Article:

Yi, C.Y. orcid.org/0000-0002-0516-6590, Peng, C. and Robinson, D. (2023) Modelling urban dwellers' indoor heat stress to enhance heat-health warning and planning. Building and Environment, 243. 110623. ISSN 0360-1323

https://doi.org/10.1016/j.buildenv.2023.110623

Building and Environment 243 (2023) 110623

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Modelling urban dwellers' indoor heat stress to enhance heat-health warning and planning

Choo-yoon Yi *, Chengzhi Peng, Darren Robinson

School of Architecture, University of Sheffield, United Kingdom

ARTICLE INFO

Keywords:
Heat-health plan
Heat-health warning systems (HHWSs)
Heatwaves
Indoor heat stress
Building typologies
Urban heat island

ABSTRACT

Due to climate change, the intensity, duration and frequency of heatwaves are likely to increase in the coming years. Excessive heat events can increase local urban heat island intensity affecting the health and wellbeing of urban dwellers vulnerable to heat stress. Heat-Health Warning Systems (HHWSs) have been developed to warn the public of impending heat events and to advise on preventable negative health outcomes. However, metrics upon which action triggers are made in HHWSs rely on reported critical outcomes, such as heat-related excess death. Thus, human exposure to heat is underestimated in current metrics and consequently, their capacity to prevent heat-related health risks remains uncertain, particularly indoors. This study investigates how indoor heat stress in urban dwellings at a city-scale can be modelled to enhance Heat-Health Warning and Planning. First, the effects of housing typologies on indoor thermal conditions are quantified in a local urban microclimate context. We then model the dynamic relationships between outdoor climate and indoor heat exposure to identify specific outdoor climatic thresholds as *action triggers* for alerting urban dwellers' indoor heat stress. Based on urban microclimate data available for a city of Birmingham UK, a proof-of-principle study is presented. The result shows the presence of large variances in the heat-health action triggers across different housing typologies. This is further extended to consider the Birmingham climate projection scenarios provided by the UKCP18. Compared to the current UK Heat-Health Alert Service, we show how indoor heat stress warnings may look like and the implications for long-term heat-health planning.

1. Introduction

Climate change and associated extreme urban heat events in major cities have been closely monitored and analysed, pointing to a trend that the intensity, duration, and frequency are very likely to increase in the coming decades [1–3]. Consequently, there is increasing concern about the likelihood of increasing indoor heat exposure, leading to heat-related illness and even mortality [4,5]. This is particularly important to urban dwellers, considering the compounding effects of population ageing, intensified urban heat islands and increased frequency of urban heatwave episodes.

Historically, many parts of the world have already experienced unexpected heat-related risks caused by events such as heatwaves, resulting in mortality and morbidity. The heatwave in Chicago in 1995 is reported to have caused 700 excess deaths in only one week [6], and 70, 000 excess deaths were linked to the heatwave in Europe in 2003 [7], including 2000 in the UK alone [8] and 15,000 in France [9]. In South Korea, about 4.1% of increased excess deaths were observed to be related to heatwaves across the seven major cities from 2000 to 2007 and it reached up to 8.4% in Seoul [10].

In response to climate change and heatwaves, the World Health Organisation's (WHO) Regional Office for Europe developed Heat-Health Action Plans to help prevent adverse heat-related health effects, based on meteorological early warning systems and a heat-related health information plan, to inform long-term development and urban planning [11]. For instance, the UK's Heat-Health Alert Service is part of the Heatwave Plan for England [12]. This is a plan intended to prepare for, alert people to, and prevent the major avoidable effects on health during periods of severe heat in England. The meteorological early warning is based on the exceedance of a certain threshold of a weather variable or index defined by the regional context.

The existing warning system is in principle developed on the basis of an assessment of weather-health outcomes, such as human bio-meteorological responses [13]. However, these warnings tend to be entirely based upon outdoor climates at the regional or city scale, owing to the capacity of weather forecasting, representing less consideration of

* Corresponding author. School of Architecture, Arts Tower, Western Bank, Sheffield, S10 2TN, UK
E-mail addresses: choo.yi@sheffield.ac.uk (C.-y. Yi), c.peng@sheffield.ac.uk (C. Peng), d.robinson1@sheffield.ac.uk (D. Robinson).

https://doi.org/10.1016/j.buildenv.2023.110623
Received 25 May 2023; Received in revised form 11 July 2023; Accepted 15 July 2023
Available online 20 July 2023

urban climatic diversity [14]. More importantly, these warnings and plans do not explicitly account for the characteristics of the dwellings in which people, particularly vulnerable people, spend the overwhelming majority of their time.

Several studies have assessed occupants' indoor heat exposure and the corresponding health risks [15–18]. Building indoor thermal conditions can be determined by multiple factors of heat (energy) flow pathways, such as building thermal characteristics and their geometric configuration, combined with internal heat loads derived from occupants' activities and related behaviours under on-site ambient climates [16,19]. The consideration of those pathways in Heat Health Plans is particularly important in the urban built environment where mechanical cooling has not been widely adopted yet (i.e., the UK households), especially when unexpected extreme heat events may occur [20,21].

The question therefore is how Heat-Health Plans can effectively account for urban dwellers' indoor heat exposure, given the physical characteristics of their homes as well as spatial variations in the urban climatic. As noted earlier, this is significant given that people spend the majority of their life indoors: over 90% in developed countries [18,22], with around 66% of their time spent in their homes (i.e. [23]). The proportion of vulnerable groups staying in their homes could be much higher. A study highlighting the implication of the effects of indoor heat on health indicates that buildings are clear modifiers of the impacts of climate on health outcomes [24], so that building characteristics are one of the key drivers on heat exposure.

This study intends first to provide evidence for why the Heat Health Warning Systems need to consider urban dwellers' indoor heat exposure, accounting for buildings' thermal characteristics under urban climatic diversity as a short-term Heat-Health Plan; then to suggest how those climate-building-heat flow pathways can contribute to enhancing mid- and long-term Heat-Health Plans. This can be achieved by quantifying the effect of housing thermal characteristics and geometric configurations on indoor thermal conditions at local (microclimate) scale; then, modelling the relationship between outdoor climate and indoor heat exposure to identify specific outdoor climatic thresholds (as an action trigger) for urban dwellers' indoor heat exposure (stress). We anticipate this will allow for mapping local differences in urban dwellers' indoor heat exposure in present and future climates, enhancing the utility of Heat Health Planning for urban dwellers' health and wellbeing.

2. Indoor heat stress to enhance heat-health planning

A literature review was first carried out to address what we know about indoor heat stress within the urban context, and why the effect of both building physical characteristics and urban climatic diversity on occupants' indoor heat stress needs to be considered in enhancing Heat-Health Planning.

2.1. Indoor heat stress in urban dwellings

Most heat-related risk projections were developed on the basis of epidemiological studies of the relationship between external climate (temperature) and excess deaths [25,26]. Those heat-related risk (mortality) projections encompass a wide range of risk factors, such as personal health conditions and circumstances. In addition to mortality risks, attention should also be paid to human exposure to heat stress and illness, leading to potentially deteriorating chronic disease and hospitalizations [27]. This human exposure to heat affects entire populations [28] but it does not seem to be clearly quantified and reported, compared to heat-related excess deaths.

A more comprehensive understanding of heat-related risk factors is crucial, to identify the specific triggers for interventions to mitigate potential heat-related risks. The 'causal chain' from heat exposure to heat death can be threefold [29]: *Heat* affects *Heat stress* with factors affecting exposure. Then *Heat stress* leads to *Heat illness* with factors affecting sensitivity to a given heat exposure. Finally, *Heat illness* results in *Heat death* with factors affecting access to treatment. This suggests that preventing heat stress is a key step towards avoid potential heat-related risks to public health.

Heat is a complex physical phenomenon and air temperature alone does not sufficiently explain the reason for heat stress [30]. Factors of heat-related risk to public health include a large number of determinants. Fundamentally in a bio-meteorological perspective, all relevant weather variables should be taken into account in terms of human thermoregulation but some associated factors, such as relative humidity [31], solar radiation [32] and wind [33] are rarely considered, compared to air temperature, despite them being substantially impactful to human thermal responses for public health (i.e., Universal Thermal Climate Index [34].

Heat stress indices were initially developed for industrial and military setting, e.g., ISO 7243 Web Bulb Globe Temperature Index [35]. According to Havenith and Fiala [36], existing climatic stress models (indices) may be classified by the setting for which they were developed: for occupational settings (industrial and military) at short-term imminent risk (e.g., high workloads while wearing protective clothing); for perception of the circumstances and longer-term risk on a population basis, representing varied physiological responses to the ambient climate. For public weather services related to public health in particular, the Apparent Temperature (AP), Heat Index (HI) and Humidex were developed, with the purpose of advising the public on thermal condition/risk for short-time scales; mitigating the adverse health effects of extreme weather events, e.g., heat waves, as precautionary planning; increasing public awareness of climate change impacts on health, such as climate impacts in the health sector [36].

Common to those indices is some form of human heat balance model combined with heat (temperature) and humidity, but they differ from the climate contexts. For instance, the apparent temperatures (AP) are estimated as temperatures at a reference humidity, such as an absolute humidity measured at 14 °C of dew point temperature [37]. A simplified heat budget model of AP developed for hot climates is the Heat Index (HI), used by the National Weather Service in the United States. HI was developed by Rothfusz [38] based on regression analysis of the results of the Steadman heat budget model [39,40]. Similarly, Humidex (Humidity Index) was developed by the Canadian Meteorological service, as an alternative to the heat index, being related to atmospheric moisture (the dew point temperature) [41].

Studies have predicted increases in outdoor human exposure to heat owing to the changing climate [42–44], leading to increased heat-related mortality [45]. However, relatively less attention has been paid to heat-related health risks arising from *indoor* heat stress [46]. A field study of low- and middle-income urban dwellings in New York highlights their indoor heat stress is strongly associated with outdoor climates and is predicted to reach a dangerous level when applied to historical heatwaves [15]. Similarly, more than 40% of monitored bedrooms (from 36 dwellings), where internal heat loads (gains) from home appliances are relatively sparse, were deemed to have overheated during a hot period in London [47]. Moreover, in the urban context, localised climatic diversity caused by the urban heat island (UHI) tends to be overlooked especially at night-time, when UHI intensity tends to be most pronounced [48].

However, indoor heat-related risks cannot be solely determined by the outdoor and indoor climates. Heat-related risk factors can be more severe for specific populations [29], such as the aged and ageing [49–51], those with clinical or pathophysiological factors of people with depression [52] and with diabetes [53]. These risks may be exacerbated by buildings with poor thermal characteristics and ventilating systems [54–56] which may be linked with indices of deprivation [57]. This suggests a need to deepen our understanding of local contexts in terms of demography, building characteristics and local urban climates to better anticipate heat-related health risks.

2.2. Indoor heat exposure to enhance Heat Health Planning

As noted earlier, the Heat Health (Action) Plan was developed to prevent adverse heat-related health effect, responding to climate change and extreme heat events. One of the core elements described in the Plan is accurate and timely alert systems as an immediate action as well as a reduction in indoor heat exposure [11]. Heat Health Warning Systems (HHWSs) are weather-based alerts that are designed to warn decision-makers and the public of impending extreme heat events and to advise on preventable negative health outcomes [58]. These systems determine the likelihood of exceedance of an 'action trigger', such as a threshold temperature or bio-meteorological index at which there could be significant health impacts, based on weather forecasting [58]. The action trigger is typically determined by the relationship between historical heat and health outcomes, and the capacity of weather forecasting regionally, suggesting varied HHWSs from location to location [13,58]: i.e., daily maximum air temperature in England [59] and $32.2^{o}C_{HI}$ of Heat Index in Switzerland [60]. The level of warning varies depending on the heat intensity, the duration and target populations (general or older).

Metrics upon which action triggers in Heat Health Warning Systems (HHWSs) are determined are based on 'historical' (hence, reported) health outcomes under the 'heat event' or 'heatwave' at the individual city or county level, according to the capacity of weather forecasting in each country [58]. However, the use of historical health outcomes implies a reliance on critical outcomes, such as heat-related excess death. It is difficult to directly attribute mortality occurrences to the human exposure to heat so that this can easily be ignored, and thus underestimated in current metrics [13]. Consequently, the predictive capacity of existing HHWSs to prevent heat-related risk remains uncertain [61], as shown in Table 1, especially for particular vulnerable groups, such as the 65+ year old category.

In free-running built environments in the European urban context, indoor heat stress or heat exposure has been clearly monitored during (even mild) summers [62–64]. In line with the indoor heat stress risk, the Housing Health Safety Rating System [65] in the UK sets a threshold of $25^{o}C_{AT}$, where mortality increases in likelihood, in line with increases in thermal stress, cardiovascular strain and trauma, and strokes. Nonetheless, existing Heat Health Warning Systems are limited in their ability to account for indoor heat stress as their warnings are mainly based on outdoor climate forecasts only [58]. Studies highlight the strong needs for consideration of indoor heat stress in developing HHWSs as well as a reduction of indoor heat exposure [58,66].

