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Transformational IoT sensing for air pollution and thermal exposures

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Cities today encounter significant challenges pertaining to urbanization and population growth, resource availability, and climate change. Concurrently, unparalleled datasets are generated through Internet of Things (IoT) sensing implemented at urban, building, and personal scales that serve as a potential tool for understanding and overcoming these issues. Focusing on air pollution and thermal exposure challenges in cities, we reviewed and summarized the literature on IoT environmental sensing on urban, building, and human scales, presenting the first integrated assessment of IoT solutions from the data convergence perspective on all three scales. We identified that there is a lack of guidance on what to measure, where to measure, how frequently to measure, and standards for the acceptable measurement quality on all scales of application. The current literature review identified a significant disconnect between applications on each scale. Currently, the research primarily considers urban, building, and personal scale in isolation, leading to significant data underutilization. We addressed the scientific and technological challenges and opportunities related to data convergence across scales and detailed future directions of IoT sensing along with short- and long-term research and engineering needs. IoT application on a personal scale and integration of information on all scales opens up the possibility of developing personal thermal comfort and exposure models. The development of personal models is a vital promising area that offers significant advancements in understanding the relationship between environment and people that requires significant further research.

KEYWORDS

IoT environmental sensing, air quality, indoor air quality, thermal comfort, personal exposure, personal comfort

1 Introduction

The United Nations projects that 68% of the population by 2050 will live in the cities (UN, 2018). Numerous challenges arise for the cities that will need to provide a livable environment for such a large portion of the human population housed in a high-density environment. The global increase in air pollution represents one of the world's growing concerns. WHO states "almost all of the global population (99%) breathe air that exceeds air quality limits (WHO, 2021)." Air pollution impacts cardiovascular health (Mills et al., 2009), pulmonary health (Pope, 2000), and cognitive performance (Peters et al., 2015). Sources of indoor pollution are cooking, cleaning, candle/incense burning, smoking (Habre et al., 2014), and building materials (Liu et al., 2013) while ambient sources include combustion products, photochemical reaction products, and metals (Habre et al., 2014). A combination of ambient and indoor air pollution exposure is associated with (Liu et al., 2013) million premature deaths annually (Air pollution, 2022), highlighting the significance and magnitude of the problem. On the other hand, cities face significant challenges of urban overheating driven by global climate change and urban development (Nazarian et al., 2021a). These compounding effects represent a threat to human thermal comfort in outdoor spaces as well as indoor environments where buildings have to provide comfort under warmer summer conditions utilizing low-energy design strategies (Holmes and Hacker, 2007). One of the critical problems in alleviating the air pollution exposures and thermal comfort is understanding the complete set of contributing factors that impact the entire ecosystem and the effectiveness of potential mitigation strategies. The effectiveness of mitigation strategies needs to be quantified to implement solutions based on the knowledge. This requires the ability to quantify various aspects of the urban environment, motivating integrated and multi-scale environmental sensing in cities. The Internet of Things (IoT) technologies are the paradigm that emphasizes such ubiquitous sensing installed using modern wireless communications enabling quantification of a full set of environmental parameters that affect air pollution exposure and thermal comfort. It is a novel approach to monitoring, assessing, and ultimately addressing challenges related to air pollution exposure and thermal stress and comfort (Grimm et al., 2008; Bibri, 2018). Compared to conventional sensing, IoT sensing offers increased environmental information with higher spatial granularity and reduced and less centralized resources. These sensor networks focus on data volume and the potential to train machine learning models to allow informed decision-making.

The emergence of new green certification schemes for buildings and communities, businesses that offer IoT environmental sensing, analytics, and building management system integration, alongside wearable tech ecosystems focusing on human wellness, increased concerns about the

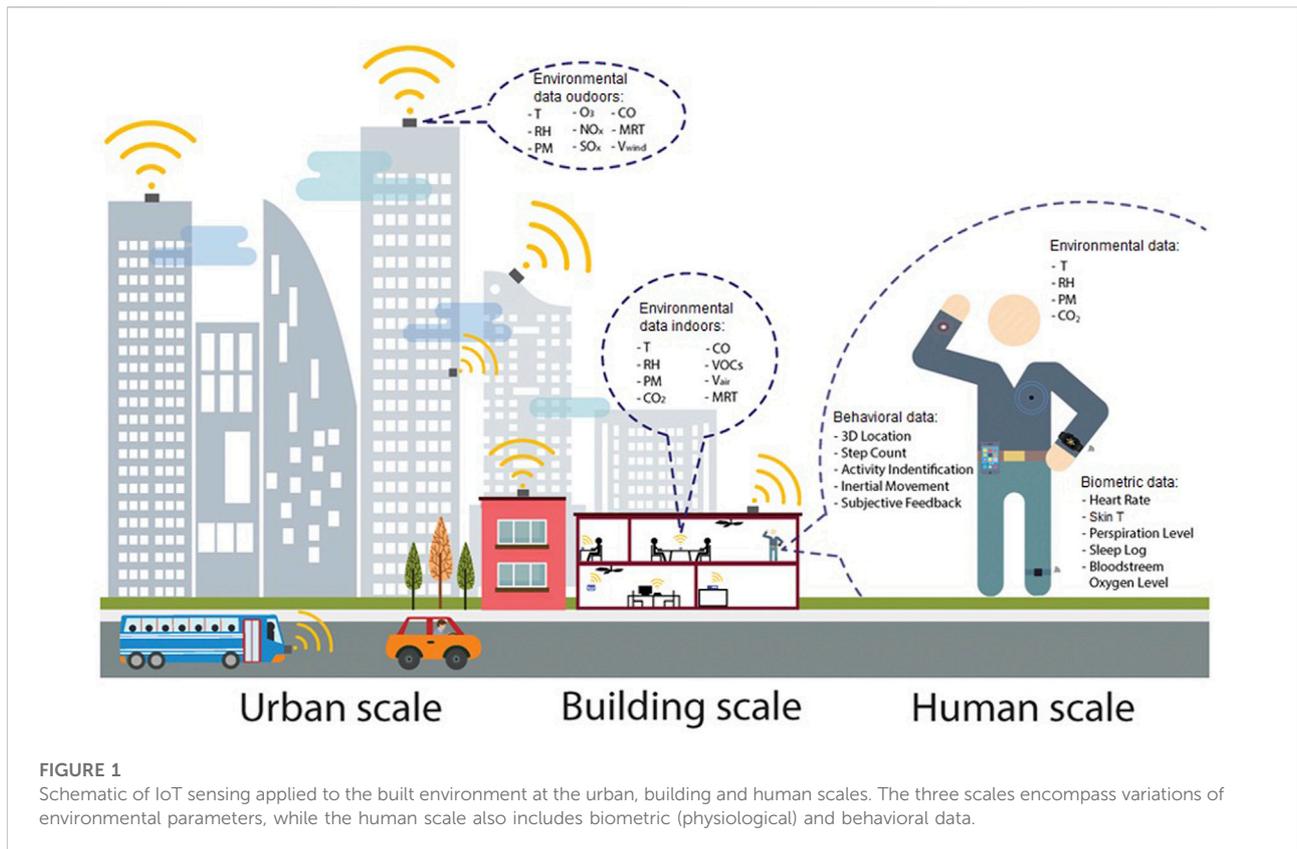
indoor air quality in the COVID-19 pandemic, represent the driving forces behind widespread IoT adaptation (Parkinson et al., 2019a). These new trends, however, do not come without challenges. At the moment, there is still a set of technological, scientific, and legal challenges regarding data acquisition and analytics that provides critical information necessary to solve environmental challenges on the human, building, and urban scales.

1.1 Systematic review

Existing reviews focus on either urban scale (Jovašević-Stojanović et al., 2015; Muller et al., 2015; Kumar et al., 2016; Morawska et al., 2018), intended to address outdoor air quality and comfort, building scale (Schieweck et al., 2018; Parkinson et al., 2019a; Cahill et al., 2019) that deals with the indoor air quality and comfort, or personal scale (Ghahramani et al., 2019a; Nazarian and Lee, 2021). This separation between scales of the application keeps the research areas completely isolated. Several existing reviews summarized the conceptual application of IoT technology, sensor accuracy, challenges of field calibration, data acquisition, and storage (Morawska et al., 2018; Ullo and Sinha, 2020; Hajjaji et al., 2021). Moreover, despite the ongoing expansion of knowledge, challenges regarding data analytics and convergence perspectives across various spatial and temporal scales, which enable the conversion of data into knowledge, are yet to be addressed.

This paper fills the knowledge gap by synthesizing research and applying IoT sensing for air quality and thermal comfort indoors and outdoors. The presented research evidence is based on a critical synthesis of the existing literature drawn from broadly used databases such as Web of Science, Scopus, and Google Scholar. The selection process intended to identify relevant, high-quality papers on which the authors could base their conclusions. Each section of the current review covers a fairly distinctive area of research. Therefore, each section had a different and unique literature search that covered the application of IoT sensing on air quality and thermal comfort.

