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Digital ID framework for human-centric monitoring and control of smart buildings

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Research Article

Abstract
Smart offices can help employers attract and retain talented people and can positively impact well-being and productivity. Thanks to emerging technologies and increased computational power, smart buildings with a specific focus on personal experience are gaining attraction. Real-time monitoring and estimation of the human states are key to achieving individual satisfaction. Although some studies have incorporated real-time data into the buildings to predict occupants' indoor experience (e.g., thermal comfort and work engagement), a detailed framework to integrate personal prediction models with building systems has not been well studied. Therefore, this paper proposes a framework to predict and track the real-time states of each individual and assist with decision-making (e.g., room assignment and indoor environment control). The core idea of the framework is to distinguish individuals by a new concept of Digital ID (DID), which is then integrated with recognition, prediction, recommendation, visualization, and feedback systems. The establishment of the DID database is discussed and a systematic prediction methodology to determine occupants' indoor comfort is developed. Based on the prediction results, the Comfort Score Index (CSI) is proposed to give recommendations regarding the best-fit rooms for each individual. In addition, a visualization platform is developed for real-time monitoring of the indoor environment. To demonstrate the framework, a case study is presented. The thermal sensation is considered the reference for the room allocation, and two groups of people are used to demonstrate the framework in different scenarios. For one group of people, it is assumed that they are existing occupants with personal DID databases. People in another group are considered the new occupants without any personal database, and the public database is used to give initial guesses about their thermal sensations. The results show that the recommended rooms can provide better thermal environments for the occupants compared to the randomly assigned rooms. Furthermore, the recommendations regarding the indoor setpoints (temperature and lighting level) are illustrated using a work engagement prediction model. However, although specific indoor metrics are used in the case study to demonstrate the framework, it is scalable and can be integrated with any other algorithms and techniques, which can serve as a fundamental framework for future smart buildings.

Keywords
smart office;
digital ID (DID);
comfort prediction;
space recommendation;
human-centric monitoring;
real-time visualization

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1 Introduction

A good indoor environment is essential for the occupants in many aspects. It has a significant impact on their well-being and lead to the improvement of their productivity (Huizenga et al. 2006; Humanyze 2018; MIRVAC 2019) and vice versa (Milton et al. 2000; Wargocki et al. 2000; Lan et al. 2011). In order to have better management of the indoor environment, many studies have focused on developing smart building management platforms (Tang et al. 2019). The rapid growth of high-speed commercial internet (Rathore et al. 2016), advances in building

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management systems (BMSs) (Zhan et al. 2021), as well as personal electronic devices such as smartphones (Li et al. 2017) have supported the concept of a smart building (Dong et al. 2019). A smart building is equipped to automatically control the building systems to address energy waste and improve the indoor environment quality based on smart sensors (Deng et al. 2021b). The sensors are installed in different locations in the building to collect environmental data such as temperature and humidity (Nakama et al. 2015; Riaz et al. 2015; Lee et al. 2016; Pasini et al. 2016; Chang et al. 2018; Ioannou et al. 2018; Pasini 2018; Machado et al. 2019; Rafsanjani and Ghahramani 2020). In addition, technologies such as Wi-Fi, WSN, 5G, and LP-WAN 01(Lu et al. 2019; Marzouk and Abdelaty 2014; Tang et al. 2019) have been applied to allow for seamless data communication. With the sensing data, real-time visualization platforms for indoor environments were developed, which aimed to provide the building manager with a more efficient decision-making process. For example, Revel et al. (2014) developed a low-cost thermal comfort monitoring system by means of the predicted mean vote (PMV) index of multiple positions calculated through the collected environmental parameters such as temperature, relative humidity, and air velocity. Chang et al. (2018) presented a framework to achieve colorful visualization of indoor temperature and humidity associated with adaptive thermal comfort values, which used Dynamo to import real-time sensing data into Autodesk Revit through the Arduino microcontroller. In addition to thermal comfort, other factors such as acoustic comfort were also investigated. In addition, different platforms were developed to evaluate the real-time indoor air quality. A battery-free device was designed by Tran et al. (2017) to monitor the concentration of VOC, air temperature, relative humidity, and the atmospheric pressure of the indoor environment. Similarly, Kim et al. (2014) developed an integrated monitoring system with multiple sensors to evaluate the real-time indoor air quality. By examining the level of seven gases (i.e., ozone (O3), particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_2), sulfur dioxide (SO_2), carbon dioxide (CO_2), and the volatile organic compound (VOC)), the system was able to provide a timely alert regarding the air quality.

Even with such efforts to improve the indoor environment, a survey involving more than 52,000 people in 351 office buildings showed that only half of the occupants are satisfied with their indoor environments (Frontczak et al. 2012). One major reason behind this is that the conventional methods for indoor environment control rely on adaptive comfort models and standards (ASHRAE 2017; Gan et al. 2019), which adopt one-size-fits-all approaches that assume all the occupants have similar preferences (Sood et al. 2020) resulting in an indoor environment that can only satisfy a small proportion of occupants (Frontczak et al. 2012). However, it is well established that different people have distinct preferences for indoor environments resulting from differences in age, gender, physiological features to name a few (Földváry Ličina et al. 2018; Cheung et al. 2019). For example, it is suggested that females prefer higher room temperatures than males (Karjalainen 2007) and the thermal sensation of people in different age groups (under 25 years old, 26–45 years old, and over 65 years old) are statistically different (Calis and Kuru 2017). In addition, it is shown that the occupants' physiological features such as brain signal (Matthews et al. 2017; Wang et al. 2019; Deng et al. 2021c), skin conductance level, heart rate, and skin temperature may vary across individuals under the same indoor environment (i.e., temperature and lighting conditions) (Deng et al. 2021c). Therefore, it is essential to consider the individual differences in the decision-making of the building systems.

To meet occupants' diverse preferences of the indoor environment, previous studies have focused on approaches regarding individual indoor experiences. The idea of activity-based workplaces (ABWs) (Stone and Luchetti 1985) was proposed to offer people more flexible workplaces. The utilization of ABWs aims to provide flexible workplaces for the occupants depending on their personal preference (e.g., the location and microclimate of the workplace) (Appel-Meulenbroek et al. 2011). It has shown an advantage in improving people's performance (Jahncke and Hallman 2020), physical activity, and relationships with co-workers (Arundell et al. 2018) compared with traditional offices. A review involving 36,039 participants also highlights the benefits of ABW particularly in improving communication, control of time, and workplace satisfaction (Engelen et al. 2019). Recently, some efforts have already been paid to integrate the ABW with smart building systems. For example, a robust system named *OccuSpace* was developed by Rahaman et al. (2019) for workplace management. The system allowed the occupants to use the statistical features of the Received Signal Strength Indicator (RSSI) of Bluetooth card beacons to predict the utilization of the shared workplace. Similarly, Sood et al. (2020) presented a platform with a mobile interface for the occupants to find suitable workplaces by collecting their experience feedback at different indoor workplaces.

However, the application of ABW needs precise control of the indoor environment, as a poor indoor space management strategy may lead to extra energy consumption (Masoso and Grobler 2010) and insufficient indoor comfort improvement for the occupants (Deng et al. 2021a). Therefore, to maximize the gains from ABW, a human-centric smart decision-making system is required. In addition, a comprehensive survey regarding the worker perspectives on incorporating artificial intelligence (AI) into office spaces is conducted. The results show that it is expected that future buildings should be able to interact with the occupants and create better indoor environments for individuals (Ho et al. 2015).

To achieve this, real-time estimation of the occupants' states (e.g., comfort level and work engagement) is the key to mapping personal behavior patterns and performance to improve the comfort level and well-being of each individual (Humanyze 2018). Prediction models for human comfort as the references for the decision-making of the indoor environment have been investigated in several studies. For example, Ho et al. (2015) developed a platform that could connect the real-time indoor air quality to a personal health reporting system through a mobile app. The system was able to analyze the data and give alerts to the occupants once the concentration of air pollution exceeded a certain threshold. Moreover, after collecting subjects' thermal comfort feedback and physiological data under different environmental conditions, Li et al. (2017, 2018, 2019) developed different approaches including smartphone applications and thermal camera-based frameworks to estimate the occupants' personal thermal comfort. Based on the developed personal thermal comfort models, a dynamic determination of the optimum room condition mode was achieved. Similarly, Ma et al. (2019) applied an ANN model which took human parameters (e.g., clothing type, activity type, human relative position, gender, age, height, and weight) and environmental parameters (e.g., air temperature, air humidity, air velocity) as inputs to train a personal prediction model for thermal comfort.

Based on the existing technologies, research has started to focus on occupant-centric environmental control. For example, Kim et al. (2018) has proposed a unified modeling framework to achieve smart control of indoor thermal environments based on personal prediction models. The framework discussed the data collection, model selection, and learning process of the systems, as well as the architecture for integration of models in thermal control. In addition, a review conducted by Yang et al. (2022) summarized the concepts of making the HVAC control based on occupant information. The utilization of occupant-related data in improving the performance of HVAC systems has been identified. However, these frameworks only focus on thermal comfort and have not explored the capabilities of incorporating other indoor experiences. In addition, there is no case study to demonstrate how the proposed systems work. In order to further improve the indoor experience of the occupants, it is essential to develop a generic framework with an illustrative case study. Taking the concept of the digital twins (Deng et al. 2021b) as a departure point, this study proposes a novel framework for human-centric monitoring and control of smart buildings. Based on personal information, the framework incorporates different building systems but is fully scalable. The contributions of this framework include: (1) a new concept of human digital ID (DID), which refers to the digital replica of human biographic data; (2) a DID-based framework for real-time human-centric indoor monitoring and room management; and (3) a case study to demonstrate the feasibility and practicability of the framework.

