INTEGRATED MODELING AND MONITORING FOR A HEALTHY AND SUSTAINABLE BUILDING ENVIRONMENT

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ABSTRACT

The transmission of airborne diseases indoors is a significant challenge to public health. Buildings are hotspots for viral transmission, which can result in adverse effects on human health and quality of life, especially considering that individuals spend approximately 87% of their time indoors. The emergence of the COVID-19 pandemic has highlighted the importance of considering health aspects during the development of sustainable built environments. Consequently, maintaining a healthy, sustainable, and comfortable built environment represents a major challenge for facilities management teams. However, research on the infection risks associated with emerging pandemics is still in its infancy, and the effectiveness of intervention strategies remains uncertain. Furthermore, the complex interplay between health, energy consumption, and human comfort remains poorly understood, impeding the development of comprehensive control strategies that encompass all three critical dimensions of building sustainability. In addition, existing technologies have limitations to conduct real-time monitoring, while current communication methods between occupants and facilities management teams suffer from a lack of effectiveness, user-friendliness, and informativeness. These deficiencies hinder their ability to address the pressing needs of occupants during pandemics.

To address these challenges, this dissertation proposes a convergent framework that integrates modeling, simulation, and monitoring methodologies for the development and maintenance of a sustainable built environment. Airborne transmission risks were first modeled and estimated under different epidemic scenarios, allowing for the evaluation of

various intervention strategies. Facility data was then used to develop methods for modeling and simulating the dimensions of energy consumption and thermal comfort, allowing for the identification of tradeoff relationships among health, energy, and comfort, and quantitatively analyzing the impact of indoor environments through HVAC control strategies on the three major dimensions. Finally, an integrated platform was developed to enable the real-time assessment of health, energy, and comfort, including monitoring, visualization, and conversational communication functionalities. The developed framework thus encompasses modeling, simulation, monitoring, and communication capabilities and can be widely adopted by facility management teams, providing insights and guidance to governments and policymakers based on their specific needs. The applicability of the framework extends beyond specific pandemics and can be used to address a broader range of infectious diseases.

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CHAPTER ONE

INTRODUCTION

1.1 Background

Throughout the entirety of human history, pandemics have represented a prolonged and persistent public health threat. Over the last two decades, multiple disease outbreaks have raised global concerns about the threat of pandemics in human society. In particular, the globally extensive COVID-19 pandemic posed a significant threat to human life, having rapidly spread across more than 220 countries and territories [1]. This unprecedented crisis has shed light on the urgent need to prioritize the improvement of human health as a crucial objective of sustainable development [2]. Given that people spend a significant amount of their time indoors, buildings are major hotspots for pathogen exposure and transmission. Consequently, epidemics and everyday infections can wreak havoc on urban populations, particularly in high-risk environments such as mass-gathering infrastructure facilities, where the close and frequent contact between individuals facilitates the transmission of infectious diseases. Indeed, the transmission of airborne diseases within indoor spaces poses a significant challenge to public health and has raised concerns regarding the creation and maintenance of a healthy and sustainable indoor environment. The COVID-19 pandemic has consequently introduced health considerations as a new dimension in building operations—especially in the context of sustainable development—which must be addressed alongside energy efficiency and human thermal comfort: the three primary dimensions of building sustainability.

Given the emergence of new pandemics as well as the continuous evolution of their variants, there is an urgent need for a holistic approach that allows for the quantitative analysis of the impact of pandemics on human health. It is thus essential to develop a methodology that allows for the modeling of infection risks across diverse population groups. Furthermore, efficient intervention strategies must be formulated; these strategies must be flexible enough to accommodate different virus transmission patterns, building characteristics, occupant profiles, as well as the specific concerns of certain demographic groups. In addition, since health, energy consumption, and occupant comfort are closely interconnected, understanding the intricate relationships between these dimensions is essential for maintaining building sustainability. This understanding will facilitate the adoption of different environmental control strategies based on the priorities of decision-makers in terms of their health, energy efficiency, and comfort. Consequently, to gain a comprehensive understanding of real-world conditions, it is imperative to integrate real-time sensing data and building information that accurately reflects the interactions between the immediate indoor environment and human behavior. By quantifying real-time changes in health, energy consumption, and comfort, teams can effectively monitor building sustainability and provide timely recommendations for the adjustment of operational strategies and occupant behaviors. Facilitating effective interactive communication with facility management teams and occupants is thus crucial for the management of a healthy and sustainable building environment.

1.2 Problem statement

Airborne infectious pathogens, such as SARS-CoV-2 and influenza, have the potential to rapidly spread within the built environment, even among individuals practicing social distancing. Consequently, it is crucial to identify and understand the risks associated with disease transmission to ensure the maintenance of a healthy building environment during pandemics.

However, there is currently a lack of knowledge on the influence of different various building characteristics on infection risks, especially in buildings located in different regions with diverse climates; consequently, the quantitative influence of control strategies on these risks remains uncertain. This limited understanding further hampers the accurate estimation of changes in building energy consumption and human thermal comfort that may result from the different control strategies that are implemented for risk mitigation during pandemics. Furthermore, the intricate relationship between the three essential dimensions for building sustainability—i.e., health, building energy consumption, and human thermal comfort—are poorly understood, which poses challenges in implementing appropriate tradeoffs between these dimensions while still maintaining building sustainability. Finally, the absence of an integrated methodology that allows for the real-time monitoring of health, energy, and comfort, as well as the limited ability to communicate between facility management teams and occupants, impedes the implementation of sustainable building management and limits the potential for effective interactions based on monitored information.

1.2.1 Modeling of infection risks

The problem to be addressed involves understanding infection risks within critical infrastructure facilities, specifically schools, due to their diverse characteristics and functionalities. These infection risks are influenced by various building-specific characteristics and occupant behaviors, which can exhibit spatial and temporal variations as a result of pathogen-specific characteristics as well as the evolving epidemic situation. Despite this, the impact of school characteristics on infection risks, particularly in K-12 schools with different levels (e.g., elementary vs. high schools) and types (e.g., public vs. private schools), remains unexplored. Furthermore, the quantitative influence of intervention strategies in different pandemic scenarios in schools of varying levels and types is poorly understood. There is, therefore, a need to address these problems to develop models that describe the transmission of viruses to evaluate effective intervention strategies while accounting for the diverse characteristics of buildings and students in the context of the current state of the epidemic.

1.2.2 Relationships among infection risks, energy consumption, and thermal comfort

The management and control of building environments have been significantly impacted by the COVID-19 pandemic. Operation strategies aimed at controlling infection risks have an inevitable influence on building energy consumption and human thermal sensation. However, there is a lack of understanding regarding the complex interactions between the three critical aspects of building sustainability: 1) health measured as exposure to pathogens and infection risk, 2) building energy consumption as a result of different

heating, ventilation, and air conditioning (HVAC) control strategies, and 3) thermal comfort in different climate zones. This problem hinders the development of appropriate building operation strategies that collectively consider all three aspects during pandemics. In addition, the impact of the characteristics of the built environment on these three aspects remains unclear. These issues prevent the accurate simulation of these three major aspects in indoor environments, consequently preventing researchers from gaining a comprehensive understanding of the relationships among health, energy, and comfort. These issues must be tackled by establishing clear links that connect these three aspects, enabling a deeper understanding of their interactions and relationships.

1.2.3 Monitoring and communication in building management

Building-specific characteristics play a crucial role in shaping aspects of health, energy, and comfort. Furthermore, the fluctuating nature of building occupancy, as well as dynamic changes in building environments, have a significant impact on these three dimensions. Therefore, real-time building monitoring is extremely valuable because it allows for the timely and accurate assessment of changes in health, energy, and comfort within a facility of interest. Furthermore, this would allow building operation strategies to adapt in response to these fluctuations. However, there is no standard methodology for integrating the real-time data collected by sensors into simulations of risk, energy, and comfort; the lack of such a system hinders the development of a comprehensive monitoring approach. In addition, there is a dearth of comprehensive and dynamically updated tools for the communication of essential information to facility management teams and/or the

provision of user-friendly recommendations to workers and occupants. These problems impede the establishment of technology that can achieve real-time monitoring while also allowing for efficient, effective interactions during epidemics.

1.3 Knowledge gaps

1.3.1 Lack of a standard modeling approach for nationwide quantitative analysis

1) Lack of awareness of facility- and pathogen-specific characteristics

Existing studies have not adequately discussed the development of a standardized modeling approach required for a nationwide assessment of infection risks, especially considering the unique characteristics of facilities such as schools with different types and levels across the United States. Variations in school characteristics and student demographics across different school types and levels can lead to significant differences in infection risks and affects the selection of appropriate facility operation strategies. Higher-level schools tend to have longer operating hours and higher occupancy density, while students from different age groups have different breathing rates. Furthermore, there is a lack of understanding regarding the infection risks in schools of different levels as well as how various intervention strategies quantitatively influence infection risks in different epidemic scenarios, especially in the context of the relevant school and disease characteristics. Neglecting these knowledge gaps can lead to inaccuracies during the estimation of infection risks.

2) Lack of consideration of epidemic scenarios

The rapid evolution of virus variants has had a strong influence on their infectivity, which in turn impacts the accuracy of current infection estimations as well as the ability to predict disease transmission patterns. However, existing studies have failed to consider variations in epidemiological scenarios and how they might affect the insights and guidance that should be provided to decision-makers in facilities or governments considering the risk-mitigation strategies for schools with different levels. It is, therefore, crucial to address these knowledge gaps in order to develop comprehensive and flexible approaches for assessing and mitigating infection risks in public facilities such as schools.

1.3.2 Lack of a modeling approach that analyzes the tradeoffs in relationships between infection risk, energy, and thermal comfort

Existing studies have focused on developing separate models that analyze health, energy consumption, and thermal comfort within the built environment; however, the relationships governing the tradeoffs between these three aspects remain elusive. Two significant knowledge gaps exist in this area:

1) Lack of a systematic framework for the investigation of influential parameters in models of health, energy, and thermal comfort.

Existing studies have been unable to establish a comprehensive link between models of health, energy, and thermal comfort. This is primarily due to the neglect of mutually related parameters, which hinders the development of a systematic framework. Without such a framework, it is challenging to analyze and understand the relationships between these three important dimensions. Consequently, addressing this knowledge gap

is crucial for advancing our understanding of the complex interactions and tradeoffs between health, energy consumption, and thermal comfort in the built environment.

2) The absence of simultaneous and reliable quantitative analysis of the three major aspects of building sustainability during the pandemic.

This knowledge gap exists due to three primary reasons. Firstly, the impact of HVAC-controlled environment factors on these models is relatively unclear. The COVID-19 pandemic has significantly changed the requirements for indoor environments, especially concerning public health. However, the lack of real data on control factors and related aspects is a major challenge in the analysis of tradeoff relationships. Furthermore, current studies tend to use constants to represent environmental factors during infection estimation [3–5]. However, these environmental factors tend to be dynamic, especially in the context of HVAC settings.

Secondly, the impact of occupancy settings on infection risk is generally neglected. When computing infection risks, studies tend to assume a closed space without changes in occupancy during the estimation period [6–8]. This simplification in occupancy inevitably leads to inaccuracies in the evaluation of energy and thermal comfort.

Finally, the climate characteristics are generally ignored during tradeoff analysis. The lack of climate-related data, as well as the absence of a systematic framework that links the models of health, energy, and thermal comfort, impedes the detailed and quantitative analysis of tradeoff relationships.

1.3.3 Lack of an integrated real-time building monitoring and communication system

Existing studies have not yet developed an integrated platform that consolidates the essential functionalities of monitoring, simulation, alerts, and persuasion into smart building management. Three significant knowledge gaps exist in this area:

1) The absence of integrated technology that consolidates all of the necessary functionalities into a single platform.

Such an integrated platform should be capable of completing multiple tasks in real-time, including data acquisition and processing, simulations using different models, providing alerts and enabling communication, and effectively persuading occupants by obtaining an understanding of their preferences. Each of these capabilities is complex and requires advanced technological infrastructure to fully realize its functionality. In addition, the platform should allow for the efficient exchange of data between its different functionalities while also providing interoperability, allowing a broad range of users to effortlessly access and utilize the platform, making it accessible to various stakeholders in building management.

2) Inability to simultaneously monitor and simulate health, energy, and thermal comfort in real-time, while still considering both aspect-specific and mutually related parameters.

There are several distinct challenges associated with real-time health, primarily stemming from the difficulty of retrieving timely epidemiologically related parameters for specific building locations. The effective implementation of measures aimed at protecting public health and safety within buildings requires access to up-to-date and location-specific data on epidemiological factors. The real-time assessment of energy consumption and

thermal comfort also faces similar difficulties, including the development of reliable methods for the real-time simulation of occupancy fluctuations, which would enable the tradeoff analysis between health, energy, and thermal comfort.

3) Absence of an AI-based application for the built environment that can interact with both facility management teams and occupants as well as promote healthy behaviors and energy-saving practices

This application should include crucial functionalities such as alerting facility management teams about abnormal situations (e.g., poor indoor environment, occupant discomfort, and health risks). These alerts provide essential information to facility management that allows for timely intervention and remediation. Furthermore, the application should feature a persuasive conversational system that attempts to convince occupants to adopt environmentally friendly behaviors, actively participate in improving their living conditions, and promote energy savings. For instance, the application could suggest adjusting the occupant's risk levels by moving to a healthier room instead of applying extensive mitigation measures to the current room, or changing clothes rather than adjusting temperature setpoints (which would result in increased energy use). However, existing technologies often lack these capabilities and fail to recognize the significance of occupant engagement in building management.

1.4 Research questions and objectives

This dissertation addresses three primary research questions and establishes specific objectives in response to each of these questions.

Figure 1-1 provides an overview of how this research was designed to achieve the stated objectives.

1) How to develop computational mathematical models capable of quantifying infection risks, while also considering the characteristics of specific infrastructure facilities and the current state of the epidemic?

The main purpose of developing these models is to assist policymakers with understanding and addressing infection risks, as well as help design effective facility operation strategies for infrastructure facilities such as K-12 schools. To achieve this, a comprehensive nationwide assessment will be conducted, encompassing different school levels, to gain a thorough understanding of infection risks across the country. The models will be designed to accommodate various epidemiological scenarios that reflect the diverse contexts of different pandemics, and validated to ensure their adaptability and practicality. Evaluating the effectiveness of different operation strategies involves the consideration of factors such as building and occupant characteristics, as well as the current state of the pandemic.

2) How to develop a comprehensive framework that allows for the tradeoff analysis of energy, health, and thermal comfort?

This framework aims to help with the development of models that can describe the relationships and interactions between the three major dimensions of building sustainability while also incorporating mutually related parameters, with a specific focus on HVAC-controlled environmental factors.

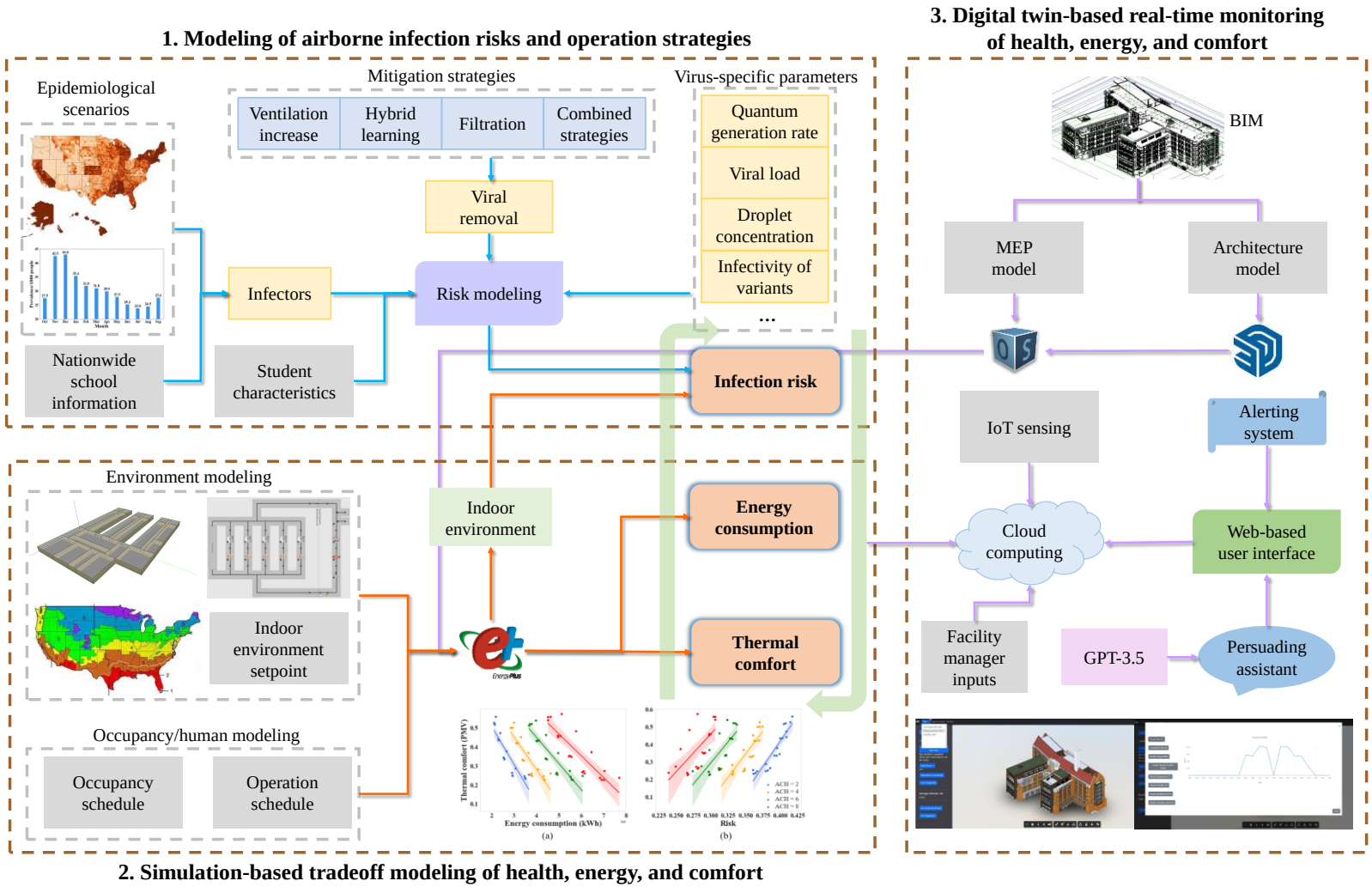


Figure 1-1 Research overview.

The framework will utilize simulations to predict the interactions between health, energy consumption, and thermal comfort, allowing for a comprehensive analysis based on dynamic values of the environmental factors. The framework will also investigate the impacts of various environmental factors on health, energy consumption, and thermal comfort in buildings situated in different climate zones. Furthermore, it will demonstrate the tradeoff relationships between these aspects, providing insights for facility management teams for decision-making purposes.

3) How to create an integrated platform that allows for real-time monitoring as well as effective communication between occupants and building management during pandemics?

This platform aims to improve overall building management by seamlessly integrating multiple functionalities, which include the gathering of building characteristics, the monitoring of real-time information from the environment and its occupants, and the developing of a comprehensive web-based app that possesses a wide range of functionalities ranging from data collection to information distribution and communication. To accomplish this, digital twin-based technology will be employed to retrieve building information and occupant data, as well as monitor changes in the environment. Cloud computing technology will allow for real-time data retrieval, utilization, and integration during the simulation process. The web app will be designed to incorporate various features, such as information visualization, an alert system, and an AI-based recommendation system, to provide users with an efficient, user-friendly interface that enables effective building management for maintaining a healthy and sustainable environment.

1.5 Contributions

This dissertation presents the results of a multidisciplinary study that focuses on three fundamental dimensions of building sustainability: health, energy consumption, and human thermal comfort. This research aims to develop a comprehensive framework that systematically explores these three dimensions through the implementation of modeling, simulation, and monitoring methods. In particular, this works aims to alleviate transmission risks during pandemics by identifying effective mitigation strategies through the development of infection risk models. Furthermore, the dissertation uses an integrated simulation of building energy consumption, human thermal sensation, and infection risks to investigate the interactions and relationships between these three dimensions through the utilization of building data. This contributes to our understanding of HVAC operation strategies in the context of pandemics. Lastly, the dissertation proposes the development of an interactive tool that provides real-time monitoring of the three major aspects and provides recommendations for the implementation of appropriate and timely building operation strategies. The detailed contributions of this dissertation can be categorized into three main aspects.

1) Establishing scenario-based analyses for risk assessment in K-12 schools

This study developed infection risk models and conducted analyses to examine the influence of different intervention strategies on the risk of airborne infection in 111,485 public and private schools in the U.S. The research considers infection risks at different schooling levels, such as in elementary and high schools, and quantitatively assessed the impact of different intervention strategies on infection risk while taking into account

relevant school factors such as occupant density, school hours, and pulmonary ventilation rate. The results provide insights for schools and governments regarding the use of effective mitigation measures to control infection risk.

Two distinct epidemiological scenarios were utilized to forecast the short-term and long-term risks associated with different intervention strategies. Monte Carlo simulation (MCS) and sensitivity analysis were used to assess the influence of diverse school characteristics as well as the prevailing state of the epidemic. The scenario-based analyses employed in this research can be readily expanded to account for the emergence of new SARS-CoV-2 variants or the study of other infectious diseases.

2) Developing a simulation methodology to perform a comprehensive tradeoff analysis of energy, health, and thermal comfort during school building operations

This research proposed a new convergent framework that links computational models of health, energy consumption, and thermal comfort in built environments by identifying and modeling influential and mutually related parameters. Understanding HVAC-controlled indoor environments and their related health, energy, and comfort implications are the primary outcomes of the proposed framework and are expected to present new paradigms in sustainable building environment assessment.

This research quantitatively analyzed the influence of indoor environment modifications on energy consumption, infection risks, and thermal sensation in schools during the COVID-19 pandemic. The data obtained were used to conduct simulations that revealed new insights into the tradeoffs between health, energy, and thermal comfort under various control strategies and climate characteristics.

3) Developing an integrated building management system that includes monitoring and communications features for use during pandemics

This research proposed an integrated platform for real-time building monitoring and communication aimed at improving overall building management. An Internet of Things (IoT) sensor network was deployed to enable real-time monitoring, which allowed for the collection of data such as room occupancy and air quality. Off-the-shelf occupant counters were used to determine room occupancy, while air quality sensors were used to measure the levels of indoor pollutants like carbon dioxide (CO_2), volatile organic compounds (VOCs), and fine particulate matter ($PM_{2.5}$). Cloud computing technology was used to ensure seamless real-time data acquisition, storage, processing, simulation of the health, energy, and comfort models, and tradeoff analysis. The cloud-hosted platform also allowed for all functionalities to be accessed in real time through an integrated web-based application.

The platform possesses two key features that allow for effective communication. Firstly, it provides visualizations of the monitored data and simulated results and is equipped with an alert system that notifies facility management teams of any abnormalities detected in the indoor environment. This capability primarily assists facility management teams with decision-making processes. Secondly, the platform provides recommendations and utilizes an AI-based communication system empowered by GPT targeted at persuading building occupants, encouraging them to adopt more environmentally friendly measures. By raising awareness of the positive impact of such behaviors on indoor environment quality and energy savings, occupants may be motivated to make conscious,

environmentally friendly choices. In addition, the interaction between occupants and facility management teams allows for the adoption of occupant-preferred operation strategies, improving occupant satisfaction.

The dissertation led to two publications [9,10].

CHAPTER TWO
MODELING OF AIRBORNE INFECTION RISKS AND IMPACTS OF DIFFERENT INTERVENTION STRATEGIES

2.1 Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and its variants are identified as the viruses that causes the coronavirus disease 2019 (COVID-19). The outbreak of COVID-19 spreads over 220 countries and territories [1], causing global pandemic and threatening human life, which reveals the urge of improving human health as an important goal of sustainability development [11]. Schools are considered high-risk environments for the transmission of infectious diseases due to the close and frequent contact and communication that occur among students and teachers. The negative impacts of crowded and poorly-ventilated indoor environments further raise concerns about the student health in schools.

The COVID-19 pandemic has resulted in the enactment of social distancing policies, with school closures existing among the first actions taken by governments worldwide. In the United States, prolonged school closures have affected about 55 million students enrolled in more than 130,000 K–12 schools and their parents in the U.S. [12], impacting their mental and physical health as well as education due to the variable efficiency of remote learning and by placing additional childcare burdens on their parents. At this stage in the pandemic, which is marked by increasing vaccine rollout, many schools in the U.S. are considering reopening or have already reopened for in-person instruction. However, concerns persist as the chance of contracting and transmitting COVID-19 increases in crowded indoor environments. Although several studies have indicated that

children are less susceptible to experiencing severe COVID-19 [13,14], those with mild or asymptomatic cases without confirmed diagnoses and treatment may facilitate rapid transmission of the disease within schools and to households and the surrounding communities. So far, it is not recommended for K–12 schools to screen all students for symptoms of COVID-19 on a routine basis [15], which poses a potential risk for the spread and outbreak of the disease within schools. In addition, no vaccines have yet been approved for children and, even in vaccinated people, the risk of SARS-CoV-2 infection is not entirely eliminated [16]. Due to the important role of schools in children's growth and the high prevalence of COVID-19 across the U.S., nonpharmacological interventions are required to help limit the spread of COVID-19 and other respiratory illnesses and maintain a healthy environment in schools.

Despite the transmission of the original variant of SARS-CoV-2, the Omicron variant is an emerging variant of SARS-CoV-2 and has become the dominant variant that accounts for the spread of COVID-19 against all other variants. The variant was first detected in South Africa in 2021 [17], and resulted in an unprecedented outbreak in SARS-CoV-2 cases around the world. Compared with the Delta variant, the other rapidly spread coronavirus variant, Omicron multiplied around 70 times faster in the bronchi [18], and is found to be 2 to 3 times more contagious [19]. Although generally, Omicron infection causes less severe cases than other variants, the hyper-transmissibility in the crowd could overwhelm the healthcare system since some of the cases may develop severe symptoms and need hospitalization. The immunity through vaccination remains unclear since some variants reduce the efficacy of vaccines and lead to reinfection. Thus, despite getting

vaccinated, other mitigation measures are required to curb the transmission of SARS-CoV-2 variants in K-12 schools.

Several studies have demonstrated that SARS-CoV-2 and its variants, like other respiratory viruses (e.g., influenza, tuberculosis, and measles [20], can be transmitted by way of an airborne route [21,22], wherein the infectious aerosols are dispensed and suspended over long distances in the air, and inhaled by the susceptible individuals [23]. The spread of airborne diseases indicates the significance of dedensification and introducing fresh air into the crowded and poorly-ventilated buildings. For schools, dedensification can effectively help students to maintain adequate physical distancing and can be achieved by the use of hybrid learning. Meanwhile, improved ventilation and air filtration can introduce fresh air and dilute the concentration of airborne infectious particles indoors. However, the infection risks in schools of different levels (e.g., elementary vs. high schools) and how different intervention strategies quantitatively influence infection risk in different pandemic scenarios given various relevant school and disease factors (e.g., occupant density, school hours, pulmonary ventilation rate) remain elusive.

To close this gap, in this chapter, scenario-based analyses were conducted to examine the relationship between the risk for airborne infection and different intervention strategies in 111,485 public and private schools in the U.S., using the COVID-19 pandemic as the epidemiological context. Specifically, two epidemiological scenarios were employed to predict both the long- and short-term risks under different intervention strategies. Monte Carlo simulation (MCS) and sensitivity analysis were also performed to exploit the impacts of various school characteristics and epidemic situation. The analysis of airborne

transmission is also applicable to the Omicron variants, given the heightened infectivity illustrated in airborne transmission modeling. The results provide insights for schools and governments regarding the control of infection risk using effective mitigation measures. Although this methodology focuses on controlling the infection risks of SARS-CoV-2 and its variants in U.S. schools, the framework can be extended to other infectious diseases within other indoor environments in other countries, to maintain a healthy and sustainable environment.

2.2 Literature review

Mathematical models have been widely used to estimate the airborne transmission of diseases in indoor environments. Epidemic modeling frameworks such as susceptible-infectious-recovered (SIR) [24] and susceptible-infector-susceptible (SIS) [25] models are used to analyze the transmission of disease in a population and may fail to describe the airborne diseases alone [26]. The epidemic models should be used together with other mathematical models to estimate airborne risks. One mathematical model that can describe airborne transmission is the dose-response model. The model estimates the airborne transmission risks given the dose of infectious aerosols deposited in the upper and lower respiratory tracts of susceptible people. The information on the number of deposited pathogens to the sites in the respiratory tracts is acquired using models such as Markov chains, multi-zone balance models, and computational fluid dynamics (CFD) [27–29]. The complexity of the models restricts the application to the sophisticated simulation of the environment and well-studied viruses such as influenza [30].

The Wells-Riley (W-R) model is the most extensively used mathematical model [31]. The model was developed by Wells [32] and Riley et al. [33], and is utilized to evaluate the indoor airborne transmission of infectious agents. The W-R model is relatively simple and can be applied to diseases with less information regarding the ambient environment and the characteristics of the viruses such as SARS-CoV-2 and its variants. The model illustrated the hypothetical concentration of virus-laden aerosols using material balances.

Rudnick and Milton [34] further derived the model to estimate the received dose and the probability of infection transmission. The received dose is estimated as the integral of aerosol concentration over time multiplied by the individual exposure rate. The probability of infection is subject to an exponential relationship to the received dose multiplied by a constant that reflects the infectivity of the dose. Wells used a hypothetical infectious dose unit to measure the amount of the infectious particles, which was defined as “infectious quanta”, and is commonly back-calculated from the observation of epidemiological studies. From Wells, the infection probability of exposure to one quantum is 63%. For the W-R model, there is a common assumption that airborne aerosols are well-mixed in the indoor environment.

The W-R model has been considered a valid method to estimate the airborne transmission of various viruses [35]. Table 2-1 summarizes the comparison of various mathematical models concerning their suitability for modeling indoor airborne transmission.

Table 2-1 Comparison of Mathematical models for the estimation of airborne disease transmission in indoor environments.

