Integrated Environment-Occupant-Pathogen Information Modeling to Assess and Communicate Room-Level Outbreak Risks of Infectious Diseases

Abstract

Microbial pathogen transmission within built environments is a main public health concern. The pandemic of coronavirus disease 2019 (COVID-19) adds to the urgency of developing effective means to reduce the pathogen transmission in mass-gathering public buildings such as schools, hospitals, and airports. To inform occupants and guide facility managers to prevent and respond to infectious disease outbreaks, this study proposed a framework to assess the room-level outbreak risks in buildings by modeling built environment characteristics, occupancy information, and pathogen transmission. Building information modeling (BIM) is exploited to automatically retrieve building parameters and possible occupant interactions that are relevant to pathogen transmission. The extracted information is fed into an environment pathogen transmission model to derive the basic reproduction numbers for different pathogens, which serve as proxies of outbreak potentials in rooms. A web-based system is developed to provide timely information regarding outbreak risks to occupants and facility managers. The efficacy of the proposed method was demonstrated by a case study, in which the building characteristics, occupancy schedules, pathogen parameters, as well as hygiene and cleaning practices are considered for outbreak risk assessment. This study contributes to the body of knowledge by computationally integrating building, occupant, and pathogen information modeling for infectious disease outbreak assessment, and communicating actionable information for built environment management.

Keywords

Building Information Modeling; Pathogen Transmission; Outbreak Risk; COVID-19; Health

1. Introduction

People spend most of their time in buildings, including homes, offices, schools, stores, restaurants, theaters, and many others. The buildings become hotspots for pathogen transmission and exposure, decimating populations through epidemics and everyday infections. The disastrous impacts of infectious diseases highlight the urgent need to reduce the transmission of pathogens, and their exposure to occupants in buildings. Humans can be infected by microbial pathogens via contacting contaminated objects, referred to as fomites. Fomite-based transmission is an important route in built environments for transferring disease-causing microbiomes to a new human host [1]. The mechanism of fomite-mediated transmission involves three steps. First, a surface is contaminated by infectious pathogens. The contamination can occur when an infected person touches the surface or bioaerosols containing pathogens settle down on the surface. Second, a person touches a contaminated surface with his or her hand, transferring the pathogens to the hand. Third, the person touches susceptible sites (mucous membranes) on his or her body with the contaminated hand, which inoculates the site with pathogens, resulting in potential infection. A recent study [2] found that contamination of a single doorknob or tabletop can spread the infectious pathogens to other commonly touched objects, exposing 40-60% of people in the buildings.

Many pathogens can be transmitted via fomites. For example, during flu seasons, measurable levels of influenza virus can be found on all common building surfaces [1,3], underlining the importance of fomite in influenza transmission. The pandemic of coronavirus disease 2019 (COVID-19) has swept the entire world with more than 29.6 million infections and 935,898 deaths as of September 16, 2020 [4]. During the pandemic of COVID-19, viable severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) can be detected on various surfaces. High concentration of SARS-CoV-2 are found on surfaces in healthcare facilities where COVID-19 patients are treated [5,6]. Norovirus can also be transmitted via fomite [7,8], causing 93% of nonbacterial gastroenteritis outbreaks in the U.S. In addition, pathogens including staphylococcus aureus, Clostridium difficile, Staphylococcus aureus, Pseudomonas aeruginosa, Pseudomonas putida, and Enterococcus faecalis can also be transmitted by surface contact [9].

Models have been developed for environmental risk assessment and environmental infection transmission [10]. Fomite-mediated transmission has received increased attention [11,12]. To assess pathogen transmission to susceptible hosts, the models such as the environmental infection transmission system modeling framework consider the dynamics of contact and pathogen transfer between individuals via their hands and fomites, pathogen persistence in the environment, pathogen shedding, and recovery of infected individuals. Studies [13–15] also exploited experimentation approaches to measure the transfer of microbiomes between fomites and humans. The measured microbiological and epidemiological data can be used to assess the transmissibility of the pathogens and used in the models for risk assessment. Despite research efforts made in epidemiology, the modeling of building, occupant, and pathogen has not been well linked to predict the microbial burdens and outbreak risks.

Predicting outbreak risks in buildings and communicating actionable information to occupants and facility managers are challenging. First, pathogen burdens could differ considerably in rooms even in the same building. Building design and operation can influence indoor microbial communities [16,17]. The microbial communities in different rooms with different functionalities and spatial configurations are found to exhibit very different patterns [18,19]. Occupancy also significantly affects the microbial communities in buildings. For example, bacteria taxa in spaces with a high occupant diversity and a high degree of physical connectedness are different from that in spaces with low levels of connectedness and occupant diversity [16]. Humans can transfer microbiomes including pathogens to the environment via skin-to-surface contact and direct shedding of large biological particles [20,21]. The microbial exchange between occupants and surfaces can occur in both directions [12]. With different uses and occupancy levels, outbreak risks could vary depending on the locations in a building, underlining the need for a spatially-adapted modeling approach. However, there lacks a computational modeling approach to link the coupled physical-biological processes of buildings, occupants, and pathogens to automatically assess the spatially-varying infection and outbreak risks at unprecedented scales. Therefore, it is imperative to establish the computational framework to quickly compute the risk in buildings to inform end-users and guide adaptive operations.

Second, due to the absence of an effective means for information communication, end-users have limited access to easy-to-understand information regarding the outbreak risks to make necessary interventions. Building information modeling (BIM) uses standardized machine-readable information created or gathered about a facility throughout its lifecycle for all stakeholders involved [22]. Information can be extracted from building information models, as they are the shared digital representations of physical and functional characteristics of any built objects [22]. In addition, BIM has also been used as a powerful tool to visualize the parametric building model with computed rich information [23]. However, to the authors' best knowledge, existing studies have not explored the capability of BIM in environmental pathogenic infection assessment, and leverage BIM as a platform to visualize and communicate outbreak risk information to end-users for facility management.

This study aims to develop a framework for room-level outbreak risk assessment based on integrated building-occupancy-pathogen modeling to mitigate the spread of infectious disease in buildings. The rationale is twofold. First, buildings are highly heterogeneous with a variety of compartments of distinctive functionalities and characteristics, providing diverse habitats for humans and various pathogens [17,18]. Modeling the pathogen transmission and exposure within a building at the room level will provide useful information at an unprecedented resolution to implement appropriate disease control strategies. Second, the spread of infectious diseases can be mitigated if occupants and facility managers have adequate and timely information regarding the outbreak risks within their buildings. Communicating actionable information to occupants and facility managers through an easily accessible interface will help occupants to follow hygiene and social distancing practice, and help facility managers to schedule disinfection for rooms with high outbreak risks.

2. Method

To address the knowledge gaps, a novel environment-occupant-pathogen modeling framework and a web-based information visualization system are developed to assess the outbreak risks and mitigate the spread of infectious diseases in buildings (Fig. 1). First, to assess the outbreak risks, the fomite-based pathogen transmission model proposed in [24] is adopted in this study. The limitation of the model is that the environmental parameters and occupant characteristics are not automatically extracted and incorporated in the model, hindering the computation of the spatially-varying environmental infection risks in buildings. To overcome this limitation, BIM is exploited to automatically retrieve venue-specific parameters including building characteristics and occupancy information that are relevant to pathogen transmission and exposure. Then, the extracted building and occupant parameters are used with pathogen-specific parameters in a human-building-pathogen transmission model to compute the basic reproduction number R_0 for each room in a building. R_0 is used as a proxy to assess the outbreak risks of different infectious diseases. Second, a web-based system is developed to enable information visualization and communication in an interactive manner to provide guidance for occupants and facility managers. This study innovatively establishes the computational links among building, occupant, and pathogen modeling to predict outbreak risks. The risk prediction for spatially and functionally distributed rooms in a building provides useful information for end-users to combat and respond to the spread of infectious diseases, including the seasonal flu and COVID-19. The developed method and system add a health dimension to transform the current building management to a user-centric and bio-informed paradigm.

