

Jiannan CAI, Jianli CHEN, Yuqing HU, Shuai LI, Qiang HE

# Digital twin for healthy indoor environment: A vision for the post-pandemic era

© Higher Education Press 2023

**Abstract** Indoor environment has significant impacts on human health as people spend 90% of their time indoors. The COVID-19 pandemic and the increased public health awareness have further elevated the urgency for cultivating and maintaining a healthy indoor environment. The advancement in emerging digital twin technologies including building information modeling (BIM), Internet of Things (IoT), data analytics, and smart control have led to new opportunities for building design and operation. Despite the numerous studies on developing methods for creating digital twins and enabling new functionalities and services in smart building management, very few have focused on the health of indoor environment. There is a critical need for understanding and envisaging how digital twin paradigms can be geared towards healthy indoor environment. Therefore, this study reviews the techniques for developing digital twins and discusses how the techniques can be customized to contribute to public health. Specifically, the current applications of BIM, IoT sensing, data analytics, and smart building control technologies for building digital twins are reviewed, and the knowledge gaps and limitations are discussed to guide future research for improving environmental and occupant health.

Received March 19, 2022; accepted October 5, 2022

Jiannan CAI  
School of Civil & Environmental Engineering, and Construction Management, The University of Texas at San Antonio, San Antonio, TX 78249, USA

Jianli CHEN  
Department of Civil & Environmental Engineering, The University of Utah, Salt Lake City, UT 84112, USA

Yuqing HU  
Department of Architectural Engineering, The Pennsylvania State University, University Park, PA 16802, USA

Shuai LI (✉), Qiang HE  
Department of Civil and Environmental Engineering, The University of Tennessee, Knoxville, Knoxville, TN 37996, USA  
E-mail: sli48@utk.edu

This research was funded by the US National Science Foundation (NSF) (Grant Nos. 1952140, 2038967, and 2026719).

Moreover, this paper elaborates a vision for future research on integrated digital twins for a healthy indoor environment with special considerations of the above four emerging techniques and issues. This review contributes to the body of knowledge by advocating for the consideration of health in digital twin modeling and smart building services and presenting the research roadmap for digital twin-enabled healthy indoor environment.

**Keywords** digital twin, healthy indoor environment, building information modeling, occupant–building interaction, COVID-19

## 1 Introduction

People spend about 90% of their time in the indoor environment that encompass all facets of our lives, such as homes, offices, schools, and stores (Popkin, 1999; Klepeis et al., 2001). Buildings harbor various biotic and abiotic exposomes, including bacteria, viruses, fungi, particulate matter 2.5 (PM<sub>2.5</sub>), and volatile organic compounds (VOCs), which circulate in the buildings' air and on surfaces from the most inaccessible to most touched places. Transmission of and exposure to these biotic and abiotic exposomes have significant impacts on human health. For example, the coronavirus disease 2019 (COVID-19) pandemic has swept the entire world, infecting more than 250 million people with the death toll surpassing 5 million worldwide as of November 2021 (Worldometer, 2021). The airborne and fomite-based transmission of SARS-CoV-2 and many other pathogens in the mass-gathering building environment is a significant concern as it has led to significant health and economic loss worldwide. Chemical exposure in buildings, such as VOCs and PM<sub>2.5</sub>, also affects human health. Exposure to these pollutants may cause sick building syndrome, a collection of nonspecific syndromes linked to the indoor environment, the symptoms of which have an annual cost of \$60 billion due to reduced worker productivity (Fisk,

2002). Given the significant impacts of indoor exposure on human health, there is a crucial need to develop effective means of intelligently preventing the transmission of pathogens and people's exposure to harmful pollutants in buildings.

The advancements in building information modeling (BIM), the Internet of Things (IoT), and data analytics have accelerated building digitalization for design, construction, operation, and maintenance. The concept of building digital twins (DTs) has also gained momentum to realize the full potential of exploiting the rich information in BIM and sensing data to continuously monitor indoor environment and maintain healthy indoor environment. In the context of buildings, a DT is the digital counterpart of a physical asset that integrates real-time sensor readings and 3D virtual models of building assets to analyze and control the building's interactions with its environment and users (Jiang et al., 2021). DTs enable unprecedented monitoring, understanding, and optimization of the functions of physical entities via seamless data transmission between the physical and virtual worlds, deriving relevant solutions for real-life systems and informing and influencing human behaviors. In the Architecture, Engineering, and Construction (AEC) field, there has been a proliferation of studies aiming to develop fundamental principles and techniques for DT, including DT creation, data collection, processing, and analytics, simulation, and control. The primary applications of such research include construction management (Boje et al., 2020; Pan and Zhang, 2021), building operation and maintenance (Lu et al., 2020a), and energy management (Kaewunruen et al., 2019; Agostinelli et al., 2021). However, very few studies have focused on leveraging DT techniques to improve human health outcomes in the indoor environment.

The COVID-19 pandemic has raised awareness of indoor environment health as multiple pathogens are transmitted in indoor environments with the potential to infect people. Thus, new visions have aspired to make the indoor environment healthy. For instance, new streams of data on indoor environment and their occupants could be exploited in the buildings' DTs to assess infection and exposure risks, and the corresponding physical components, such as building control systems (e.g., heating, ventilation, and air conditioning (HVAC) systems), could be adaptively controlled to reduce biotic and abiotic exposure of occupants and increase human comfort while maintaining efficient and cost-effective operations. Despite these fundamental studies and technological developments, research has largely ignored the prospect of digital twinning for health management. Hence, the answers to these important questions remain ambiguous: 1) What existing technologies are available and how can these technologies be extended and linked to indoor environmental and human health? 2) What are the barriers to and gaps in linking the DT to human health in indoor

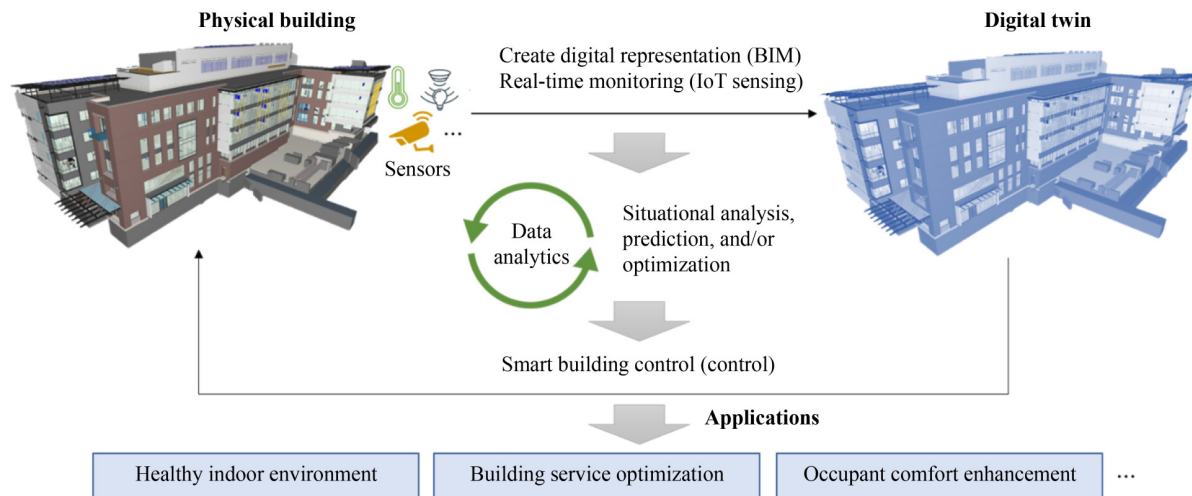
environment? And 3) what future research is needed to further exploit the potential of DTs for improving human health in indoor environment?

Therefore, this research aims to summarize and discuss DT techniques in the context of environmental health and infection prevention and highlight the gaps that must be closed for the seamless integration of healthy buildings, paving the road for future research. To contribute to the body of knowledge, we compared and summarized the state-of-the-art techniques developed for building DTs, discussed their potential applications for and limitations of improving human and environmental health, and highlighted the knowledge gaps in extending it to ensure a healthy indoor environment. To the authors' best knowledge, this review is the first to discuss these issues and present roadmaps for adding health to DTs. The remainder of this paper is organized as follows. Section 2 introduces the background and concept of DTs, as well as their enabling technologies. It also highlights the significance of DTs for a healthy indoor environment. Section 3 introduces the method and procedure of literature review. Sections 4–7 review the current applications of building DTs and knowledge gaps in healthy indoor environment research from the perspective of BIM, IoT sensing, data analytics, and smart building control. Section 8 summarizes and concludes the paper and discusses future research directions for cultivating a DT-enabled smart and healthy indoor environment, elaborating on a future vision of integrated DTs with special consideration of the above four emerging techniques and corresponding issues.

---

## 2 Digital twins for healthy indoor environment

A DT is a holistic simulation and representation of an as-built system that uses physical model and sensor updates to enable the flow of information between the physical and virtual systems to allow mirroring, or twinning, of the real space condition and optimization of the service or production (Jiang et al., 2021). To this end, a DT has three components: The physical system, the virtual model, and connected data and associated analytics. Four steps are required for building a foundational DT for indoor environment, as presented in Fig. 1, including: 1) develop a virtual and digital representation of a physical facility using 3D modeling (create); 2) establish a real-time bidirectional connection between the physical and cyber systems to allow real-time data acquisition and control (data sensing and control); 3) develop data analytics in virtual models to inform optimized control of physical systems for improved monitoring, production, and service (analyze); and 4) test, calibrate, and update the DT (evolve). The DT can exploit BIM approach and sensor networks to establish a real-time view of the facility. The



**Fig. 1** Establishment of digital twin and its applications in indoor environment.

collected data will capture the dynamics to enable real-time analytics and inform decision-making to actuate control of the physical components of the indoor environments to achieve healthy indoor environment, building service optimization, occupant comfort enhancement, etc. As such, existing buildings can benefit from implementing a DT to enhance building operation and maintenance.

The AEC industry has conducted studies on building DTs. For instance, research efforts have been made to develop DTs from BIM models and IoT sensor networks (e.g., Lu et al., 2020a; Pan and Zhang, 2021). Data processing methods have been established to detect data irregularity, support decision making, understand occupants' behavior and states (Saha et al., 2019; Piscitelli et al., 2021), and provide a basis for physical control for building operation and service. The primary application domains are building energy efficiency (Kaewunruen et al., 2019; Francisco et al., 2020), occupant comfort (Clausen et al., 2021), building safety (Liu et al., 2020), and proactive maintenance (Lu et al., 2020b). Despite the partial success of previous research efforts, there remains a challenge to integrate health considerations into DTs. The rationale for digital twinning for health is manifold. First, the indoor environment is highly heterogeneous with various functionalities and characteristics, providing diverse habitats for various pathogens. Microbiomes differ considerably in rooms with different usages in the same building (Adams et al., 2016; Gilbert and Stephens, 2018). Thus, exposure risks vary depending on the exact locations, underlining the need for spatially adapted risk management practices. Second, pathogens present in distinctive habitats in indoor environment, such as surfaces, air, and water, and have different transmission and exposure pathways (Ijaz et al., 2016; Prussin et al., 2017; Kraay et al., 2018). The transmission of pathogens that persist on surfaces could be prevented by minimizing physical contact or enhancing surface disinfection; however, the same strategy would not be fully effective if

the pathogens were also airborne. Third, the transmission and exposure pathways of pathogens are complicated by the building occupants' behaviors, particularly in indoor environment with many users (Zhang et al., 2018; 2020). Fourth, approaches such as prolonged access control and cleaning to reduce pathogen transmission and exposure could significantly disrupt the standard functionalities of indoor environments. The highly dynamic and connected nature of human behavior, microbial transmission, and building operations in the indoor environment requires the deployment of adaptive and advanced systems to enable real-time monitoring and control responses to constant changes in the building–human–pathogen system. Digital twinning holds significant promise in addressing these challenges.