Models	Description	Advantages	Disadvantages	Reference
SIR	Characterizes the fraction of population (susceptible, infectious, recovered) getting infected that varies over time	Used to analyze the transmission in a population	Simplified assumptions for the population; Require combining other models to describe airborne transmission	[24,26]
SEIR	Introduces a new compartment 'E' for exposed people compared with SIR model	Included more state and parameters to provide reliable prediction for the transmission in a population.	May fail to describe airborne disease alone; more complex and requires assumptions compared with SIR model	[36,37]
Dose response model	Estimates airborne transmission risks given the dose of infectious aerosols deposited in the respiratory tracts of susceptible people	More reliable with the use of other models to acquire the deposited pathogens in respiratory tracts	High complexity model; Can only be applied to sophisticated simulation of environment and well-studied viruses	[27–29,38]
Wells-Riley model	Illustrates the hypothetical concentration of virus-laden aerosols and estimates the probability of infection transmission	Comprehensive and well-structured, widely adopted to various viruses; Relatively simple to use	May oversimplify and lead to limited accuracy	[32–34,39]

2.3 Methodology

2.3.1 Data collection and processing

A total of 111,485 schools in the U.S., including 90,160 public schools and 21,325 private schools, were analyzed in this research. Basic information about schools was retrieved from the National Center for Education Statistics [40], including school type, school level, school location, and total numbers of students and teachers.

Schools were divided into public schools and private schools and, based on the lowest and highest grades offered, stratified as follows: pre-kindergarten, elementary, middle, high, and secondary schools for public schools and elementary, secondary, and combined schools for private schools, respectively. The school population was determined as the sum of students and full-time–equivalent teachers.

To assess the airborne infection risk in schools, the occupant density of school buildings was estimated from 1,433 representative schools across different levels. The representative schools with clear building characteristics shown in Google Maps were selected from the aforementioned 111,485 schools to retrieve the gross floor area. To reduce human errors in acquiring the gross floor area of the representative schools, a standard process was designed and followed: 1) the schools were observed using Google Maps street view to ensure that the building boundaries, the number of buildings, and the number of floors of each building can be clearly recognized; 2) For the buildings that were clearly recognized, the building area was manually collected using the area calculator tool in the Google Maps API by drawing an enclosed line along the building boundary; 3) A total of 1,433 schools were finally selected to calculate the gross floor area. The gross floor

area of each school building was computed as the product of the building area and number of floors; The gross floor area of the school was the sum of space of all school buildings. The occupant density of a school was computed as the ratio of school gross floor area to the school population. The mean and standard deviation values of occupant density of each school level were then estimated based on the corresponding representative schools. The relevant descriptive statistics are provided in Table 2-2.

2.3.2 Modeling of epidemiological scenarios

In this research, the following two epidemiological scenarios were considered: a one-year pandemic scenario based on long-term projections of COVID-19 prevalence and the current epidemiological scenario across the U.S. based on recorded COVID-19 infection cases to date. The one-year pandemic scenario indicated the temporal-varying prevalence, considering the seasonal variation and immunity duration of SARS-COV-2, and was used to provide insights into long-term strategies in school operations by estimating the general trend of infection risk in schools. Separately, the current epidemiological scenario demonstrated the county-level prevalence based on the records of confirmed cases and was used to provide guidance for timely adjustment of school operations based on local conditions.

2.3.2.1 One-year pandemic scenario

The long-term projection model developed in the study by Kissler et al. [41] was adopted to estimate the nationwide prevalence of SARS-CoV-2 during the post-pandemic period.

Table 2-2 School information descriptive statistics.

School	Total Schools	Representative schools	Students		FTE teachers		Occupant density (m^2/student)	
			Mean	SD	Mean	SD	Mean	SD
All schools	111,485	1,433	427	432	30	25	14.93	5.45
Public	90,160	1,106	538	440	33	25	14.99	5.07
Private	21,325	327	192	250	16	21	14.72	6.6
PK	1,131	56	175	171	9	10	16.04	5.88
Elementary (K–5)	64,998	944	396	246	25	15	14.19	5
Middle (grades 6–8)	16,087	127	595	350	37	21	16.52	5.54
High (grades 9–12)	20,785	148	717	743	43	41	16.02	5.6
Secondary (grades 6–12)	2,475	72	306	351	26	26	17.39	6.19
Combined (PK–12)	6,009	86	242	356	24	31	15.9	7.07

FTE: full-time–equivalent; PK: pre-kindergarten; SD: standard deviation.

The transmission dynamics of SARS-CoV-2 were determined according to seasonal variation, duration of immunity, and cross-immunity due to prior transmission of other coronaviruses (e.g., HCoV-OC43, CoV-HKU1). Seasonal variation affected the peak incidence and severity of wintertime outbreaks, while the duration of immunity and the level of cross-immunity impacted the total incidence and the pattern of recurrent circulation. Specifically, this research used a one-year pandemic scenario with moderate seasonal forcing (i.e., the R_0 in summertime is 0.8 of that in wintertime), an immunity duration of 10 weeks, and no cross-immunity between SARS-CoV-2 and other coronaviruses. The relatively short immunity duration was assumed, considering the rapid decrease of SARS-CoV-2 antibody levels and the short duration between reinfections [42–44]. The resulting prevalence of COVID-19 (i.e., number of infections per 1,000 people) is illustrated in Figure 2-1.

2.3.2.2 Current epidemiological scenario

Identifying the COVID-19 infection rate in local areas is critical to understand the current epidemiological scenario and develop corresponding intervention strategies to mitigate infection risk in schools. However, the true number of infections is typically underestimated because a large proportion of infected individuals—especially those who are asymptomatic or only mildly symptomatic—develop the disease without a confirmed diagnosis. A study from the University of Texas at Austin [45] indicated that the reported cases should be multiplied by 3 to 10 as the lower and upper estimate of true infections. The Centers for Disease Control and Prevention (CDC) stated that approximately 1 in 4.3 total infection cases nationwide were reported [46].

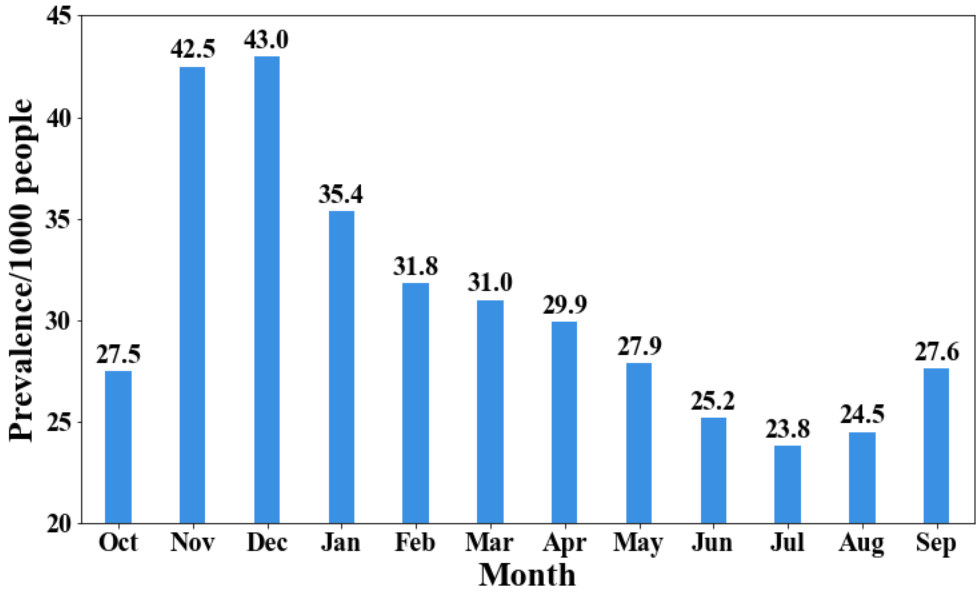


Figure 2-1 Prevalence of COVID-19 in the population (generated based on Kissler et al. [41]).

In this research, the true number of current infection cases in each county was estimated based on the method developed by Gu (2021), where the relationship between the ratio of true infections to confirmed cases and the standardized test positivity rate can be computed using Equation 2-1:

$$\rho = \frac{1500}{d_c + 50} r^{0.5} + 2 \tag{2-1}$$

where ρ is the ratio of true infections to confirmed cases; d_c is the number of days from February 12, 2020 to the current date; and r is the standardized daily test-positivity rate. The model standardizes the test-positivity rate across all states in the U.S. due to differences in the criteria and units of test reports. Most states use "test encounters" (TE) or "test specimens" (TS) to report test totals, but nine states use "unique individuals" (UI). TE, TS, and UI are three ways of counting the number of total tests. TE or TS is the number of people or specimens been tested per day, including the multiple tests on the same person. UI is the number of individuals being tested during the reporting period, with multiple tests on the same person removed. In [48], TE and TS results are treated as equivalent units, while UI results are converted to TE or TS values. The unit conversion factor (α_m) was estimated as the daily average ratio of daily test totals, reported as TE or TS, to those reported as UI of states that provide data using both units (e.g., TE and UI or TS and UI). The adjusted daily TE or TS test total is the product of α_m and the test total reported as UI. The daily standardized test-positivity rate can be determined with the state-adjusted test total. The parameters in Equation 2-1 are determined through curve-fitting on historical test positivity, serological surveys, and hospitalization data, where the constants are estimated using grid search. The true number of people becoming infected is the product

of daily confirmed cases and ρ, and the county infection rate is computed as the true number of infections divided by the county population size.

2.3.3 Modeling of Infection Risk

With a focus on airborne transmission, infection risk in this chapter was defined as the probability that susceptible individuals will be infected via airborne transmission after one day of in-person school attendance. Infection risk was calculated using the Gammaitoni–Nucci (G-N) equation, a widely adopted method [49] for indoor airborne infection risk assessment (e.g., influenza, tuberculosis, SARS-CoV-2). The G-N equation is a variation of an earlier model proposed by Wells-Riley et al. (W-R equation) [33]; this latter equation is based on the concept of the "quantum of infection," according to which the probability of infection is determined by the intake dose of airborne pathogens in terms of the number of quanta. Randomly distributed infectious particles in the air are considered to follow a Poisson distribution. The assumption of a steady-state particle concentration is the main limitation of the W-R equation. To overcome this limitation, the G-N equation demonstrates concentration changes in quanta level using a differential equation and considers the time-weighted average pathogen concentration rather than assuming the steady-state concentration [35]. In the G-N equation, the probability of susceptible individuals becoming infected (IR) after a certain duration of exposure can be calculated using Equation 2-2 [3,50,51], where I is the number of infectors, V is the room volume (m^3), N is the total disinfection rate of the environment (hr^{-1}), t is the exposure duration

of susceptible individuals to infectors (h), p is the pulmonary ventilation rate (m^3/h), and φ is the quantum generation rate (quanta/h).

$$IR = 1 - e^{-\frac{pI\varphi}{V}\left(\frac{Nt+e^{-Nt}-1}{N^2}\right)} \quad (2\text{-}2)$$

In this chapter, I was calculated differently according to the two epidemiological scenarios. In the one-year pandemic scenario, I was estimated as the product of the school population and the prevalence of COVID-19 in the population divided by 1,000 (note the prevalence of COVID-19 is the number of positive cases per 1,000 people in the one-year pandemic scenario). In the current epidemiological scenario, I was the product of the county infection rate and school population. V was estimated as the product of the occupant density, school population, and the height of the classroom, where a height of 3 m was assumed for all schools [52]. t was set as the number of hours in a typical school day, varying across different states according to [53]. N is the effect of introducing and circulating fresh air in the building. A ventilation rate of 2 hr^{-1} was set as the baseline rate [54]. Because p varies with different age groups [55], different values were assigned to each school level (Table 2-3), and φ for SARS-CoV-2 was estimated as a function of p using Equation 2-3 as follows according to [3]:

$$\varphi = \beta c_v c_i p\left(\sum_{i=1}^{4} V_{d,i} N_{d,i,j}\right) \quad (2\text{-}3)$$

To describe the hyper-transmissibility of the Omicron variant, a new parameter β was introduced in the model. For Omicron variant, β was set to be 3.3 to reflect the increased transmissibility compared with the original SARS-CoV-2 strain [56]; c_v is the SARS-CoV-2 viral load in the sputum, set at 10^9 RNA virus copies mL^{-1} [57]; c_i is a

conversion factor between the infectious quantum and infectious dose, set as 0.02 [57]; p is the pulmonary ventilation rate based on school level (m^3/h); $V_{d,i}$ is the volume of a droplet calculated by the droplet diameter D_i; and $N_{d,i,j}$ is the droplet concentration per cm^3 of droplet diameter i and expiratory activity j (see Table 2-4 for details). Since the quantum generation rate is related with the degree of infection, the individual difference of pulmonary ventilation rate, the activity the patient involved in, and the range of the quantum generation rate of SARS-CoV-2 varies in the literatures. The quantum generation rate for different school levels is in accordance with recent studies. Shen *et al*. [58] indicated that the quantum generation rate for children under 16 is 58 ± 31 h^{-1}; The quantum generation rate used in [3] is 142 h^{-1} for subjects performing speaking and light activity. The estimated quantum generation rate in [59] is 14–48 h^{-1}. Generally, the quantum generation rates are from tens to hundreds in the literatures. In this chapter, the quantum generation rate is set as 31.16, 42.72, and 51.94 h^{-1} for prekindergarten, elementary and combined school students respectively, and is 61.16 h^{-1} for middle, high, and secondary school students.

2.3.4 Modeling the Impact of Intervention Strategies

The impact of different intervention strategies on the airborne infection risk was modeled by modifying the parameters in Equation 2-2. The considered intervention strategies included increasing the outdoor ventilation rate, implementing air filtration, adopting hybrid learning (students learning partially online), and a combination of these three strategies.

Table 2-3 Pulmonary ventilation rate of each school level based on student age groups.

Parameter	PK	Elementary	Middle	High	Secondary	Combined	Reference
Age (years)	3–5	5–11	11–14	14–18	11–18	3–18	NCES
Pulmonary ventilation rate (m^3/day)	7.28	9.98	14.29	14.29	14.29	12.135	Literature [55]

NCES: National Center for Education Statistics; PK: pre-kindergarten

Table 2-4 Droplet concentration (per cm^3) of different droplet size distributions during speaking activity.

Expiratory activity	D_1(0.8 μm)	D_2 (1.8 μm)	D_3 (3.5 μm)	D_4 (5.5 μm)
Voiced counting	0.236	0.068	0.007	0.011
Unmodulated vocalization	0.751	0.139	0.139	0.059

Note: Regarding respiratory activity, speaking is considered the main activity during school hours and is defined as the mean value between unmodulated vocalization and voiced counting.

1. Increase in outdoor ventilation rate (S1)

Increasing the outdoor ventilation rate will bring in more fresh outdoor air to dilute contaminated indoor air, thus reducing the infection risk. This research modeled the impact of increasing the baseline ventilation rate by various levels (from 25% to 200% in steps of 25%) on the infection risk.

2. Implementation of air filtration (S2)

When filtration is applied in a building's heating, ventilation, and air conditioning (HVAC) system, the total disinfection rate of the environment (*N*) can be modeled as a combined effect of outdoor ventilation and filtration, computed as $N = \lambda_{ventilation} + k_{filtration}$, where $k_{filtration}$ is the particle removal rate due to filtration [51], which can be calculated using Equation 2-4 [60] as follows:

$$k_{filtration} = \lambda_{recirculated}\eta_{filter} \quad (2\text{-}4)$$

where $\lambda_{recirculated}$ is the recirculation rate, set as 6.4 hr^{-1} [61], and η_{filter} is the filtration efficiency weighted by infectious particle size. American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) specifies the method by which to determine η_{filter} based on the minimum efficiency reporting value (MERV) and particle size range [62] and has suggested that filters with MERVs of at least 13 can efficiently capture airborne viruses [63]. Therefore, the impact of adopting MERV 13 filters is estimated in this chapter. The filtration efficiency of MERV 13 filters is 67.5% based on the assumed particle size range of SARS-CoV-2. [64] indicates that more than half of the viral RNA of SARS-CoV-2 have aerosols smaller than 2.5 μm. In this study, it is assumed

that half of the particles are 0.3 to 1 μm in size (50% average particle size efficiency) and the other half are 1 to 3 μm (85% average particle size efficiency).

3. Hybrid learning (S3)

Having part of the student body learn online reduces the school population and thus decreases the number of infectors (I) given the specific prevalence of COVID-19 estimated from two epidemiological scenarios. In this chapter, the impact of switching 10%, 20%, 30%, 40%, and 50% of the students to online learning, respectively, was computed.

4. Combined strategies

The impacts of different combinations of strategies—including increasing the ventilation rate and implementing filters (S1 + S2, denoted as S4; increasing the ventilation rate and switching part of the student body to online learning (S2 + S3, denoted as S5); and increasing the ventilation rate, implementing filtration, and switching part of the student body to online learning (S1 + S2 + S3, denoted as S6)—were considered.

2.3.5 Modeling the Impact of Parameter Uncertainties

The risk of COVID-19 infection in schools may vary due to the uncertainty of multiple parameters, such as occupant density, pulmonary ventilation rate, and exposure duration. In this study, MCS and sensitivity analysis were used to quantify the influence of uncertainties of multiple parameters.

2.3.5.1 Monte Carlo simulation

MCS is a method widely used to calculate possible outcomes as well as the associated uncertainty using multiple variables with different probability distributions.

Based on Equation 2-2, a stochastic MCS was developed to represent the uncertainty of infection risk. MCS demonstrates the uncertainty and stochasticity of the factors, and the outcomes reveal the possible results with a large variation, indicating both average and extreme case scenarios of school infection risk [65]. In this study, the MCS contained three steps: random variable determination, random number generation, and simulation result acquisition.

1. Random variable determination

Three parameters with uncertainties that will influence infection risk in schools were treated as random variables, including occupant density, pulmonary ventilation rate, and exposure duration in a school day. The possible range and empirical probability distribution of each variable were estimated based on school information and existing literature and are detailed in Table 2-5.

2. Infection risk simulation

Given a specific ventilation rate, 10,000 simulations were conducted to estimate the school infection risk. In each simulation, a random number was generated using repeated random sampling from the empirical distributions of each input variable and used to compute the infection risk of all schools. In this study, 10,000 simulations were performed under a ventilation rate varying from 2 to 6 hr^{-1}. Specifically, the peak prevalence of COVID-19 in the one-year pandemic scenario was used when calculating the infection risk.

3. Simulation result acquisition

For each school, 10,000 simulation results could be achieved using Equation 2-2. For each simulation, the average infection risk was computed among all schools. The

obtained result of 10,000 simulations indicates the distribution of average infection risk of schools nationwide.

2.3.5.2 Sensitivity analysis

Sensitivity analysis was conducted to evaluate the influence of individual parameters, including infection rate, exposure time, occupant density, and pulmonary ventilation rate. The estimated ranges and default values of the parameters are listed in Table 2-6. The infection rate was determined based on the current epidemiological scenario across the U.S. and ranged from 50% of the minimum estimated infection rate to 150% of the maximum estimated infection rate as of January 30, 2021. The pulmonary ventilation rate used in the sensitivity analysis was the average pulmonary ventilation rate of elementary school students (aged 6–11 years), because elementary schools account for more than 50% of the total number of schools nationwide.

2.4 Results

2.4.1 Infection risks under one-year pandemic scenario

Adopting the one-year pandemic scenario [41], the infection risk of SARS-CoV-2 in 111,485 U.S. schools was estimated for a 12-month period and reported per month. A ventilation rate of two air changes per hour (ACH) in schools [54] was used as the baseline to represent normal ventilation operation. The daily infection risk was derived based on the exposure time for each single school day, and was considered to remain unchanged within a single month.

Table 2-5 Random variables used in MCS.

Parameter	PK	Elementary	Middle	High	Secondary	Combined	Distribution	Reference
Occupant density (m^2/people)	5.34–27.97	3.49–28.82	6.76– 28.92	6.38– 29.26	4.08– 28.64	4.03– 37.75	Truncated normal	Table 1
Pulmonary ventilation rate(m^3/day)	5.29– 9.27	7.11–12.85	9.56– 19.02	9.56– 19.02	9.56– 19.02	9.37–14.9	Truncated normal	EPA, 2011
School day (hrs/day)				6.25–7.08			Truncated normal	NCES, 2008

NCES: National Center for Education Statistics; PK: pre-kindergarten

Table 2-6 Parameters used in the sensitivity analysis.

Parameter	Max.	Min.	Default value	Reference
Infection rate (%)	48.9	0	2.18	Gu, 2020
Exposure time (h)	7.08	6.25	6.67	NCES, 2008
Occupant density (m^2/people)	3.48	37.75	14.93	Table 1
Pulmonary ventilation rate (m^3/day)	19.02	5.29	9.98	EPA, 2011

As shown in Figure 2-2, the average infection risks in schools exhibit strong patterns of seasonality, reaching a peak in winter months and a trough in summer months (e.g., the school average infection risk reaches 6.83% in December and drops to 3.85% in July), suggesting that adaptive measures could be implemented as a function of the seasonal risk to control infection. The prediction of a greater prevalence of COVID-19 (i.e., number of cases per 1,000 people) from November to February (Figure 2-2) indicates a higher number of infectious students attending schools, elevating the infection risk. High schools exhibit the greatest average infection risk, followed by middle and secondary schools, while the infection risk in pre-kindergarten and elementary schools remains lower. Infection risk is largely affected by human pulmonary ventilation rate, which determines the amount of virus in aerosols exhaled by infectious people and inhaled by susceptible people. The pulmonary ventilation rate of teenagers (14.29 m^3/day) is almost twice that of younger children (7.28 m^3/day) [55]. Thus, with the same baseline ventilation and similar occupant density, middle and high schools would have higher risks than pre-kindergarten and elementary schools. The differences among schools in terms of infection risk suggest that time-varying intervention strategies could be adopted according to a school's risk level and characteristics. Different intervention strategies have different impacts on the infection risk (Figure 2-3). The results illustrate that, among the three basic intervention strategies—increasing the ventilation rate by 100% (S1), implementing MERV 13 filters (S2), and having half of the student body learn online (S3)—the infection risk under S3 is slightly lower than that under S1, while S2 is the most effective strategy and results in a significantly reduced infection risk relative to both S1 and S3.

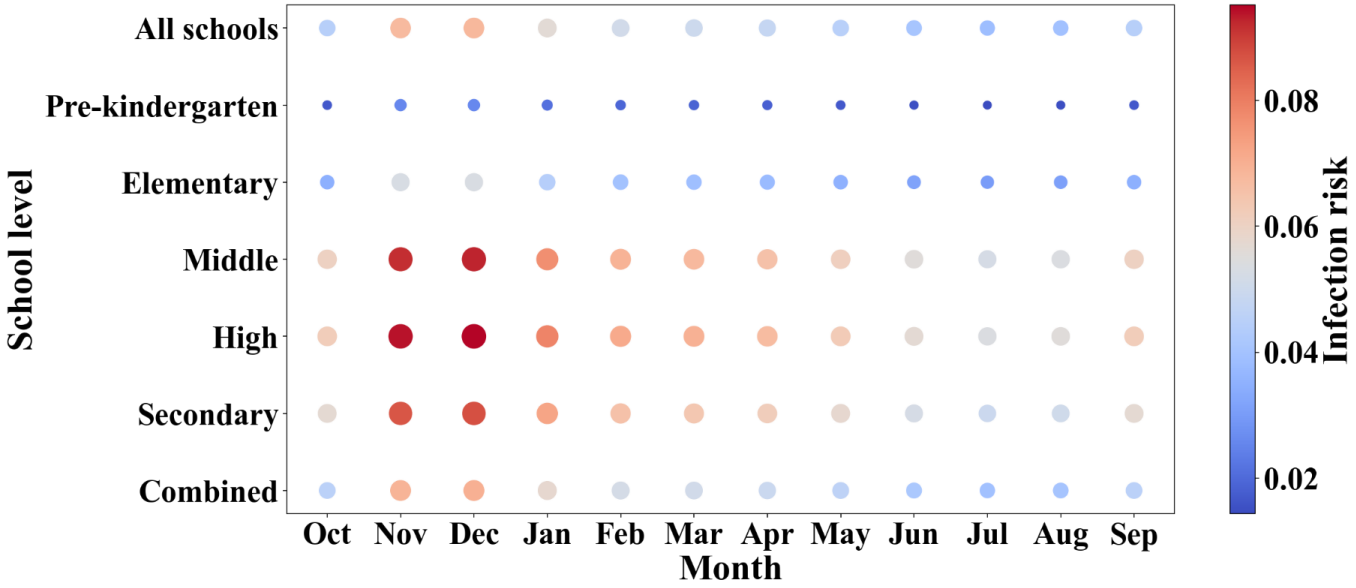


Figure 2-2 Monthly average infection risk with normal school operation.

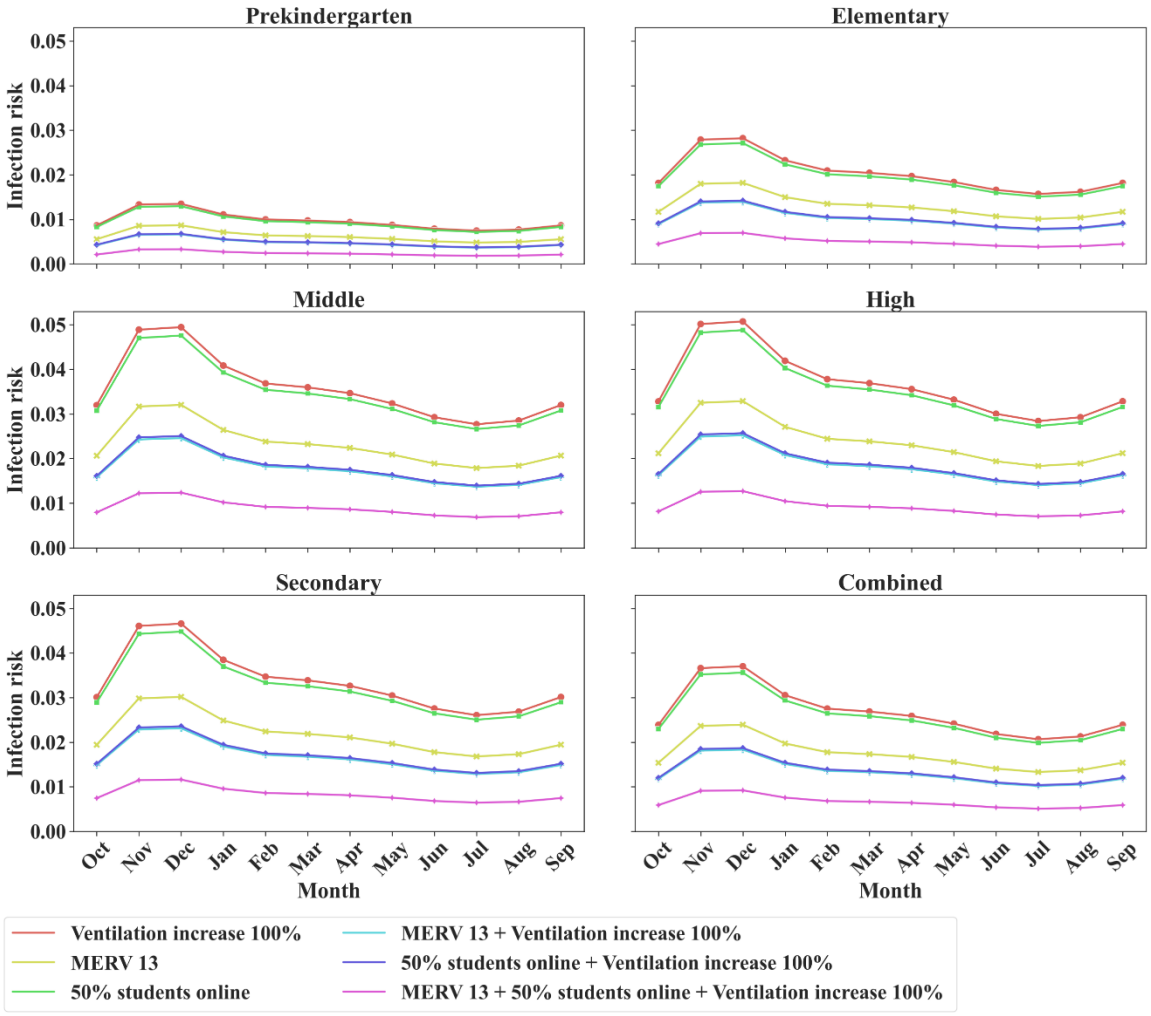


Figure 2-3 Monthly average infection risk under different intervention strategies.

Among all schools, pre-kindergarten maintains the lowest average infection risk throughout the year, which can be controlled below a sufficiently low threshold (1% in this study) solely by implementing S2. In contrast, for the other school levels, combined intervention strategies are required to keep the infection risk below 1% throughout the year. The considered combined intervention strategies include the combination of S1 and S2 (denoted as S4), the combination of S1 and S3 (denoted as S5), and the combination of S1 through S3 (denoted as S6). It was observed that the effects of S4 and S5 are almost the same, indicating that, if MERV 13 filters are not compatible with the existing HVAC system, schools may have to consider S5 to achieve a similar degree of infection risk reduction. By implementing S6, elementary and combined schools can keep the infection risk below 1% throughout the year.

However, in middle, high, and secondary schools, the infection risk may exceed 1% during wintertime, where more restrictive measures (e.g., further increasing the ventilation rate, implementing filters with a higher MERV rating, and increasing the proportion of students enrolled in online learning) may be necessary to maintain the infection risk at a sufficiently low level. Given the varying prevalence throughout the year, schools may select different strategies to ensure an acceptable risk while considering other factors, such as energy costs and learning outcomes.

The distribution of infection risk under various ventilation rates was obtained using MCS. The results illustrate that the variation of infection risk decreases as the ventilation rate increases. For schools with the baseline ventilation rate (2 hr^{-1}), the mean infection risk is around 7% and the highest infection risk is 10%, demonstrating a high level of

uncertainty and the significance of adopting intervention strategies (Figure 2-4). The efficiency of increasing the ventilation rate decreases as the ventilation rate increases: the infection risk decreases by 16.5% when the ventilation rate is increased from 2 hr^{-1} to 2.5 hr^{-1}, while it only decreases by 8% when the ventilation rate is increased from 5.5 hr^{-1} to 6 hr^{-1}. Therefore, to further reduce the infection risk, increasing the ventilation rate alone may not be the most efficient strategy when considering the energy required. Schools might also contemplate adopting complementary mitigation measures to maintain low infection risk levels and energy costs.

