Agent-based modeling and simulation of pandemic propagation in a school environment

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Abstract
Spatial behavior is a principal aspect for architects to consider. Unfortunately, it is sometimes hard to predict, as users of space seldom follow a standard routine. However, predicting user behavior in a space can potentially illuminate the entire design process. Moreover, it is a key factor in fighting the recent COVID-19 pandemic. Until most of the public gets their vaccine, health officials recommend social distancing as the primary means of fighting the pandemic. This paper uses an agent-based modeling and simulation (ABMS) approach to reproduce, analyze, and predict spatial behavior during the pandemic in a school environment and its impact on disease propagation. The simulation reproduces the behavior of teachers and students at a sample elementary school. By manipulating parameters that simulate the school officials’ response to the pandemic, stakeholders can assess the most effective preventive measures. As a result of running multiple scenarios, the study demonstrates how varying starting conditions and alternate spatial behaviors could lead to different results, providing insight to stakeholders on how to handle disease spread in school environments.

Keywords
spatial behavior, agent-based modeling and simulation, human behavior simulations, multi-agent system, COVID-19

Introduction
Understanding the relationship between the spatial behavior of people and their built environment is of paramount importance, especially during pandemics. Space plays a vital role in fighting the spread of the disease. In December 2019, Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) surfaced in Wuhan, China, causing the swiftly spreading pandemic (COVID-19). Social distancing has been the number one line of defense against contagion. Although schools are among the most affected spaces, it is unclear how reopening them will affect the health of their users.

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This paper uses an Agent-Based Modeling and Simulation (ABMS) approach to reproduce the spatial behavior of the users of an elementary school. Furthermore, the paper investigates different scenarios of health preventive measures without exposing real humans to risk. For instance, is it better for teachers to remain in the front of the class while teaching, or move freely about the class? Further scenarios support the notion from literature that mobility increase infection rate, restricting students to their desk and canceling activities where they move from their desks. Thus, stakeholders can use the simulation results to guide the strategies by which schools can handle the pandemic. Moreover, the simulation provides crucial information to guide the design process, allowing architects to reevaluate their design and modify it accordingly.

While multiple studies simulate the disease propagation, most use a standard simulation approach, generally adhering to variations to the susceptible-infected-recovered (SIR) epidemic model. The nature of the pathogen that causes a disease is indeed detrimental in causing a pandemic. However, the heterogeneity of the behavior of the affected population plays a key role in pandemic propagation. Epidemic studies regard this behavior as movement, sociodemographic composition and how it affects mobility, and the intervention measures. The current study attempts to add to the knowledge in this area of research.

Background

Human spatial behavior describes people’s utilization of their spatial environments personally, interpersonally, and on a group level. Spatial behavior can act as a measure of architectural design success, as curbed spatial behavior can be a sign of users’ dissatisfaction. Moreover, spatial behavior can elucidate wasted design resources such as space and functionality. Therefore, predicting this behavior and accounting for it during the design process benefits both the designers and users.

One way to study spatial behavior is to simulate a real-world phenomenon. Doran and Gilbert refer to the phenomenon in question as the “target.” Since the target is usually overly complex, researchers can study a model of that target instead. By studying the simpler model, researchers seek to understand the target phenomenon based on their similarity. Information about two elements are needed for a successful spatial behavior simulation: the behavior itself, and the space at which the behavior is observed.

Sociologists have been able to examine patterns in human behavior regarding space, enabling researchers to create a model of spatial behavior. Furthermore, researchers can visualize space in that simulation by using Computer Aided Design (CAD). Thus, by experimenting with various parameters within this simulation, researchers could infer various information pertaining to the relationship between a space and its occupants.

John Archea developed specialized human spatial behavior modeling. Yan and Kalay, however, developed a more general-purpose solutions that simulate spatial behavior by employing virtual users or agents. This work provided the building blocks for researchers to propose the notion of virtual users, which can simulate real humans’ spatial behavior. Numerous studies emerged afterward that deployed these virtual users to visualize the interactions between virtual users and the built environment.

Further work in this area has included investigating workspace activities, using behavioral units (events) to drive the simulation, using spatial behavior simulations as a pre-occupancy evaluation study. A subset of simulation is (ABMS) a paradigm that can investigate spatial behavior and analyze the relationship between a space and its occupants based on simulated user behaviors. Gilbert and Terna describe the paradigm as a breakthrough in computation for social sciences.