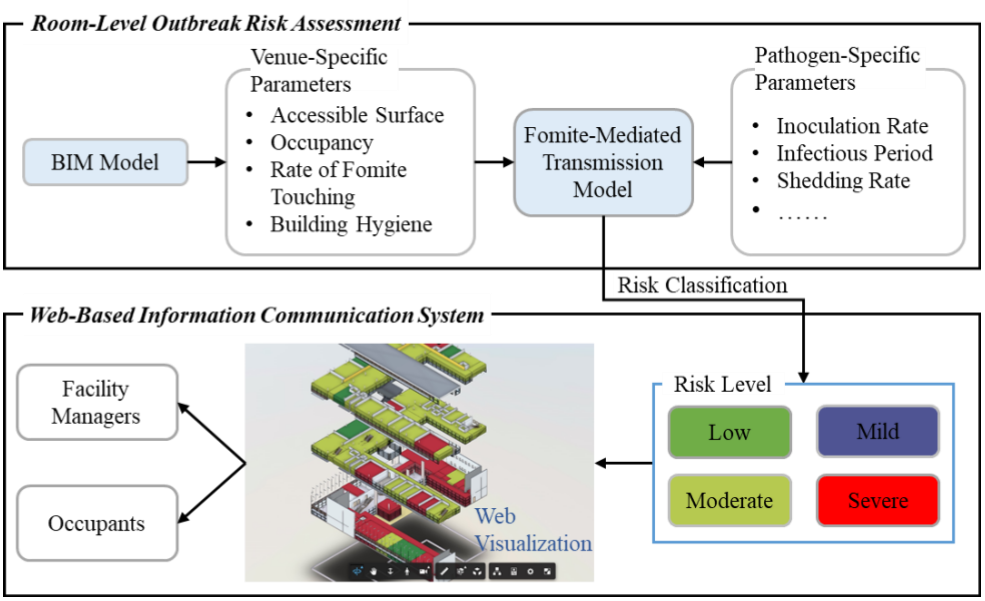


Fig. 1. Research Framework

2.1. Room-Level Outbreak Risk Assessment

Employing the model proposed in [24], individuals are divided into three categories, i.e., susceptible, infectious, and recovered. Pathogens may survive outside the host and contaminate either object surfaces or human hands. The pathogen exchange in built environments can occur through hand-surface contacts. Contaminated hands of hosts can contaminate surfaces of accessible objects, while susceptible people can get infected by touching the contaminated surfaces and self-inoculation. Fig. 2 shows the fomite-mediated pathogen transmission process in built environments. Building characteristics, occupant behavior, and pathogen parameters collectively determine the transmission ability through the dynamic processes of pathogen inoculation, fomite touching and transfer, pathogen excretion, pathogen decay, individual recovery, and building disinfection and individual hygiene. Characteristics of the built environment (e.g., contaminated objects and building hygiene) and occupant behavior (e.g., fomite touching and hand cleaning) are critical in the process of fomite-mediated pathogen transmission in the built environment and are considered as venue-specific parameters. In addition, the transmission efficiency of different diseases also depends on pathogen-specific parameters, such as recovery rates and pathogen excretion. The determination and acquisition of venue-specific and pathogen-specific parameters are detailed as follows.

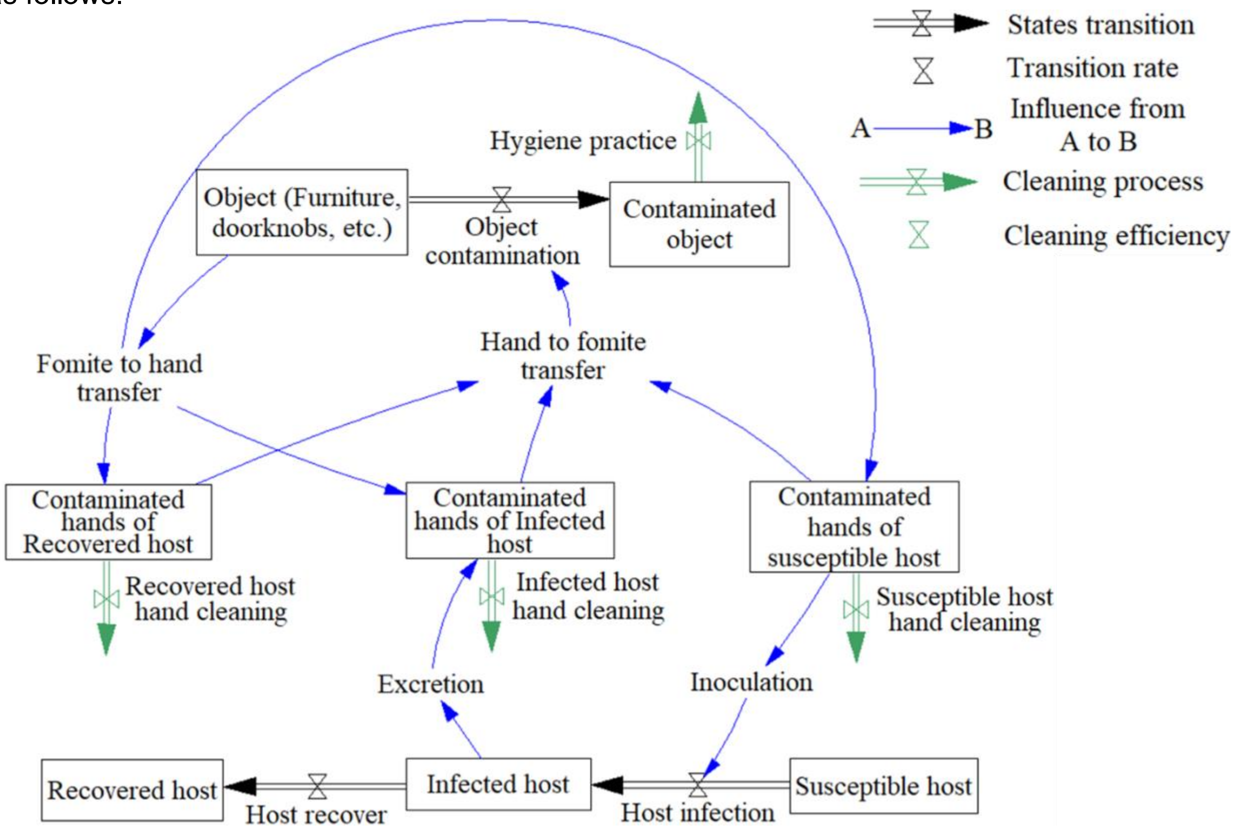


Fig. 2. Fomite-mediated pathogen transmission in built environments (Adapted from [24])

2.1.1. Venue-specific parameters

Because venue-specific parameters vary across rooms with different functions and occupancy levels, it is important to develop an effective means to accurately and automatically extract the venue-specific parameters to assess the outbreak risks at the resolution of room level. A building information model captures the relationships among different elements in a building, and allows the storage and extraction of detailed geometric and non-geometric information in a

3D virtual representation. The non-geometric information includes semantic and topological information, describing the attributes of elements and the relationship between components, respectively [25]. Hence, it is feasible and efficient to extract venue-specific parameters from a building information model.

The BIM model can be divided into six Levels of Development (LOD) [26] that are suitable for conceptual design (LOD 100), schematic design (LOD 200), design development (LOD 300), construction documentation (LOD 350), fabrication and assembly (LOD 400), and maintenance and operation (LOD 500). To effectively capture the characteristics of buildings and occupants, this study uses LOD 500 BIM model that reflects the as-built conditions regarding the geometry information and non-graphical building attributes, as well as occupancy information. Fig. 3 shows an example of a representative classroom in the BIM model. For most public buildings such as schools and hospitals, and particularly during the pandemic, the occupancy can be predetermined and incorporated in the BIM model as attributes.