Furthermore, urban settlements are well known to be subjected to urban heat islands (UHI), in which the urban air temperature can be significantly greater than its local rural counterpart, due to anthropogenic heat gains, enhanced shortwave radiation absorption and diminished longwave radiation emission and mean wind speeds. This UHI has a substantial impact on heat-related mortality [68,69] and thus, most heat-related mortality occurs in urban areas in which the UHI intensity is large [70]. This is particularly important where urban dwellers are not well adapted to warm climates, such as heating dominant countries, as epidemiological studies reveal that even small increases in temperature can substantially increase heat-related risks [71].

Under these circumstances, efforts have recently been made to develop HHWSs taking into account the urban heat island [14] and building indoor heat stress for specific older populations at room level in line with their lifestyle indoors [72]. However, as indicated earlier, a successful Heat Health Plan should also consider socio-demographic and building characteristics, to develop a heat-related health information plan, including where, when and who is at heat-related health risk, leading to mid- and long-term urban planning [11]. This suggests quantifying urban dwellings' indoor heat exposure locally in present and future climates. This however brings considerable complexity, owing to the number and variance of the underlying parameters, and the fact that existing metrics are not fully fit for this purpose, as they rely on outdoor climate predictions.

To this end, this study models urban dwellers' indoor heat exposure to investigate the characteristics of indoor heat stress derived from housing with different physical characteristics and exposed to different urban microclimates, as a potential basis for enhancing the existing Heat Health Plan for urban dwellers.

3. Materials and methods

Here we propose to combine the virtues of dynamic building energy simulations with a technique to be practically deployed to the existing Heat Health Warning Systems (HHWSs), of which action triggers are currently made based upon the outdoor climate, to provide a basis for a high fidelity of indoor HHWSs as well as of mid- and long-term public Heat Health Planning. For this, we first estimated the effect of housing physical characteristics and urban microclimates on indoor heat stress (section 3.1). We then investigated the relationship between outdoor climate and indoor heat stress (section 3.2). The city of Birmingham in the UK was selected as a case study owing to the availability of historical high density urban meteorological datasets for summer periods in 2013, when a heatwave occurred [73].

3.1. Housing climate-energy-heat models in urban microclimatic contexts

To effectively examine urban dwellers' indoor heat stress, it is essential to obtain corresponding measurements of their indoor climates. However, obtaining such large-scale field measurements would be prohibitively expensive, if not impossible. We have therefore used dynamic building energy simulations of reference housings to estimate occupants' indoor heat stress, for two distinctly different urban neighbourhoods. The idea here is to account for the effect of building physical characteristics and urban climatic diversity on residential indoor thermal environments in urban areas.

The two selected urban neighbourhoods (Appendix A.1) expressed the largest differences in the Mean of the recorded air temperature and of the estimated Universal Thermal Climate Index (UTCI, a multi-node physiological heat balance model between human body and the ambient environment, see Appendix 1 in more detail) during July and August in 2013 over the available high density urban meteorological datasets in Birmingham.[1] W007 is the thermally warmest neighbourhood while W011 is the relatively coolest area in the city of Birmingham. The name of weather stations we used follows those published Warren et al. [73]. This assumes that the effect of urban neighbourhood climatic diversity on urban dwellings' indoor thermal conditions can possibly be distributed within these two extremes of the urban microclimate.

Secondly, this study used existing standards and references of housing physical characteristics and occupancy internal heat load profiles. For instance, the UK domestic reference buildings developed by Allen and Pinney [74] were used for housing geometric configurations and thermal characteristics (See Appendix B.1 for detailed input parameters of building physical configurations as reference housing types used in this study). There are 5 types of housing identified and each housing type contains 4 types of insulation, giving 20 combinations of reference housings.

Building heat (energy) flow pathways also depend upon internal heat gains generated by a wide range of indoor heat sources, such as occupants' presence (and associated metabolic heat gains) and their use of appliances and lighting. Reasonably acceptable scheduling profiles of those heat sources and their placement of room (thermal zone) would be important to meet agreeable model reliability in estimating households' indoor thermal conditions [75,76].

We used an existing stochastic model to generate these internal heat

[1] Available at: https://data.ceda.ac.uk/badc/hitemp/data/WXT_Data/WXT_Data_BADCcsv.

Table 1
Estimated excess all-cause mortality during recent heatwave episodes in England. (): proportion of excess mortality of the 65+ years old to total. Lv.: level of heatwave episode. Days: number of days in each heatwave episode. No. Mort.: number of mortality (Source from [67]).

		Episode 1	Episode 2	Episode 3	Episode 4	Episode 5	Total No. Mort./day
2016	Lv., Days	Lv.3, 5	Lv.3, 5	Lv.3, 6	–	–	
	No. Mort.	612 (100%)	296 (100%)	x	–	–	56.8 (100%)
2017	Lv., Days	Lv.3, 8	CET20, 3	–	–	–	
	No. Mort.	666 (89.8%)	222 (81.1%)	–	–	–	80.7 (87.6%)
2018	Lv., Days	Lv.3, 3	Lv.3, 11	Lv.3, 9	CET20, 9	–	
	No. Mort.	210 (89.5%)	337 (78.9%)	455 (89.9%)	165 (63.0%)	–	36.5 (82.8%)
2019	Lv., Days	CET20, 3	Lv.3, 8	Lv.3, 7	–	–	
	No. Mort.	16 (25.0%)	496 (115.3%)[a]	361 (88.6%)	–	–	48.5 (102.6%)
2020[c]	Lv., Days	Lv.3, 5	CET20, 3	CET20, 11	–	–	
	No. Mort.	576 (94.6%)	246 (86.6%)	1733 (85.5%)	–	–	134.4 (87.8%)
2021[c]	Lv., Days	Lv.3, 8	CET20, 4	–	–	–	
	No. Mort.	916 (92.8%)	719 (86.2%)	–	–	–	136.3 (89.9%)
2022[c]	Lv., Days	Lv.3, 4	Lv.4, 16	Lv.3, 7	Lv.3, 10	CET20, 3	
	No. Mort.	187 (113.4%)[a]	1256 (94.7%)	−157 (79%)[b]	1633 (90.0%)	119 (78.2%)	76.0 (93.5%)

Heatwave Alert Levels and Defining episodes of heat [12].
- Level 3 (Lv.3): 'Heatwave action' - temperature reached in one or more Met Office National Severe Weather Warning Service regions.
- Level 4 (Lv.4): 'Major incident – Emergency response' – central government will declare a Level 4 alert in the event of severe or prolonged heatwave affecting sectors other than health.
- CET20: day(s) when the mean Central England Temperature (CET) is greater than 20 °C.

[a] More than 100% is the case when the excess mortality of 0–64 years olds is minus.
[b] Minus is the case when the excess mortality of both 0 to 64 and 65+ years olds is minus.
[c] Excess all-cause mortality (Heatwave and COVID-19).

gain schedules for UK housing. This model is integrated within the UK Energy Hub (EnHub), an open-source simulation platform.[2] To support the formulation of housing stock decarbonisation strategies, initially developed by Sousa et al. [77] and further enhanced by Sousa and Robinson [78]. EnHub was developed in response to a lack of modularity and transparency in housing stock energy models, as well as to facilitate dynamic energy simulations of stocks of housing [79]. This enables us to effectively replace the conventional aggregated average internal load with a synthetic representation of various usage profiles depending on household activities and circumstances [78]. This is based on a set of eleven energy-related activity categories. See Appendix B.2 for further details.

3.2. Modelling indoor heat stress in relation to outdoor climate

Given the measurement of outdoor climate and the estimations of residential indoor thermal conditions, we quantified the effect of local climates on indoor heat stress in each of reference 20 housing types. The Heat Index (HI, $^{o}C_{HI}$) was used as an indicator of occupants' indoor heat stress,[3] as it is developed for hot climates, considering the time frame of climate change projections for enhancing the Heat-Health Plan in this study. We used the U.S. National Weather Service's metric[4] to estimate the heat index based on its coherence with the original concept of Steadman's apparent temperature [80].

As presented earlier, there are two input parameters, air temperature and relative humidity, which are available at outputs of the building energy-climate modelling proposed in this study. The effect of HI ($^{o}C_{HI}$, https://www.weather.gov/ama/heatindex), under 'shade' conditions can be interpreted to four classifications.

- Caution (27–32): Fatigue is possible with prolonged exposure and activity. Continuing activity could result in heat cramps.
- Extreme Caution (32–41): Heat cramps and heat exhaustion are possible. Continuing activity could result in heat stroke.
- Danger (41–54): Heat cramps and heat exhaustion are likely; heat stroke is probable with continued activity.
- Extreme Danger (over 54): Heat stroke is imminent.

The daily timeline was divided into night-time (10pm – 6am) and daytime (6am–10pm) due to the different household occupants' activities (Appendix B.2): i.e., night-time accounts for sleeping (10pm-6am), while daytime for other activities (6am-10pm), which also accounts for internal heat gains derived from occupants' activities. Accordingly, the indoor heat index (HI) was calculated in the consideration of spatial-temporal occurrence of activities. Thus, the residential thermal zones (rooms) simulated were differently applied into calculating indoor HI as inputs of indoor climatic outcomes simulated. For instance, for the night-time HI estimations, hourly bedroom air temperature and relative humidity datasets were used, while for daytime HI, a living room was used due to the dominant occurrence of residential indoor activities.

We selected air temperature ($^{o}C_{AT}$) as an indicator of outdoor climate, in response to the existing national (or regional) weather service for public health in the UK. This was to evaluate how our modelling approach addresses how the effects of outdoor air temperature on indoor heat stress can practically be deployable to the existing Heat Health Warning Systems, which allows for instant implementations of the current systems as a short-term intervention, as well as for enhancing Heat-Health Planning as mid and long-term, considering the availability of future climate projections.

However, the question here is how the outdoor air temperature can effectively account for the indoor heat stress (spatially and temporally), which may be substantially dynamic in each housing type. Owing to the complex nature of building energy (heat) flow pathways, the relationship between outdoor climate and indoor heat stress may not be linearly fitted. We therefore first investigated the characteristics of indoor heat stress with respect to urban climates in different types of housing: 1) to assess whether there is significant difference in indoor heat stress of each of our 20 housing types under the different urban microclimates selected; 2) to evaluate whether the current daily Max. Temperature-

[2] Available at: https://github.com/EnHub-UK/TUS-to-HSEM-converter.
[3] However, there is a growing need for further development of the HI, accounting for indoor environments, such as occupancy characteristics and activities, and particular distinction of night-time due to increased sensitivity to heat stress for sleeping [66].
[4] Available at: https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml.

based metric of heat health warning systems (HHWSs) can be applicable to developing the indoor HHWSs; 3) to reveal whether there are distinctive features in the indoor heat stress between single hot days and consecutive warm (or hot) spells, and thus it should be divided in the modelling process; 4) to decide whether the different daily timeframe must be considered to account for the effect of building thermal characteristics, e.g., times before or after the outdoor Max. Temperature.

Then, a probabilistic approach to examining the relationship between outdoor climate and indoor heat stress (i.e., "caution", where HI is greater than 26.7$^{o}C_{HI}$ vs. No heat stress) was performed to identify the thresholds of outdoor temperature leading to indoor heat stress, using a binary logistic regression modelling. This is because logistic regression effectively accounts for the distribution of indoor thermal conditions with probabilities alongside their location (microclimate) and housing types (building physical characteristics).

Finally, K-fold cross validation was used to assess the predictive accuracy. Samples were split into two cases derived from the two urban climates of W007 and W011 for both training and validating samples, (hence, K = 2). This was because we selected two extreme urban neighbourhoods to assess the effect of the localised weather conditions on the indoor heat stress. Therefore, our intention was to identify a certain threshold of outdoor air temperature as action trigger for warning indoor heat stress (Caution heat stress, HI > 26.7$^{o}C_{HI}$) at neighbourhoods to city scale, and finally, to draw local difference in indoor heat exposure in future climates for enhancing long-term Heat Health Plan.

4. Results

4.1. Characteristics of indoor heat stress relating to urban climates and building characteristics

We first examined the effect of urban microclimate (air temperature, $^{o}C_{AT}$) and building characteristics on residential indoor heat stress (heat index, $^{o}C_{HI}$), where our 20 housing types were simulated under the two extreme urban climates during summer months (July and August).

The city of Birmingham selected for the case study in 2013 shows only one type of heat stress effect estimated in all housing types, which is 'Caution' (26.7$^{o}C_{HI}$ < HI < 32$^{o}C_{HI}$) during the daytime (6am-10pm) only, as shown in Fig. 1. Also, there was no heat index predicted above 26.7$^{o}C_{HI}$ after 3rd of August. Thus, this study excluded samples of the night-time exposure to heat as well as the daytimes after 3rd of August. Regarding the occurrence of indoor heat stress, there was one characteristic of outdoor air temperature found between single hot days and consecutive hot spell days. For instance, during 12–19 July, indoor heat stress was predicted under the relatively lower outdoor temperatures than those of single hot days. It suggests that a single outdoor temperature can be an inadequate marker for the effects of heat accumulation within the building structure and how this propagates to the indoor climate and corresponding heat stress.