In ABMS, virtual models of human users, which the literature describes as agents, interact with each other and the environment, generating a phenomenon that can be studied, recreated, and predicted. There is no consensus on the exact definition of an agent. However, the consensus is that agents are autonomous entities that can interact with their environment and other agents. The agents can use these interactions to gather and act upon the collected data. This approach to modeling does not describe a holistic phenomenon
but observes its formulation as the agents interact in the simulation. Its bottom-up structure distinguishes it from other top-down approaches because agents can make up their own “mind.” They can decide which action(s) they can take and interact with each other and the environment. This way, unpredicted or emergent behavior can organically occur from the simulation, allowing researchers to understand the target phenomenon further.

While simulating spatial behavior is encouraging, it is still new and in need of further studies. Nevertheless, some trends have already started to form, the first is the reliance on ABMS as their study approach, and the second is the use of three-dimensional space applications to compute and visualize their work. The current study belongs to this category, employing an ABMS to simulate the spatial behavior of the users, as well as computing and visualizing the simulation using the Unity game engine.

**Method**

*Modeling the school*

The authors intend for the simulation to be general, as the simulation design is a dynamic one that allows the modification of space before the simulation starts without changing the code behind it. This process occurs by simply providing a new school 3D model. However, as a point of start, the authors chose an operational elementary school as a reference space for the simulation. While parameters such as the school space are easily modifiable, the spatial behavior itself needs a more experienced user to change the code behind it. This includes parameters of the simulation such as student age and certain behaviors, which in this case is proper for an elementary level school students aged (6–11 years). School officials supplied the necessary architectural drawings to create a 3D model of the facility. The authors created the 3D model inside Unity (version 2020.3.7f1), a popular game engine, opting for simpler geometry representation and focusing more on the agents’ behavior.

*Modeling spatial behavior*

Interviews with teachers provided the authors with general information about the school’s daily routine. Observation was not available due to the pandemic, furthermore, it is generally not allowed for non-school personnel to be on the school premises during the school day. The authors have performed a semi-structured interviews with three teachers, inquiring about the daily routine and the behavior of the students, and the teachers. Furthermore, the authors inquired about the pandemic strategies the school officials intend to execute. Based on the collected information, the authors devised a sample school day that comprises six school periods, each 50 minutes long. At the start of each period, some classes are relocated to visit specialized classrooms like physics and art classes. Furthermore, the teachers described the behavior of the students and their teachers during the school day, which helped the authors model agents’ behavior in the simulation.

School regulations and students’ behavior are the main drivers of the agents’ spatial behavior. A school is a structured space where every user has their role. School regulations dictate the school schedule, informing teachers and students where they should always be. Thus, students do not leave their classes without permission, and teachers cannot leave classrooms unattended. In the classrooms, teachers initiate various activities. The authors modeled those activities in the simulation as two distinct types. The first is the group activity, where the teacher divides the class into three or four groups and directs students to convene around a single desk. The second is board activity, where students move towards the whiteboard to perform various exercises or presentations. In the previous actions, the school informs the students, directing them to where they should be.
Students can take bathroom breaks or go to lockers. The frequency of these actions increases during classroom breaks, but they can take permission from their teacher to do one of these actions while the class is in session.

With each action the agents undertake, they change their physical activity level, which in turn affects their breathing level, a crucial factor to the virus transmission modeling described later.

The study abstracts the behavior of agents (i.e., students and teachers) into two parameters: movement and activity level. The reason for this is that two distinct parameters affect disease spread. The first is the spatial position of agents, as being near an infected individual increases the chance of infection, and vice versa. The other parameter is the level of activity of agents, as various levels of activity lead to different rates of air consumption and production.

Agents can make their own choices in a set environment according to the instructions set by the simulation designer. The simulation has distinct kinds of agents, each with its own goals. To allow agents to achieve their goals, a decision-making algorithm typically drives the simulation. One algorithm that addresses decision-making is Finite State Machine (FSM.) In FSM, each agent is in a singular state. Depending on a specific condition, it can move to another state. Another algorithm is Decision Trees, in which agents have access to different hierarchical states. Depending on a specific condition, the agent chooses which path of the tree to traverse and repeats this process to reach the next state. The downside of decision trees is that agents cannot backtrack to the tree root. Behavior trees algorithm solves this problem, as these algorithms allow the state to pass or fail, which lets the agent traverse back into the tree upon completion or failure of the task, that is, they ensure the safety of the simulation. Behavior trees also allow the performance of parallel tasks. Goal-Oriented Action Planning (GOAP) is another algorithm that divides an agent’s tasks into smaller modular actions. The simulation assigns the agents an end goal. Agents then piece together a list of actions they can sequentially perform to reach their end goal. For architectural applications, Schaumann, Date, and Kalay have developed Event Modeling Language (EML) an algorithm in which a behavior tree manages agents’ behavior according to “events,” which is an entity that regulates and modularizes the simulation.