2.4.2 Infection risks under current epidemiological scenario

The infection risk for each state under different intervention strategies is presented in Figure 2-5. The average infection risk of a state is computed as the mean value of the infection risks over all counties in the state, and the range of the infection risk of a state is represented as the range of the infection risk of the counties with 95% confidence interval. The infection risk for each county is computed based on county epidemic situation and the characteristics of schools in the county.

For most states, schools with the baseline ventilation rate show a high infection risk, with an average infection risk of 3.75%. Under the current epidemiological scenario, more than 90% of counties exhibit an infection risk of greater than 1%, indicating the significance of implementing intervention strategies to decrease the infection risk. The impacts of increasing the ventilation rate by 100% (S1) and having half of students learn online (S3) are similar, resulting in average infection risks of 1.98% and 1.90%, respectively.

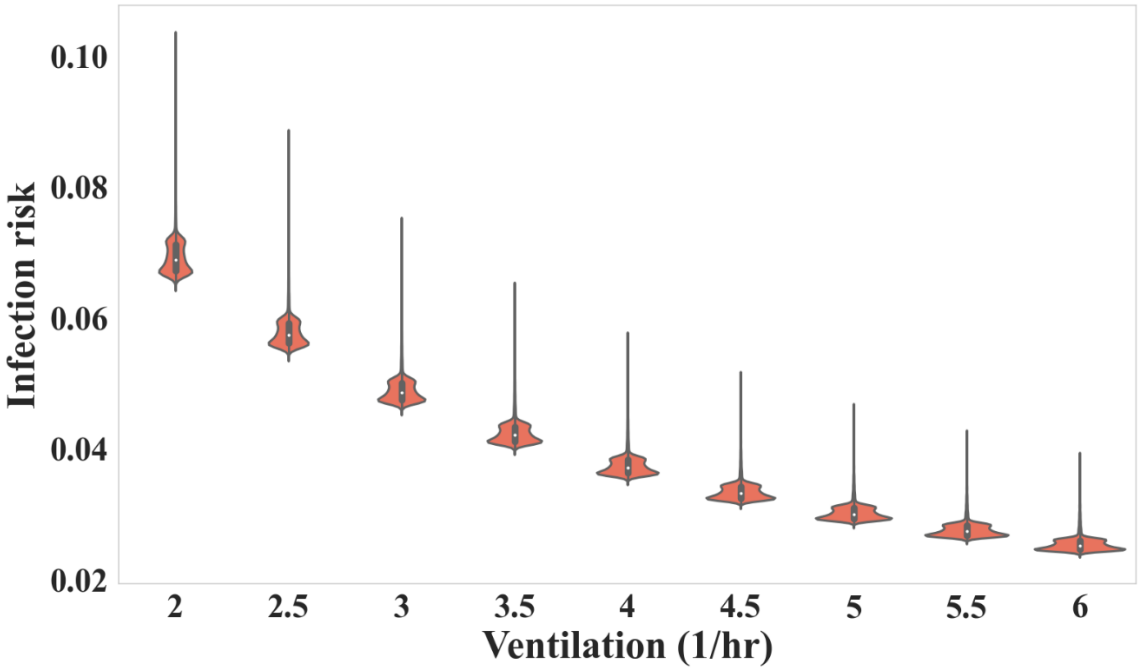


Figure 2-4 Distribution of average school infection risk under various ventilation rates.

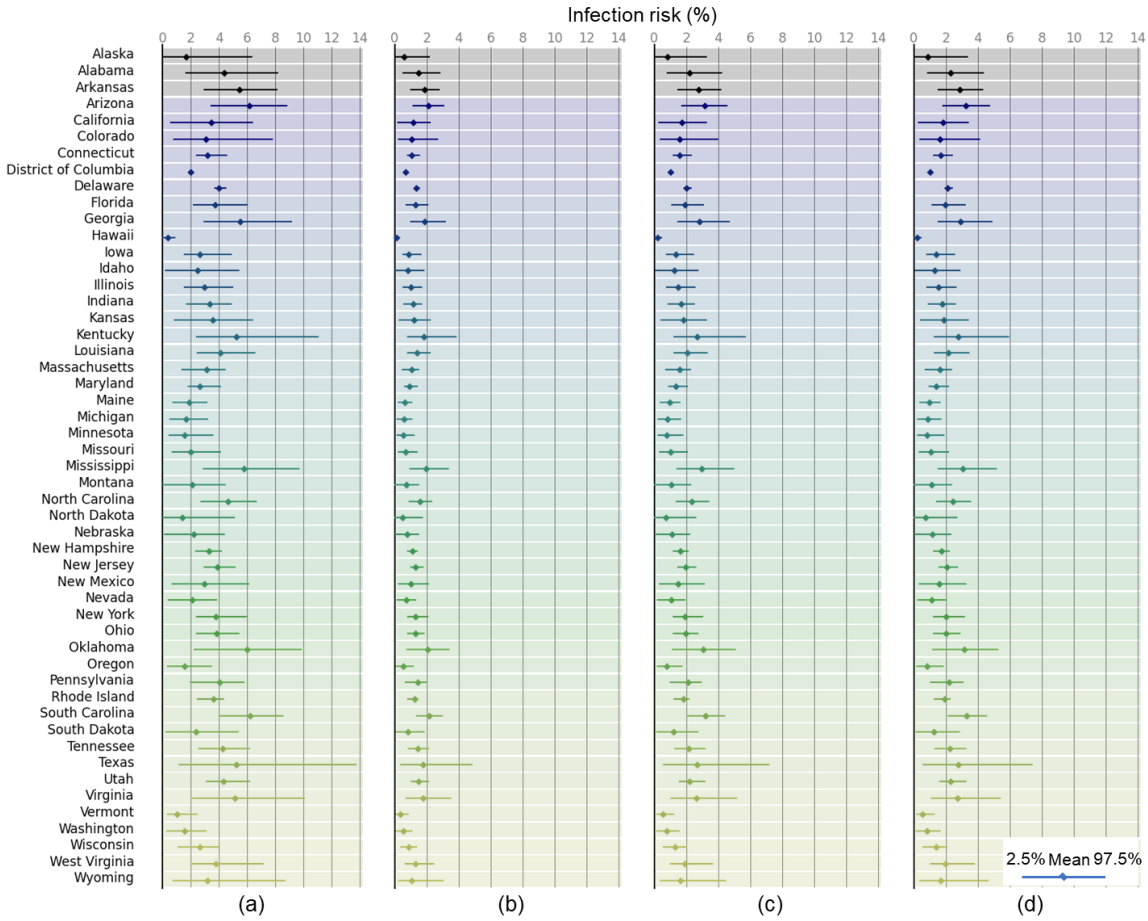


Figure 2-5 Infection risk for each state with different intervention strategies: (a) the baseline scenario; (b) with MERV 13 filtration; (c) with 50% of students learning online; and (d) when increasing the ventilation rate by 100%.

Under both strategies, the infection risk of nearly 20% of counties nationwide falls below 1%. Implementing MERV 13 filters (S2) outperforms both S1 and S3, with an average infection risk of 1.28%—35% and 33% lower than the infection risks calculated under S1 and S3, respectively—resulting in an infection risk below 1% for approximately 40% of counties nationwide.

The average infection risk of a given county is determined by the infection rate and the characteristics of the schools in that county. Counties with higher prevalence rates generally exhibit greater infection risk in schools. Figure 2-5 shows that schools in the southeastern and southwestern U.S. are exposed to higher infection risks. Specifically, Arizona, South Carolina, Oklahoma, Mississippi, and Georgia are the five states with the highest infection rates ($\geq 3.18\%$), and the schools in these states also have the highest levels of infection risk ($\geq 5.5\%$). In addition, the infection risk in each county is also influenced by the characteristics of individual schools, especially the school level, which determines the school occupant density and the student pulmonary ventilation rate.

Table 2-7 shows that the distribution of schools is similar across different states, indicating that a state's average infection risk depends crucially upon the infection rate. However, as shown in Table 2-7, the county-level school distribution varies significantly, especially for elementary and high schools, demonstrating that, in addition to the county infection rate, school distribution contributes to the variation in infection risk. These results suggest that schools and policymakers should consider and adopt specific intervention strategies based on various factors, including the local epidemic situation, school characteristics, and school HVAC system conditions.

Table 2-7 School distribution by state and county.

School level	Max.		Min.		Mean		SD	
	State	County	State	County	State	County	State	County
PK	5.13%	40%	0.00%	0%	1.11%	1.04%	0.011	0.032
Elementary	67.76%	100%	49.67%	0%	58.15%	51.61%	0.039	0.118
Middle	24.73%	50%	7.10%	0%	14.47%	15.71%	0.030	0.089
High	31.21%	100%	11.02%	0%	18.73%	25.63%	0.042	0.113
Secondary	5.46%	100%	0.53%	0%	2.18%	1.37%	0.011	0.037
Combined	14.07%	100%	1.97%	0%	5.36%	4.64%	0.026	0.071

PK: pre-kindergarten; SD: standard deviation.

S2 is cost-effective and efficient at reducing infection risks. If MERV 13 filters are not accommodated in the school HVAC system, S1 and S2 can be used, and further increases in ventilation or in the proportion of hybrid learning may be adopted according to the infection risk, school system capacity, and teaching quality.

2.4.3 Sensitivity analysis

In addition to different intervention strategies, the infection risk in schools is also sensitive to changes in multiple factors, including the infection rate of the population, exposure time in schools, occupant density, and the students' pulmonary ventilation rate. In this study, a sensitivity analysis was conducted to quantify the influence of these factors given the estimated ranges detailed in Table 2-6; the results of this analysis are shown in Figure 2-6.

As depicted in Figure 2-6, the infection risk shows a near-linear relationship with the exposure time. The change in exposure time within the estimated range has a limited impact on infection risk because the average number of hours in the school day do not vary distinctly across the U.S. The infection risk increases with an increase in the infection rate parameter. The infection rate varies significantly across counties, leading to great changes in school infection risks. For instance, Forest County, Pennsylvania, exhibits the highest infection rate among all counties of 32.6% and a county infection risk of 32.9%, whereas the average infection risk for all counties nationwide is only 3.8%. Schools located in counties with high infection rates are expected to be exposed to greater risk levels and will need to adopt much stricter mitigation measures to effectively control the infection risk.

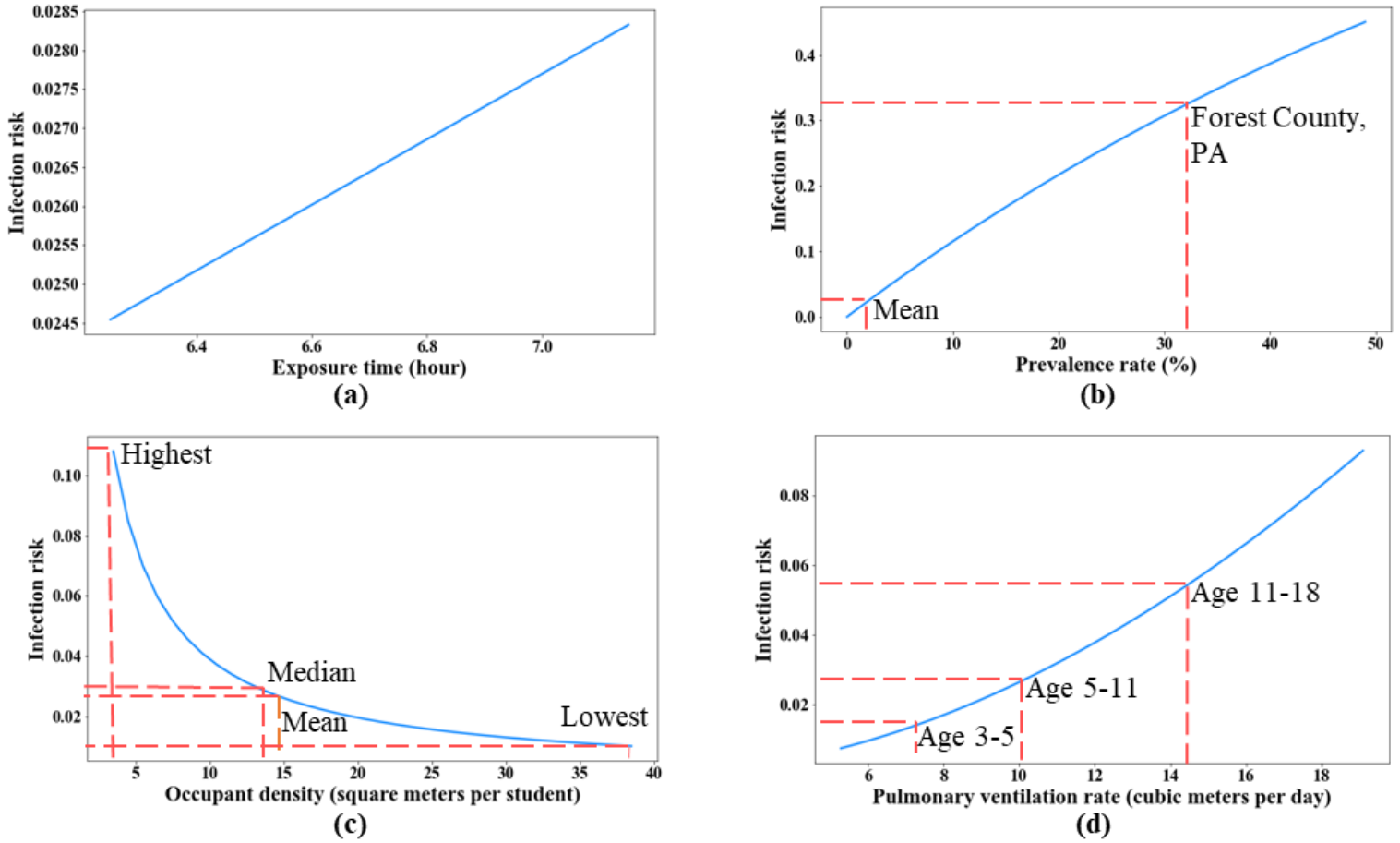


Figure 2-6 Sensitivity analysis of parameters: (a) exposure time; (b) infection rate; (c) occupant density; and (d) pulmonary ventilation rate

Considering occupant density, the results show a sharp decrease in the infection risk, with the parameter changing from 3 to 10 square meters per student; the trend then flattens after this point. Nationwide, the infection risk reaches 10.8% for schools with the highest occupant density, while the lowest value is 1%. The mean and median values are close, and the infection risk is 2.6% with a mean value of 14.93 and 2.8% with a median value of 14.04, respectively.

These results indicate that, for most schools, the current occupant density is appropriate, and further reductions in occupant density may not lead to a significantly reduced infection risk. For schools with high occupant density (e.g., 3 to 10 square meters per student), it is recommended that the density be reduced to the average level (e.g., 14.93 square meters per student). The infection risk increases as the pulmonary ventilation rate rises, with the rate of change increasing as well. The annotation in red dashed lines in Figure 2-6(d) indicates the mean pulmonary ventilation rates of different school levels (as shown in Table 2-3) and the corresponding infection risk. The infection risk is 1.4% for pre-kindergarten students (aged 3–5 years); 2.6% for elementary school students (aged 5–11 years); and 5.3% for middle, high, and secondary school students (aged 11–18 years). The pulmonary ventilation rate increases with the maturation of children, leading to an even greater infection risk. Intervention strategies are necessary for schools with higher levels of infection risk to adopt to reduce the infection risk to a sufficiently low level.

2.4.4 Airborne infection risk of Omicron variant

The county level airborne infection risk was computed based on the current Omicron epidemic situation and the school characteristics.

Figure 2-7 presents the Omicron airborne infection risk of each state under different control measures. The overall average airborne infection risk under was 4.51%, and more than 90% of the states had a greater than 2% of average airborne infection risk, which is higher than the infection risks in previous epidemic situations (e.g., the prevalence for original SARS-CoV-2 strain).

Kruskal–Wallis one-way analysis of variance (ANOVA) test was conducted to figure out if the impact of modeled mitigation measures was statistically significant [66]. The One-way Kruskal–Wallis test is a nonparametric method for analyzing if there is a difference of the population medians among all the groups under one categorical variable. In this study, the groups were identified as different mitigation measures, and the categorical variable was the airborne infection risks.

A Kruskal–Wallis test was conducted to demonstrate the significance of different mitigation strategies. The p-value of the test was nearly 0, indicating that the null-hypothesis of same median among all groups can be rejected. The result demonstrated that there were significant differences among the mitigation strategies within 99% confidence interval (CI).

A Conover squared ranks test was conducted as the post-hoc comparison to identify significant differences between pairs of groups [67]. The result indicated that among all the pairs of strategies, the difference between two combined control measures were insignificant with a p-value of 0.2809. The two combined measures are AM1+AM3 and AM2+AM3. All other pairs of strategies were found to be significantly different within 99% CI.

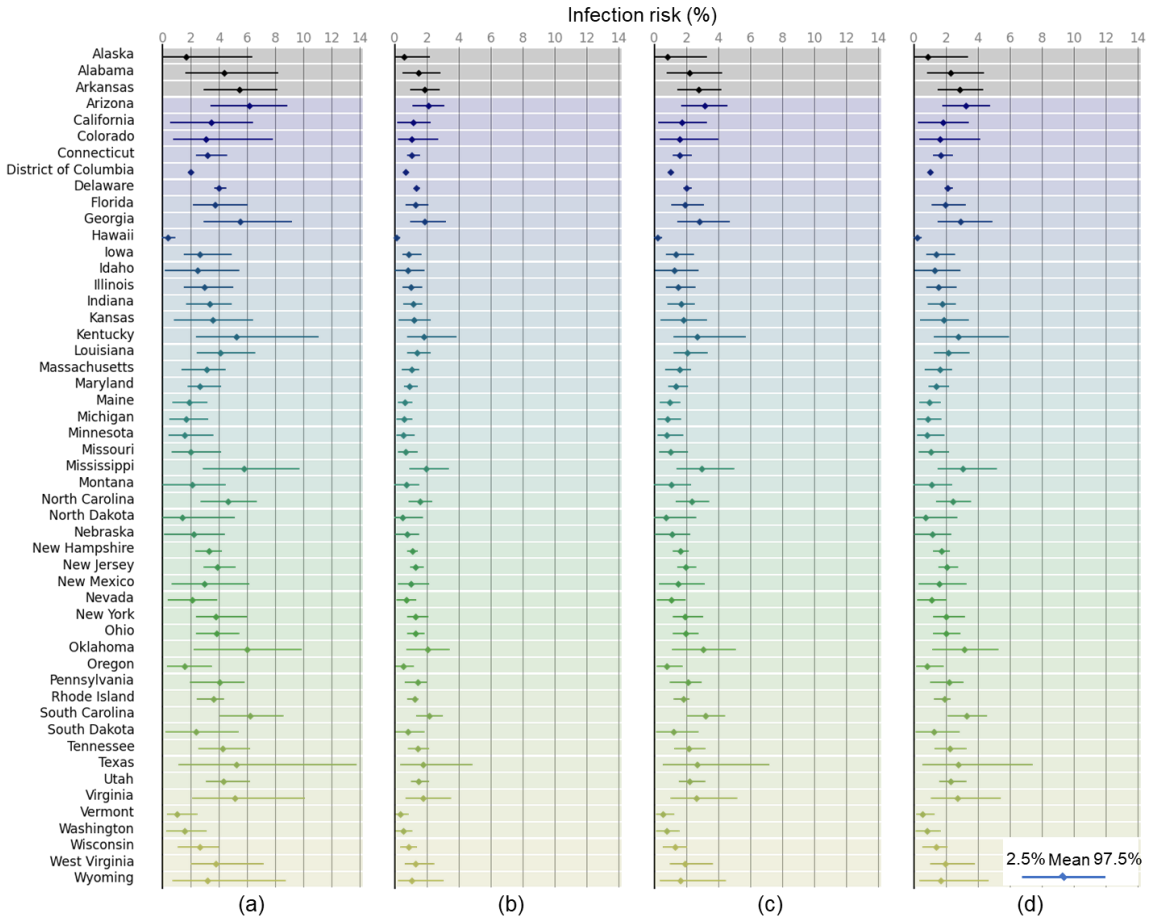


Figure 2-7 Infection risk for each state with different intervention strategies: (a) the baseline scenario; (b) with MERV 13 filtration; (c) with 50% of students learning online; and (d) when increasing the ventilation rate by 100%.

Similar to the results in Section 2.4.2, The impact of implementing AM1 indicated a significant improvement in reducing the airborne infection risk, and outperformed all the three interventions. The overall average airborne infection risk was reduced to 1.55% and the variation range of all states was reduced, which was illustrated by the smaller ranges. Airborne infection risk in more than 90% of states decreased to less than 2% under this control intervention. AM2 displayed a similar result as AM3. The overall average airborne infection risks under these two control measures were 2.40% and 2.30%, respectively. About 70% of states had the airborne infection risk lessen to 2%. The variation in airborne infection risk was reduced for all states as well.

As stated in Section 2.4.2, the airborne infection risk is significantly influenced by both the county prevalence and school characteristics. States such as Alaska, Idaho, Kentucky, Maine, Rhode Island, and Vermont had more than twice the overall average airborne infection. Vermont exposed the highest average airborne infection risk among all states, which was 17.19% under baseline ventilation situations. Figure 2-8 shows the airborne infection risks of different school levels under various airborne transmission control measures. The figure indicates that high school had the highest median airborne infection risk of 4.29% and the highest interquartile range (IQR) among all six levels of schools that were considered in this study. Elementary school showed the lowest median airborne infection risk and the lowest IQR among all school levels. Distinct control measures indicated a diverse impact on airborne infection risk. For individual controls, similar results are shown in Figure 2-7. AM1 had the best solo control performance among all school levels. The median risk was reduced to 1.46% using AM1 in high school. The

combination of AM1, AM2, and AM3 revealed the best performance among all control measures at all school levels. The median airborne infection risk in high school decreased to 0.56% under this combined control measure.

2.5 Discussion

COVID-19 pandemic leads to significant education crisis all over the world. The worldwide school closure has affected over 80% of total enrolled students, and half of the students in more than 200 countries have experienced partially or fully school closures [68]. Long-time school closures raise public concerns about the negative impacts on children health, education, and financial burdens on the households [69]. Therefore, as schools reopen and resume in-person instruction, effective operation strategies are essential to maintain a healthy and sustainable learning environment.

Ventilation, social distancing, and filtration are three broadly utilized strategies during the pandemic. Several studies have been dedicated to discussing the impact of these strategies in the control of COVID-19 transmission, and achieved compatible results with this chapter, despite of different pandemic scenario, indoor environment, and countries considered.

Sun and Zhai [70] introduced a distance index and a ventilation index in the Wells-Riley model to compute the infection risks in buses in China. Similar to our study, their results suggest a near-linear relationship between infection risk and the exposure time and demonstrate the efficiency of increasing ventilation and reducing occupant density in mitigating the infection risk.

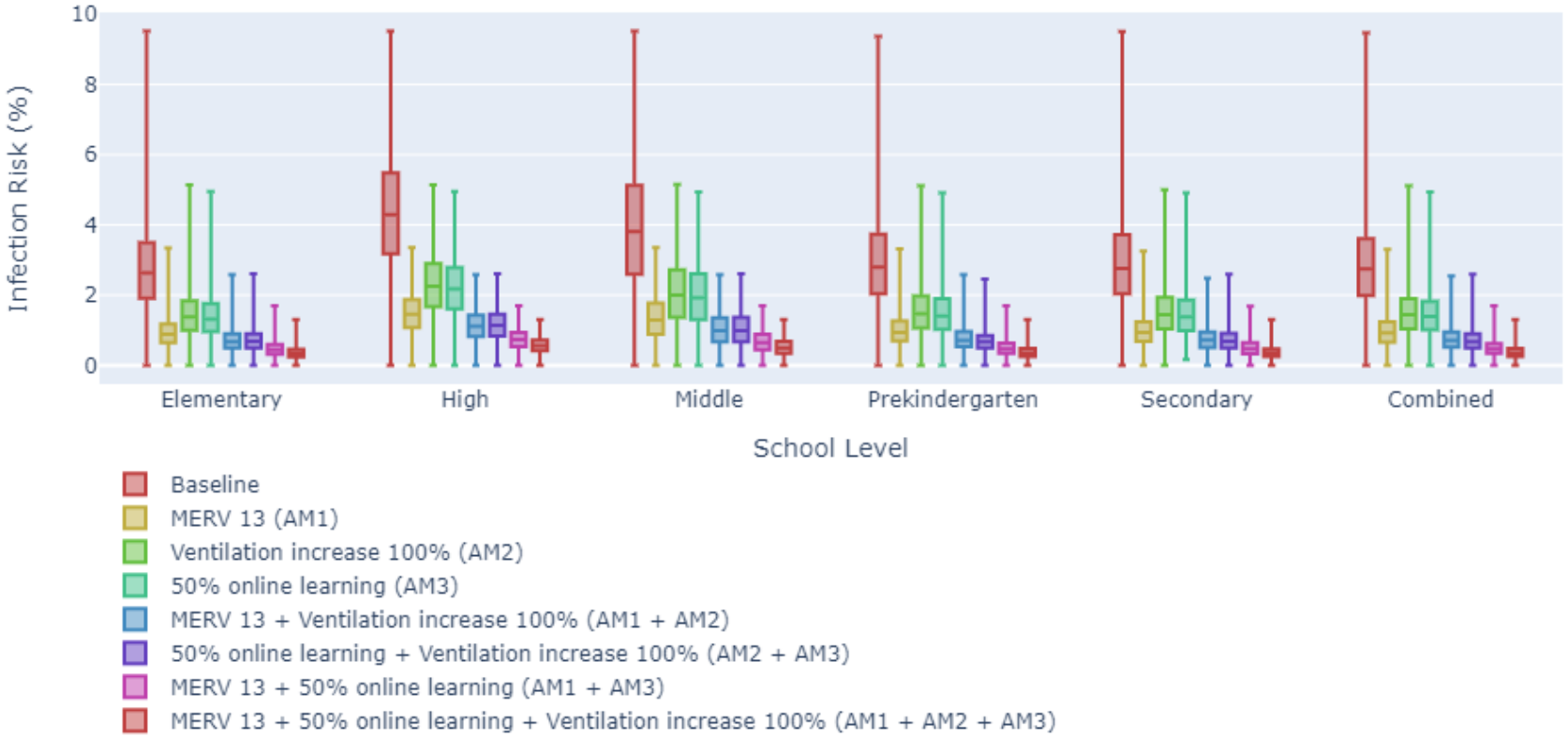


Figure 2-8 Airborne Infection Risks of the Omicron Variant Across Different School Levels under Varying Airborne Transmission Control Measures.

Shen et al. [58] discussed the effectiveness of multi-scale strategies for reducing airborne infection risk of SARS-CoV-2 using Wells-Riley model for indoor spaces, and suggested the higher efficiency of applying filters compared to solely increasing airflow rate, which aligns with our conclusion. However, in previous studies, the number of infectors were either set to be 1 for each room which is unlikely in the actual situation, or calculated using the infection rate estimated from limited sample size. To overcome the limitation, this study leveraged data-driven and scenario-based analysis to evaluate school infection risk under various intervention strategies considering both long-term and short-term realistic pandemic scenarios.

Regarding the selection of intervention strategies in this study, given the importance of in-person interaction for student learning, the intervention strategy only considers that up to 50% of students would be learning online. Considering the current condition of most school HVAC systems, although increasing room ventilation rates is efficient in reducing infection risks, the ventilation rate cannot be increased beyond the system capacity. In this chapter, doubling the baseline ventilation rate was considered to ensure that the proposed strategy would be affordable for most schools. Implementing filters with higher MERV ratings (e.g., MERV 14–16) would only have a slight effect on decreasing the infection risk but would generate additional product and energy costs. For instance, the average school infection risk in December is 2.34%, 2.04%, 1.96%, and 1.85% for implementing MERV 13–16 filters, respectively. With the increase of MERV ratings, more energy is required to overcome additional pressure drop, and the purchase cost increases from $ 11 per filter for MERV 13 filters to $50, $90, $125, $150 for MERV

14–16 filters, respectively [60]. Thus, implementing MERV 13 filters was adopted as filtration intervention strategy. It is found that filtration is most effective in reducing the infection risk, resulting in a risk reduction of more than 30% relative to that achieved with either ventilation increase or hybrid learning in both considered pandemic scenarios. However, to maintain a healthy school environment, it is suggested that multiple intervention strategies be adopted simultaneously. Beside the direct impact of intervention strategies to the airborne infection risk, it has been proved that poor air quality caused by pollutants (e.g., particulate matters and volatile compounds) may lead to acceleration of the contagion of SARS-CoV-2 [71]. The intervention strategies can also improve the indoor air quality, and further reduce the transmission of SARS-CoV-2. Other technologies can be considered for sustainable building retrofitting together with the intervention strategies (e.g., natural ventilation, botanical biofilters [72], passive cooling techniques [73] to maintain healthy indoor environment and human comfort.

The infection risk may vary significantly across countries due to the differences in population size, disease prevalence, infection-hospitalization ratios, fraction of immunity, etc. However, the findings in this study can provide insights for other countries regarding the risk control during the pandemic. For instance, the effectiveness of intervention is analyzed and compared, including filtration, ventilation, and social distancing achieved by online learning, indicating that filtration strategy can be widely adopted for schools worldwide. In addition, the framework can be extended to other infectious diseases in other counties by considering specific disease characteristics and epidemic and operation scenarios.

2.6 Summary

The airborne infection risk of SARS-CoV-2 and its variants in U.S. schools has been estimated under different epidemiological scenarios. Multiple intervention strategies, including increased ventilation, air filtration, and hybrid learning, are modeled to evaluate their effectiveness in reducing the infection risk. Two epidemiological scenarios were considered, including a one-year pandemic scenario and a current epidemiological scenario. A series of findings and important insights were derived as follows, which will provide insights for schools and governments to develop guidelines on adopting appropriate intervention strategies to mitigate airborne infection risk considering epidemic situation and school characteristics.

1. The airborne infection risk in schools exhibits seasonal patterns, with the average infection risk in all schools ranging from 3.85% in the summer to 6.83% in the winter under the one-year pandemic scenario, indicating the necessity of adjusting mitigation measures over the year.
2. The effectiveness of intervention strategies varies with different school levels and pandemic periods and, thus, requires individual schools to adopt variable intervention strategies over the long term. In general, schools with higher school level experience higher risk. For instance, the infection risk in pre-kindergarten remains low throughout the year, and the implementation of MERV 13 filters can limit the infection risk to below 1%. For elementary schools, implementing all strategies are suggested in most months, while, in months with lower prevalence rates (e.g., summertime), schools can adopt fully in-person learning in concert with filtration and increased ventilation. For

other school levels (e.g., middle, secondary, and high schools), the infection risk may persist above 1% in some months even after implementing all strategies. Additional mitigation measures, such as wearing masks and enacting further social distancing, are needed to ensure an acceptable risk level.