The paper is organized as follows. The concept of the DID-based framework is described in Section 2, followed by a case study to demonstrate the framework in Section 3. Discussion of the case study results is conducted in Section 4, the conclusions are given in Section 5.

2 Methodology

In this study, a new concept of human Digital ID (DID) is proposed as the core of the real-time human-centric monitoring framework. As per definition, the concept of DID refers to a digital replica of human biographic data, environment preferences, and personal prediction models that can be used to help with the evaluation of their indoor experience. The systems and information flow of the framework are shown in Figure 1. The DID supports interactions in different connected systems that are important for the decision-making and control of indoor spaces. These systems include: (1) recognition system; (2) prediction system; (3) visualization system; (4) feedback system; and (5) control system. The information stored in DID serves

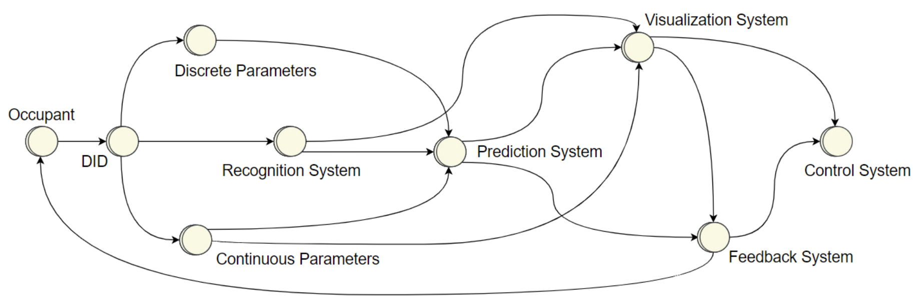

Fig. 1 Components and information flow of the DID-based system

as the personal prediction model to estimate the personal comfort or indoor environment preference of the occupant. After the occupant is recognized by the recognition system, the profile for the specific individual is obtained. In the prediction system, the personal DID combines with the real-time environmental data to estimate the human states (e.g., thermal comfort, visual comfort, mental states). In addition, to sufficiently represent the collected and predicted information, a virtualization platform is implemented as a tool for real-time monitoring and decision-making. The details of each system are discussed in the following sections.

2.1 Digital ID (DID)

2.1.1 DID data components

The information contained in DID for an individual is shown in Figure 2. Human information can be categorized into two major categories: (1) dynamic parameters; and (2) static parameters. Dynamic parameters include the parameters that continuously change over time such as clothing type, location, activity intensity, and physiological data (e.g., galvanic skin response (GSR), skin temperature (ST), and heart rate (HR)), when available. In contrast, the static parameters do not change significantly within a short period of time, such as human physical parameters (e.g., age, gender, height, and weight), general environmental perceptions (e.g., preference of temperature, humidity, and lighting level), lifestyle (e.g., level of physical activity), and long-term working style (e.g., sedentary or long-standing). In practice, the dynamic parameters can be obtained through wearable or non-intrusive sensors (Li et al. 2017, 2018). The static parameters are used to categorize the profiles of different people and do not need to be collected continuously. In addition, the personal prediction models are also considered a part of DID. They refer to the mathematical models (e.g., standardized equations and learned models from machine learning) that are capable of predicting the occupants' states such as thermal comfort, visual comfort, and work engagement. The prediction models use the static or dynamic parameters, sometimes combined with the environmental parameters, to make the estimation. For example, human activity level and clothing type associated with room temperature and humidity are generally considered good features for predicting thermal comfort (Ma et al. 2019; Gan et al. 2021).

2.1.2 A framework to establish and update the DID database

A framework for the establishment and update of the prediction models is proposed as shown in Figure 3. Based on the functionalities of the building, a target group of people is determined. For example, for an educational building with study rooms, the target group of people is students while for an office building the target group of people should be the employees. An initial database is established by collecting the data from the target group. For this study, the educational building is used in the case study, thus the data is mostly collected from students. The static parameters of the people including age, gender, weight, height, thermal preference, and lighting preference are collected. Based on the collected information, further processes of the data are conducted to establish the personal prediction models for occupants' states (e.g., thermal comfort, visual comfort, sound comfort, odor comfort, and work engagement).

However, the existence of personal models for all the occupants cannot be assumed, due to the lack of data or because someone is a new occupant. Therefore, for the new

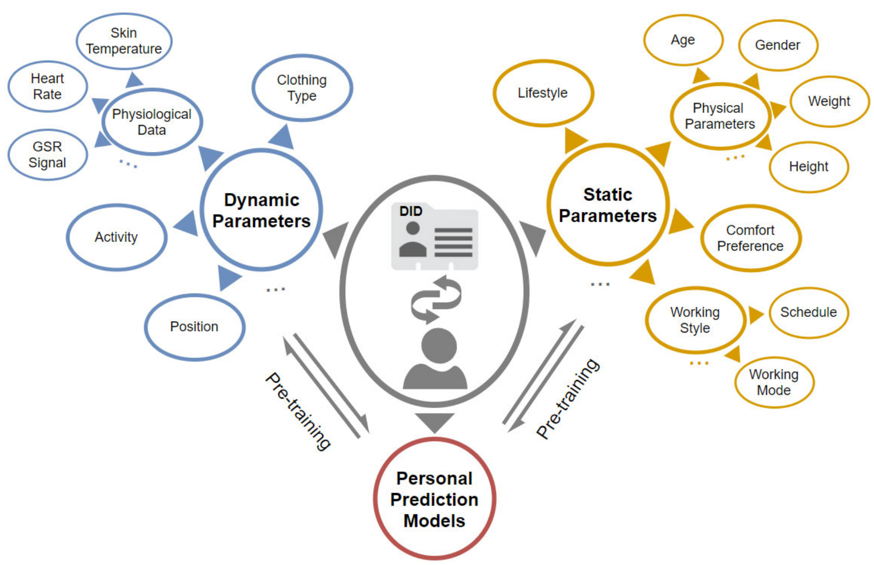

Fig. 2 Components of Digital ID

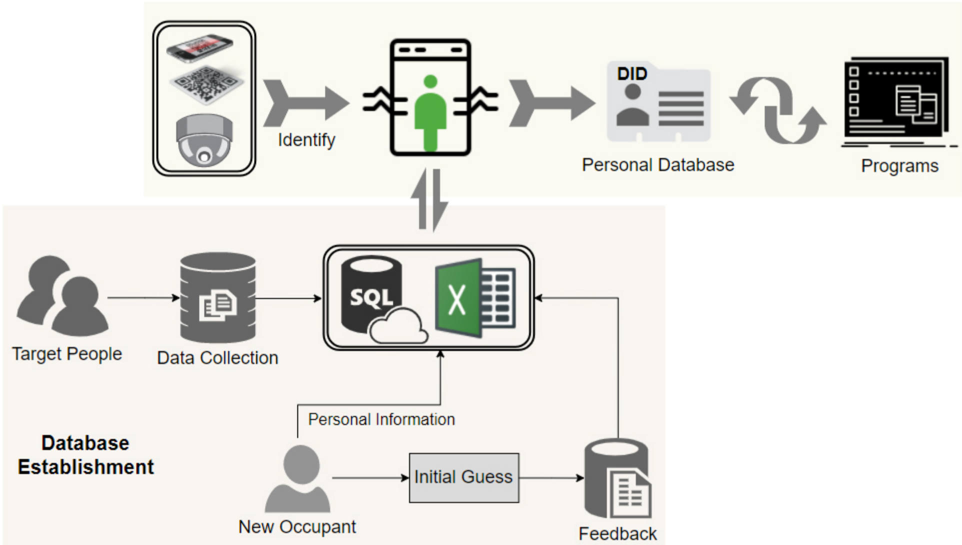

Fig. 3 The schematic diagram for the establishment, access, and update of the database

occupants without existing DID databases, public databases will be applied to give the initial guess of their states. The public databases usually contain a large number of datasets collected from different studies. Based on the databases, general prediction models can also be well-trained, thus they serve as potential sources to initialize the system for new occupants. The details for establishing the prediction models are described in Section 2.3. A good example of a public general database being used in this study is the ASHRAE Global Thermal Comfort Database II (Földváry Ličina et al. 2018), which will be described in detail in the case study. While the initial guess of the human states is conducted, the occupants will give feedback to the system and allow the establishment of their personal database. An example approach to collecting feedback is through a mobile app developed in the previous studies (Gupta et al. 2016; Li et al. 2017; Sood et al. 2020). The collection of feedback can not only apply to new occupants but also be feasible for existing occupants so as to update their existing databases.