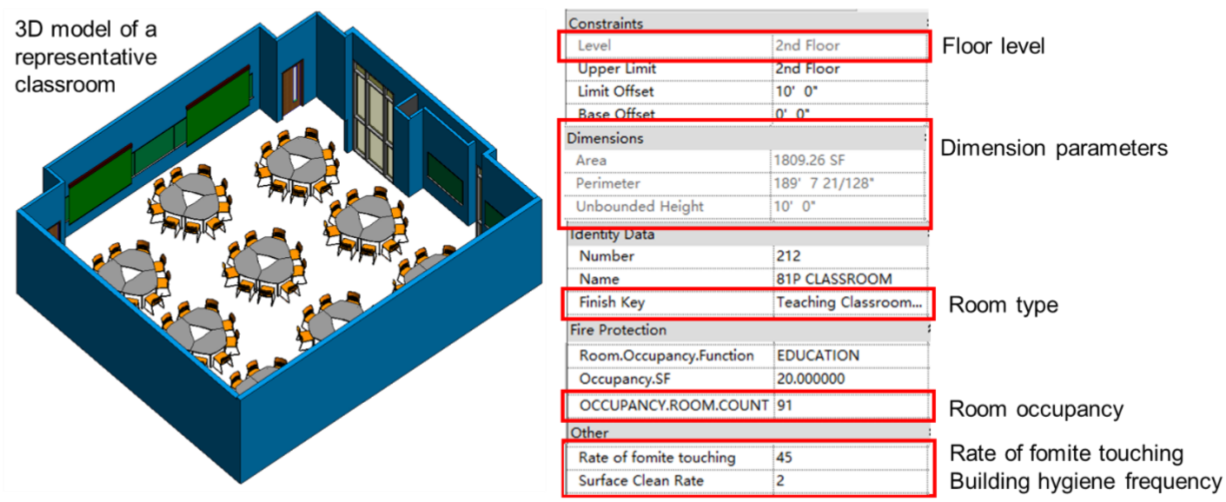


Fig. 3. Building and Occupancy Information Modeling

The following venue-specific parameters will be extracted from the model.

1) *Accessible surface*. The surfaces of objects, including doorknobs, stair railings, tables, and chairs, which people frequently interact with are considered as accessible surfaces. The accessible surface is computed as the summation of surface area of all touchable objects in a room. The proportion of accessible surface λ is defined as the ratio of accessible surface to the total area of surfaces within a room that includes both accessible surface and interior surface. The calculation is shown in Eq. 1.

$$\lambda = \frac{\sum Accessible\ surface\ area}{\sum Accessible\ surface\ area + Room_{InnerArea}} \tag{1}$$

2) *Occupancy*. The occupancy is the number of individuals present in a room per day. In this study, it is assumed that the occupancy of each room is predefined based on room capacity. During the pandemic of COVID-19, many buildings such as university campus buildings and office buildings have developed detailed occupancy schedules, which can be updated in the BIM model and then extracted for analysis. Consistent with the prior study [24], it is assumed that all individuals are identical within each room regarding susceptibility, contact rates, and infectiousness as well as other individual characteristics. This assumption

simplifies the model to capture the complex nature of pathogen transmission process. The only difference among the individuals is the state associated with them: Susceptible *S*, Infected *I*, or Recovered *R* during the pathogen transmission process.

3) *Rate of fomite touching*. The rate of fomite touching is the frequency that occupants interact with the objects inside a room on an hourly basis. A higher frequency of interaction indicates a higher possibility of pathogen transmission between objects and hosts. In this study, the rate of fomite touching is determined based on different functionalities of the rooms considering the primary age group present in the rooms. For example, classrooms and offices in a school building are two main types of rooms considered in this study. It is assumed that the rate of fomite touching in classrooms is higher than that in offices because the occupants in classrooms are younger people who are more likely to interact with the built environment. According to the observations in [27], an average rate of touching common areas (e.g., chairs, desks, facilities) in a school office is 12 times per hour. Therefore, in this study, the rate of fomite touching is set as 12 times per hour for offices, and that for classrooms is set as 45 times per hour based on [28]. Furthermore, to incorporate the possible variation in different scenarios, a range of (0, 30) and (30, 60) is considered for offices and classrooms, which also aligns with the setting in [28]. Analyses will be conducted to examine the influence of the rate of fomite touching on outbreak risk.

4) *Building Cleaning and Hand Hygiene*. Building cleaning plays an important role in object decontamination. For fomite-mediated transmission, surface cleaning can significantly decrease the pathogen reproductive process. The frequency of building cleaning is determined by the adopted sanitation schedule of the building. Hand hygiene removes pathogens picked up from contaminated objects. For infected individuals, hand cleaning also removes pathogens excreted to hand, and thus, preventing contaminating objects through hand touching.

In this study, a computational tool is developed based on Dynamo [29] to extract the geometry and properties of each room in a building, and to compute the corresponding venue-specific parameters. Fig. 4 shows the workflow of the information retrieval process. Lines in Fig. 4 indicate direct information retrieval from the models and arrows indicate the information retrieval involving calculations.

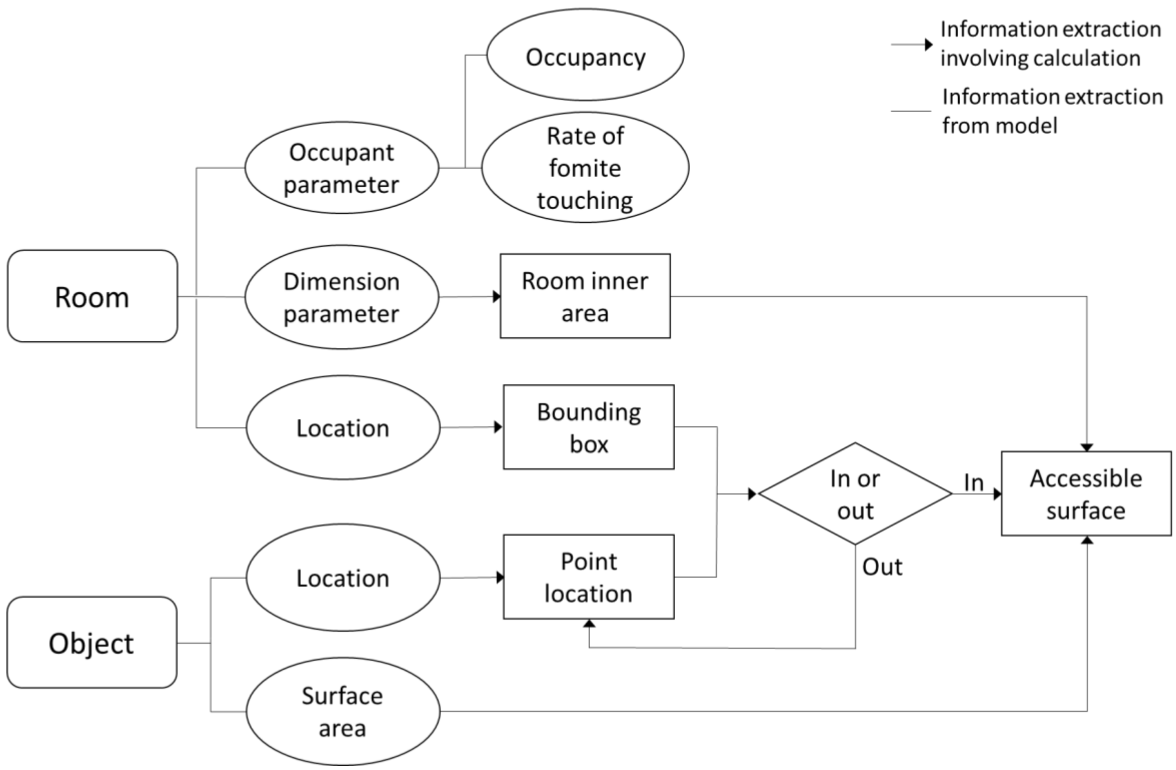


Fig. 4. Workflow of information retrieval process.

The workflow for information retrieval is detailed as follows.

The steps for *extracting room parameters* are:

1) Room element selection. Starting from a building information model, all elements are selected from the Room category, which is a predefined category including all the rooms in the model.
2) Room information extraction. The essential room-related and occupant-related parameters are extracted from all the room elements. The room-related parameters include room area (the floor area of each room, named $room_A$), room perimeter (the summation of the length of all walls, named $room_P$), room height (the height of the walls, named $room_H$) and the rate of building hygiene. Occupant-related parameters include room occupancy and rate of fomite touching. With room dimension parameters, the interior surface of a room ($room_{InnerArea}$) can be calculated by Eq. 2:

$$room_{InnerArea} = 2 * room_A + room_P * room_H \quad (2)$$

3) Acquisition of room bounding box. The bounding box of a room element indicates the location of the boundaries of the room and is defined by two 3D point coordinates, i.e., the minimum point and maximum point. The bounding box can be used to determine if an object is inside a room by checking if the coordinate of an object is inside the range from the minimum point to the maximum point. The bounding box results are used for object parameter extraction.