### 3 Methodology for literature search

According to the background and concepts introduced in Sections 1 and 2, the DT of the indoor environment can be perceived as the interaction between the buildings' indoor environment and its digital representation model to provide real-time monitoring, analytics, and control for the environments. Therefore, four research clusters that develop key technologies to enable the establishment of DT have been identified, i.e., BIM, IoT sensing, data analytics, and smart building control. Specifically, BIM serves as the foundation to create information-rich building models, which is the repository to accommodate the virtual space and relevant data. IoT sensing enables data acquisition regarding physical spaces and humans, such as environmental parameters, occupant behaviors, and the status of physical assets. The IoT data are critical links to connect the physical and virtual spaces. Then, with the advances in artificial intelligence (AI) as well as modeling techniques, we can retrieve useful information to support intelligent decision-making based on collected data. The

derived information can be used to control the physical space.

Once determined the four research clusters, keyword-based search method was used to identify related studies for each research theme, where Google Scholar is the main search engine. Specifically, the keywords consist of three lists that cover research target object, approach, and objective, and are illustrated in Table 1. The keywords in different lists are combined in the search, such as “building information modeling, health”, “sensing, building environment”, and “indoor air quality, building control, comfort”. Considering the large volume of literatures from the search, we have narrowed down the literatures to the ones published from 2015 to 2021. We performed initial screening by checking paper title and abstract to ensure the inclusion of most relevant papers. Specific criteria are employed to further exclude irrelevant papers, including 1) conference publications, 2) duplicated papers or papers discussing very similar contents from the same authors, and 3) papers focusing on hardware development. It should be noted that conference papers in fields of computer science and information technology were not excluded considering most of their innovations are first published in conferences. Based on all identified literatures, we reviewed four techniques related to DTs and discussed the potential applications and barriers to promote environmental and human health.

## 4 Building information modeling

### 4.1 Background and related studies on BIM for building management

BIM is a digital representation of a facility throughout its lifecycle for all stakeholders involved to exchange information and facilitate decisions (Wang, 2012). Since the concept of BIM was proposed in the 1970s, it has been viewed as one of the most promising developments of the AEC industries in decades. Many applications have been developed for a facility’s lifecycle, e.g., design visualization, design performance analysis, clash detection, 4D schedule simulation, 5D cost estimation, and maintenance planning. By integrating with other advanced technologies (e.g., AI, virtual reality, 3D printing, and IoT), BIM has evolved as an open platform for facility information integration, exchange, and management (Pan and Zhang, 2021) and has become an important data source for

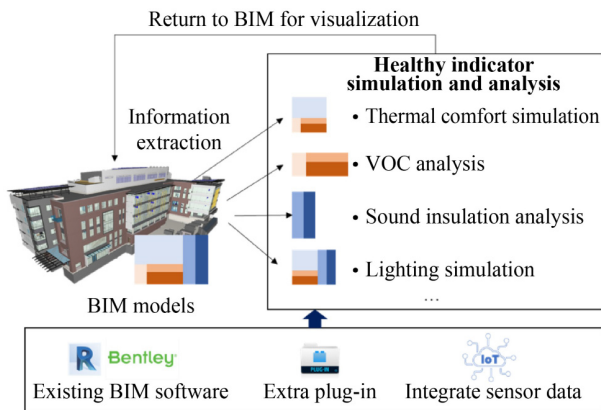
building DTs (Boje et al., 2020). Some DT frameworks have been developed in the AEC industry for construction management (Pan and Zhang, 2021), asset management (Lu et al., 2020a), and energy management (Kaewunruen et al., 2019). In these frameworks, BIM typically serves as a database, combining with sensor networks to achieve real-time monitoring for a facility. Based on these data, AI and machine learning techniques are used for knowledge mining, performance prediction, and real-time controls. In the process, industrial foundation classes (IFC)-based BIM models are often used to overcome data interoperability issues among variant software or tools because IFC is a platform-neutral file format for representing AEC data. Since different applications typically have specific data requirements, model view definition (MVD)—a subset of IFC schemas—has been used to clarify specific information requirements and overcome information redundancy issues. With the development of semantic web technologies, ontology-based information exchange methods are also gaining more attention (Zhong et al., 2018).

A noticeably small amount of research has focused on BIM applications for healthy indoor environment. This area of study is often viewed as a sub-category of design performance or facility management with an emphasis on the management of indoor air quality, daylighting, ventilation, etc. COVID-19 has caused a significant increase in attention paid to using BIM to facilitate healthy indoor environment. Rice (2021) summarized 14 building health indicators, including thermal comfort, VOCs, and sound insulation, and discussed the potential to use BIM models to measure and assess these indicators through questionnaires. Most of the respondents in the study agreed that BIM models can measure these indicators, though they have argument about the measurement complexity for different indicators. Three complexity levels were identified, listed here from simple to complex: Direct measurement based on BIM models, extra plug-in required, and extra sensors and detectors required. Some studies have focused on specific indicators (e.g., indoor air quality (Utkucu and Sözer, 2020) and lighting (Montiel-Santiago et al., 2020)) and have discussed how BIM can be used to assess and monitor them. In addition to human perceptible indicators, studies (e.g., Adams et al., 2014; Li et al., 2021a) have been conducted from the building microbiology perspective to extract building information such as layout and link it with microbial communities acquired through high-throughput sequencing techniques to

**Table 1** Keyword search list

List	Keyword
List 1 – Target object	building, indoor environment, building environment, indoor air quality, occupant
List 2 – Approach	building information modeling, sensing, Internet of Things, simulation, data analytics, data-driven, building control
List 3 – Objective	health, comfort

understand the impacts of design on microbial risks. For instance, Adams et al. (2014) documented the variations in microbial communities between different room types. A pilot study conducted by Li et al. (2021a) linked BIM with the microbial transmission model for the first time to assess the infection risks at the room level, paving the way for integration of BIM with microbial risk assessment to promote health. In summary, the current BIM usage for a healthy indoor environment involves two processes (as illustrated in Fig. 2): 1) integrating information extracted from BIM with other data to assess health or health-related factors based on simulation or data-driven methods (Sporr et al., 2019; Kwok et al., 2020; Gan et al., 2021); and 2) utilizing visualization capabilities of BIM to represent and communicate health or health-related factors to users (Alavi et al., 2021; Valinejadshoubi et al., 2021).



**Fig. 2** Building information modeling for a healthy built environment.

#### 4.2 Knowledge gaps in BIM for a healthy indoor environment

Despite the scarce literature, we must address the two main research gaps to exploit BIM for a healthy indoor environment. First, an integrated healthy indoor environment assessment and simulation are required. Existing results focus on the simulation of individual indicators. However, these health indicators are not independent. For example, wall insulation will impact sound insulation as well as indoor temperature (thermal comfort) (Yang and Moon, 2019), and indoor temperature alters the rate at which indoor environment inhabitants shed microorganisms (Horve et al., 2020). Depending on one indicator to optimize design or operation may impact other health conditions. Therefore, figuring out the relationships among these indicators and designing an integrated simulation platform are critical to designing and maintaining a healthy indoor environment. BIM, as an integrated platform, can serve this integration function. However, the connection of BIM models with indoor environment

health assessments or simulations may result in data interoperability issues that must be addressed. The interoperability exists at both the semantic level and syntactic level. At the semantic level, the data requirements for various indoor environment simulations are still unclear. BIM is an integrated model with multi-disciplinary information, but simplifying BIM models is necessary for specific simulations. At the syntactic level, multi-software exists for various simulations. To develop a BIM-based DT platform for healthy indoor environment management, it is necessary to enable model transfer between tools to avoid duplicating modeling efforts and maintain information consistency. IFC-based system development can be a potential solution, and this future direction includes identifying information requirements, clarifying information exchange process maps, and developing an MVD for healthy indoor environment.

Second, a closed-loop system is required to facilitate an environment that promotes health. Despite some progress made toward a healthy indoor environment, a significant gap remains in understanding how indoor environment design and operation will mediate occupant health. This knowledge gap stems from the lack of a generalizable framework and tools to quantitatively model the indoor environment and correlate the design and operation with health indicators. To close this gap, instead of using BIM as a pure data repository, it may be beneficial to create and test a computational framework and tools to explore the mechanistic relationships between design features/operation strategies and health indicators. In addition to simulation, with the application of the IoT for indoor environment monitoring, environmental and occupant data can be collected, which can then be linked back to BIM models to maintain a living BIM. The living BIM can serve as a source for knowledge mining (e.g., the relations between operation strategies and healthy indicators) based on data-driven methods and can also be used to calibrate simulations. A feedback loop must also be created based on simulation/data-driven models to guide healthy building design and maintain a healthy indoor environment with predictive operation and control.

## 5 Internet of Things sensing

The IoT connects massive sensing and actuating devices and allows them to exchange and share information via a communication network. Thus, it can deliver adequate information about environments to users to enable innovative and intelligent applications in various areas, including smart cities (Gaur et al., 2015; Singh et al., 2020), smart and connected healthcare (Wu et al., 2017; Pramanik et al., 2019), and smart building management (Verma et al., 2019; Daissaoui et al., 2020). IoT is a highly interdisciplinary field with various enabling

technologies including sensing technologies, network communication, cloud computing, data analytics, and system control. IoT sensing is an indispensable component of digital twinning as it captures the attributes and statuses of physical systems (primarily the environment and occupants of the indoor environment), which are then used to establish the virtual twin and enable various analyses. Figure 3 illustrates the typical applications of IoT sensing in indoor environments, which can be divided into two categories: Environmental sensing and occupancy sensing.

### 5.1 Environmental sensing

Indoor environmental quality (IEQ) is critical to occupant health, comfort, and productivity (Lee et al., 2019; Marques and Pitarma, 2019; Mujan et al., 2019). IEQ monitoring captures environmental attributes of the indoor environment and is a fundamental component of digital twinning, which can be achieved using IoT sensing technologies for thermal comfort optimization (Salamone et al., 2018; Zahid et al., 2021), indoor air quality assessment and control (Benammar et al., 2018; Jo et al., 2020), energy conservation (Khanna et al., 2019; Wu and Liu, 2020), and many other smart building applications. Various IoT sensors are used to measure IEQ, such as thermal comfort (e.g., temperature and humidity) sensors. The collected data can be used to estimate occupant comfort satisfaction (Lee et al., 2019; Alsaleem et al., 2020) and can provide rich information for the control of HVAC systems for energy conservation (Rajith et al., 2018; Ruano et al., 2018). Air velocity sensors may also be used to measure the airflow rate in the indoor environment (Dong et al., 2019), which is another indicator used to

assess and control the thermal comfort of occupants (Uğursal and Culp, 2013; Cheng et al., 2015). Furthermore, the collected data could be coupled with computational fluid dynamics (CFD) and BIM to model and assess the transmission of air pollutants and airborne pathogens (Shi et al., 2019).

