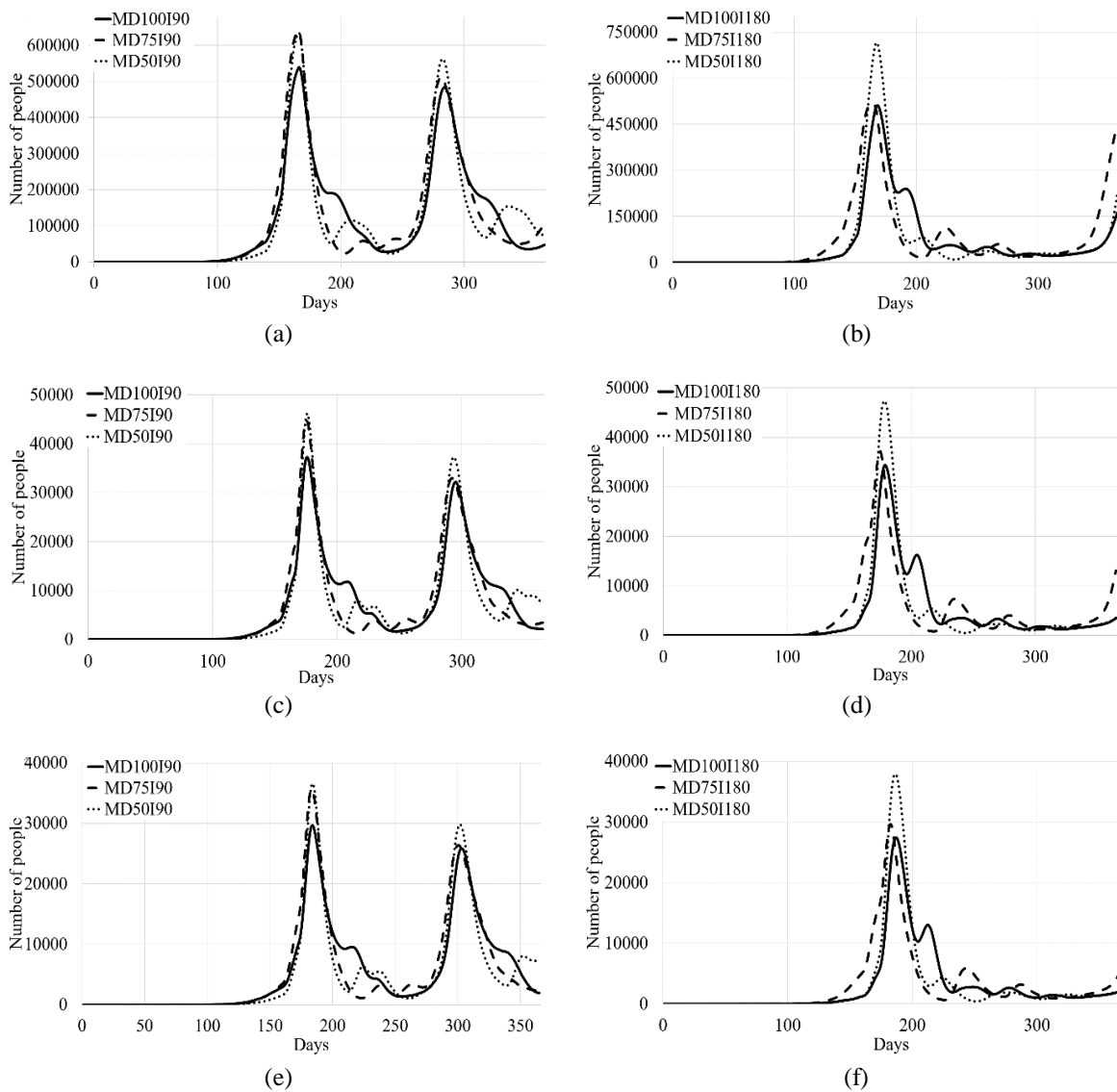


Figure 3. Time trend of hospitalized cases (a) number of admitted people (90 days immunity), (b) number of admitted people (180 days immunity), (c) number of people in ICU (90 days immunity), (d) number of people in ICU (180 days immunity), (e) number of people on ventilators (90 days immunity), (f) number of people on ventilators (180 days immunity)