3. The relationships between infection risk and ventilation rates are depicted using Monte Carlo simulation, illustrating the efficiency of increasing the ventilation rate on reducing the infection risk and demonstrating the significance of combined intervention strategies when considering the capacity of school systems.
4. The infection risk for each state is computed based on the infection risk of the counties in the state under normal operations as well as various intervention strategies based on the current epidemiological scenario. Schools with the baseline ventilation rate show a high infection risk across the U.S., with more than 90% of the counties exhibit an infection risk of greater than 1%, indicating the necessity of intervention strategies to maintain a sustainable indoor environment. The results show that increasing the ventilation rate by 100% and having half of students learn online have similar impacts on reducing infection risks, while implementing air filtration is more efficient than either of the strategies, with over 30% less than the risk levels correlating with ventilation enhancement and hybrid learning.
5. Sensitivity analysis is conducted to further illustrate the impact of the characteristics of schools and the epidemic situation on infection risk. In general, the infection risk shows a near-linear relationship with the exposure time in schools. It is also found that the current occupant density is appropriate for most schools, while it is recommended that

the density be reduced to the average level (e.g., 15 square meters per student) for schools with higher occupant density.

6. The airborne transmission of Omicron variant spread fast in U.S. schools, and the average infection risk reaches 4.51% without any mitigation measures. The effectiveness of the mitigation measures is similar to the original strain, while multiple interventions are required to maintain low infection risks.

CHAPTER THREE
SIMULATION-BASED TRADE-OFF MODELING FOR HEALTH, ENERGY, AND THERMAL COMFORT

3.1 Introduction

The prolonged COVID-19 pandemic has prompted concerns regarding the establishment and maintenance of a healthy and sustainable indoor environment as schools resume full in-person instruction. Due to their crowded and inadequately ventilated nature, schools are often regarded as spaces where frequent interactions take place among students and teachers. Several studies have confirmed that the airborne route is the main pathway for the transmission of SARS-CoV-2 [22,74–76]. The special environmental condition of schools could accelerate the transmission of airborne diseases and lead to an outbreak during the pandemic. The indoor environment can affect the virus infectivity, survival, and the suspension time in the air. Thus, maintaining an appropriate indoor air environment in the building operation is of significance to prevent the airborne transmission of the virus. Increased ventilation rate and implementation of air filtration, as the primary mitigation measures for risk control, can dilute the aerosol concentration in the air, and result in a decrease in infection risk [9]. In addition, recent research has demonstrated that indoor temperature and humidity can affect the transmission of the virus by aerosols since both factors are influential on the decay and deposition rate of the virus, and thus affect the survival time of the virus. Dabisch et al. [77] reported that both the temperature and air humidity will be influential on the infectivity of SARS-CoV-2 in aerosols, especially for temperature. For instance, when air humidity remains constant, the time needed for a 90% virus decay increases from 11.5 min to 19.5 min when temperature decreases from 30°C

to 10°C. Under constant temperature, the decay rate increases from $0.6 \pm 0.6\%$ to $1.5 \pm 0.5\%$ with increased relative humidity from 20% to 70%. Bazant et al. [78] indicated air humidity can affect the drop size distributions. Thus, despite the influence on virus infectivity, relative humidity can affect the deposition rate, since the deposition rate is relevant to the virus radius. Building HVAC systems, as a primary means to regulate the indoor environment, is essential for the control of indoor disease transmission.

The HVAC sector is a significant contributor to energy consumption. According to the Commercial Buildings Energy Consumption Survey, electricity and natural gas are the primary energy sources for commercial buildings, comprising 60% and 34% of energy consumption, respectively. In terms of expenditure, commercial buildings allocated $119 billion for electricity and $16 billion for natural gas to fulfill their energy needs [79]. Growth in population, increasing demand for building services and occupant comfort levels, and the increased time spent in buildings will continue to increase the energy demand. Thus, improving the energy-saving efficiency of HVAC systems is an essential objective for the building operation. HVAC energy demand is directly related to the building configuration, local climate, and the indoor environment status such as internal loads and temperature setpoint [80]. Appropriate operations can reduce energy use while maintaining a satisfactory thermal sensation and a healthy environment. However, currently, there is a lack of study that quantitively illustrates the relationships among the above three important aspects of the indoor environment. Therefore, this chapter aimed to find the relationships and investigate the tradeoff among health, energy, and thermal comfort. The tradeoff exists due to the assumable inverse relationships among variables.

For example, mitigation strategies such as improved ventilation can be adopted by the operation of HVAC systems to reduce infection risks, which may lead to increased energy consumption and dissatisfied thermal sensation. As stated above, there is a tradeoff among the important aspects of school operations during the pandemic.

Existing studies have developed various models to analyze health, energy consumption, and thermal comfort in the built environment, while the tradeoff among the three aspects considering mutual-related parameters remains elusive. Two significant knowledge gaps exist in this area. The first knowledge gap is the lack of a systematic framework to investigate the influential parameters in the models of health, energy, and thermal comfort, as the linkage between these models remains elusive without consideration of mutual-related parameters. The second knowledge gap is the absence of reliable quantitative analysis for the three major aspects during the pandemic simultaneously. This is due to three primary reasons. The first reason is the unclear impact of HVAC-controlled environment factors on these models. The COVID-19 pandemic has significantly changed the requirement for the indoor environment with the consideration of the health aspect. However, the lack of real data on all the control factors and concerned aspects is a major challenge for the tradeoff analysis. In addition, current studies tend to use constants to represent the environment factors for infection estimation [3–5]. However, the actual values of the environment factors are dynamic in terms of the HVAC settings. Second is the ignorance of the impact of occupancy settings on the infection risk. Studies tend to assume a closed space without occupancy variation during the estimating period when computing the infection risks [6–8]. This simplification in occupancy will lead to

inaccuracies in the evaluation of energy and thermal sensation. Third is the ignorance of climate characteristics for the tradeoff analysis. The lack of utilization of school and climate data and the absence of a systematic framework that links the models of health, energy, and thermal comfort holds back detailed and quantitative tradeoff analysis.

To close these knowledge gaps, this chapter proposes to develop a convergent framework to perform the tradeoff analysis of energy, health, and thermal comfort in the school building operation. The framework considers the impacts of various room-level control methods, including temperature, ventilation, and humidity control, on the three important aspects. Additionally, this study provides insights into how different environment factors affect health, energy consumption, and thermal comfort for buildings located in different climate zones and demonstrates the tradeoff between these aspects. The predicted results of the three major aspects are estimated based on the set values of different environment factors, and the simulation results are used as a reference to illustrate the tradeoff based on the priorities of health, cost, or comfort as determined by the facility management team. The contributions of this study are two-fold. Firstly, this research proposed a new convergent framework to computationally link models of health, energy consumption, and thermal comfort in built environments with the identification and modeling of influential and related parameters. The HVAC-controlled indoor environment and related implications of health, energy, and comfort outcomes of our proposed framework are expected to present new paradigms in sustainable building environment assessment. Secondly, this chapter quantitatively analyzed the influence of indoor environment modifications on energy consumption, infection risks, and thermal sensation

in schools during the COVID-19 pandemic. Using school data, this research conducted simulations to reveal new insights regarding the trade-offs among health, energy, and thermal comfort under various control strategies and climate characteristics.

3.2 Literature review

3.2.1 Impacts of indoor environment on transmission mechanisms

Traditionally, it was believed that respiratory pathogens spread mainly through large droplets produced by coughing or sneezing, or through contact with contaminated surfaces (fomites). However, studies have shown that several respiratory pathogens, including measles [81], influenza [82], severe acute respiratory syndrome coronavirus (SARS-CoV) [83], and SARS-CoV-2 [84,85], can spread through small respiratory aerosols. These aerosols can remain suspended in the air for extended periods and travel long distances. Respiratory aerosols are small droplets that are formed when people exhale during activities such as breathing, talking, and coughing, and these droplets can dry out partially, becoming aerosols that can transmit pathogens. Studies have shown that the concentration of infectious viruses is enriched in small particles with sizes smaller than 5 μm [86]. Such small aerosol particles are the main concern of airborne transmission, and the World Health Organization (WHO) and the US Centers for Disease Control and Prevention (CDC) have acknowledged that the inhalation of infectious aerosols is the primary transmission mode of COVID-19 [23,87].

The transmission and persistence of infectious aerosols in the air are influenced by both the virus characteristics and environmental conditions. Aerosol particle size changes

over time due to processes such as evaporation, coagulation, and deposition, impacting virus viability and transmission. Larger particles tend to deposit to the ground faster than smaller ones, with particles of 5 μm taking approximately 33 minutes to deposit from a height of 1.5 m, while those of 1 μm can take over 12 hours to deposit [86]. The travel distance of aerosols in indoor environments is influenced by the particle size, the initial velocity induced by various respiratory activities, and the environment factors, such as the room air velocity, controlled by natural or mechanical ventilation [88]. Furthermore, environment factors can significantly affect the decay mechanisms in aerosols. Temperature plays a critical role in virus persistence and transmission by influencing the stability of the composition of viruses such as proteins and lipids. Several respiratory viruses that tend to infect the upper airways in the respiratory tract such as influenza and SARS-CoV-2 are more stable in environments with lower temperatures [89,90]. Relative humidity affects the survival of viruses in the air through the evaporation process. Once the infectious aerosols are exhaled from the respiratory tract with the saturated conditions to the ambient environment, the aerosols begin to evaporate due to the decrease in relative humidity [91]. The sensitivity of virus persistence to the relative humidity is determined by both the characteristics of the virus and the ambient environment [86]. For instance, influenza A viruses are reported to remain active over a wide range of relative humidity [92], while influenza viruses prefer environments with low relative humidity [93]. Given the substantial influence of environment factors on virus properties, assuming a constant environmental condition could potentially result in an erroneous estimation of virus transmission.

3.2.2 Energy and thermal comfort

The environment factors are essential for occupant thermal comfort. Achieving thermal comfort is vital for human well-being, satisfaction, and performance, and is an essential consideration in building design and operation [94]. To estimate occupant thermal comfort, the most popular model was proposed by P.O. Fanger [95]. The model takes into account all the thermal factors in the environment to predict thermal comfort, expressed as the largest possible percentage of a given group of people. The predicted mean vote (PMV) model has become an internationally recognized tool for estimating the predicted mean thermal perception of occupants. According to Fanger's definition, PMV is the index that indicates the mean thermal sensation vote for any combinations of thermal factors, human activities, and clothing levels for a large group of people. The results of the PMV model are demonstrated by the ASHRAE 7-point thermal sensation scale, which ranges from "cold" to "hot," with results ranging from -3 to +3 [96]. The PMV index can be computed using Equation 3-1, where M is the metabolic rate, and L is the thermal load defined as the difference between the human internal heat production and the heat loss to the environment due to evaporation.

$$PMV = (0.303\, e^{-0.036M} + 0.028)\, L \tag{3-1}$$

Human thermal comfort perception is significantly impacted by indoor air temperature, which, if not set appropriately, can lead to negative effects such as low performance and health problems such as shivering, inattentiveness, and muscular tension [97]. The relative humidity level is also related to indoor thermal comfort. Inadequate air humidity levels can cause dry skin and throat irritation. A recent study has indicated that a

low-humidity environment can significantly increase the degree of fatigue in undergraduate students compared to a high-humidity environment [98]. Additionally, different ventilation modes can affect thermal comfort. Fan et al. [99] reported that various non-uniform ventilation modes can decrease the floor-to-ceiling temperature difference and increase thermal comfort by 45%. However, unsteady ventilation modes may result in lower thermal comfort levels.

The principal objective of HVAC systems is to uphold thermal comfort, which necessitates energy consumption for heating and cooling purposes. Energy consumption is largely influenced by both external weather conditions (e.g., outside air temperature, relative humidity, and wind characteristics) and internal conditions (e.g., occupancy, heat flow, and moisture flow). HVAC systems regulate indoor air temperature and moisture levels to maintain them within desired thresholds [100]. During the pandemic, the need for increased room ventilation leads to a further increase in building energy demand.

3.2.3 Studies for tradeoff relationships

Several recent researches have investigated the tradeoffs between energy consumption, infection risks, and thermal comfort. Mokhtari et al. [101] examined the effect of occupant distribution on energy consumption and COVID-19 infections using a university building, and the optimal occupant distribution pattern was found to reduce the number of infectors and building energy consumption. Jung et al. [102] demonstrated the potential for energy efficiency gains by integrating personal thermal comfort models into building operational conditions. Risbeck et al. [103] proposed dynamical optimization

models to estimate indoor airborne transmission risk and building energy consumption based on HVAC controller setpoints and a weather forecast. They found that infection risk and energy-efficient disinfection measures varied significantly across different spaces and were heavily dependent on the season. Guo et al. [104] developed a quantitative model to balance infection risk and energy consumption, resulting in a 13.7% reduction in energy consumption on weekdays and 45.1% on weekends when considering the combined effects of multiple mitigation measures. However, there lack the studies that analyze the tradeoff for all three major aspects (e.g., infection risk, energy consumption, and thermal comfort), and the tradeoff analysis over different climate zones remains elusive.

3.3 Methodology

The proposed framework consists of three phases: preparation, simulation, and tradeoff analysis, as illustrated in Figure 3-1. During the preparation phase, U.S. school data was gathered and prepared for both simulation and risk modeling, and building models were edited to incorporate energy and thermal comfort simulation. The selection of weather data is contingent on the climate zone in which the building is situated. The simulation phase involved utilizing the simulation methods to produce energy and comfort-related outcomes, as well as incorporating disease data of the SARS-CoV-2 virus into risk models to simulate infection risk outcomes. The tradeoff analysis phase analyzed the outcomes generated by the simulation models and compared them to explain the observed phenomenon. The methodology utilized quantitative analysis and simulation to obtain a comprehensive understanding of the tradeoff between infection risk, energy consumption, and thermal comfort in U.S. schools.

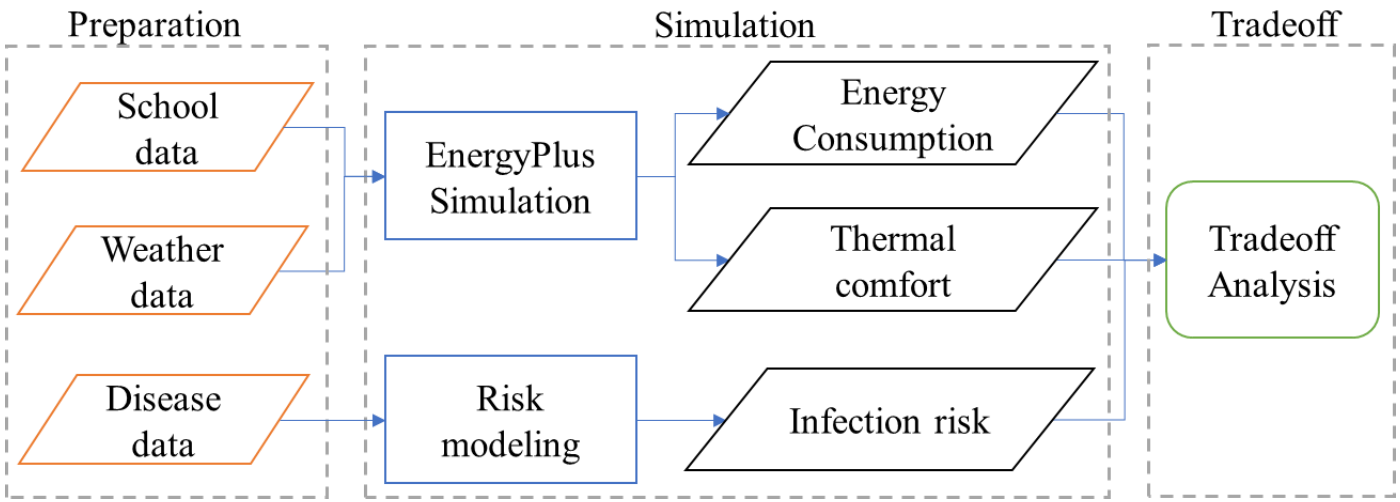


Figure 3-1 Framework of research methodolog

3.3.1 Data and model preparation

In this chapter, a reference building model of a primary school, developed by the Department of Energy (DOE) [105], was used for simulation. DOE has developed 16 baseline building models, which represent approximately 70% of the US commercial building stock. The reference building model used in this study was derived from one of the commercial prototype buildings and was modified based on Standard 90.1 and International Energy Conservation Code (IECC) evolve [106]. The weather data for the 16 climate zones corresponding to the building models were utilized respectively. The zone-specified parameters such as zone area, height, and infiltration were retrieved from the building model as inputs for risk assessment. The disease data, such as the epidemiological parameters of COVID-19 were obtained from relevant literature to compute the infection risks.

3.3.2 Simulation

The simulation methodology encompasses three aspects: 1) environment modeling, i.e., physics-based building modeling with indoor environment control; 2) occupancy/human modeling, i.e., setting occupancy and operation schedules, which is used as inputs to the risk model; 3) Health modeling, including the estimation of viral-specific parameters (e.g., viral decay rate, viral deposition rate, and viral removal rate) and local prevalence. The simulation for energy consumption and thermal comfort is based on environment modeling and occupancy/human modeling, and the simulation for infection risk relies on health modeling. The simulation outcomes obtained under various settings of

environment variables will be utilized for tradeoff analysis, whereby the tradeoff relationship is represented by blue circular arrows. Figure 3-2 illustrates the data processing and simulation methodology.

3.3.2.1 Simulation of energy and thermal comfort

EnergyPlus was used to estimate building energy consumption and thermal comfort. Ventilation rate, relative humidity level, and temperature were the three focused environment factors in this study, which were controlled as needed in the simulation. These three factors are identified as the key influential variables for thermal comfort, energy, and health [101,107]. Besides the settings relevant to the control of environment factors, the default settings of the reference building model were applied for energy and thermal comfort simulation.

The building model used in this study is a single-story building structure consisting of 25 zones, including a bathroom, a cafeteria, a computer laboratory, corridors, a gymnasium, a kitchen, a library, a lobby, a mechanical room, offices, and classrooms classified into four distinct types. The building features steel-framed exterior walls and roofs insulated entirely above deck (IEAD) with non-residential insulation. The window-to-wall ratio is 0.35, and the overall total floor area is 6871 m^2. Figure 3-3 shows the 3-D geometry of the reference building model. The building employs both gas and electricity as its primary fuel sources. The HVAC system for the reference model employs both constant air volume (CAV) and variable air volume (VAV) systems, depending on the functionality of the building zones.

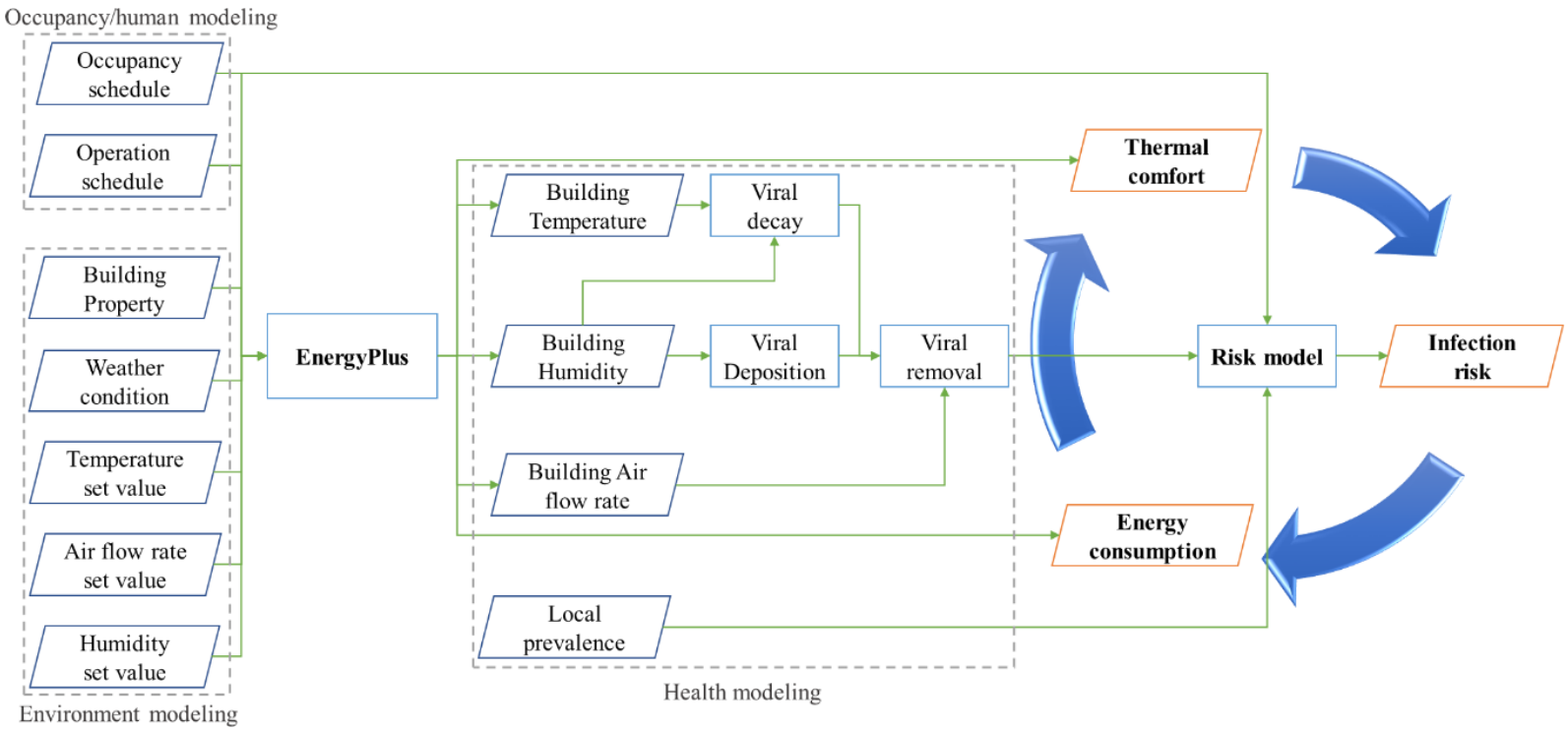


Figure 3-2 Data processing and simulation methodology for tradeoff analysis.

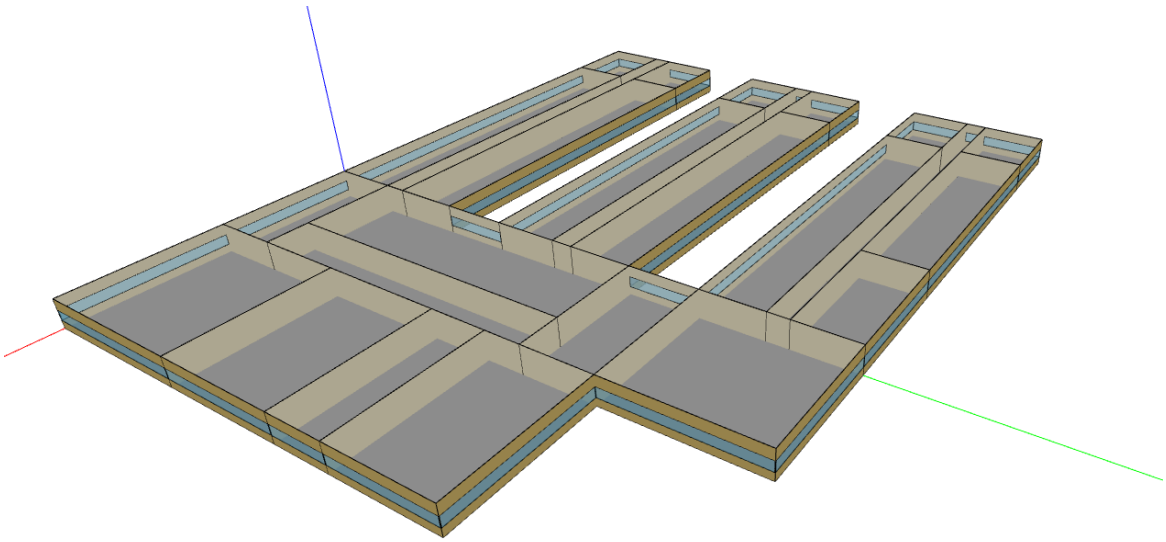


Figure 3-3 3-D geometry of the reference building model [105].

The heating system utilizes both gas boilers and gas furnaces, while the cooling system is a packaged air conditioning unit (PACU). Further details of the DOE reference model are presented in Table 3-1, where the key parameters that vary across different climate zones are summarized. HVAC sizing, HVAC efficiency, and fan maximum flow rate vary according to building zone and climate zone. The values presented in the table represent the range retrieved from all zones in the building that correspond to the given climate zones. The table also outlines the installation of economizers. Other key parameters, such as building infiltration, lighting density, appliance density, occupancy fraction, and economizer maximum limit dry bulb temperature, remain constant across all climate zones, with values of 0.00133 $m^3/s * m^2$, 9.68–21.52 W/m^2, 4–25.29 W/m^2, 0–0.95, and 28°C, respectively. In order to manipulate environmental conditions, the minimum ventilation rate of each room can be adjusted to regulate room ventilation rates. For humidity control, the original HVAC system of the reference building model cannot adjust the level of relative humidity in each room. Our simulation incorporated the addition of humidifiers and dehumidifiers to the HVAC system to facilitate indoor air humidity control. The humidifiers are electrically heated, self-contained steam humidifiers. Each humidifier was set to provide at most $4 * 10^{-5}\ m^3/s$ water flow rate to humidify the room air [108]. The dehumidifiers were conventional mechanical dehumidifiers. This system uses a direct expansion cooling coil to cool and dehumidify the airstream. Default settings of this equipment were utilized, with the ability to dehumidify airstreams ranging from 10°F to 95°F.

Table 3-1 Key parameters of the DOE reference model in different climate zones [105].

Climate zone	1A	2A	2B	3A	3B-CA	3B	3C	4A
R-value (exterior walls)	0.32	1.17	0.73	1.36	0.80	1.10	1.36	1.98
R-value (roof)	2.38	2.67	3.83	2.44	1.76	3.66	2.00	3.03
AC (kW)	[20.62, 204.32]	[17.59, 170.31]	[16.45, 157.70]	[18.00, 169.11]	[19.83, 150.77]	[14.52, 133.12]	[20.68, 151.32]	[15.54, 138.26]
Heating (kW)	[32.15, 440.67]	[36.20, 451.59]	[28.57, 363.53]	[39.97, 472.75]	[32.16, 442.62]	[27.26, 351.00]	[47.24, 534.37]	[38.42, 433.08]
AC (COP)	3.23, 3.3 3.5	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3 3.5	3.23, 3.3, 3.5, 3.67	3.23, 3.3 3.5	3.23, 3.3, 3.5, 3.67
Economizer	-	-	- / Diff dry bulb	-	Diff dry bulb	- / Diff dry bulb	Diff dry bulb	-
Fan max flow	[0.2, 8.23]	[0.2, 6.86]	[0.2, 6.35]	[0.20, 6.9]	[0.20, 8.02]	[0.20, 5.82]	[0.20, 9.04]	[0.20, 5.57]
Climate zone	4B	4C	5A	5B	6A	6B	7	8
R-value (exterior walls)	1.76	1.92	2.15	2.15	2.71	2.44	3.04	3.91
R-value (roof)	2.99	2.75	3.38	3.51	3.97	3.65	4.41	5.75
AC (kW)	[14.40, 97.58]	[11.59, 99.88]	[14.99, 129.43]	[12.99, 85.08]	[14.17, 114.16]	[10.37, 85.44]	[12.23, 116.09]	[8.14, 93.38]
Heating (kW)	[30.46, 347.96]	[27.77, 376.05]	[43.29, 467.19]	[32.51, 336.32]	[44.22, 439.91]	[36.90, 414.54]	[39.05, 433.79]	[48.31, 663.20]
AC (COP)	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67	3.23, 3.3, 3.5, 3.67
Economizer	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb	- / Diff dry bulb
Fan max flow	[0.20, 5.52]	[0.20, 5.5]	[0.20, 5.21]	[0.20, 4.6]	[0.20, 4.6]	[0.20, 5.16]	[0.20, 4.68]	[0.20, 5.64]

Diff dry bulb: All zones in the reference building model are equipped with differential dry bulb economizers.
- / Diff dry bulb: Some zones are not equipped with economizers, while others have differential dry bulb economizers.
-: Economizer is not equipped in any of the zones of the reference building model.
The unit of R-value is m^2kW

The humidifiers were connected to each HVAC branch, with one humidifier allocated for each branch, while the dehumidifiers were positioned in each zone and connected to the zone's exhaust fan. The relative humidity level of each zone was detected by a humidistat and regulated by the humidity ratio setpoint. Economizers were installed in five of the seven HVAC branches. The HVAC system was set to operate from 6:00 to 21:00 during weekdays and to shut down at other times and on non-working days. With the implementation of specific controller settings of the indoor environment, the hourly room temperature, humidity, and air flow rate were simulated, which enabled the prediction of the building energy consumption and room thermal comfort.

3.3.2.2 Modeling of disease transmission

As stated in Chapter 2, the W-R equation can be used to estimate the indoor airborne transmission of an infectious agent using Equation 3-2 [32,33].

$$P_{infection} = 1 - e^{-\bar{\mu}} \tag{3-2}$$

Where $P_{infection}$ is the probability of a susceptible person being infected, and $\bar{\mu}$ is the number of quanta breathed by a susceptible person.

Azimi et al. [30] considered several school microenvironments or spaces and developed a model based on the W-R equation to estimate the transmission risk of infectious aerosols between students when one index case is present in the school. The average number of quanta inhaled by a susceptible student during a typical school day is estimated using Equation 3-3.

$$\bar{\mu} = \frac{1}{N_{total}} * \bar{p} * \sum_{i} \int_{0}^{\bar{t_i}} N_i(\tau) C_{quanta,i}(\tau) d\tau \quad (3\text{-}3)$$

i: Index of the spaces, which are classroom and common area.

N_{total}: Total number of students.