Air quality sensors can monitor the concentrations of indoor pollutants such as PM<sub>10</sub>, PM<sub>2.5</sub>, and VOCs (Marques et al., 2018; Palmisani et al., 2021), which are major environmental carcinogens and have significant negative impacts on human health (World Health Organization, 2021). Therefore, these levels are usually monitored using IoT sensors to assess indoor air quality for healthy environments. Moreover, CO<sub>2</sub> sensors can measure the concentrations of CO<sub>2</sub> in the indoor environment, which is typically used to capture the presence and number of occupants by leveraging the estimated amount of CO<sub>2</sub> exhaled by an individual (Mumma, 2004; Nassif, 2012). In addition to air quality, light and noise conditions also affect occupant comfort and health and are monitored using IoT sensors. For instance, light sensors are used to monitor the illumination intensity, and the collected data are commonly used for the intelligent control of lighting systems considering the interplay of energy costs, visual comfort, and occupants' activities (Leephakpreeda, 2005; Navada et al., 2013; Gentile et al., 2016; Choi et al., 2016). Sound level sensors are further used to monitor noise in the indoor environment. Environmental noise directly affects occupant health and productivity, as high noise levels can cause various health symptoms, such as high blood pressure and stress. Therefore, sound sensing has been leveraged to detect noise levels to contribute to the assessment and control of acoustic comfort (Marques and Pitarma, 2020).

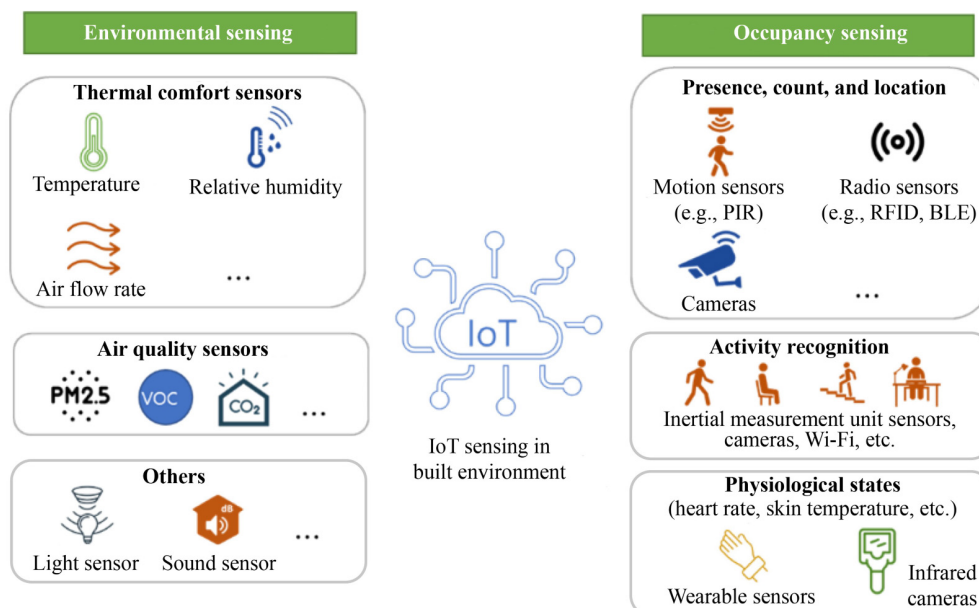


Fig. 3 Applications of Internet of Things sensing in built environments.

## 5.2 Occupancy sensing

Occupants interact with building systems and indoor environments through their presence and activities, and such occupant behavior affects pathogen transmission and energy consumption in buildings, thus influencing the health outcomes and sustainability of the indoor environment. A variety of sensing technologies have been developed and used for occupant presence detection, counting, and localization. The passive infrared (PIR) sensor is one of the most widely used sensors for occupancy detection given its low cost and ease of deployment. It determines the presence of occupants by detecting the infrared radiation changes caused by an occupant's movements (Chen et al., 2018b). The outputs of PIR sensors can also be used to extract occupant movement patterns and estimate the number of occupants using algorithms developed in previous studies, such as distance- and direction-based algorithms (Wahl et al., 2012) and statistical regression algorithms (Raykov et al., 2016). Environmental sensors have also been used in occupancy detection. Specifically, as demonstrated by several studies (Dong et al., 2010; Candanedo et al., 2017), CO<sub>2</sub> sensors are the most effective environmental sensors as indoor CO<sub>2</sub> concentrations are directly related to the number of occupants. This data can further be fused with data from other environmental sensors, such as temperature and humidity sensors, for occupancy sensing (Candanedo and Feldheim, 2016). Several radio-based sensing technologies, such as radio frequency identification (RFID), Bluetooth low energy (BLE), and Wi-Fi, have been increasingly used to estimate the presence and number of occupants in the indoor environment (Filippopolitis et al., 2017; Wang et al., 2017a; Zou et al., 2017). Such approaches rely on radio signals transmitted between receivers and transmitters and typically assume that each occupant carries one smartphone that receives Wi-Fi and Bluetooth signals, which may not always be true. Other studies (Zhuang et al., 2016; Topak et al., 2018) have leveraged the strength of received signals as well as changes in the strengths to localize occupants. However, radio-based localization is very sensitive to environmental configurations and is subject to multi-path errors, thus resulting in relatively low accuracy and reliability. With the advances of deep learning and computer vision techniques, cameras have been increasingly used in occupancy sensing considering the rich contextual information they provide. With multi-camera systems, the presence (Silvestre-Blanes and Pérez-Lloréns, 2011), number (Liu et al., 2013), and location (Cai and Cai, 2020) of occupants can be estimated. However, vision-based occupancy sensing suffers from some issues, such as high computational costs, sensitivity to illumination conditions, the requirement of line-of-sight, and privacy concerns.

Occupant activity recognition is a key enabler of

user-centered control in building management systems by providing context-aware and occupant-centered information. There are two primary streams of approaches, i.e., sensor-based and vision-based approaches, used to recognize daily activities for occupants in the buildings, such as running, walking, sitting, and jumping. Accelerometers embedded in wearable sensors or smartphones are the main sensors used to recognize activities, where motion signals are pre-processed to reduce noise and then analyzed via statistical or machine learning models to classify activities (Chen et al., 2017; 2019a). Such approaches require occupants to carry sensors, which may not result in continual sensing of all occupants in the environment. Furthermore, the results are sensitive to the mounting positions of the sensors. Depth and RGB cameras are used to obtain joint positions and appearance information of occupants in the scene, which are then used to recognize human activity via computer vision techniques (Cippitelli et al., 2016; Zerrouki et al., 2018; Zhao et al., 2019b). Vision-based activity recognition is relatively accurate and can capture rich scene contexts, though privacy and security are the main concerns in building applications. Recently, several studies (Wang et al., 2017b; Chen et al., 2019b) have also developed methods to leverage Wi-Fi signals that are becoming ubiquitous in the indoor environment for activity recognition. Wi-Fi channel state information (CSI) is exploited because it can measure the multipath variation influenced by occupants' movements, thus providing fine-grained information on human activity. However, because body motions in a wireless environment can induce fluctuations in the received signal, ensuring the accuracy and robustness of such a system remains challenging.

Occupants' physiological states, such as heart rate and the temperatures of different body parts, have also been collected using various sensors to assess occupant thermal comfort. Wearable sensors, such as smart wrist bands, are used to acquire wrist temperature, heart rate and other states, which can be correlated with activity levels using embedded internal sensors (Hasan et al., 2016; Li et al., 2018). Non-contact and non-invasive sensors, such as infrared cameras (Pavlin et al., 2017; Li et al., 2019), are alternatives for capturing the skin temperatures of multiple occupants at a distance. Despite the advantages of non-invasiveness and high efficiency, the accuracy of this method needs significant improvement. The sensed physiological states of occupants provide rich data for thermal comfort models, thus facilitating adaptive control to ensure thermal comfort while mitigating energy costs.

## 5.3 Knowledge gaps in IoT sensing for environmental and human health monitoring

Despite numerous studies, IoT sensing in buildings for human well-being and health is still superficial because of many issues. First, although various environmental

sensors and wearable sensors have been used to monitor IEQ and occupants’ physiological states, the direct measurement of health-related factors, such as pathogens, using sensors remains underdeveloped. Airborne pathogens, such as Influenza, Rhinovirus, and SARS-CoV-2, pose a significant threat to occupant health and may cause infectious diseases in the indoor environment. However, the direct detection of airborne pathogens from the air is extremely challenging considering the heterogeneous characteristics of pathogens and the low concentrations found in aerosol samples. The currently developed biosensors are expensive and their sensitivity is still largely unsatisfactory (Fronczek and Yoon, 2015). This leaves a critical need for low-cost real-time biosensors for pathogen detection in the indoor environment.

Second, although low-cost environmental sensors could measure IEQ, the accuracy and reliability of their measurements mainly rely on the configuration and placement of the sensors, particularly in complex indoor environments. For instance, it is extremely challenging to place sensors in a way that covers all building areas to measure CO<sub>2</sub> concentration. Moreover, photometric sensors are subject to the impacts of sunlight when placed near a window. Considering various sensor configurations and placements, effective methods are also needed to convert point measurements to model the continuous states of the 3D space and to determine optimal sensor configuration considering the trade-offs among multiple factors, such as cost, installation efforts, measurement accuracy, and spatial resolution. Furthermore, data fusion algorithms should be developed to fuse various environmental and occupant sensors to obtain more comprehensive and accurate information.

Third, current occupant sensing can only provide approximate occupancy information. The accurate localization and tracking of multiple occupants in complex indoor environments remain challenging. Moreover, current occupant activity monitoring mainly focuses on daily activities conducted by individuals; the interactions

among multiple occupants and those between occupants and the environment are overlooked, hindering the assessment of potential disease transmission and health impacts due to occupant–environment interactions. This will be further elaborated in the next section.

Fourth, IoT sensors, especially cameras and wearable sensors, suffer from security and privacy concerns. Recent advances in edge-computing and privacy-preserving techniques have great potential to mitigate such issues. For instance, depth and thermal images can be used instead of RGB images for video analysis. Edge devices can also be used to allow local and decentralized data analytics without having to store and transmit data. However, more studies are required to ensure privacy and security in IoT sensing for the indoor environment. Furthermore, as the use of IoT sensing in the indoor environment increases, the real-time transmission of big data remains challenging. 5G mobile networks could offer a promising solution through integration with the building sensing network.

## 6 Data analytics

Data analytics has been used as an important tool to facilitate the operation and maintenance of buildings to improve building performance, such as indoor air quality, thermal comfort, and energy conservation. Data collected through multiple channels, including building design and operation information, IoT sensors, and public domain datasets (e.g., outdoor weather and air quality data and land use data), are processed and analyzed to predict the status and performance of the building and derive information-based control decisions. Figure 4 illustrates the typical approaches of data analytics in various applications of building management, which can be divided into two categories: Simulation-based methods and data-driven methods.

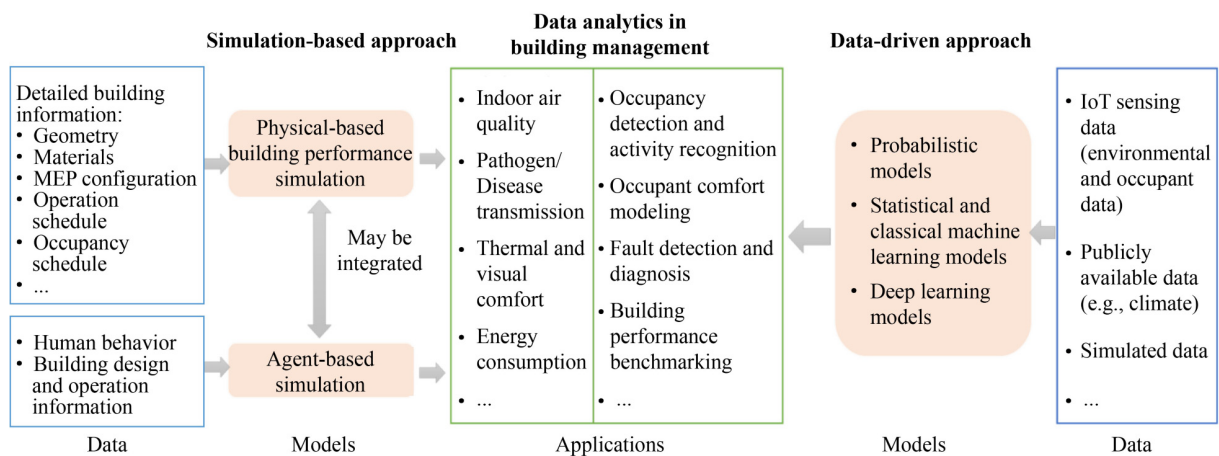


Fig. 4 Data analytics in building management.

