



# Testing Different COVID-19 Vaccination Strategies Using an Agent-Based Modeling Approach

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## Abstract

Vaccination has been the long-awaited solution ever since the COVID-19 pandemic started. But the problem is that vaccine shots cannot be delivered at the same time to all populations, because of their limited quantity from one side, and their high demand from the other side. Therefore, countries need a way to test the effect of different distribution strategies before applying them. But how can they do this? To assist countries with this task, we built an agent-based model that runs on top of the Monte Carlo algorithm. This model simulates the spread of COVID-19 in a country where we can apply different NPIs at different times, and we can supply different kinds of vaccines using different strategies. In this study, we tested the outcomes of four vaccination strategies: older first, younger first, a mixed strategy, and a random strategy. We simulated these strategies in two different countries: France and Colombia. Then, we performed a comparative analysis to find which strategy might be the best for each country. Our results show that what is good for a country is not necessarily the best for the other one. Therefore, we proved that a vaccination strategy should be adapted to the structure of the population we are vaccinating. The system we built helps countries in this direction by allowing them to test the outcomes of their strategies before applying them in real life to select the one that minimizes human losses (deaths and infections).

**Keywords** COVID-19 · Vaccination · Agent-based modeling · Multi-agent systems · Monte Carlo simulation

## Introduction

Learning online, working remotely, being stuck at home, wearing a mask, or even a double mask when going out ... all of this sounds very familiar. We all have been living it for a year and even more. Although governments tended to apply different control measures since the beginning of the pandemic to limit the spread of the virus [1], the situation is still not under control in most countries, and this is why people are still supposed to take precautions and protect themselves to #StaySafe as much as possible. When the vaccination process was still at its early stages, other drugs and therapeutic agents were considered as alternative treatment

options for COVID-19 [2], but for the long run, vaccination will always be the most effective solution. The good news is that earlier this year, the vaccination process started in most countries, and this is what gives hope that the situation will become better soon. For this purpose, countries are aiming to vaccinate as many as possible of their citizens to boost their immunity against COVID-19 and its emerging variants before they spread more and cause a new outbreak.

Although vaccination remains the most effective solution to limit the spread of COVID-19, there are several challenges associated with it [3].

The first challenge resides in development and production. Given that the virus is still new, manufacturers had to develop vaccines in a relatively short time to ensure global immunity. Despite that, scaling up the production to meet the world demand is a real challenge [4]. It is important to ensure that enough doses are available globally, so that we do not experience a shortage.

The second challenge is affordability. In fact, vaccine nationalism led to difficulties for low-and-middle-income countries (LMICs) accessing vaccines such as India [5], Afghanistan [6], and Bangladesh [7]. These countries-and

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many others—struggled to adapt and change their vaccination strategies to limit the effects of emerging new waves, and all of this is due to their shortage in vaccine supply. This shortage is not only causing elevated numbers of infections and deaths but is also responsible for letting countries deal with COVID-19 for longer, which impacts the strain of the healthcare system on many levels [7–9]. Even in high-income countries, it is important to ensure that vaccine distribution happens equally among citizens including poor and marginalized populations [3].

Aside from choosing which nations would receive vaccination doses, when, and at what prices, a significant challenge that countries are facing is knowing how to distribute the limited amount of vaccines that they have among their citizens in a way to return to normal with minimal human losses (infections and deaths). Some countries, such as the United States and Berlin, intended to vaccinate the elderly before the younger ones because the elderly, when infected, are more likely to require hospital care or die [10]. While others, such as Indonesia, have decided to begin immunizing younger people (workers and adults) because these are at a higher risk of contracting the virus in the first place [11].

Since multiple strategies are being used, the goal of this study is to build a system that shows the difference between vaccination strategies, compare their outcomes, and see which one is better in a given country. The importance of such a system resides in giving countries the ability to test the effects of different vaccine distribution strategies virtually before applying them in real life, and this would allow them to select the best strategy accordingly.

To achieve our goal, we built an agent-based model that simulates the spread of COVID-19 in a virtual country. In this technique, humans are modeled as agents having specific characteristics and needs. These agents go into the world, interact with each other, and possibly, infect each other spreading, therefore, the virus. To limit the virus spread in the simulation, we can always introduce different NPIs (lockdown, mask-wearing, etc.), but just as in real life, we needed a more robust procedure to make the country return to its normal state, the sooner the better. Therefore, we integrated the ability to vaccinate our agents to reach global virtual immunity in the simulation environment. We used our model to test the outcomes of four vaccine distribution strategies and understand their possible outcomes in different countries. We tested the effect of starting the vaccination campaign with older people (older first), then, we saw what differs if we start with younger people (younger first), we also tested a mixed strategy—where we started with workers and older people at the same time before vaccinating younger ages, and finally, we saw the effect of vaccinating people randomly (without taking any restriction concerning their age or their profession). We tested the outcomes of the mentioned strategies in two different countries: France and

Colombia. After comparing the outcomes within each country and across countries, our results show that the efficiency of a given strategy is directly dependent on the country's structure and population characteristics.

Therefore, what might be good for a country might not be the best for another country given the difference in structure between them. This means that vaccination strategies should be “personalized”, which means that each country should adopt a strategy that goes with its population characteristics. For this reason, countries need a way to see the effect of their strategies before applying them, and a simulation system like ours is designed to help them achieve this.

Our main contributions in this work are:

- Designing and implementing an agent-based model that allows countries to test the effect of different vaccination strategies before applying them in real life.
- Analyzing the outcomes of four vaccination strategies in two countries (France and Colombia) and recommending the best one for each of them.
- Proving that vaccination strategies should be “personalized” according to the population characteristics.

Our outline will be as follows: we will start by introducing COVID-19 and vaccination. After that, we will talk about the agent-based modeling technique highlighting its relevance to this problem. Then, we'll talk about the simulator that we built and validated in previous studies [12, 13]. We will discuss the vaccination process we integrated, we will see the effect of different vaccination strategies on two countries: France and Colombia, and discuss the results we obtained. Finally, we will conclude and talk about the limitations of the study along with some future work.