$N_i(\tau)$: Number of students in space i.

$\bar{p}$: Average inhalation rate (m^3/hour), set as 10.59 m^3/day according to [55], which is estimated as the average breathing rate for students from 6 to 11 years.

$\bar{t_i}$: Average time students stay in space i.

$C_{quanta,i}(\tau)$: Concentration of quanta in space i, τ hours after the index case is present in space i (quanta/m^3).

$C_{quanta,i}(\tau)$ can be estimated using Equation 3-4 [30].

$$C_{quanta,\,i}(\tau) = \frac{Iq}{V_i K_{total,i}} (1 - e^{-K_{total,i}\boldsymbol{\tau}}) \quad (3\text{-}4)$$

I: Number of infectors

q: quanta generation rate (quanta/hour)

V_i: Volume of space i (m^3)

$K_{total,i}$: Total removal rate of infectious viruses in space i (per hour), and is computed using Equation 4-5.

$$K_{total,i} = \lambda_{infiltration,i} + \lambda_{ventilation,i} + k_{deposition} + k_{decay} \quad (4\text{-}5)$$

$\lambda_{infiltration,i}$: Natural ventilation rate or infiltration air exchange rate in space i (per hour).

$\lambda_{ventilation,i}$: Mechanical ventilation rate of the HVAC system in space i (per hour).

$k_{deposition}$: Deposition rate of infectious particles in space i (per hour). The viral deposition rate is computed based on the radius of the infectious particles, which is varied according to the room relative humidity, and can be calculated using Equation 4-6 and Equation 4-7 [78].

k_{decay}: decay rate for viral infectivity in space i (per hour).

$$r = r_0 * \sqrt[3]{0.4/(1 - RH)} \tag{4-6}$$

$$k_{deposition} = 2\Delta\rho g r^2/(9\mu_a H) \tag{4-7}$$

The viral decay rate can be estimated by a series of empirical equations related to relative humidity and temperature, which is shown in Equation 4-8 to 4-13 [109].

$$k_{decay} = 16.9803 + 0.0622E_s - 0.796p_v - 21.95V_s \tag{4-8}$$

$$E_s = (1.007T - 0.026) + C_m(2501 + 1.84T) \tag{4-9}$$

$$p_v = \frac{RH * p_s}{100} \tag{4-10}$$

$$V_s = (0.287 + 0.461C_m)(\frac{273.15 + T}{p_b}) \tag{4-11}$$

$$C_m = \frac{0.622p_v}{p_b - p_v} \tag{4-12}$$

$$p_s = 0.61078e^{\frac{17.2694T}{T+237.99}} \tag{4-13}$$

Where T is the room air temperature (°C), RH is room relative humidity, E_s represents specific enthalpy (kJ/kg), p_v is the vapor pressure (kPa), p_s is the saturated vapor pressure (kPa), V_s is the specific volume per kilogram of dry air (m^3/kg), C_m is the moisture content, and p_b is the barometric pressure (101.325 kPa).

For the school buildings, the occupancy schedule specifies the hourly occupancy for each room. In addition, the indoor environment such as temperature, humidity, and air flow rate, is subject to continuous changes over time for each room. In this chapter, to

account for the time-dependent parameters, the value of μ was calculated with 1-hour time step. $\mu(t)$ indicates the number of quanta breathed by a susceptible student from time t to $t+1$, and is estimated using Equation 4-14. This equation assumes that the quanta generated before time t are all inhaled by susceptible hosts.

$$\mu(t) = \frac{1}{N_{total}(t)} \times \bar{p} \times \sum_i (N_i(t) \int_t^{t+1} C_{quanta,i}(t,\tau)\, d\tau) \quad (4\text{-}14)$$

$$C_{quanta}(t) = \frac{I_i(t)q}{VK_{total,i}(t)}\left(1 - e^{-K_{total,i}(t)}\right) \quad (4\text{-}15)$$

$$K_{total,i}(t) = \lambda_{infiltration,i}(t) + \lambda_{ventilation,i}(t) + k_{deposition}(t) + k_{decay}(t) \quad (4\text{-}16)$$

t: Time step with step size of one hour from t_0. $t \in t_0, t_0+1, \ldots, t_n - 1$. t_n is the end of operation hour.

$N_{total}(t)$: Total number of students in schools at time t. $N_{total}(t) = \sum_i N_i(t)$.

$N_i(t)$: Number of students in space i at time step t, which is achieved from room occupancy schedule.

$I_i(t)$: Number of index cases at time step t in space i, and can be estimated using Equation 4-17.

$$I_i(t) = IR * N_i(t) \quad (4\text{-}17)$$

$\lambda_{infiltration,i}(t)$: Natural air ventilation rate or infiltration air exchange rate in space i (per hour), retrieved from the EnergyPlus model.

$\lambda_{ventilation,i}(t)$: Mechanical ventilation rate of the HVAC system in space i (per hour), retrieved from the simulation result of the hourly room air flow rate.

$k_{deposition}(t)$: Deposition rate of infectious particles in space i (per hour), which is computed based on the room air relative humidity retrieved from the hourly simulation result.

$k_{decay}(t)$: decay rate for viral infectivity in space i (per hour), which is computed based on the room temperature and relative humidity retrieved from the hourly simulation result.

q: quanta generation rate, set as 142 $quanta/h$ according to the study conducted by Buonanno et al. [3].

V_i: Volume of space i (m^3)

$K_{total,i}(t)$: Total removal rate of infectious viruses in space i at time t (per hour).

IR: Local infection rate (%), assumed to be 5% in this chapter.

The average infection risk for a student staying in the school for an hour is calculated using Equation 4-18. *P* is the infection risk for a typical school day, and is calculated using Equation 4-19.

$$\mu_n = \sum_{t=t_0}^{t_n-1} \mu(t) \tag{4-18}$$

$$P = 1 - e^{-\mu_n} \tag{4-19}$$

μ_n indicates the total number of quanta breathed by a susceptible student during a typical school day. *P* is the infection risk of a typical school day.

3.3.3 Tradeoff analysis

To perform the tradeoff analysis, different sets of environment parameters were identified and evaluated to aid school facility managers in decision making for HVAC operation. For temperature control, the thermostat placed in each room regulates the

heating and cooling setpoints. In the simulation, five groups of cooling and heating setpoints were adopted, including [24℃, 24℃], [25℃, 23℃], [26℃, 22℃], [27℃, 21℃], and [28℃, 20℃]. The increased differences between cooling and heating setpoints were set to ensure the workload of the HVAC system decreasing both in winter and summertime, and to better understand the relationship between thermal comfort and energy use. Therefore, the cooling setpoint should increase while the heating setpoint should decrease simultaneously. For humidity control, the ranges of the set values were specified to define the minimum and maximum values of the room relative humidity, and were regulated via the humidistat in each room. Four humidity ranges were used, which were [30%, 40%], [40%, 50%], [50%, 60%], and [60%, 70%], since the indoor comfort range is typically between 30% and 60% relative humidity. Furthermore, relative humidity in northern U.S. cities is approximately 30%, while in southern cities it can reach 70% [110]. For ventilation control, the set values were identified as the designed minimum outdoor air flow rate in each room. Four values of the ventilation rate were considered: 2 air changes per hour (ACH), 4 ACH, 6 ACH, and 8 ACH. Research indicates that the average air change rate in U.S. school classrooms is 2 ACH [54], and during the pandemic, the classroom ventilation rate should be increased according to CDC instructions [111]. In total, 80 combinations of set values (5 temperature set values × 4 humidity set values × 4 ventilation set values) were generated, resulting in 80 simulation runs for analysis.

The simulation process leverages EnergyPlus to model indoor dynamics and PMV values in the hourly resolution and annual building energy consumption based on the building and environment configurations. The annual average values for each environment

factor were computed as the average of the hourly results. For thermal comfort, the predicted mean vote (PMV) model was used, with PMV indexes ranging from -3 to +3, representing cold to hot thermal sensations on the ASHRAE thermal sense scale. Neutral thermal conditions are achieved at a PMV index of 0. In this study, the annual average result for thermal comfort was computed as the average of the absolute value of the hourly results, considering the consequences of both the positive and negative values of the PMV index. The trade-off analysis considered annual building energy consumption, annual average thermal comfort, and infection risks on a typical school day within the year.

To simulate infection risks, the number of quanta inhaled by a susceptible individual during a typical school day was computed, with details provided in Section 3.3.2.2 and illustrated in Figure 3-2. This calculation was performed using a 1-hour time step, taking into account the school population, occupancy schedule, and simulated hourly results of the environment factors. Specifically, the number of infectors was estimated based on occupancy schedule and local epidemic prevalence; The virus total removal rate was estimated based on hourly result values of the environment factors, including the room temperature, humidity, and ventilation, which affect the viral decay, deposition and decay, and removal rates, respectively. The total number of quanta inhaled by a susceptible student during a school day was determined by summing the hourly breathed quanta, and the infection risk of a typical school day was estimated based on the total quanta inhalation.

To conclude, in the tradeoff analysis, temperature, humidity, and air flow rate are the variables representing different indoor environments. The three aspects of consideration, i.e., energy consumption, infection risk, and occupant thermal comfort were

simulated based on set values of the three environment factors. The tradeoff analysis is presented at the building level with the averaged modeling results over all building zones.

3.4 Results

In this chapter, simulations were conducted to model building energy consumption, thermal comfort, and infection risks using building reference models representative of their respective climate zones. The results show that the general tradeoff patterns between the three aspects and the relationships between the aspects and environment factors are similar. Therefore, in Sections 3.4.1 and 3.4.2, the simulation of a building located in climate zone 5A with a cool and humid climate was chosen as a representative case to illustrate the result of the tradeoff analysis. The reason for selecting climate zone 5A was its extensive geographic coverage, as well as its recognized status as a representative of a typical climate within the United States.

3.4.1 Influence of environment factors

This study involved specifying different set values for the room air flow rate, humidity, and temperature as environment factors, resulting in 80 simulation runs and corresponding simulation results of health, energy consumption, and thermal comfort sensation. The results of the three aspects are annual building energy consumption, average daily infection risk, and average occupant thermal comfort for a year. The relationships between the environment factors and the three aspects are shown in Figure 3-4. Specifically, figure 3-4(a-c) demonstrate the impact of temperature set values on the infection risk, building energy, and thermal comfort, respectively. Likewise, Figure 3-4(d-

f) depict the impact of air flow rate, and Figure 3-4(g-i) demonstrate the impact of humidity. The results indicate that lowering cooling setpoints leads to a decrease in infection risks, as the increased cooling load of the HVAC system could lead to an increase in economizer operation. Since the economizer introduces a massive amount of outdoor air, it is advantageous in reducing infection risks. Furthermore, an increase in the differences between heating and cooling setpoints results in decreased building energy consumption due to the decrease in both heating and cooling load. Temperature setpoints also significantly impact thermal comfort sensation, with an increase in temperature deviation from neutral temperature resulting in higher PMV values, indicating greater dissatisfaction with the thermal environment. A linear relationship between air flow rate and infection risk was observed, as increased ventilation leads to the dilution of indoor air and a subsequent decrease in infection risk. In addition, increased ventilation leads to increased energy consumption, with a near-linear relationship between ventilation and building energy consumption. The impact of air flow rate on thermal comfort was found to be minor. Finally, the effects of air humidity on the three aspects were found to be insignificant for this climate zone.

Figure 3-4(a-c) utilized color schemes to identify the distinct effects of environment factors. It can be inferred that, holding the air flow rate constant, decreasing cooling setpoints results in an increase in infection risks and a decrease in energy consumption. Similarly, at constant temperature setpoints, an increase in air flow rate is correlated with a reduction in infection risks and increased energy use. Temperature setpoints are the

dominant factor in determining thermal comfort, while the impact of ventilation and humidity is minimal.

3.4.2 Tradeoff analysis

The tradeoff was analyzed based on the 80 simulation runs of the three aspects, and is illustrated in Figure 3-5, which presents a 3-dimensional view of the relationship between the three aspects and the 2-dimensional representations between each two aspects, as shown in Figures 3-5(b-d). The color of each point in the figures represents the value of the other aspect, with darker colors indicating smaller values. The results demonstrate that there are tradeoffs between energy consumption and thermal comfort, and between infection risk and thermal comfort. The detailed relations are shown in Figure 3-6.

There is a near-linear relationship between energy consumption and PMV values, indicating that increased energy consumption leads to improved thermal comfort. In addition, a near-linear relationship is observed between decreased infection risk and increased thermal satisfaction for the same room ventilation rate. The increased deviation from neutral temperature will lead to reduced operating hours of HVAC and more a dissatisfied environment for occupants. The tradeoff between infection risk and energy consumption is shown to be nearly linear, as increasing the air flow rate to decrease infection risk also increases energy consumption. Therefore, increased energy consumption can lead to reduced infection risk and improved thermal comfort simultaneously.

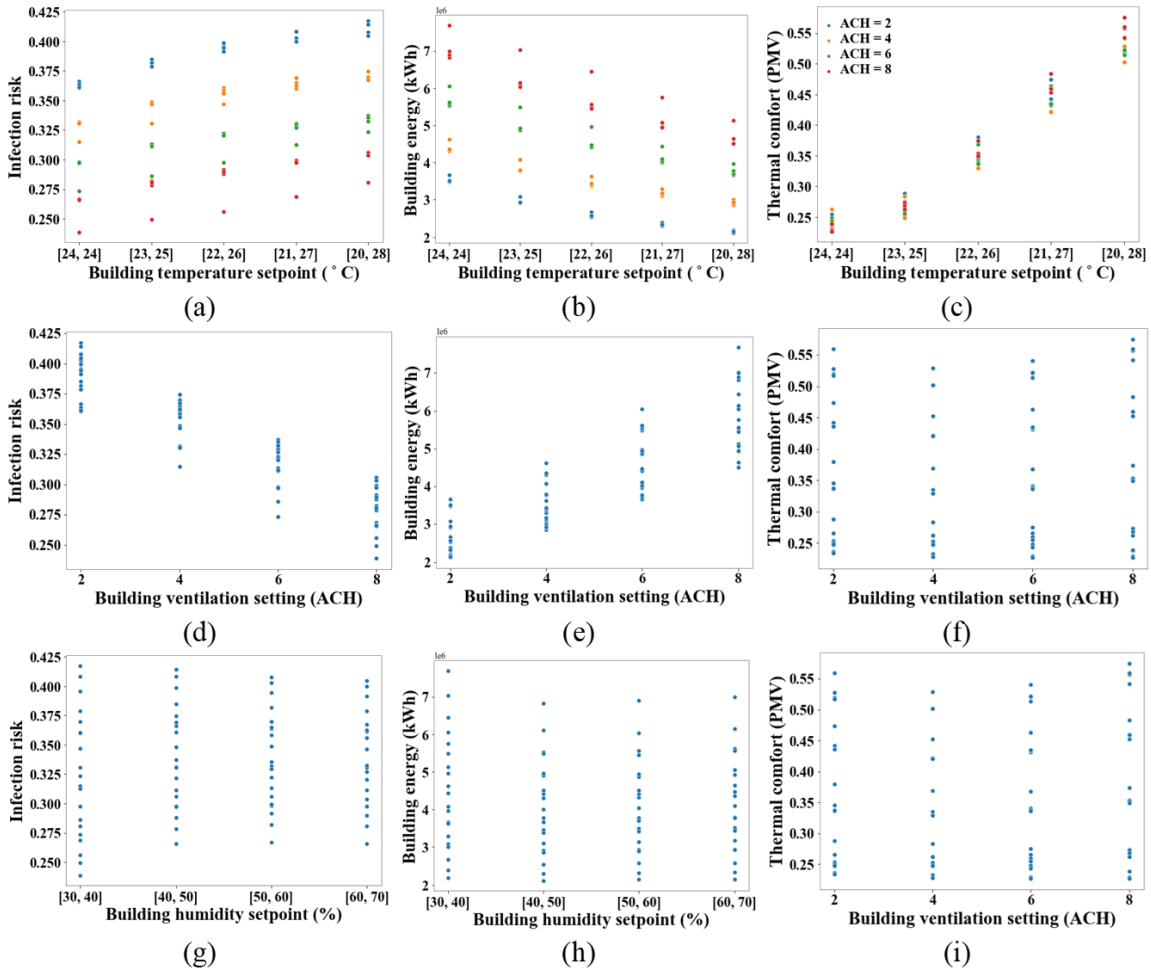


Figure 3-4 The impact of environment factors on energy consumption, infection risk, and thermal comfort.

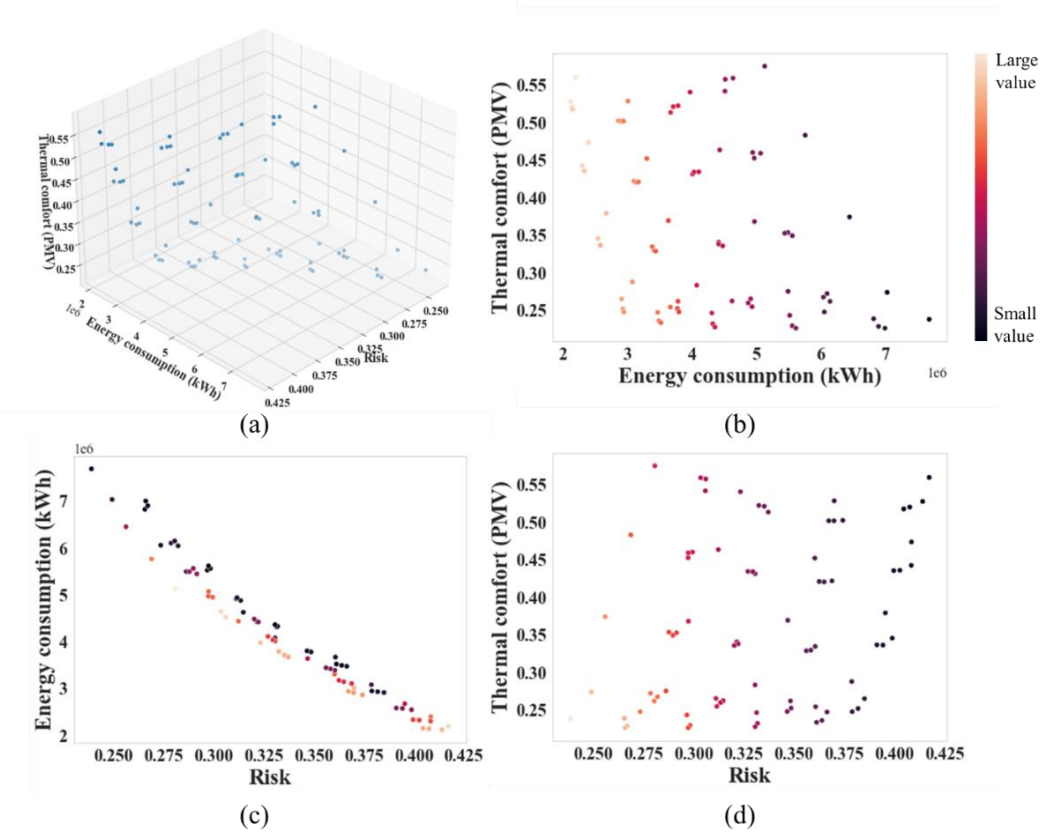


Figure 3-5 Tradeoff among energy consumption, infection risk, and thermal comfort.

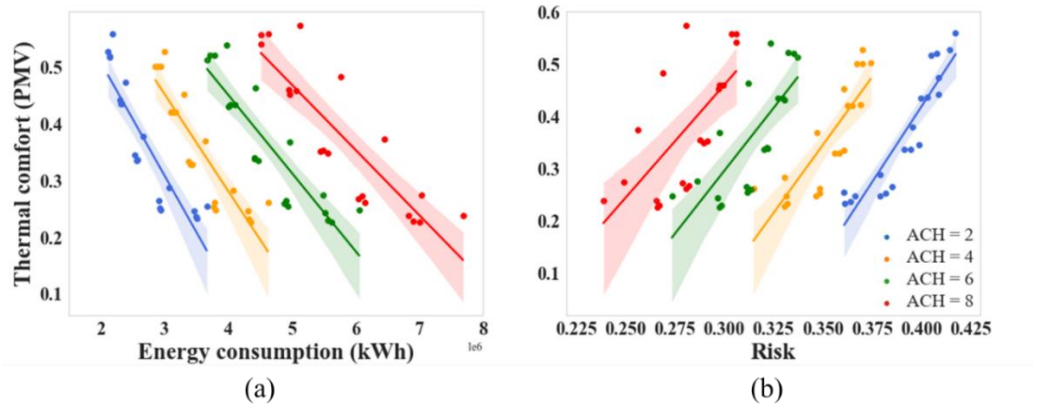


Figure 3-6 (a). The relationship between building energy consumption and thermal comfort with controlled ventilation. (b). The relationship between infection risk and thermal comfort with controlled ventilation.

3.4.3 Analysis for buildings in different climate zones

A nationwide assessment of energy, risk, and thermal comfort was conducted to analyze the impact of climate characteristics on buildings across the U.S. The findings indicate that the overall tradeoff patterns and the relationships between environment factors and the concerned aspects are similar for buildings located in different climate zones under most circumstances. The results suggest that an increase in building energy consumption can lead to improved thermal sensation and reduced infection risks. However, the simulated outcomes of the three aspects vary significantly across different climate zones. Figure 3-7 displays the distributions of the average values of infection risks, building energy consumption, and thermal comfort with different set values of environment factors in the climate zones. The median values presented in the boxplots provide an intuitive illustration of the impact of climate on the three aspects, and the variation in the simulated results indicates the influence of different set values of environment factors.

Regarding energy consumption, buildings located in cold climates tend to consume more energy, and the range of simulated energy consumption is larger compared with those in warm climates. For instance, the energy consumption in zone 1A is less than half of that in zone 7, and the range of the energy consumption in zone 1A is reduced by 36% compared to zone 7. In subarctic climates, the annual median energy consumption and the corresponding range reach the highest values over all climate zones. In warm climates, the heating and cooling load are usually mild due to the small difference between indoor and outdoor environment. Hence, changing setpoints will not produce discernible influences on energy consumption, leading to smaller variances in energy use.

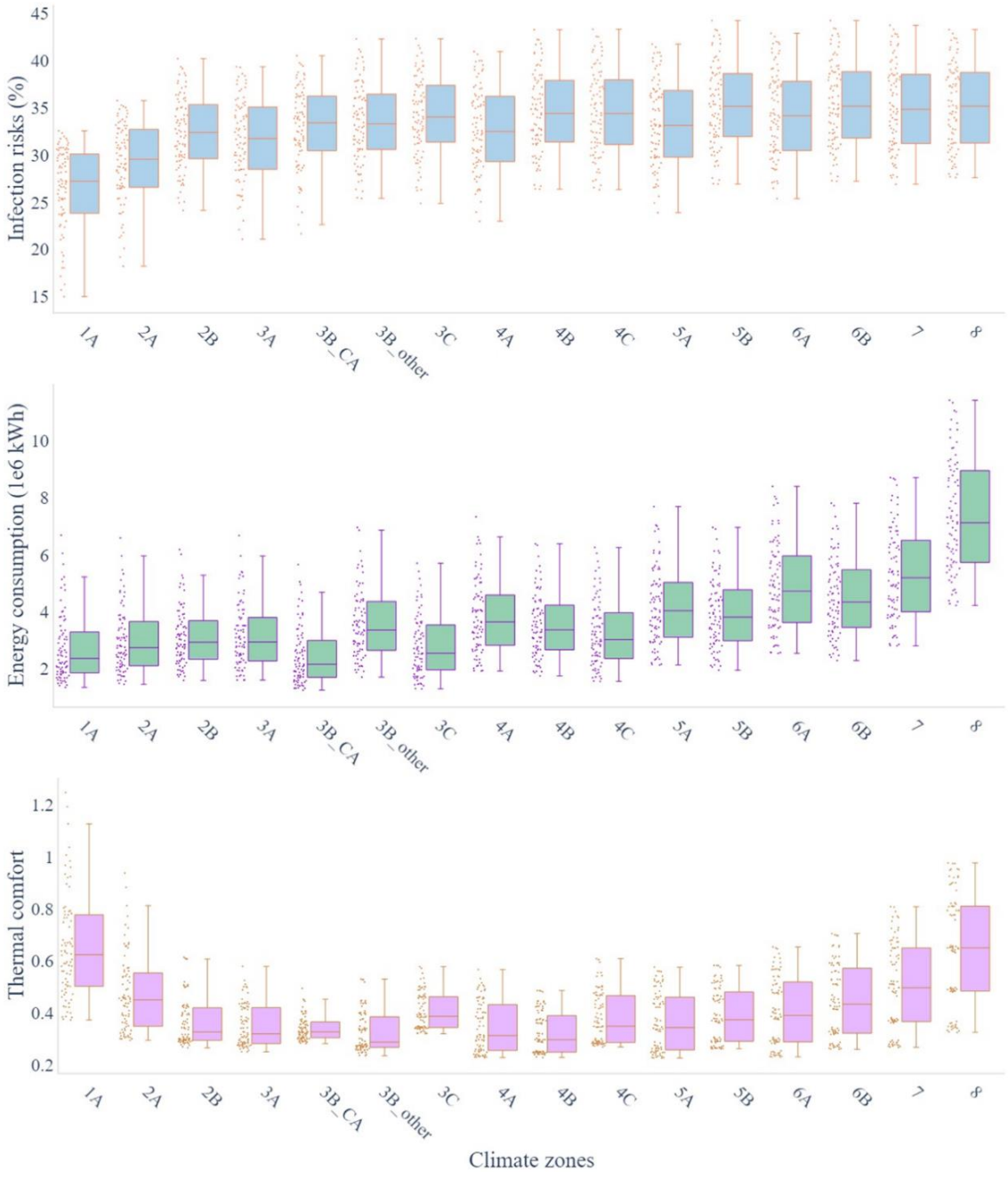


Figure 3-7 The distribution of infection risks, energy consumption, and thermal comfort in 16 climate zones.

While in colder climates with large temperature differences between indoor and outdoor environment, any decrease in the heating temperature setpoint will lead to an observable reduction in energy consumption. Hence, the variances of energy use in cold climates tend to be larger. For hot climate zones, the VAV system can help reduce energy consumption. Regarding thermal comfort, buildings in mild climate zones are more likely to achieve better thermal sensation than those in hot or cold climates. For instance, in zone 2A and zone 8, representing very hot and subarctic climates respectively, the median PMV values are around 0.63 and 0.65. Mixed climates like Zone 4A and 4B achieve satisfactory thermal sensation with a median value of 0.3. The spread of the data tends to decrease from extremely hot or cold climates to mild climates, indicating that although the deviation of the temperature setpoints increases, the indoor temperature remains around neutral temperature in mild climates. Improper indoor temperature settings are more likely to result in thermal dissatisfaction in hot or cold climates. As for infection risks, the median and variation of the simulated result values are not subject to change significantly across different climate zones. Room ventilation rate dominates this aspect compared with the other environment factors, which is not varied significantly over most climate zones. Consequently, infection risks do not vary significantly across different climate zones, except in very hot regions. Buildings in climate zone 1A exhibit the lowest infection risks due to higher ventilation rate associated with much longer cooling season and economizer operation hours that introduce a larger volume of outdoor air intake to dilute the infection virus. Generally, buildings in climate zone 1A require cooling almost all through the year, compared to limited summer cooling months in other climate zones (e.g., June to August

as the cooling season in climate zone 5A). With the setting of maximum limit dry bulb temperature of economizer operation in reference buildings, the economizer will diligently operate to introduce natural cooling from November to May in climate zone 1A when outdoor temperature falls in the appropriate operation range. While in other climate zones, the economizer are only active in summer months or shoulder seasons. Hence, the total economizer operation hours and ventilation rate are significantly larger in zone 1A than other climate zones.

The influence of humidity setpoints on energy consumption is negligible except for regions with high humidity levels, such as zone 1A. In these areas, energy consumption reduces with the increase of humidity setpoint. For instance, in zone 1A, the average annual energy consumption decreases by 49% when the humidity setpoint is raised from [30%, 40%] to [60%, 70%]. The prominent influence of humidity setpoint on HVAC energy use in zone 1A results from the extremely humid climate, where raising the humidity setpoint reduces the energy required for dehumidification.

3.5 Discussion

This study investigates the impact of various indoor environment factors on three critical aspects that are of concern for school management teams during the COVID-19 pandemic: building energy consumption, thermal comfort, and infection risks. To illustrate the tradeoff analysis and the interrelationships between environment factors and the aforementioned aspects, a representative building model of a primary school was employed. Furthermore, climate data from 16 different zones in the U.S. developed by the Department of Energy (DOE) were incorporated into the simulation to highlight the

influence of climate characteristics. By controlling the indoor environment, the study obtained the results of health, energy consumption, and thermal comfort sensation based on the building characteristics and climate data.

3.5.1 Impacts of environment factors

The results suggest that the environment factors have a certain degree of influence on the concerned factors. Room ventilation rate and temperature setpoints are identified as the two key factors that affect energy use in all climate zones, with room ventilation being the most significant factor. In most climate zones, humidity has minimal impact on building energy consumption, except for humid zones like 1A, where the energy use of dehumidifiers can be influential. To reduce infection risks, decreasing cooling temperature setpoints and increasing ventilation rates are effective measures. However, indoor temperature alone does not significantly affect infection risks. Lowering the cooling setpoint can increase the cooling load of the HVAC system and the operation hours of economizers to bring in more outdoor air for cooling purposes, thus influencing infection risks. Room ventilation rate dominates the changes in building infection risks and energy consumption, and both have near-linear and positive relationships. These findings align with recent studies that also indicate the significant impact of ventilation on the infection risks of SARS-CoV-2 [4,9,74]. The study further suggests that increased temperature deviation from the neutral temperature reduces thermal sensation satisfaction, and the influence of room ventilation on thermal sensation is minimal. This result conclusion is similar to the study proposed by Miranda et al. [107], who investigated the influence of

ventilation on thermal comfort in classrooms during COVID-19. The study concludes that room ventilation does not have a decisive influence on comfort when the temperature is above 12 ℃. The effect of room air relative humidity is not significant to infection risks and thermal sensation, which is consistent with the conclusions of other studies. For instance, Zuo et al. [112] indicated that the increase in relative humidity from 50% to 70% at 26 ℃ had trivial influences on physiological responses and thermal comfort.