The authors have opted for FSM as it provides the most extensibility to the agent’s actions, without overly complicating the overall behavior. For example, student agents “know” school regulations from their environment and follow them. Figure 1 illustrates the student agent FSM diagram.

The agents’ FSM drives their behavior. The simulation instructs the students on their actions when classes are in session. However, students have a certain freedom. For example, they can visit class lockers or go to the bathroom with permission from their teacher. Each action the agents undertake changes their physical activity, and breathing levels, which is imperative to the virus transmission modeling described later.

The teachers’ FSM is simple (Figure 2). At the start of each period, working classrooms request teachers. When teachers reach their classroom, their activity level changes to simulate loud talking as they move around and interact with students. During a pandemic, this behavior might not be desirable. Another model for teachers is restricting their movement to the space in front of the classroom board. At the end of the school period, the teachers head back to their room, attending to their administrative duties. During that time, teachers can move in the room to simulate bringing paperwork from a file cabinet. They also talk to each other, and if they chose, they could visit the bathroom, stopping along the way to observe any points of interest if that caught their attention.

The school’s FSM regulates the school day. It alternates the school state between the classes in sessions state and the break time state until the school day is over. The FSM then transitions to an egress time state. After all the students have egressed, the FSM transitions into the off-time state while agents are home. The simulation records this time to calculate the dissipation of viral concentration in classroom air during that off-time. The school directs its spaces at the corresponding states, such as classrooms, labs, and teacher rooms, to perform the relative actions. For classrooms, these actions are starting new classes, moving a class to a lab, ending class, going on break, and sending the students on their way home. For labs, these actions are starting
the lab and sending the students back to their classroom after the lab is over. Figure 3 illustrates the general flow of the simulation.

**Modeling disease propagation**

The mathematical model used in the paper depends on the work of Bazant and Bush. The Centers for Disease Control and Prevention (CDC) classifies COVID-19 as an airborne disease. Contagious individuals create liquid droplets in their respiratory system and eject them into the air during expiratory events. The number of droplets depends on the level of activity the individual is undergoing. The Wells–Riley model suggests that a droplet of radius $r$ could be too big, so it is heavy enough to settle on surfaces, causing the first mode of transmission: surface infection or fomites. Researchers have found that the risk of transmission via this mode is minimal, so it is not accounted for in this simulation. Alternatively, the droplets could be too small, thus evaporating in the air before touching the ground. However, the droplets do not consist solely of water. When the water content evaporates, the other elements of the droplets, called solutes, could be too light to settle. The solutes potentially contain virions, and due to their lightweight, the partially evaporated droplets hang in the air in the form of aerosols (airborne transmission). Aerosols are the second and primary mode of infection of COVID-19. The Aerosols droplets are those that fall below a
certain radius; the critical radius $r_c$. They fill the air, increasing viral concentration $C$ in a room of volume $V$, potentially infecting susceptible individuals breathing the same air. The third transmission mode is direct exposure to the droplets or short-range infection, which happens when a susceptible individual is exposed to droplets ejected from a contagious individual during expiratory events.

The model in hand assumes a well-mixed room, where contagious individuals release pathogens in the air. The epidemic literature defines the number of released pathogens as the infection quanta $C_q$.\textsuperscript{35} Infection quanta depend on several factors, the breathing flow rate of the contagious individual, which is estimated to be 0.5 m\textsuperscript{3}/h for normal breathing, 0.75 m\textsuperscript{3}/h for speaking, and 1.0 m\textsuperscript{3}/h for shouting or singing.\textsuperscript{33} Infection quanta also depend on the number of droplets per breathed volume of air $n_d$ or droplet concentration, ranging from 0.1 per cm\textsuperscript{3} for breathing to 1.1 per cm\textsuperscript{3} for singing or shouting.\textsuperscript{38} Each droplet has a volume $V_d$ with a concentration of virions in that volume $C_v$. Virion concentration or the viral load is measured in copies per liquid volume, which varies according to the stage of infection. Buonanno, Stabile, and Morawska\textsuperscript{39} estimate the number to be 108–1011 copies per mL in peak infection of COVID-19. Face masks reduce the stream of infection quanta. The mask penetration factor is the chance for a droplet to penetrate the mask. Average cloth
Figure 3. Simulation flowchart.
masks have a penetration factor of 0.8, while surgical masks’ 0.15. N95 mask penetration factor is 0.05,\textsuperscript{40} and no face mask is one. Equation (1)\textsuperscript{1} demonstrates the increase in viral concentration for each breath.