2.1.3 DID data storage and exchange

All data of the DID is stored in a local or cloud database. In this study, a text file on the local disk is used to store the personal information of any occupant, while there is no restriction on the data storage and other approaches such as SQL database are also feasible to keep the database in the cloud. Within the database, each individual has a separate sub-database that contains the previously mentioned information (Section 2.1.1). The database is dynamic as the information of the person changes over time. When the database is needed by the system, it is accessed by scripts that are based on computer programs developed in languages such as python, java, C++, and MATLAB (depending on the program platforms). In this study, the back-end programs are mostly written in python. For example, when the system needs to estimate the thermal comfort of the occupants using the environmental parameters (e.g., temperature and humidity), the specific thermal comfort prediction model is accessed and applied to make the estimations. Note that there can be multiple models to estimate the same human state, and they take different input features. For instance, temperature and humidity are often used as the input features for thermal comfort (Li et al. 2017; André et al. 2020) while personal physiological data such as skin temperature and heart rate are also useful predictors of thermal comfort (Li et al. 2017). The required information from the database thus depends on real-world scenarios.

2.2 Recognition system based on DID

To track the human states, a recognition system based on DID is proposed as shown in Figure 3. Once a person enters the building, the system will recognize the occupant so as to match him/her with the corresponding DID database (if it exists). One example of the identification method is the QR code. If the QR code is attached to a phone or an identity card, the occupants only need to swipe the card or an identifiable marker on the phone, which they would typically have to do at the entrance of office buildings. Alternatively, computer vision techniques can be another method to recognize the occupants through indoor surveillance cameras (Adjabi et al. 2020). As both QR scanning and vision-based human recognition are mature techniques in the real world and have been widely used, details of the human identifying processing will not be discussed in this paper as they are out of the scope of this study. Once the DID of the occupant is recognized, the database becomes an open resource for the systems. However, for the new occupants, recognition is considered to fail, and a new database will be generated at the back end of the systems, newly collected data from the specific occupants will be allocated into the database.

2.3 Prediction system

The proposed system can deal with the different scenarios: (1) existing occupants with their DID databases well established; and (2) new occupants without DID databases or without enough data to deliver accurate personal prediction models. For the first scenario, it is assumed that there is enough data collected from the occupants and the mathematical models have been established. Therefore, the existing personal database is used to estimate the occupants' states.

However, for the second scenario, there is no personal database for the programs to access. Therefore, it is proposed to conduct the initial guess based on the public open-source database. The process of the model training is shown in Figure 4. For an existing public database with occupants' information, corresponding environment parameters, and associated comfort feedback (e.g., ASHRAE Global Thermal Comfort Database II), a general prediction model can be established using machine learning. Take the thermal sensation as an example, the input includes personal information such as age, gender, weight, height, and clothing level. The environmental parameters include temperature and humidity, while the outputs are the thermal sensation indices (e.g., integer numbers range from −3 to 3). Here, it is considered the baseline prediction model.

However, an alternative method is proposed to establish separate models based on the profiles of humans. Based on the findings in previous studies (Indraganti and Rao 2010; Indraganti et al. 2015; Thapa 2019), one hypothesis here is that people with similar profiles tend to have similar perceptions and preferences of the environment. Therefore, human profiles are assigned into different categories according to their static parameters such as age, gender, weight, and height. This method requires the new occupants to enter their basic information right after they enter the building through the same app as mentioned in Section 2.1.2. For each category of the human profile, a prediction model is established. The categories are distinguished by human profile, and several pre-defined categories are used to establish the initial prediction models based on the data collected in different indoor environments (IE). When the building is used for a specific group of people, the establishment of the initial database can thus be based on data from the target group of people. The potential benefit of this method is that less data is required to establish the prediction model for a specific group of people. The validation of this hypothesis is conducted in the case study in Section 3.2.1.

2.4 Human-centric visualization system

Different from indoor environment monitoring, the visualization platform required for DID needs to be human-centric. It should be able to show the state of individuals, such as their location in the building, comfort levels, and preferences of the indoor environment. It can help the building manager to provide a better strategy of indoor environment control. To keep the privacy of the occupants, the visualization system contains no identifiable personal information (e.g., name, age, gender, height, weight) and only the building managers can access it. A comprehensive comparison of existing platforms that allow real-time visualization of the built environment is provided. BIM platforms such as Revit are commonly used in previous studies (Lee et al. 2016; Deng et al. 2021b). The developed interactive interfaces achieved through the Application

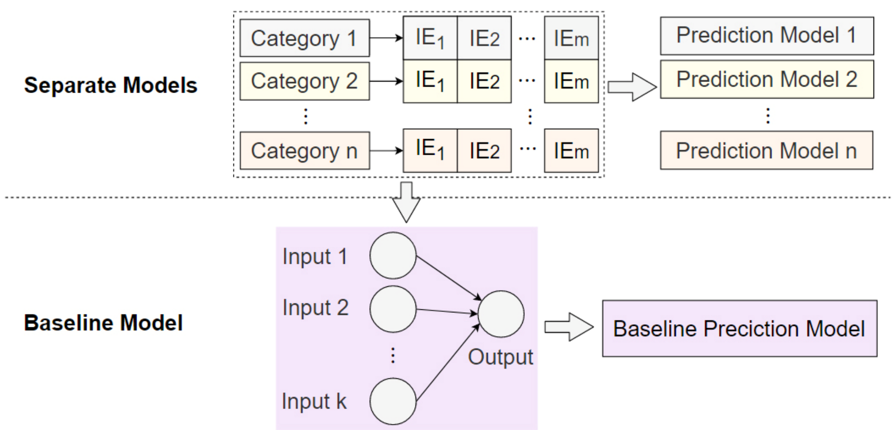

Fig. 4 The proposed method for model training

Programming Interfaces (APIs) using C# programming can show the status quo of the indoor environment such as temperature and humidity (Teizer et al. 2017; Ferreira et al. 2018; Kang et al. 2018; Pasini 2018; Machado et al. 2019). However, due to the model updating mechanism, most of the BIM platforms are not suitable for real-time visualization of moving components such as human subjects, because it requires the model to update from time to time, which may crash the models. To be specific, any modifications of BIM models in Revit will cause a reload of the entire model.

In contrast, game engines such as Unity can not only be efficiently connected to BIM models but also provide functionalities that allow the human models to update their locations with high frequencies (e.g., >100 Hz). In addition, data connection and visualization interfaces can also be achieved using C# scripts. The game engine is thus considered the most practical platform. Therefore, in this study, Unity is used as the tool for developing the real-time visualization platform. Revit model is converted to FBX. Format and pre-processed by the 3D Max (retain some semantic information) and then imported into the Unity. In addition to the building model, human models are also created to represent the occupants. Separate programs are written in C# scripts to allow the data exchange between the local data files. The scripts will read the local data file which contains the environmental parameters (e.g., temperature and humidity) and human state (e.g., thermal sensation). These data files are generated from the back-end programs (written by python) mentioned in previous sections. An example scene of Unity is described in Section 3.5.

2.5 Feedback system

The feedback system includes recommendations for the occupants based on the DID. With a variety of smart sensors installed in different locations of the buildings, real-time environmental data such as temperature and humidity are readily available. In this study, the real-time environmental data is collected and stored in the text files, which are not only connected to the Unity visualization platform but also being used to provide feedback based on the results from the prediction system. After processing the obtained information, recommendations are sent to the occupants or the building managers. The notifications regarding the recommendation are delivered through a mobile app to the occupant, thus they can know the most suitable places for them to visit.

With the capability of estimating the comfort levels of the occupants in different aspects, a recommendation system regarding the best-fit rooms for the occupants is proposed. A composite index is designed to represent the overall comfort score of each room. The indoor environment comfort metric for an occupant includes different aspects such as thermal comfort (TC), lighting comfort (LC), sound comfort (SC), and odor comfort (OC). The score for each aspect can be predicted using a method that is similar to the estimation of thermal sensation (i.e., range from −3 to 3). In order to evaluate the environment of the room in a more straightforward way, a linear method is proposed to evaluate the overall indoor comfort. A schematic diagram of the linear method is shown in Figure 5. As shown in Eq. (1), a normalized score for each comfort level is first obtained. Based on the preference of the occupants, different weights are assigned to each type of indoor comfort. The weights in the case study are obtained by questionnaires. To normalize the final score, the sum of the weights should be 1 as indicated in Eq. (2). The Comfort Score Index (CSI) of a room can thus be represented as Eq. (3), which ranges from 0 to 1 (the higher the better). However, a higher final score does not necessarily mean the IEQ for a