## COVID-19

Coronavirus Disease 2019—mainly referred to as COVID-19—is a highly infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This disease originated in Wuhan, Hubei Province, China, in December 2019 [14], then its spread escalated and caused an outbreak in almost every country on the globe. Since its beginning, governments are struggling to find different ways to reduce its impact on their countries. With the absence of vaccines at the early stages of the pandemic because of the newness of this virus back then, a lot of Non-Pharmaceutical Interventions (NPIs) have been taken to limit its spread as much as possible. These NPIs range from universal mask-wearing and social distancing to global lockdowns. Their levels varied depending on the severity of the situation in

different countries (defined by the daily number of infections or deaths for example). But earlier this year, the vaccination process started in most countries which resulted in a reduction of the applied control measures.

## Vaccine

The vaccination process started near the end of 2020 [15], and by 5 June 2021, 1,900,955,505 doses have been administered worldwide [16]. Although these numbers may sound promising, the process varies between countries. In France for instance, by 6 June 2021, 18.8% of the population have been fully vaccinated, and 41.9% of the population have taken at least their first dose [15]. On the other hand, by that time in Colombia, only 6.9% of the population have been fully vaccinated, and 16.2% have taken at least their first dose [15]. This tells us that countries are not progressing in parallel with respect to vaccination. In addition to that, the vaccine acceptance rate also differs between the countries [17]. Despite that, many vaccines have been developed and administered to different countries to combat the spread of the virus more effectively. Some of those vaccines include Pfizer [18, 19], AstraZeneca [20], Sputnik V [21–23], Moderna [24], Johnson and Johnson [25], etc. Although these vaccines have some differences in specific characteristics, all of them provide good immune-mediated protection for vaccinated individuals preventing them from reaching severe or critical situations in case infected according to the CDC [26].

## Agent-Based Modeling

To understand Agent-Based modeling, we should take a step back and understand other techniques that were used for forecasting in the context of COVID-19, and by forecasting, we mean predicting what would happen in the future to act based on it. Some of those techniques rely on pure signal processing and time series analysis [27, 28]. The problem with those techniques is that they just take the curve and try to predict based on a trend how the pandemic will progress. Although these techniques have many advantages, their main disadvantage is that they don't take into consideration the real cause of the virus spread-which is, human interaction. This is what takes us to the mathematical modeling technique where we model a population using a set of differential equations that we solve to get our results [29–31]. The problem with this technique is that it does not take into consideration the complex human

behavior that plays an important role in the spread of the virus: they consider the population to be homogeneous which is not the case in real life. This is where the Agent-Based Modeling technique comes in [32–34]. In this technique, individuals are modeled as agents having specific needs and characteristics, and thus, are singular by the actions that they do. These agents interact with each other and with their environment, and based on their behavior, the pandemic situation evolves [35]. This is what happens in reality: individuals are always contributing in one way or another to the spread of the virus, and this is what makes the simulation process more realistic.

Agent-Based Modeling is a go-to when we need to model complex dynamic systems [36]. This modeling technique is considered a “from the ground up” approach [37] where based on the agents' interactions with each other and with their environment we get the results that we're looking for, without explicitly programming them. We only have to program the agents.

More detailed information and simulation examples about Agent-Based Modeling can be found in [38–40].

## Simulator Overview

The goal of our simulator is to forecast the evolution of COVID-19 inside a country with the presence of different control measures and different vaccine distribution strategies. The good thing about the simulator is that it can give an idea about how the pandemic situation can become after a decision is made. This way governments can benefit from it while seeing the effect of their actions before doing them, and then adapt the best measures and strategies to limit the virus spread and save a lot of trouble for their citizens.

The four key components in our simulator are:

- The Virus (which is the Coronavirus in our case).
- The corresponding Vaccines (Pfizer, Sputnik V, Johnson & Johnson, Moderna, AstraZeneca, etc.).
- The Country where the virus will spread.
- The Agents living inside of the country.

We will discuss each of them in the next sections.

## The Virus

The virus that we want to simulate in our study is the SARS-CoV-2, but other viruses can also be modeled simply by changing the parameters. Those parameters are:

**Table 1** Different kinds of symptoms for different age groups

Age group	Asymptomatic (%)	Mild/moderate (%)	Severe (%)	Critical (%)
0–17	43	57	0	0
18–39	14	79	5	2
40–59	7	77	10	6
60–79	3	50	33	14
80+	0	33	17	50

### **The Latent Period**

It is the period that lies between the time when a person becomes infected (or exposed), and the time he becomes infectious (or can infect others). The Coronavirus is defined by a latent period of 3 days [41].

### **The Incubation Period**

It is the period that lies between the time when a person is infected, and the start of his symptoms to appear. The Coronavirus is defined by an incubation period of 5 days [42].

### **The Infectious Period**

The time during which a person can infect others. After the start of the symptoms, a person can infect the others for 10 days in most cases according to CDC [43]. So, the infectious period in the Coronavirus starts 2 days before symptoms develop (when the latent period finishes) and it ends 10 days after symptoms start.

### **Symptoms**

Each virus has specific symptoms. The symptoms of COVID-19 include coughing, fatigue, fever, etc. [44]. These symptoms can be categorized between Mild/Moderate, Severe, or Critical. A person can also be asymptomatic (does not develop symptoms). Usually, children and adolescents are more likely to be asymptomatic compared to adults [45, 46]. After developing a symptom, a person can recover or die. Death and recovery rates vary depending on the severity of the symptom: Asymptomatic and Mild cases always recover, but Severe and Critical cases have a death rate of 15% and 50% respectively [47]. If the person has severe or critical symptoms, he will require hospital care after 9, and 10 days respectively of his infection [47]. People develop specific symptoms according to their age. In [48], they tested a group of infected people and classified them according to their symptoms and their ages, and the results that interest

us are in Table 1. We will use all these findings to model the virus in the most possible accurate way.

### **The Vaccine**

In our simulator, we can supply different kinds of vaccines at different times for different clusters of the population.