\[ C_q = P_m Q_b \int_0^{r_c} n_d V_d C_v dr \]  

(1)

\( C_q \) is the infection quanta, \( P_m \) the mask factor, \( Q_b \) the breathing flow rate of the contagious individual, \( n_d \) the droplet concentration, \( V_d \) the droplet volume, \( C_v \) the viral load. This is calculated for all droplets up to the droplets of the critical radius \( r_c \), which is 2.6 μm for COVID-19.\textsuperscript{33}

For simulation purposes, instead of continuously calculating all radii up to the critical radius in a continuous fashion, the authors have assumed a discrete model, calculating the quanta for radii at a step of 0.1 μm up to the critical radius.

As per the well-mixed room model, the pathogens are evenly distributed in the room air. Thus, all susceptible individuals have the same chance of catching contagion. The contaminated air in a well-mixed room transmits to susceptible individuals by breathing at a transmission rate. Equation (2) shows the rate of transmission \( \beta(t) \) for every breath.

\[ \beta(t) = Q_b \int_0^{r_c} C(t) c_i P_m dr \]  

(2)

\( \beta(t) \) is the transmission rate, \( Q_b \) the breathing flow rate of the susceptible individual, \( C(t) \) the viral concentration in the room at time (t), \( C_i \) the viral infectivity, which is 10% in COVID-19.\textsuperscript{39} The face mask penetration factor \( P_m \) also filters that rate.

Due to the spatial placement of the agents, they can receive the infection quanta differently. If a susceptible individual happens to be in the way of a turbulent jet emitted from a contagious individual during expiratory events, the susceptible individual is exposed to a direct stream of infected droplets. The amount of transmitted infection quanta depends on the distance (x) between both individuals. As droplets dissipate into the air, they lose their concentration depending on the distance traveled. Equation (3) shows how to resolve the concentration near the contagious individual \( C_q \).

\[ C_q(x) = \frac{C_q \sqrt{A_m}}{\alpha x} \]  

(3)

\( C_q(x) \) is the concentration at x distance from the contagious individual, \( A_m \) the area of the contagious person’s mouth (approximal 2 cm\textsuperscript{2}), \( \alpha \) the jet entrainment coefficient which ranges from 0.1–0.15.\textsuperscript{40} With each breath, equation (4) shows the transmission rate \( \beta \) of a susceptible person receiving infection quanta from the room.

\[ \beta(t,x) = Q_b \left( C(t) + C_q(x) \right) c_i P_m \]  

(4)

\( t \) is the time of the calculation, \( x \) the distance to contagious person, \( Q_b \) the susceptible person’s breathing flow rate, \( C \) the viral concentration at time \( t \), \( C_q \) the infection quanta near a contagious individual at a distance \( x \), \( c_i \) the viral infectivity, and \( P_m \) the mask penetration factor.

To model the viral air concentration, each indoor space looks for the agents inside, and if any of them are contagious, the room increases its concentration by the infection quanta of the contagious person(s) as resolved in equation (1). Equation (5) shows how the room adjusts its viral concentration with the incoming infection quanta \( C_q \).

\[ C = \frac{C_q}{\lambda a V} \]  

(5)
C is the viral concentration, $C_q$ the infection quanta received from all contagious individuals in space, $\lambda_a$ the air exchange rate, which is the rate at which the room air is renewed. This rate ranges from 0.1 in a closed room and reaches 3–8 with mechanical ventilation. For school rooms, it is 0.12 when the room is closed and goes up to 7.92 when windows are open, with AC and fans operating. Finally, $V$ is the room volume. If there are no contagious persons in the room, the concentration dissipates. Equation (6) demonstrates the rate of dissipation.

$$C = C - C_0 \lambda_a V$$

$C$ is viral concentration, $C_0$ the concentration level recorded when the contagious individual leaves the room, $\lambda_a$ the air exchange rate, $V$ the room volume.