Objects in the rooms such as furniture can be contaminated via hand-surface contact, and involved in the fomite transmission pathway. The furniture in a room is considered as accessible object.

The steps for extracting the object parameters are:

1) Furniture element selection. All the elements under the category “Furniture” are selected from the model. This category contains information of all the furniture in the model.

2) Furniture information extraction. The essential furniture parameters are extracted from all the furniture elements. The parameters include area (the surface area of furniture) and location (the point location of each furniture element). The location of furniture is transformed to a 3D point (a point with x, y, z coordinates) using a default function in Dynamo. The coordinates represent the location of the furniture.

3) Location relationship between room and furniture. For each room element, the coordinates of furniture in the model are compared with the coordinates of the room bounding box. This process checks the 3D location relationship between each room and furniture.

Thereafter, the total furniture area in each room (Named $furniture_A$) is calculated by summing up the surface area of all furniture inside the room. The proportion of accessible surface (λ) of each room is calculated using Eq. 3.

$$\lambda = \frac{furniture_A}{furniture_A + room_{innerArea}} \tag{3}$$

2.1.2. Pathogen-specific parameters

Pathogen characteristics affect the transmission process through inoculation, excretion, inactivation (decay), and recovery. According to the study [24], Table 1 lists the pathogen-specific parameters used in the fomite-mediated transmission model.

Table 1. Description of pathogen parameters

Pathogen parameters	Symbol	Unit	Parameter description
Infectious period	$1/\gamma$	days	The period that an infectious individual can excrete and transmit pathogens
Shedding rate	α	pathogens/ (hours × people)	Infectious individual releases pathogens at rate α
Pathogen inactivation rate on surfaces	μ_F	1/hours	Pathogens decay at rate μ_F on surfaces
Pathogen inactivation rate on hands	μ_H	1/hours	Pathogens decay at rate μ_H on hands
Transfer efficiency from fomite to hand	τ_{FH}	1/touch	Pathogens transfer from fomite to hand at rate τ_{FH}
Transfer efficiency from hand to fomite	τ_{HF}	1/touch	Pathogens transfer from hand to fomite at rate τ_{HF}
Pathogen excreted to hand	φ_H	unitless	The proportion that pathogens are shed on hands
Dose response of pathogens on mucosa	π	unitless	The infectivity of a pathogen
Inoculation rate	ρ	1/hours	Rate of touching mouth or other routes of infection

In this study, three pathogens, i.e., influenza, norovirus, and SARS-CoV-2 are considered. Table 2 shows the parameter values used in the model. The pathogen-specific parameters of the first two viruses are determined based on [24]. The parameters of SARS-CoV-2 were determined based on a number of studies up to date. For the parameters that are still under research, the values are set based on surrogate viruses and assumptions, which are described as follows.

Table 2. Values of pathogen-specific parameters of four viruses

Pathogen-specific parameter	Influenza	Norovirus	SARS-CoV-2
$1/\gamma$	6	15	8 [30]
α	1E4	2.88E3	1.99E4 (1.8E3, 2.39E4)
μ_F	0.121	0.288	0.059
μ_H	88.2	1.07	0.8
τ_{FH}	0.1	0.07	0.37
τ_{HF}	0.025	0.13	0.14
φ_H	0.15	0.9	0.15
π	6.93E-05	4.78E-04	6.58E-06 [31]
ρ	15.8	15.8	15.8

1) The inactivation rates on surfaces (μ_F) and hands (μ_H). The inactivation rate on surfaces is determined based on the study [32], which provides the half-life of infectivity ($t_{0.5}$) on surfaces under common temperature and relative humidity. The inactivation process of the virus is assumed as a first-order kinetic model in this paper, and the inactivation rate is calculated as $ln2/t_{0.5}$. Under the circumstance of 74°F and 40 of relative humidity, the estimated half-life of infectivity on surfaces is 11.78 hours, and the approximate inactivation rate is 0.059 per hour. Due to the lack of exact data of μ_H, the parameter inactivation rate on skin of Middle East Respiratory Syndrome (MERS-CoV) is used in the paper, which is 0.8 per hour [33].

2) Transfer efficiency from fomite to hand (τ_{FH}) and transfer efficiency from hand to fomite (τ_{HF}). The transfer efficiency coefficients are estimated using parameters of MERS-CoV in [33] due to the absence of data. The transfer efficiency varies with surface materials. Compared with porous surfaces (e.g. fabrics, clothes, and sponges), non-porous surfaces such as desks, chairs, and door handles are more appropriate to represent the material of furniture surfaces considered in this paper. Thus, the transfer rates between hands and non-porous surfaces are used to indicate the transfer efficiency between hands and fomites. According to the results in [33], τ_{FH} is set as 0.37, and τ_{HF} is set as 0.14.

3) Pathogen excreted to hand (φ_H). Because the virus excretion behavior of SARS-CoV-2 such as coughing, sneezing, and exhaling is similar to the excretion behavior of influenza, φ_H of SARS-CoV-2 is estimated using the same parameter of influenza.

4) Shedding rate (α). In the paper, coughing is considered as the primary way for virus shedding. The shedding rate is determined by the number of viruses in the respiratory tract that is shed via coughing per hour per infectious individual. The equation for shedding rate calculation is shown in Eq. 4.

$$\alpha = V_{droplet} \times F_{cough} \times N_{droplet} \times L \tag{4}$$

$V_{droplet}$ indicates the volume per infectious droplet in cm^3, F_{cough} is the coughing frequency per hour, $N_{droplet}$ is the number of droplets excreted per cough, L is the viral load in the respiratory tract in $copies/mL$. According to [34], the viral load of SARS-CoV-2 for children aging 0-22 is 6.2 $\log_{10}$ RNA copies/ml, which is adopted in this study as the occupants are primarily children in school buildings. Due to the lack of data, other parameters are estimated using parameters of MERS-CoV in [33]. $V_{droplet}$ is calculated considering the largest diameter for infectious droplets that best fits the scenario of fomite transmission. The diameter is set as 100 μm. F_{cough} is set as 12 times per hour. $N_{droplet}$ is set to be 2000 per cough. Based on the calculation above, α is set to be 1.99E4. Besides, as the accurate shedding rate is still not well understood, it is assumed within the range of (1.8E3, 2.39E4), where the lower bound is set according to [28], and the higher bound is set as 1.2 times of the estimated value to allow potential higher shedding rate value.

5) Dose response of pathogens on mucosa (π). The infectivity is determined based on study [31]. [31] found that the exponential model $p = 1 - \exp(-d/k)$ can well demonstrate the dose-response function of SARS-CoV-2, where the constant k ranges from 6.19E4 to 7.28E5. In the paper, k is set as 1.52E5, representing 50% of contribution from airborne particles to the total dose. π is set as the inverse of k, which is 6.58E6.

2.1.3. Risk Assessment

In epidemic dynamics, the basic reproductive number (R_0) is an estimation of a pathogen's transmission ability of an infectious disease. R_0 is the expected number of cases generated by one single infected person, supposing all other individuals are susceptible to the epidemic [35]. In this study, R_0 is used to represent the outbreak potential of each pathogen across different rooms in the building. Given the fomite-mediated transmission model described in the previous section, R_0 is computed using the next generation matrix method [36], which consists of two matrices, i.e., the matrix of disease transmission and matrix of host state transition. R_0 is identified as the dominant eigenvalue of the product of the two matrices, computed using Eq. 5 proposed in [24].

$$\begin{cases} R_0 = R_{0,F} + R_{0,H} \\ R_{0,F} = \frac{a_F}{\gamma} P_{inoculation} P_{pickup} P'(0) \\ R_{0,H} = \frac{a_H}{\gamma} P_{inoculation} P_{pickup} P_{deposit} P'(0) \\ P_{inoculation} = \frac{\rho\chi}{\mu_H + \rho_{HF} + \rho\chi + \theta_H} \\ P_{pickup} = \frac{\frac{N\rho_{FH}}{N\rho_{FH} + \mu_F + \theta_F}}{1 - \frac{N\rho_{FH}}{(N\rho_{FH} + \mu_F + \theta_F)} \frac{\rho_{HF}}{(\mu_H + \rho_{HF} + \rho\chi + \theta_H)}} \\ P_{deposit} = \frac{\rho_{HF}}{\mu_H + \rho_{HF} + \rho\chi + \theta_H} \end{cases} \tag{5}$$

$R_{0,F}$ represents direct fomite contamination route, $R_{0,H}$ is hand-fomite contamination route, $P_{inoculation}$ is the proportion of pathogens that are self-inoculated to susceptible hosts; P_{pickup} is the proportion of pathogens picked up by hands from fomites; $P_{deposit}$ is the proportion of pathogens excreted to hands that are deposited to the fomites. $P'(0)$ is the slope of the dose function, indicating the infectivity of a dose of the pathogen.