Cumulative distribution function (CDF) was performed to investigate the cumulative probabilities less than 26.67$^{o}C_{HI}$ of each of 20 housings between W007 and W011. As shown in Table 2, the difference in the effect of two extreme urban climates on indoor heat stress is clearly observed in all housing types. In addition, we observe a difference in the density of CDF between the two urban climates, as illustrated in Fig. 2, suggesting the effect of building characteristics on indoor heat stress can possibly be large particularly under the relatively mild-warm climate.

Also, there were large variations of cumulative probabilities less than 26.67$^{o}C_{HI}$ in each of housings, but common to insulation existence (and non-), there was similarity of cumulative probabilities as well as percentage (%) of 'Caution' hours to total occupations in the same housing types. On average, the difference of the effect of the insulation types (cavity and solid) on indoor heat stress was not significant, as Sig. > 0.05 in all cases (See the differences (T-test) in indoor heat stress ($^{o}C_{HI}$) between the cavity and solid insulation in each housing type in Appendix

Table 2

Cumulative probabilities less than 26.67$^{o}C_{HI}$ (Caution indoor heat stress) and percentage (%) of 'Caution' hours to total occupations for daytime in each of 20 housings for W007 and W011, 3 July – 2 August, where values for W011 are presented in parentheses. *Cavity insulated (Cav-Ins); cavity uninsulated (Cav-Unins); Solid insulated (Sol-Ins); Solid uninsulated (Sol-Unins).

	Bungalow	Detached	Semi-Detached	Mid-Terraced	Mid-Flat
Cumulative probabilities					
Cav-Ins	0.91 (0.97)	0.87 (0.92)	0.86 (0.90)	0.86 (0.90)	0.88 (0.94)
Cav-Unins	0.86 (0.91)	0.85 (0.90)	0.84 (0.89)	0.86 (0.89)	0.88 (0.92)
Sol-Ins	0.92 (0.97)	0.87 (0.93)	0.86 (0.90)	0.86 (0.90)	0.88 (0.93)
Sol-Unins	0.85 (0.90)	0.84 (0.89)	0.84 (0.89)	0.85 (0.89)	0.88 (0.92)
% of hours of 'Caution' indoor heat stress					
Cav-Ins	9.48 (1.01)	10.89 (4.03)	11.90 (5.44)	13.10 (6.45)	11.69 (4.64)
Cav-Unins	12.90 (6.05)	13.71 (6.86)	14.92 (8.67)	13.10 (5.65)	12.50 (8.07)
Sol-Ins	7.86 (1.41)	11.09 (4.23)	12.10 (5.44)	12.70 (6.25)	11.29 (4.64)
Sol-Unins	13.71 (6.45)	14.11 (7.06)	14.72 (8.07)	13.31 (7.06)	12.70 (8.07)

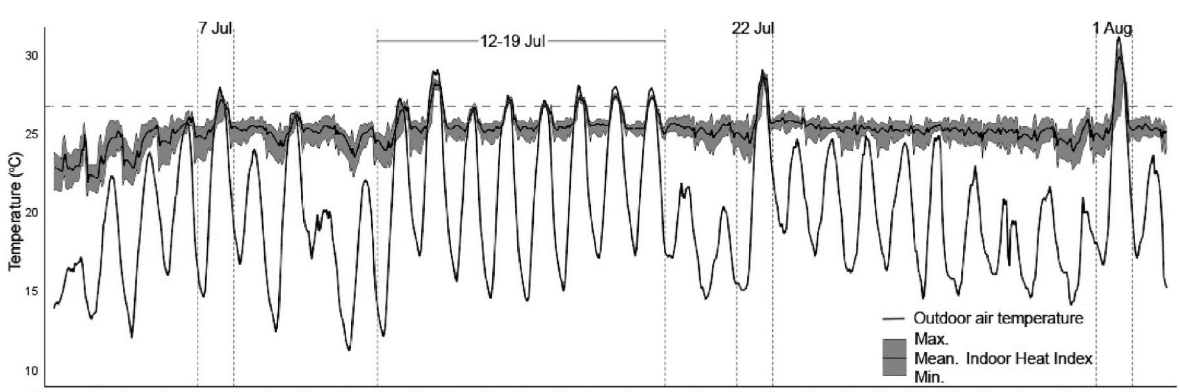


Fig. 1. Distribution of Hourly indoor heat index (HI, $^{o}C_{HI}$) of 20 housing types and outdoor air temperature ($^{o}C_{AT}$) of W007 (warmest urban climate selected in the city of Birmingham).

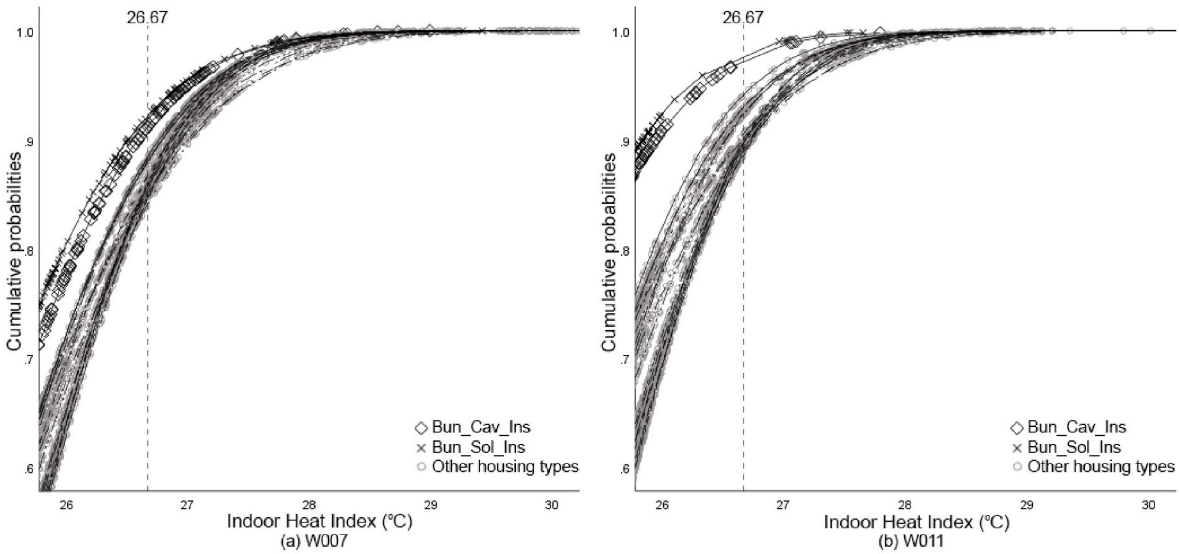


Fig. 2. Plots for cumulative distribution function less than 26.67°C_{HI} (Caution indoor heat stress) in each of 20 housings between W007 (a) and W011 (b), 3 July – 2 August.

C.1).

Following the examination of the effect of urban microclimate and building characteristics on residential indoor heat stress, we further investigated whether the different daily timeframe must be considered in modelling indoor heat stress with respect to outdoor temperature to account for the effect of building thermal characteristics, e.g., sampling hours before or after the outdoor Max. Temperature. This is since there is a complexity in the heat flow pathways to building indoors as internal heat gains derived from occupants' activities and building thermal mass also play a key role in building indoor thermal conditions. For instance, Fig. 3 shows the different linear fits (slopes) between hourly outdoor temperatures and the indoor heat index according to stepwise regressions in different timeframes (aggregating all housing types over the indoor heat stress days). The amplitude of the indoor temperature signal exhibits the expected dampening as well as a shift in phase.

Nonetheless, there is a great interest in developing high-resolution (e.g., hourly) predictions of indoor heat stress, according to the corresponding outdoor temperatures, which also account for the effects of a building's characteristics and the activities of its occupants. This is since public health planning can potentially provide useful guidelines in relation to the internal heat sources to mitigate indoor heat-related health risk. As seen in Fig. 3, the indoor heat stress typically appeared before the daily Max. Temperature (also seen in Table 3), and lasted longer times, implying the prolonged exposure to heat stress. Furthermore, this exposure time frame may be unique to each type of building. We examined the frequency (proportions) of indoor heat stress appearing before the Max. Temperature. Table 3 shows that all housing types have very high proportions, except insulated Bungalows,

Table 3
Frequency (proportions) of indoor heat stress appearing before the daily outdoor Max. Temperature in each housing.

	Bungalow	Detached	Semi-Detached	Mid-Terraced	Mid-Flat
Cav-Ins	0.62	0.86	0.86	0.93	1.00
Cav-Unins	0.94	1.00	0.95	0.93	1.00
Sol-Ins	0.58	0.86	0.86	1.00	1.00
Sol-Unins	1.00	1.00	0.95	0.94	1.00

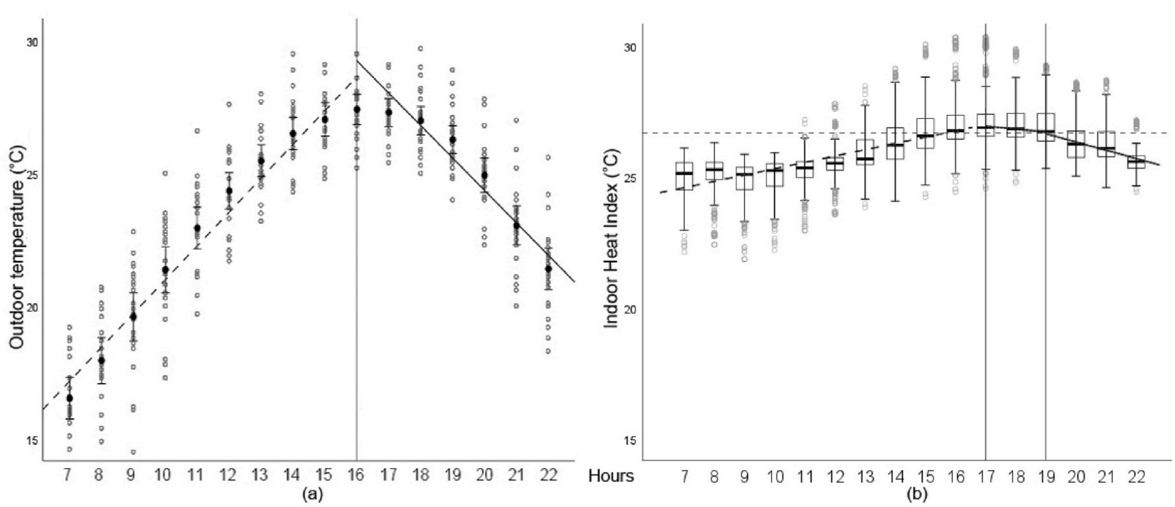


Fig. 3. Differences in stepwise regression linear fits and slops between outdoor air temperature (a) and indoor heat index (b) in different timeframes, in case of aggregate all 20 housings over the indoor heat stress days.

suggesting a need for modelling high-resolution predictions of indoor heat stress, corresponding to the hourly outdoor temperatures before the daily Max. Temperature.

In following subsections, we performed two types of modelling to identify the outdoor temperatures affecting the occurrence of indoor heat stress in each housing. One is the daily Max. Temperature-based models, which is designed to be directly applicable and deployable to the existing heat health warning systems discussed in Section 2 as a short-term intervention (Section 4.2). Another is the hourly temperature-based model, which is designed to identify specific thresholds of outdoor hourly temperature before the daily Max. Temperature (Section 4.3).

4.2. Daily max. Temperature-based models

Using our simulation results we have performed a binary (No heat stress vs. Caution heat index) logistic regression to model the Birmingham's residential indoor heat stress with respect to daily outdoor Max. Temperature. This is to examine the distribution of indoor heat stress with probabilities in responding to the daily Max. Temperature. Samples were selected based on days for occurrence of the indoor heat stress in each housing type, and daily Max. Temperature were given accordingly.

Fig. 4 (a) suggests a useful understanding of how daily outdoor Max. Temperature can probabilistically affect the indoor heat stress. Although it presents 26.8 °C at P (0.5), it is questionable whether the median value can be standard definition of an acceptable threshold as population characteristics and the compositions are not considered. For instance, attention should be paid around 26 °C (even the lower) at P (0.1), where the likelihood of indoor heat stress appeared, leading to potential heat-related health risk to specific populations vulnerable to heat exposure.

We also modelled this at the individual housing level. Fig. 4 (b) shows that given the study year of 2013, specific but various thresholds of outdoor daily Max. Temperature were identified in each housing, which should be compared to a single existing threshold of Heat Health Warning System (HHWS). This suggests consideration of the diversity of outdoor-indoor heat transition at building level in enhancing Heat-Health planning.

Such diversity was also found between single hot days and consecutive hot spell days in terms of the daily occurrence of indoor heat stress according to the daily Max. Temperatures as previously highlighted in Fig. 1. Fig. 5 shows the daily outdoor Max. Temperature during single hot days (as thresholds for daily indoor heat stress occurrence) tends to be higher than those during consecutive hot spell days. This, however, needs further confirmations based on larger samples and other years.