## 6.1 Simulation-based methods

Over the past decades, physical-based building performance simulation (BPS) has been widely studied and classically applied to predict building performance in terms of energy consumption, carbon emissions, and other occupant comfort-related metrics (Azar et al., 2020). BPS is based on physical principles and thermodynamical heat and mass transfer, and requires detailed building information, such as building geometry, construction materials, mechanical, electrical and plumbing (MEP) system configuration and operation schedules, and occupancy schedules of the building. From the perspective of a healthy indoor environment, various BPS models, typically integrated with CFD techniques, are used to model, assess, and control indoor air quality (Li and Wen, 2014; Zhuang et al., 2014), pathogen transmission (Peng et al., 2020; Motamedi et al., 2022), and thermal and visual comfort (Costanzo and Donn, 2017; Cheong et al., 2020). A main limitation of BPS models is the simplicity of occupant behavior, which will influence the accuracy and reliability of simulation outputs. Agent-based simulation (ABS) has been used to better model the dynamic interaction between occupants and the indoor environment and can be integrated with BPS to study the influence of such interaction on building performance, such as energy consumption (Zhang et al., 2011; Ding et al., 2019) and disease transmission (Zhou et al., 2021; Islam et al., 2022), to guide building operation and control. In addition, given the rich building design and operation information (both spatial and semantic information) in BIM, it has become an indispensable tool in data analytics and has been coupled with BPS to generate more accurate and reliable outputs in terms of building performance (Zhou et al., 2020b).

## 6.2 Data-driven methods

With the advances in sensing technologies and machine learning algorithms, big data analytics and data-driven approaches have attracted growing interest in predicting building performance and occupancy behavior. With minimal requirements for prior knowledge regarding building and occupancy, such an approach can rapidly learn from data with high computational efficiency. In data-driven analysis, the IoT sensors described in the previous section serve as a major source of real-time environmental and occupant data. Other data sources include publicly available data (e.g., climate and air quality data), and simulated data collected from BPS models for either virtual or real buildings (e.g., light distribution and thermal comfort). Once the data are collected, pre-processing techniques, such as data cleaning, data reduction, data transformation, and feature engineering, are used to organize the data in structured format (Fan et al., 2021). Then, various models are developed to learn from

the data for the prediction of either building performance or occupant behavior. Typical data-driven models in building management include probabilistic models (e.g., Bayesian networks (He et al., 2016) and the hidden Markov model (Lam et al., 2009)), statistical and classical machine learning models (e.g., support vector machines (Jain et al., 2014) and decision trees (Yu et al., 2010)), and, most recently, deep learning models (e.g., convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Zhao et al., 2019a; Chen et al., 2021)). Data-driven methods are applied to model a wide range of information in the context of a healthy indoor environment, including occupancy detection and activity recognition (Saha et al., 2019), occupant comfort modeling (Chen et al., 2015a; Zhou et al., 2020a), fault detection and diagnosis (Piscitelli et al., 2021; Xia et al., 2021), and building performance benchmarking (Wang, 2015; Yang et al., 2018b), which provide further insights for occupant-centered building design and control.

## 6.3 Knowledge gaps in data analytics for assessing environmental and human health

Despite the numerous techniques developed for data analytics, there are significant gaps in processes of linking the data with environmental and human health. First, indoor environment health is a broad concept. Most existing studies focus on indoor air quality and thermal comfort to ensure occupant comfort and well-being. Significantly less attention is paid to the pathogen transmission and exposure risk caused by IEQ and occupant behavior. Considering the current COVID-19 pandemic and other infectious diseases (e.g., seasonal flu) that can easily be transmitted within the indoor environment through indoor airflow and occupant behavior, substantial research efforts are necessary to join the modeling of occupant–environment interactions, building environmental quality, and the microbial (e.g., pathogen) transmission process to estimate spatiotemporal infection risks. New data analysis methods should be developed to monitor human–environment interactions using IoT sensors, with more focus on personalized assessment.

Second, the connection between environmental and human health has not been well exploited. Dose-response models are usually used to quantify the effects of exposure (e.g., bioaerosol concentration) on human health (US Environmental Protection Agency, 2019), which must be integrated into the data analytics of building performance in order to derive meaningful insights and control decisions to improve occupant health.

Third, due to diverse occupant characteristics and the complex and dynamic interaction between occupants and the indoor environment, individuals may suffer different exposure risks or exhibit different comfort levels. However, personalized assessments are challenging because most sensing and data analysis methods consider

occupants at an aggregate level instead of individuals. Although wearable sensors can be used to acquire individual data, privacy and security issues must be considered in the development of data analysis methods. Federated learning could be a promising solution as models are trained locally and the trained model parameters, instead of sensing data, are transmitted to and aggregated in the central server.

Forth, both simulation-based and data-driven methods have their own limitations. For instance, a simulation-based approach relies heavily on assumptions and cannot capture real-time situations or determine when reality deviates from modeled assumptions. Data-driven approaches require a large amount of data for model training and may fail to learn the physical principles of the real world. Methods should be developed to strategically integrate real-time sensing data and physical-based simulation to model building performance at a fine resolution to accurately simulate the real-world indoor environment without losing the high fidelity of the real-time data. In addition to building and occupant data, broader contextual data can be incorporated in building analysis. For example, during the COVID-19 pandemic, contact-tracing data and epidemiology surveillance data could be linked with a pathogen transmission model and building information to assess the infection risks at the building level or room level.

## 7 Smart building control

### 7.1 Traditional building control and its limitations

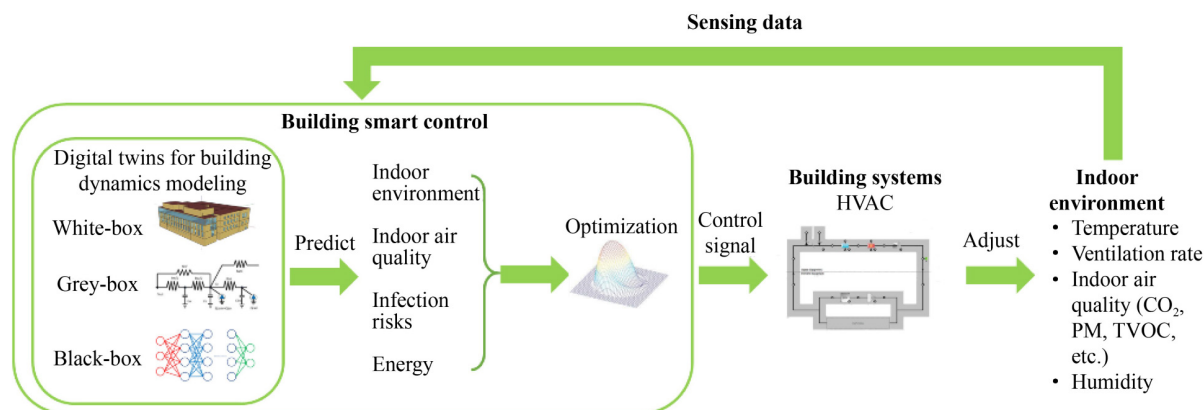
The building operation phase, accompanied by more than 80% of energy consumption and 50% of greenhouse gas emissions, constitutes one of the most important phases in the lifecycle of a building (Sharma et al., 2011). Smart building control is important to facilitate improved energy efficiency and indoor environment status in building operation such that a healthy and comfortable environment is provided to building occupants in a sustainable manner. In the past, building controls have usually been rule-based: Simplified “if/else” conditions have been defined to operate the building systems (May-Ostendorp et al., 2011; Schulze and Eicker, 2013; de Coninck et al., 2014). Control variables in building systems are adjusted, e.g., based on the proportional-integral-derivative (PID) scheme (Blasco et al., 2012), to ensure successful implementation of controls and to achieve well-defined objectives in the control process. With explicit control rules and logic, rule-based control is easily understandable and not computationally demanding; hence, it is readily integrated into building management systems. Nevertheless, without any predictive power or reflection on the dynamics of continuously changing building operations, this control

strategy is likely to output suboptimal control sequences that result in degraded building operation performance (Alimohammadisagvand et al., 2018). More advanced techniques are essential to further enhance the development of building physics control.

### 7.2 IoT and digital twin-enabled smart building control

The advancement of IoT techniques reveals a new opportunity for intelligent decision-making in building operations by introducing sensing data streams that describe building dynamics in real time. DTs of buildings, integrating these IoT sensing data and advanced building modeling, have arisen to empower smart building operation in a predictive way. The model predictive control (MPC) is the most widely used smart building control strategy (see Fig. 5). Specifically, MPC techniques employ the central building model to predict building dynamics based on the ambient environment and measured building status (e.g., indoor environment and energy) and then optimize the building operations for different purposes (Rockett and Hathway, 2017; Serale et al., 2018). To support the accurate prediction of indoor dynamics and reliable decision-making, the useful sensing data include indoor environment status, building energy consumption, indoor occupant activities, outdoor weather conditions, etc. (Oldewurtel et al., 2012; Halhoul Merabet et al., 2021; Zhan and Chong, 2021). This sensing information is then passed into digital building models capable of simulating building dynamics as outcomes of the proposed control actions.

Specifically, physics-based white-box modeling (Salakij et al., 2016; Schirrer et al., 2016; Ruusu et al., 2019), grey-box modeling (Li et al., 2021b), and data-driven black-box modeling (Zhang et al., 2021a) of buildings have all been exploited for building digital replicas of different complexities to aid in building system control decision-making. White-box modeling utilizes the principles of heat transfer and thermodynamics to describe various building dynamics under internal and external disturbance (Li and Wen, 2014). Modeling engines such as EnergyPlus (Crawley et al., 2001) and TRNSYS (TRNSYS, 2019) have been developed to reliably simulate the indoor environment and energy dynamics across diverse circumstances with different fidelities despite the extensive expertise required to establish physics-based building models. Data-driven black-box modeling fully relies on mathematical models to predict building dynamics with model inputs (Wang and Chen, 2019). Unlike white-box modeling that requires possibly massive numbers of inputs while being computationally intensive, black-box building models are usually lightweight in calculation; hence, they are more readily applied in the iterative optimization process of MPC implementation. However, it is difficult to explicitly interpret the parameters of black-box models, which impacts their practical acceptability in



**Fig. 5** Framework for smart building control.

building engineering. As a combination of white-box and black-box modeling, grey-box models are reduced-order physics-based building models (Harb et al., 2016). Grey-box models have been widely adopted in smart building control due to certain advantages, including being 1) more easily interpretable compared to black-box models with aggregated physical meanings in model parameters, and 2) less computationally intensive compared to high-fidelity and physics-based white-box models. The resistance–capacitance model (Yang et al., 2018a) is the most widely used grey-box building model for supporting smart building operation.