In the above equations, $a_F = \alpha(1 - \varphi_H)\lambda$, representing the rate pathogens excreted to surfaces, where α is the shedding rate, φ_H is the proportion that pathogens are shed on hands, both defined in Table 1. λ is the proportion of accessible surfaces, calculated by parameters extracted from the BIM model. $a_H = \alpha\varphi_H$, representing the rate pathogens excreted to hands. Infectious period $1/\gamma$, inoculation rate ρ, and pathogen inactivation rate in hands μ_H and in fomites μ_F, are all pathogen-specific parameters that are defined in Table 1. χ is the proportion of pathogens self-inoculated by susceptible hosts, set as 1 in this study. $\rho_{HF} = \rho_T\tau_{HF}$, indicating the rate of pathogen deposited from hand to fomite, where ρ_T is the rate of fomite touching extracted from the BIM model, τ_{HF} is the transmission efficiency defined in Table 1. θ_H is the effective hand cleaning rate, which is set as the rate of hand washing. *N* is the occupancy of each room, extracted from the BIM model. $\rho_{FH} = N\rho_T\tau_{FH}\kappa$, representing the rate of pathogen picked up by hands, where τ_{FH} is the transmission efficiency from fomites to hands, κ is the fingertip to surface ratio, set as $\frac{6E-06}{\lambda}$ according to study [24]. θ_F is the effective fomite cleaning rate, which is set as the rate of building cleaning and can be extracted from BIM model.

In epidemiology literature, R_0 is one of the most widely used indicators of transmission intensity to demonstrate the outbreak potential of an infectious disease in a population. Commonly, $R_0 > 1$ means the epidemic begins to spread in the population, $R_0 < 1$ means the disease will gradually disappear, and $R_0 = 1$ means the disease will stay alive and reach a balance in the population. With the increase of R_0, the outbreak risk will increase, and more severe control measures and policies will be needed [37]. In this study, we categorize the level of outbreak risk into low, mild, moderate, and severe based on the range of R_0. Specifically, the risk is low when $R_0 < 1$; the risk is mild when $1 \leq R_0 < 1.5$ because there is a fair chance that the transmission will fade out as R_0 is not much larger than 1 [38]; the risk is moderate when $1.5 \leq R_0 < 2$, indicating an epidemic can occur and is likely to do so [39,40]; and the risk is severe when $R_0 > 2$ and immediate actions should be taken by facility managers, such as cleaning the surfaces, to reduce the risk.

2.2. Web-Based Information Communication System

To better communicate the infection risk to occupants and facility managers, a web-based system was developed to visualize the outbreak risk of different pathogens in each room within a building. Fig. 5 illustrates the architecture of the web-based system, which consists of four modules, i.e., data management, model derivative, web application, and user. The data management module is maintained by the management team and allows them to upload building models. In the model derivative module, the uploaded model is translated into the SVF format which is the format used by the web application. The web application module displays the building model and provides customized functionalities to facilitate visualization of pathogen risk within the building. Finally, the user can access the web-based system and visualize the room-level risk of pathogens. The web-based system is developed using Autodesk Forge that is a collection of APIs to develop cloud-based platforms to access, manage, and visualize design and engineering data. Each module is detailed below.

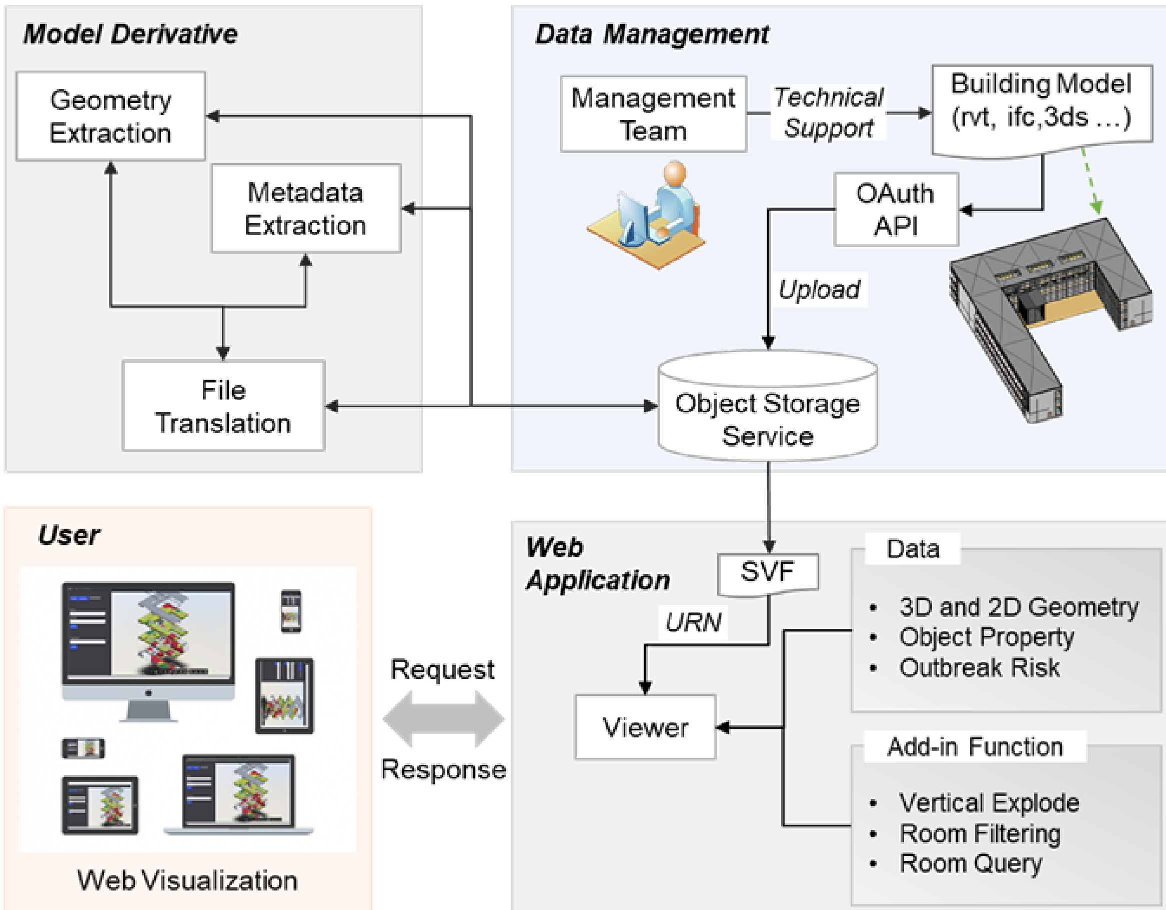


Fig. 5. Web-based alert system

The data management module supports a variety of 3D model formats such as rvt, ifc, and 3ds, where rvt is the file format used by the Autodesk Revit; ifc is an open international standard data schema for BIM data that are supported by various software products such as AutoCAD, Revit, and Tekla Structures; 3ds is the file format used by the Autodesk 3ds Max 3D modeling, animation and rendering software. The management team needs to log into their account to obtain authorization from the Forge OAuth API to access the Object Storage Service (OSS). Model files are uploaded to the OSS and stored as objects in buckets. In the second module, the model derivative translates the uploaded model into SVF format and extracts design metadata such as geometric data and object properties (e.g. room area and occupancy). The translated model and extracted data are also stored in the OSS. The model derivative component generates a unique identifier called URN for each translated model. The URN is then fed into the web application for the building model visualization.