4.3. Hourly outdoor temperature-based models

Given the finding that the actual indoor heat stress appeared earlier than the time of daily Max. Temperature, we also performed the hourly temperature-based models to probabilistically predict specific thresholds of outdoor temperature before the daily Max. Temperature in each housing. Samples were selected based on an hourly timeframe made up to the time of daily Max. Temperature. This allowed binary models to effectively account for the occurrence of the indoor heat stress affected by the hourly outdoor temperatures in different timeframe, such as no stress – first appearance – lasting by the time of Max. Temperature.

Table 4 shows detailed parameters estimates of binary logistic models in each housing. This suggests a useful understanding for the relationship between the hourly outdoor air temperature and the corresponding indoor heat stress which varies in each of housings, where the timeframe is before the daily Max. Temperature during the daytime.

It shows that the predicted probabilities of the 'Caution' HI are well fitted to their observed proportions with respect to outdoor temperature. Common to all housings, an increase of the outdoor air temperature is associated with an increase in the probability of 'Caution' heat index but their magnitude (Exp(B) for outdoor temperature) varies. This led that the specific outdoor temperatures were differently identified for indoor heat stress occurrence probabilistically. Of those 20 housings, two insulated bungalows had distinctively higher outdoor temperature in each of probabilities for indoor heat stress occurrence, even compared to the uninsulated bungalows. However, the effect of insulations on indoor heat stress and the corresponding outdoor climate can be inconclusive in this study. This is since these have very different morphologies and fabrics, effecting surface to volume ratio and overall building volumetric heat loss coefficients.

4.4. Model validation and predictive accuracy

We performed independent two-fold cross validation to assess the predictive accuracy at the scale of each building level for the daytime. Samples were split into two cases derived from the two urban climates of W007 and W011 for both training and validating samples as we used models for one typology in one location to estimate outcomes for the same typology in other location: hence, K = 1 (W007 training to W011 testing) and K = 2 (W011 training to W007 testing). This was to evaluate the model applicability to different urban climatic contexts as well as predictive accuracy. Training datasets were used to identify the specific thresholds of outdoor temperature affecting indoor heat stress in each of housings. Then, the identified were applied into testing samples to

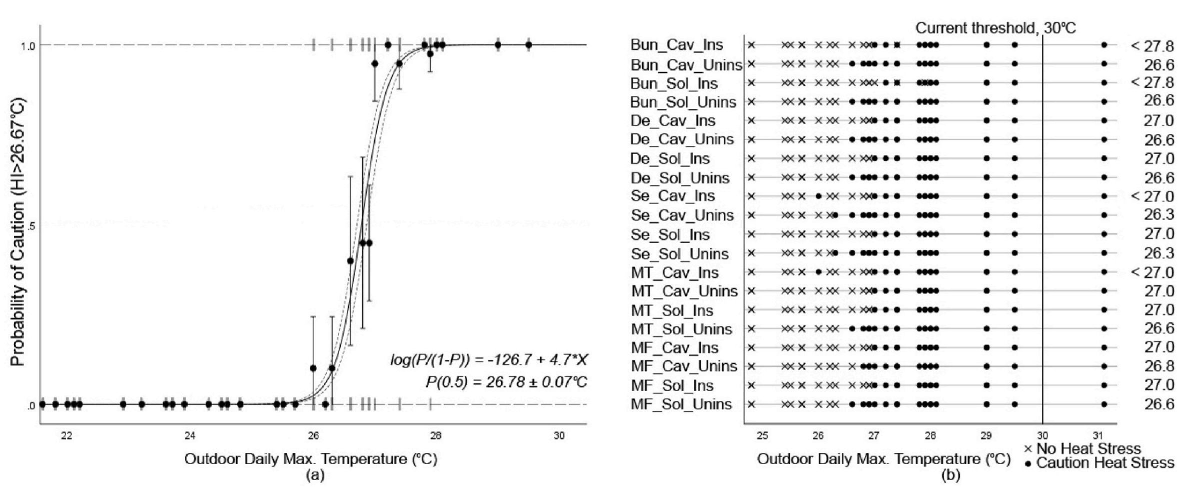


Fig. 4. (a) Probabilities of indoor Heat Index of 'Caution' (HI > 26.7°C_{HI}) fitted with outdoor daily Max. Temperature (°C_{AT}) at aggregation of all housings with their 95% confidence intervals (dash lines) and observed proportions of 'Caution' HI with their binomial 95% confidence intervals. (b) Thresholds of outdoor daily Max. Temperature with respect to the occurrence of the indoor heat stress in each housing.

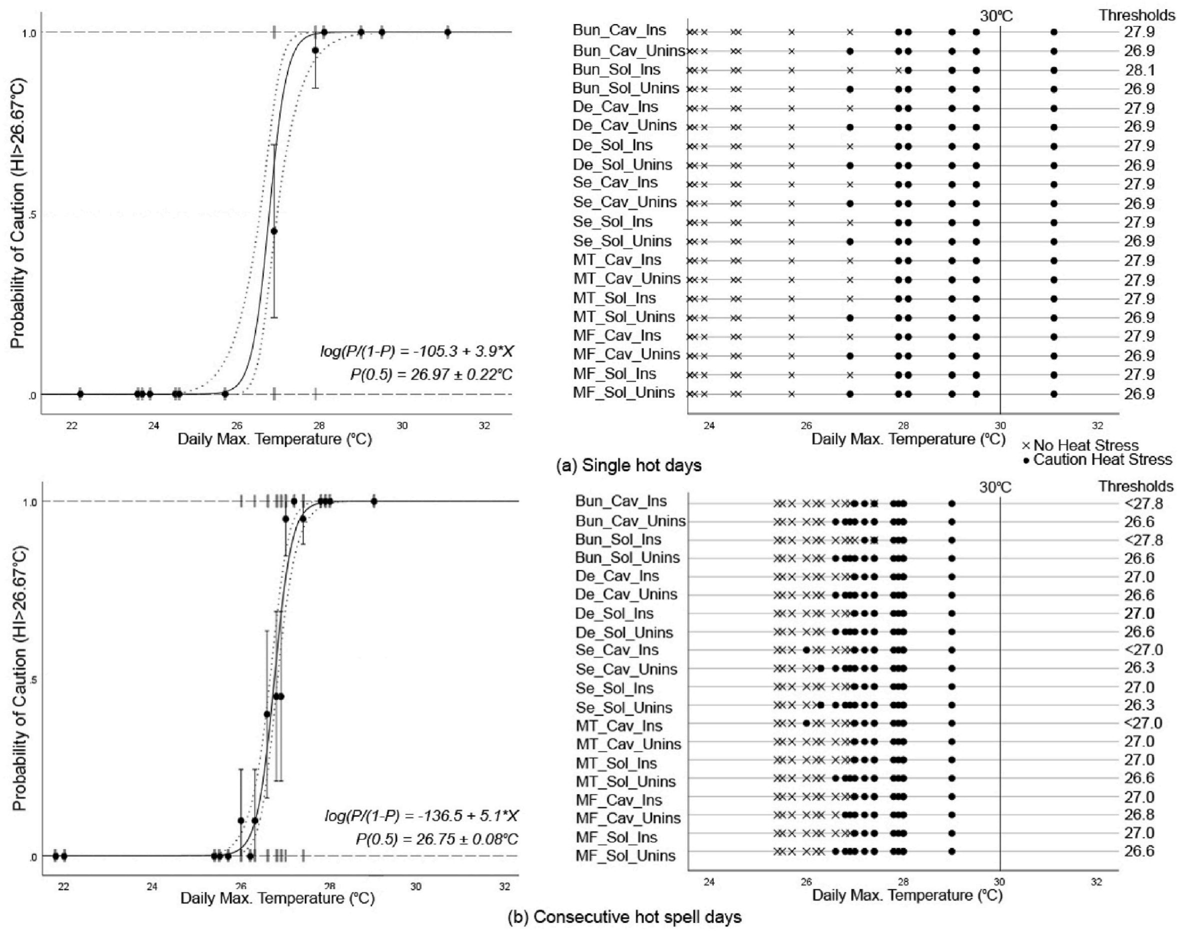


Fig. 5. Probabilities of indoor Heat Index of 'Caution' (HI > 26.7$^{o}C_{HI}$) fitted with outdoor daily Max. Temperature ($^{o}C_{AT}$) at aggregation of all housings, and thresholds of outdoor daily Max. Temperature with respect to the occurrence of the indoor heat stress in each housing between single hot days (a) and consecutive hot spell days (b).

calculate proportion of predicted correctly classified outcomes (% of correct at P = 0.5).

To assess how the predicted outdoor temperatures identified from training samples (W007 or W011) can correctly predict the testing samples (W011 or W007 respectively), we checked the sensitivity (true positive rate) and specificity (true negative rate) (e.g., Haldi and Robinson [81]). Thus, we obtained (i) truly positive (*TP*), (ii) falsely positive (*FP*), (iii) truly negative (*TN*), (iv) falsely negative (*FN*). We computed *TPR (true positive rate)* = *TP*/(*TP* + *FN*) and *FPR (false positive rate)* = *FP*/(*FP* + *TN*); *SPC (specificity)* = 1 − *FPR*; *ACC (accuracy)* = (*TP* + *TN*)/(*P* + *N*), where *P* is the number of the positive ('Caution' Heat Index) and *N* is the number of the negative. Two insulated bungalows were excluded as there was no indoor heat stress observed under W011. Table 5 shows the outcomes of the model validation.

The result of the cross validation shows the proportion of correct in testing samples assessed by the thresholds identified by training sample are reasonably acceptable for the model reliability. Though the accuracy (ACC) of K = 2 is relatively less than that of K = 1, there is no considerable difference found in between the two folds. However, particular attention should be paid in case of the aggregated all housings, where K = 1 fold has much lower accuracy, suggesting less ability to apply a single threshold into the diverse housings. Therefore, it can be concluded that the fitted binary logistic regression model (Table 4) has a predictive capacity in "Caution of Heat index" with respect to the identified daytime outdoor temperature (0.5 probability to cut) only at individual housing type independently.

4.5. *Short-mid-long-term indoor heat-health planning*

Combining with urban heat islands as a result, the localised outdoor climate impacts on indoor thermal conditions needs to be better understood to inform urban dwellings' heat stress. Given the identified daytime outdoor air temperature with different probabilities as action triggers for each of housings (Table 4), the present model capacity to account for local climatic impact on indoor heat stress allows implementation of the indoor heat stress alert locally as part of the short-term indoor Heat-Health Planning. Also, a benefit of probabilistic approach to modelling action triggers is that a decision for indoor heat stress warning can be made upon probabilities based on the identified outdoor climates for the distribution of households' indoor heat stress.

Fig. 6 graphically illustrates how the urban dwellings' indoor heat health warnings can vary depending on housing characteristics at urban neighbourhood scale (W007 and W011), as an example of the city of Birmingham's indoor heat stress alert for July and August in 2013 for general populations. This should be compared to the application of the existing UK Heat-Health Warning System into two neighbourhoods, where the action triggers of 30$^{o}C_{AT}$ of daily Max. Air temperature for daytime are equally applied to.

Furthermore, the ability of modelling indoor heat stress with respect to outdoor climate can potentially be extended for the mid- and long-term Heat-Health Planning, given the availability of daily Max. Temperature projected for future climate at local scale. For instance, UK Climate Projections (UKCP18) provides the most up-to-date assessment of how climate of the UK (and global) may change over the 21st century

Table 4
Daytime (7am-10pm) parameter estimates of binary logistic regression of hourly indoor heat index (HI > 26.67$^oC_{HI}$, Caution) with respect to the corresponding outdoor temperature (θ_{out}, ^oC) before the daily Max. Temperature, and probabilistic thresholds of outdoor temperature on indoor heat index for "Caution". ** Sig.<0.001. Area under ROC curve (AUC); Nagelkerke's generalised R^2.