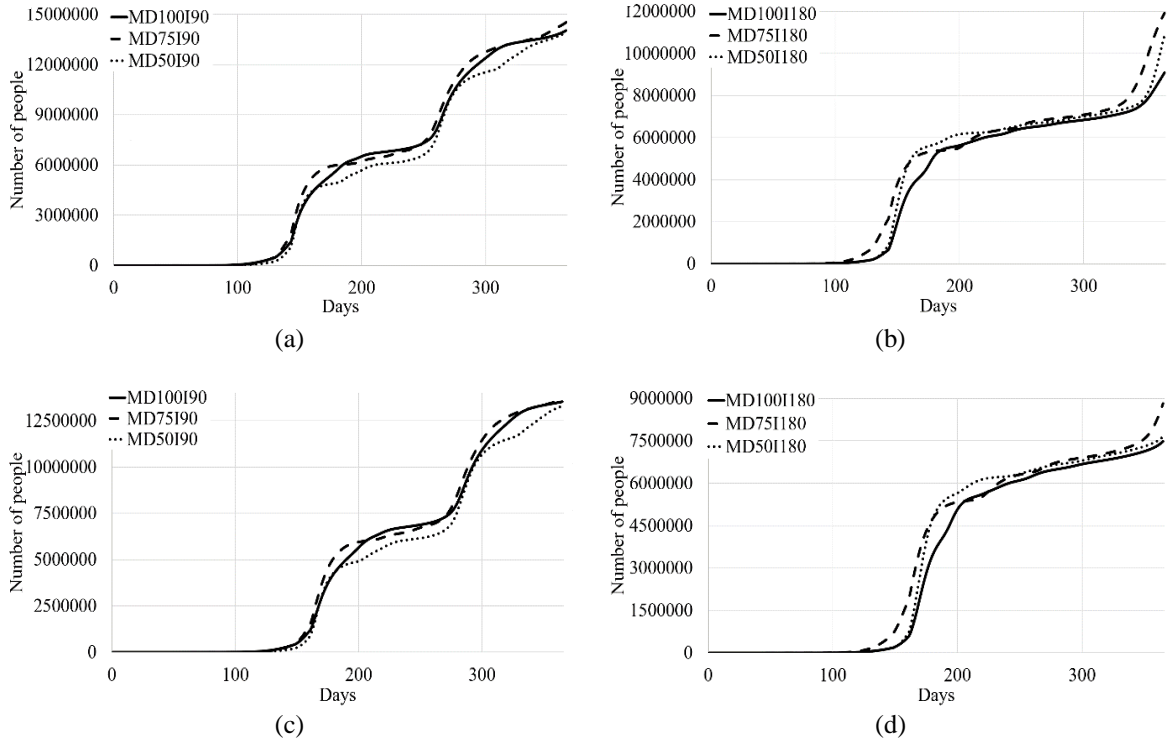


Figure 4. Total infections and recoveries (a) number of cumulative infections (90 days immunity), (b) number of cumulative infections (180 days immunity), (c) number of recoveries (90 days immunity), and (d) number of recoveries (180 days immunity)

Table 3. Peak values

Peak values/ Scenarios/	MD100I90		MD75I90		MD50I90		MD100I180		MD75I180		MD50I180	
	Value	Day	Value	Day	Value	Day	Value	Day	Value	Day	Value	Day
Asymptomatic	2491332	160	2950047	157	2842052	158	2416859	161	2440704	154	3341037	161
Symptomatic	416618	152	498176	152	513427	152	377067	155	405197	152	532776	154
Admitted	538683	166	639556	166	634877	166	511264	168	516807	164	715501	167
ICU	37256	176	44739	175	46224	176	34393	179	37176	175	47353	178
Ventilator	29641	184	35580	183	36589	184	27389	187	29574	183	37891	186
Immune	6443023	228	6508198	333	6620998	358	6724187	323	6853529	302	6895030	325