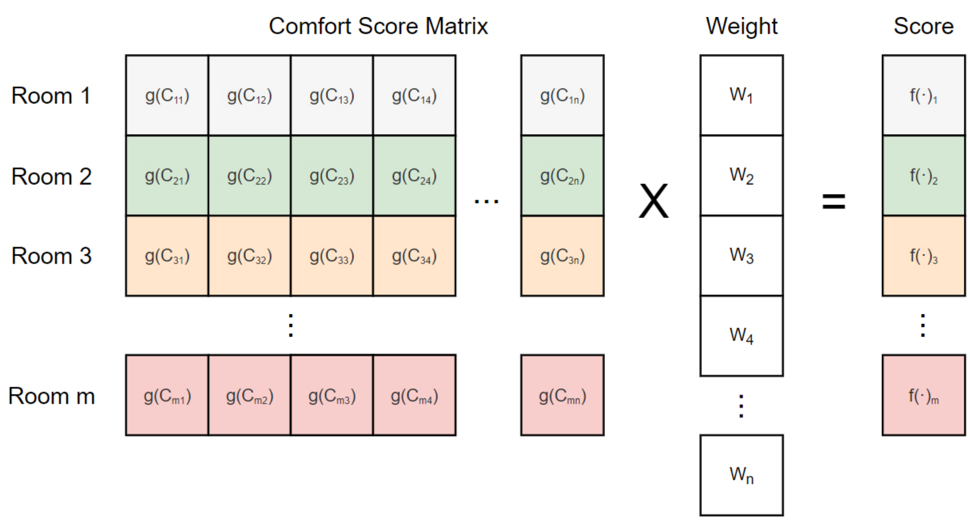

Fig. 5 Computation of the scores for building rooms

specific room is good in every aspect. For example, a room may achieve the highest final score but has a score of zero for specific comfort types. Therefore, a constraint of scores (p) for individual comfort types is added to the final choice. The problem can then be written as shown in Eq. (4). Based on the strategy, the best-match rooms will be assigned for the occupants based on DID.

$$g\left(C_{ij}\right)=\frac{\left|C_{j\_\text{bound}}\right|-\left|C_{ij}\right|}{\left|C_{j\_\text{bound}}\right|} \tag{1}$$

$$\sum_{j=1}^{n} W_j = 1 \tag{2}$$

$$\begin{aligned} f\left(\mathrm{TC}_i,\mathrm{LC}_i,\mathrm{OC}_i,\mathrm{SC}_i,\cdots\right) &= \sum_{j=1}^{n} W_j \cdot g\left(C_{ij}\right) \\ &= \sum_{j=1}^{n} W_j \cdot \frac{\left|C_{j\_\text{bound}}\right|-\left|C_{ij}\right|}{\left|C_{j\_\text{bound}}\right|} \end{aligned} \tag{3}$$

$$\begin{aligned} &\max f\left(\mathrm{TC}_i,\mathrm{LC}_i,\mathrm{OC}_i,\mathrm{SC}_i,\cdots\right), \\ &\text{s.t. } g\left(C_{ij}\right)\in\left[p,1\right] \end{aligned} \tag{4}$$

where C_{ij} refers to the jth parameter (e.g., TC, LC, OC, and SC) in the ith room, W_j represents the weight of a specific indoor comfort type for the occupant.

2.6 Control system

The feedback system provides a valid reference for the building control system. On one hand, the predicted human state of the occupants is used as a signal sent to the control terminal regarding the adjustment of the indoor systems. For example, given the occupants are feeling warm, the corresponding signal will be a trigger to lower the temperature setpoint. The final decision can be transferred to a smart thermostat (e.g., NEST) to control the indoor environment. Similarly, a signal that reflects that the occupants feel the room is too bright can drive the dimming of the lighting systems. On the other hand, the real-time monitoring of the occupants' states provides more insights into the interaction between the occupants and the building. A more flexible control strategy can then be applied by the building manager based on the results of the systems and the visualization platform.

3 Case study

To provide a better understanding of the proposed methods, a case study is used to showcase the capabilities of the DID framework. A schematic diagram of the case study is shown in Figure 6. The thermal comfort metric (i.e., thermal sensation) is selected as the example of human comfort as it is ranked as one of the most important factors that affect the occupants' satisfaction in buildings (Zhang 2003; Frontczak and Wargocki 2011). Based on the thermal comfort prediction models, the recommendation system is used to pick the suitable rooms for the subjects. After the occupants are assigned to the rooms, the real-time physiological data is used to make a dynamic estimation of thermal sensation thus providing further recommendations regarding the settings of the indoor thermal conditions. In order to demonstrate the scalability of this framework, another example where it is applied can be to determine the lighting level that helps support occupants' work engagement. In this case, recommendations regarding the indoor lighting levels can also be given. More details are described in the following sections.

3.1 Description of the scene

Three rooms (Figure 7) in the GG Brown Building at the University of Michigan are used as the scenes to demonstrate the DID system, all the rooms are student labs. Figure 8

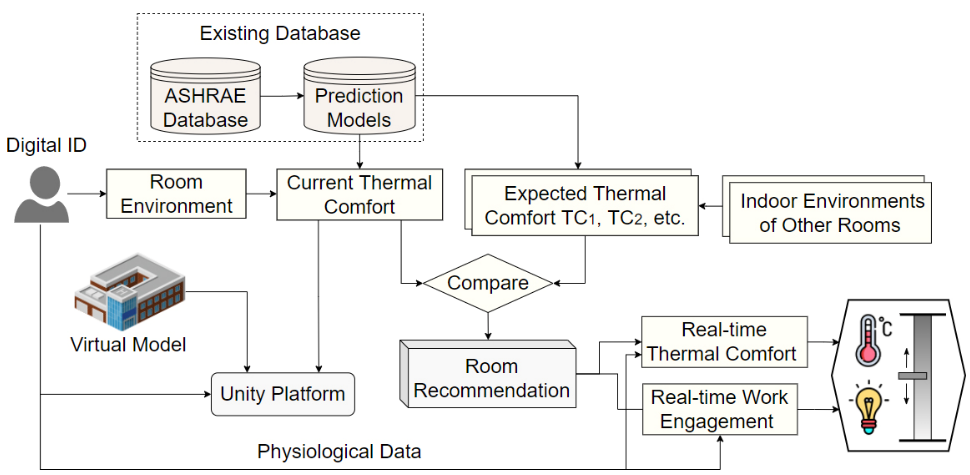

Fig. 6 The framework of the case study

Fig. 7 Example rooms (1006, 1140, and 1105)

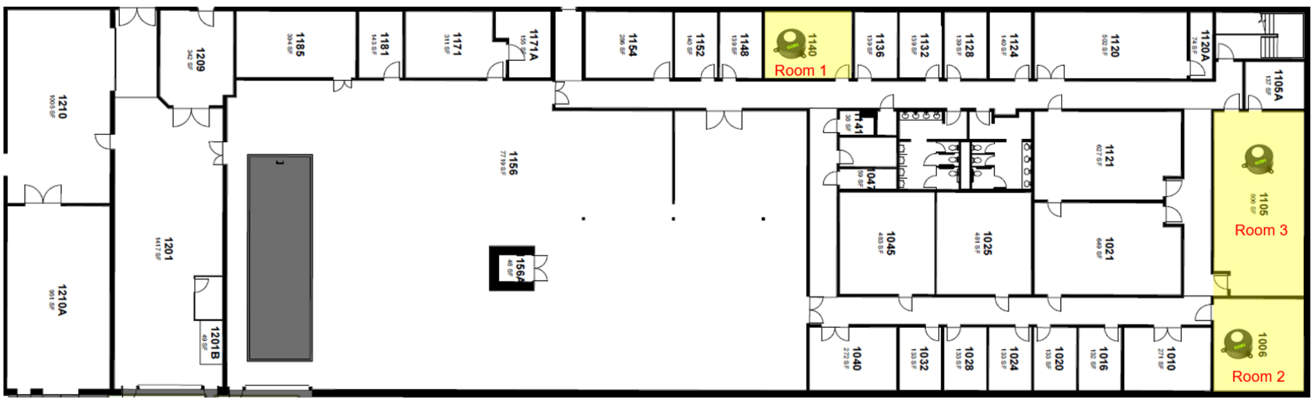

Fig. 8 The layout of the GGB basement

shows the floor layout of the basement of GGB, and the locations of these rooms are highlighted. The areas of rooms 1006, 1140, and 1105 are around 40, 30, and 75 square meters, respectively. These rooms do not have any windows, thus there is no natural ventilation, and the indoor environments are fully controlled by the central heating, ventilation, and air conditioning (HVAC) system through thermostats, which allows the occupants to directly control the indoor temperature. Corresponding environment sensors (i.e., COZIR) are selected and installed in the three rooms to obtain the real-time temperature and humidity data.

3.2 Digital ID of the subjects

Based on previous studies, personal prediction models can have higher prediction accuracies compared to general prediction models (Kim et al. 2018; Arakawa Martins et al. 2022), thus this framework aims to use the personal datasets to establish the personal prediction models. However, the system might not necessarily have the personal data of all occupants. For example, the database may miss the personal datasets for new occupants. Therefore, two groups of occupants are used as examples to demonstrate how the DID framework works in different scenarios. It is assumed that there are 12 occupants, 6 of them (group #1) are the existing occupants who have their personal DID information stored in the database while another 6 people (group #2) are considered new occupants without any existing personal databases. Group #2 is considered as an alternative method when there are no personal models for occupants in the building. Therefore, the case study can demonstrate how the framework handles the different scenarios. The proposed DID framework is applied to estimate the thermal comfort of those occupants in different rooms and give the room recommendation regarding the best-fit rooms for each of them.