The selection of papers was generally done in two steps: by systematic bibliographic search and supplementary literature additions. The systematic bibliographic search relied on a combination of the following keywords: IoT sensing, low-cost sensing, indoor air quality, thermal comfort, urban heat, exposure, sensors, MRT, and proxy sensing. Based on the author's expert knowledge in each area of the current review, we included supplementary literature additions. The search included papers published between 2008 and March 2022, but more recent papers received substantial emphasis given the novelty and recent research and application development in IoT sensing. Since this review covers interdisciplinary research, where each discipline has a unique publishing culture, we need to emphasize that supplementary literature



additions were crucial to cover all relevant papers in the field. We were extra careful to cite previous review papers in each of the disciplines covered in this review.

Criteria for exclusion from the review included papers that only presented frameworks without demonstrating implementation and precise data collection and analysis methods. In order to give recommendations that could be relevant to building monitoring and benchmarking and uptake of IoT sensing implementation, the present authors decided to go beyond the simple synthesis of the otherwise sparse and broadly archival literature. Instead, the study also relied on the ‘grey’ literature (e.g., government reports, white papers, and other documentation, etc.) and on the authors’ collective long-term practical experience in the field globally.

1.2 Objectives

To bridge the knowledge gaps and respond to the fast-emerging trends, this review aims to interpret and synthesize the current state-of-the-art research on developing, employing, and assessing IoT technologies from the data convergence perspective for better assessment and response to issues

related to human health and comfort. The current review aims to highlight the key scientific and technological questions that form an integrated vision for future directions in the field. We categorize three spatial scales for assessments: urban, building, and human scales (Figure 1). Based on the published literature for each scale, we evaluated the level of development of the field. In assessing air quality and thermal comfort in the urban (Section 2) and building context (Section 3), we focus on mapping the environment that causes “an exposure” of a population subgroup. Centered on assessing personal comfort and exposure directly at the point of contact with a specific individual, Section 4 addresses the emergence of the “Human-Centric” IoT sensing that overcomes the one-size-fits-all solutions promoted by traditional guidelines and measurement approaches. Section 5 addresses challenges related to data, technology, academic, and industry silos, privacy security, and human and data interaction. Although we mention issues involving privacy detail review of this complex legal topic is outside the scope of this review. Technological and scientific needs, challenges, and opportunities for cross-disciplinary advancement in short- and long-term future research efforts are further discussed in Section 6. We summarized our conclusions in Section 7.

2 IoT sensing applied to urban scale

Urban scale sensing network in the city-state of Singapore covers 142 km² (Haze - The National Environment Agency, About Singapore), with the single air quality measurement stations, the San Francisco Bay Area air quality network covers 47.6 km² (Wikipedia contributors 2022, BAAQMD - Air Quality Data) per station while the state of Nebraska air quality monitoring network covers 10543.7 km² (NDEE home) with the single station. These examples depict challenges in precisely defining urban scale as a particular surface area or distance.

Motivated by pressing environmental issues such as air pollution and thermal stress, this section discusses the emerging IoT technologies applied to air quality and thermal comfort sensing at the urban scale. In addition to summarizing the current state-of-the-art knowledge, issues related to the granularity of sensing, field calibration of sensors, existing methods for the IoT-based description of the urban environment, and the utility of collected information to improve air quality pollutants and heat exposure are reviewed. Lastly, we discuss the development of air quality exposure and thermal comfort models while highlighting the need for future developments.

2.1 Outdoor IoT sensing of air quality

Increasingly frequent episodes of elevated air pollution across different cities have evoked new questions related to the concentrations of urban air pollutants and their spatio-temporal patterns. Traditionally, information about human environmental exposure outdoors has been derived from the data gathered from governmental or environmental weather stations (Baxter et al., 2013; Özkaynak et al., 2013). Such information typically comes from gravimetric techniques and high-grade optical and chemical analyzers capable of integrated or longitudinal detection of a bouquet of ambient air pollutants. Collectively, this approach has offered important insights into ambient air quality that have been used to regulate air pollutant emissions, to propose control measures, and evaluate their efficiencies. Also, such monitoring stations have been long utilized as a benchmark for epidemiologists and public health authorities to produce formal guidelines for population exposures to specific air pollutants (Ott and Roberts, 1998; Xie et al., 2017; Dias and Tchepel, 2018; Caplin et al., 2019).

However, traditional monitoring of urban air quality faces several shortcomings. First and foremost, the conventional monitoring of urban air is stationary, sparse, and typically remote from human activities, and as such, it poorly resembles air inhaled by people (Miller et al., 2007; McKone et al., 2009; Goldman et al., 2010; Harrison et al., 2015; Pearce et al., 2016). This has been confirmed in studies that deployed

wearable monitors and samplers for measuring PM₁₀ (Jenkins et al., 1996; Scapellato et al., 2009; Broich et al., 2011), PM_{2.5} (Andresen et al., 2005; Crist et al., 2008; Steinle et al., 2015), PM₁ (Williams et al., 2000; Johannesson et al., 2007; Velasco and Tan, 2016), CO₂ (Gall et al., 2016), CO (Huang et al., 2012), NO_x (Xu et al., 2017) and various volatile organic compounds (Rotko et al., 2000; O'Connell et al., 2014; Manzano et al., 2018). Failure of traditional approaches in representing the air pollution gradients at the urban, neighborhood, and parcel of land level points to a need for increased measurement granularity. Second, the high cost of conventional monitoring equipment (Clemithshaw, 2004), which includes costs related to instrument maintenance, data collection, and processing impedes their ubiquitous deployment. Finally, the information acquired is typically used by experts only and there is a lack of accessibility and interpretation of the information that supports citizen activities.

With the recent emergence of low-cost IoT sensors applied to urban scale, an opportunity has opened up to make use of affordable, accessible, robust, and non-expert friendly solutions. Dozens of projects have investigated the application of IoT sensing in urban environments, pointing toward the need for a paradigm shift in air quality monitoring that creates new information services tackling human needs, management of urban spaces, and environmental policies (Kumar et al., 2015; Castell et al., 2017; Schneider et al., 2017; Morawska et al., 2018). The specific goals are set at refined spatio-temporal air pollutant mapping of urban spaces in order to 1) pinpoint localized air pollution hotspots, 2) improve source apportionment, 3) enhance assessment and predictive models for air pollutant exposures. In addition, easy-to-use ubiquitous IoT sensing technologies can raise citizen awareness and enable both professionals and non-experts to acquire insights.

To date, the air quality IoT sensing deployment at the urban scale has been mostly based on the high placement density of stationary IoT sensors in areas commonly occupied by humans (Gao et al., 2015; Moltchanov et al., 2015; Castell et al., 2017; Zikova et al., 2017; Ahangar et al., 2019; Bulot et al., 2019; Johnston et al., 2019). These studies conclude that optimal granularity of low-cost IoT sensors can drastically improve 2D and 3D air quality mapping, which is essential information to be translated to urban planners, building designers, the general public, and other stakeholders. Without optimal sensing granularity that results in considerable spatial data gaps, it is impossible to accurately map the urban air quality—a challenge that can be overcome by combining the crowdsourced measurements with model data with comprehensive spatial coverage (Schneider et al., 2017). Other deployment methods include IoT sensor installation on mobile sensing platforms such as bicycles, cars, buses, and trams that can improve spatial coverage (Devarakonda et al., 2013; Mead et al., 2013; Castell et al., 2015; Hasenfratz et al., 2015; Lim et al., 2019). While economically more appealing due to the significantly reduced number of sensors, the mobility of the platform in conjunction

with a prolonged response time of typical sensors can cause large signal distortion—an issue that can be overcome through the application of active sampling that employs pumps/fans as actuators (Arfire et al., 2016). Finally, urban air pollution mapping has also been conducted by means of wearable IoT sensors and smartphones (see Section 4.2) (Zhang et al., 2017; Nyarku et al., 2018; Ueberham and Schlink, 2018).

Despite the rapid progress in method development for IoT sensors in an urban context, several challenges persist. First, the identification of air pollution hotspots is limited as both scientific literature and regulations lack approaches to provide optimal spatial sensor granularity and placement across different urban typologies (Castell et al., 2017; Schneider et al., 2017). In addition, a disconnection between urban and building scales impedes our ability to better design and operate buildings. For example, building ventilation standards such as ASHRAE 62.1 requires a two-step investigation of outdoor air quality—1) compliance verification with the national outdoor air quality standards, and 2) an observational survey of the building site (American Society of Heating and Engineers, 2016). But for 1) the verification is based on measurements only at remote governmental stations and for 2) the building site survey lacks guidance on the type, duration, and location of measurements. Additionally, once the IoT-based information is acquired at the urban scale, it is necessary to trigger the right chain of actions, either *via* a feedback loop to encourage human actions and/or through an IoT gateway that links a cloud platform with automated controllers and devices. At present, methodologies on how to utilize that information are sparse, resulting in enormous data sets that are heavily underutilized (Zanella et al., 2014). The other challenges include a need for a framework to integrate different types of existing air quality sensors into a single monitoring network and a lack of standardized protocols that specify the required sensor robustness and data quality (Morawska et al., 2018). Lastly, the spectrum of air pollutants that should be monitored by IoT sensors is relatively vague with regard to environmental health knowledge. While it is neither practical nor technically feasible to measure all the air pollutants relevant to humans, future research should examine how to optimize the types of sensors to capture relevant air quality indicators.