Overall, building DTs with advanced dynamic modeling capabilities serves as the intelligent brain in smart building control. With inputs and outputs from digital building models, building control is formulated as an optimization problem to generate optimal control sequences of building systems. Different optimization techniques (e.g., mixed integer problem and nonlinear programming) can be employed to efficiently solve the problems (Xi et al., 2007; Široký et al., 2011). MPC techniques have been applied in real buildings with demonstrable performance to improve building operation practices (Široký et al., 2011; Ferreira et al., 2012; Ruusu et al., 2019). Regarding the control purpose, DT-enabled smart building controls mainly focus on improving indoor health and environmental comfort with energy efficiency in building operations (West et al., 2014; Chen et al., 2015b). Achieving improved building services, including both enhanced occupant health and comfort with energy efficiency, is the most commonly set target for smart building control (Halhoul Merabet et al., 2021). The health and comfort of indoor occupants are comprised of various qualities, such as indoor air quality, thermal comfort, and visual comfort. By incorporating building modeling and indoor and outdoor air quality monitoring, building DTs have enabled consistently optimal ventilation by switching ventilation modes (Chen et al., 2018a; Cao et al., 2020) and adjusting ventilation rates (Cho et al., 2015; Ganesh et al., 2019; Li and Wang, 2020) to reduce the indoor air

pollutant concentration (Kim et al., 2019a) while saving energy in ventilation operation (Kim et al., 2016). The controlled indoor air pollutants include CO<sub>2</sub> (Jreijiry et al., 2007; Hesaraki and Holmberg, 2015), total VOC (TVOC) (Hesaraki and Holmberg, 2015; Guyot et al., 2018), respiratory particle matters (Morgan et al., 2017; Kim et al., 2019b; Cao et al., 2020), and ozone (Walker and Sherman, 2013), among others. Multiple categories of air pollutants are usually simultaneously considered in the control development (Ganesh et al., 2019; Afroz et al., 2020; Saini et al., 2020). Effective indoor environmental sensor deployment is important to sufficiently control indoor air pollutants in building operation (Zeng et al., 2020). Furthermore, occupant behaviors and modeling could be additionally critical components in effective indoor air pollutant management (Kim et al., 2019a), especially in demand-controlled ventilation strategies that require accurate occupancy information to determine ventilation rates (Wang et al., 2018).

With the spread of COVID-19, methods of controlling airborne infection have received increasing attention. Smart ventilation strategies, including both mechanical and natural ventilation (Qian et al., 2010) along with occupancy adjustments, have been proposed to reduce virus transmission risks in building operations (Wang et al., 2021; Xu et al., 2021; Zhang et al., 2021b). The on/off thresholds of HVAC systems or thermostat set points are typically adjusted to minimize the building's energy consumption while ensuring the thermal comfort of occupants (Castilla et al., 2011) based on the Predicted Mean Vote/Predicted Percentage of Dissatisfied or adaptive thermal comfort model (Enescu, 2017). To ensure satisfactory indoor illuminance conditions without wasting energy, smart lighting control strategies have also been developed to optimize lighting operation schedules (using on/off or dimming controls) based on measured environmental status and occupancy (Kandasamy et al., 2018; Zou et al., 2018). Moreover, to broadly improve regional sustainability with reduced greenhouse gas and air pollutant emissions associated with fossil fuel-based power

generation, building DTs utilizing system-sensing data are also emerging to facilitate the integration of renewable energy and building operations with demand response support, considering power generation, energy storage (e.g., thermal or battery storage), and building and occupant needs (Albadi and El-Saadany, 2007; Biyik and Kahraman, 2019; Kathirgamanathan et al., 2021).

### 7.3 Knowledge gaps in building control for healthy building operation

The existing gaps in the research on smart control for healthy building operations are threefold, including lack of sensing data and DT integration, the negligence of health factors in the control loop, and insufficient consideration of social interactions in the control design.

First, with the advancement of sensing techniques, massive amounts of sensing data, related to not only the indoor environment (e.g., temperature and humidity) but also occupancy and indoor air quality, are continuously collected as time-series streams during building operation. These data provide valuable resources to construct building intelligence with smart control for healthy building operations. However, depending on the building size, number of sensing dimensions and deployed sensors, and data collection frequency, effective management and optimal integration of these sensing data with DTs are essential—yet, with room for improvement—to fully uncover the data values for healthy building operation. In practice, this requires improvements to both hardware, e.g., data storage techniques, and software, e.g., computing and optimization algorithms, to sufficiently support smart control applications. Efficient data processing is critical to ensure real-time implementation and enhance the adaptiveness of intelligent building management. To standardize the sensor integration process and better utilize sensing data, the building metadata schema and semantic data descriptions should be further improved. Recent efforts such as Brick and Project Haystack represent important steps toward facilitating the IoT sensing data integration with DTs.

Second, based on the literature review, existing building smart control strategies have largely focused on achieving building energy efficiency and comfort while neglecting health and infection prevention. Due to the lack of digital information regarding the infection risks and different pathogens' transmission routes, the operation of the physical components of buildings has not been fully linked with health evaluations. Devising bio-informed adaptive control can address this limitation. For instance, ventilation strategies that consider infection risks and pathogen transmission routes in the control loop (Qian and Zheng, 2018) could be developed to dilute the concentrations of bioaerosols and the pathogens. Furthermore, sunlight could significantly deactivate the pathogens (Hobday and Dancer, 2013), making adaptive façade design and

control of a potential method for disinfection (Xie et al., 2021). As service robots have grown in popularity, there has been development in their ability to clean and disinfect surfaces (Hu et al., 2020). It is also possible to control induct ultraviolet light and ozone generators more precisely for air decontamination (Ijaz et al., 2016).

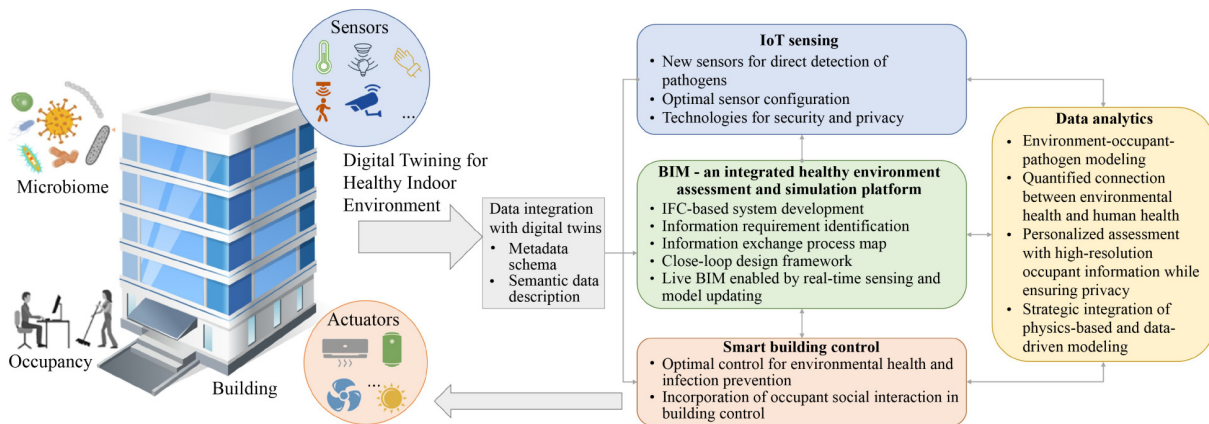
Third, the existing smart control strategies only consider individual human factors while neglecting social interactions between occupants in healthy building operations. The social interactions of occupants may increase virus transmission in buildings. Thus, social interactions must be considered when adapting the physical components of building systems. Incorporating human interaction and the associated infection risks as additional dimensions in smart control development will further improve the practice of healthy building operation, although this integration should be achieved while considering the other goals of building control, such as energy efficiency and comfort, to operate buildings in a smart and sustainable manner.

---

## 8 Conclusions and future research directions

The COVID-19 pandemic raised awareness of indoor environmental health, particularly the infection risks within buildings. There is increasing advocacy for smart buildings to create more healthy environments. This paper reviewed the techniques developed for building DTs, i.e., BIM, IoT sensing, data analytics, and smart building control, as well as the numerous applications of such DTs, and confirmed the lack of necessary consideration of environmental and occupant health. This research identified knowledge gaps and discussed future research directions for each technique toward promoting healthy indoor environment. Figure 6 illustrates our vision of digital twinning for a healthy indoor environment, which requires connecting the four important components of a DT for seamless integration. A DT for a healthy indoor environment must include real-time monitoring and integrated modeling of the complex environment–occupant–microbiome interaction, as well as quantitative assessment and adaptive control for both environmental and human health.

- The advance of IoT sensing is expected to provide unprecedented real-time data for every aspect of the indoor environment. To achieve this, new cost-effective sensors are needed for direct detection of microbiome communities (e.g., pathogens), and methods must be developed for optimal sensor configuration to ensure both measurement accuracy and cost efficiency. New technologies, such as edge devices and privacy-preserving sensors, should be used in IoT sensing to ensure security and privacy. Moreover, with the large volume and heterogeneity of data, future research should develop standard



**Fig. 6** Future research directions for digital twins for a healthy built environment.

metadata schemas and semantic data descriptions for data integration with DTs.

- In the future healthy indoor environment, BIM should serve as an integrated assessment and simulation platform to provide actionable information for building control systems by combining environment–occupant–microbiome information with multi-disciplinary simulations (e.g., energy, air quality, and pathogen transmission simulations). This highlights the challenge of data interoperability. IFC-based system development could be a potential solution, and future directions should include information requirement identification and information exchange process map clarification. For real-time sensory data, future BIM is expected to be continuously updated, thus calibrating the simulation. In addition to the assessment and simulation in support of smart building control, a closed-loop design framework is needed to identify the relationships between indoor environment characteristics and health indicators to guide building design.

- The current smart building control, which mainly emphasizes energy efficiency and comfort, must be augmented with the capability to ensure environmental health and mitigate infection risk. The relationship between building operations (e.g., ventilation and surface disinfection) and infection risk must be quantified to achieve bio-informed adaptive control. Furthermore, occupants are important as active components of the indoor environment, and their behavior will largely influence the infectious disease transmission. Therefore, the interactions among occupants, and between occupants and the environment, must be considered in building control strategies.

- Advanced data analytics is an essential part of digital twinning for a healthy indoor environment, providing valuable information for each of the other three techniques. New methods leveraging rich, real-time sensing data, building design and operation data, and external contextual data are needed to strategically integrate physics-based simulations and data-driven analysis for environment–occupant–pathogen modeling. Furthermore, methods are

needed to establish a quantified relationship between environmental and human health. Another future research direction may include personalized assessments to fulfill diverse requirements for occupants with different characteristics and preferences. To achieve this, it is critical to obtain high-resolution occupant information, which calls for both advanced sensing technology and data analysis algorithms that can preserve occupant privacy. Federated learning could be a potential solution for personalized and privacy-preserving analysis.

Health has multifaceted dimensions and is very difficult to address. As the COVID-19 pandemic raises awareness of pathogenic infection within the indoor environment, we believe that health can be incorporated into the DT paradigm by first digitalizing the infection risks to prevent infections. The paradigm could be further adapted to include other elements of environmental exposure such as VOCs and PM<sub>2.5</sub>. For other aspects of health and human well-being, such as mental health, productivity, and sick building syndrome, it is important to further understand the influencing factors and link the sensing data, building model, and health performance in DTs.