The characteristics of a vaccine can be summarized as follows:

#### **Number of Doses**

It is the number of shots a person should take to maximize his immunity against COVID-19.

#### **Time Between Doses**

It is the number of days that should be between the two doses. This is only applicable for vaccines that have more than one dose.

#### **Effectiveness After Each Dose**

This reflects how much a person is expected to be protected after taking a specific dose of the vaccine. In other words, let us say the effectiveness of the first shot of a random vaccine is 50%. This means that if a person—that has already taken his first dose—was in a situation where he should have been infected, there is a 50% chance of him not becoming infected. This is how the vaccination protects from infection. A more detailed explanation regarding the effectiveness of a vaccine can be found in [49].

#### **Time for Effectiveness**

It is the time that should pass for one shot to become fully effective. So, the effectiveness that we just mentioned is not acquired directly after taking a shot. There is a certain time that should pass for the person to develop immunity.

Since the goal of our study is to test the effect of different vaccination strategies, we will use only one kind of vaccine which is Pfizer. However, different kinds can also be supplied, and note that they can be supplied simultaneously just like what happens in real life.

The Pfizer vaccine is characterized by 2 doses separated by 21 days [50], with respective effectiveness of 52% and 95%. The time until the first dose becomes effective is 12 days, and the time until the second dose becomes effective is 7 days [51]. These findings are represented in Fig. 1.

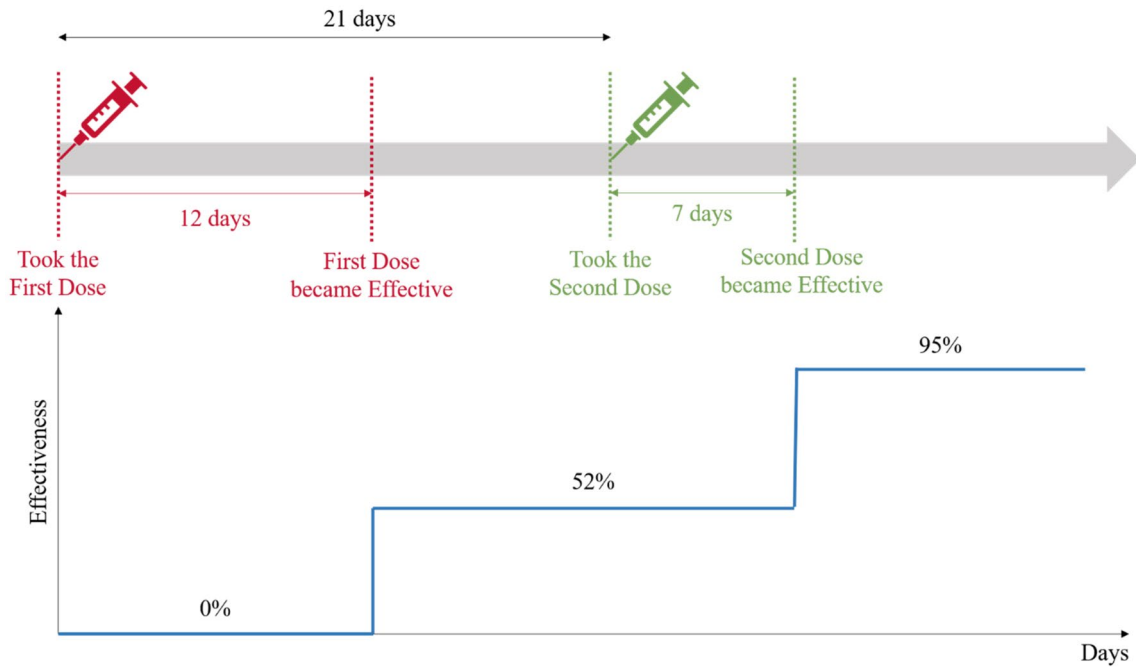


Fig. 1 Pfizer vaccine characteristics [50, 51]

Table 2 Age distribution in France and Colombia

Age range	0–4 (%)	5–9 (%)	10–19 (%)	20–29 (%)	30–39 (%)	40–49 (%)	50–59 (%)	60–69 (%)	70–100 (%)
France	5.7	6.1	9.5	11.4	12.3	12.9	13.2	12	14.6
Colombia	7.6	7.6	17.1	17.4	15	12	10.5	6.9	5

### The Country

In our study, we simulated the spread of COVID-19 in 2 countries: France, and Colombia. Each of them has several characteristics:

#### Locations

Each country has several locations or places where an agent might be: houses, hospitals, markets, malls, restaurants, nightclubs, companies, churches, mosques, universities, and schools. Each location has a specific opening and closing time on each day of the week (except houses of course).

#### Age Distribution

This is a statistical distribution. It shows us the percentage of people having a specific age range inside of a country. The age distributions for France and Colombia are taken from [52] and [53] respectively and are represented in Table 2.

Table 3 Workers percentage according to different age ranges in France and Colombia

Age range	15–24 (%)	25–54 (%)	55–65 (%)
France	34	68	54
Colombia	28	81	54

### The Agent

The agent is defined by several characteristics when created at the beginning of the simulation:

#### Age

The first thing an agent gets is his age. This is the most significant factor for an agent because it will define its other characteristics. The age of the agent is sampled from the Age distribution in the country using the Monte Carlo Algorithm.

**Table 4** Infection rate during 1 h in different locations

	School (%)	Univer- sity (%)	House (%)	Church mosque (%)	Restaurant (%)	Nightclub (%)	Market mall (%)	Hospital (%)	Company (%)
No Mask	3	4	14	21	32	42	16	2	21
Mask	1	1	4	1	1	3	1	1	1

### Profession

Each agent will have a profession based on his age that can be: School Student, University Student, a Worker, or none of them. In our simulations for this study, we kept schools and universities closed. So, what interests us is the percentage of workers in each age range in the country. This information is taken from [54] and is represented in Table 3.

Note that a worker can work in a restaurant, a nightclub, a market, a mall, a hospital, a company, a school, or a university.