4. CONCLUSION

Localized research just as the present one provides tailored and accurate insights that are more suitable to be materialized by policymakers for specific geographies. The use of the ABM approach promotes the level of detail offered to individuals in the population. Important factors such as protective factors could provide insights on the proportion of the population that would be shielded by imposing control measures. A total of 31738240 agents that represent 90.67% of Telangana’s population were generated to be used for simulation. The simulation coded in python was run to compare the six different NPI scenarios for 365 days. Time series corresponding to each health state were obtained for each district to get localized measures that could help policymaking. The study also measures the effect of the use of control measures and the role of immunity in the spread of infection. Understanding the variation in the spread of infection with respect to the interventions provide better insights to the policymakers on how to strategize the policies to curtail the spread in different areas. Defining interactions of agents based on GIS coordinates and considering contacts at workspace and closer circle allow us to show variations in the spread of disease during different lockdown setups. This has more practical implications to deliver healthcare services with capacity requirements to more vulnerable people. The ethical good practices in modeling and ISPOR-SMDM modeling good research practices have been adopted throughout the study. As evident from the results, the interventions help to curtail the transmission of the infection which provides more time window for the policymakers to devise apt strategies locally and to research on developing vaccination programs. Lockdown was found to be the most efficient intervention to curtail the spread as its lifting drastically increased the infections in a much shorter

time. The risk estimates further support these as the RR, AR, and PAR% values revealed higher protection during the lockdown period and in scenarios where a higher proportion of the population followed control measures. These values indicated the level of protection offered in each scenario and the proportion of the population that could be shielded by the control measures (exposure). The effect of immunity provides information about possible secondary infections after the loss of immunity. These estimates could be of practical significance to plan the interventions based on the population to be shielded. Limitations to the study include the exclusion of comorbidities, transportation modes, and indirect transmission through suspended particles, which could be considered to improve the accuracy.

DATA AVAILABILITY

The python code, supplementary file, and detailed district-wise estimates files shall be shared by the authors upon request.