2.2 Outdoor IoT sensing of the thermal environment

Similar to air quality monitoring in urban areas, the information regarding outdoor thermal environments is often derived from the stationary and at times remote, weather stations, neglecting the significant intra-urban variability of temperature, humidity, wind and radiation exposure (Fenner et al., 2017a). The advantages of IoT-based sensing in addressing such shortcomings are indisputable: crowd-sourced measurements 1) provide real-time data from various cities

around the globe (inter-urban variability in urban temperature (Wörner et al., 2014), 2) span a wider range of spatial and temporal distributions within the built environment (intra-urban variability in thermal environment (Meier et al., 2017), 3) overcome the high and centralized costs for installation and maintenance over time (low-cost sensing and/or Web 2.0 technologies (Dayan and Hartley, 2013; Young et al., 2014), and 4) provide dynamic information regarding heat exposure and the population impact of thermal comfort (Grasso et al., 2017).

Accordingly, in the last few years, several studies have taken crucial steps in tackling the challenges in IoT thermal sensing in the built environment. Previous research was mainly focused on monitoring of environmental parameters primarily temperature and humidity and largely divided into the employment of stationary or mobile sensors, with only a few studies combining the two to span a larger spatial and temporal distribution to improve accuracy (Muller et al., 2015; Shi et al., 2021). Among stationary amateur thermal sensors applied outdoors, there has been the emergence of low-cost citizen weather stations with connectivity to smartphones, local Wi-Fi networks and cloud in real time. Such units have become mainstream consumer peripherals in recent years with tens of thousands now deployed in cities across the world, including the United Kingdom (Chapman et al., 2017; Chapman and Bell, 2018), Germany (Meier et al., 2015; Fenner et al., 2017b; Meier et al., 2017), France (Napoly et al., 2018), Russia (Varentsov et al., 2021), and the Netherlands (de Vos et al., 2017). The crowdsourced datasets have also been combined with high-resolution data on urban form and fabric to provide more in-depth analyses of urban design impacts on thermal environments (Potgieter et al., 2021); or compared with remotely-sensed measurements of urban thermal environments globally (Venter et al., 2021) demonstrating the shortcomings of satellite data for urban heat risk assessments.

Although the low cost and ease of use of citizen weather stations have promoted their widespread use, they are largely focused on urban temperature and humidity as a proxy for thermal comfort, while other environmental parameters (such as radiation and wind speed), as well as physiological and behavioral factors, are often neglected. Several efforts are emerging to crowdsource urban wind (Droste et al., 2020; Chen et al., 2021), focusing on quantifying the uncertainty in wind speed data based on the realistic application of sensors in the built environment. Overall, such quantification of bias appears to be one of the key challenges of using citizen weather stations. Bell et al. (2015) provided a detailed assessment of data accuracy and concluded that any application of such low-cost sensing monitoring stations will require a quality-control system capable of removing gross errors, correcting instrument bias, and providing an uncertainty estimate, which is collectively needed to ensure effective outdoor IoT sensing of the thermal environment.

Responding to this need, more holistic quality-control measures for crowdsourced air temperature observations are recently developed (Fenner et al., 2021), enabling a more consistent use of citizen weather station data in worldwide applications.

IoT platforms' reduced size and cost further enable distributed and mobile deployments at the urban scale. Several mobile sensing methodologies deployed to date can be categorized in four major formats: 1) portable amateur weather stations, 2) smartphones, 3) vehicle-based sensors, and 4) wearable devices (Section 4). It is worth noting that compared to the IoT air quality measurements (Section 2.1), the portable and smartphone sensors for thermal comfort are distinguished from wearables, as the latter can provide physiological parameters, such as heart rate and skin temperature, corresponding to the thermal environment.

In the first category, the National Science Experiment in Singapore (low-cost wireless SENSg devices (Wilhelm et al., 2016) is arguably the largest deployment of portable amateur weather stations with 50,000 sensors employed in Singapore for the assessment of thermal comfort among various other objectives (Monnot et al., 2016a; Happle et al., 2017). However, the data regarding the thermal environment has not been extensively utilized, perhaps due to measures required for data quality controls in dynamic use. Second, temperature and pressure obtained from smartphone batteries are proposed to obtain a spatial and temporal map of air temperature in cities (Overeem et al., 2013; Pape et al., 2015; Droste et al., 2017; Martilli et al., 2017). Although this methodology provides an unprecedented dataset on city-scale thermal environment, the uncertainties of data collection are of concern and increase in cities with more extreme weather and higher precipitation when the smartphone is most likely to be held enclosed (Martilli et al., 2017). A closer comparison of mobile measurements with scientific-grade sensors reveals that, even when smartphones are exposed to ambient air, uncertainties are increased with higher humidity (where the smartphone hygrometer is saturated) and bias corrections are needed for Sun exposure and high wind speeds (Cabrera et al., 2021), which is yet to be developed for realistic and dynamic data measurements. In the third category, mobile sensors mounted on vehicles, bicycles, and public transit systems have been used to make strategic transects through cities to observe thermal comfort variables, providing valuable real-time data, particularly in the face of extreme events in cities (Heusinkveld et al., 2014; Castell et al., 2015; Anjomshoaa et al., 2018). Lastly, vehicle-based data, while still understudied, are more comprehensive in obtaining behavioral patterns and can be used to develop personal comfort models given a rich dataset (Mahoney and O'Sullivan, 2013; Fugiglando, 2018). Overall, it is important to consider that if the spatial distribution of thermal exposure in urban areas is of interest, data collected using mobile sensors require post-processing in the form of time-detrending and sensor lag correction (Häb et al., 2015; Middel and Krayenhoff, 2019).

In addition to stationary and mobile IoT environmental sensing, a few novel data-driven analyses can be noted which, in combination with previously described methods, represent a paradigm shift in thermal comfort assessments at the urban scale. First, IoT technologies have enabled the assessment of thermal comfort on human activity and behavior in the built environment. For instance, in addition to environmental measurements, Wi-Fi connectivity data in outdoor spaces have been used to obtain real-time occupancy data and to explain outside dwelling patterns modified by thermal environments (Reinhart et al., 2017; Dhariwal et al., 2019). Using Wi-fi scanners in public courtyards, Reinhart et al. (2017) recorded occupancy patterns over 10-month in addition to measurements of air temperature, relative humidity, wind speed and direction, and solar radiation. The thermal environment (characterized by biometeorological thermal comfort indices) was found to strongly correlate with lunch-time activity by regular users. These correlations suggest that IoT measurements of the thermal environment outdoors can be used by designers and planners to predict the spatiotemporally differentiated use of outdoor areas. Second, in the last decade, additional proxy datasets, such as social media data on Facebook and Twitter have introduced an alternative approach to crowdsensing urban heatwaves and the consequent impact on human activity (Grasso et al., 2017). Lastly, methodologies in urban climate informatics (Middel et al., 2022), such as crowdsourcing urban form information in the WUDAPT project (Bechtel et al., 2019) and crowdsourcing the Street View Imagery (Juhász and Hochmair, 2016; Middel et al., 2019) have enabled the city-scale calculation of thermal comfort parameters such as sky view factor and mean radiant temperature (MRT), which can complement low-cost IoT sensing of air temperature and humidity implemented across cities to achieve a comprehensive analysis of thermal comfort outdoors.

Despite a great deal of progress, the assessment of thermal comfort has been slow in harnessing crowdsourcing and IoT-based technologies for data collection (Chapman et al., 2017). Several challenges contribute to this fact. The first challenge pertains to the extent of the parameters that need to be monitored: an accurate thermal comfort assessment requires a range of environmental, behavioral, and physiological (Section 4) parameters which are complex to include in one sensing unit. Air temperature and humidity are far easier to obtain than radiation exposure and wind speed. Additionally, thermal comfort is defined as the "state of mind" (ASHRAE Standard 55) in response to the thermal environment, and therefore, the heat transfer in the environment cannot sufficiently describe the "comfort for all" (Nikolopoulou et al., 2001). The characteristics of urban spaces and the mode of activity of the occupants dramatically influence the thermal comfort perception, increasing the need for comprehensive, yet accurate, data collection mechanisms that include subjective

feedback. The second challenge relates to the ease of use for widespread adoption of sensing units. The size of the devices, power (cordless vs. corded) and the lifetime of the devices in the field, and more importantly, the data communication method (wired vs. wireless) are crucial factors for long-term and scalable employment. Ideally, the IoT-based thermal comfort sensor that can record all relevant parameters is 1) of a size that is employable in a non-intrusive way 2) able to log data with sufficient storage for the long term, and 3) able to communicate the data wirelessly with a sufficient frequency. Lastly, even when all the above-mentioned conditions, the cost must not be prohibitive. Large city-scale deployment of IoT sensing for thermal comfort still faces substantial price barriers, particularly in research.

3 IoT sensing applied to building scale

Since people spend around 90% of their time indoors (Klepeis et al., 2001), building scale thermal environments and air quality have proportionally the highest influence on occupants' thermal comfort and one if not the most important influences on air pollution exposure. Therefore, it is absolutely critical to characterize the indoor environment. IoT environmental sensing has the goal to enable an understanding of the dynamics of building operations. This section summarizes the capabilities of IoT sensing to characterize the thermal environment and indoor air quality, sensing methodologies for longitudinal evaluation of buildings operations, and the field of proxy sensing.