### Locations to Visit

Besides his work and study locations, an agent can go to random locations like restaurants, markets, companies, hospitals, etc.

One thing to note is that the study location and the work location for an agent are fixed, which means he has to go there every day (or at least when they are open). But regarding other locations, he can visit them during random times when he has nothing to do. For example, a hospital worker does not have to go to the market every single day, but he should go to the hospital each day during the week.

### House

Each agent has his own house where he stays if he has no other occupations.

### Simulation Process

The simulation starts with one agent being infected, and the others are susceptible (can become infected). The infected agent will go into the world, interact with other agents, and possibly infect them. This is how the number of infected agents grows. The simulation process runs for several days. At the beginning of each day, an agent is assigned a list of locations where he will be during each hour of the day (like a schedule). This list is given based on the profession of the agent (it should include his fixed locations), and on the

locations where he can go (markets, malls, etc.). This is how agents meet at different locations.

Note that when an agent is present in a specific location, he is considered to be in a room inside of this location. This is why different locations are modeled as different rooms, each of them having specific characteristics, and based on that, each location has a defined infection rate. This rate indicates the chance of an infected agent infecting another agent within the same location (or room) during 1 h. In our study, we used a COVID-19 risk calculator developed by the Harvard School of Public Health [55] that is based on the peer-reviewed paper of Azimi et al. [56]. This calculator helped us approximate the risk of infection for different kinds of rooms where an agent might be. This risk percentage takes into consideration a lot of factors related to the room: its space, the activity done inside of it, the precautions taken by the agents, the quality of the HVAC system, the natural air condition, the time spent in the room, the fact that people in the room are wearing masks or not, and what kind of masks they are wearing, the amount of social distancing, etc. So, each of our locations was modeled as a room that has specific characteristics, and based on that we got the infection rates that are summarized in Table 4. Note that these rates are for one hour inside of the location.

An agent is capable of infecting others only during the infectious period that lies between the latent period, and 10 days after the incubation period [43]. Once an agent becomes infected, he might develop symptoms. If these symptoms require hospitalization (Severe, and Critical), we assume that the agent will be locked in a hospital and will not be able to infect others because people who visit him will be extra protective.

At any time during the simulation, we can introduce specific measures to reduce the severity of the pandemic.

These measures can be forcing people to wear masks, closing some locations for a specific number of days, or even introducing a full lockdown. The effects of these actions can be monitored from real-time charts through the simulator and can give an insight into the effectiveness of a control measure at a specific time.

Another complementary way to limit the virus spread is through vaccination. Once the simulation starts, there is a

specific number of agents that register for the vaccine, so that when it becomes available they can have it.

At any time during the simulation, we can supply a specific quantity of vaccines for a specified cluster of the population (according to age range or profession). The vaccines we are supplying can be of any kind (Pfizer, Moderna, Astra-Zeneca, Sputnik, etc.). These vaccines will be given only to people who have registered at the beginning, and the distribution happens according to the strategy we want to use.

But how can the vaccine help in preventing the infection?

When Agent A (who is infectious) and Agent B (who is vaccinated) are present in the same room, we decide if A will infect B according to the following process. First, we use Monte Carlo Algorithm to determine if according to the infection rate of the room, Agent B will become infected or not. If yes, we use again Monte Carlo algorithm to determine if Agent B will truly become infected, and this is according to the effectiveness of the most recent vaccine dose that he took. This is how the vaccine can protect an agent. It is like it gives the agent a second chance if he was supposed to become infected.

One thing to note is that if a person is vaccinated, and becomes infected at some point, he won't have severe or critical symptoms. He will most likely be symptomless or experience mild symptoms. Another thing to note is that when a person is vaccinated, he has less chance of infecting others. In the Pfizer case, the risk of transmission after one dose is between 45 and 50% according to England Public Health reports [57], and after 2 doses it is still not determined. In our study, we assumed a transmission risk of 50% after taking the first dose, and 20% after the second dose.

The agent's behavior during the simulation process for each day is summarized by the flowchart represented in Fig. 2.

At the beginning of the day, Agent A gets a schedule for the day. Each hour, Agent A goes to a location according to this schedule. If the Agent is not infected or is not in his infectious period, he cannot infect other agents, he stays in the location for one hour and moves to the next location or stays in the current one (according to the schedule). However, if the Agent A is currently infected and in his infectious period, he might infect others, so for each Agent B present in the same location as Agent A, if B has not been infected before, we use Monte Carlo Algorithm (based on the infection rate in this location) to determine if he will be infected by Agent A or not. If Agent B should become infected, we see if he got a vaccine before. If yes, we apply Monte Carlo Algorithm again to see if according to the effectiveness of the vaccine Agent B will become truly exposed (infected) or not.

## Testing Different Vaccination Strategies

Now it is time to see how the strategy we follow while vaccinating people will impact the pandemic situation in a given country. Shall we start with the most active people (younger age)? Or shall we start with people having the highest risk of infection and death (older age)? Shall we opt for a mixed strategy where we vaccinate old people first along with workers before vaccinating younger people? What about vaccinating people randomly regardless of their age or profession? To obtain the answer to those questions, we ran 5 simulations for 2 different countries: France and Colombia. In both cases, we started our simulation with 2% of the population already infected, and here is where we will start supplying the vaccine. The vaccine is supplied at a rate of 1000 doses per day, and the people registering for the vaccination are 75% of the whole population. The age ranges we can vaccinate are 60–100, 40–59, and 18–39. We assume that people of younger age (between 1 and 17 years old) will not be vaccinated. In both countries, we have initially 60,000 agents. We normalize our results with this number to get a better insight into the effectiveness of a specific strategy. During the simulations, we keep schools, universities, restaurants, and nightclubs closed. Here are the scenarios we considered.

Scenario 1: No Vaccination: we ran the whole simulation without administering any dose to any of our agents.

Scenario 2: Older First Strategy: we start by vaccinating the old people before the young ones (decreasing age ranges).

Scenario 3: Younger First Strategy: we start by vaccinating the young people before the old ones (increasing age ranges).