3.5.2 Impact of considering health aspect on building operation

The COVID-19 pandemic has introduced health considerations as a new dimension to building operations, which are closely associated with thermal comfort and energy use. The study reveals a clear linear relationship between infection risks and energy consumption, which can be attributed to the dominant effect of room ventilation rate on both aspects. Moreover, a near-linear relationship between infection risks and thermal satisfaction is observed due to the working principle of VAV systems. Therefore, there are evident tradeoffs among the three dimensions, indicating that the lowest infection risk and optimal thermal sensation can be achieved by setting appropriate indoor conditions, such as utilizing the maximum ventilation rate and setting cooling and heating temperature setpoints to 24℃. The appropriate indoor temperature can achieve satisfactory thermal sensation based on the PMV model, while increasing energy consumption through reduced cooling setpoint and increased ventilation can both decrease the infection risk.

The ASHRAE 62.1-2019 standard regulated the minimum ventilation rate for classrooms as 10 cfm/person and 0.12 cfm/ft^2. According to the building characteristics

and occupancy schedule, the room minimum ventilation rate is between 0.54 ACH to 3.56 ACH for the prototype primary school building. During the pandemic, CDC encourages increasing room ventilation as much as possible [111], and according to the study conducted by Guo et al. [104], the requirements for fresh air ventilation rate ranges from 0.8 ACH to 5.75 ACH given the characteristics of the reference building. Taking zone 5A for example, the increase of ventilation rate by 1 ACH implies an increase in energy use by 19.7%. The implications of ventilation rate on energy use do not vary significantly across different climates.

3.5.3 Impact of climate characteristics on tradeoff relationships

According to the analysis based on the weather data of different climate zones, it is concluded that climate characteristics can have influential impacts on the concerned factors. In cold climate zones, the building energy consumption is sensitive to the adjustment in temperature setpoints. On the contrary, energy consumption in hot and warm climate zones is relatively low, and increasing the cooling setpoint has a less efficient impact on energy savings than decreasing the heating setpoint in cold climates. Regarding thermal comfort sensation, occupants in buildings located in cold and hot climate zones (e.g., 1A, 2A, 6A, 6B, 7, and 8) are more likely to experience discomfort. Therefore, facility management teams must implement more restrictive temperature set values around the neutral temperature to maintain a comfortable indoor environment for such buildings. However, the effect of temperature control is not as significant for some mild climate zones, including 3B-CA, 3C, and 5A, where thermal sensation variation is minor, and

restricted temperature control could result in a significant increase in energy consumption for marginal improvements in thermal comfort. Regarding the infection risks, climate characteristics do not appear to have a significant influence except for zones with extremely hot weather. Therefore, in order to establish a healthy indoor environment in buildings located in other climate zones, it is imperative to implement alternative mitigation measures such as air filtration and social distancing.

This study highlights the interdependent nature of energy consumption, infection risks, and thermal comfort in building operations. The findings suggest a near-linear relationship between energy consumption and thermal comfort across all climate zones with constant ventilation levels, as a result of considerable influence of temperature settings. Similarly, with constant ventilation levels, there is a near-linear relationship exists between infection risks and thermal comfort, attributable to the increased cooling load that necessitates additional outdoor air additional cold air from central air handling units and more economizer operation. There is a clear linear relationship between infection risks and energy consumption attributable to building ventilation and temperature setpoints that affect both factors linearly, and an insignificant effect of relative humidity on these two aspects.

3.6 Summary

The prolonged COVID-19 pandemic has prompted school management teams to prioritize maintaining a healthy and sustainable indoor environment through effective HVAC system control. This chapter presents a tradeoff analysis of three crucial aspects of

the built environment during the pandemic: health, energy consumption, and thermal comfort. A novel and convergent framework was developed to perform a quantitative analysis of the intricate tradeoff relationships between these aspects, taking into account the influence of dynamic environment factors and fluctuations in occupancy. The study used EnergyPlus to simulate building energy consumption and occupant thermal comfort, and a revised Wells-Riley model was developed to estimate indoor airborne infection risks. The simulation was carried out across all climate zones in the U.S. to account for the diverse range of climate characteristics.

A case study utilizing a reference building model of a primary school was conducted to demonstrate the framework. The analysis investigated the effects of various environment factors regulated through the HVAC systems on health, energy consumption, and thermal comfort. The examined environment factors comprised temperature, humidity, and air flow rate, and their set values were determined based on practical operation ranges. The study concludes that variations in the set values of environment factors, in addition to the environment factors themselves, have a significant impact on the three key aspects of indoor environments: health, energy consumption, and thermal comfort. These impacts are influenced by the HVAC system and climate characteristics. The optimal thermal comfort and lowest infection risk can be achieved simultaneously with the highest energy consumption. Taking zone 5A as an example, the infection risks decrease by 43%, and the thermal satisfaction increases by 61% when using the optimal environment settings (e.g., highest ventilation rate and neutral temperature) compared to the worst environment settings (e.g., lowest ventilation rate and largest deviation from neutral temperature).

However, the increase of ventilation rate by 1 ACH implies an increase in energy use by 19.7%, and an increase of over 70% energy consumption is observed when comparing the two scenarios. Therefore, the school budget is the main restriction to achieve a healthy environment and thermal comfort. To lower the energy cost, reducing ventilation is more effective than increasing the temperature variation. The effectiveness of the change in environment factors varies over different climate zones. For instance, increasing the deviation of the temperature setpoints from neutral setpoints can significantly reduce the energy consumption of buildings located in cold climate zones, while the effect of hot and warm climate zones on energy saving is not that significant. For the tradeoff among the three major aspects, the findings suggest a near-linear relationship between energy consumption and thermal comfort, as well as between infection risks and thermal comfort when the ventilation level is constant. Additionally, there exists a distinct linear relationship between infection risks and energy consumption.

Although this chapter focuses on the tradeoff relationship between energy consumption, thermal comfort perception, and infection risks for U.S. primary schools during the COVID-19 pandemic, The generalizability of the framework is not limited to COVID-19 and can be extended to other infectious diseases. Furthermore, it can incorporate other important aspects to cater to the specific needs of other countries and facilities, thereby contributing to the maintenance of a sustainable indoor environment. In order to ensure accuracy and relevance in practical implementation, the detailed building model can be tailored to account for specific building envelopes and HVAC configurations in a given context.

CHAPTER FOUR
A REAL-TIME INTEGRATED PLATFORM FOR MONITORING AND COMMUNICATION IN BUILDING MANAGEMENT

4.1 Introduction

The emergence and spread of various pandemics—such as influenza and SARS-CoV-2—over the past few decades have resulted in increasing concerns about public health and safety. As the world grapples with the unprecedented challenges posed by these infectious diseases, health has emerged as a pivotal dimension in building monitoring and operational strategy development. The need to create healthy environments has become paramount in ensuring the well-being of building occupants. Additional factors such as human comfort and energy consumption are also pivotal dimensions that must be considered for effective building management when aiming to maintain a healthy and sustainable built environment. However, there are significant challenges in the real-time assessment and analysis of the tradeoffs between these three dimensions, which prevents the proactive control of and response to pandemics. Facility management teams play a crucial role in implementing timely control measures, and they must have a comprehensive understanding of the built environment. In addition, it is equally important to engage with and persuade occupants to actively participate in improving their quality of life and contributing to a healthy and sustainable environment. Such occupancy engagement is essential for the promotion and implementation of acceptable sustainable practices, which will lead to improved health outcomes, enhanced comfort, and reduced energy consumption.

Indoor environments play a crucial role in daily life, with individuals spending approximately 90% of their time indoors; indeed, students spend around 30% of their waking hours in schools [113]. Low-quality indoor environments can have negative effects on residents, leading to increased health issues such as respiratory problems, the exacerbation of asthmatic issues, headaches caused by pollutants, and symptoms of sick building syndrome (SBS) [114]. SBS is a condition in which occupants experience discomfort and health symptoms while spending time in a building, often associated with poor indoor air quality and inadequate ventilation. In addition, inadequate indoor environments can accelerate the spread of diseases, especially airborne viruses. In addition to health concerns, suboptimal indoor environments can result in reduced performance, productivity, and discomfort among occupants. Implementing effective building management measures is crucial for facility management teams to ensure a healthy and sustainable environment while reducing energy consumption. Hence, a timely awareness and understanding of the built environment are essential for facility management teams to make informed decisions and take appropriate actions. An additional challenge for facility management teams is that variations in occupant behavior can lead to significant differences in the built environment and building energy consumption [115]. For example, studies have found that identical housing units can exhibit electricity consumption variations of up to 600% during certain periods of the year [116], while energy consumption in townhouses can vary by a factor of two [117]. These findings highlight the significant influence of human activities and decision-making on energy use and indoor environmental conditions. Improper occupant behaviors can also negatively impact living

quality and the built environment, having adverse effects that not only influence the occupants themselves but also others sharing the same space. Conversely, the adoption of appropriate occupant behaviors can result in significant energy savings and contribute to a better indoor environment for all occupants. Therefore, the development of an integrated platform that caters to the needs of both facility management teams as well as that of occupants is crucial for ensuring the maintenance of a sustainable and healthy built environment.

There are currently no existing integrated platforms that can consolidate the essential functionalities of monitoring, simulation, alerting, and persuasion in the context of smart building management. There are three significant knowledge gaps that pose challenges to the development of such a service. Firstly, there is the absence of an integrated technology that consolidates all of the necessary functionalities into a single platform. This platform should be capable of completing multiple tasks in real time, including data acquisition and processing, conducting simulations for different models, providing alerts and communication, and effectively persuading occupants through an understanding of their preferences. Each of these capabilities is complex and requires advanced technological infrastructure to fully realize its functionalities. Secondly, there is the inability to simultaneously monitor and simulate variations in health, energy, and thermal comfort in real-time, while still considering both aspect-specific and mutually related parameters. Real-time health assessment poses distinct challenges, primarily stemming from the complexity of retrieving timely epidemiological-related parameters from specific building locations. To implement effective measures for the protection of

public health and safety within buildings, it is imperative to have access to up-to-date and location-specific data on epidemiological factors. The real-time assessment of energy consumption and thermal comfort also faces similar difficulties, including the development of reliable methods for the real-time simulation of occupancy fluctuations, which would enable the tradeoff analysis between health, energy, and thermal comfort. Finally, there is an absence of an AI-based application for the built environment that can interact with both facility management teams and occupants as well as promote healthy behaviors and energy-saving practices. This application should include functionalities, such as alerting facility management teams about abnormal situations (e.g., poor indoor environment, occupant discomfort, and health risks) while featuring feature a persuasive conversational system that attempts to convince occupants to adopt environmentally friendly behaviors, actively participate in improving their living conditions, and promote energy savings. However, current technologies lack these capabilities and often overlook the importance of occupant engagement in building management.

To address these knowledge gaps, this research proposes the development of an integrated platform for real-time building monitoring and communication aimed at improving overall building management. An IoT sensor network was deployed to enable real-time monitoring, which allowed for the collection of data such as room occupancy and air quality. Off-the-shelf occupant counters were used to determine room occupancy, while air quality sensors were used to measure the levels of indoor pollutants like carbon dioxide (CO_2), volatile organic compounds (VOCs), and fine particulate matter ($PM_{2.5}$). Cloud computing technology was used to ensure seamless real-time data acquisition, storage,

processing, simulation of the health, energy, and comfort models, and tradeoff analysis. The cloud-hosted platform also allowed for all functionalities to be accessed in real time through an integrated web-based application. To enable effective communication, the platform incorporates two key capabilities. The platform possesses two key features that allow for effective communication. Firstly, it provides visualizations of the monitored data and simulated results and is equipped with an alert system that notifies facility management teams of any abnormalities detected in the indoor environment. This capability primarily assists facility management teams with decision-making processes. Secondly, the platform provides recommendations and utilizes an AI-based communication system empowered by GPT targeted at persuading building occupants, encouraging them to adopt more environmentally friendly measures. By raising awareness of the positive impact of such behaviors on indoor environment quality and energy savings, occupants may be motivated to make conscious, environmentally friendly choices. In addition, the interaction between occupants and facility management teams allows for the adoption of occupant-preferred operation strategies, improving occupant satisfaction.

4.2 Literature review

4.2.1 IoT integrated digital twin technology

The emergence of digital twin technology has revolutionized the field of asset management and monitoring, providing new opportunities for enhanced control and efficiency. A digital twin refers to a virtual model that replicates a physical asset and continually adapts to changes based on real-time data and information from a variety of sources. Liu et al. [118] defined a digital twin as a living model that represents a physical

asset, capable of capturing its dynamic behavior and responding to changes through the integration of virtual and real-world data. Madni et al. [119] described digital twins as more than just virtual prototypes; instead, they would be better defined as a virtual instance that incorporates real-time performance data throughout the lifecycle of the physical asset. In essence, digital twin technology enables the creation of a virtual counterpart that mirrors the physical asset, leveraging the power of IoT to collect and integrate real-time data from sensors installed in the asset of interest. In this case, IoT refers to the network of physical devices embedded within the asset, composed of sensors, software, and other technologies that enable the exchange of data with other devices and systems over the internet [120]. The interconnectedness provided by IoT facilitates the seamless exchange of information between the physical and virtual realms, providing a wealth of information that can be used to monitor, control, and inform decision-making processes. Recent studies have explored IoT-integrated digital twin technologies to enhance building management practices. Zaballos et al. [121] focused on a smart campus concept involving the integration of BIM tools with IoT-based sensor networks. Their work aimed to monitor the environment, detect emotions, and provide insights into student comfort, leading to the development of an updated digital twin for the campus. Tagliabue et al. [122] utilized digital twin technology to conduct a sustainability assessment of an educational building by employing an IoT-enabled dynamic approach involving real-time evaluation to provide user-centered control of sustainability criteria. This involved constant interaction between the digital twin and the sensors that monitored indoor comfort, air quality conditions, and energy behavior. The digital twin framework supported decision-making processes associated with

sustainability. Yitmen et al. [123] proposed a modified cognitive digital twin model focused on using their cognitive ability to detect actions and reasons to inform dynamically processed optimization strategies. By integrating machine learning, cyber-physical systems, artificial intelligence, and IoT technologies, their model aimed to support decision-making in building lifecycle management. However, none of these studies utilized IoT-based digital twin technologies to monitor, model, and simulate health and infection risks associated with hazardous viruses. In addition, the ability to analyze the tradeoff relationships between health, energy, and thermal comfort in the context of smart building operations remains relatively unexplored. Addressing these limitations is essential for advancing the application of IoT-based digital twin technologies aimed at maintaining a healthy and sustainable built environment.

4.2.2 Communications technology in building management

Communication is an essential component of smart building monitoring and operation due to the importance of sharing information with facility management teams. Various studies have developed different methods of sharing this information with users, including web-based and mobile applications. Mataloto et al. [124] developed an IoT system as part of a larger building energy management system (BEMS), including a platform that used data visualization templates to create a dashboard that allowed facilities management to identify appropriate actions that could lead to potential energy savings. Marinakis and Doukas [125] developed a recommendation system for intelligent BEMS in residential settings that was capable of pushing notifications when parameters exceeded

certain thresholds as well as providing analytical, tailor-made recommendations and energy-saving tips. Fernando et al. [126] developed a web application that acted as a dashboard through which users could control the platform and access the energy consumption service. Ribino et al. [127] proposed a human-like social robot-based approach to monitoring indoor environment quality. The robot interacted with occupants in a friendly manner and provided appropriate suggestions, while also demonstrating cognitive capabilities by assessing indoor air quality (IAQ). Currently, communication systems in building operation and management applications primarily focus on tasks such as data visualization and notifications. Recommendations provided during communication are often targeted towards specific, singular objectives, such as reducing energy consumption or improving IAQ. However, there remains a significant gap in terms of the comprehensive analysis of tradeoff relationships between different dimensions such as energy, the indoor environment, and health risks within these systems. In addition, there is a notable knowledge gap associated with the integration of interactive tools that can understand and communicate with users in the field of building management systems (BMS). The effectiveness of these tools would be significantly increased should they be able to fully comprehend simulation results and current environmental conditions, as well as understand user concerns and preferences as expressed through natural language. Developments in this area are expected to bridge this knowledge gap and enhance communication between users and the BMS.

With the recent developments in natural language processing (NLP) as well as groundbreaking advancements in the sophistication of large language models (LLMs) such

as ChatGPT, the integration of similar technology into communication systems is extremely promising. ChatGPT is an AI language model developed by OpenAI based on the GPT-4 architecture [128]. Trained on a diverse range of textual data, including scientific literature, technology articles, and other written sources, ChatGPT is designed to generate human-like text in response to user prompts. The GPT-4 model—upon which ChatGPT is built—has gained a considerable amount of attention in the field of NLP [129]. Its applications span various domains, including content generation, language translation, and virtual assistance. ChatGPT is exposed to a vast corpus of textual information during training, including books, articles, websites, and publicly available written content. Consequently, ChatGPT is uniquely capable of effectively parsing the suggestion features present in BMS platforms, while also having the potential to persuade end-users to make rational changes to their behavior by providing them with an understanding of the current condition of the building. However, the integration of this technology into the field of BMS has not been explored in existing studies. Consequently, the novel and unique approach of integrating a ChatGPT-like conversational system with simulation results in a BMS platform to provide persuasive suggestions holds significant promise.

4.3 Methodology

The proposed framework comprises three phases: preparation, simulation, and web app development. In the preparation phase, a BIM of the target building was developed, composed of mechanical, electrical, and plumbing (MEP) as well as architectural components. This facilitates the development of the energy model used for the EnergyPlus

simulation. Specifically, the MEP model was used to configure the HVAC system, which was further developed using OpenStudio. In addition, an IoT sensor network was set up in the building to enable the real-time monitoring of relevant indoor environment parameters and occupancy status. In the simulation phase, a comprehensive methodology was implemented to generate outputs describing energy consumption, thermal comfort, and infection risks based on the collected IoT data and building configurations. Energy consumption and thermal comfort were simulated through the EnergyPlus API, while infection risk was simulated using programming scripts that incorporated up-to-date disease data on the COVID-19 pandemic. During the web app development phase, the platform that integrated the entire process, ranging from data acquisition to data visualization, was designed and hosted on a web server environment. This phase focused on providing three primary features. Firstly, it involved the retrieval of IoT data and up-to-date disease data from cloud storage, which was then provided to the simulation process. Secondly, the app ran simulations and collected these results. Finally, the interactive app visualized and communicated the simulated outcomes to users through the integration of BIM and GPT technologies. The interactive app allowed real-time access to health, energy, comfort, and air quality information in selected rooms of interest. The developed platform integrated the three phases within a cloud environment, leveraging cloud computing technology to store IoT data, perform simulations, and host the web app on the same server. This integrated framework allowed for efficient computation and real-time communication with users based on monitored and simulated results, as depicted in Figure 4-1.

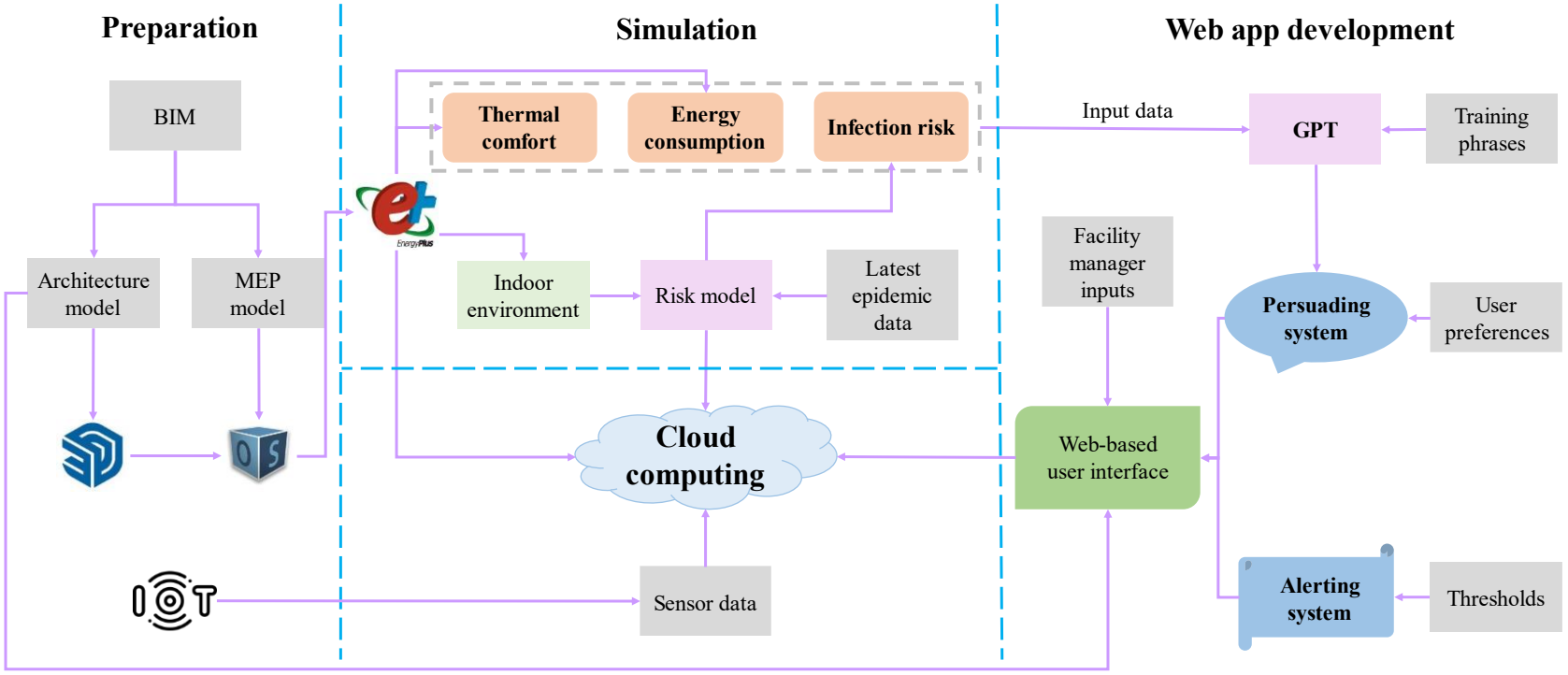


Figure 4-1 Framework for the development of the web-based application.

4.3.1 Preparation

4.3.1.1 Creating the building energy model

The building energy model used in the simulations was generated by combining the building architecture model and the MEP model. The architectural model was imported into Sketchup, enabling adjustments to the building envelope to accurately depict the building envelope and streamline the energy simulations. The HVAC systems of the building were subsequently incorporated into the model using OpenStudio based on the HVAC configuration from the MEP model. These modifications were then saved, resulting in a comprehensive model that could be used for energy simulations using EnergyPlus API.

4.3.1.2 Configuring the IoT sensing system

An IoT sensing system was implemented in our case study area to allow for the real-time monitoring of the building environment. The off-the-shelf IoT hardware devices were used to collect data on air quality and occupancy at the room level. The architecture of this system is depicted in Figure 4-2, illustrating the components and their connections within the IoT sensing system.

The IoT system consists of two main types of devices: IoT sensors and a wireless gateway. The off-the-shelf IoT sensors employed in the system included IAQ sensors for monitoring indoor air quality and a room occupancy sensor that tracked the number of people in the room. The IAQ sensors were composed of pollutant-specific sensors, including CO_2, VOC, and $PM_{2.5}$ sensors, with data collected and measured in parts per million (PPM) for CO_2, and micrograms per cubic meter (µg/m3) for $PM_{2.5}$ and VOC.

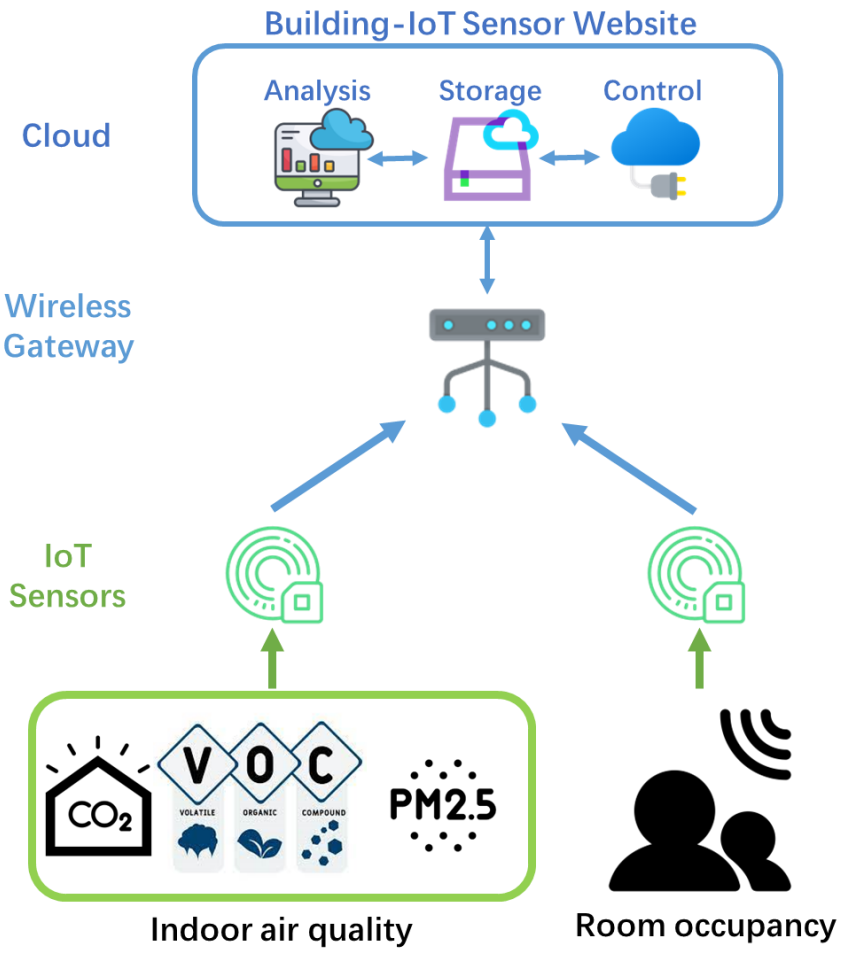


Figure 4-2 Architecture of IoT system.

The VOC sensors measured the concentration of various pollutants, such as carbon monoxide, ethane, isoprene, and acetone. The system also collected other environmental data, such as temperature (°C), and relative humidity (%). The room occupancy sensor utilized overhead counters to count the number of occupants. The wireless gateway was used to manage the IoT sensors and was responsible for collecting data from the sensors and transmitting them to the Microsoft Azure Cloud Portal where it was saved and accessed by Amazon Web Services (AWS) for further analysis. Figure 4-3 presents an example of a set-up of the hardware environment, with the IAQ sensor highlighted in the green box, and the gateway highlighted within a blue box.

In addition to the hardware setup, a building-IoT sensor solution website was used to create a virtual representation of the case study site. In this virtual representation, different rooms were defined as spaces, facilitating the mapping and identification of device locations within the building. In addition, the website was used to create virtual devices, including the gateway and sensors, and synchronized them with their corresponding physical devices. The status and location of these devices were visualized on the website, with different shapes representing different devices (Figure 4-4).

4.3.2 Simulation

Once the data have been collected from the off-the-shelf sensors, appropriate simulations must be used to effectively utilize the data. The simulation phase involves two main components: 1) energy consumption and thermal comfort simulation, and 2) infection risk simulation.

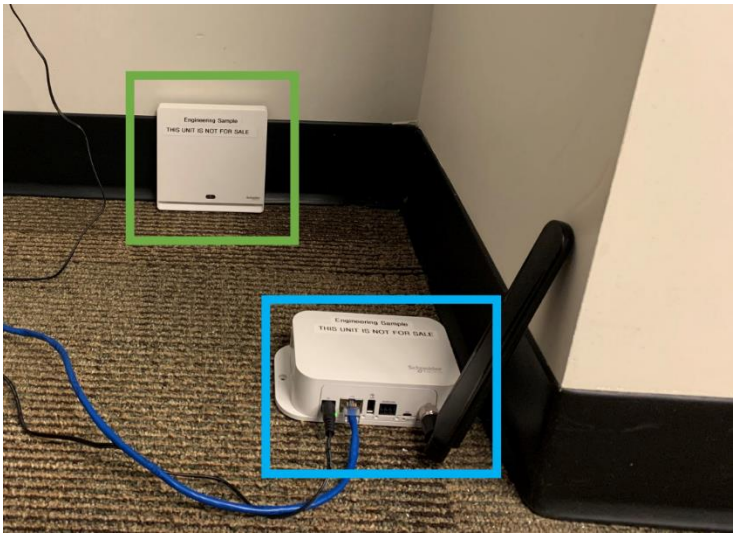


Figure 4-3 An example set-up of the hardware environment.

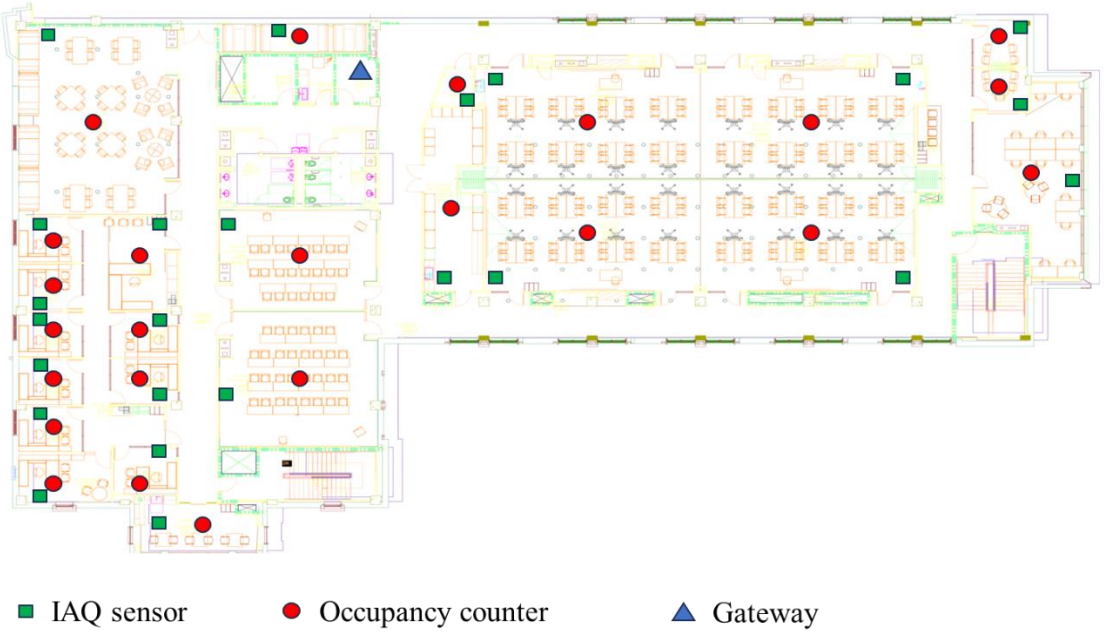


Figure 4-4 Layout of hardware in the case study site.