REFERENCES

- [1] MoHFW, "Ministry of health and family welfare," *MoHFW, Government of India*, 2020. <https://www.india.gov.in/ministry-health-and-family-welfare-6> (accessed Feb. 04, 2021).
- [2] Worldometer, "Worldometer - Coronavirus Update (Live)," *Worldometer*, 2020. <https://www.worldometers.info/coronavirus/> (accessed Apr. 12, 2020).
- [3] Covid19India, "Coronavirus Outbreak in India - covid19india.org," 2020. <https://www.covid19india.org/> (accessed Mar. 05, 2021).
- [4] A. Kimball *et al.*, "Asymptomatic and presymptomatic SARS-CoV-2 infections in residents of a long-term care skilled nursing facility-King County, Washington, March 2020," *MMWR. Morbidity and Mortality Weekly Report*, vol. 69, no. 13, pp. 377–381, Apr. 2020, doi: 10.15585/mmwr.mm6913e1.
- [5] C. Rothe *et al.*, "Transmission of 2019-nCoV infection from an asymptomatic contact in Germany," *New England Journal of Medicine*, vol. 382, no. 10, pp. 970–971, Mar. 2020, doi: 10.1056/NEJMc2001468.
- [6] EpiRust, "An agent-based epidemiology simulation framework built in Rust," *GitHub, Inc.*, 2020. <https://github.com/thoughtworks/epirust> (accessed Oct. 20, 2020).
- [7] J. M. Epstein, R. Pankajakshan, and R. A. Hammond, "Combining computational fluid dynamics and agent-based modeling: a new approach to evacuation planning," *PLoS One*, vol. 6, no. 5, May 2011, doi: 10.1371/journal.pone.0020139.
- [8] P. Cooley *et al.*, "Protecting health care workers: a pandemic simulation based on Allegheny county," *Influenza and Other Respiratory Viruses*, vol. 4, no. 2, pp. 61–72, Mar. 2010, doi: 10.1111/j.1750-2659.2009.00122.x.
- [9] M. E. Halloran, I. M. Longini, A. Nizam, and Y. Yang, "Containing bioterrorist smallpox," *Science*, vol. 298, no. 5597, pp. 1428–1432, Nov. 2002, doi: 10.1126/science.1074674.
- [10] W. T. A. Ananoria *et al.*, "The effect of contact investigations and public health interventions in the control and prevention of measles transmission: a simulation study," *Plos One*, vol. 11, no. 12, Dec. 2016, doi: 10.1371/journal.pone.0167160.
- [11] M. Murray, "Determinants of cluster distribution in the molecular epidemiology of tuberculosis," *Proceedings of the National Academy of Sciences*, vol. 99, no. 3, pp. 1538–1543, Feb. 2002, doi: 10.1073/pnas.022618299.
- [12] M. Jalayer, C. Orsenigo, and C. Vercellis, "CoV-ABM: A stochastic discrete-event agent-based framework to simulate spatiotemporal dynamics of COVID-19," *arXiv*, Jul. 2020, [Online]. Available: <http://arxiv.org/abs/2007.13231>.
- [13] M. S. Shamil, F. Farheen, N. Ibtehaz, I. M. Khan, and M. S. Rahman, "An agent-based modeling of COVID-19: validation, analysis, and recommendations," *Cognitive Computation*, Feb. 2021, doi: 10.1007/s12559-020-09801-w.