## References

- Adams R I, Bhangar S, Dannemiller K C, Eisen J A, Fierer N, Gilbert J A, Green J L, Marr L C, Miller S L, Siegel J A, Stephens B, Waring M S, Bibby K (2016). Ten questions concerning the microbiomes of buildings. *Building and Environment*, 109: 224–234
- Adams R I, Miletto M, Lindow S E, Taylor J W, Bruns T D (2014). Airborne bacterial communities in residences: Similarities and differences with fungi. *PLoS One*, 9(3): e91283
- Afroz Z, Higgins G, Shafiqullah G M, Urmee T (2020). Evaluation of real-life demand-controlled ventilation from the perception of indoor air quality with probable implications. *Energy and Buildings*, 219: 110018
- Agostinelli S, Cumo F, Guidi G, Tomazzoli C (2021). Cyber-physical systems improving building energy management: Digital twin and artificial intelligence. *Energies*, 14(8): 2338

- Alavi H, Forcada N, Bortolini R, Edwards D J (2021). Enhancing occupants' comfort through BIM-based probabilistic approach. *Automation in Construction*, 123: 103528
- Albadi M H, El-Saadany E F (2007). Demand response in electricity markets: An overview. In: *IEEE Power Engineering Society General Meeting*. Tampa, FL: IEEE, 1–5
- Alimohammadisagvand B, Jokisalo J, Sirén K (2018). Comparison of four rule-based demand response control algorithms in an electrically and heat pump-heated residential building. *Applied Energy*, 209: 167–179
- Alsalem F, Tesfay M K, Rafaie M, Sinkar K, Besarla D, Arunasalam P (2020). An IoT framework for modeling and controlling thermal comfort in buildings. *Frontiers in Built Environment*, 6: 87
- Azar E, O'Brien W, Carlucci S, Hong T, Sonta A, Kim J, Andargie M S, Abuimara T, El Asmar M, Jain R K, Ouf M M, Tahmasebi F, Zhou J (2020). Simulation-aided occupant-centric building design: A critical review of tools, methods, and applications. *Energy and Buildings*, 224: 110292
- Benammar M, Abdaoui A, Ahmad S H M, Touati F, Kadri A (2018). A modular IoT platform for real-time indoor air quality monitoring. *Sensors*, 18(2): 581
- Biyik E, Kahraman A (2019). A predictive control strategy for optimal management of peak load, thermal comfort, energy storage and renewables in multi-zone buildings. *Journal of Building Engineering*, 25: 100826
- Blasco C, Monreal J, Benftez I, Lluna A (2012). Modelling and PID control of HVAC system according to energy efficiency and comfort criteria. In: *Proceedings of the 3rd International Conference on Sustainability in Energy and Buildings*. Marseilles: Springer, 365–374
- Boje C, Guerriero A, Kubicki S, Rezgui Y (2020). Towards a semantic Construction Digital Twin: Directions for future research. *Automation in Construction*, 114: 103179
- Cai J, Cai H (2020). Robust hybrid approach of vision-based tracking and radio-based identification and localization for 3D tracking of multiple construction workers. *Journal of Computing in Civil Engineering*, 34(4): 04020021
- Candanedo L M, Feldheim V (2016). Accurate occupancy detection of an office room from light, temperature, humidity and CO<sub>2</sub> measurements using statistical learning models. *Energy and Buildings*, 112: 28–39
- Candanedo L M, Feldheim V, Deramaix D (2017). A methodology based on Hidden Markov Models for occupancy detection and a case study in a low energy residential building. *Energy and Buildings*, 148: 327–341
- Cao Q, Li F, Zhang T, Wang S (2020). A ventilator that responds to outdoor conditions for ventilation and air filtration. *Energy and Buildings*, 229: 110498
- Castilla M, Álvarez J D, Berenguel M, Rodríguez F, Guzmán J L, Pérez M (2011). A comparison of thermal comfort predictive control strategies. *Energy and Buildings*, 43(10): 2737–2746
- Chen J, Augenbroe G, Song X (2018a). Lighted-weighted model predictive control for hybrid ventilation operation based on clusters of neural network models. *Automation in Construction*, 89: 250–265
- Chen K, Zhang D, Yao L, Guo B, Yu Z, Liu Y (2021). Deep learning for sensor-based human activity recognition: Overview, challenges, and opportunities. *ACM Computing Surveys*, 54(4): 77
- Chen X, Wang Q, Srebric J (2015a). A data-driven state-space model of indoor thermal sensation using occupant feedback for low-energy buildings. *Energy and Buildings*, 91: 187–198
- Chen X, Wang Q, Srebric J (2015b). Model predictive control for indoor thermal comfort and energy optimization using occupant feedback. *Energy and Buildings*, 102: 357–369
- Chen Z, Jiang C, Xie L (2018b). Building occupancy estimation and detection: A review. *Energy and Buildings*, 169: 260–270
- Chen Z, Jiang C, Xie L (2019a). A novel ensemble ELM for human activity recognition using smartphone sensors. *IEEE Transactions on Industrial Informatics*, 15(5): 2691–2699
- Chen Z, Zhang L, Jiang C, Cao Z, Cui W (2019b). WiFi CSI based passive human activity recognition using attention based BLSTM. *IEEE Transactions on Mobile Computing*, 18(11): 2714–2724
- Chen Z, Zhu Q, Soh Y C, Zhang L (2017). Robust human activity recognition using smartphone sensors via CT-PCA and online SVM. *IEEE Transactions on Industrial Informatics*, 13(6): 3070–3080
- Cheng Y, Lin Z, Fong A M L (2015). Effects of temperature and supply airflow rate on thermal comfort in a stratum-ventilated room. *Building and Environment*, 92: 269–277
- Cheong K H, Teo Y H, Koh J M, Acharya U R, Man Yu S C (2020). A simulation-aided approach in improving thermal-visual comfort and power efficiency in buildings. *Journal of Building Engineering*, 27: 100936
- Cho W, Song D, Hwang S, Yun S (2015). Energy-efficient ventilation with air-cleaning mode and demand control in a multi-residential building. *Energy and Buildings*, 90: 6–14
- Choi H, Hong S, Choi A, Sung M (2016). Toward the accuracy of prediction for energy savings potential and system performance using the daylight responsive dimming system. *Energy and Buildings*, 133: 271–280
- Cippitelli E, Gasparrini S, Gambi E, Spinsante S (2016). A human activity recognition system using skeleton data from RGBD sensors. *Computational Intelligence and Neuroscience*, 4351435
- Clausen A, Arendt K, Johansen A, Sangogboye F C, Kjærgaard M B, Veje C T, Jørgensen B N (2021). A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings. *Energy Informatics*, 4(Suppl 2): 40
- Costanzo V, Donn M (2017). Thermal and visual comfort assessment of natural ventilated office buildings in Europe and North America. *Energy and Buildings*, 140: 210–223
- Crawley D B, Lawrie L K, Winkelmann F C, Buhl W F, Huang Y J, Pedersen C O, Strand R K, Liesen R J, Fisher D E, Witte M J, Glazer J (2001). EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings*, 33(4): 319–331
- Daissaoui A, Boulmakoul A, Karim L, Lbath A (2020). IoT and big data analytics for smart buildings: A survey. *Journal of Ubiquitous Systems & Pervasive Networks*, 13(1): 27–34
- de Coninck R, Baetens R, Saelens D, Woyte A, Helsen L (2014). Rule-based demand-side management of domestic hot water production with heat pumps in zero energy neighbourhoods. *Journal of Building Performance Simulation*, 7(4): 271–288
- Ding Z, Hu T, Li M, Xu X, Zou P X W (2019). Agent-based model for simulating building energy management in student residences.

- Energy and Buildings, 198: 11–27
- Dong B, Andrews B, Lam K P, Höyneck M, Zhang R, Chiou Y S, Benítez D (2010). An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network. *Energy and Buildings*, 42(7): 1038–1046
- Dong B, Prakash V, Feng F, O’Neill Z (2019). A review of smart building sensing system for better indoor environment control. *Energy and Buildings*, 199: 29–46
- Enescu D (2017). A review of thermal comfort models and indicators for indoor environments. *Renewable & Sustainable Energy Reviews*, 79: 1353–1379
- Fan C, Yan D, Xiao F, Li A, An J, Kang X (2021). Advanced data analytics for enhancing building performances: From data-driven to big data-driven approaches. *Building Simulation*, 14(1): 3–24
- Ferreira P M, Ruano A E, Silva S, Conceição E Z E (2012). Neural networks based predictive control for thermal comfort and energy savings in public buildings. *Energy and Buildings*, 55: 238–251
- Filippoupolitis A, Oliff W, Loukas G (2017). Bluetooth low energy based occupancy detection for emergency management. In: *Proceedings of the 15th International Conference on Ubiquitous Computing and Communications and the 8th International Symposium on Cyberspace and Security (IUCC-CSS)*. Granada: IEEE, 31–38
- Fisk W J (2002). How IEQ affects health, productivity. *ASHRAE Journal*, 44(5): 56–58
- Francisco A, Mohammadi N, Taylor J E (2020). Smart city digital twin-enabled energy management: Toward real-time urban building energy benchmarking. *Journal of Management Engineering*, 36(2): 04019045
- Fronczek C F, Yoon J Y (2015). Biosensors for monitoring airborne pathogens. *SLAS Technology*, 20(4): 390–410
- Gan V J L, Luo H, Tan Y, Deng M, Kwok H L (2021). BIM and data-driven predictive analysis of optimum thermal comfort for indoor environment. *Sensors*, 21(13): 4401
- Ganesh H S, Fritz H E, Edgar T F, Novoselac A, Baldea M (2019). A model-based dynamic optimization strategy for control of indoor air pollutants. *Energy and Buildings*, 195: 168–179
- Gaur A, Scotney B, Parr G, McClean S (2015). Smart city architecture and its applications based on IoT. *Procedia Computer Science*, 52(1): 1089–1094
- Gentile N, Laike T, Dubois M C (2016). Lighting control systems in individual offices rooms at high latitude: Measurements of electricity savings and occupants’ satisfaction. *Solar Energy*, 127: 113–123
- Gilbert J A, Stephens B (2018). Microbiology of the built environment. *Nature Reviews: Microbiology*, 16(11): 661–670
- Guyot G, Sherman M H, Walker I S (2018). Smart ventilation energy and indoor air quality performance in residential buildings: A review. *Energy and Buildings*, 165: 416–430
- Halhoul Merabet G, Essaaidi M, Ben Haddou M, Qolomany B, Qadir J, Anan M, Al-Fuqaha A, Abid M R, Benhaddou D (2021). Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques. *Renewable & Sustainable Energy Reviews*, 144: 110969
- Harb H, Boyanov N, Hernandez L, Streblow R, Müller D (2016). Development and validation of grey-box models for forecasting the thermal response of occupied buildings. *Energy and Buildings*, 117: 199–207
- Hasan M H, Alsaleem F, Rafaie M (2016). Sensitivity study for the PMV thermal comfort model and the use of wearable devices biometric data for metabolic rate estimation. *Building and Environment*, 110: 173–183
- He S, Wang Z, Wang Z, Gu X, Yan Z (2016). Fault detection and diagnosis of chiller using Bayesian network classifier with probabilistic boundary. *Applied Thermal Engineering*, 107: 37–47
- Hesaraki A, Holmberg S (2015). Demand-controlled ventilation in new residential buildings: Consequences on indoor air quality and energy savings. *Indoor and Built Environment*, 24(2): 162–173
- Hobday R A, Dancer S J (2013). Roles of sunlight and natural ventilation for controlling infection: Historical and current perspectives. *Journal of Hospital Infection*, 84(4): 271–282
- Horve P F, Lloyd S, Mhuireach G A, Dietz L, Fretz M, MacCrone G, van den Wymelenberg K, Ishaq S L (2020). Building upon current knowledge and techniques of indoor microbiology to construct the next era of theory into microorganisms, health, and the built environment. *Journal of Exposure Science & Environmental Epidemiology*, 30(2): 219–235
- Hu D, Zhong H, Li S, Tan J, He Q (2020). Segmenting areas of potential contamination for adaptive robotic disinfection in built environments. *Building and Environment*, 184: 107226
- Ijaz M K, Zargar B, Wright K E, Rubino J R, Sattar S A (2016). Generic aspects of the airborne spread of human pathogens indoors and emerging air decontamination technologies. *American Journal of Infection Control*, 44(9): S109–S120
- Islam M T, Jain S, Chen Y, Chowdhury B D B, Son Y J (2022). An agent-based simulation model to evaluate contacts, layout, and policies in entrance, exit, and seating in indoor activities under a pandemic situation. *IEEE Transactions on Automation Science and Engineering*, 19(2): 603–619
- Jain R K, Smith K M, Culligan P J, Taylor J E (2014). Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Applied Energy*, 123: 168–178
- Jiang F, Ma L, Broyd T, Chen K (2021). Digital twin and its implementations in the civil engineering sector. *Automation in Construction*, 130: 103838
- Jo J, Jo B, Kim J, Kim S, Han W (2020). Development of an IoT-based indoor air quality monitoring platform. *Journal of Sensors*, 8749764
- Jreijiry D, Husaunndee A, Inard C (2007). Numerical study of a hybrid ventilation system for single family houses. *Solar Energy*, 81(2): 227–239
- Kaewunruen S, Rungskunroch P, Welsh J (2019). A digital-twin evaluation of Net Zero Energy Building for existing buildings. *Sustainability*, 11(1): 159
- Kandasamy N K, Karunagaran G, Spanos C, Tseng K J, Soong B H (2018). Smart lighting system using ANN-IMC for personalized lighting control and daylight harvesting. *Building and Environment*, 139: 170–180
- Kathirgamanathan A, de Rosa M, Mangina E, Finn D P (2021). Data-driven predictive control for unlocking building energy flexibility: A review. *Renewable & Sustainable Energy Reviews*, 135: 110120
- Khanna A, Arora S, Chhabra A, Bhardwaj K K, Sharma D K (2019).