3.1 State-of-the-art continuous measurement capabilities indoors

Several IoT platforms for monitoring air quality and thermal environment have been deployed in residential and commercial buildings (Edirisinghe et al., 2012; Abraham and Li, 2014; Kim et al., 2014; Salamone et al., 2015; Ali et al., 2016; Scarpa et al., 2017; Pantelic et al., 2018a; Carre and Williamson, 2018; Coleman and Meggers, 2018; Idrees et al., 2018; Martín-Garín et al., 2018; Parkinson et al., 2019a), educational facilities (Palacios Temprano et al., 2020; Ulpiani et al., 2021), industrial settings (Li et al., 2018), occupant exposure assessments (Jackson-Morris et al., 2016; Kelly et al., 2017; Curto et al., 2018; Pantelic et al., 2020) and on mobile platforms (Jin et al., 2018a).

With regard to assessing thermal environments, indoor IoT sensing platforms typically measure air temperature and relative humidity and often lack the capabilities to measure comprehensive sets of thermal environment indicators that include air velocity or mean radiant temperature (MRT). Monitoring air velocity is particularly important in spaces that

use elevated air movement as a means to achieve thermal comfort (Zhai et al., 2015; Schiavon et al., 2017). Advancements in air velocity measurements have been made with the development of low-cost ultrasonic velocity sensors (Ghahramani et al., 2019b) and the integration and deployment of 2D hot-wire anemometers in indoor sensing platforms¹³. With the increasing popularity of high-rise glass towers, radiative heat transfer can make up approximately half of the heat transfer between occupants and the surrounding indoor environment (Teitelbaum et al., 2019), making MRT measurements critical for indoor thermal comfort assessments. The black globe thermometer provides a reasonable and affordable solution for MRT measurements (Thorsson et al., 2007; Parkinson et al., 2019a) but recent works have shown that black globes cannot accurately measure MRT due to the significant impact of airspeed on the measurement (Guo et al., 2018; Teitelbaum et al., 2020a; Teitelbaum et al., 2020b; Teitelbaum et al., 2022). Uncertainty of MRT measurement is proportional to globe diameter and depends on the convection regime (Teitelbaum et al., 2022). When ambient air velocity is lower than 0.2 m/s, the black globe sensor used for MRT measurement is in the mixed convection regime that is challenging to account for using the correction factor (Teitelbaum et al., 2022). Accurate measurement of MRT on a building scale can be achieved with infrared thermal scanning and mapping of the physical environment with LiDAR (Light Detection and Ranging) technology (Houchois et al., 2019).

With regards to air quality, the common air quality indices at the building scale include CO, CO₂, PM_{2.5}, PM₁₀, TVOC, O₃, CH₂O, NO₂, and radon. The current IoT sensors for PM_{2.5} have reasonable accuracy, within a factor of 2 from a reference, which suggests their suitability for indoor air quality management; however, their accuracy can be compromised if the dominant source includes particles of the ultrafine size range (Wang et al., 2015; Manikonda et al., 2016; Singer and Delp, 2018; Wang et al., 2020; Demanega et al., 2021). A more recent study showed very good agreement between low-cost IoT PM_{2.5} sensors with scientific-grade instruments (Hegde et al., 2020; He et al., 2021) especially after applying RH corrections (Tagle et al., 2020; Zou et al., 2021). The CO₂ sensors generally have good agreement with reference monitors (Demanega et al., 2021). Measurement of PM₁₀ in most proposed platforms is based on models that derive concentration from the same dataset as PM_{2.5} (Kim and Oh, 2018), and not from direct measurement. Although studies indicated that low-cost TVOC sensors can be deployed indoors despite their poor quantitative agreement (Moreno-Rangel et al., 2018; Demanega et al., 2021), the common issue is that they cannot differentiate physicochemical properties of hundreds of individual organic compounds (Jackson-Morris et al., 2016; Kelly et al., 2017; Curto et al., 2018) some of which are strongly linked to health effects (Schieweck et al., 2018). O₃ sensors have been utilized in several studies (Firdhous et al., 2017; Zhang et al., 2021). Low-cost O₃

sensors can be calibrated to measure concentrations encountered in indoor environments (Pang et al., 2017) with recent studies addressing machine learning-based learning-based calibration improvements (Ferrer-Cid et al., 2020). A review of low-cost IoT sensor operation by the Air Quality Sensor Performance Evaluation Center suggested that O₃ sensors are able to provide useful qualitative and quantitative measurements when used off the shelf (Collier-Oxandale et al., 2020). Measurement of indoor radon with IoT environmental sensing has been recently proposed (Blanco-Novoa et al., 2018; Pereira et al., 2020) CO sensor detection range is a topic that needs further research (Nandi et al., 2019) and both metal-oxide and optical-based sensors need improvement on the lower end of detection limit (Nandy et al., 2018). At the moment a low-cost IoT CH₂O sensor capable of measuring CH₂O is under development (van den Broek et al., 2020). NO₂ was previously measured (Coleman and Meggers, 2018; Collier-Oxandale et al., 2020), but general methods for calibration are still missing for these sensors deployed on a building scale. Based on scientific evidence it can be argued that IoT sensing of indoor chemistry is still in its early stages.

Existing IoT sensing platforms can measure the basic parameters of the indoor air quality matrix (Pantelic et al., 2018b). Various studies have used different evaluation methods to assess IoT environmental sensors' accuracy and reliability. The sensing drift of low-cost sensors over time is yet another unknown that requires further investigation (Chojer et al., 2020). Nonetheless, the quality and variety of the low-cost sensors have been increasing over the years, but the development of standards and guidelines for testing methods, sensing network accuracy, repeatability, and reliability should be considered a priority (Schieweck et al., 2018; Chojer et al., 2020). Further research efforts are necessary to understand the relationships between single point sensor accuracy (Rackes et al., 2018) and the whole network accuracy (Parkinson et al., 2019a).

3.2 Characterization of indoor air quality and thermal comfort

Monitoring air quality and thermal environment enable characterization of buildings performance, which is useful for management and benchmarking. Measurement with conventional methods and instruments can provide a temporal snapshot of building operation. Similar to the urban scale, limitations of conventional methods include cost, the time necessary to measure a large number of points in time and space (Parkinson et al., 2019a; Parkinson et al., 2019b), size and noise of equipment, and accessibility of sampling locations (Kumar et al., 2016). The low-cost IoT sensing has the potential to overcome some of these limitations and provide a longitudinal evaluation of building performance with refined spatio-temporal

representation. Certification schemes offer credits for the implementation of continuous monitoring (RESET, 2022; WELL, 2022) and represent one of the key drivers of the widespread application of IoT sensing (Parkinson et al., 2019a; Parkinson et al., 2019b). The development of continuous monitoring guidelines for temporal and spatial sensing resolution has become one of the critical research priorities (Heinzerling et al., 2013; Parkinson et al., 2019b; Licina and Bhangar, 2019). At the moment the set of indicators required by standards is not covered by available IoT sensing platforms which present another area that needs development.

Some of the most used current indoor air quality continuous monitoring guidelines/standards are summarized in Table 1. These consider air pollutants that need to be measured, the accuracy of equipment, sensor placement, measurement time, and analytical tools. Guidelines summarized in Table 1 describe different approaches, data collection methodologies, instrument requirements, and various analytical performance indicators. The development of these guidelines is largely expert-based and usually not scientifically validated. Regarding sensor density and placement, several research studies explored sensing densities from ~9 m² up to ~100 m² per sensor (Ali et al., 2016; Pantelic et al., 2018a; Li et al., 2018; Parkinson et al., 2019b; Clements et al., 2019). Although some of these studies demonstrated significant spatial variation of measured parameters, their results cannot be used for the validation of existing continuous monitoring guidelines/standards due to significant differences in objectives and sensor placement methodologies. The failure of the well-mixed assumption in some environments (Pantelic and Tham, 2013) brings additional potential complexities to the sensor granularity and placement problem. Other location recommendations for example to place a sensor 1 m away from doors, windows, and diffusers are simply practice-based, and not grounded in research. The upscaling sensor deployment sensors have to be named systematically so that data collected in multiple buildings can be correctly understood and interpreted. Naming schemas are a critical aspect of integration and are addressed later in Section 5. Measurement frequency is another variable where the recommendation of 1 min or 10 min sampling frequency is not well-grounded in research. From the certification perspective as discussed earlier the current IoT technology cannot capture all relevant parameters. As a result, for proper characterization of the indoor environment, we still need to couple continuous monitoring with conventional industrial-hygienist practices like measuring individual VOCs. This also extends to the thermal environment and the necessity for the maturation of measurement technology. Considering the speed with which the industry adopts green building certification schemes and the impact they have on the built environment, the development of science-based validated building benchmarking should be made a top priority.

TABLE 1 Summary of guidelines/standards available for deployment of air quality sensors for continuous monitoring in buildings.