- [14] N. Hoertel *et al.*, "A stochastic agent-based model of the SARS-CoV-2 epidemic in France," *Nature Medicine*, vol. 26, no. 9, pp. 1417–1421, Sep. 2020, doi: 10.1038/s41591-020-1001-6.
- [15] M. S. Narassima *et al.*, "An agent based model for assessing transmission dynamics and health systems burden for COVID-19," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 24, no. 3, pp. 1735–1743, Dec. 2021, doi: 10.11591/ijeecs.v24.i3.pp1735-1743.
- [16] N. Hoertel *et al.*, "Facing the COVID-19 epidemic in NYC: a stochastic agent-based model of various intervention strategies," *medRxiv*, 2020, doi: 10.1101/2020.04.23.20076885.
- [17] Z. Zhang and S. Jain, "Mathematical model of Ebola and Covid-19 with fractional differential operators: Non-Markovian process and class for virus pathogen in the environment," *Chaos, Solitons and Fractals*, vol. 140, no. 1, p. 110175, Nov. 2020, doi: 10.1016/j.chaos.2020.110175.
- [18] A. Mahajan, N. A. Sivadas, and R. Solanki, "An epidemic model SIPHERD and its application for prediction of the spread of COVID-19 infection in India," *Chaos, Solitons and Fractals*, vol. 140, no. 1, Nov. 2020, doi: 10.1016/j.chaos.2020.110156.
- [19] B. Ambikapathy and K. Krishnamurthy, "Mathematical modelling to assess the impact of lockdown on COVID-19 transmission in India: model development and validation," *JMIR Public Health and Surveillance*, vol. 6, no. 2, May 2020, doi: 10.2196/19368.
- [20] M. S. Narassima, K. V. Shriram, and M. Thenarasu, "Performance improvement in Cardiology department of a hospital by Simulation," *International Journal of Advanced Intelligence Paradigms-in press*, 2022.
- [21] R.-H. Bai, W.-Y. Dong, Y. Shi, A.-Z. Feng, A.-D. Xu, and J. Lyu, "Simulation of epidemic trends for a new coronavirus under effective control measures," *New Medicine*, vol. 30, no. 2, pp. 8–12, 2020.
- [22] I. Grigoryev, *Anylogic in three days. A quick course in simulation modeling*, Fifth. The AnyLogic Company, 2021.
- [23] S. L. Chang, N. Harding, C. Zachreson, O. M. Cliff, and M. Prokopenko, "Modelling transmission and control of the COVID-19 pandemic in Australia," *Nature Communications*, vol. 11, no. 1, Dec. 2020, doi: 10.1038/s41467-020-19393-6.
- [24] W. K. V. Chan, Y.-J. Son, and C. M. Macal, "Agent-based simulation tutorial-simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation," in *Proceedings of the 2010 Winter Simulation Conference*, Dec. 2010, pp. 135–150, doi: 10.1109/WSC.2010.5679168.
- [25] J. Y. Noh, J. Y. Song, J. G. Yoon, H. Seong, H. J. Cheong, and W. J. Kim, "Safe hospital preparedness in the era of COVID-19: The Swiss cheese model," *International Journal of Infectious Diseases*, vol. 98, no. September, pp. 294–296, Sep. 2020, doi: 10.1016/j.ijid.2020.06.094.
- [26] I. Ferwana and L. R. Varshney, "Social capital dimensions are differentially associated with COVID-19 vaccinations, masks, and