3.2.1 *Existing database for new occupants*

For new occupants (group #2) without existing personal thermal comfort models, general prediction models are required. ASHRAE Global Thermal Comfort Database II is a public thermal comfort database that contains 107,583 datasets, and it allows end-users to only export the data with specific parameters through a web-based tool (Földváry Ličina et al. 2018). Because it is open source and contains a large number of datasets, it is used as an example public database to establish the general thermal comfort models for the new occupants. The datasets are carefully selected with meaningful static parameters by referring to the previous studies (Liu et al. 2019; Ma et al. 2019). According to the previous study (Wang et al. 2020a), the thermal sensation is a subjective thermal metric that is most widely used. Therefore, although thermal sensation might not always equal thermal comfort (Schweiker et al. 2020), it is used as an example to illustrate the prediction models. However, it is worth noting that although the thermal sensation is used as an illustrative example, the method is fully scalable and can be applied to other thermal comfort metrics (e.g., thermal satisfaction and thermal preference). In the real world, the system might not use only one single thermal metric but incorporate different thermal comfort metrics into the building systems. In order to obtain as many data points as possible, rather than using the web tool, the original full database is downloaded and manually filtered. The retained datasets include thermal sensation, age, gender, occupant height, occupant weight, cloth insulation, air temperature, relative humidity, and air velocity. The datasets that miss any of these parameters are removed. In addition, as the office or educational buildings are the main focus, the datasets for residential buildings are excluded. The details of the final datasets are summarized in Table 1.

Table 1 Details of the filtered dataset

Count	8574
Age range	18–68
Gender	Male/female
Height (cm)	120–203
Weight (kg)	34–130
Clothing level (Clo)	0.08–2.14
Air temperature (°C)	13.4–40.5
Relative humidity (%)	15.2–88.8

Regarding the machine learning algorithms for the demonstration, random forest (RF) is proven to have the highest accuracy in relevant studies (Kim et al. 2018), thus it is chosen to test the training strategy in this section. Figure 9 shows the machine learning process of the demonstration. Based on the previous study (Ma et al. 2019), human profile data including gender, age, height weight, clothing level, room temperature, and relative humidity are taken as the input features of the model. In addition, since the cooling/heating strategy (categorized as air-conditioned, mixed-mode, and naturally ventilated) can also affect thermal sensation (Wang et al. 2020b), it is also included as one of the input features. The thermal sensation ranges from −3 to 3 (ASHRAE 2017) are encoded as the outputs.

To show the accuracies of the prediction models, the hypothesis proposed in Section 2.3 is validated. Therefore, a systematic comparison of different data training strategies is developed as shown in Figure 10. Category C refers to any categories of human profiles based on their age, gender, height, and weight. n samples (30%) from category C are randomly selected as the test set. In this case, for a dataset that contains N data points in total, the training set in case 1 is the whole dataset minus the selected test set ($N - n$), while case 2 used the rest of the dataset (m) in category C as the training set. Case 3, on the other hand, used the same amount (m) of randomly sampled data from case 1 as the training data. In this case, three cases used different training sets to establish prediction models while the test set is the same, which provided a fair comparison strategy.

Based on the comparison strategies, 6 example categories of human profiles are selected and the detail for each category is shown in Table 2. To ensure the reliability of the prediction models, the categories with less than 100 data points are excluded. Referring to Figure 10, for category 1, n is 93 (30% of 310) and m is 217 (70% of 310). The hyper-parameters of the random forest are set as follows: the number of estimators is set to be 100, the maximum tree

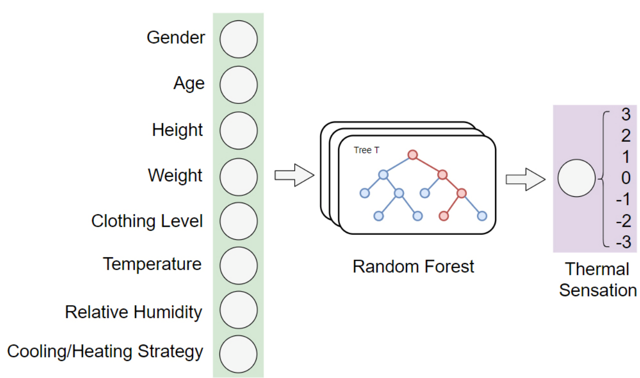

Fig. 9 Machine learning for thermal sensation

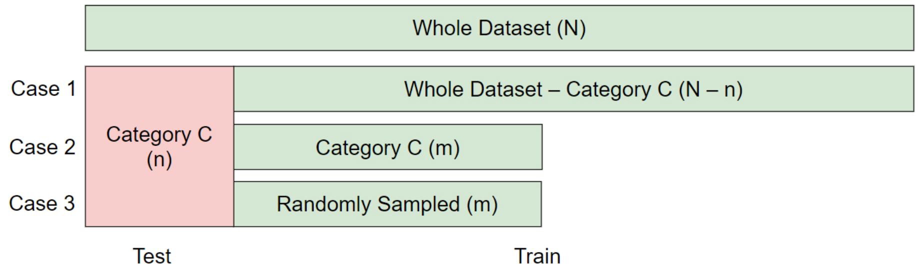

Fig. 10 Different data training strategies

Table 2 Results of the comparison of the data training strategies

Category	Age	Gender	Height (cm)	Weight (kg)	Count	Case 1		Case 2		Case 3	
						Train	Test	Train	Test	Train	Test
1	20–30	Male	160–170	50–70	310	0.814	0.615	0.809	0.555	0.790	0.433
2	20–30	Male	170–180	60–80	665	0.813	0.594	0.793	0.593	0.792	0.433
3	30–40	Male	170–180	60–80	285	0.814	0.610	0.770	0.574	0.770	0.489
4	20–30	Female	150–160	40–60	705	0.813	0.669	0.808	0.671	0.785	0.463
5	20–30	Female	160–170	50–70	1146	0.813	0.687	0.807	0.690	0.783	0.496
6	30–40	Female	160–170	50–70	292	0.813	0.693	0.804	0.683	0.769	0.545
Average						0.813	**0.645**	0.799	**0.627**	0.782	**0.477**

depth is set to expand until all leaves are pure or until all leaves contain less than the minimum number of samples required to split an internal node (i.e., 2). The minimum number of samples required to be at a left node is set to be 4 and the number of features for the best split is set to be "auto". The results are computed 100 times, and the test data set is randomly selected at each time. The accuracy is indicated by the fraction of the predictions our model gets right. The results of the training and test accuracies for the three cases are summarized in Table 2. The training accuracies indicate that there is no significant overfitting in the prediction models. In addition, the corresponding confusion matrices for the three cases are shown in Table 3, which further support the feasibility of the prediction models. Although more data points are associated with thermal sensations of −1, 0, and 1, the prediction accuracies for other values are also reasonable. In addition, even when the models fail to give the correct prediction, the predicted values are still close to the actual ones. Take the thermal sensation of 0 as an example, even if the predicted values are not 0, they will most likely be predicted as −1 or 1.

Regarding the data collection and training strategy in the initial guess for the new occupants, it can be observed that case 1 and case 2 achieve almost identical prediction accuracies without significant difference ($p > 0.05$), with the fact that case 1 has more than 10 times larger datasets compared with case 2. On the other hand, the prediction accuracies from case 3 are significantly lower compared to case 1 and case 2 ($p < 0.05$), with more than 0.15 lower

Table 3 Confusion matrices for the three cases

Case 1		Predicted						
		−3	−2	−1	0	1	2	3
Actual	−3	0.19	0.19	0.00	0.00	0.00	0.00	0.00
	−2	0.10	2.03	1.83	0.77	0.48	0.00	0.00
	−1	0.00	0.77	16.59	5.40	3.18	0.00	0.00
	0	0.00	0.00	4.24	22.76	2.80	0.19	0.00
	1	0.00	0.00	3.47	4.53	16.68	1.25	0.00
	2	0.00	0.00	0.39	0.48	2.03	6.46	0.68
	3	0.00	0.00	0.00	0.00	0.68	0.87	0.96
Case 2		Predicted						
		−3	−2	−1	0	1	2	3
Actual	−3	0.30	0.30	0.10	0.00	0.00	0.00	0.00
	−2	0.10	2.08	1.69	0.89	0.79	0.00	0.00
	−1	0.00	0.79	15.97	6.15	3.77	0.10	0.00
	0	0.00	0.10	4.27	22.22	3.97	0.30	0.00
	1	0.00	0.00	3.97	4.17	12.10	2.58	0.20
	2	0.00	0.00	0.69	0.69	3.08	5.65	0.40
	3	0.00	0.00	0.10	0.00	0.79	0.79	0.89
Case 3		Predicted						
		−3	−2	−1	0	1	2	3
Actual	−3	0.22	0.11	0.11	0.11	0.00	0.00	0.00
	−2	0.00	2.21	1.65	1.21	0.44	0.00	0.00
	−1	0.00	0.44	14.77	7.28	4.85	0.33	0.00
	0	0.00	0.00	5.73	18.08	4.41	0.55	0.00
	1	0.00	0.00	5.40	5.62	11.47	2.32	0.11
	2	0.00	0.00	0.55	1.32	4.52	3.20	0.33
	3	0.00	0.00	0.00	0.00	0.55	0.88	1.21

average accuracy. The reason is that the dataset in case 3 covers all categories of the human profiles but only has the same sizes of datasets as case 2. The results can provide valuable insights regarding the establishment of the database as well as the data training plan. At the initial stage for establishing the DID database, it is suggested that the collection of the training dataset should be maintained within a category of occupants that fits the usage of the buildings. In this way, higher prediction accuracies can be achieved with a much smaller dataset, referring to the accuracy comparison between case 2 and case 3. In addition, if there already exists a large dataset across all the categories of human profiles, the prediction models can be trained using either the whole dataset or the dataset within target categories, as they can provide similar performance, referring to the comparison between case 1 and case 2. Furthermore, assume the database will be updated with more data samples within specific categories, the performance of using the categorized dataset to train the model may outperform the whole dataset, as their dataset size will get closer, referring to the tendency of prediction accuracy from case 1 to case 3 compared to case 2. It can be seen that once the sizes of the dataset are similar, the prediction model obtained by the categorized dataset can have much higher accuracy.