		B (Std.E)		AUC	% of correct, cut at P (0.5)		R^2	θ_{out} (^oC) in P(i) with 95%CI		
		Constant	θ_{out} (^oC)		No Stress	Stress		i = 0.1	i = 0.3	i = 0.5
Bun-galow	Cav-Ins	−27.75**(6.15)	.96**(.22)	.943	97.7	16.7	.444	26.59	28.00	28.88 ± 1.30
	Cav-Unin	−127.55**(30.20)	4.73**(1.12)	.994	97.9	88.4	.890	26.51	26.79	26.96 ± .20
	Sol-Ins	−35.29**(8.21)	1.22**(.30)	.956	98.2	26.7	.505	27.03	28.14	28.83 ± 1.10
	Sol-Unin	−139.73**(34.72)	5.19**(1.29)	.995	98.4	88.6	.900	26.49	26.75	26.92 ± .18
Deta-ched	Cav-Ins	−130.21**(31.31)	4.75**(1.14)	.994	99.0	87.5	.877	26.94	27.22	27.40 ± .19
	Cav-Unin	−207.20**(62.39)	7.73**(2.33)	.997	98.9	91.5	.931	26.52	26.69	26.80 ± .13
	Sol-Ins	−148.62**(36.73)	5.45**(1.35)	.995	99.0	97.1	.901	26.87	27.12	27.27 ± .17
	Sol-Unin	−207.20**(62.39)	7.73**(2.33)	.997	98.9	91.5	.931	26.52	26.69	26.80 ± .13
Semi-Deta-ched	Cav-Ins	−183.22**(51.29)	6.70**(1.88)	.997	98.5	93.9	.919	27.03	27.23	27.36 ± .17
	Cav-Unin	−106.45**(23.72)	3.98**(.89)	.991	98.4	90.0	.877	26.16	26.50	26.72 ± .19
	Sol-Ins	−231.09**(69.97)	8.51**(2.58)	.998	99.0	94.6	.944	26.92	27.07	27.17 ± .15
	Sol-Unin	−198.82**(58.88)	7.43**(2.20)	.997	97.8	91.7	.929	26.47	26.65	26.77 ± .14
Mid-Terra-ced	Cav-Ins	−236.94**(76.23)	8.78**(2.83)	.998	99.5	90.2	.942	26.75	26.90	27.00 ± .14
	Cav-Unin	−247.63**(78.19)	9.13**(2.89)	.999	99.5	94.7	.949	26.88	27.03	27.12 ± .14
	Sol-Ins	−236.94**(76.23)	8.78**(2.83)	.998	99.5	90.2	.942	26.75	26.90	27.00 ± .14
	Sol-Unin	−196.99**(57.81)	7.31**(2.15)	.997	98.4	90.7	.929	26.64	26.82	26.94 ± .14
Mid-flat	Cav-Ins	−447.89**(221.2)	16.58**(8.20)	.999	99.5	92.5	.969	26.88	26.96	27.01 ± .12
	Cav-Unin	−65.11**(12.23)	2.43**(.46)	.981	98.9	89.6	.799	25.91	26.47	26.82 ± .25
	Sol-Ins	−445.04**(215.7)	16.45**(7.99)	.999	99.5	94.9	.972	26.92	27.00	27.05 ± .12
	Sol-Unin	−64.32**(12.02)	2.40**(.45)	.981	97.8	89.8	.799	25.87	26.44	26.78 ± .25
All Housings		−81.40**(3.66)	3.00**(.14)	.987	98.4	85.9	.818	26.39	26.84	27.13 ± .05

Table 5
Daytime model validation parameters: true positive rate (TPR, %); false positive rate (FPR, %); Accuracy (ACC, %); Proportion of positive (heat stress) to total N (Prop. P, %).

		Training, W007→ Testing, W011 (K = 1, N_{W011} = 117)				Training, W011→ Testing, W007 (K = 2, N_{W007} = 115)			
		TPR	FPR	ACC	Prop. P	TPR	FPR	ACC	Prop. P
Bungalow	Cav_Unins	90.9	2.9	95.7	11.1	90.3	2.4	94.8	26.1
	Sol_Unins	90.9	2.9	95.7	11.1	93.6	2.4	95.7	27.0
Detached	Cav-Ins	70.0	0.0	96.6	6.0	100.0	8.3	92.2	21.7
	Cav_Unins	92.9	2.0	96.6	12.8	93.8	2.4	95.7	27.8
	Sol-Ins	80.0	0.0	97.4	6.8	100.0	5.4	94.8	23.5
	Sol_Unins	92.9	2.0	96.6	12.8	93.8	2.4	95.7	27.8
Semi-detached	Cav-Ins	80.0	0.0	97.4	6.8	95.5	4.4	94.8	21.7
	Cav_Unins	87.5	2.0	95.7	13.7	96.9	3.7	95.7	29.6
	Sol-Ins	90.0	0.9	97.4	8.6	100.0	1.1	98.3	23.5
	Sol_Unins	87.5	1.0	96.6	12.8	93.8	3.7	94.8	28.7
Mid-terraced	Cav-Ins	100.0	1.9	97.4	10.3	96.4	2.3	96.5	25.2
	Cav_Unins	90.0	0.0	98.3	7.7	100.0	7.6	93.0	25.2
	Sol-Ins	100.0	1.9	97.4	10.3	96.4	2.3	96.5	25.2
	Sol_Unins	100.0	3.8	95.7	12.0	93.6	0.0	97.4	25.2
Mid-flat	Cav-Ins	100.0	0.9	98.3	9.4	93.6	0.0	97.4	25.2
	Cav_Unins	92.9	3.9	94.9	14.5	96.8	1.2	97.4	27.0
	Sol-Ins	100.0	0.9	98.3	9.4	90.3	0.0	96.5	24.4
	Sol_Unins	92.9	3.9	94.9	14.5	96.8	2.4	96.5	27.8
All Housings		85.5	34.4	11.5	9.5	65.4	24.1	75.8	24.6

(see Met Office Hadley Centre [82] in more detail). Especially, UKCP18 provides local (2.2 km) climate change projections simulated under RCP8.5 (representative concentration pathway), downscaling from the 12 km simulations using HadREM3-RA11 M, including 12 members of convection permitting models in Met Office Hadley Centre climate model [83]. This local model is re-gridded to 5 km resolutions for the UK's OSGB (ordnance survey national grid, which is a system of geographic grid references used in Great Britain), and daily Max. Temperature is available. Further data available can be seen at https://ukclimateprojections-ui.metoffice.gov.uk/ui/home.

Given the availability of future daily Max. Temperature projected at local scale, we assessed the local differences in the urban dwellings' indoor exposure to heat stress of the two selected OSGBs' areas, where W007 (SP075875, OSGB grid reference) and W011 (SP025775) weather stations are placed in (Fig. 7). Here we used 26.78 °C of outdoor daily Max. Temperature identified at Fig. 4 (a), as an example of threshold to count the number of days of indoor exposure to heat stress, 'Caution' (HI > 26.7$^oC_{HI}$) during summer period, 1st Jun to 15 Sep defined by Heat-waves Plan for England. Due to the uncertainties in selecting which scenario would best fit to local context in future years, we used all 12 climate change model outputs in counting to present the overall trend of heat exposure locally.

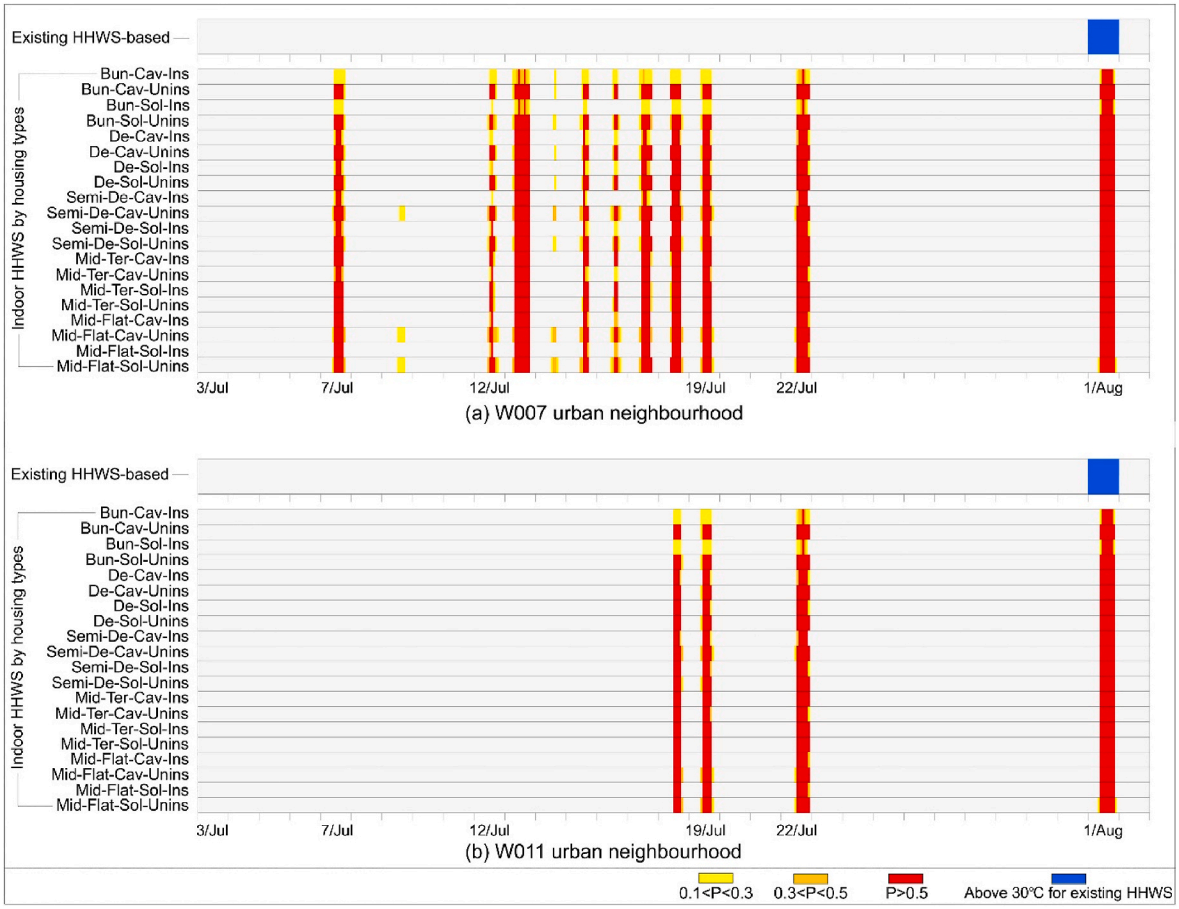


Fig. 6. As a short-term planning, probabilities-based (colour-coded) Indoor Heat Health Warning System (iHHWS) for general populations of each housing type in the city of Birmingham on 3rd July - 2nd August in 2013 at neighbourhood scale (W007 and W011), compared to the current HHWS determined by the existing action triggers of $30^{o}C_{AT}$ of daily maximum air temperature for daytime.

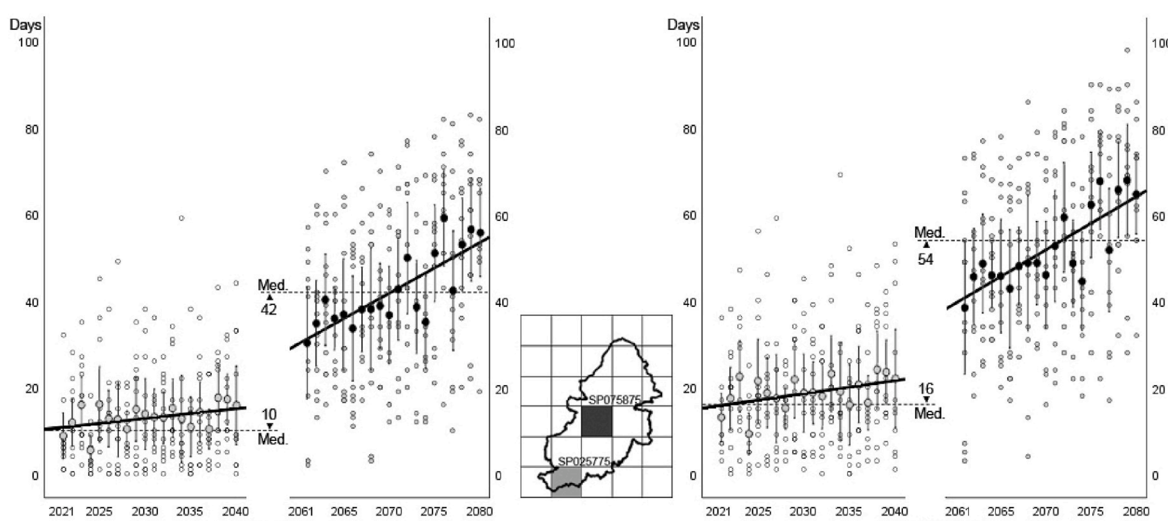


Fig. 7. Local differences in the predicted days of the urban dwellings' indoor exposure to heat stress, 'Caution' (HI > $26.7^{o}C_{HI}$) for summer period (1st June to 15 Sep) at the selected two local areas (5 km * 5 km resolutions), where W007 (SP075875) and W011 (SP025775) weather stations are placed in, according to the UKCP18.

Finally, Fig. 7 provides evidence for why Heat-Health Planning needs to account for the unban dwellings' indoor heat stress at local level as well as the mid- (2021–2040) and long-term (2061–2080) difference. Furthermore, even within a single local climatic context, the diversity of urban dwellings' indoor exposure to heat stress at each housing level can possibly be more dynamic as we investigated earlier. This suggests that better understanding of the relationship between climate, buildings and people pathway will protect and promote urban dwellings' health and wellbeing over the time frame of climate change projections. Thus, heat-health planning will have better capacity to assess and identify when, where, and who is at the heat-related risk (e.g., heat stress) in present and future climate, and thus, to effectively develop on-site and context-sensitive environmental design as adaptation or mitigation strategies.