The energy consumption and thermal comfort simulation were conducted in EnergyPlus. The default setpoints for the indoor environment were configured based on common operational scenarios. For example, during working hours, the heating and cooling setpoints were maintained at 22°C and 26°C, respectively, while during non-working hours, the setpoints were adjusted to 15.6°C and 26.7°C, respectively. The outdoor air supply rate was set to 0.0094 m^3/s per person, and an economizer operational temperature of 28°C was implemented. The default relative humidity range was set to be between 30–60%. Real-time room occupancy was monitored using the occupancy sensor system, which was collected, transmitted, and saved on a Windows server hosted on an Amazon Elastic Compute Cloud (Amazon EC2). This integrated approach ensures that the simulation process uses up-to-date occupancy information, allowing for the accurate analysis and assessment of energy consumption, thermal comfort, and infection risks.

The web application allows facility managers to customize their desired setpoints for the indoor environment with the capability of reading idf files as text, a file format commonly used by EnergyPlus. When users input their desired setpoints, the application allows direct adjustments to the idf file by overwriting the original text. This functionality provides facility managers with a comprehensive understanding of the changes in energy consumption, thermal comfort, and infection risks associated with their desired settings, giving them insights into the effects of different HVAC operation strategies.

In the context of infection risk simulations, our approach considered the dynamic indoor environment within each zone, including factors such as temperature, humidity, and ventilation rate, as well as fluctuating occupancy levels. A derivative of the Wells–Riley

equation was used to estimate room infection risk. Detailed information about the risk model is described in Chapter 3. All estimated infection risk data refers to the degree of infection risk at the time when the web app was executed.

4.3.3 Cloud computing

4.3.3.1 Real-time data retrieval and storage

Real-time data was retrieved and stored using IoT sensors, including the latest updates on the epidemic situation. The IoT data is collected using sensors deployed throughout the building, which are then transmitted to the Amazon EC2 for storage and processing. Epidemic situation data is obtained through an API provided by Covid Act Now [130]. This API can be seamlessly integrated into the cloud-based system, ensuring that the latest epidemic data is readily available for analysis and simulation. Specifically, the epidemic data provided include the county hospitalizations per 100,000 people. The infection rate is then estimated using Equation 4-1:

$$IR = \frac{CH}{IHR * 100{,}000} \tag{4-1}$$

where IR is the county infection rate, CH is county hospitalization data, IHR is the infection-hospitalization ratio [131]. IR is the prevalence parameter used in the risk simulation model.

4.3.3.2 Computation of health, energy, and comfort parameters

The cloud computing approach determines the health, energy, and comfort parameters through a combination of mathematical models and simulation programming

on the cloud server. Health parameters are calculated using the Python implementation of a revised W–R model, which is then saved in a Windows server hosted within the AWS infrastructure. An interface was included in the Python script to facilitate the retrieval of prevalence data from the front end of the web app, allowing for seamless communication between the two scripts. The Windows server described above was specifically built using the EC2 service.

The Python API provided by the EnergyPlus simulation software was used to compute the energy consumption and thermal comfort parameters. This simulation software utilizes the building energy model, along with real-time occupancy data, to calculate energy consumption and assess thermal comfort. These Python scripts are responsible for triggering the simulation process as required as well as generating the relevant outputs pertaining to energy consumption and thermal comfort. Similar to the scripts responsible for the computation of health parameters, these Python scripts are stored within the same Windows server hosted on AWS, ensuring seamless integration and accessibility.

4.3.3.3 App hosting

The web app is seamlessly hosted on a Windows server, which also serves as a repository for IoT data and the Python scripts responsible for cloud computing tasks. This integrated setup allows for the smooth integration of the app and the computing environment. Python scripts that handle various calculations and simulations are triggered by the web app whenever necessary. To facilitate this dynamic interaction, the web app sends inputs to the programming scripts via an XMLHttpRequest object. This enables users

to provide inputs through the web app's user interface (UI), which are then passed on to the scripts for processing. The outputs generated by the Python scripts are read by the web app using the same XMLHttpRequest object and are promptly presented using the app's UI, providing users with relevant information in real time. This hosting configuration establishes a cohesive ecosystem in which the web app and programming scripts collaborate harmoniously, ensuring a seamless and efficient user experience. Furthermore, the web app eliminates the need for users to install additional software, as all of the provided functions are easily accessible through a simple URL. This streamlined approach enhances the app's ease of use, in terms of both setup and interactivity, allowing a broader range of potential users to benefit from its functionalities. The app is not only designed for facility management teams but also for occupants, workers, or anyone temporarily present in the building. By removing the requirement for software installation, the app becomes more inclusive and user-friendly, catering to a wider audience and ensuring convenient access to its features.

4.3.4 Web app development

The web app developed in this study incorporates several key components aimed at assisting with facility management practices. Firstly, the app allows for the 3D visualization of the building model and time series data visualization, allowing for the real-time monitoring of the building environment. These visualizations aid facility managers by providing them with a comprehensive understanding of the current state of the facility. Facility managers can adjust the setpoints of the indoor environments based on their

preference, while also providing them with any changes in the energy consumption or building environment that may arise as a result of these changes. In addition, an alerts system allows facility managers to promptly identify and address any abnormalities or deviations from the desired conditions by providing timely alerts and notifications. An AI-based persuasion system was also developed to encourage desirable occupant behaviors and preferences. This integrated system provides facility managers with a deeper understanding of occupant-preferred measures, fostering effective interactions between occupants and facility managers. By leveraging AI technologies, this system offers personalized recommendations and suggestions to optimize both occupant satisfaction and facility management efficiency. Together, these components encompass a robust methodology that integrates visualization, alerts and notifications, and AI-based persuasion systems that allow facility managers to effectively monitor, respond to, and engage with the built environment and its occupants.

4.3.4.1 Visualizations

The web app was developed using the NodeJS and Bootstrap frameworks, creating a user-friendly interface that facilitates efficient data visualization and interaction. One notable feature of the app is the 3D visualization of the building model made possible through its integration with Autodesk Platform Services. This functionality allows users to select specific rooms of interest and observe them highlighted within the 3D building model. The 3D view of the building model can also highlight specific rooms to emphasize the presence of any abnormalities, drawing attention to rooms that require immediate attention or further investigation, aiding in effective decision-making and the prioritization

of actions. The 3D building model is also fully interactive, allowing users to zoom in, pan around, and explore different parts of the building. This immersive and interactive visualization system enhances the user experience and provides users with a better spatial understanding of the layout of the building.

The app is also capable of visualizing the fluctuation of key parameters over time. Line plots are used to illustrate the dynamic changes in energy infection risk, energy consumption, and thermal comfort in specific rooms, allowing users to easily observe trends and identify potential areas of concern. Line plots are also utilized to visualize room temperature, humidity, and ventilation, providing insights into indoor environmental conditions. Finally, line plots are also used to show the cumulative infection risks of each room, allowing users to assess their individual infection risks based on the time spend in each room. This information can be used for high-infection risk alerts and proactive measures.

4.3.4.2 Alerting system

An alerting system was seamlessly integrated into the app to provide comprehensive guidance and support to facilities management. This system effectively utilizes simulation results associated with the user's selected room to proactively trigger alerts. An alert can be triggered based on the following conditions:

1. Cumulative Infection Risk: If the cumulative infection risk exceeds a predetermined threshold (e.g., 1%), then an automatic alert is triggered, notifying facility managers of potential health risks and providing recommendations on various mitigation measures,

such as increasing ventilation, reducing room occupancy, and implementing disinfection strategies such as the use of ultraviolet lights.

2. Relative Humidity: When the relative humidity exceeds specified thresholds, such as exceeding 60% or falling below 30%, an alert will be sent to facility managers, informing them about these humidity-related issues. These issues can be mitigated through the activation of humidifiers or dehumidifiers at low or high humidities, respectively.
3. Thermal Comfort: Alerts are pushed if the thermal comfort levels deviate from predefined thresholds, such as when the predicted mean vote (PMV) exceeds 1 or falls below -1. This allows facility managers to take timely action in response to comfort-related concerns, such as adjusting the room temperature setpoints.
4. Indoor air quality (IAQ): An alert is triggered when the IAQ exceeds acceptable thresholds. These thresholds are set for specific parameters, which are 500 ppm [132], $15\ \mu g/m^3$ [133], and $500\ \mu g/m^3$ [134] for the concentration of CO_2, $PM_{2.5}$, and VOCs, respectively. Exceeding these thresholds indicates that the IAQ may pose potential health risks, and facility management teams should take actions to address the situation, such as increasing the room ventilation rate or reducing the concentration of pollutants.

4.3.4.3 AI-based persuasion system

The functionality of the web app extends beyond facility managers and can cater to the needs of other users, such as occupants or workers, by providing them with information

about the facility as well as receiving and providing suggestions to their concerns. In addition to the visualization capabilities described earlier, the app incorporates an AI-based persuasion system that offers personalized suggestions to this user group through the use of conversations informed by the current environment data and simulation results. This persuasion system takes the form of a conversational interface powered by the highly regarded GPT-3.5-turbo LLM [135]. This LLM has been specifically optimized for conversational tasks and is thus highly effective at generating meaningful responses.

The LLM has three main functions: data retrieval, data comparison, and the provision of suggestions. After the web app simulates the current state of the building, the real-time environmental data from IoT sensors (such as IAQ and temperature) and the simulation results (including energy consumption, thermal comfort, and infection risk) are automatically transmitted to the GPT model through the OpenAI API [136] in the JSON format. The LLM then utilizes the retrieved JSON data to identify differences between neutral and current conditions, such as variations in simulated energy use. The LLM is trained using predefined decision-tree-based training phrases to provide conversational suggestions to end-users. To ensure accurate responses, a manual check is performed after each training session.

Users can engage with the app's conversational UI to express their concerns, share their feelings, or ask questions about the current environment. The LLM is capable of providing relevant and personalized responses based on the real-time data it receives. This comprehensive approach allows the app to provide users with appropriate guidance and effectively address their specific concerns, fostering an informative, user-centric

experience. The fundamental concepts behind the persuading system are founded in the tradeoff relationships between health, energy, and thermal comfort. Two adaptive persuasion algorithms were developed in this study: one focused on the occupant's perception of thermal comfort and the other on their perception of the IAQ. These qualities are important for occupants, as they directly relate to what occupants can feel and are most concerned about in an indoor environment. The persuasion algorithms are presented using a decision-tree format and are utilized as training data for the GPT. Specifically, they were provided in the form of descriptive phrases, allowing the model to learn and understand how to generate effective and persuasive suggestions. Figure 4-5 provides a comprehensive illustration of the entire process.

4.3.4.3.1 Adaptive persuasion algorithm based on user perception of thermal comfort

The first of the two adaptive persuasion algorithms utilized in the app focuses on the user's perception of thermal comfort. The algorithm involves three decisions, with the result of each decision based on user input or environmental conditions. A demonstration of how outputs are generated by the persuasion algorithm is shown in Figure 4-6. The algorithm distinguishes between cooling and heating seasons based on the current date retrieved from the device's system time. It then obtained the occupant's thermal perception through the conversational interface, capturing their feelings about the state of the indoor thermal environment. It then compares the current temperature—acquired from real-time IoT sensing data—with the preset neutral temperature (e.g., 24°C).

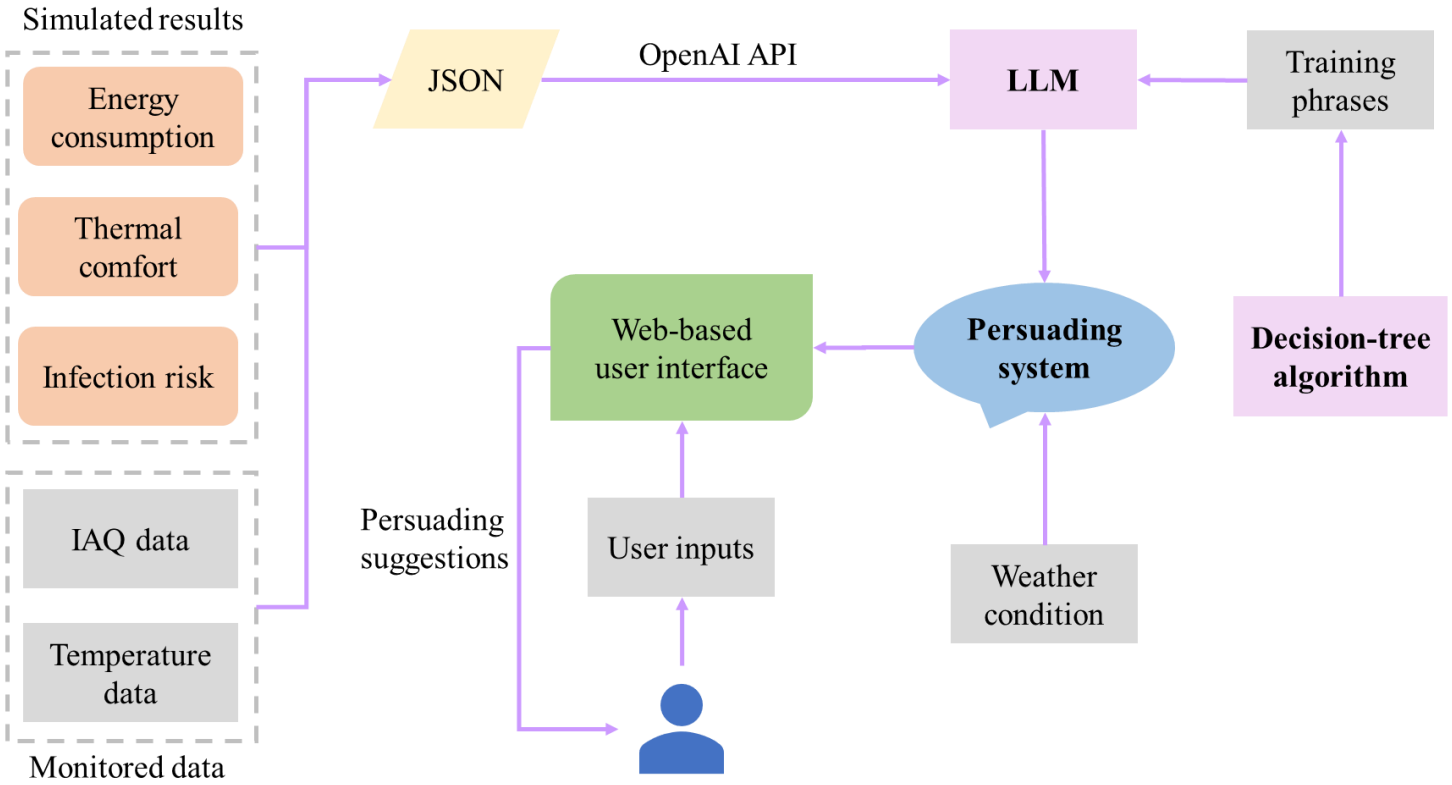


Figure 4-5 Integrated operations of the AI-based persuasion system.

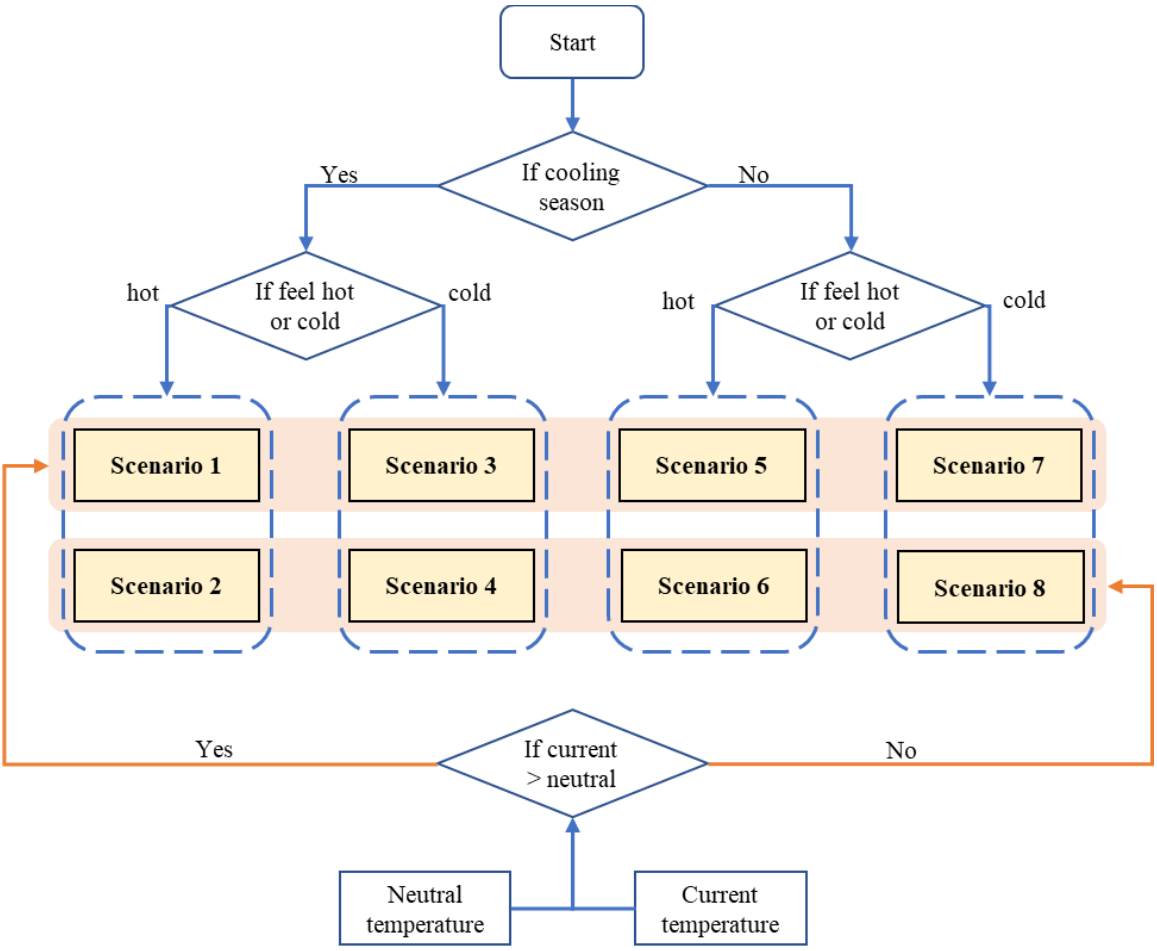


Figure 4-6 The persuasion algorithm according to the occupant perception of indoor temperature and environmental conditions.

The simulation results under current and neutral conditions are then used to calculate the difference in energy use. Based on the outcomes of these three decisions, the algorithm generates eight distinct scenarios, with specific suggestions and persuasive phrases formulated for each scenario. The contents of the persuasion system were developed by considering the tradeoff between energy consumption and thermal sensation. If changing temperature setpoints will result in increased energy use, the system initially recommends that users change their clothing levels to reduce energy consumption. If changing setpoints will reduce energy use while also satisfying user thermal requirements, the system will suggest adjusting setpoints accordingly.

To enhance user engagement, the system provides suggestions while demonstrating the energy savings achieved by user actions. This approach helps users better understand the impact of their behavioral changes while making the system more persuasive, improving thermal comfort and energy conservation by encouraging the active participation and collaboration of occupants. In each scenario, multiple recommendations are offered to users, allowing them to choose their preferred course of action. The system then responds according to user choices and informs the facility management teams of the user's preference. The detailed persuading phrases based on different scenarios are as follows:

Scenario 1 (cooling season, the user feels hot, and the current temperature is higher than neutral): Shall I communicate with the facility managers and advise them to lower the indoor temperature? Alternatively, if you are comfortable adjusting your clothing to lighter attire, it could potentially save an estimated Y kWh of energy (where Y is the number

retrieved from the result of cloud-computed energy simulation). Please let me know your preference regarding contacting the facility managers.

Scenario 2 (cooling season, the user feels hot, and the current temperature is lower than neutral): The current temperature is already below the neutral level, and lowering it further may cause people to feel cold. In this case, I recommend wearing additional layers or a light blanket if you're still feeling chilly.

Scenario 3 (cooling season, the user feels cold, and the current temperature is higher than neutral): The current temperature is already higher than the neutral level. In this situation, I recommend considering removing some layers of clothing to help you feel more comfortable and alleviate your thermal discomfort.

Scenario 4 (cooling season, the user feels cold, and the current temperature is lower than neutral): The current temperature is below the neutral level. I will inform the facility managers to increase the temperature cooling setpoint, which will help save energy by Y kWh.

Scenario 5 (heating season, the user feels hot, and the current temperature is higher than neutral): The current temperature is above the neutral level. I will communicate with the facility managers to lower the temperature heating setpoint, which will help save energy by Y kWh.

Scenario 6 (heating season, the user feels hot, and the current temperature is lower than neutral): Should I communicate with the facility managers to decrease the temperature? Alternatively, you could remove some layers of clothing to help us save Y energy. Please let me know your preference regarding contacting the facility managers.

Scenario 7 (heating season, the user feels cold, and the current temperature is higher than neutral): The current temperature is already higher than the neutral level, and further increasing it may cause people to feel hot and lead to higher energy consumption. In this situation, I recommend removing some layers of clothing to help you feel more comfortable and reduce the need for additional adjustments to the indoor temperature.

Scenario 8 (heating season, the user feels cold, and the current temperature is lower than neutral): Should I communicate with the facility managers to increase the temperature? Alternatively, you could put on more layers of clothing to help us save Y energy. Please let me know your preference regarding contacting the facility managers.

4.3.4.3.2 Adaptive persuasion algorithm based on user perception of IAQ

Like the algorithm described in Section 4.3.4.3.1, this algorithm generates responses based on three key decisions (Figure 4-7), involving a consideration of the environmental conditions, user perception, and health risks. It first prompts the user to input their perception of the air quality through the conversational interface of the application. It then compares the current infection risk level to a predefined risk threshold to determine if the room's infection risk is high. Finally, it evaluates the IAQ with close consideration of the concentration of air pollutants such as CO_2, $PM_{2.5}$, and VOC. This data is gathered in real-time through IoT sensing devices and compared against preset thresholds as demonstrated in Section 4.3.4.2. From this data, the algorithm generates outputs based on one of six scenarios.

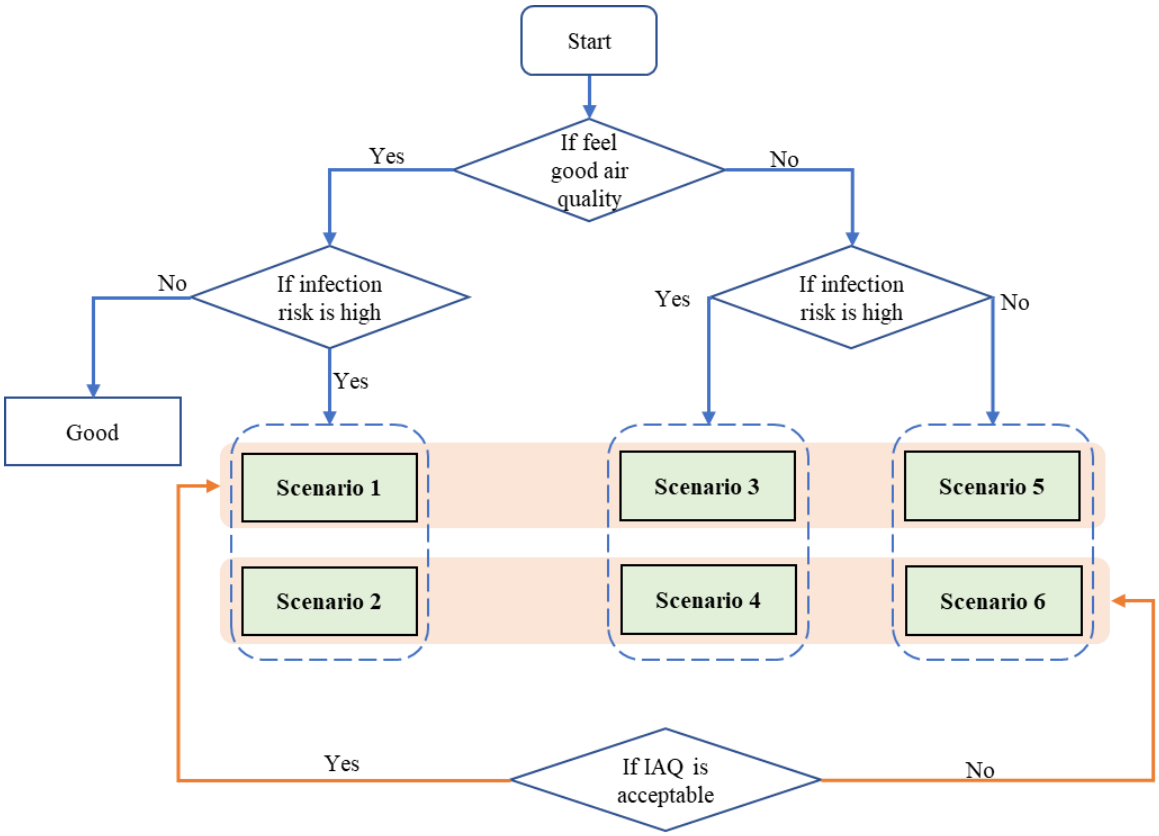


Figure 4-7 The persuasion algorithm according to the indoor infection risks and occupant perception of the IAQ.

The system considers two crucial factors: the health risks associated with airborne diseases and air pollutants. The system acquires the infection risk through real-time simulation results, while the health risks related to air pollutants are obtained from the IoT monitoring system. The algorithm presents users with different mitigation measures, allowing them to choose the option that best aligns with their preferences.

The persuasion system's initial strategy is to encourage occupants to consider moving to another room, which helps to reduce potential health risks while minimizing the need for the extensive implementation of mitigation measures, thus promoting energy and cost savings. Furthermore, the system acts as a communicative link between the building occupants and the facility management teams, providing insights into occupant preferences and needs. This promotes the adoption of preferred mitigation measures, leading to a healthier environment, energy savings, and improved occupant satisfaction. The detailed persuading phrases based on different scenarios are as follows:

Scenario 1 (the user feels good, infection risk is high, and IAQ is acceptable): Although the air quality in this room may feel comfortable, it's important to be aware that the current infection risks are high. To address this concern, I strongly recommend moving to another room. The healthy room numbers are Z (recommended rooms are determined based on risk simulation). Would you be willing to move to one of these healthier rooms? (Response from the user). If moving to another room is not feasible for you, I can promptly contact the facility management teams to implement one of three mitigation measures: 1. An increase in room ventilation. 2. Room disinfection procedures. 3. Occupancy control measures. Which of these mitigation measures would you prefer?

Scenario 2 (the user feels good, infection risk is high, IAQ not acceptable): While you may currently feel good, it's crucial to be aware that both the infection risks and the air quality in this room are not at an acceptable level. To address these concerns, I strongly suggest moving to another room, such as room Z_1, Z_2, or Z_3. If you do not wish to or cannot change rooms, I can contact the facility manager to increase the ventilation rate in this room.

Scenario 3 (the user feels bad, infection risk is high, IAQ is acceptable): Thank you for expressing your concerns. The current room's infection risk is indeed not at an acceptable level for maintaining a healthy environment. (At this point, the same recommendations from Scenario 1 will be provided).

Scenario 4 (the user feels bad, infection risk is high, IAQ is acceptable): Thank you for acknowledging the concerns. It is crucial to note that both the infection risk and the air quality in the room are not at a healthy level. (Same recommendations from Scenario 2 will be provided).

Scenario 5 (the user feels bad, infection risk is low, IAQ is acceptable): Although you feel unwell, please note that the room environment is healthy and has an acceptable level of air quality. However, considering your discomfort, I recommend taking a break outside the building to refresh yourself.

Scenario 6 (the user feels bad, infection risk is low, IAQ not acceptable): Thank you for expressing your concerns. The air quality in this room is not at an acceptable level, which can potentially affect your performance and well-being. (Same recommendation from Scenario 2 will be provided).

4.4 Case study

This section presents the development of a real-time, cloud-based, integrated platform aimed at monitoring crucial aspects of building management, including energy consumption, thermal comfort, infection risks, and overall building environments, as well as communicating this information to users. The infrastructure integrates various components, such as sensor APIs, web servers, cloud computing, and EnergyPlus simulations. The UI of the web app was designed to effectively communicate the dynamic information collected to facility management teams. To demonstrate the application's capabilities, a case study was conducted using a section of the Zeanah Engineering Complex, the largest academic building on the campus of The University of Tennessee, Knoxville, with the results of the simulation presented within the app. This platform offers a comprehensive solution for real-time monitoring, analysis, and communication in building management scenarios.

4.4.1 Energy model generation

The capabilities of the platform were demonstrated by using a specific section of the Zeanah building as a case study. The selected region included the left wings of the second floor, which is composed of various spaces, including seven classrooms, thirteen offices, two laboratories, one learning space, one wellness room, two restrooms, two stair rooms, one electric room, and one data room. The total area of this building section is approximately 1848.9 m^2, and the layout of the building is presented in Figure 4-8. The

HVAC systems employed in the building include three centralized variable air volume (VAV) systems equipped with economizers (Figure 4-9).

Figure 4-9 illustrates a sample configuration of a deployed HVAC system. The building uses both gas and electricity as primary fuel sources. The heating system utilizes gas boilers, while the cooling system uses a packaged air conditioning unit (PACU). A VAV box with a reheat function is installed within each zone to regulate the airflow and temperature.

The architectural model was imported into Sketchup using OpenStudio plugin to accurately represent the building envelope and facilitate the energy simulation process. OpenStudio was then used to incorporate the building's HVAC systems into the model based on the configuration provided in the MEP model. These modifications resulted in a comprehensive model for energy simulation using EnergyPlus as described in Section 4.3.2.