Scenario 4: Mixed Strategy (Older & Workers First): we start by vaccinating old people along with workers and then continue by decreasing age ranges.

Scenario 5: Random Strategy: we vaccinate registered people randomly regardless of their ages or professions.

In all of those scenarios, we looked at 4 key components to see the efficiency of a specific strategy:

- The Active Cases: people who are currently infected in the country.
- The cumulative cases: people who have already been infected cumulatively.
- The Hospital Cases: people that require hospitalization.
- Deaths: people who die from the virus.

Let us start by analyzing the case of France (Figs. 3, 4, 5, 6):

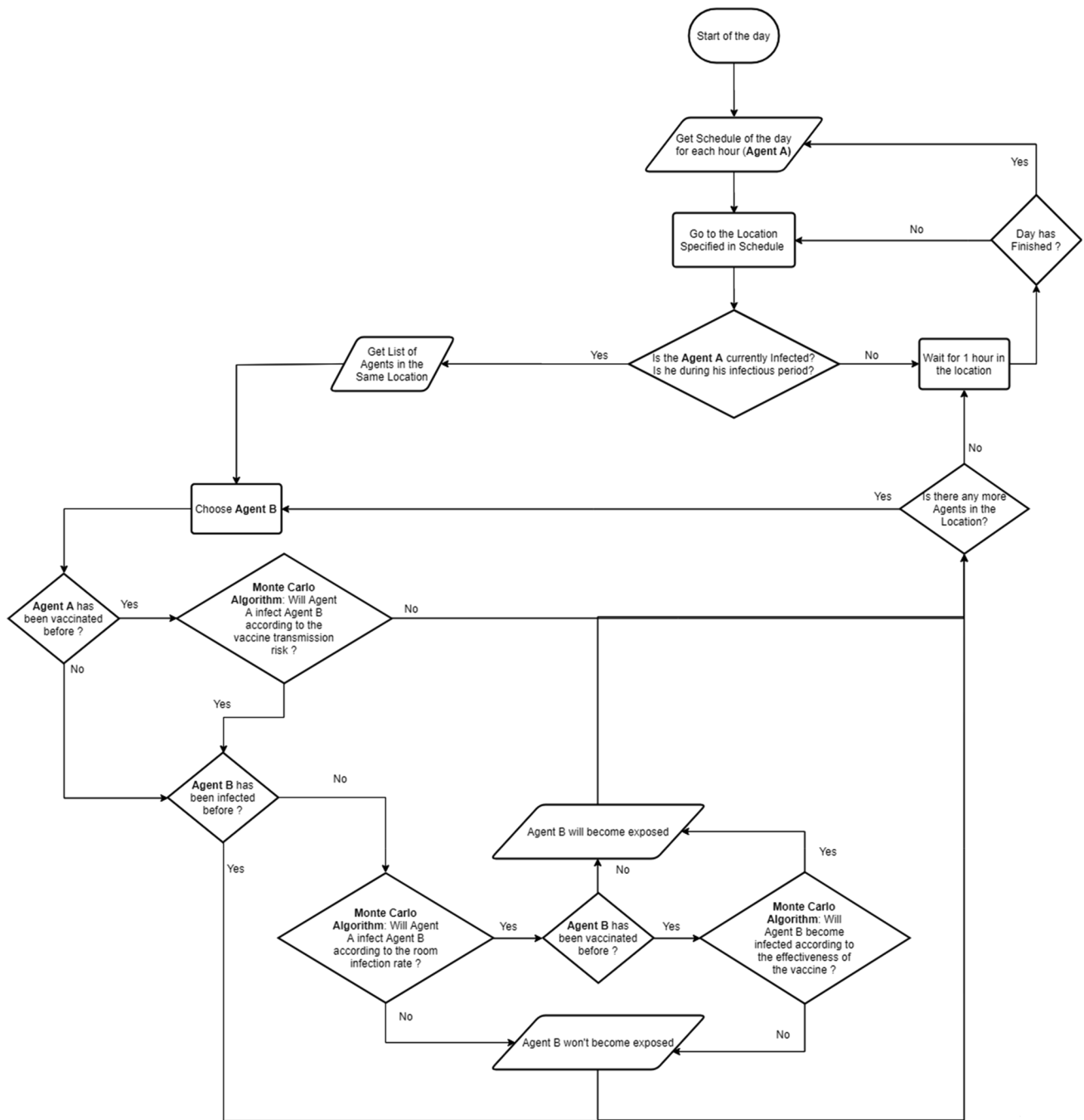


Fig. 2 Flowchart representing a typical agent's behavior

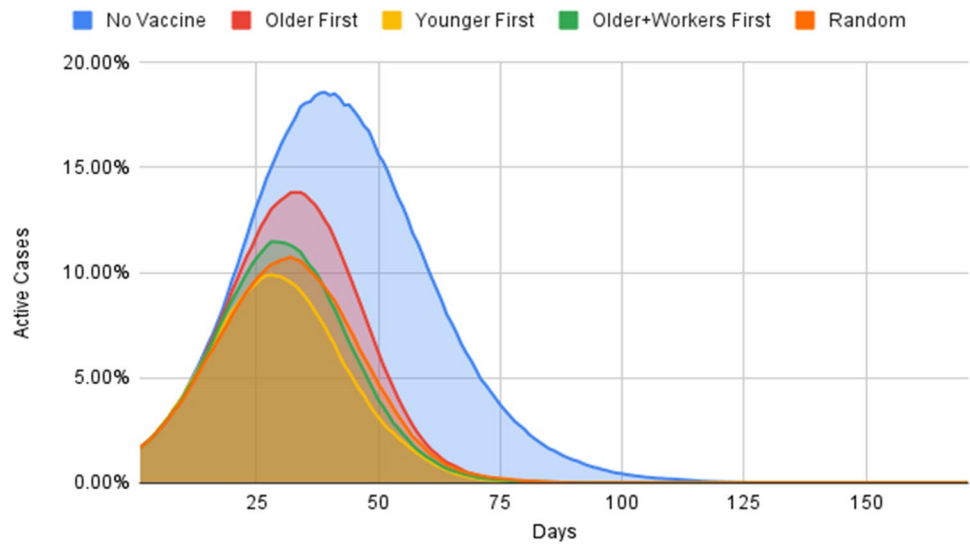
If we look at the curves in the specified figures, we can see the positive effect that the vaccination has from all perspectives. So whatever strategy we apply, it will give us a better outcome compared to when we don't give anyone the vaccine.