The results prove that the hypothesis is correct, and the selected public database (ASHRAE Global Thermal Comfort Database II) can help with the establishment of prediction models with acceptable accuracies. Therefore, the baseline prediction models obtained here are used for the initial guess of the new occupants (group #2) in this case study.

3.2.2 *Personal database for existing occupants*

For the occupants with an existing prediction model (group #1), personal thermal sensation models are used. In addition to the database for the room recommendation, the example database for real-time monitoring of the occupants' states is also included. Figure 11 shows an example dataset, the left one shows the personal thermal sensation based on the indoor temperature and humidity, the middle one shows the thermal sensation based on physiological responses (e.g., skin conductance, heart rate, and skin temperature) of the subject, the right one is for the prediction of work engagement based on indoor lighting level and physiological responses of the subject. The prediction models for the work engagement can be used to make recommendations of lighting levels. The dataset regarding the physiological responses will not be used in the recommendation system but will be discussed in Section 3.4.1. Note that the human static parameters (e.g., age, gender, height, and weight) are not needed for the personal thermal sensation models as the data for each model come from one single occupant.

For the thermal sensation database used in the room recommendation, the data are collected from the experiments in our previous studies (Li et al. 2017, 2018; Deng et al. 2021c). People are asked to report their thermal sensation (from −3 to 3) under different indoor environments, and the random forest (RF) algorithm is used to establish a thermal sensation prediction model based on the indoor environment (e.g., temperature and relativity humidity). Therefore, given the indoor temperature and relative

Room Temp	Humidity	TC_EV
20	36.6	-1
17.9	55.3	-3
15.3	53.2	-3
29.4	46.8	3
15	32.1	-3
28.3	29.9	2
16.8	39.7	-3
16.5	56.6	-3
32	46.8	3
29.6	35	3
29.2	33.4	2
28.2	31.3	1
29.5	46.8	2
23.8	53.2	0
13.5	47.2	-3
31.2	55.3	3
18.1	30	-3
29.3	47.2	2
21.2	55.2	-1
22	42.6	-1
20.8	49	-1
25.6	42.6	0
17.9	47.2	-2
28.5	37.2	2
25.9	42.5	1
22.1	47.4	-1
28.8	22.3	2
27.5	43.2	1

Skin Conductance	Heart Rate	Skin Temp	TC_PHY
0.292460317	56.4577098	29.2505313	-2
0.449192821	53.4132757	29.4353257	-2
0.432888986	55.3580443	33.041612	0
0.389399142	55.4267165	34.0122227	1
0.257795677	59.3632791	29.0832424	-2
0.250172397	61.9034627	29.1450057	-2
0.350139444	56.1964813	34.1332221	1
0.456654803	58.9315602	29.1662701	-2
0.391406163	54.3063236	32.7634419	0
0.284680597	55.8233849	28.932524	-2
0.271645715	56.7525828	29.135024	-2
0.257598651	59.6234844	29.1364742	-2
0.391336788	55.4191704	33.8932475	1
0.433809246	55.0436309	29.4747531	-2
0.399149808	55.9636932	33.8699053	1
0.454631479	57.1741638	29.223824	-2
0.252355284	56.9778185	29.1001834	-2
0.419220363	56.562519	33.7037563	1
0.442370477	55.539859	33.0759168	0
0.361974137	57.3676851	32.9766013	0
0.430650599	58.5996499	33.6459379	1
0.362414322	55.9472857	33.9999314	1
0.406461941	58.8667689	33.0612919	0
0.326695874	56.0108938	29.4569293	-2
0.360345904	57.5870749	33.7234833	2
0.420017136	54.7853457	33.041797	0
0.245263764	56.4494764	29.1716108	-2
0.367777361	56.7900395	34.049367	1

Lighting Level	Skin Conductance	Skin Temp	Heart Rate	Engagement
200	0.279176986	33.4255069	74.3830586	0
200	0.287174631	32.92335339	66.8263683	0
500	1.157017462	30.44195509	69.0793774	0
500	0.550005116	30.97578856	75.5309995	0
500	1.054047081	30.29731151	63.6401602	-1
1000	0.609844149	31.58552033	76.7030619	-1
1000	1.028192727	32.36726903	66.432231	0
1000	0.329496025	32.88669994	72.2049056	0
200	0.28971029	32.91944757	63.0538732	-1
1000	0.315555104	32.89671395	69.6257618	0
1000	0.595781822	31.85521834	71.3503616	0
200	0.275759831	32.94396791	64.9811874	0
500	0.552036939	30.89144779	67.6713965	0
200	0.290060634	34.06448472	79.0497788	1
200	0.293855017	34.09970424	87.6784532	0
200	0.189905147	32.76376207	74.2810896	2
1000	1.053404061	32.33254067	73.9124066	0
200	0.285714286	33.46083545	70.8799433	0
500	1.006666077	30.53898048	68.1524302	-1
500	0.775350517	30.80182352	68.9777701	0
200	0.287574404	34.05247466	75.6950136	0
500	0.773631317	30.81859876	69.0352614	0
500	0.782813974	30.85215132	67.7009144	0
1000	0.77615787	32.35406102	66.348323	-1
500	1.15005524	30.4623416	66.9378832	-1
500	1.155308234	30.33409703	64.8425667	0
200	0.316467387	34.35036884	78.1873202	-2
500	1.076536311	30.32552396	68.7818927	-1

Fig. 11 Example of the dataset for existing DID database

humidity, the models can estimate the thermal sensation of occupants. On average, the prediction accuracy of the models from our example datasets is 79.4% using RF.

3.3 The room recommendation strategy

The recommendation strategy follows the approach described in Section 2.5. In this case study, the thermal sensation is the only index that needs to be considered. The indoor thermal environments of the three example rooms are measured using the COZIR sensors. As an illustrative example, the parameters in Table 4 are some random initial settings. Based on these initial indoor conditions, the implementation of the framework regarding the room recommendation is demonstrated. Here, ids 1 to 6 are used to indicate the people in group #1 and ids 7 to 12 for people in group #2. At first, the occupants are randomly assigned to different rooms by assuming that they have no information regarding the room conditions. Then the prediction models mentioned in previous sections are used and the CSI for each room is computed. The scores of different rooms and recommendations regarding the best-fit rooms for each occupant are shown in Table 5. According to the results, for most of the occupants (1, 2, 3, 4, 5, 6, 9, 10, and 11), there is at least one room that is expected to give the most suitable (score of 1) indoor environments. In this case, the recommendations regarding the best-fit rooms are given to these occupants. For example, occupant 1 is suggested to go to room 2, occupant 2 is suggested to stay in room 1, and so on.

However, not every occupant can have a room with the optimal thermal environment for them. In this case, the occupants will be suggested to a relatively more suitable room and the room setting will be changed to minimize discomfort. The strategy of modifying the room settings is explained in the next section. Therefore, the rooms with the highest Room CSI are chosen. Figure 12 shows the comparison of the Room CSI before and after applying our recommendations, which shows the potential improvement of the occupants' thermal sensation. Note for this section, people in both group #1 and group #2 have databases to

Table 4 The indoor environment of different rooms

	Room temperature (°C)	Relative humidity (%)
Room 1	23.8	53.2
Room 2	20.7	61.1
Room 3	18.2	67.3

Table 5 Scores of different rooms for each occupant

	Occupant	1	2	3	4	5	6	7	8	9	10	11	12
Thermal sensation	Room 1	1	0	1	1	1	0	−1	−1	0	2	1	−1
	Room 2	0	−1	0	0	0	−1	−1	−2	0	1	1	−1
	Room 3	−1	−2	−1	0	−1	−2	−2	−3	−2	0	0	−2
Room score index	Room 1	0.67	1	0.67	0.67	0.67	1	0.67	0.67	1	0.33	0.67	0.67
	Room 2	1	0.67	1	1	1	0.67	0.67	0.33	1	0.67	0.67	0.67
	Room 3	0.67	0.33	0.67	1	0.67	0.33	0.33	0	0.33	1	1	0.33
Room assignment	Original	1	3	3	2	1	3	1	3	1	1	2	3
	Recommended	2	1	2	2&3	2	1	1&2	1	1&2	3	3	1&2

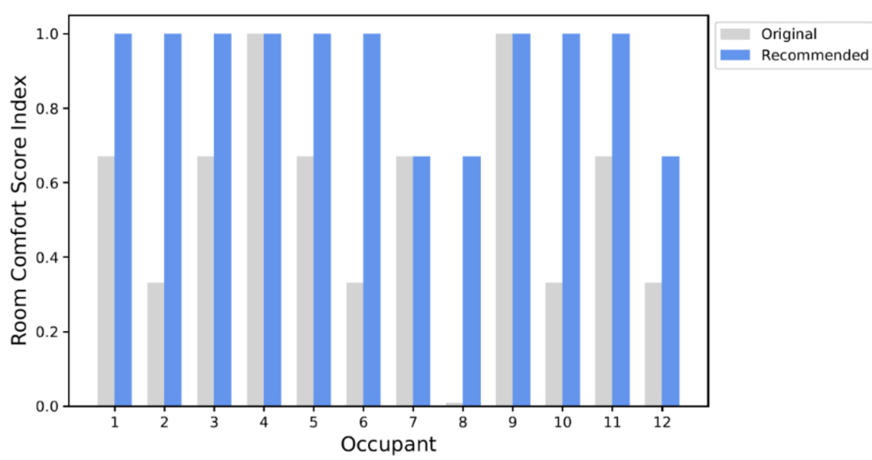

Fig. 12 Room Score Index comparison

support the recommendation system, the only difference is that people in group #1 use the personal database while those in group #2 use the public database described in Section 3.2.1.