	Arc scoru	ASHRAE/ USGBC PMP (2010)	RESET v2.0	WELL v2	LEED v4
Quantities to measure	<ul style="list-style-type: none"> ● Outdoors: None ● Indoors: CO₂, VOC 	<ul style="list-style-type: none"> ● Outdoors: EPA nonattainment zones ● Indoors: PM_{2.5}, CO₂, TVOC, bioaerosols 	<ul style="list-style-type: none"> ● Outdoors: None ● Indoors: PM_{2.5}, CO₂, TVOC, CO ● T, RH - suggested (not required) 	<ul style="list-style-type: none"> ● Outdoors*: PM_{2.5}, CO, NO₂, SO₂, O₃ ● Indoors**: PM_{2.5}, CO₂, CO, TVOC, NO₂, O₃, CH₂O 	<ul style="list-style-type: none"> ● Outdoors: PM_{2.5}, O₃, CO ● Indoors: PM_{2.5}, CO₂, TVOC, CH₂O
Data Collection	<ul style="list-style-type: none"> ● Physical measurement ● Occupant satisfaction survey min 25% response rate 	<ul style="list-style-type: none"> ● Continuous monitoring ● Data loss—not defined ● Occupant satisfaction survey 	<ul style="list-style-type: none"> ● 3 levels accuracy ● Cloud Interface; Data Structure; Resolution; Frequency ● 3 levels of data loss 	<ul style="list-style-type: none"> ● Accuracy defined for each pollutant ● 10 min minimal collection 	<ul style="list-style-type: none"> ● Physical measurement ● Occupant satisfaction survey
Measurement density and location	<ul style="list-style-type: none"> ● In locations representative of all occupied spaces ● Within the breathing zone ● During occupied hours ● Under typical minimum ventilation conditions ● Specified measurement technologies 	<ul style="list-style-type: none"> ● Representative locations in space (not specified) ● Ducts 	<ul style="list-style-type: none"> ● 80% of occupants represented ● All space types represented ● 500 m² per sensor 	<ul style="list-style-type: none"> ● 325 m² per sensor; or one sensor per floor at 1.1–1.7 m height (if floor is smaller) 	<ul style="list-style-type: none"> ● Not specified
Measurement time	<ul style="list-style-type: none"> ● Not specified 	<ul style="list-style-type: none"> ● 7 days minimum ● Continuous 	<ul style="list-style-type: none"> ● Continuous 	<ul style="list-style-type: none"> ● Continuous 	<ul style="list-style-type: none"> ● Not specified
Analytics tools	<ul style="list-style-type: none"> ● Arc performance score: Perceived occupant satisfaction and ● Variance CO₂ and VOC concentration >95% of the time normalized for floor area and occupancy 	<ul style="list-style-type: none"> ● Communicating data to occupants - not encouraged ● ASHRAE 62.1 compliance ● Time weighted exposure ● Exceedance 	<ul style="list-style-type: none"> ● Communicating data to occupants <i>via</i> display ● Calculating daily averages from IAQ monitors during occupied hours ● Consider data loss (>20%) ● Thresholds standard/high performing buildings 	<ul style="list-style-type: none"> ● Communicating data to occupants <i>via</i> display ● Benchmarking measurement against thresholds at 3 levels (Platinum/Gold/Silver) during occupied hours ● Annual Report 	<ul style="list-style-type: none"> ● Benchmarking measurement against different levels of thresholds during occupied hours ● Consider outdoor air quality (2 levels of indoor conditions)

Outdoor*: WELL, does not explicitly ask for continuous monitoring on the building, but does require continuous information from the weather station within a 4 km radius; WELL** requires monitoring of 3 of listed pollutants.

Thermal environment and thermal comfort studies that address the application of IoT sensing on the building scale can be classified into two groups. In the first group of studies, the objective of continuous monitoring of the thermal environment is to provide information as an input parameter to estimate thermal comfort (Parkinson et al., 2019b; Valinejadshoubi et al., 2021). Although the effectiveness of PMV/PPD models to

estimate occupant satisfaction in the field using thermal environment measurement can be questioned (Cheung et al., 2019), this approach is used to assess building operation compliance with certification schemes and standards (Revel et al., 2014a; Parkinson et al., 2019b; Wang et al., 2019). The second group of studies surveys individuals alongside thermal environment monitoring to obtain assessments of thermal

comfort and develop personal comfort models (Kim et al., 2018a; Kim et al., 2018b; Kim et al., 2019). Utilization of this approach demonstrated that personal comfort devices can increase occupants' satisfaction by over 95% (Kim et al., 2019). The use of infrared thermography for real-time monitoring of personal thermal comfort (Revel et al., 2012; Revel et al., 2014b) represents another opportunity for human-centric assessments of comfort at the building scale, but so far has mainly relied on a single parameter (e.g., skin temperature) tracking of thermal environment and is yet to be integrated with comprehensive IoT thermal environment monitoring. Published studies point towards the development of personalized thermal comfort models, but actual use in the building operation of these models is still unclear. The combination of thermal environment mapping and survey of occupant satisfaction is an important research area that can improve the operation of existing and new buildings by providing optimal thermal comfort setpoints.

3.3 Proxy sensing

When several environmental parameters are measured in space and that information is used to infer knowledge about some other property or process, that can be considered proxy sensing or context-aware computing. Prior research suggests that humans have a unique environmental footprint, including CO₂ (Persily and de Jonge, 2017), particulate matter and bioaerosols (Bhangar et al., 2016; Licina et al., 2016), various volatile organic compounds (Tang et al., 2016), as well as sound (Li et al., 1991; Sabatier and Ekimov, 2008), that can form a basis for the use of context-aware computing to detect occupants and their activities in the space. Occupants proxy sensing was explored using a combination of CO₂, Lux, T and RH (Candanedo and Feldheim, 2016), passive infrared, TVOC, and CO₂ (Pedersen et al., 2017), only CO₂ (Dong et al., 2010; Jin et al., 2018b), CO₂, energy consumption of lighting, and energy consumption of appliances (Ryu and Moon, 2016), CO₂, RH, T and pressure (Chen et al., 2016), passive infrared, CO₂ and RH (Han et al., 2012), PM_{2.5}, PM₁₀, T and RH (Jeon et al., 2018). The number of occupants in a building is an important parameter for understanding space utilization and energy use patterns. The presence of people can be measured directly with the surveys, based on radio frequency signals, passive infrared, ultrasonic, video cameras or global positioning information, Bluetooth, wireless local area network signals (Yang et al., 2016), but all these methods require significant labor and are usually very costly to perform, especially at the large scale. The use of proxy sensing with environmental IoT sensors has the potential to significantly reduce the cost of these processes. Besides the detection of the number of occupants in the space, Ghahramani et al. (2018) used environmental sensing to detect occupants' workplace social interactions. The challenge remains to demonstrate that proxy

detection of the number of occupants and type of social interactions can be generalized and upscaled.

4 IoT sensing applied at the human scale—Wearable IoT sensing

Unlike stationary IoT sensing which often aims to assess exposures of a population subgroup, wearable devices, i.e., smart electronic devices that can be worn or be integrated into clothing (i.e., standoff sensors), are at the heart of new capabilities that pervasive connectivity can bring at the human scale. Currently, various health- and fitness-oriented wearables are commercially available which can sense, store, and track the temporal variability in human activities (such as steps and locations) and biometric data (including heart rate, perspiration levels, and oxygen levels in the bloodstream). The potential of wearables in promoting positive health outcomes and enhancing human comfort and well-being is indisputable and scientific research has been able to evaluate and validate various wearable technologies. This section aims to review such applications in wearable IoT sensing, particularly focused on air pollution exposure, physiological monitoring, and thermal comfort.

4.1 Physiological and health monitoring

It is likely that the impending increase in air pollution and urban overheating in many cities around the globe will discourage outdoor physical activity and therefore impact the health of individuals (Chan and Ryan, 2009; Paulin and Hansel, 2016; Nazarian et al., 2021b; Romanello et al., 2021). Generic recommendations and guidelines have been developed to address these concerns, but given the fact that environmental health impacts vary greatly for individuals, the adoption of general guidelines often does not optimize the health and performance of every individual and even can at times induce negative health implications (Tan et al., 2015). As there is extensive variability intolerance to a given absolute level of stress, individual monitoring of physiological status has the potential to optimize health and performance (Piwiek et al., 2016; Notley et al., 2019). The development of individualized guidelines for environmental health through IoT sensing at a human scale that accounts for intrinsic and extrinsic factors is envisaged.

In recent years, the use of smart devices is becoming more prevalent to provide users with personalized data for self-diagnosis and behavior alterations to optimize health and performance (Piwiek et al., 2016). In occupational settings, smart devices can be used to monitor workers in real-time and therefore protect them from excessive heat strain (Notley et al., 2018), which is particularly useful for high-risk workers. These smart devices offer unprecedented opportunities to collect rich sources of data to guide interventional strategies.

While the proliferation of smart devices at times serves as motivational tools to initiate health and performance programs, accuracy can be lacking, and more importantly, there is an absence of validated models to translate the raw data to actionable advisory for the users. Dias and Paulo Silva Cunha (Dias and Cunha, 2018) reviewed important aspects of smart devices for health, listing the state-of-the-art wearable vital signs sensing technologies, including their system architectures and specifications. There are also a number of concerns about the safety, reliability, and security of using consumer wearables in healthcare (Piwiek et al., 2016), which are similarly applicable to the use of wearables for environmental monitoring at the human scale. To this end, the Electronic Patient-Reported Outcome Consortium proposed a framework by listing a set of recommendations in relation to the selection of and evidentiary considerations for wearable devices to ensure adequate precision, accuracy, and reliability of data collected (Byrom et al., 2018), which to date are not widely used in wearable environmental sensing.