Concerning the strategies, we can see that each of them has advantages in some perspectives and disadvantages in other ones. If we take for example the Older First Strategy, we can see that the peak active cases and the cumulative

cases reach a higher level than other strategies (13.8% and 30.38% respectively). On the other side, we can see that the peak hospital cases and the deaths reach the lowest levels among strategies (0.74% and 0.62% respectively), and this is logical. Mainly, when we start vaccinating old people, our purpose is to protect the ones that are more susceptible to death and hospital care. However, the population that is more active, and goes to different places is not protected at first, and this is why the number of infections grows, but



**Fig. 3** Active cases in France for different vaccination strategies



**Fig. 4** Cumulative cases in France for different vaccination strategies



since young people have less chance of developing critical or severe symptoms, the vast majority of them will not go the hospital or die, and this is what keeps these numbers low in such a strategy.

If we take a look at the Younger First Strategy, we can see that it is somehow the opposite of the Older First Strategy. Basically, in this strategy, we vaccinate people that are more active and go to different places. In this case, the peak number of active cases and the cumulative number of infected people are the lowest (9.8% and 21.2%), but the peak number of hospital cases and the number of deaths are the highest (1.3% and 1%), and this is also logical because we are postponing the protection of old people who are more susceptible to death and hospital care, and this is why these numbers will evolve. The most active people are protected and this is

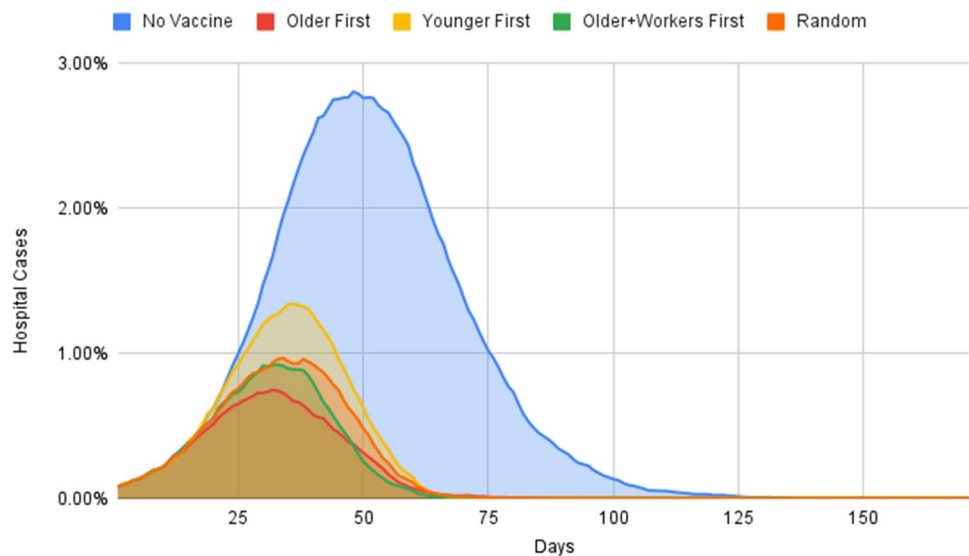
what makes the active cases and cumulative cases numbers lower than what they were initially were in other strategies.

This is what drives us to find a strategy that can be somehow in between.

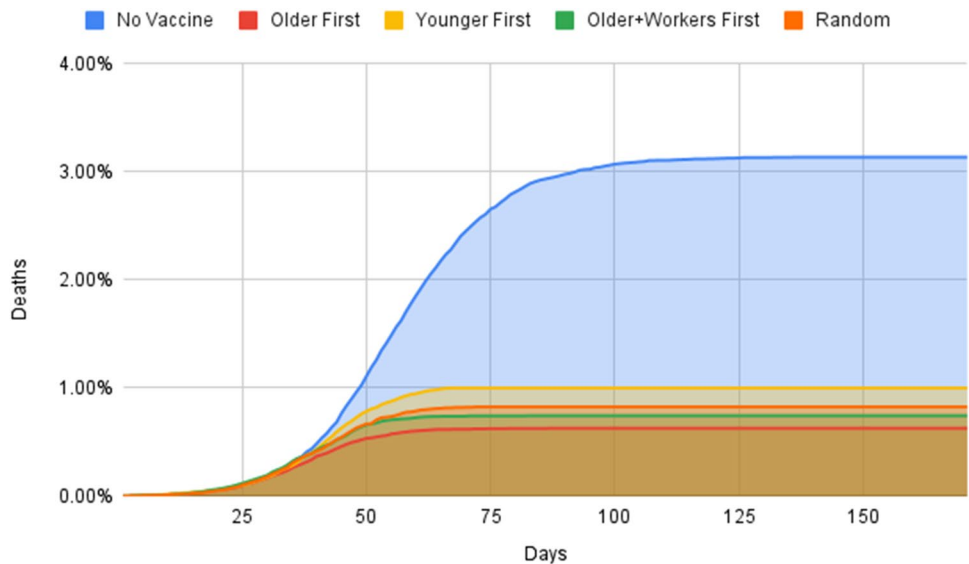
If we begin with the mixed strategy where we start by vaccinating old people along with workers at the same time (regardless of their age but they should be older than 17 years old). This way, we would be protecting people who contact others the most, and at the same time, we protect people who are most sensitive to severe and critical infections.

The last strategy is the random strategy where we vaccinate registered people randomly regardless of their ages. This is again one of the strategies that represent a kind of an optimum between the older first and younger first strategies.