3.4 Feedback of room environment control

3.4.1 *Feedback strategy based on physiological responses*

Based on the results shown in the previous section, there may not necessarily be a room that provides the perfect indoor environment for them. Therefore, adjustment of the indoor environment may be required. As mentioned in Section 3.2.2, for occupants with an existing DID database (group #1), the system can not only establish the personal thermal sensation prediction models based on static parameters but also use dynamic parameters to obtain the personal prediction models for thermal sensation and work engagement. Assuming the physiological is accessible, it can be used to estimate the real-time states of the occupants. Therefore, real-time recommendations regarding the setpoints for thermal environments and lighting levels can be given to maximize the occupants' thermal sensation and work engagement, respectively.

Based on previous studies, the ST and HR are confirmed to be good features to estimate the thermal sensation of a person (Li et al. 2017; Nkurikiyeyezu et al. 2017). In addition, it is suggested that the general autonomic changes in the skin's electrical properties can be reflected by the GSR signal (Braithwaite et al. 2013), and manipulation of GSR may affect central neural activity (Critchley et al. 2001, 2002; Nagai et al. 2004), which implies the correlation between GSR signal and brain activity, thus it can be used to reflect the mental activity. Therefore, in the DID database, the GSR, ST, and HR are used as the dynamic parameters to estimate the thermal sensation and work engagement of the subjects. In our previous studies, Shimmer3 GSR+ Unit is used to collect the GSR signal of the occupants, Optical Pulse Ear-Clip, and Skin Surface Temperature Probe are used to collect the HR and ST of the subjects, respectively. More information on the data collection process can be found in our previous study (Deng et al. 2021c). In the real world, a more portable device such as a wristband can be used to collect these data and connect these physiological responses to the computer terminal through Bluetooth. In this study, it is assumed that the physiological responses are easily obtainable to support the decision-making of the system. The overall idea of using physiological responses is to leverage the real-time physiological responses to provide a dynamic estimation of the human states, which will be used to help with indoor environment control.

Figure 13 shows the schematic diagram regarding the estimation of thermal sensation and work engagement based on physiological responses (and lighting level for work engagement). Different algorithms such as RF and neural network (NN) could potentially be used to establish the prediction models. For the thermal sensation models, they take these physiological data (e.g., GSR, HR, and ST) as the input features, while the thermal sensation values are the output. Therefore, given the GSR, HR, and ST data, the models can output estimations of people's thermal sensations. Based on the previous study (Deng et al. 2021c), lighting level is selected to be the environmental parameter associated with GSR, HR, and ST values to establish the prediction models for work engagement. As for the outputs, the discrete indices range from −2 to 2. The value −2 is for very low engagement, −1 for low engagement, 0 for a neutral level of engagement, 1 for high engagement, and 2 for very high work engagement, respectively. The hyper-parameters of the RF are set identical to the one described in Section 3.2.1. The designed NN contains three hidden layers, the first layer contains 4 neurons, the second and third layers contain 8 neurons, and it implements SoftMax Activation and Categorical Cross-Entropy Loss. The RF and

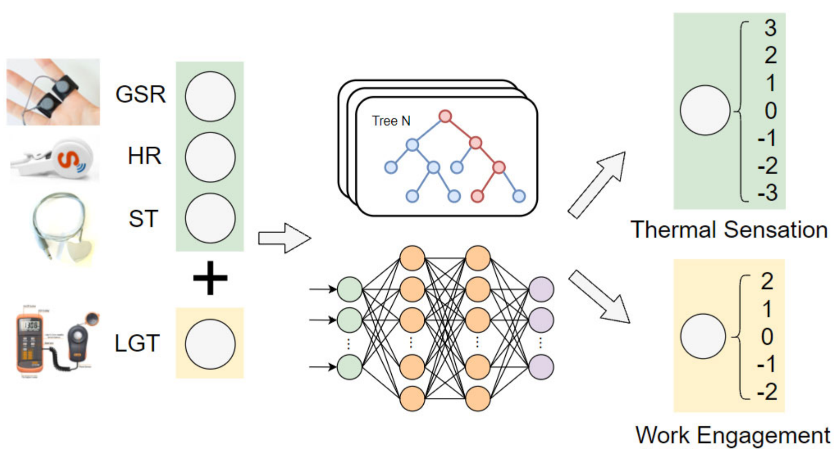

Fig. 13 Estimation of thermal sensation and work engagement using physiological responses

NN algorithms are compared for the example datasets, and the results show that RF outperforms NN for our datasets based on the same evaluation method as Section 3.2.1. However, the accuracies of the prediction models may vary a bit while different datasets are applied, thus NN is mentioned here as another potential algorithm as it might be a better option for other datasets. For people in group #1, these prediction models are pre-trained and can be directly used to estimate the thermal sensation and work engagement. Table 6 shows the detailed information of these two types of models (accuracies are the average of people in group #1). Please note that there could be many different input features to build the prediction models for either thermal sensation or work engagement, two existing models are used as illustrative examples.

Therefore, corresponding room environment recommendations are made based on the results from the physiological responses. If the model predicts the thermal sensation of −3, −2, and −1 for the occupant, it is recommended to increase the indoor temperature of the room where he/she stays, while for the value of 1, 2, and 3, it is recommended to decrease the indoor temperature. Similarly, the prediction models for work engagement are applied to help with the setting of the indoor lighting level. For the existing database, several common lighting levels (i.e., 200 lux, 500 lux, and 1000 lux) are used to see which one gives the highest work engagement. Therefore, a lighting level can be recommended for the occupant. For example, if the lighting level of 500 lux gives the predicted work engagement higher than 1000 lux or 200 lux, then the lighting level is chosen to be 500 lux. However, these models are used for demonstration, in the real-world system, there can be a higher resolution of lighting levels in the models.

Table 6 Details of the personal prediction model for thermal sensation and work engagement

Input data	Thermal sensation	Work engagement
GSR	√	√
HR	√	√
ST	√	√
Lighting level	×	√
Data points	370	680
Accuracy (RF)	89.2%	79.3%

3.4.2 Feedback strategy based on the public database

For people in group #2, until the personal models containing the physiological responses are established, the public database is still used to give feedback on the indoor environment. When an occupant is assigned to the room where the thermal sensation is not 0 (the Room Comfort Score is not 1), then corresponding feedback can be directly given based on the previously predicted thermal sensation. For example, occupant 8 is assigned to room 1 with the thermal sensation of −1, indicating that although room 1 has the most suitable indoor environment among the three rooms, he/she will still feel a bit cool. In this case, the feedback for room 1 is to increase the temperature. Meanwhile, corresponding data collection for the occupant can be used to establish or update their DID database.

3.4.3 Example feedback

The different models mentioned in the previous section indicate that the framework is compatible with any form of prediction model or any related human database. For example, based on either the physiological responses or the public open sources database, corresponding feedback for the room can be given. To demonstrate the feedback from the occupant, an example of the feedback based on Table 5 and random physiological responses is given in Table 7 and Table 8. The strategy here is to only give feedback to the rooms that are recommended for the occupants. Take the thermal sensation as an example, assume the occupants

Table 7 Feedback regarding the thermal environments of different rooms

Occupant	1	2	3	4	5	6	7	8	9	10	11	12
Room 1							↑	↑				↑
Room 2							↑					↑
Room 3												

Note: ↑ indicates feedback for increasing the temperature, ↓ indicates feedback for decreasing the temperature (where applicable).

Table 8 Feedback regarding the lighting levels of different rooms

	Occupant	1	2	3	4	5	6	7	8	9	10	11	12
Lighting level	Room 1		200				500	200	500	500	1000		1000
	Room 2	500		500	200	1000		200		500		200	1000
	Room 3				200								

follow the room recommendations, the thermal sensation of occupants 1, 2, 3, 4, 5, 6, 9, 10, and 11 will be 0. Therefore, there is no feedback from them. However, for the occupants 7, 8, and 12, no perfect rooms are found for them. By following the recommendations, occupants 7 and 12 are suggested to stay in room 1 or 2, and occupant 8 is recommended to stay in room 1. In this case, corresponding feedback will be given to their assigned rooms. As shown in Table 7, considering the feedback from all the occupants, the final feedback is that both room 1 and room 2 are suggested to have a higher temperature.