The web application is built on the Forge Viewer API with customized functions. The Viewer API is a WebGL-based JavaScript library to render both 2D and 3D models. It is developed to display translated models generated by the model derivative component. ExpressJS was selected to develop the web application due to its flexibility and scalability. ExpressJS is a prebuilt NodeJS framework that is designed to create server-side web applications [41], and it allows the web application to handle multiple requests concurrently. As such, pathogen risk information can be quickly communicated to facility users even at times of peak traffic of the website. ExpressJS allows the developer to design customized functionalities in the web application. The routing technique was adopted to handle the Hypertext Transfer Protocol

(HTTP) request. The routing technique manages the way the web application responds to user requests. This technique is derived from the HTTP method [42] and attached to the ExpressJS router instance. POST and GET methods were used to send and retrieve data from the webserver.

Three add-in functions were developed to help users visualize the interior layout of the building and color-coded rooms with their corresponding risk levels, as well as search specific room-related disease outbreak risk information. The first add-in function is “vertical explode”, which is used to view each level of the building. This function can help the user visualize the interior and room layout. The facility users can also use this function to visualize the outbreak risk of rooms on each floor and take appropriate practices. For facility managers, the “vertical explode” function enables them to obtain a holistic view of risk distribution at each level and take informed actions, such as limiting the number of occupants and implementing cleaning and disinfection protocols, to control the spread of the disease. This function is integrated with the web-based system, and clicking buttons were created to activate and deactivate it. The second function is “room filtering”, which is used to highlight rooms at different risk levels for a specific pathogen. The user needs to first select one of the three pathogens from the dropdown menu: SARS-CoV-2, Influenza, and norovirus. Thereafter, the user can set a risk threshold to highlight rooms with R_0 greater than a specific value. In addition, different highlighting colors are used to represent different infection risk levels. Low, mild, moderate, and severe risks are represented by color green, blue, celery, and red, respectively. The third function is “room query”, which enables the user to search for a specific room and retrieve infection risk for the three pathogens. The “room query” function is displayed as a search box on the web-based system. The users can easily find the potential risk of a specific room using this function. Finally, end users can access the web-based information communication system and obtain information about outbreak risk in each room of the building through various channels, including laptops, smartphones, and tablets.

3. Case Study

A hypothetical case study is used as an example to demonstrate the efficacy of the proposed framework and the newly developed web-based system. The building information model of a six-floor school building with 221,000 square feet is used. The building contains classrooms and faculty and graduate assistant offices.

3.1. Disease Outbreak Risk in Different Rooms

The room types considered in the case study include offices and classrooms. Five offices and five classrooms were selected. The venue-specific parameters of the rooms are extracted and listed in Table 3, and the computed R_0 values of the three diseases are listed in Table 4.

Table 3. Venue-specific parameters in representative rooms

Room Type	Room #	Accessible surface area (square feet)	Proportion of accessible surface	Occupancy (number of people)	Rate of fomite touching (times per hour)
Classroom	#1	45.5	0.018	36	45 (30, 60)
	#2	45.5	0.017	37	45 (30, 60)
	#3	176.3	0.138	19	45 (30, 60)
	#4	1328.9	0.194	91	45 (30, 60)
	#5	410.9	0.151	26	45 (30, 60)
Office	#1	36.6	0.052	2	12 (0, 30)

#2	106.8	0.115	13	12 (0, 30)
#3	52.1	0.062	10	12 (0, 30)
#4	1289.8	0.306	9	12 (0, 30)
#5	53.7	0.053	15	12 (0, 30)

Table 4. R_0 values of the three diseases of representative rooms

Room Type	Room #	R_0 values		
		Influenza	Norovirus	COVID-19
Classroom	#1	0.078	9.704^{2}	0.962
	#2	0.079	10.441^{2}	0.970
	#3	0.014	0.092	0.168
	#4	0.237	2.603^{2}	1.803^{1}
	#5	0.020	0.117	0.224
Office	#1	0.002	0.023	0.022
	#2	0.010	0.073	0.118
	#3	0.008	0.098	0.099
	#4	0.007	0.023	0.078
	#5	0.011	0.169	0.146

Note: The superscripts indicate the risk level of the diseases, where 1 represents a moderate risk level and 2 represents a severe risk level. Values without superscripts indicate the risk level is low.

From Table 4, the values of R_0 vary across different rooms and different diseases. R_0 values in offices are smaller than the values in classrooms, which stems from the small occupancy and the low rate of fomite touching in offices compared to those in classrooms. For influenza, the R_0 values in all the rooms are less than 1, indicating that influenza is unlikely to outbreak in the building through the fomite-mediated transmission. This could be partially explained by the relatively short infectious period, high inactivation rate in hands, low hand-to-fomite pathogen transmission efficiency, and relatively low infectiousness with the same amount of pathogens. For COVID-19, the R_0 values in all rooms are higher than those of influenza, and the risk in Classroom 4 reaches a moderate level, indicating that COVID-19 has the potential to outbreak in the classroom. COVID-19 has a relatively high outbreak risk in most cases because it has a high shedding rate, small surface inactivation rate, and high transfer efficiency from fomites to hands. For norovirus, the R_0 values are high in most classrooms, which might be because of its high infectivity, long infection period, and high hand-to-fomite transmission efficiency compared to the other two diseases. This finding also aligns with the trend obtained in [24]. The above results prove that the outbreak risk of an infectious disease is influenced by both venue-specific and pathogen-specific parameters, which highlights the significance of integrating BIM and the pathogen transmission model in assessing spatial-varying disease outbreak risk.

Sensitivity analysis was further conducted to evaluate the influence of the rate of fomite touching (ρ_T) and the shedding rate (α) of SARS-COV-2 on R_0 based on the estimated ranges of the two parameters (listed in Table 2). Fig. 6 illustrates the changes in R_0 with the increase of ρ_T for all three diseases in both classrooms and offices. From Fig. 6, the disease outbreak risk increases as the increase of ρ_T. The values of R_0 for norovirus and COVID-19 in Classroom 1, 2, and 4 may exceed 1 with the increase of ρ_T. On the other hand, the infection risk in offices and that for influenza in classrooms will remain low even occupants touch objects in the rooms more frequently. Therefore, it is particularly important to educate students in classrooms with relatively high occupancy to not touch the common areas frequently. Fig. 7 illustrates the changes in R_0 of COVID-19 with varying shedding rates. From the figure, α has a significant impact on the outbreak risk of COVID-19 in Classroom 1, 2, and 4. Therefore, for classrooms with relatively large occupancy, control strategies should be taken to reduce pathogen shedding from the occupants, such as using face masks, and covering the mouth when coughing.

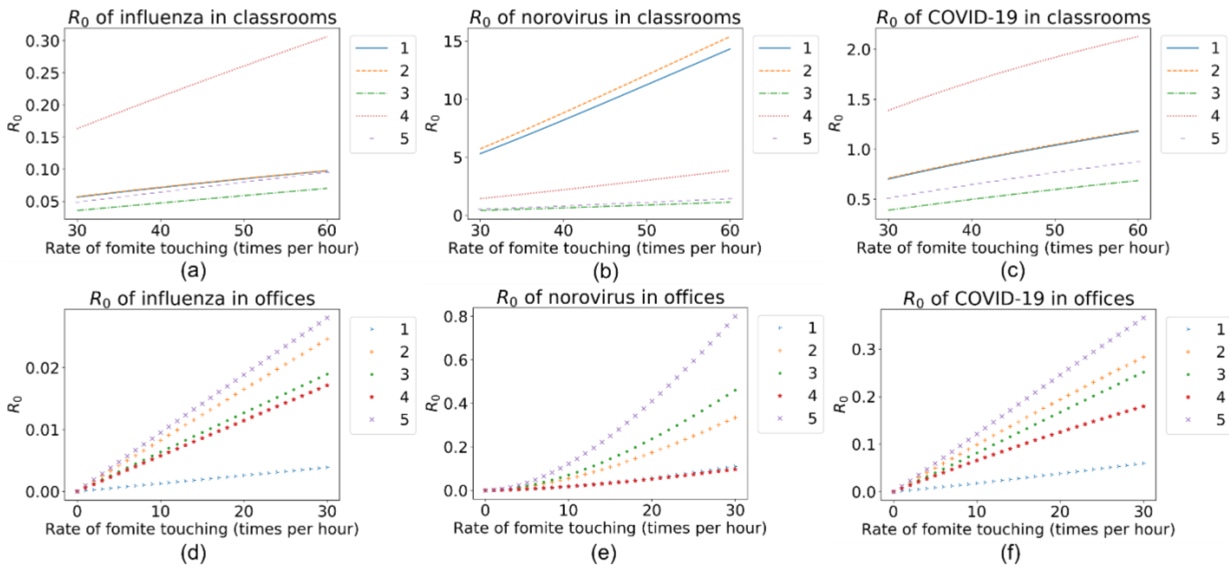


Fig. 6. R_0 values with various rates of fomite touching (ρ_T)