**Running the simulation**

The authors developed the simulation in Unity using the programming language C#. Unity allows the visualization of the simulation in real-time. C# is an object-oriented programming (OOP) language, which facilitates the modeling of various simulation entities as objects. The object is a template that has information on how it should interact with other objects. By instancing that template, the language creates instances of that object, which gets its general behavior from the base template, while locally holds internal variables representing its “mind.” This process facilitates modeling of agents, where all agents of the same type follow a general behavior, yet each agent adapts and interacts uniquely based on its internal variables.

The simulation updates itself every fraction of time or “time step” which is set to 1 minute to strike a balance between the accuracy and speed of the simulation. Unity’s NavMesh; a pathfinding technology that utilizes the A* algorithm, directly controls the agents’ movement, which is the only continuously evaluated element in the simulation. The authors configured NavMesh to analyze the space before the simulation starts, instructing it on which areas are accessible to agents. Thus, FSM informs the agents of their destination at runtime, allowing NavMesh to direct them to their target positions.

The simulation has a “time scale” parameter which scales the time step during runtime to allow the simulation to run from 1/60th of the real-time to full real-time. The time scale directly controls the speed of agents. For example, the walking speed for adults is set to be 1.4 m/s and 1.2 m/s for children. These values are multiplied by the time scale during the simulation runtime.

**Simulating the environment**

Users can set up the environment at the simulation start (Figure 4). Table 1 illustrates the description of these parameters. It is worth noting that as per the well-mixed room model, the assumption is that air circulates evenly throughout the room due to parameters such as general air flow, individuals’ movements, thermal flows, as well as breathing and other respiratory events. Therefore, the researchers have aggregated the locations of AC units, or windows to the space’s total air exchange property.

**Simulation of the spatial behavior**

At the start of each period, the simulation picks a random number of classrooms, not exceeding the number of the labs in the school. Then, it directs selected classrooms to the labs to start their classes there. Each classroom is associated with a group of students. When the school informs the classroom to start, it requests a new teacher and directs its students to their desks. During class, if classrooms activities were enabled, each classroom may fire an activity event at random. If there is an activity, the classroom directs its students to their
accord places until the activity is over. Afterward, the classroom directs the students back to their desks. During class, the teacher moves around the classroom to simulate talking to students. Users can restrict this behavior to the area around the whiteboard during the simulation.

At the end of the period, the classroom releases its teacher back to the teacher room, recalls any student groups in a lab, and starts break time. During class, if no activity requires the participation of students, they

Figure 4. Setting up the simulation environment user interface.

Table 1. The description of the simulation parameters.

| Parameter                              | Description                                                                 |
|----------------------------------------|-----------------------------------------------------------------------------|
| Time scale slider                      | The slider represents the number of seconds in simulation time equivalent to a minute in real-time. This number ranges from 1 (1/60th real-time) to 60 (real-time) |
| Simulation runtime                     | The number of school days the simulation will run                             |
| Number of periods per school day       | The number of periods in a school day                                        |
| Period and break length in minutes    | The duration of period and break length in minutes, respectively              |
| Enable classroom activities toggle     | Enable or disable classroom activities                                       |
| Enable class relocation toggle         | Enable or disable relocation to other classrooms                             |
| Initial number of infected agents      | The initial number of infected students and/or teachers                      |
| Egress waiting time in minutes         | The time between egresses for each classroom                                 |
| Initial mask settings dropdown         | Types of masks students/teachers are wearing; options are no masks/cloth/surgical/N95 |
| Global air control dropdown           | Setup of air in school spaces                                               |
| School runs at half capacity checkbox  | When checked, the parameter switches the number of working classrooms to half |
| Classroom running at half capacity checkbox | When checked, the parameter switches the number of students in the classroom to half |

accord places until the activity is over. Afterward, the classroom directs the students back to their desks. During class, the teacher moves around the classroom to simulate talking to students. Users can restrict this behavior to the area around the whiteboard during the simulation.