5. Discussion

This proof-of-principle study illustrates the viability of using a housing stock energy modelling platform to evaluate indoor heat health. Whilst a statistical model can be estimated to trigger indoor heat health alerts, the diversity amongst housing typologies suggests that this process would be more reliable if performed using a full model of the housing stock; as is the case for the 1024 archetypes with which the UK housing stock is represented using EnHub [77]. However, the dependency of the heat health triggers on microclimate (and on future climate) suggests that a finer spatial discretisation of the UK climate would be desirable for this purpose. More work also needs to be conducted to empirically determine the thresholds used to trigger indoor heat health warnings, perhaps even for different classes of population vulnerability. If this work is done, we would have a solid basis with which to evaluate the effectiveness of renovation measures to reduce this vulnerability through passive means.

For instance, general principles applicable to Heat-Health Planning developed in WHO [11] suggest long-term approaches to mitigating climate change and reducing its impact by adapting the built environment. This implies that long-term plans should contribute to the global target of Net Zero CO_2 emissions by 2050, consistent with limiting warming to 1.5 °C above the preindustrial level [84]. Given the capacity of the proposed modelling strategy to identifying which housing (and for whom) is at risk, specific urban planning interventions may be effectively developed e.g., green infrastructure and enhanced urban shading and ventilation. Those can be efficiently synergised with passive cooling measures and on-site green energy (e.g., reversible heat pumps coupled with PV panels) solutions developed at the building level.

Also, successful Heat-Health Plan (or Adverse Weather-Health Plan) requires further consideration of other built environments. It cannot only be limited into free-running buildings. In the mechanically cooled dwelling context, the households' cooling energy affordability, such as deprivation would play a key role in maintaining indoor thermal comfort [85]. This suggests careful consideration of individual or local specific socio-economic circumstances, which also can be integrated to cold stress for heating period based on the heating energy affordability. Given that the UK is a heating dominant country, for instance, heat decarbonisation is becoming a national priority. Especially, many older people, relatively more vulnerable to thermal related health risk than general populations, are in fuel poverty and thus, cold-related stress probably causes more excess deaths than heat-related stress. The problems are entirely symmetrical in both cold and heat characters.

Other indices (e.g., universal thermal climate index, UTCI [34]) would be a useful indicator to cover a wide range of regional climatic conditions from hot to cold for application in the fields of human biometeorology though UTCI itself is a complicated multi-node physiological model, which should in principle be calibrated for regional populations specifically [86]. For instance, the effects of other bio-meteorological parameters (e.g., radiation, wind and humidity) on human thermal regulation can be further considered in indoor heat stress assessment, as described earlier in Section 2.1. This may then be complemented with a more refined representation of the urban microclimate within the urban canopy, to investigate the effectiveness of local shading, ventilation and the contribution of evapotranspiration from green infrastructure to mitigate occupants' heat stress indoors. Such micro-level approaches may be particularly desirable for vulnerable populations who may be less able to regulate their indoor environment effectively e.g., older people residing in care settings; particularly those in free-running care homes in the European context. Indeed, the World Health Organisation highlights that more research is needed on overheating risk and adaptive solutions [87].

6. Conclusions

In this paper, we have discussed a strong requirement of a new and rigorous framework for enhancing the existing Heat-Health Planning. This requires to effectively provide evidence of local difference in urban dwellings' indoor heat-related (even cold-) health risk locally over the time frame of climate change projections. Such weather-related public health plan needs to consider building physical characteristics and urban climate diversity as well as population compositions and characteristics (e.g., age and fuel poverty). To explicitly account for the effect of those parameters on a city's heat-related health risk, a bottom-up approach to housing stock energy modelling is suggested particularly at urban neighbourhood scale due to localised microclimate variability.

The analytical modelling used in investigating characteristics of urban dwellings' indoor heat stress shows that the observed outdoor air temperature probabilistically accounts for the distribution of indoor heat stress locally in present and future climates but more importantly this relationship is only applicable when the type of house is explicitly modelled. A further application of this approach to the specific populations can be achieved by archetype development carefully characterised for those populations with model inputs where they are living in (building characteristics and local climate). Thus, it will deepen our understanding of downscaled heat-related risk up to neighbourhoods with consideration of building characteristics and the populations, leading to enhancing the existing Heat-Health Planning.

To what extent, this framework would be further specified based on the development of reliable heat stress index (or guideline) for occupants' exposure to heat (or cold), which represents the variation of age, gender, and personal health conditions in urban populations. For instance, older people have generally impaired thermoregulation, making them exposed to the impact of even moderate fluctuations in thermal environments [88]. Prolonged exposure to thermally uncomfortable indoor can have an adverse impact on pre-existing disease and health conditions under extreme weather events [49]. Applying the suggested framework into older people, (specifically older-old or frail populations with and without dementia residing care homes as discussed earlier) requires a full set of modelling inputs, such as care home archetype development and reliable heat stress index specified for and applicable to those populations. Especially, existing thermal related indices have been mainly established through measurements made upon healthy adults. It is unclear if they are sufficiently applicable to older populations with and/or without dementia [89]. Successful public health interventions for extreme weather to vulnerable populations can be made through identifying thermal (heat-cold) exposure and the health outcomes, leading to a wider Heat Health Action Plan, which includes not only Heat Health Warning Systems but also long-term elements, such as education, seasonal awareness and the development of workable intervention strategies for extreme heat events [58].

CRediT authorship contribution statement

Choo-yoon Yi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chengzhi Peng:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Darren Robinson:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported by the Economic and Social Research Council (R/166432), the Higher Education Innovative Fund (X/175120) and AXA Research Fund (R/177282). We thank Dr Gustavo Sousa and Shizhe Huang. They generously gave of their time to assist and support the study.

Appendix A. Universal Thermal Climate Index

A.1. *Differences (T-test) in air temperature ($^oC_{AT}$) and Universal Thermal Climate Index (UTCI, $^oC_{UTCI}$) between the selected two weather stations of W007 and W011, and total hours of outdoor thermal (cold or heat) stress according to the effect of UTCI during July and August in 2013. (): W011*

		N	Mean	St. Dev.	Sig.	Eta squared	Magnitude of effect size	Hours_Cold stress	Hours_Heat stress
Day-time	Air Temp	992	19.32 (18.24)	3.79 (3.79)	<.001	.039	Medium	–	–
	UTCI	992	18.31 (17.60)	3.64 (3.75)	<.001	.018	Medium	0 (8)	40 (16)
Night time	Air Temp	496	15.40 (14.29)	2.12 (2.07)	<.001	.124	Large	–	–
	UTCI	496	15.37 (14.78)	2.27 (2.50)	<.001	.030	Medium	0 (9)	0 (0)

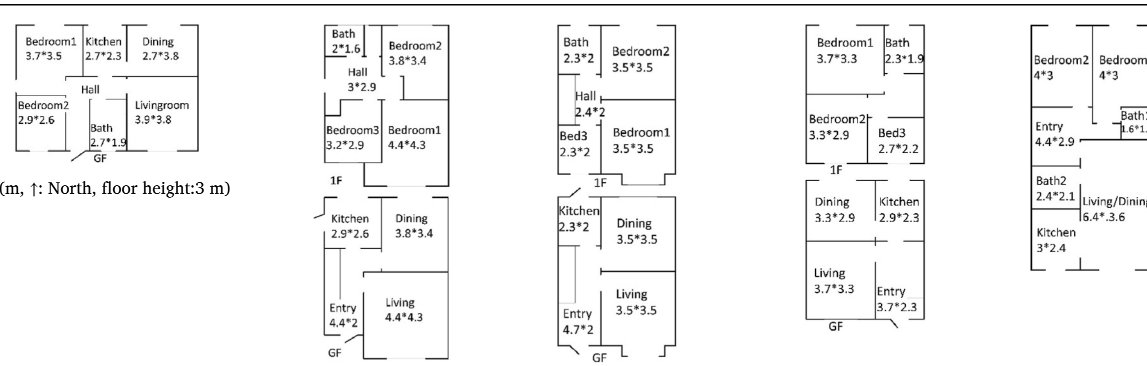
The Universal Thermal Climate Index (UTCI, $^oC_{UTCI}$) has been developed through an initiative of ISB (International Society of Biometeorology) Commission 6 with an extension to COST (a European programme promoting Cooperation in Science and Technology) Action 730, including 45 scientists from 23 countries, based on a strong demand of a universal index which would cover a wide range of regional climatic conditions from hot to cold for application in the fields of human biometeorology [34,36]. Though UTCI may need to be calibrated regionally to ensure the applicability to local populations [86], it is based on a complex multi-node physiological model [90,91], which accounts for the heat exchange between human body and the ambient environment (combination of air temperature, wind, radiation and humidity), and hence the associated responses of thermal stress.

Appendix B. Modelling inputs for building energy simulations

B.1. *Detailed thermal characteristics and geometric configurations of reference housings (source from Ref. [74])*

Floor plan by housing type

Bungalow (64.07m²)	Detached (98.52m²)	Semi-detached (79m²)	Mid-terraced (73.92m²)	Mid-flat (72m²)



(m, ↑: North, floor height:3 m)

Insulation type (U-value, W/m²*K)

	External wall	Ground floor	Roof	Internal floor	glazing	Door	Internal wall
Cav-Ins	0.499	0.764	0.136	1.482	1.450	2.3	1.88
Cav-Unin	1.417	0.764	0.353	1.482	4.303	2.3	1.88
Sol-Ins	0.283	0.764	0.136	1.482	1.450	2.3	1.88
Sol-Unin	2.114	0.764	0.353	1.482	4.303	2.3	1.88

Windows ratio to wall (%)

	Bun-galow	Deta-ched	Semi-deta	Mid-terra	Mid-flat
South	9.03	14.97	12.00	11.24	16.05
East	–	–	–	–	–
West	3.70	1.81	1.81	–	–
North	24.83	22.41	19.82	22.87	28.43

Surface ratio to Volume (%)

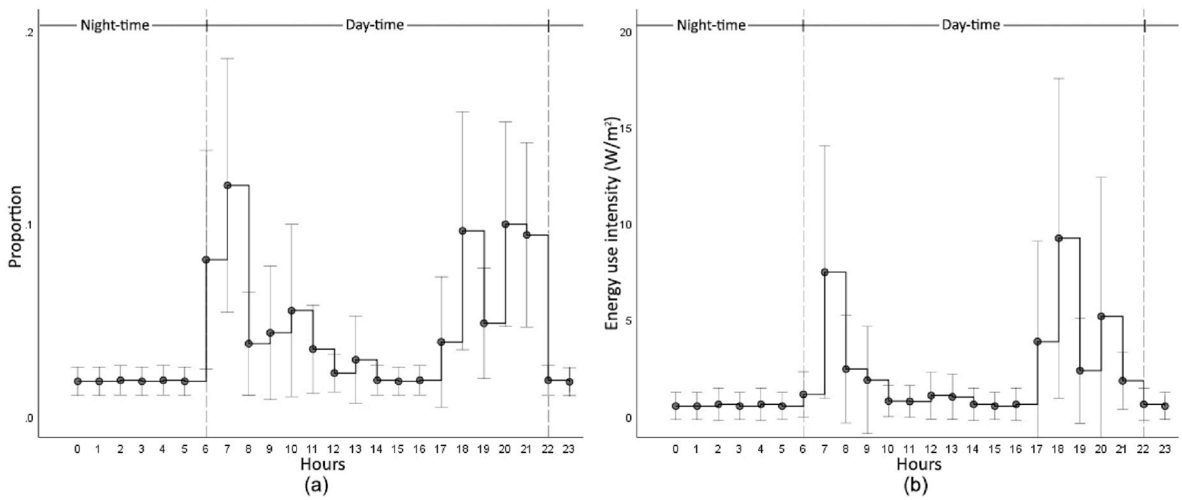
(continued on next page)

(*continued*)

Surface ratio to Volume (%)					
	Bun-galow	Deta-ched	Semi-deta	Mid-terra	Mid-flat
	Bun-galow	Deta-ched	Semi-deta	Mid-terra	Mid-flat
South	13.79	10.04	12.84	13.45	8.08
East	10.75	15.38	–	–	–
West	10.35	15.10	17.85	–	–
North	11.38	9.16	11.46	11.69	6.89

* Infiltration of room to external (ach/h): Living (1), Kitchen/Dining (2), Bedroom (0.5), Bathroom (2), Hall and Entry (1.5).
** Infiltration between rooms is set to 1ach/h.

B.2. *Internal heat load profiles. (a) Mean time-dependent (hourly) profile (proportions) of occupancy scheduling for utilising home appliances and lighting, and (b) accordingly, Mean hourly energy use intensity (W/m^2) profile for internal heat gains with their 95% confidence intervals*



Although internal heat load profiles help to initially emulate the existing asymmetry or complexity in the variety of energy flows, they are often and expectedly limited to represent unpredictable occurrence of internal heat sources in large scale housing stock energy modelling. Recently, the state-of-the-art method in modelling internal heat load profiles seems indeed to agree with a stochastic approach by the use of non-homogeneous Markov-chains [92,93], which is able to represent unpredictable events with a reasonable computational cost. This is particularly more pertinent at large scale of building energy-climate modelling, because it provides a means to represent usages and activities comprehensively under the complexity of heat loads profiles, i.e., [76].