- IoT architecture for preventive energy conservation of smart buildings. In: Mittal M, Tanwar S, Agarwal B, Goyal L, eds. *Energy Conservation for IoT Devices*. Singapore: Springer, 179–208
- Kim H, Hong T, Kim J (2019a). Automatic ventilation control algorithm considering the indoor environmental quality factors and occupant ventilation behavior using a logistic regression model. *Building and Environment*, 153: 46–59
- Kim J, Kong M, Hong T, Jeong K, Lee M (2019b). The effects of filters for an intelligent air pollutant control system considering natural ventilation and the occupants. *Science of the Total Environment*, 657: 410–419
- Kim W, Jeon S W, Kim Y (2016). Model-based multi-objective optimal control of a VRF (variable refrigerant flow) combined system with DOAS (dedicated outdoor air system) using genetic algorithm under heating conditions. *Energy*, 107: 196–204
- Klepeis N E, Nelson W C, Ott W R, Robinson J P, Tsang A M, Switzer P, Behar J V, Hern S C, Engelmann W H (2001). The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *Journal of Exposure Science & Environmental Epidemiology*, 11(3): 231–252
- Kraay A N M, Hayashi M A L, Hernandez-Ceron N, Spicknall I H, Eisenberg M C, Meza R, Eisenberg J N S (2018). Fomite-mediated transmission as a sufficient pathway: A comparative analysis across three viral pathogens. *BMC Infectious Diseases*, 18(1): 540
- Kwok H H L, Cheng J C P, Li A T Y, Tong J C K, Lau A K H (2020). Multi-zone indoor CFD under limited information: An approach coupling solar analysis and BIM for improved accuracy. *Journal of Cleaner Production*, 244: 118912
- Lam K P, Höynck M, Dong B, Andrews B, Chiou Y S, Zhang R, Benitez D, Choi J (2009). Occupancy detection through an extensive environmental sensor network in an open-plan office building. In: 11th International Building Performance Simulation Association Conference. Glasgow, 1452–1459
- Lee J Y, Wargocki P, Chan Y H, Chen L, Tham K W (2019). Indoor environmental quality, occupant satisfaction, and acute building-related health symptoms in Green Mark-certified compared with non-certified office buildings. *Indoor Air*, 29(1): 112–129
- Leephakpreeda T (2005). Adaptive occupancy-based lighting control via Grey prediction. *Building and Environment*, 40(7): 881–886
- Li D, Menassa C C, Kamat V R (2019). Robust non-intrusive interpretation of occupant thermal comfort in built environments with low-cost networked thermal cameras. *Applied Energy*, 251: 113336
- Li S, Xu Y, Cai J, Hu D, He Q (2021a). Integrated environment-occupant-pathogen information modeling to assess and communicate room-level outbreak risks of infectious diseases. *Building and Environment*, 187: 107394
- Li W, Wang S (2020). A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering indoor air quality and energy use. *Applied Energy*, 275: 115371
- Li W, Zhang J, Zhao T, Liang R (2018). Experimental research of online monitoring and evaluation method of human thermal sensation in different active states based on wristband device. *Energy and Buildings*, 173: 613–622
- Li X, Wen J (2014). Review of building energy modeling for control and operation. *Renewable & Sustainable Energy Reviews*, 37: 517–537
- Li Y, O'Neill Z, Zhang L, Chen J, Im P, DeGraw J (2021b). Grey-box modeling and application for building energy simulations: A critical review. *Renewable & Sustainable Energy Reviews*, 146: 111174
- Liu D, Guan X, Du Y, Zhao Q (2013). Measuring indoor occupancy in intelligent buildings using the fusion of vision sensors. *Measurement Science & Technology*, 24(7): 074023
- Liu Z, Zhang A, Wang W (2020). A framework for an indoor safety management system based on digital twin. *Sensors*, 20(20): 5771
- Lu Q, Xie X, Heaton J, Parlikad A K, Schooling J (2020a). From BIM towards digital twin: Strategy and future development for smart asset management. In: 9th International Workshop on Service Oriented, Holonic and Multi-agent Manufacturing Systems for Industry of the Future. Valencia: Springer, 392–404
- Lu Q, Xie X, Parlikad A K, Schooling J M (2020b). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Automation in Construction*, 118: 103277
- Marques G, Pitarma R (2019). mHealth: Indoor environmental quality measuring system for enhanced health and well-being based on Internet of Things. *Journal of Sensor and Actuator Networks*, 8(3): 43
- Marques G, Pitarma R (2020). A real-time noise monitoring system based on Internet of Things for enhanced acoustic comfort and occupational health. *IEEE Access*, 8: 139741–139755
- Marques G, Roque Ferreira C, Pitarma R (2018). A system based on the Internet of Things for real-time particle monitoring in buildings. *International Journal of Environmental Research and Public Health*, 15(4): 821
- May-Ostendorp P, Henze G P, Corbin C D, Rajagopalan B, Felsmann C (2011). Model-predictive control of mixed-mode buildings with rule extraction. *Building and Environment*, 46(2): 428–437
- Montiel-Santiago F J, Hermoso-Orzáez M J, Terrados-Cepeda J (2020). Sustainability and energy efficiency: BIM 6D, study of the BIM methodology applied to hospital buildings, value of interior lighting and daylight in energy simulation. *Sustainability*, 12(14): 5731
- Morgan D T, Daly T, Gallagher J, McNabola A (2017). Reducing energy consumption and increasing filter life in HVAC systems using an aspiration efficiency reducer: Long-term performance assessment at full-scale. *Journal of Building Engineering*, 12: 267–274
- Motamedi H, Shirzadi M, Tominaga Y, Mirzaei P A (2022). CFD modeling of airborne pathogen transmission of COVID-19 in confined spaces under different ventilation strategies. *Sustainable Cities and Society*, 76: 103397
- Mujan I, Andelković A S, Muncan V, Kljajić M, Ružić D (2019). Influence of indoor environmental quality on human health and productivity: A review. *Journal of Cleaner Production*, 217: 646–657
- Mumma S A (2004). Transient occupancy ventilation by monitoring CO<sub>2</sub>. *IAQ Applications*, 5(1): 21–23
- Nassif N (2012). A robust CO<sub>2</sub>-based demand-controlled ventilation control strategy for multi-zone HVAC systems. *Energy and Buildings*, 45: 72–81
- Navada S G, Adiga C S, Kini S G (2013). A study on daylight integration with thermal comfort for energy conservation in a general office. *International Journal of Electrical Energy*, 1(1): 18–22
- Oldewurtel F, Parisio A, Jones C N, Gyalistras D, Gwerder M, Stauch