Prospectively, as smart devices become more accurate, more sophisticated modeling techniques will also be harnessed. For example, an artificial intelligence platform solely based on patient data is used to prospectively guide drug dosage to the patient with prostate cancer, resulting in durable response and no disease progression (Pantuck et al., 2018). Instead of using population-based algorithms, this platform only harnesses data from the individual of interest to enable small data set-driven optimization. This could be particularly amenable to human performance and health optimization, considering the fact that human responses to a given stressor are varied. In addition, the profile of an individual is expected to shift during the course of time. The ability to dynamically modulate inputs to affect optimal outcomes therefore will drive a powerful and unique ability to truly personalize health and performance in a sustained manner.

4.2 Wearable sensors for air quality

Direct assessment of personal level exposure accounting for the dynamic nature of human activities has been identified as a central area in air pollutant exposure research (Steinle et al., 2013; Health Effects Institute, 2015; Marć et al., 2015; Borghi et al., 2017; Spinelle et al., 2017). Portable air quality monitors with local data storage have been previously used in air quality studies to quantify individual exposures (Steinle et al., 2013; Marć et al., 2015; Borghi et al., 2017; Spinelle et al., 2017). The use of portable air monitors with local data storage is associated with a limited number of study participants, laborious manual work, frequent data download, cataloging, and keeping of activity diaries which prevents real-time use of the data (Steinle et al., 2013; Marć et al., 2015; Borghi et al., 2017; Spinelle et al., 2017). On the contrary, wearable IoT sensors represent the progression of technology for

personal exposure estimation and offer a promise for automation of environmental data collection, simultaneous GPS tracking (Predić et al., 2013; Antonić et al., 2014; Wong et al., 2014; Zhuang et al., 2015; Tian et al., 2016; Zhang et al., 2017; Yang et al., 2018), and upscaling to citizen scientist data collection strategies (Piedrahita et al., 2014; Nikzad et al., 2012; Jerrett et al., 2017; von Schneidmesser et al., 2019). Improvements in personal exposure assessment were suggested by combining (wearable/portable) behavioral sensors with wearable sensors that capture environmental and biometric data (Fletcher et al., 2014; Hu et al., 2014) as illustrated in Figure 1. A recent survey of occupant needs rated wearable PM_{2.5} sensors just behind wearable air cleaners (Wang et al., 2021) indicating an increase in population awareness of the importance of environmental impacts on health.

There has been significant development of wearable IoT environmental sensors in recent years. Deng et al. (2016) developed a portable wireless VOC sensing kit and demonstrated its application for measuring personal exposure. Zhang et al. (2017) show the application of wearable IoT sensors for PM_{2.5} monitoring integrated with location and temperature data and demonstrated how they can be used for IAQ mapping of underground stations. Hojaiji et al. (2017) develop wireless wearable PM and N₂ sensors for personal exposure measurement. Xu et al. (2019) developed a wearable PM_{2.5} sensor and demonstrated how crowdsourcing can be used to detect large variations of air pollution in the city. Zhong et al. (2020) used wearable CO₂ sensors for monitoring and forecasting the indoor environment. Cureau et al. (2022) developed and implemented a wearable wi-fi connected system for mapping urban environments from the pedestrian's perspective as an aid to city planners. Kane et al. (2022) developed wearable IoT PM sensors for personal exposure measurement and modification of people's behavior based on the results of communication. Kortoci et al. (2022) showed how wearable air quality monitors provide insights into personal pollution exposure and the micro-climates of the city measuring PM, CO, NO₂, and O₃. Besides insight into personal exposure through crowdsourcing wearable air quality sensors is a useful tool in mapping air pollution hot spots on the urban scale (Buehler et al., 2021; Hernández-Gordillo et al., 2021; Cureau et al., 2022).

In a recent systematic review of the environmental monitoring with the wearable sensor application, Salamone et al. (2021) included 39 papers that address air quality monitoring among them 5 addressed wearable IoT sensors and pointed out that air quality monitoring calibration is an issue and not often reported. Hernández-Gordillo et al. (2021) reviewed recent advancements in low-cost IoT wearable sensors and pointed out that sensors still have challenges related to sensitivity, selectivity, measurement accuracy, and drift. Authors also concluded that further development of models for data processing in addition to lack of community

engagement is the challenge to overcome. [Abboushi et al. \(2022\)](#) reviewed the use of wearable devices for studying the connection between personal exposure and health and reported issues related to missing data points, data resolution, and measurement of a limited number of pollutants. [Narayana et al. \(2022\)](#) reviewed state-of-the-art low-cost IoT environmental sensing and concluded that sensing quality is still an issue and proposed a framework for enhancing data reliability. To address issues related to wearable low-cost IoT sensor drift due to sensitivity to environmental conditions [Buehler et al. \(2021\)](#) an online calibration method. Wearable devices with sensors for real-time gas-phase air pollutants measurement have issues with calibration ([Cao and Thompson, 2016](#)).

Wearable air quality IoT sensors are still facing significant challenges in application. The accurate positioning on humans that can capture true exposures still remains a research question. Human micro-environment concentrations are influenced by chemical and particle emissions from skin oils, clothing, cosmetics, and exhalation ([Rim et al., 2009](#); [Licina et al., 2017](#); [Licina et al., 2019](#)). These local emissions create a cloud of TVOC, CO₂, and particles ([Pantelic et al., 2020](#)) that can affect the readings of other air pollution sensors ([Maag et al., 2018](#)). For air pollutants coming from exhaled breath, determining accurate sensor location is the key open challenge. For instance, when personal exposure to CO₂ was estimated with sensors worn around the neck, results showed that exhaled CO₂ from some of the users directly impacts sensor reading, which led to a personal exposure overestimation ([Ghahramani et al., 2019a](#)).

Wearable IoT air quality sensors offer great potential for determining and potentially mitigating personal air pollutant exposures, and through crowdsourcing, increasing spatio-temporal air pollution mapping on building and urban scales. To be successfully implemented, they require further development on the hardware side to improve sensing accuracy, an array of pollutants they can measure, size, and battery life. On the application side, determining a wearable sensing location on a person that best represents personal inhalation exposure at the minimal level of physical intrusiveness represents a key open research question. Wearable air quality sensors have not reached measurement accuracy and non-intrusiveness levels that would enable their massive deployment and ultimately, refinement of personal exposure models.

4.3 Wearables for thermal comfort prediction

Unlike the air quality measurements in the built environment, thermal comfort is highly subjective and greatly depends on the individual's physiology and psychology. Conventional methods of thermal comfort assessment, however, are often either based on the thermal physical

models of the environment or focused on the physiological, behavioral, and psychological factors that form the individual's thermal comfort perception ([Rupp et al., 2015](#)). To address this shortcoming, wearable technologies have introduced a more comprehensive perspective of thermal comfort in the past few years by combining environmental measurements with physiological and behavioral assessments. A combination of these factors leads to personal thermal exposure assessments, aiming to determine how different individuals and subpopulations not only experience different heat exposures but also experience different levels of discomfort, physiological strain, or psychological stress when subjected to the same thermal environments ([Nazarian and Lee, 2021](#)). For instance, wearable sensing of skin is proposed, as human skin is considered the mediator between the environment and the human body, and therefore, skin temperature and conductance play a major role in thermoregulatory processes involved in thermal comfort and heat stress ([Zhang et al., 2010](#); [Takada et al., 2013](#); [Dai et al., 2017](#)). Studies such as [Sim et al. \(2016\)](#) showed that wrist skin temperatures can be used to predict whole-body thermal sensation. Additionally, several recent studies have identified the potential of heart rate and heart rate variability data to indicate thermal sensation in the built environment ([Buller et al., 2013](#)). This, in addition to the advancement of ubiquitous sensing and IoT in the built environment domain, has opened new doors for the use of wearables in thermal comfort assessments. A range of wearable solutions, either for activity (fitness) or health-tracking, has gained traction in the market and is enabling a shift in approaches presented in thermal comfort assessment and physiological assessments.