4.4.2 Web app UI

The web app UI was designed with a focus on user-friendliness and clarity. By incorporating the principles of simplicity and intuitive navigation, the interface was designed to be both easy to use and comprehend. The concise UI design, combined with the same page display function, allows users to efficiently access and absorb information. The core design principles and features are demonstrated on the main page of the web app (Figure 4-10).

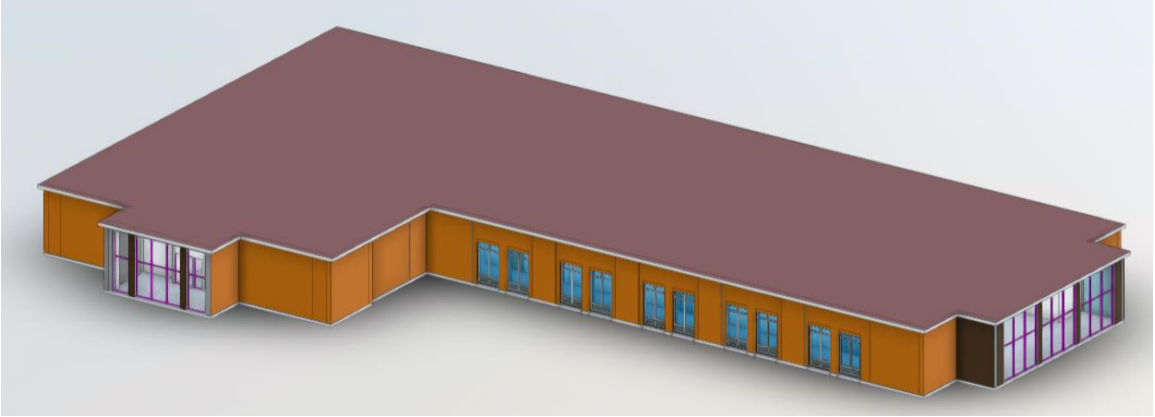


Figure 4-8 The architectural configuration of the selected building section.

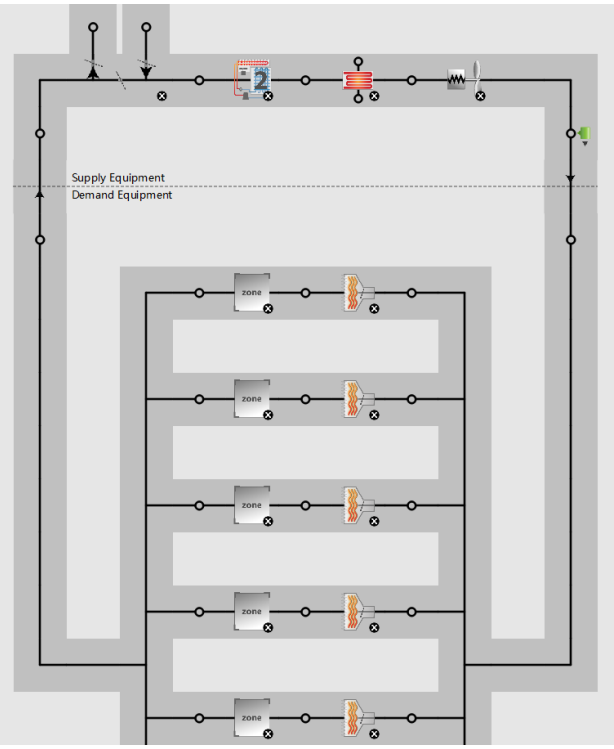
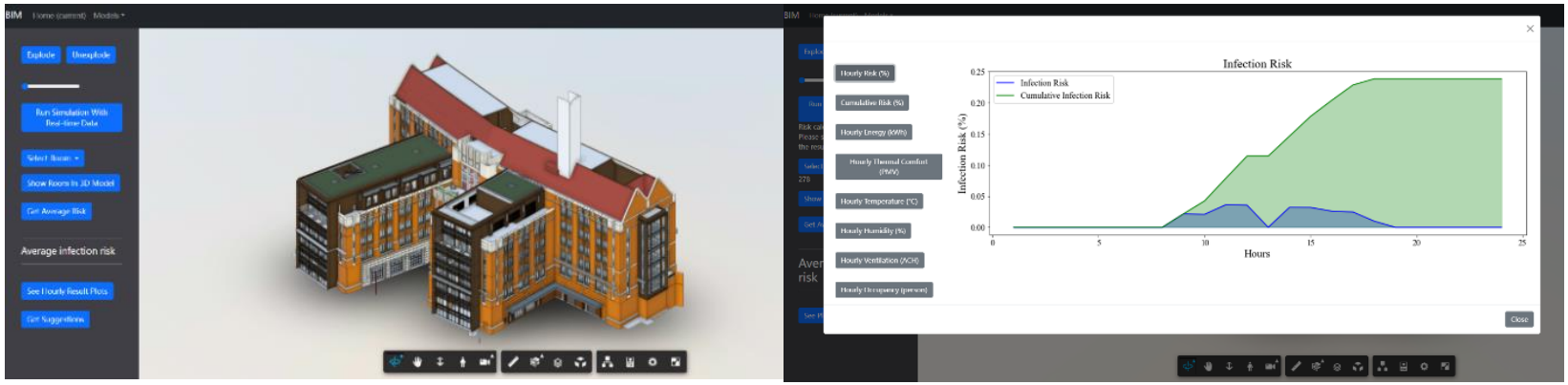


Figure 4-9 Diagrammatic representation of the HVAC configuration in the selected building section.



(a) (b)

Figure 4-10 The UI of the web app. (a) Main page and (b) simulation results visualized using line plots.

4.4.3 Sample simulation results

A test simulation was conducted to demonstrate the capabilities of the web app, as well as to showcase the range of information that can be displayed. This simulation utilized data and information specifically collected from classroom 278, located on the second floor of the Zeanah building. The simulation was performed for a whole day using weather and IoT data retrieved on June 22, 2023. The simulated hourly outcomes included infection risk, cumulative infection risk, energy consumption, and thermal comfort. Room temperature, relative humidity, occupancy, and the concentration of different pollutants were monitored by the IoT sensors. Figure 4-11 illustrates the time series results of the simulation and monitoring for room 278, as would be presented within the app's UI.

4.4.4 Alerting system and conversational persuasion system

The app's alerting system is designed to automatically trigger when predefined thresholds are exceeded. Popup alerts are displayed immediately after the user selects a room. To provide a comprehensive view of the alerts related to the selected room, all identified alerts are presented using a dropdown menu. Users can conveniently explore the dropdown menu and select specific problems they are interested in and access the relevant suggestions. In addition, the app utilizes a persuasive conversational interface powered by GPT-3.5 to provide appropriate suggestions and recommendations. Users can engage in a conversation-like interaction to receive personalized suggestions based on user inputs and current environmental conditions. Figure 4-12 illustrates the visual representation of the alerting system and the conversational interface within the app.

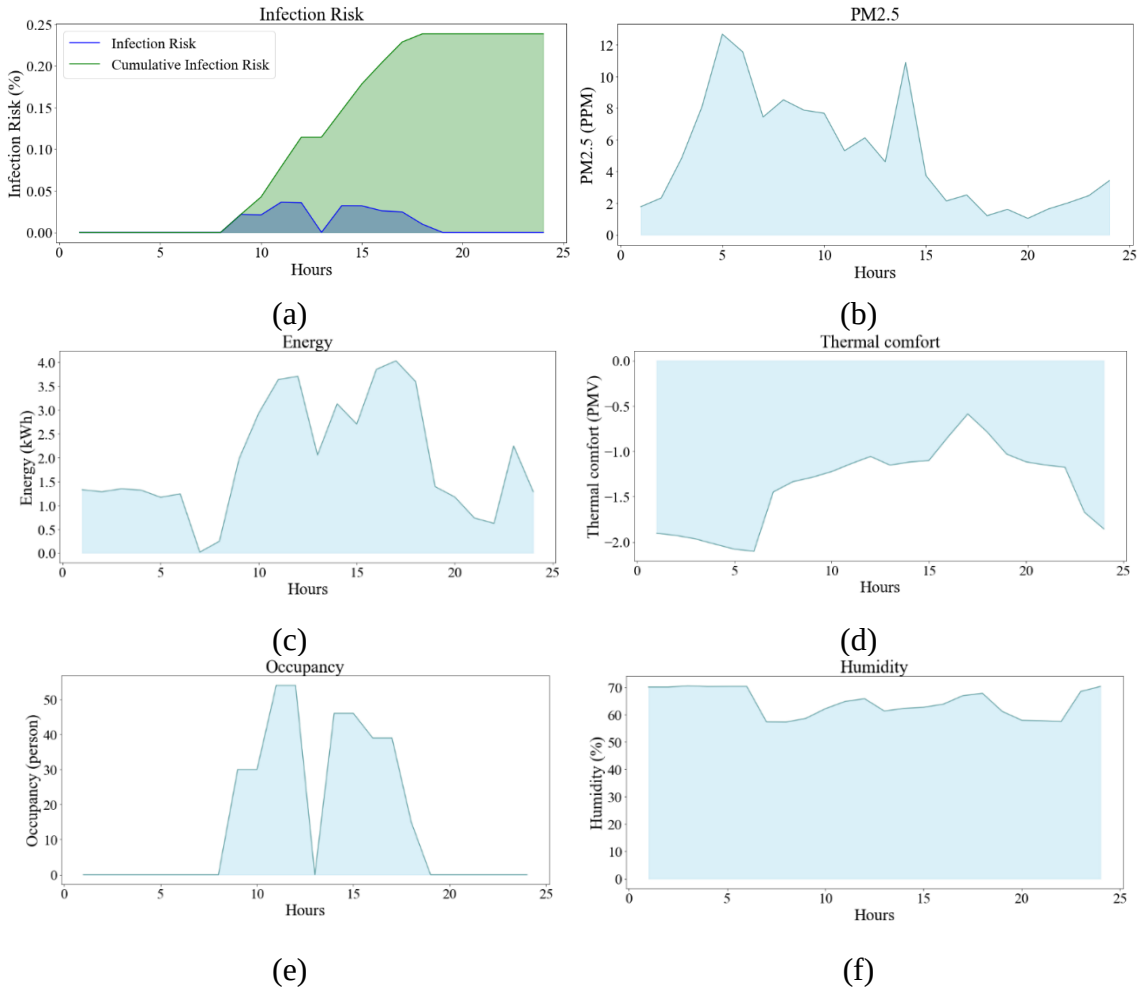


Figure 4-11 Simulation results from a sample room. Hourly outcomes included: (a) infection risk (%); (b) $PM_{2.5}$ (PPM); (c) Energy consumption (kWh); (d) Thermal comfort (PMV); (e) Occupancy (no. of persons); (f) Relative humidity (%).

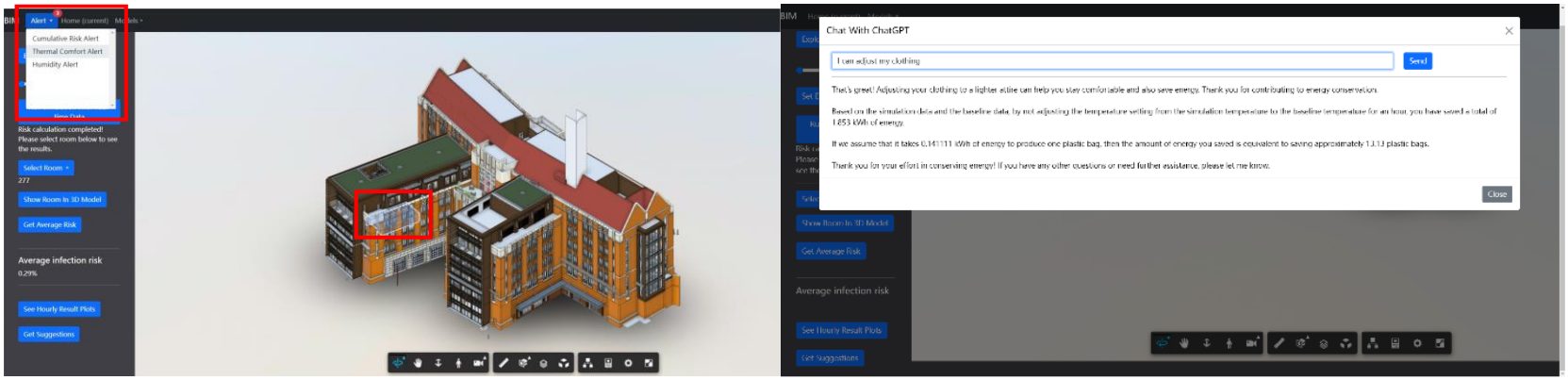
This user-friendly design allows users to easily navigate and access alert information, obtain tailored suggestions, and engage in interactive conversations to enhance their experience and address specific concerns.

In addition to offering persuasive strategies, the AI-powered conversational persuasion system also encourages user participation by offering the user several energy-saving tips by considering the tradeoffs between energy consumption, thermal comfort, and infection risks.

By explicitly informing the user of the amount of energy saved, this approach helps occupants better understand the positive effects of their actions and promotes responsible behavior. Furthermore, the system not only encourages positive occupant behavior but also provides multiple mitigation measures that occupants can choose from. These measures can be implemented by the facility management teams, offering occupants a range of options based on their preferences to address their specific needs.

Figure 4-12(b) illustrates an example of the persuasion system's response when the user feels overly hot in a room. The system suggests adjusting their clothing as a potential solution that addresses the user's discomfort. To enhance the persuasiveness of these suggestions, the app presents the estimated potential energy savings that can be achieved through clothing adjustments.

By indicating the potential energy savings and environmental benefits tied to specific actions, users are encouraged to adopt sustainable behaviors, resulting in a more informed and eco-conscious user experience.



(a) (b)

Figure 4-12 The UI of (a) The alerting system and (b) the GPT-powered suggestion system.

A sample conversation between the LLM-powered persuasion system and an occupant is provided in Table 4-1, demonstrating the interactive nature of the system and how it facilitates informative discussions. This dialogue exemplifies the interactive capabilities of the LLM-powered assistant, allowing for personalized suggestions and engaging conversations.

4.5 Discussion

This study proposes the use of an innovative real-time integrated platform for building management that integrates a variety of features from building environment monitoring to the effective communication of information with the express purpose of fostering a healthy and sustainable built environment. To demonstrate the capabilities of the platform, a case study was conducted within a section of Zeanah Engineering Complex in Knoxville, Tennessee.

The building's architectural model and MEP model were used to create a building energy model, which served as the basis for the digital twin. An IoT sensor network was deployed throughout the selected study area to allow for comprehensive building monitoring. This network continuously collects real-time data on various environmental factors in each room, including temperature, humidity, as well as the concentrations of pollutants such as CO_2, $PM_{2.5}$, and VOC.

The platform conducts simulations at the room level to assess three crucial aspects that are essential for building sustainability: health, energy consumption, and thermal comfort.

Table 4-1 Sample conversation between the LLM-powered assistant and an occupant.

Occupant	I feel hot in room 278.
Assistant	I'm sorry to hear that you're feeling hot in room 278. I have two suggestions for you: 1. Should I communicate with the facility managers and advise them to lower the indoor temperature? 2. If you are willing to adjust your clothing to a lighter attire, it could potentially save energy. Please let me know your preference regarding contacting the facility managers.
Occupant	I can adjust my clothing.
Assistant	That's great! Adjusting your clothing to a lighter attire can help you stay comfortable and also save energy. Thank you for contributing to energy conservation. Based on the simulation data, by not adjusting the temperature setting for an hour, you have saved a total of 1.853 kWh of energy. Thank you for your effort in conserving energy! If you have any other questions or need further assistance, please let me know.

The UI of the platform facilitates information sharing and visualization for facility management teams and occupants and uses an enhanced communications system involving a conversational persuasion system to provide occupants with a user-friendly experience.

4.5.1 Health aspects of building management

The occurrence of several severe pandemics over the past two decades, including influenza, SARS, and COVID-19 pandemic, has emphasized the critical significance of health considerations in building management. Although the threat of the COVID-19 pandemic has subsided recently, the need to prevent potential disease outbreaks remains crucial due to the pandemic's devastating impact on human lives and the economy. Airborne transmitted diseases pose a particularly severe threat due to their potentially rapid spread and limited means of transmission control. Indoor environments, often lacking adequate ventilation in typical operation scenarios, can become breeding grounds for airborne viruses. Hence, the development and implementation of a health-focused platform that monitors indoor environments is vital in curbing potential disease outbreaks. In addition to disease transmission, traditional concerns about IAQ continue to be significant in building management. Low-quality indoor environments can adversely affect occupants' health, leading to increased absenteeism due to SBS as well as reduced productivity and performance among occupants and workers. SBS is primarily caused by contaminations from various pollutants and insufficient indoor ventilation [137]. Consequently, IAQ detection was also considered in this study as a means of mitigating health risks and ensuring a healthier and more productive indoor environment.

It is essential to recognize that mitigation measures, such as increased ventilation, can effectively address health risks arising from both airborne diseases and pollutants. However, these two aspects should be considered separately to improve building performance. During pandemics, it becomes crucial to prioritize the reduction of disease transmission; consequently, room ventilation rates must be set to higher levels to enhance air circulation and minimize the risks of infection. Despite the implementation of these measures, the infection risks can remain high depending on the current state of the epidemic, while the IAQ can remain at low levels. Conversely, during non-pandemic periods, priority shifts to the management of IAQ during building operations. Maintaining a high-quality indoor environment is essential to promote the well-being and productivity of occupants and workers.

4.5.2 Interoperability achieved by cloud computing

To effectively conduct real-time energy simulations, researchers often rely on additional software for programming and data storage. In general, the energy simulation process is conducted locally before the data is transferred to a cloud server for retrieval. For instance, Pang et al. [138] introduced a framework for the real-time performance assessment of entire buildings, utilizing Building Controls Virtual Test Bed (BCVTB) as the software platform to which inputs from the Energy Management and Control System (EMCS) were provided. The acquired data were then sent to EnergyPlus for simulation, with the results archived in a separate database. Pallonetto et al. [139] proposed a grid co-simulation software platform that integrated BCVTB with a MySQL database using Java

Database Connectivity (JDBC). By accessing the database, this platform allowed for real-time simulation and visualization through a web application. However, such approaches still require the local installation of BCVTB software, which poses challenges to users, impacting accessibility and ease of use. The need for additional software installation may limit user's access to information, especially in the context of the wide variety of user devices, excluding potential users who may not require the app for professional purposes but still seek information or interaction about the building environment. In this study, a cloud-based integrated platform was developed to address these problems. This technology allows for interoperability within the same device, eliminating the need for additional software installation. This cloud-based approach supports cross-platform accessibility, allowing users to easily access the platform from any device and at any time (as long as they have Internet access) through the simple use of a URL. This innovation allows for room-level monitoring and simulation, laying the foundation for efficient building operations.

4.5.3 Human-centric conversational persuasion system

This study introduced an innovative AI-based conversational persuasion system powered by GPT technology that can generate personalized responses to specific user inputs. The development of this conversational system expands the scope of human-centric interactive services in the context of smart building operations. While such technologies are finding wide usage in fields like healthcare and services, it has not been extensively applied to the field of building management for indoor environments. This conversational

system effectively bridges this gap, allowing facility management teams to promptly address occupant needs and preferences. It also enhances occupant participation and fosters a healthier and more sustainable building environment. This system offers significant improvements in the interactive process compared to traditional conversational agents or chatbots. Traditional chatbots tend to provide consistent, rigid responses to similar questions, leading to user boredom and dissatisfaction due to repetitive interactions. However, the integration of a GPT-empowered interface as a conversational tool addresses these issues while introducing several advantages. Firstly, the widespread usage and human-like interface of GPT contribute to improving the users' trust and acceptance of the information provided, establishing credibility and fostering user engagement. Furthermore, GPT's ability to generate diverse sentences during communication ensures dynamic and varied conversations enhances the overall user experience, and makes interactions more engaging and enjoyable. This contributes to increased user satisfaction and promotes sustained user engagement with the system.

The monitoring data and simulated results are automatically transferred to the GPT model in real time. Through a comprehensive, predefined set of training phrases, the system gains the ability to understand the current environmental conditions and respond appropriately to user inputs by providing accurate and relevant responses. In particular, information regarding the tradeoffs between health, energy use, and thermal comfort serves as a powerful motivator, causing building occupants to actively engage with and embrace energy-saving strategies. The use of human-like conversational tones to demonstrate the energy savings allows occupants to gain a sense of awareness regarding their actions and

informs them of their direct impact on the building's overall performance. This creative approach allows for the effective and relatable visualization of energy consumption, making it easier for occupants to understand the extent of the environmental implications of their daily activities. This engagement encourages occupants to take a more active role in enhancing indoor environments and living quality through their participation.

4.6 Summary

The COVID-19 pandemic and other severe airborne diseases have highlighted the critical importance of health monitoring in the context of facilities management, as improper operation strategies can have severe implications for public health. Consequently, monitoring health and infection risks alongside energy consumption and thermal comfort has become essential for the maintenance of a sustainable built environment. The real-time, cloud-based integrated platform presented in this study represents a significant advancement in adaptive built environment management due to its incorporation and consolidation of various innovative functionalities.

The platform offers distinct advantages over existing solutions for three key reasons. Firstly, it combines all essential functionalities into a single platform, facilitating efficient data exchange and interoperability regardless of the device used to access this platform. Secondly, the platform enables the real-time simulation of crucial aspects of smart building management, such as health, energy, and thermal comfort. By utilizing the data collected from IoT sensing networks as inputs, the platform generates comprehensive results based on the interconnected relationships between these three critical aspects.

Thirdly, an interactive AI-based conversational agent was developed to promote healthy occupant behaviors and energy-saving practices in the context of the tradeoffs between health, energy, and thermal comfort. The platform offers real-time room-level information and presents a comprehensive view of the building environment through simulated results and monitored data. Via this interface, facility management teams can visualize their changes in the building environment when adjusting the setpoints of environment factors, allowing them to implement timely operation strategies at a granular level. In addition, the persuasion system fosters effective interactions between occupants and management teams while also encouraging occupant behaviors that align with sustainability objectives. By considering occupant preferences when implementing mitigation measures, the platform aims to enhance occupant satisfaction and contribute to the overall sustainability of the building. A case study was conducted on a section of a university building to demonstrate the capabilities of the proposed platform and the wealth of information it can provide.

The practical applications of this platform extend beyond disease control, and it can be deployed in various built environments where managing health, energy, and thermal comfort is essential. The platform's broad potential user base includes facility managers and individuals living or working in the building, making it a versatile and impactful tool for enhancing indoor environments and promoting sustainability.

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

This final chapter serves as a comprehensive conclusion to the dissertation, summarizing its key findings and contributions. It serves as a thorough consolidation of the research journey and emphasizes its significance in the literature. In addition, it describes the limitations of the current study and provides recommendations for avenues of future research, paving the way for additional advancements and developments.

5.1 Conclusions

The COVID-19 pandemic has caused over 6 million deaths worldwide [1] and ranks among the top three leading causes of mortality worldwide [140]. The global impact of the pandemic has raised concerns about public health, particularly in mass-gathering infrastructure facilities that often serve as hotbeds for disease transmission due to their crowded and high-contact nature. It is also essential to recognize that COVID-19 will not be the last pandemic to impact global health. The integration of health considerations into the process of long-term building maintenance is thus crucial to prevent potential outbreaks in the future. By emphasizing health and well-being in building maintenance strategies, we can proactively safeguard public health and create resilient infrastructures capable of effectively addressing current and future health crises.

In response to these urgent needs, this dissertation focused on three primary research objectives to facilitate the maintenance of a healthy, comfortable, and sustainable built environment during viral outbreaks. In particular, this thesis examines three essential

dimensions: health, energy consumption, and thermal comfort. The overarching goal was to develop a comprehensive framework that systematically explores these dimensions through the implementation of models, simulations, and monitoring methods. The thesis comprises three primary research areas, each contributing to the overall goal of the study. Firstly, a modeling approach was devised to estimate the infection risks of SARS-CoV-2 and assess the effectiveness of various intervention strategies in mitigating transmission. Secondly, a simulation-based modeling method was employed that incorporated health as a new dimension in building operations. This approach integrated facility, weather, and occupancy data to conduct simulations, providing insights into the relationship between health, energy use, and thermal comfort. Finally, a platform utilizing a coupling between digital twin-based technology and cloud computing was developed to perform real-time monitoring of these three dimensions. This innovative tool provides users with an interactive platform that includes a variety of integrated functionalities for monitoring, visualization, environmental alerts, and behavioral persuasion. The detailed methodologies are described in Chapters 2–4 as follows.

In Chapter 2, a mathematical model was developed to estimate the airborne infection risks of SARS-CoV-2 and the Omicron variant in 111,485 U.S. public and private schools, as well as evaluate the impacts of different intervention strategies, including increased ventilation, air filtration, and hybrid learning. It was found that schools in more than 90% of counties exhibit infection risks greater than 1%, highlighting the importance of implementing intervention strategies. Among the studied control strategies, air filtration was found to be most effective: the school's average infection risk when employing MERV

13 filters was over 30% less than the risk levels correlating with the use of increased ventilation and hybrid learning strategies. Most schools required the combined adoption of multiple intervention strategies to reduce the infection risk below 1%. The results provide insights into airborne infection risk in schools under various scenarios and guide schools and policymakers aiming to develop effective operations strategies to maintain environmental health.

In Chapter 3, a simulation-based trade-off modeling method was developed to understand the intricate relationships between 1) human health measured in terms of exposure to pathogens and infection risk; 2) building energy consumption as a result of differential heating, ventilation, and air conditioning (HVAC) control strategies; and 3) human thermal comfort in different climate zones. This research developed a modeling framework that evaluated the trade-offs among health, energy, and human thermal comfort and conducted simulations using school building data, which included a variety of temperature, humidity, and ventilation control parameters. The key findings of this study revealed that indoor temperature profoundly influences infection risk, energy consumption, and thermal comfort. Ventilation rates were found to influence the fluctuations in infection risks and building energy usage, while indoor relative humidity demonstrated negligible impacts. Notably, maintaining thermal comfort and low infection risk can be accomplished simultaneously, albeit at the expense of high energy consumption. A comparison of the optimal and the worst environmental settings in a typical U.S. climate zone revealed a 43% decrease in infection risks and a 61% increase in thermal comfort, accompanied by an over 70% increase in energy consumption. The influences and tradeoffs between infection risks,

energy consumption, and thermal comfort were additionally modulated by climate characteristics.

In Chapter 4, a novel platform integrating IoT-based BIM technology, cloud computing-based real-time simulations, and an AI-based conversational suggestion system powered by GPT was developed to enhance smart building operations. This integrated platform combines monitoring, simulation, alerting, and persuasion capabilities into a single comprehensive solution. The integration of these technologies enables the real-time monitoring of health, energy consumption, and thermal comfort, perform simulations to assess the tradeoffs between these aspects, provides timely alerts and recommendations, and employs persuasive techniques to encourage occupants to adopt more sustainable practices. Furthermore, the suggestion system serves as a communicative link between the building occupants and the facility management teams, promoting mutual understanding and enabling the timely implementation of occupant-preferred mitigation measures. A case study was carried out in a university building, which involved the establishment of an IoT sensor network, to evaluate the platform's performance. This case study demonstrated the platform's ability to monitor and analyze the building environment, assess tradeoffs between the three major dimensions of building sustainability, and provide timely recommendations as a persuasive social interactive tool.

By accomplishing its three primary objectives, this dissertation has produced a comprehensive framework that integrates modeling, simulation, and monitoring methods that significantly improve the sustainability of building operations. This framework provides insights to local governments and facility management teams, allowing them to

implement effective operational strategies based on the current status of an evolving epidemic situation. The proposed findings are expected to introduce new paradigms and novel technologies within the field of sustainable building environments. By combining theoretical advancements with practical applications, this research contributes to the broader goal of enhancing the sustainability and resilience of built environments, thereby fostering healthier and more sustainable communities. While this research primarily focuses on the COVID-19 pandemic and its application to school environments, the framework developed herein can be extended to encompass other airborne diseases as well as applied to a diverse range of infrastructure facilities.

5.2 Recommendations

This section outlines several specific limitations of this dissertation that provide intriguing opportunities for future investigation to offer insights and assistance in the maintenance of sustainable buildings during pandemics.

5.2.1 Limitations of the modeling approach for airborne infection risks

The estimated infection risk generated by the model refers to the daily infection risk based on exposure time in a single day, ignoring probability transition effects due to continuous exposure in schools, which may lead to an underestimation of infection risk. Future studies may wish to consider the effects of previous school days—particularly in the context of different school schedules—on cumulative infection risk.

As this model utilizes a scenario-based analysis, the derived results and findings on infection risk and intervention strategies were based on a one-year pandemic scenario and a short-term county-level epidemiological scenario, which may be different from actual epidemic situations. Leveraging the findings and insights of this work about the impacts of various intervention strategies on infection risk under different scenarios, schools and governments can design their own strategies based on their specific characteristics and epidemic conditions. Future work may wish to consider how the adoption of mitigation measures causes changes in disease transmission patterns.

5.2.2 Limitations of the simulation-based modeling approach for tradeoff analysis

The approach used to model the tradeoffs between infection risks, thermal comfort, and energy consumption was carried out on a one-year timescale. In reality, the outcomes and corresponding environmental factors may vary across different simulation periods. Consequently, future studies should consider the impact of seasonal variations on the three aspects as well as HVAC operation strategies.

While this study elucidates the nature of tradeoff relationships, it does not present a single optimal solution that considers all three aspects. Further research is thus necessary to develop an optimization method that provides intuitive decision-making suggestions.

5.2.3 Limitations of the integrated platform for real-time monitoring and communication.

This study focuses on estimating the indoor infection risk for specific viruses. However, it's important to recognize that the impact of indoor environmental factors, such as temperature and humidity, can vary depending on the specific virus or bacteria. Therefore, understanding the optimal indoor environment and mitigation measures for different pathogens, especially when multiple pathogens are present in the building, remains an area for further exploration.

The suggestions provided by the persuasion system, such as any recommendations in which occupants are encouraged to move to a different room with better indoor conditions, may potentially lead to congestion when multiple occupants adopt the same suggestion and converge on the same room, inadvertently turning the initially healthy room into a high-risk area. Future developments may wish to improve the persuasions algorithms through the integration of appropriate traffic models and/or optimization methods to ensure the balanced and effective distribution of occupants.

Additional research on human behavior would also allow for the implementation of more effective persuading methods, further enhancing the user experience and encouraging user participation and interaction.

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