- V, Lehmann B, Morari M (2012). Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, 45: 15–27
- Palmisani J, Di Gilio A, Viana M, de Gennaro G, Ferro A (2021). Indoor air quality evaluation in oncology units at two European hospitals: Low-cost sensors for TVOCs, PM<sub>2.5</sub> and CO<sub>2</sub> real-time monitoring. *Building and Environment*, 205: 108237
- Pan Y, Zhang L (2021). A BIM-data mining integrated digital twin framework for advanced project management. *Automation in Construction*, 124: 103564
- Pavlin B, Pernigotto G, Cappelletti F, Bison P, Vidoni R, Gasparella A (2017). Real-time monitoring of occupants' thermal comfort through infrared imaging: A preliminary study. *Buildings*, 7(1): 10
- Peng S, Chen Q, Liu E (2020). The role of computational fluid dynamics tools on investigation of pathogen transmission: Prevention and control. *Science of the Total Environment*, 746: 142090
- Piscitelli M S, Brandi S, Capozzoli A, Xiao F (2021). A data analytics-based tool for the detection and diagnosis of anomalous daily energy patterns in buildings. *Building Simulation*, 14(1): 131–147
- Popkin B M (1999). Urbanization, lifestyle changes and the nutrition transition. *World Development*, 27(11): 1905–1916
- Pramanik P K D, Upadhyaya B K, Pal S, Pal T (2019). Internet of Things, smart sensors, and pervasive systems: Enabling connected and pervasive healthcare. In: Dey N, Ashour A S, Bhatt C, Fong S J, eds. *Healthcare Data Analytics and Management: A Volume in Advances in Ubiquitous Sensing Applications For Healthcare*. Chennai: Academic Press, 1–58
- Prussin II A J, Schwake D O, Marr L C (2017). Ten questions concerning the aerosolization and transmission of Legionella in the built environment. *Building and Environment*, 123: 684–695
- Qian H, Li Y, Seto W H, Ching P, Ching W H, Sun H Q (2010). Natural ventilation for reducing airborne infection in hospitals. *Building and Environment*, 45(3): 559–565
- Qian H, Zheng X (2018). Ventilation control for airborne transmission of human exhaled bio-aerosols in buildings. *Journal of Thoracic Disease*, 10(S9): S2295–S2304
- Rajith A, Soki S, Hiroshi M (2018). Real-time optimized HVAC control system on top of an IoT framework. In: 3rd International Conference on Fog and Mobile Edge Computing (FMEC). Barcelona: IEEE, 181–186
- Raykov Y P, Ozer E, Dasika G, Boukouvalas A, Little M A (2016). Predicting room occupancy with a single passive infrared (PIR) sensor through behavior extraction. In: *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing*. Heidelberg: Association for Computing Machinery, 1016–1027
- Rice L (2021). Healthy BIM: The feasibility of integrating architecture health indicators using a building information model (BIM) computer system. *Archnet-IJAR*, 15(1): 252–265
- Rockett P, Hathway E A (2017). Model-predictive control for non-domestic buildings: A critical review and prospects. *Building Research and Information*, 45(5): 556–571
- Ruano A, Silva S, Duarte H, Ferreira P M (2018). Wireless sensors and IoT platform for intelligent HVAC control. *Applied Sciences*, 8(3): 370
- Ruusu R, Cao S, Manrique Delgado B, Hasan A (2019). Direct quantification of multiple-source energy flexibility in a residential building using a new model predictive high-level controller. *Energy Conversion and Management*, 180: 1109–1128
- Saha H, Florita A R, Henze G P, Sarkar S (2019). Occupancy sensing in buildings: A review of data analytics approaches. *Energy and Buildings*, 188–189: 278–285
- Saini J, Dutta M, Marques G (2020). A comprehensive review on indoor air quality monitoring systems for enhanced public health. *Sustainable Environment Research*, 30(1): 6
- Salakij S, Yu N, Paolucci S, Antsaklis P (2016). Model-based predictive control for building energy management, I: Energy modeling and optimal control. *Energy and Buildings*, 133: 345–358
- Salamone F, Belussi L, Currò C, Danza L, Ghellere M, Guazzi G, Lenzi B, Megale V, Meroni I (2018). Application of IoT and Machine Learning techniques for the assessment of thermal comfort perception. *Energy Procedia*, 148: 798–805
- Schirrer A, Brandstetter M, Leobner I, Hauer S, Kozek M (2016). Nonlinear model predictive control for a heating and cooling system of a low-energy office building. *Energy and Buildings*, 125: 86–98
- Schulze T, Eicker U (2013). Controlled natural ventilation for energy efficient buildings. *Energy and Buildings*, 56: 221–232
- Serale G, Fiorentini M, Capozzoli A, Bernardini D, Bemporad A (2018). Model Predictive Control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. *Energies*, 11(3): 631
- Sharma A, Saxena A, Sethi M, Shree V, Goel V (2011). Life cycle assessment of buildings: A review. *Renewable & Sustainable Energy Reviews*, 15(1): 871–875
- Shi Z, Lu Z, Chen Q (2019). Indoor airflow and contaminant transport in a room with coupled displacement ventilation and passive-chilled-beam systems. *Building and Environment*, 161: 106244
- Silvestre-Blanes J, Pérez-Lloréns R (2011). Energy efficiency improvements through surveillance applications in industrial buildings. *Energy and Buildings*, 43(6): 1334–1340
- Singh S K, Jeong Y S, Park J H (2020). A deep learning-based IoT-oriented infrastructure for secure smart city. *Sustainable Cities and Society*, 60: 102252
- Široký J, Oldewurtel F, Cigler J, Privara S (2011). Experimental analysis of model predictive control for an energy efficient building heating system. *Applied Energy*, 88(9): 3079–3087
- Sporr A, Zucker G, Hofmann R (2019). Automated HVAC control creation based on building information modeling (BIM): Ventilation system. *IEEE Access*, 7: 74747–74758
- Topak F, Pekerçili M K, Tanyer A M (2018). Technological viability assessment of bluetooth low energy technology for indoor localization. *Journal of Computing in Civil Engineering*, 32(5): 04018034
- TRNSYS (2019). TRNSYS Transient System Simulation Tool
- Uğursal A, Culp C H (2013). The effect of temperature, metabolic rate and dynamic localized airflow on thermal comfort. *Applied Energy*, 111: 64–73
- US Environmental Protection Agency (2019). Benefits Mapping and Analysis Program (BenMAP)
- Utkucu D, Sözer H (2020). Interoperability and data exchange within BIM platform to evaluate building energy performance and indoor comfort. *Automation in Construction*, 116: 103225

- Valinejadshoubi M, Moselhi O, Bagchi A, Salem A (2021). Development of an IoT and BIM-based automated alert system for thermal comfort monitoring in buildings. *Sustainable Cities and Society*, 66: 102602
- Verma A, Prakash S, Srivastava V, Kumar A, Mukhopadhyay S C (2019). Sensing, controlling, and IoT infrastructure in smart building: A review. *IEEE Sensors Journal*, 19(20): 9036–9046
- Wahl F, Milenkovic M, Amft O (2012). A distributed PIR-based approach for estimating people count in office environments. In: *Proceedings of the 15th IEEE International Conference on Computational Science and Engineering (CSE) and the 10th IEEE/IFIP International Conference on Embedded and Ubiquitous Computing (EUC)*. Paphos: IEEE, 640–647
- Walker I S, Sherman M H (2013). Effect of ventilation strategies on residential ozone levels. *Building and Environment*, 59: 456–465
- Wang E (2015). Benchmarking whole-building energy performance with multi-criteria technique for order preference by similarity to ideal solution using a selective objective-weighting approach. *Applied Energy*, 146: 92–103
- Wang J, Huang J, Feng Z, Cao S J, Haghghat F (2021). Occupant-density-detection based energy efficient ventilation system: Prevention of infection transmission. *Energy and Buildings*, 240: 110883
- Wang W, Chen J, Song X (2017a). Modeling and predicting occupancy profile in office space with a Wi-Fi probe-based Dynamic Markov Time-Window Inference approach. *Building and Environment*, 124: 130–142
- Wang W, Liu A X, Shahzad M, Ling K, Lu S (2017b). Device-free human activity recognition using commercial WiFi devices. *IEEE Journal on Selected Areas in Communications*, 35(5): 1118–1131
- Wang W, Wang J, Chen J, Huang G, Guo X (2018). Multi-zone outdoor air coordination through Wi-Fi probe-based occupancy sensing. *Energy and Buildings*, 159: 495–507
- Wang X (2012). BIM handbook: A guide to Building Information Modeling for owners, managers, designers, engineers and contractors. *Construction Economics and Building*, 12(3): 101–102
- Wang Z, Chen Y (2019). Data-driven modeling of building thermal dynamics: Methodology and state of the art. *Energy and Buildings*, 203: 109405
- West S R, Ward J K, Wall J (2014). Trial results from a model predictive control and optimisation system for commercial building HVAC. *Energy and Buildings*, 72: 271–279
- World Health Organization (2021). Air Pollution
- Worldometer (2021). COVID-19 Coronavirus Pandemic. Online Data
- Wu I C, Liu C C (2020). A visual and persuasive energy conservation system based on BIM and IoT technology. *Sensors*, 20(1): 139
- Wu T, Wu F, Redoute J M, Yuce M R (2017). An autonomous wireless body area network implementation towards IoT connected healthcare applications. *IEEE Access*, 5: 11413–11422
- Xi X C, Poo A N, Chou S K (2007). Support vector regression model predictive control on a HVAC plant. *Control Engineering Practice*, 15(8): 897–908
- Xia Y, Ding Q, Li Z, Jiang A (2021). Fault detection for centrifugal chillers using a Kernel Entropy Component Analysis (KECA) method. *Building Simulation*, 14(1): 53–61
- Xie H, Yu B, Wang J, Ji J (2021). A novel disinfected Trombe wall for space heating and virus inactivation: Concept and performance investigation. *Applied Energy*, 291: 116789
- Xu Y, Cai J, Li S, He Q, Zhu S (2021). Airborne infection risks of SARS-CoV-2 in US schools and impacts of different intervention strategies. *Sustainable Cities and Society*, 74: 103188
- Yang S, Wan M P, Ng B F, Zhang T, Babu S, Zhang Z, Chen W, Dubey S (2018a). A state-space thermal model incorporating humidity and thermal comfort for model predictive control in buildings. *Energy and Buildings*, 170: 25–39
- Yang W, Moon H J (2019). Combined effects of acoustic, thermal, and illumination conditions on the comfort of discrete senses and overall indoor environment. *Building and Environment*, 148: 623–633
- Yang Z, Roth J, Jain R K (2018b). DUE-B: Data-driven urban energy benchmarking of buildings using recursive partitioning and stochastic frontier analysis. *Energy and Buildings*, 163: 58–69
- Yu Z, Haghghat F, Fung B C M, Yoshino H (2010). A decision tree method for building energy demand modeling. *Energy and Buildings*, 42(10): 1637–1646
- Zahid H, Elmansoury O, Yaagoubi R (2021). Dynamic predicted mean vote: An IoT-BIM integrated approach for indoor thermal comfort optimization. *Automation in Construction*, 129: 103805
- Zeng L, Gao J, Lv L, Zhang R, Tong L, Zhang X, Huang Z, Zhang Z (2020). Markov-chain-based probabilistic approach to optimize sensor network against deliberately released pollutants in buildings with ventilation systems. *Building and Environment*, 168: 106534
- Zerrouki N, Harrou F, Sun Y, Houacine A (2018). Vision-based human action classification using adaptive boosting algorithm. *IEEE Sensors Journal*, 18(12): 5115–5121
- Zhan S, Chong A (2021). Data requirements and performance evaluation of model predictive control in buildings: A modeling perspective. *Renewable & Sustainable Energy Reviews*, 142: 110835
- Zhang L, Wen J, Li Y, Chen J, Ye Y, Fu Y, Livingood W (2021a). A review of machine learning in building load prediction. *Applied Energy*, 285: 116452
- Zhang N, Chen W, Chan P T, Yen H L, Tang J W T, Li Y (2020). Close contact behavior in indoor environment and transmission of respiratory infection. *Indoor Air*, 30(4): 645–661
- Zhang N, Li Y, Huang H (2018). Surface touch and its network growth in a graduate student office. *Indoor Air*, 28(6): 963–972
- Zhang S, Ai Z, Lin Z (2021b). Occupancy-aided ventilation for both airborne infection risk control and work productivity. *Building and Environment*, 188: 107506
- Zhang T, Siebers P O, Aickelin U (2011). Modelling electricity consumption in office buildings: An agent based approach. *Energy and Buildings*, 43(10): 2882–2892
- Zhao J, Frumkin N, Ishwar P, Konrad J (2019a). CNN-based indoor occupant localization via active scene illumination. In: *Proceedings of the International Conference on Image Processing (ICIP)*. Taipei: IEEE, 2636–2640
- Zhao Y, Tu P, Chang M C (2019b). Occupancy sensing and activity recognition with cameras and wireless sensors. In: *Proceedings of the 2nd Workshop on Data Acquisition to Analysis*. New York, NY: Association for Computing Machinery, 1–6
- Zhong B, Gan C, Luo H, Xing X (2018). Ontology-based framework for building environmental monitoring and compliance checking under BIM environment. *Building and Environment*, 141: 127–142
- Zhou X, Xu L, Zhang J, Niu B, Luo M, Zhou G, Zhang X (2020a).

- Data-driven thermal comfort model via support vector machine algorithms: Insights from ASHRAE RP-884 database. *Energy and Buildings*, 211: 109795
- Zhou Y, Nikolaev A, Bian L, Lin L, Li L (2021). Investigating transmission dynamics of influenza in a public indoor venue: An agent-based modeling approach. *Computers & Industrial Engineering*, 157: 107327
- Zhou Y W, Hu Z Z, Lin J R, Zhang J P (2020b). A review on 3D spatial data analytics for Building Information Models. *Archives of Computational Methods in Engineering*, 27(5): 1449–1463
- Zhuang R, Li X, Tu J (2014). CFD study of the effects of furniture layout on indoor air quality under typical office ventilation schemes. *Building Simulation*, 7(3): 263–275
- Zhuang Y, Yang J, Li Y, Qi L, El-Sheimy N (2016). Smartphone-based indoor localization with bluetooth low energy beacons. *Sensors*, 16(5): 596
- Zou H, Jiang H, Yang J, Xie L, Spanos C J (2017). Non-intrusive occupancy sensing in commercial buildings. *Energy and Buildings*, 154: 633–643
- Zou H, Zhou Y, Jiang H, Chien S C, Xie L, Spanos C J (2018). WinLight: A WiFi-based occupancy-driven lighting control system for smart building. *Energy and Buildings*, 158: 924–938