**Fig. 5** Hospital cases in France for different vaccination strategies



**Fig. 6** Deaths in France for different vaccination strategies

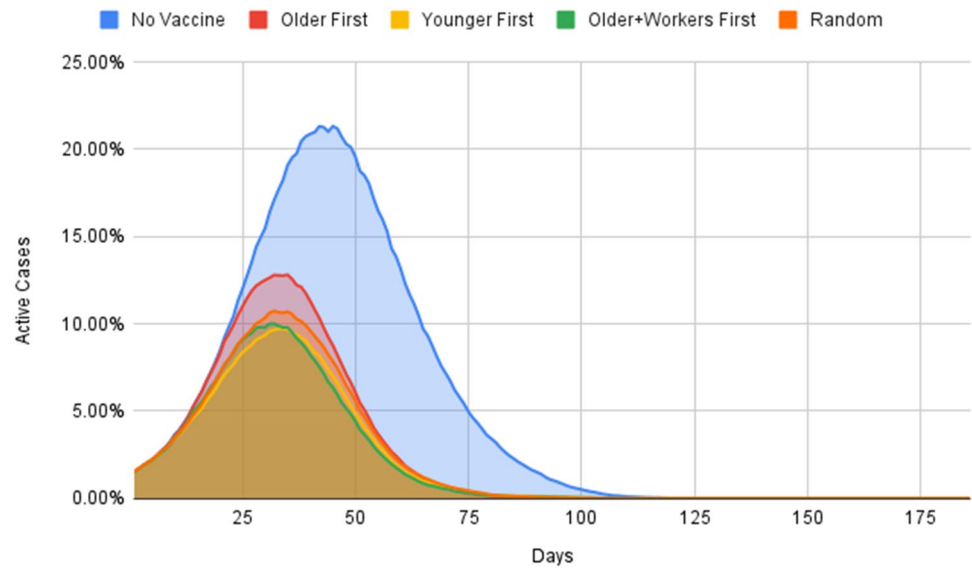


The random strategy distributes the vaccines randomly, and this is why different age ranges will get shots during one day that are proportional (in one way or another) to the original number of people having those age ranges. In other words, if the number of agents having a specific age range is high, then the number of registered people from this age range will also be high, and as a result, when giving the limited daily supply of vaccines randomly, this age range will also get a high supply.

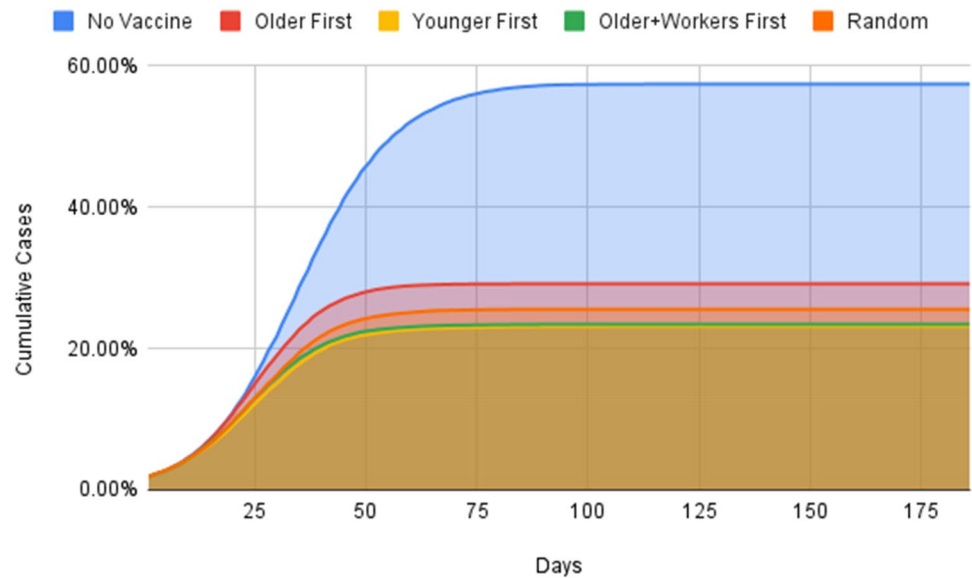
Although the random and the mixed strategies lead to a very similar result, if we need to compare them, we can see that the random one is better in terms of active cases and cumulative cases, however, it is not as good as the Mixed (Older + Worker) strategy in terms of hospital cases and

deaths. In fact, the percentage of old people in France is relatively high. So, when we are distributing vaccines randomly, definitely a lot of them would take the vaccine, but as if they were prioritized. And this is what makes the mixed strategy better in terms of hospital cases and deaths. Even more, the percentage of workers in France is the highest among middle-age ranges but it does not cover the majority of them, and this is why, when distributing the vaccines randomly, we are giving these age ranges more importance and hence, we are protecting them more, and this is why, the random strategy performs better than the mixed one in terms of active and cumulative cases. What you should note here is that these results cannot be generalized to any country, and this is what we will prove when simulating Colombia.

**Fig. 7** Active cases in Colombia for different vaccination strategies



**Fig. 8** Cumulative cases in Colombia for different vaccination strategies



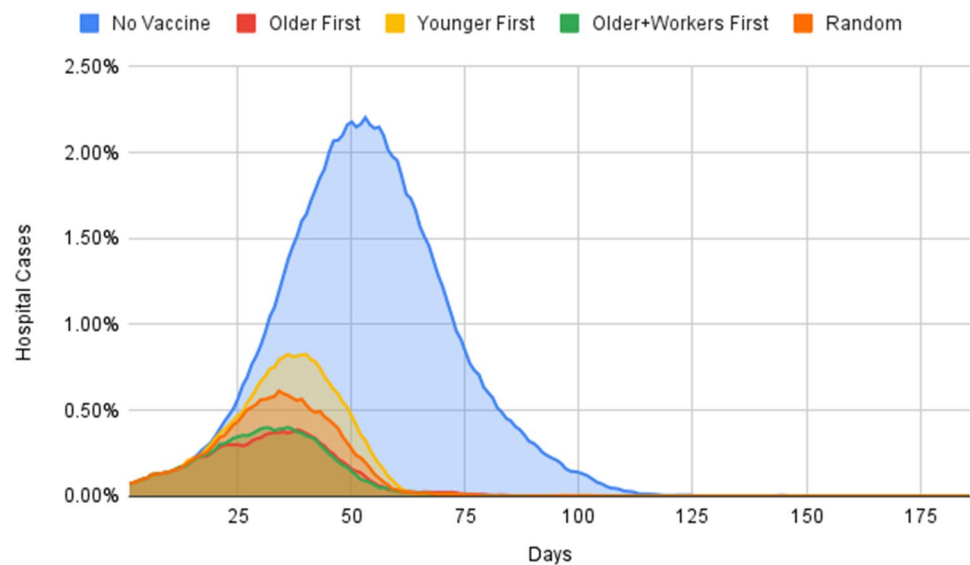
Those results are directly dependent on the age structure (distribution) that we have in the country, along with the percentage of workers we have in different age ranges. So, if we compare France and Colombia, we can see that the first one has a higher percentage of old people in its population, and a lower percentage of workers across different age ranges, and this is what makes the same strategies have different outcomes in the two countries.