Nevertheless, it is still possible for the recommendation to give a wrong signal due to the limited accuracies of the prediction models. On one hand, the occupants can have full access to adjust the setting of the indoor environment, which will be a feedback signal to the system to update the database. On the other hand, as demonstrated in Section 3.4.1, when the occupants are in a specific room, the model established from the physiological data is used, which could rectify the potential errors of the systems. In addition, there can be a conflict in the feedback from different occupants. For example, two occupants are assigned to the same room but the feedback from them is opposite (e.g., one feels warm/hot while the other feels cool/cold). Similarly, for the recommended lighting levels of the rooms, conflicts between occupants may be found. It will be a much more complex situation and require more advanced algorithms to compute the final results, which is out of the scope of this paper. However, some existing methods regarding the optimization of the indoor assignment and environmental control can be found in our previous studies (Li et al. 2020; Deng et al. 2021a).

3.5 Real-time visualization in Unity

Unity is used to develop a real-time visualization platform because it is compatible with BIM models and allows a real-time update of the human models. A BIM model is generated and imported into Unity for the virtual environment. As shown in Figure 14, the building model is a basement described in Section 3.1. COZIR sensors are connected to the computer and the environmental data are read and

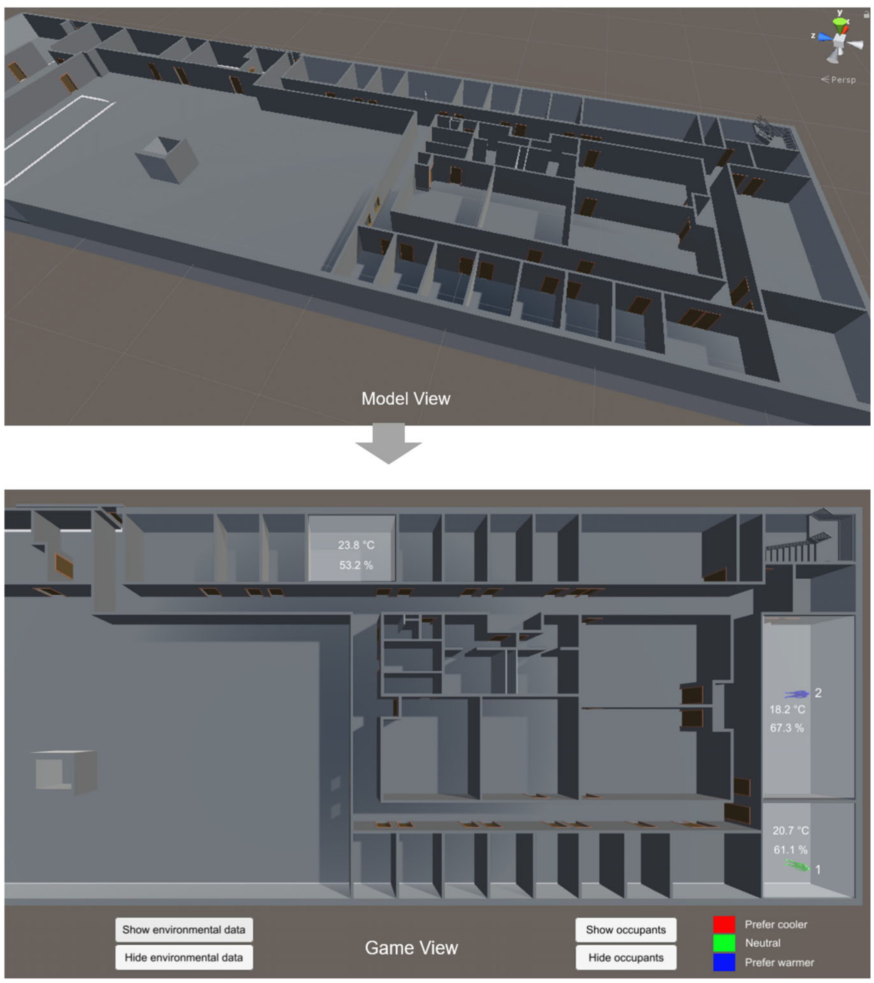

Fig. 14 Developed real-time visualization platform based on Unity

saved in local .csv files. A C# script is generated in Unity to read the imported data in .csv files. It can be seen that the indoor environmental parameters (i.e., temperature and humidity) can be visualized explicitly, and there are two buttons to display or hide the texts of sensing data. In addition, two human models are created to demonstrate how the different occupants can be represented, and distinct rendering colors are assigned to them based on the estimated thermal preferences. In this example, blue indicates that the occupant is feeling cool or cold (with the thermal sensation of −3, −2, and −1), and prefer a warmer environment, while red means the occupant feels warm or hot (with the thermal sensation of 1, 2, and 3) and prefers a cooler environment, green implies a neutral feeling of the occupant. Once the corresponding occupants change their locations (e.g., shift to another room), the new thermal comfort preferences will be given based on the new environmental parameters. Similarly, two buttons for displaying and hiding the occupant models are given, and in this way, the user can have better control of the visualization interface. In general, the platform can provide real-time information about the indoor environment and occupants' comfort levels.

4 Discussion

In general, a case study is used to demonstrate the proposed framework and how the DID could be incorporated. Different personal databases are used to demonstrate occupants with different profiles (group #1). The scenarios when people are new occupants (group #2) are also illustrated. Various types of database and prediction models are incorporated into our framework. An explicit example is given to show how these databases are used and how the systems make use of them to provide recommendations and feedback. The results show that compared to the randomly assigned rooms, the recommended rooms can provide better thermal environments for the occupants.

It is worth noting that the proposed framework is generic, and any other types of building information or technologies can be implemented. Although the case study used specific human parameters and prediction models as examples, the framework can fit any other occupant-related parameters or states (e.g., lighting comfort, sound comfort, and odor comfort). The only difference will be the input parameters. In addition, after comparing the capabilities of different platforms, a real-time visualization platform based on Unity is developed. The functionalities of the developed platform are also extendable, and the case study intends to provide an example of the capabilities of the platform as well as the key functionalities. The interfaces can be re-designed based on the requirement of the projects or personal preferences. By integrating the real-time sensing data and the predicted values, the developed platform can provide real-time information for both the overview of the indoor environment and the occupants' states, which can be valuable references for the building managers. With the help of the proposed framework, unnecessary space conditioning when the room is unoccupied or over-conditioning can be reduced. As a result, the indoor experience of the occupants as well as the energy efficiency of the building can be improved.

There are several advantages of the proposed framework. Compared with the occupant-centric environmental control framework in previous studies (Kim et al. 2018; Yang et al. 2022), our framework focuses not only on thermal comfort models but also on the overall indoor experience of the occupants based on the concept of DID and CSI. The concept of CSI can incorporate different indoor comfort indexes of the occupants and allow the systems to estimate occupants' overall indoor experience. In addition, rather than only proposing a concept, the framework is validated using a detailed example to demonstrate the mechanism of the systems. The case study contains two different types of prediction models (e.g., thermal sensation and work engagement) to show the scalability of the framework. In the case study, the ASHRAE Global Thermal Comfort Database II is used as a publicly available dataset for pre-training the model, which guarantees the reproducibility of the results. Furthermore, a visualization platform that serves as an auxiliary tool for the building control systems is also developed and demonstrated.

It is also worth acknowledging some limitations of this study. To allow the system to work based on individual preferences, the DID database contains some private information of the occupants, thus people may concern about their privacy. Therefore, data security needs to be ensured in a real-world implementation. In addition, to implement the framework, the buildings need to be equipped with a number of sensors and preferably with a building automation system (BAS). Furthermore, this study provides a general idea of the framework with several example methods. The framework is scalable and allows different technologies and algorithms to be incorporated, while the detailed discussion of optimization algorithms is not the scope of this paper. For example, the recommendation strategy does not discuss the maximum capacity of the rooms and the conflict perceptions of different occupants.

5 Conclusions

This paper proposes a novel concept of DID for human-centric monitoring and control of the indoor environment, which provides valuable insights into next-generation smart buildings. The concept of DID is defined and explicitly explained. Based on the DID, the interaction between different systems in the framework is presented, and possible approaches and algorithms for specific systems are discussed. A case study using the scene of the GGB building at the University of Michigan is presented to demonstrate the framework. Two groups of occupants are used to demonstrate how the DID, in different scenarios, can be adopted into the framework to provide recommendations for room allocation and indoor environment control. As thermal sensation is used as the target index to recommend the rooms, the results show an improvement in the thermal sensation of the occupants if they follow the recommendations compared with randomly assigned rooms. Different types of database and prediction models are used during the process to demonstrate the scalability of the framework. Example feedback for the building systems is also demonstrated based on previous results. Furthermore, a Unity-based platform that enables the real-time visualization of indoor environmental parameters and occupants' states is developed. In general, DID-based indoor environment monitoring and control allows efficient human-centric management of the indoor environment. It is scalable and considered a valuable framework for future smart building.

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