The EnHub contains programmed codes, written in *R* (the statistical computing software) for processing data to represent the housing stock characteristic readily available for dynamic building simulation platform, employing the EnergyPlus engine [77]. For instance, the UK Time Use Survey (TUS) data [94], which is the national scale of household survey about how people (aged 8 and more) in the UK spend their time at home, can be employed to generate heat load profiles as a function of household and housing characteristics. These profiles directly link to the corresponding modules in EnHub and are then accessed by EnergyPlus during the simulation. The implementation is publicly available at https://github.com/EnHub-UK/TUS-to-HSEM-converter, which is the EnHub-UK/TUS-to HSEM-converter, making the Jaboob's stochastic model [95] more producible.

B.2. Shows the internal heat load profiles used in this study as an example, aggregated time-dependent hourly profile of all scheduling home appliances and lighting with their applied energy use intensity (W/m^2). Given the energy use intensity profiles, 0.25 of radiant fraction was assumed for internal sensible heat gains derived from the energy use of electricity home appliances [96]. Similarly for lighting, the approximate fraction value of return air, radiant and visible assumed in this study is 0.21, 0.08 and 0.79 respectively. The opening scheduling of windows and doors was set to 26 °C of indoor temperature.

Appendix C. Characteristics of indoor heat stress in each of 20 housings

C.1. *Differences (T-test) in indoor heat stress ($^oC_{HI}$) between the cavity and solid insulation in each housing type. (): Solid insulation; N = 352, total daytime hours in heat stress days, 16 h × 11 days × 2 weather station neighbourhoods*

		Mean	St. Dev.	t (df = 702)	Sig.
Bungalow	Ins	25.49 (25.39)	1.09 (1.13)	1.202	.230
	Unins	25.91 (25.83)	1.25 (1.39)	.781	.435
Detached	Ins	25.92 (25.93)	1.08 (1.10)	−.078	.938
	Unins	26.09 (26.02)	1.16 (1.29)	.773	.440
Semi-detached	Ins	26.10 (26.17)	.98 (.96)	−1.003	.316

(*continued on next page*)

(*continued*)

		Mean	St. Dev.	t (df = 702)	Sig.
	Unins	26.24 (26.21)	1.05 (1.08)	.329	.742
Mid-Terraced	Ins	26.20 (26.20)	.98 (.98)	−.030	.976
	Unins	26.16 (26.15)	1.00 (1.02)	.176	.860
Mid-Flat	Ins	25.91 (25.90)	1.15 (1.16)	.113	.910
	Unins	26.03 (26.03)	1.17 (1.18)	.049	.961

On average, the difference of the effect of the insulation types (cavity and solid) on indoor heat stress was not significant (as $p > 0.05$ in all cases).

References

[1] E.M. Fischer, C. Schär, Consistent geographical patterns of changes in high-impact European heatwaves, Nat. Geosci. 3 (6) (Jun. 2010) 398–403, https://doi.org/10.1038/ngeo866.

[2] I. IPCC Working Group 1, IPCC, 2013: Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, AR5, IPCC, 2013, p. 1535.

[3] M. Morabito, et al., Increasing heatwave hazards in the southeastern European union capitals, Atmosphere 8 (7) (Jun. 2017) 115, https://doi.org/10.3390/atmos8070115.

[4] A.J. McMichael, R.E. Woodruff, S. Hales, Climate change and human health: present and future risks, Lancet 367 (9513) (Mar. 2006) 859–869, https://doi.org/10.1016/S0140-6736(06)68079-3.

[5] P. de Wilde, D. Coley, The implications of a changing climate for buildings, Build. Environ. 55 (Sep. 2012) 1–7, https://doi.org/10.1016/j.buildenv.2012.03.014.

[6] S. Whitman, G. Good, E.R. Donoghue, N. Benbow, W. Shou, S. Mou, Mortality in Chicago attributed to the July 1995 heat wave, Am. J. Publ. Health 87 (9) (Sep. 1997) 1515–1518, https://doi.org/10.2105/AJPH.87.9.1515.

[7] J. Robine, S. Cheung, S. Le Roy, H. Van Oyen, F.R. Herrmann, Report on Excess Mortality in Europe during Summer 2003, EU Community Action Programme for Public Health, Grant Agreement, 2007, 2005114 [Online]. Available: http://ec.europa.eu/health/ph_projects/2005/action1/docs/action1_2005_a2_15_en.pdf.

[8] H. Johnson, S. Kovats, G. McGregor, J. Stedman, M. Gibbs, H. Walton, The impact of the 2003 heat wave on daily mortality in England and Wales and the use of rapid weekly mortality estimates, Euro Surveill. 10 (7) (Jul. 2005) 15–16, https://doi.org/10.2807/esm.10.07.00558-en.

[9] A. Fouillet, et al., Excess mortality related to the August 2003 heat wave in France, Int. Arch. Occup. Environ. Health 80 (1) (2006) 16–24, https://doi.org/10.1007/s00420-006-0089-4.

[10] J.-Y. Son, J.-T. Lee, G.B. Anderson, M.L. Bell, The impact of heat waves on mortality in seven major cities in Korea, Environ. Health Perspect. 120 (4) (Apr. 2012) 566–571, https://doi.org/10.1289/ehp.1103759.

[11] R. O. for E. World Health Organization, Heat-health action plans: guidance [Online]. Available: https://www.who.int/publications/i/item/9789289071918, 2008.

[12] Public Health England, Heatwave Plan for England [Online]. Available:, 2018 http://allcatsrgrey.org.uk/wp/download/public_health/Heatwave_plan_for_England_2018.pdf.

[13] A. Casanueva, et al., Overview of existing heat-health warning systems in Europe, Int. J. Environ. Res. Publ. Health 16 (15) (Jul. 2019) 2657, https://doi.org/10.3390/ijerph16152657.

[14] C.J. Tomlinson, L. Chapman, J.E. Thornes, C.J. Baker, Including the urban heat island in spatial heat health risk assessment strategies: a case study for Birmingham, UK, Int. J. Health Geogr. 10 (2011) 1–14, https://doi.org/10.1186/1476-072X-10-42.

[15] A. Quinn, et al., Predicting indoor heat exposure risk during extreme heat events, Sci. Total Environ. 490 (Aug. 2014) 686–693, https://doi.org/10.1016/j.scitotenv.2014.05.039.

[16] K.J. Lomas, et al., Dwelling and household characteristics' influence on reported and measured summertime overheating: a glimpse of a mild climate in the 2050's, Build. Environ. 201 (Aug. 2021), 107986, https://doi.org/10.1016/j.buildenv.2021.107986, 107986.

[17] S. Vardoulakis, K. Dear, S. Hajat, C. Heaviside, B. Eggen, A.J. McMichael, Comparative assessment of the effects of climate change on heat- and cold-related mortality in the United Kingdom and Australia, Environ. Health Perspect. 122 (12) (Dec. 2014) 1285–1292, https://doi.org/10.1289/ehp.1307524.

[18] S. Vardoulakis, et al., Impact of climate change on the domestic indoor environment and associated health risks in the UK, Environ. Int. 85 (Dec. 2015) 299–313, https://doi.org/10.1016/j.envint.2015.09.010.

[19] N. Willand, I. Ridley, A. Pears, Relationship of thermal performance rating, summer indoor temperatures and cooling energy use in 107 homes in Melbourne, Australia, Energy Build. 113 (Feb. 2016) 159–168, https://doi.org/10.1016/j.enbuild.2015.12.032.

[20] A. Beizaee, K.J. Lomas, S.K. Firth, National survey of summertime temperatures and overheating risk in English homes, Build. Environ. 65 (2013) 1–17, https://doi.org/10.1016/j.buildenv.2013.03.011.

[21] L. Gichuyia, K. Steemers, Indoor overheating risk and climate change. Modelling sensitivity of building design parameters for a free-running building, in: Proceedings - Windsor Conference 2014: Counting the Cost of Comfort in a Changing World, 2019, pp. 510–527.

[22] S. Vardoulakis, Human exposure: indoor and outdoor, in: Air Quality in Urban Environments, The Royal Society of Chemistry, 2009, pp. 85–107, https://doi.org/10.1039/9781847559654-00085.

[23] C. Schweizer, et al., Indoor time–microenvironment–activity patterns in seven regions of Europe, J. Expo. Sci. Environ. Epidemiol. 17 (2) (Mar. 2007) 170–181, https://doi.org/10.1038/sj.jes.7500490.

[24] M. Anderson, C. Carmichael, V. Murray, A. Dengel, M. Swainson, Defining indoor heat thresholds for health in the UK, Perspectives in Public Health 133 (3) (2013) 158–164, https://doi.org/10.1177/1757913912453411.

[25] Y. Honda, et al., Heat-related mortality risk model for climate change impact projection, Environ. Health Prev. Med. 19 (1) (2014), https://doi.org/10.1007/s12199-013-0354-6.

[26] S. Hajat, S. Vardoulakis, C. Heaviside, B. Eggen, Climate change effects on human health: projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s, J. Epidemiol. Community Health 68 (7) (2014) 641–648, https://doi.org/10.1136/jech-2013-202449.

[27] E. Choudhary, A. Vaidyanathan, Heat stress illness hospitalizations - environmental public health tracking program, 20 States, 2001-2010, MMWR Surveill. Summ. 63 (13) (2014) 1–10.

[28] R.S. Kovats, L.E. Kristie, Heatwaves and public health in Europe, Eur. J. Publ. Health 16 (6) (Dec. 2006) 592–599, https://doi.org/10.1093/eurpub/ckl049.

[29] R.S. Kovats, S. Hajat, Heat stress and public health: a critical review, in: Annual Review of Public Health, 2008, pp. 41–55, https://doi.org/10.1146/annurev.publhealth.29.020907.090843.

[30] G.R. McGregor, J.K. Vanos, Heat: a primer for public health researchers, Publ. Health 161 (Aug. 2018) 138–146, https://doi.org/10.1016/j.puhe.2017.11.005.

[31] T. Matthews, Humid heat and climate change, Prog. Phys. Geogr. Earth Environ. 42 (3) (Jun. 2018) 391–405, https://doi.org/10.1177/0309133318776490.

[32] E. Arens, T. Hoyt, X. Zhou, L. Huang, H. Zhang, S. Schiavon, Modeling the comfort effects of short-wave solar radiation indoors, Build. Environ. 88 (Jun. 2015) 3–9, https://doi.org/10.1016/j.buildenv.2014.09.004.

[33] P. Zhang, R.H. Gong, Y. Yanai, H. Tokura, Effects of clothing material on thermoregulatory responses, Textil. Res. J. 72 (1) (2002) 83–89.

[34] G. Jendritzky, R. de Dear, G. Havenith, UTCI—why another thermal index? Int. J. Biometeorol. 56 (3) (May 2012) 421–428, https://doi.org/10.1007/s00484-011-0513-7.

[35] ISO, Hot environments-{Estimation} of Heat Stress on Working Man, Based on the {WBGT}-index (Wet Bulb Globe Temperature), Geneva Int. Stand. Organ., 1989.

[36] G. Havenith, D. Fiala, Thermal indices and thermophysiological modeling for heat stress, Compr. Physiol. 6 (1) (Dec. 2016) 255–302, https://doi.org/10.1002/cphy.c140051.

[37] R.G. Steadman, A universal scale of apparent temperature, J. Clim. Appl. Meteorol. 23 (12) (1984) 1674–1687, https://doi.org/10.1175/1520-0450(1984)023<1674:AUSOAT>2.0.CO;2.

[38] L.P. Rothfusz, The heat index 'equation' (or, more than you ever wanted to know about heat index), Rep. Sci. Serv. Div. Fort Worth, Texas Natl. Ocean. Atmos. Adm. Natl. Weather Serv. Off. Meteorol. SR90-23 (1990).

[39] R.G. Steadman, The assessment of sultriness. Part I. A temperature-humidity index based on human physiology and clothing science, J. Appl. Meteorol. 18 (7) (1979) 861–873, https://doi.org/10.1175/1520-0450(1979)018<0861:TAOSPI>2.0.CO;2.

[40] R.G. Steadman, The assessment of sultriness. Part II: effects of wind, extra radiation and barometric pressure on apparent temperature, J. Appl. Meteorol. 18 (7) (1979) 874–885, https://doi.org/10.1175/1520-0450(1979)018<0874:TAOSPI>2.0.CO;2.

[41] J. Masterton, F. Richardson, Humidex, a Method of Quantifying Human Discomfort Due to Excessive Heat and Humidity," *Downsview, Ontario CLI 1-79*, Atmos. Environ. Serv., *Environ.* Canada, 1979.

[42] K.M. Willett, S. Sherwood, Exceedance of heat index thresholds for 15 regions under a warming climate using the wet-bulb globe temperature, Int. J. Climatol. 32 (2) (2012) 161–177, https://doi.org/10.1002/joc.2257.