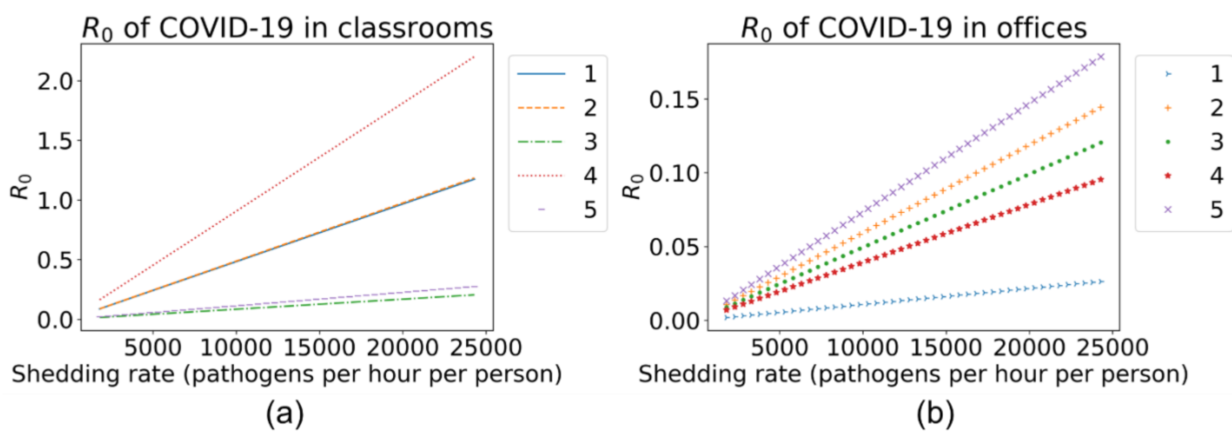


Fig. 7. R_0 of COIVD-19 with various shedding rate (α)

3.2. Influence of Cleaning Practice

Cleaning is an effective strategy to reduce fomite-mediated pathogen transmission in built environments [43]. This study examined the impact of surface cleaning at different times per day on reducing the disease outbreak risk. The timing of each cleaning practice is not included in the disease transmission model and the average R_0 is estimated on an hourly basis. Fig. 8 illustrates the changes in R_0 with respect to various times of surface cleaning each day.

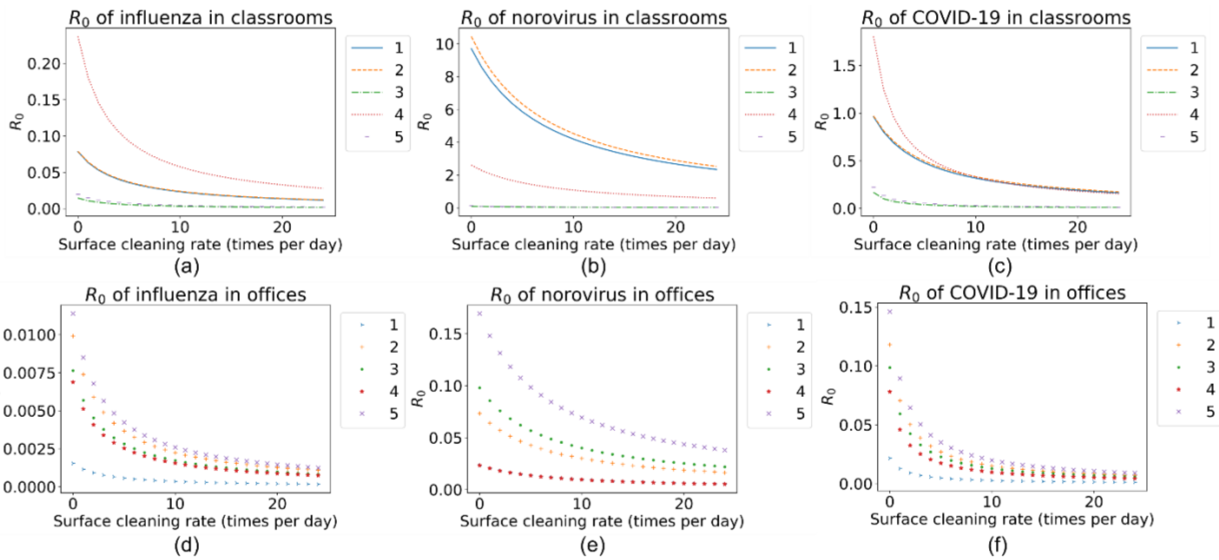


Fig. 8. R_0 values with various times of surface cleaning per day

From Fig. 8, surface cleaning can significantly reduce the outbreak risk of all three diseases in both classrooms and offices. Based on the analysis, different surface cleaning practices can be applied to different rooms to reduce the risks to an acceptable low level. Cleaning the surface five times per day will decrease R_0 by over 50%, compared to no surface cleaning. Considering the ongoing outbreak of COVID-19, classrooms with high occupancy (e.g., Classroom 4) should be given particular attention on surface cleaning. Cleaning surfaces at least two times per day is needed to achieve a low risk level. For norovirus, classrooms with relatively large occupancy (e.g., Classroom 1, 2, and 4) will require more frequent surface cleaning to reduce the outbreak risk to the low level. Other complementary strategies, such as increasing hand washing and limiting occupancy, should be adopted to maintain a low level of outbreak risks.

3.3. Infection risk visualization via web-based system

Fig. 9 presents the user interface of the developed web-based system. The developed web application provides an intuitive and responsive user interface to visualize outbreak risk information in the building. The facility manager and user can navigate to the interior model to visualize the interior layout of the building using the "*Interior Model*" button. The user can select and visualize risk-related information for different diseases: COVID-19, influenza, and norovirus. Fig. 10 illustrates the developed web visualization tool.