If we take a look at Colombia (Figs. 7, 8, 9, 10), again we can directly see the effect that the vaccination has on the pandemic situation from all of the perspectives described. Just like in France, the same reasoning applies to older and younger first strategies. What differs is in the random and the mixed strategies. We can see that the mixed strategy in this

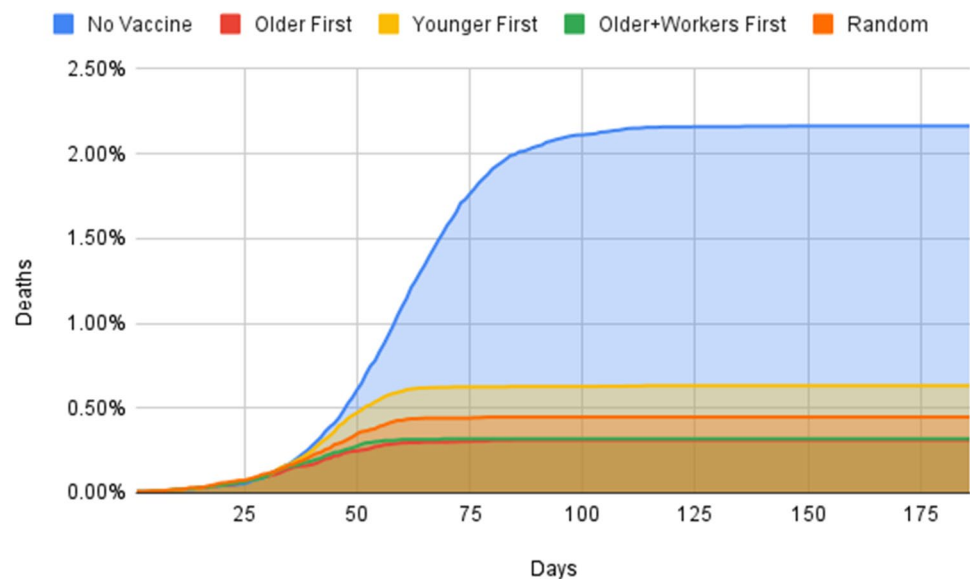
country is better than the random one in all of the results we derived, and this is because of the structure of the country.

Since in the Colombian population, the percentage of old people is small relative to other age groups, in the random strategy, they won't get enough shots, and this is what will lead to more deaths and hospital cases compared to the mixed strategy where we prioritize the two groups: old people and workers. Now since the percentage of workers in the Colombian population is relatively high, when prioritizing workers we are vaccinating a lot more people than we did in France, and this is why in the mixed strategy, we were able to protect most of the population and this is what made this strategy better than the random one in terms of actives cases and cumulative cases because when vaccinating workers,

**Fig. 9** Hospital cases in Colombia for different vaccination strategies



**Fig. 10** Deaths in Colombia for different vaccination strategies



we are-implicitly-vaccinating most of the young people, and this is supposed to bring the active and cumulative cases to a low level.

So, in a country like France, it is better to start vaccinating the old people and then move to lower ages. Although this means increasing the number of people who will become infected, it also means protecting old people from pain and death. On the other hand, in a country like Colombia, it would be better to vaccinate the old people along with workers at first and then move to lower ages, because this would lead to an optimal outcome in terms of active cases, cumulative cases, hospital cases, and deaths as we can see from the results we derived.

## Conclusion

We can conclude that following a vaccine distribution strategy inside a country is not as easy as it sounds, and there is no rule of thumb to decide which strategy we should use because things differ according to the population we are vaccinating. This is where simulations play an important role. In this study, we saw the importance of our simulator in forecasting future trends according to different strategies applied to different countries, and from several perspectives. The good thing about such a simulator is that it gives the government an idea about possible outcomes for different strategies before applying them, and hopefully, apply the one that is for the best.

## Current Limitations

In this study, we built a system that allows countries to test the effect of different vaccination strategies before applying them in real life to select the best one. We compared four different strategies for two different countries to highlight the fact that each country should follow a specific strategy and the choice should be related to the population structure. Currently, our study has two main limitations:

- The lack of medical information about different kinds of vaccines (transmission risk, effectiveness, etc.), and this is why we only simulated the Pfizer vaccine since we were able to get most of the necessary related data.
- The lack of powerful hardware resources to perform extensive and complex simulations, and this is why we settled with 60,000 agents to establish the proof of concept because the increase in this number will result in longer simulation runs.

## Perspective

If we bypass the mentioned limitations, we would be able to simulate the spread of COVID-19 among huge populations with complexities similar to the ones that we have in real life, and we would definitely be able to test more strategies to find the best one. Another perspective that we have is making our simulator function on real data from real people instead of just operating on statistical distributions. This would make our system similar to a “digital twin” for a country where the characteristics and activities of real people are reflected in the simulation environment, which is expected to give even more accurate forecasting.

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**Availability of Data and Materials** The data used for this study is mentioned inside of the paper, along with its references.

**Code Availability** Source code available upon request.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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