At the end of the period, the classroom releases its teacher back to the teacher room, recalls any student groups in a lab, and starts break time. During class, if no activity requires the participation of students, they
can transit to the free state. Students can choose to perform one of two actions. In the first action, a student moves to a random locker in the class, stays a while, and heads back to their desk. The second action is when a student can choose to get permission for a bathroom break. The student heads to the nearest bathroom, goes to a free toilet or sink, stays a while, and returns to the classroom. During the student’s journey back to the class, they could randomly stop at a point of interest, stay there for a while to simulate reading the content, then head back to class. Upon break time, students automatically transition to the free state and have even more chance of doing any of the actions above.

During egress time, the school allocates egress points, which call on its nearest classes to release their students. The user can delay the time between each egress group at the start of the simulation. Once all students have exited the school, it restarts the day, repeating previous actions until the simulation length is exhausted.

**Simulation of disease spread**

The simulation evaluates the disease spread at time steps equal to 1 minute in actual time. For all enclosed spaces, the simulation checks if there is a contagious agent inside. If there is, each space calculates its infection quanta according to equation (1), multiplied by 20 times to compensate for the times a person breathes in a minute. The space calculates infection quanta for droplets sizes ranging from 0.1 μm to the critical radius (2.6 μm in the case of COVID-19) at 0.1 μm intervals and increases its viral concentration level by the collected amount. If there were no contagious persons in the space, it decreases its viral concentration, according to equation (6).

At the same time step, the rooms transfer infection quanta to every susceptible agent inside. The rooms also detect any proximities between susceptible and contagious agents and appropriately add a short-range infection quanta according to equation (3). Each room transfers total infection quanta at the amount described in equation (4). For every agent, the chance to catch the disease is the number of infection quanta divided by a configurable number. This number could be adjusted to represent various levels of susceptibility to the disease. The chance increases relative to infection quanta in susceptible agents. If an agent catches the disease, they become infected. It takes time for them before they become contagious. The mean incubation period of COVID-19 is 5.2 days, while research had found potential transmission events 2–3 days before symptoms were displayed. Thus, the selected time before an individual becomes contagious is to two and a half days.

The simulation has a visual interface (Figure 5) that allows users to monitor and analyze how disease spreads with the spatial behavior of the agents. It is vital to observe what actions lead to more or less disease spread.

**Validation**

The validation of a social phenomenon simulation is hard for many reasons. Nigel Gilbert lists four. First, both target and simulation usually behave stochastically. Second, it is challenging to obtain the precise initial conditions in a social setting. Third, the simulation may not reproduce some aspects of the target. Fourth, the data about the target are, in most cases, based on assumptions and estimates. In this study, there is no data about the target regarding the impact of spatial behavior on pandemic propagation, and many ethical concerns stand in the way of constructing such data. Furthermore, accurate data on COVID-19 exact infection rates are not available, especially in a specific environment like this. For these reasons, according to Gilbert, it is hard to discern the validation process from verification, where the latter refers to the simulation being free of bugs and working as intended.

The authors performed multiple tests to verify the infection model. In those tests, the authors devised a hypothetical 240-min, sixteen-student classroom to test health conditions. All the tests started with a single
contagious student and varied a single parameter. For example, with standard conditions and bad ventilation, four agents were infected out of 17 after the first test was over. The authors repeated the test while improving ventilation in the class by opening windows and turning on the air conditioning. No agents were infected after 4 hours. Having all agents wear surgical masks with bad ventilation conditions resulted in only a single infection. The authors tested other conditions, and the results came to be as rationally expected.

For the behavior validation, interviews with schoolteachers have confirmed that the behavior of students and teachers concurs with the behavior depicted in the simulation. The authors turned on the simulation without the disease parameters and had two schoolteachers simultaneously observe the simulation. After the simulated school day was over, both teachers agreed that both the actions of students and teachers are relatively similar to what happens in the actual school.

Results and discussion

The authors tested multiple scenarios to assess the effect of various measures on the virus spread. For instance, restricting the movement of the teacher to the whiteboard area should theoretically decrease the infection rate. The authors devised two scenarios to test that hypothesis. The first scenario lets the teacher move through the entire classroom, while the second restricts the teacher’s movement to the whiteboard area. Each scenario started with three infected teachers. Table 2 illustrates the test conditions.

In the second scenario, test conditions are the same as the first scenario except for the teacher movement style, which is restricted in the second scenario.