- physical distancing,” *PLoS ONE*, vol. 16, no. 12 December, pp. 1–12, 2021, doi: 10.1371/journal.pone.0260818.
- [27] P. Soni, “Effects of COVID-19 lockdown phases in India: an atmospheric perspective,” *Environment, Development and Sustainability*, vol. 23, no. 8, pp. 12044–12055, Aug. 2021, doi: 10.1007/s10668-020-01156-4.
- [28] M. S. Narassima *et al.*, “Supplementary: An agent-based model to assess COVID-19 spread and health systems burden,” *Figshare*. 2022, Accessed: Feb. 04, 2022. [Online]. Available: https://figshare.com/articles/dataset/Supplementary_An_agent-based_model_to_assess_COVID-19_spread_and_health_systems_burden/19121939.
- [29] J. J. Caro, A. H. Briggs, U. Siebert, and K. M. Kuntz, “Modeling good research practices-overview,” *Medical Decision Making*, vol. 32, no. 5, pp. 667–677, Sep. 2012, doi: 10.1177/0272989X12454577.
- [30] M. Roberts, L. B. Russell, A. D. Paltiel, M. Chambers, P. McEwan, and M. Krahn, “Conceptualizing a model: a report of the ISPOR-SMDM modeling good research practices task force-2,” *Value in Health*, vol. 15, no. 6, pp. 804–811, Sep. 2012, doi: 10.1016/j.jval.2012.06.016.
- [31] L. A. Boden and I. J. McKendrick, “Model-based policymaking: a framework to promote ethical ‘Good practice’ in mathematical modeling for public health policymaking,” *Frontiers in Public Health*, vol. 5, no. APR, pp. 1–7, Apr. 2017, doi: 10.3389/fpubh.2017.00068.
- [32] Government of Telangana, “Telangana state portal,” 2014. <http://www.telangana.gov.in/about/state-profile> (accessed Oct. 12, 2020).
- [33] Census of India, “Ministry of home affairs, Government of India,” *Ministry of Home Affairs, Government of India*, 2011. http://www.censusindia.gov.in/Census_Data_2001/Census_Data_Online/Language/Statement4.aspx (accessed Sep. 12, 2020).
- [34] S. Kumar *et al.*, “Who Interacts with whom? Social mixing insights from a rural population in India,” *Plos one*, vol. 13, no. 12, Dec. 2018, doi: 10.1371/journal.pone.0209039.
- [35] D. Balk, M. Montgomery, H. Engin, N. Lin, E. Major, and B. Jones, “Urbanization in India: population and urban classification grids for 2011,” *Data*, vol. 4, no. 1, p. 35, Feb. 2019, doi: 10.3390/data4010035.
- [36] M. Day, “Covid-19: four fifths of cases are asymptomatic, China figures indicate,” *BMJ*, vol. 369, no. April, Apr. 2020, doi: 10.1136/bmj.m1375.
- [37] WHO, “WHO Coronavirus disease 2019 (COVID-19) Situation Report-46,” *World Health Organization*, 2020. <https://apps.who.int/iris/handle/10665/331443> (accessed Nov. 10, 2020).
- [38] W. Zhou, Y. He, Q. Li, Y. Li, Y. Su, and L. Yan, “Clinical characteristics of hospitalized neonates with hypofibrinogenemia: A retrospective cohort study,” *Frontiers in Pediatrics*, vol. 8, no. 1, pp. 33–44, Sep. 2020, doi: 10.3389/fped.2020.00589.
- [39] M. Arentz *et al.*, “Characteristics and outcomes of 21 critically ill patients with COVID-19 in Washington State,” *JAMA*, vol. 323, no. 16, pp. 1612–1614, Apr. 2020, doi: 10.1001/jama.2020.4326.
- [40] G. Grasselli *et al.*, “Baseline characteristics and outcomes of 1591 patients infected with SARS-CoV-2 admitted to ICUs of the Lombardy Region, Italy,” *JAMA*, vol. 323, no. 16, pp. 1574–1581, Apr. 2020, doi: 10.1001/jama.2020.5394.
- [41] WHO, “Coronavirus disease 2019 (COVID-19) situation report-73,” 2020. Accessed: Nov. 10, 2020. [Online]. Available: <https://apps.who.int/iris/bitstream/handle/10665/331686/nCoVsitrep02Apr2020-eng.pdf?sequence=1&isAllowed=y>.
- [42] D. K. Chu *et al.*, “Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis,” *The Lancet*, vol. 395, no. 10242, pp. 1973–1987, Jun. 2020, doi: 10.1016/S0140-6736(20)31142-9.
- [43] R. Automation, *Getting started with arena*. Supersedes Publication ARENA-UM001F-EN-P PN-111648, 2017.
- [44] MIDAS, “Models of infectious disease agent study (MIDAS): online portal for COVID-19 modelling research,” *MIDAS Coordination Center*, 2020. <https://midasnetwork.us/covid-19/> (accessed Oct. 09, 2021).
- [45] Contributors Wikipedia, “COVID-19 pandemic lockdown in India,” *Wikipedia, The Free Encyclopedia*, 2020.
- [46] M. J. Kahn, W. M. O’Fallon, and J. D. Sicks, “Generalized population attributable estimation,” St. Olaf College, Mayo Clinic and National Institutes of Health, U.S.P.H.S., 2000. Accessed: Oct. 11, 2021. [Online]. Available: <https://www.mayo.edu/research/documents/tech-report-54/doc-20429047>.
- [47] G. Kapoor, A. Sriram, J. Joshi, A. Nandi, and R. Laxminarayan, “COVID-19 in India: state-wise estimates of current hospital beds, ICU beds, and ventilators,” *CDDEP and Princeton University*, 2020. <https://cddep.org/publications/covid-19-in-india-state-wise-estimates-of-current-hospital-beds-icu-beds-and-ventilators/> (accessed Jun. 26, 2020).
- [48] N. M. Seshadri, A. S. P., S. K. Vasudevan, and A. J., “Physicians’ and users’ perceptions towards wearable health devices,” *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 5, no. 1, pp. 234–242, Jan. 2017, doi: 10.11591/ijeecs.v5.i1.pp234-242.
- [49] D. T. Hai, “Network coding for improving throughput in WDM optical networks with dedicated protection,” *Optical and Quantum Electronics*, vol. 51, no. 12, p. 387, Dec. 2019, doi: 10.1007/s11082-019-2104-5.
- [50] D. T. Hai, “On the spectrum-efficiency of QoS-aware protection in elastic optical networks,” *Optik*, vol. 202, no. 2062, Feb. 2020, doi: 10.1016/j.ijleo.2019.163563.

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