Wearable technologies represent a range of opportunities for comfort and health assessments in the built environment. The most prominent opportunity, perhaps, is to approach thermal comfort analysis as "human-centric" as opposed to "one-size-fits-all" by adding behavioral and physiological components. Incorporating an integrated monitoring approach to thermal exposure, physiological and behavioral parameters can be recorded alongside environmental conditions, providing opportunities for detection of heat impact as well as personalized comfort classification ([Jayathissa et al., 2019](#); [Nazarian et al., 2021b](#)). Additionally, wearables travel with the individuals in the realistic exposure scenarios, and therefore, data collected by wearables combined with the GPS data can provide the spatiotemporal distribution of environmental parameters as well as the ways in which individuals respond to that environment. Nonetheless, the use of wearable solutions for thermal comfort is an emerging field, and only a handful of studies propose wearable solutions for thermal comfort assessments ([Nakayoshi et al., 2015](#); [Hasan et al., 2016](#); [Moatassem et al., 2016](#); [Liu et al., 2018](#); [Salamone et al., 2018](#); [Ojha et al., 2019](#)). Among these, [Nakayoshi et al. \(2015\)](#) represented the most comprehensive measurements of thermal

comfort, incorporating all the relevant thermal variables, including environmental parameters (air temperature, relative humidity, wind speed, and MRT) in the proximity of a human body, physiological measurements (such as heart rate and skin temperature), and subjective feedback, which found a correlation between skin temperature and thermal comfort index (SET) with dependencies on gender. The unique wearable system that was developed in this study involved five sensing units that were all worn by the participants in multiple locations: hat, belt, hand, and forehead skin and carried in a small sash. However, this methodology, although comprehensive for research purposes, is considered impractical for implementation in real-life applications and limits the scalability of IoT sensing. Other studies further relied on a combination of fixed and wearable sensors to enhance feasibility. Studies for example, combined wearable devices for skin and heart rate monitoring with fixed indoor sensing to evaluate the distinction between different users in an indoor building space (Moatassem et al., 2016; Chaudhuri et al., 2018; Salamone et al., 2018). Lopez et al. (2018) further developed a neck-mounted wearable thermo-conditioning system that directly cools or warms the human body based on the estimation of the user's thermal sensation by biological information (such as real-time heart rate interbeat interval recorded at the earlobe). However, the efficacy of this method is not validated and is similarly facing challenges in application.

The interest in wearable solutions for thermal comfort in the built environment has grown massively, but the challenges are still manifold. As noted in several examples, scalability presents one of the main limitations. To date, the deployment of wearable technologies is done for a limited number of participants under the supervised experimental setting due to the challenges in design and performance. The limitation on the ease of use (such that participants are willing to wear the devices for an extended amount of time), reliability, and robustness under the dynamic conditions of use and data communication restrictions significantly contribute to the scalability challenge. Additionally, although the costs of wearables are lower than standard references for thermal comfort assessment, they are still significantly high compared to other IoT monitoring solutions and cannot be regarded as "low-cost" sensing. In addition to the challenges of scalability, many critical research questions still hold: There is an urgent need to assess the wearable devices developed in the commercial market to ensure that they provide accurate physiological, environmental, and behavioral parameters for thermal comfort assessment. This involves quantifying the biases associated with individual sensing as opposed to fixed/portable IoT environmental sensors. Additionally, in the absence of universal heat indices for personal exposure (Notley et al., 2019), it is crucial that future research assess the best way to describe the personalized data obtained from wearables in a comprehensive and consistent way. Accordingly, in addition to more progress on sensor solutions for monitoring personal exposure and comfort, there is a need for a

quantitative specification of the performance of wearable devices with respect to thermal comfort.

5 Challenges of multi-scale and interdisciplinary IoT

This paper has covered studies focused on the use of IoT for thermal comfort and air quality at three scales: urban, building, and human levels. The value achieved in each of these scales through the use of IoT is maturing, yet important practical challenges persist that impede the maximization of its potential through the convergence of data from the three domains. This section outlines the major barriers to the research and industrial application of IoT for addressing human thermal comfort and air quality issues at the urban, building, and human scales. The consistent theme that was found in the literature was the lack of interoperability and communication between various systems, industry stakeholders, and research cultures.

5.1 Data silos

The literature shows that IoT data sources are commonly found in various self-contained systems that collect, process, and visualize the collected, continuous IoT streams for specific purposes (Tang et al., 2019). The lack of data integration and interoperability in the United States building industry has shown to cost up \$15.8 billion per year (Gallaher et al., 2004). There are several examples in the literature of manual data convergence after data collection (Monnot et al., 2016b; Wilhelm et al., 2016; Benita et al., 2019; Ojha et al., 2019), but only a handful of studies used a combination of multi-scale sensing in an integrated manner (Pantelic et al., 2019; Jayathissa et al., 2020; Luo et al., 2021; Miller et al., 2021). Pantelic et al. (2019) and Luo et al. (2021) used indoor and outdoor air quality data measured with devices from different vendors stored in separate databases. The outdoor dataset stored in one database had a machine learning-based real-time correction factor applied while indoor sensors did not. Since inputs from both sensors were required for the calculation of performance indicators authors had to use a set of sensors placed next to each other to obtain correction factors necessary for the meaningful comparison. The necessity to provide correction factors as a part of data integration represents a significant challenge in upscaling even for the same type of data. The isolated or self-contained nature of these data sets results from fragmented implementations of IoT solutions from different vendors and stakeholders that create parallel, independent databases of data.

Jayathissa et al. (2020) developed a method to converge Micro Ecological Momentary Assessment of thermal comfort with environmental IoT sensing. The convergence of these two

data silos creates opportunities for the development of personal comfort models. Miller et al. (2021) developed a data convergence platform that combines momentarily thermal comfort assessment with Cozie Fitbit smartwatch, environmental data collection with outdoor and indoor IoT sensing network, and location data collection using Bluetooth technology mapped spatially and temporally to Building Information Model. Predicting which building zones would best fit a particular individual based on data inputs suggested by Miller et al. (2021) required significant effort to overcome data silos and integration issues. Although papers by Jayathissa et al. (2020) and Miller et al. (2021) represent significant steps towards the development of personal thermal comfort models both studies are experimental and use enrolment of a controlled number of participants. Scalability to a large population and the necessity to dynamically respond to changes in data collection are still work in progress.

5.2 Technology and industry silos

The primary reason data silos occur in the IoT domain is the lack of incentive for industry players to create solutions that emphasize data exchange and interoperability (Gallaher et al., 2004; Shen et al., 2010; Costa et al., 2013). The various stakeholders at each scale (urban designers, building architects, engineers and operations, and individual consumers) are not demanding solutions that require the convergence of data, mostly because these markets do not exist yet. Industry silos are well depicted in the design of natural and hybrid ventilated buildings where although government-owned and operated ambient air quality stations are distributed across the whole United States, a review of the pollution patterns based on those measurements is not considered, while values for indoor air quality are defined but monitoring is not required (ASHRAE Design Guide for Natural Ventilation).

A good example is the building management system (BMS) industry. Each modern commercial building with a BMS system is essentially containing an IoT system that could be a source of environmental sensor data that could enhance the data from other scales and applications (Miller et al., 2021). The interplay between lack of standardized naming schema (Quinn and McArthur, 2021) that allows making sense of the data by other machines and/or humans and any guidelines for strategic sensor placement that would generate meaningful data (Balaji et al., 2018; Wang et al., 2018; Quinn et al., 2020). This situation is increased further with the ubiquitous deployment of sensors beyond traditional BMS. The lack of unified meta-modeling schemas results in huge amounts of IoT data available, but with a limited practical overlap of use due to interoperability problems (Balaji et al., 2018; Wang et al., 2018; Quinn et al., 2020).

5.3 Research silos

Reviews of IoT implementation exclusively address urban scale (Kumar et al., 2015; Morawska et al., 2018), building scale (Kumar et al., 2016; Schieweck et al., 2018), or personal scale (Mamun and Yuce, 2019). We located only two research papers Pantelic et al. (2019) and Luo et al. (2021) that address the application of IoT environmental sensing on multiple scales simultaneously. This suggests that the current research landscape fosters traditional delineation between urban, building, and personal scales as separate research fields with marginal attempts to perform research across scales. This is an interdisciplinary field comprising of environmental, building, communication, and artificial intelligence scientists. Research communities use diverse methodologies, and experimental approaches, rank the importance of factors differently and have their own set of conferences and journal outlets as well as cultures for publication. From a technical perspective IoT environmental sensing has its foundation in computer science and electrical/electronic engineering disciplines that value conference publications hosted by the Association for Computing Machinery (ACM), where a majority of the technical innovation from the hardware, software and data science aspects of wide-scale IoT deployment is made. The conventional built environment, engineering, and air quality domains, on the other hand, value journal publications and often do not put the same emphasis on conference publications. Additionally, urban scale and building scale phenomena is kept separate by addressing exclusively ambient air quality as an environmental problem and indoor air quality referring to air inside the buildings as an engineering problem. This difference creates a gap between these categories of research that impedes the progress of interdisciplinary innovation.

5.4 Privacy, security, and liability

One may imagine that full-scale IoT integration and alignment could occur by breaking down the silos. This convergence would create a plethora of opportunities to solve major problems related to air quality, human health, and the other benefits that are discussed in this paper. For example, having the building management system understand the metabolism and activity level of its occupants using wearable devices would highly improve the ability of that building to provide thermal comfort. However, these converged data can also be used in ways that are not in the best interests of the humans involved (Atlam and Wills, 2020; Tawalbeh et al., 2020). As these scales become increasingly interconnected, challenges will increase around data ownership, data storage, access, privacy protection, and security. This ongoing digitalization must be performed with strong security and privacy guarantees that permit occupants to trust the new features and services that smart buildings offer to them. Furthermore, an

important question arising from this is whether access to the new information created by these convergences produces liability to act on the part of governments and companies. The present legal and institutional laws do not create liability for municipalities, building owners, and managers. Any future changes towards increased liability will need to be accompanied by additional guidance.