[43] Y. Zhao, A. Ducharne, B. Sultan, P. Braconnot, R. Vautard, Estimating heat stress from climate-based indicators: present-day biases and future spreads in the CMIP5 global climate model ensemble, Environ. Res. Lett. 10 (8) (2015), https://doi.org/10.1088/1748-9326/10/8/084013.

[44] J. Li, Y.D. Chen, T.Y. Gan, N.C. Lau, Elevated increases in human-perceived temperature under climate warming, Nat. Clim. Change 8 (1) (2018) 43–47, https://doi.org/10.1038/s41558-017-0036-2.

[45] C. Mora, et al., Global risk of deadly heat, Nat. Clim. Change 7 (7) (2017) 501–506, https://doi.org/10.1038/nclimate3322.

[46] R. Basu, J.M. Samet, Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence, Epidemiol. Rev. 24 (2) (2002) 190–202, https://doi.org/10.1093/epirev/mxf007.
[47] A. Mavrogianni, M. Davies, P. Wilkinson, A. Pathan, London housing and climate change: impact on comfort and health - preliminary results of a summer overheating study, Open House Int. 35 (2) (2010) 49–59, https://doi.org/10.1108/ohi-02-2010-b0007.
[48] E.M. Fischer, K.W. Oleson, D.M. Lawrence, Contrasting urban and rural heat stress responses to climate change, Geophys. Res. Lett. 39 (3) (2012), https://doi.org/10.1029/2011GL050576.
[49] A. Flynn, C. McGreevy, E.C. Mulkerrin, Why do older patients die in a heatwave? QJM - Mon. J. Assoc. Physicians 98 (3) (2005) 227–229, https://doi.org/10.1093/qjmed/hci025.
[50] E. Grundy, Ageing and vulnerable elderly people: European perspectives, Ageing Soc. 26 (1) (2006) 105–134, https://doi.org/10.1017/S0144686X05004484.
[51] N.D. Thomas, H. Soliman, Preventable tragedies: heat disaster and the elderly, J. Gerontol. Soc. Work 38 (4) (2003) 53–66, https://doi.org/10.1300/J083v38n04_06.
[52] M. Stafoggia, et al., Vulnerability to heat-related mortality: a multicity, population-based, case-crossover analysis, Epidemiology 17 (3) (2006) 315–323, https://doi.org/10.1097/01.ede.0000208477.36665.34.
[53] J. Schwartz, Who is sensitive to extremes of temperature? A case-only analysis, Epidemiology 16 (1) (2005) 67–72, https://doi.org/10.1097/01.ede.0000147114.25957.71.
[54] H.G. Mirchandani, G. McDonald, I.C. Hood, C. Fonseca, Heat-related deaths in philadelphia - 1993, Am. J. Forensic Med. Pathol 17 (2) (1996) 106–108, https://doi.org/10.1097/00000433-199606000-00004.
[55] S. Vandentorren, et al., August 2003 heat wave in France: risk factors for death of elderly people living at home, Eur. J. Publ. Health 16 (6) (2006) 583–591, https://doi.org/10.1093/eurpub/ckl063.
[56] E. Klinenberg, Review of heat wave: social autopsy of disaster in Chicago, N. Engl. J. Med. 348 (7) (2003) 666–667, https://doi.org/10.1056/nejm200302133480721.
[57] K.E. Smoyer, Putting risk in its place: methodological considerations for investigating extreme event health risk, Soc. Sci. Med. 47 (11) (1998) 1809–1824, https://doi.org/10.1016/S0277-9536(98)00237-8.
[58] World Meteorological Organization and World Health Organization, Heatwaves and Health: Guidance on Warning-System Development, 2015 [Online]. Available: https://public.wmo.int/en/resources/library/heatwaves-and-health-guidance-warning-system-development.
[59] Met Office, Heat-health Alert Service, 2022. https://www.metoffice.gov.uk/weather/warnings-and-advice/seasonal-advice/heat-health-alert-service.
[60] A. Burgstall, A. Casanueva, S. Kotlarski, C. Schwierz, Heat warnings in Switzerland: reassessing the choice of the current heat stress index, Int. J. Environ. Res. Publ. Health 16 (15) (2019), https://doi.org/10.3390/ijerph16152684.
[61] S. Hajat, et al., Heat-health warning systems: a comparison of the predictive capacity of different approaches to identifying dangerously hot days, Am. J. Publ. Health 100 (6) (2010) 1137–1144, https://doi.org/10.2105/AJPH.2009.169748.
[62] M. Langner, K. Scherber, W.R. Endlicher, Indoor heat stress: an assessment of human bioclimate using the UTCI in different buildings in Berlin, Erde 144 (3–4) (2013) 260–273, https://doi.org/10.12854/erde-144-18.
[63] N. Walikewitz, B. Jänicke, M. Langner, W. Endlicher, Assessment of indoor heat stress variability in summer and during heat warnings: a case study using the UTCI in Berlin, Germany, Int. J. Biometeorol. 62 (1) (2018) 29–42, https://doi.org/10.1007/s00484-015-1066-y.
[64] E. Oikonomou, R. Raslan, R. Gupta, A. Howard, A. Mavrogianni, Care Home Overheating Audit Pilot Project - Executive Summary, GLA, London, UK, Mayor London, 2020.
[65] Department for Communities and Local government, Housing Health and Safety Rating System: Guidance for Landlords and Property-Related Professionals, 2006 [Online]. Available: https://www.gov.uk/government/publications/housing-health-and-safety-rating-system-guidance-for-landlords-and-property-related-professionals.
[66] K.L. Kownacki, C. Gao, K. Kuklane, A. Wierzbicka, Heat stress in indoor environments of scandinavian urban areas: a literature review, Int. J. Environ. Res. Publ. Health 16 (4) (2019), https://doi.org/10.3390/ijerph16040560.
[67] UK Health Security Agency, Heat Mortality Monitoring Reports, 2023. https://www.gov.uk/government/publications/heat-mortality-monitoring-reports.
[68] S. Hajat, R.S. Kovats, K. Lachowycz, Heat-related and cold-related deaths in England and Wales: who is at risk? Occup. Environ. Med. 64 (2) (2007) 93–100, https://doi.org/10.1136/oem.2006.029017.
[69] C. Heaviside, S. Vardoulakis, X.-M. Cai, Attribution of mortality to the urban heat island during heatwaves in the West Midlands, UK, Environ. Health (Lond.) 15 (S1) (Dec. 2016) 49–59, https://doi.org/10.1186/s12940-016-0100-9.
[70] Public Health England, PHE heatwave mortality monitoring Summer 2018 [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/942648/PHE_heatwave_report_2018.pdf, 2019.
[71] S. Nakai, T. Itoh, T. Morimoto, Deaths from heat-stroke in Japan: 1968-1994, Int. J. Biometeorol. 43 (3) (1999) 124–127, https://doi.org/10.1007/s004840050127.
[72] M. Gustin, R.S. McLeod, K.J. Lomas, G. Petrou, A. Mavrogianni, A high-resolution indoor heat-health warning system for dwellings, Build. Environ. 168 (Jan. 2020), 106519, https://doi.org/10.1016/j.buildenv.2019.106519.
[73] E.L. Warren, D.T. Young, L. Chapman, C. Muller, C.S.B. Grimmond, X.M. Cai, The Birmingham Urban Climate Laboratory-A high density, urban meteorological dataset, from 2012-2014, Sci. Data 3 (1) (Jun. 2016), 160038, https://doi.org/10.1038/sdata.2016.38.
[74] E.J. Allen, A.A. Pinney, Standard dwellings for modelling: details of dimensions, construction and occupancy schedules, BEPAC Tech. Note 90 (2) (1990) [Online]. Available: https://www.aivc.org/sites/default/files/airbase_6101.pdf.
[75] S. Chen, W. Yang, H. Yoshino, M.D. Levine, K. Newhouse, A. Hinge, Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies, Energy Build. 104 (2015) 1–13, https://doi.org/10.1016/j.enbuild.2015.06.075.
[76] U. Wilke, F. Haldi, J.L. Scartezzini, D. Robinson, A bottom-up stochastic model to predict building occupants' time-dependent activities, Build. Environ. 60 (2013) 254–264, https://doi.org/10.1016/j.buildenv.2012.10.021.
[77] G. Sousa, B.M. Jones, P.A. Mirzaei, D. Robinson, An open-source simulation platform to support the formulation of housing stock decarbonisation strategies, Energy Build. 172 (2018) 459–477, https://doi.org/10.1016/j.enbuild.2018.05.015.
[78] G. Sousa, D. Robinson, Enhanced EnHub: dynamic simulation of housing stock energy systems, J. Build. Perform. Simul. 13 (5) (2020) 516–531, https://doi.org/10.1080/19401493.2020.1788641.
[79] G. Sousa, B.M. Jones, P.A. Mirzaei, D. Robinson, A review and critique of UK housing stock energy models, modelling approaches and data sources, Energy Build. 151 (2017) 66–80, https://doi.org/10.1016/j.enbuild.2017.06.043.
[80] G. Brooke Anderson, M.L. Bell, R.D. Peng, Methods to calculate the heat index as an exposure metric in environmental health research, Environ. Health Perspect. 121 (10) (2013) 1111–1119, https://doi.org/10.1289/ehp.1206273.
[81] F. Haldi, D. Robinson, Interactions with window openings by office occupants, Build. Environ. 44 (12) (Dec. 2009) 2378–2395, https://doi.org/10.1016/j.buildenv.2009.03.025.
[82] Met Office Hadley Centre, UKCP18 regional climate model projections for the UK, Centre. Environ. Data Analysis (2018) date of citation [Online], http://catalogue.ceda.ac.uk/uuid/b4d24b3df3754b9d9028447eb3cd89c6.
[83] J.J. David, M.H. Sexton, Ambarish Karmalkar, James Murphy, Ben Booth, Leighton Regayre, The elicitation of distributions of parameters in HadGEM3 versions GA4 and GA7 for use in perturbed parameter ensembles, Technical Note 101 [Online]. Available: https://digital.nmla.metoffice.gov.uk/digitalFile_70d009c8-e04e-449b-98a2-ada3be97167d, 2019.
[84] IPCC, "Annex I: glossary [Online]. Available:, in: J.B.R. Matthews (Ed.), In: Global Warming of 1.5°C.,", 2018, https://doi.org/10.1017/9781009157940.008.
[85] C.Y. Yi, C. Peng, An archetype-in-neighbourhood framework for modelling cooling energy demand of a city's housing stock, Energy Build. 196 (2019) 30–45, https://doi.org/10.1016/j.enbuild.2019.05.015.
[86] E.L. Krüger, T.J.V. Silva, S.Q. da Silveira Hirashima, E.G. da Cunha, L.A. Rosa, Calibrating UTCI'S comfort assessment scale for three Brazilian cities with different climatic conditions, Int. J. Biometeorol. 65 (9) (2021) 1463–1472, https://doi.org/10.1007/s00484-020-01897-x.
[87] World Health Organization, Regional Office for Europe, "Heat and Health in the WHO European Region: Updated Evidence for Effective Prevention. World Health Organization, Regional Office for Europe., 2021 [Online]. Available: https://apps.who.int/iris/handle/10665/339462.
[88] G. Havenith, Temperature regulation and technology, Gerontechnology 1 (1) (2001) 41–49, https://doi.org/10.4017/gt.2001.01.01.004.00.
[89] C. yoon Yi, C. Childs, C. Peng, D. Robinson, Thermal comfort modelling of older people living in care homes: an evaluation of heat balance, adaptive comfort, and thermographic methods, Build. Environ. 207 (2022), 108550, https://doi.org/10.1016/j.buildenv.2021.108550.
[90] D. Fiala, K.J. Lomas, M. Stohrer, A computer model of human thermoregulation for a wide range of environmental conditions: the passive system, J. Appl. Physiol. 87 (5) (1999), https://doi.org/10.1152/jappl.1999.87.5.1957.
[91] D. Fiala, K.J. Lomas, M. Stohrer, Computer prediction of human thermoregulatory and temperature responses to a wide range of environmental conditions, Int. J. Biometeorol. 45 (3) (2001) 143–159, https://doi.org/10.1007/s004840100099.
[92] W. Parys, D. Saelens, H. Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices - a review-based integrated methodology, J. Build. Perform. Simul. 4 (4) (2011) 339–358, https://doi.org/10.1080/19401493.2010.524711.
[93] A.M. Rysanek, R. Choudhary, DELORES – an open-source tool for stochastic prediction of occupant services demand, J. Build. Perform. Simul. 8 (2) (2015) 97–118, https://doi.org/10.1080/19401493.2014.888595.
[94] O. Gershuny, J.I. Sullivan, United Kingdom Time Use Survey, 2014-2015. [data Collection], UK Data Service. SN: 8128, 2017, https://doi.org/10.5255/UKDA-SN-8128-1 [Online]. Available:.
[95] S. Jaboob, Stochastic modelling of occupants' activities and related behaviours, in: PhD Thesis, University of Nottingham, 2015.
[96] M.H. Hosni, B.W. Jones, H. Xu, Experimental results for heat gain and radiant/convective split from equipment in buildings, Build. Eng. (1999).