At the end of the first scenario, there were two infected agents (0.7% of 273 total agents) and 27 contagious agents (9.9% of 273 total agents). The second scenario ended with 24 infected agents (8.8% of 273 total agents) and 33 contagious agents (12.1% of 273 total agents). Observing the simulation has shown that by
restricting the movement of the teacher, the students on the front row of the classroom spend more time closer to the potentially infected teacher. They received a larger amount of viral load than students in classrooms where the teacher movement was not restricted. In those classrooms, the teacher moved throughout the class, distributing their viral load on all students and sometimes on empty space. This is true in this case since the distance between the whiteboard and the first rank of desks is not large enough to protect the students from the cone of breath emanating from the teacher.

These results highlight the merit of the simulation as a tool to assess various actions to fight pandemic spread in the elementary school environment. They also demonstrate how ABMS explains the formulation of a phenomenon by visualizing how it came to be. The value of using ABMS is that it accounts for the actions of each agent rather than treating them as mindless clusters. The simulation also is adaptable. The authors could easily change the simulation variables to account for other airborne diseases, not just COVID-19. If necessary, the FSM system allows the authors to add more behaviors to the agents without breaking other behaviors. The simulation also allows for setting up any elementary school plan as the simulation space in a matter of minutes, which makes the simulation versatile and more usable.

After running the simulation multiple times to test various scenarios, the authors developed general guidelines regarding occupants’ spatial behavior.

1. It is recommended for teachers in a classroom to not stay in one place for too long, if the distance between the whiteboard and the first desk is less than two m. This value stems from equation (3), which shows that at a distance of two m, the viral concentration decreases to approximately 0.7% of its initial strength at the location of the contagious individual. This value also coincides with the guidelines of CDC of 6 feet, or 1.8 m.

2. Restricting students’ movements to their desks during class is another recommendation during pandemics. Classes usually have some activities that require students to congregate. Eliminating these events in the simulation has reduced the final infection rate from 68% to 30%.

3. Another reduction in final infected cases resulted from restricting classes to their own classrooms. Canceling class relocations to other specialized labs like physics and art decreased the final infection rate from 68% to 44% on average.

In general, mobility increases the chance of disease propagation. When agents move, their activity level increases. The simulation shows that the activity level causes an increase in the volume of breathed air, which in turn increases the amount of potential viral production and consumption. Moreover, moving to different classes increases the risk of transmitting infected air to new spaces.
There are multiple limitations to the studies; the validation of the results is one of them. As with similar studies, human behavior follows a stochastic pattern that is extremely hard to replicate. Instead, the simulation follows a similar stochastic approach, making the results similar but not exact. Another limitation is that the research on COVID-19 is still ongoing, and while there is a large volume of available data, a large part of it is still experimental, and needs more research to confirm it. A third limitation is the need for more agent types to produce more accurate results, for example, school workers, administrators, and other types of personnel. Additionally, the authors decided to expose only a subset of parameters to the user to tune the simulation. Those are the parameters that simulate intervention strategies. This decision is there to avoid overwhelming users with a torrent of parameters to tune upon running the simulation. However, this decision has the side effect of making the simulation limited to elementary schools that host students aged 6–11 years old. Additional tuning to the age and the behavior of students requires further delving into the code behind the simulation. Furthermore, the behavior itself is based on interviews with teachers from the school, which may differ in other schools.

Further studies can use this or similar ABMS strategies to consider general architectural spaces guidelines. The simulation has the potential to dictate preferred dimensions for spaces, in schools or otherwise.

Conclusions
This study introduces a simulation to evaluate the effects of spatial behavior on COVID-19 spread, using the ABMS research paradigm. First, it shows how the authors modeled spatial behavior and the disease transmission models. Next, it explains how the simulation of all elements works. The study then introduces two scenarios to evaluate two approaches to pandemic spread prevention by restricting the teachers’ movement to demonstrate its usage as an effective tool for assessing and analyzing the disease spread. Finally, as a result of multiple simulations with various parameter combinations, the study concludes that in general, mobility increases the risk of infection, as it increases the distribution of the virus in the air, as well as increases the level of physical activity of the users, which in turn leads to an increase of the amount of potential viral consumption and production. This study attempts to bridge the gap between epidemic studies that typically focus on large-scale populations and architectural behavioral studies that do not necessarily consider spatial behavior’s effects on disease propagation.

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Note
1. The equations presented in this study are adapted from the work of Bazant and Bush; however, they are modified to suit the discrete model the study employs rather than the continuous model they use.
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