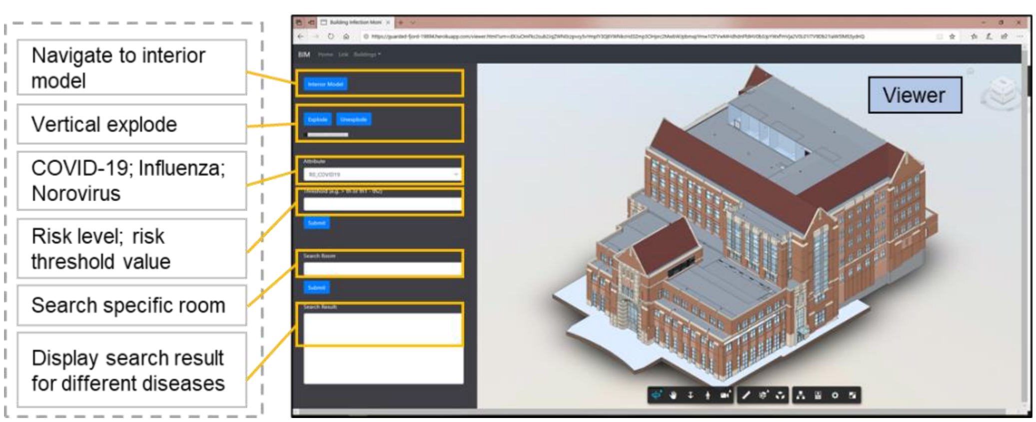
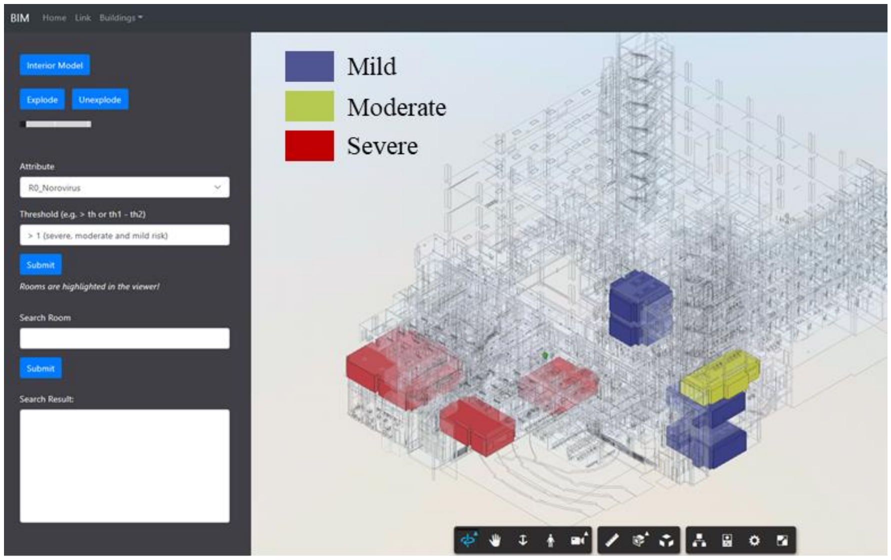
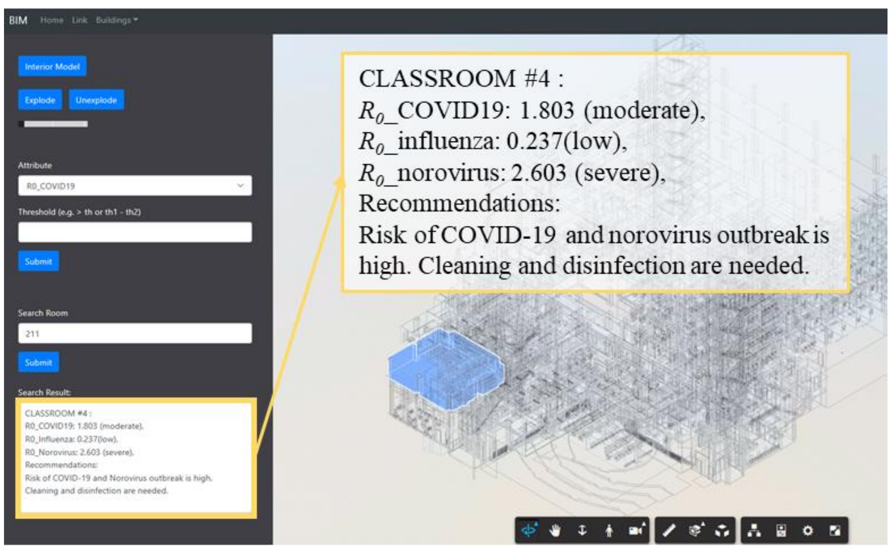


Fig. 9. The user interface of the developed web-based alert system



(a)



(b)

Fig. 10. Demonstration of pathogen risk visualization. (a) room filtering based on risk value threshold; (b) search specific room

As shown in Fig. 10, room filtering and room query functions can help the user easily locate rooms with high risk and query risk information for a specific room. Specifically, Fig. 10 (a) shows an exemplary output of the room filtering function that highlights the rooms with R_0 value greater than 1 for COVID-19. Fig. 10 (b) displays an example of the room query function in the web system. The pathogen risk information for influenza, norovirus, and COVID-19 is retrieved with corresponding recommendations. With the web-based information communication system, facility managers can take important measures to control the spread of diseases, such as designing appropriate cleaning and disinfection strategies, promoting hand hygiene, reducing maximum occupancy, and accommodating facility usage schedule based on risk distribution across rooms within the building. For instance, deep cleaning and disinfection are required for rooms with severe outbreak risk. In addition, facility managers can post signs at these high-risk areas to remind occupants to take essential practices such as social distancing and hand hygiene. The web-based system will also keep facility users, including teachers, students, and other staff, aware of up-to-date outbreak risk information within the building, and thus taking informed actions to avoid further spread of diseases. For example, facility users can avoid entering rooms with high outbreak risk.

4. Discussion

The results and insights derived from the analysis have important implications on adaptive built environment management to prevent infectious disease outbreak and respond to on-going pandemic. Due to varying building characteristics, occupancy levels, and pathogen parameters, the microbial burdens and outbreak risks differ significantly even in the same building, highlighting the need for spatially-adaptive management of the built environment. The proposed method automates the batch process for simulation and prediction of outbreak risks for different pathogens at the room level, and visualizes the risks for adaptive management. The results on outbreak risks at room level enables the paradigm for spatially-adaptive management of the built environment. With the new streams of risk information, customizable interventions can be designed. For instance, in consistent with the practice during the COVID-19 pandemic, reducing the accessible surfaces in rooms and restricting the occupancy in the room are some of the effective strategies to reduce the outbreak risks. The spatially-varying risk information can also guide the facility managers to pay close attention to high-risk areas by adopting more frequent disinfection practices.

A BIM-based information system is developed to extract the necessary information for modeling infection within buildings, and to visualize the derived information in an easy-to-understand and convenient way through web pages. As such, the information-driven interventions could alleviate the pathogenic burdens in the buildings to prevent the spread of infectious diseases. Providing information to end-users is critically important for them to change behaviors. Human behavior plays an important role in the transmission of pathogens such as the SARS-Cov-2. Changing behaviors is critical to preventing transmission. Providing timely and contextual information can be a promising option to motive the change of human behaviors. With the room-level outbreak risk information, the users could be motivated or persuaded by the visualized risks to practice appropriate behaviors such as wearing a mask, social distancing, and hand-washing. The facility managers can use the information to conduct knowledge-based management, such as limiting the occupancy in the room, managing crowd traffic, and rearranging room layout.

This study has some limitations that deserve future research. First, the model does not consider factors such as sunlight exposure, humidity, and airflow that may impact the persistence and transmission of pathogens in built environments. This is mainly because the quantitative impacts of these factors on pathogen persistence and transmission are largely ambiguous, if not unknown. If these impacts can be quantified and the environmental parameters can be monitored and modeled in BIM, our proposed framework can be extended to incorporate these factors. Second, the computation of R_0 only considers the fomite-mediated transmission, and does not consider the airborne and close contact transmission. Microbial pathogens may have different transmission routes, including airborne, close-contact, and fomite-based transmission. This study focused on fomite-based transmission to illustrate the modeling approach for assessing the outbreak risks, and demonstrate the efficacy of the developed information system to guide infection control practices and building operations. To fully assess the exposure risks and outbreak potentials, all important routes need to be considered. In addition, the outbreak potentials of a variety of pathogens can be considered together to develop an aggregate index, which could be more intuitive for occupants and facility managers who are not public health experts. Third, the system mainly relies on static models and does not make full use of dynamic and real-time data regarding built environments and occupant behaviors such as presence and interactions with objects. In future studies, the internet of things sensors can be installed in the buildings and algorithms can be developed to retrieve dynamic data for integration with the models for accurate and robust risk estimation. Fourth, the web-based system can be further improved by connecting it with smart devices such as robots for automated cleaning and disinfection and smartphones for precision notifications.

5. Conclusions

This study creates and tests a computational framework and tools to explore the connections among built environment, occupant behavior, and pathogen transmission. Using BIM-based simulations, building-occupant characteristics, such as occupancy and accessible surface, are extracted as venue-specific parameters. The fomite-mediated transmission model is used to predict the contamination risks in the built environment by calculating a room-by-room basic reproductive number R_0, based on which the level of infection risk at each room is characterized into low, mild, moderate, and severe. A web-based system is then created to communicate the infection risk and outbreak potential information within buildings to occupants and facility managers. The case study demonstrated the efficacy of the proposed methods and developed systems. Practically, the method and system can be used in a variety of built environments, especially, schools, hospitals, and airports, where transmission of infectious pathogens is of particular concern. The outbreak risks predicted at room resolutions can inform the facility managers to determine room disinfection and cleaning frequency, schedule, and standard. In addition, appropriate operational interventions including access control, occupancy limits, social distancing, and room arrangement (e.g. reducing the number of tables and chairs) can be designed based on the derived information. The occupants can access the useful information via webpage to plan their visit and staying time in the facilities, and practice appropriate personal hygiene and cleaning practice based on the information. – Shuai Li

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