5.5 Human-data interaction

People become aware of pollutants in the air when concentration levels go beyond the odor thresholds (Wolkoff, 1998; Wolkoff and Nielsen, 2001). Considering that people do not have great sensitivity to air pollution detection meaningful communication about ambient and indoor air quality represents an important tool that will help people to modify behavior and reduce their exposure (Wargocki and Da Silva, 2015). With the increased spatial and temporal granularity of air quality information, IoT sensing enables real-time data communication.

On an urban scale, air quality information is communicated to occupants using Air Quality Index (AQI) connects air pollution and health (Plaia and Ruggieri, 2011). A traditional approach to the relationship between building scale data and stakeholders was to silo them apart to avoid any potential occupant's concerns and complaints (ASHRAE, 2010). ASHRAE Standard 62 (Castell et al., 2015) does not address the communication of building indoor air quality and thermal comfort information to occupants. Recently developed measurement protocols WELL (Manikonda et al., 2016) and RESET (RESET, 2022) suggest communicating data to occupants but they do not specify how. A dashboard's objective is to convert measured data into meaningful information for stakeholders (Marini, 2011). To be effective dashboard design have to match specific users (Marini, 2011; Petersen et al., 2017). An environmental dashboard designed for community education and awareness resulted in community-level energy and water savings (Petersen et al., 2017). A dashboard designed for building managers enables them to effectively detect malfunction and save energy, but the same dashboard (Timm and Deal, 2016) had an insignificant impact on occupants' energy-related behavior (Timm and Deal, 2016). A properly designed dashboard can be a critical tool in exposure reduction, but there is a lack of research that connect dashboard design and targeted group behavior modification. With the increased data volume, effective communication with the stakeholders is an essential question that requires further research.

6 Opportunities of multi-scale and interdisciplinary IoT

6.1 Data convergence technologies

To address the data silo issue, there are several key technological research directions that can work towards

breaking down these silos. The integration of these data streams from each scale and domain is often first approached through segmentation and clustering techniques that seek to group similar behavior based on the values of the sensor readings (temporal) and the location in which the reading was taken (spatial). This type of effort is exemplified in a previously discussed Singaporean study of 50,000 students carrying IoT environmental and personal fitness devices meant to segment behavior related to activity, transport and environmental exposure patterns (Wilhelm et al., 2016). These segmented data insights were applied to other studies focused on air-conditioning (human-building data convergence) (Happle et al., 2017), routing (human-urban) (Monnot et al., 2017), and emotional well-being (Monnot et al., 2017; Benita et al., 2019). Another key study focused on the collection of various types of wearable sensors to study the influence of the urban setting on a physiological response (Blanco-Novoa et al., 2018). Both studies included a series of unsupervised machine learning steps that focused on dividing the data into spatio-temporal regions for the purpose of human understanding and interpretation. The methods created in these studies essentially seek to find the overlap between the human-building-urban scales.

Theoretically, individualized wearable data (human), the BMS (building) and city-scale environmental air quality (urban) sensors could be connected through a process of tagging convergence using these techniques as well. Metadata tagging could also start fixing information related to the spatial aspects of the IoT sensors. These systems would automatically identify data schema/model and metadata to provide context to data collection (physical installation information, orientation, nearest relevant building features like windows, ventilation diffusers, occupant(s)). From this effort, projects such as the BRICK schema have emerged (Balaji et al., 2018). BRICK allows for a consistent framework for IoT metadata tagging that enables the preservation of point hierarchies and relationships between points. The aptly named Mortar platform integrates with BRICK to test various types of analytics approaches such as automated fault detection and diagnostics (Fierro et al., 2018). The Plaster platform rounds out the stack is an open-source platform for testing various IoT metadata classification strategies (Koh et al., 2018). The BRICK schema continues to be developed to incorporate new types of data including occupants (Chamari et al., 2022; Luo et al., 2022) and building information models (BIM). There are also crucial discussions forming around the convergence of BIM and geographic information systems (GIS) (Zhu and Wu, 2022). The air quality field has also attempted to standardize the terminology of levels of data processing for various scales of implementation (Schneider et al., 2019). Portability, reproducibility, and generalizability can all be used to describe efforts in this direction. These descriptors will only be possible once the IoT networks from the various sources

outlined here are well-organized, consolidated and scalable. The development of these type of data standards are promoting the scalability and usability of the data from the larger building stock.

An example of converged use of multiscale data was demonstrated in Pantelic et al. (2019) during the episodes of wildfire air pollution where IoT environmental sensing had a crucial role in characterizing building resilience or determining natural ventilation potential and utilization (Luo et al., 2021). With the increase in global air pollution and associated negative impacts on health (Silva et al., 2017) ubiquitous sensing offers a unique opportunity to better design and operate building enclosures, especially in naturally ventilated or mix-mode buildings—a topic largely unexplored to date.

6.2 Catalysts for market change

Disruptive and transformational technology like IoT environmental sensing requires catalysts to propel market transformation. Policies can serve as necessary catalysts. For example, the State of California has legislated Wildfire Smoke Clean Air Centers for Vulnerable Populations (Legislature, 2020), and Seattle, Washington instituted clean air shelters. Quantification that buildings actually operate as clean air shelters is necessary, where continuous monitoring enabled with IoT sensing offers a transition from qualitative to quantitative. Certification schemes summarized in Table 1 award points for implementation of IoT-based continuous monitoring to characterize building operation. Alongside additional points, IoT-based continuous monitoring could become a cost-effective performance evaluation solution that can replace the current sporadic, complex and expensive evaluations by a certified assessor. These two benefits acting in synergy represent another market catalyst.

6.3 Interdisciplinary scientific research opportunities

Research domains can improve their analysis of different scales through interdisciplinary research in terms of laboratories, departments, conferences, and other key dissemination venues. From the technical perspective, one of the key immediate research opportunities across all scales includes standardization of sensor accuracy, interoperability, testing protocols, and data quality. This innovation is especially necessary for TVOC sensors where both accuracy and calibration require standardization and particulate matter sensors where differences between laboratory and field calibration need to be addressed. Another important

multidisciplinary research opportunity includes the validation of guidelines for sampling and analytics of human-related metrics across the three scales. The current absence of evidence-based guidelines for sampling and analytics of human-related metrics (e.g., thermal comfort, exposure, health, and productivity) across the three scales impedes the successful adoption of IoT technologies. The emerging guidelines for building IoT sensing (e.g., RESET, WELL v2) would benefit from the establishment of the performance metrics and from the ability to convert data into simple indicators that can be optimized for human exposures and experiences. A significant challenge to bringing these opportunities to realization is the lack of research grants opportunities that will focus on the value of interdisciplinary problems and the incentive structure of academic careers. With the industry moving at a faster pace than scientific evidence, these domains are risking creating a situation where the implementation of this technology will not realize its full potential.

6.4 Seeking consent from individuals and privacy technologies

One of the key questions is how data created by these different scales is going to interface with the humans that create them. There is much risk abatement and security that can be gained from large-scale urban sensing, but the opposite can also be true when unintended applications are derivations that create risks from the data sources. Just as no one envisions the apps that exist on smartphones today, no one realized the risks of surveillance from ubiquitous smartphone cameras. But just as with smartphones, IoT and being able to distribute it to continuous sensing will have benefits that far outweigh the risks that address health, energy security, social well-being and happiness. A solution for the integration of various scales of data includes the development of technologies and privacy standards that give users the choice as to what part of their data can be used for which purposes. The COVID-19 crisis is a great example of a situation in which the convergence of various data sources from IoT could assist in the ability to mitigate the spread of the disease and the privacy tolerances of people who provide those data are changed due to the potential impact those data convergences could have.

6.5 Data visualization and human-in-the-loop interactive technologies

In order for cities, buildings, and humans to make informed decisions based on shared information—they need to achieve more advanced means of communication with each other. Air quality information is challenging to interpret (Kovalerchuk et al.) considering that it consist of real time multidimensional

matrix (e.g., CO, NO_x, SO_x, PM_x). Besides multidimensional matrix of pollutants, citizens cannot rely on their experience because unhealthy thresholds defined by air quality standards might not be detected by olfactory systems (Wolkoff 1998; Wolkoff and Nielsen 2001). To make this complex decision making problem easier for citizens to understand and ultimately adjust their behavior to reduce exposure, traditional way to inform the public about the ambient or urban scale air pollution is through using air pollution indexes like the Pollution Standard Index (PSI), Air Quality Index (AQI) by EPA or revised AQI (RAQI) (Plaia and Ruggieri 2011). AQI, for example, converts the measured level of a single air pollutant (e.g. PM_{2.5}) into an index from 0 to 500, and based on the value of the index air quality is assigned to one of six categories that range from “Good” to “Harmful.” For different levels of citizen’s sensitivity to air pollution and for each category AQI would recommend certain behavior (e.g., people with lung problems should stay at home and close to windows). Due to the limited number of measurement stations, large areas on the urban scale would be described with the single number.

Visual analytics is an important component for humans to make decisions based on the data generated. Several visual analytics paradigms are available with the most popular giving guidance on how the data are presented (Schneider et al., 2019). Air quality information presented on a map is effective way to communicate air pollution information (Zhou et al., 2016) especially comparing to the tables with numbers (Chen 2019). An interactive web-based geo-visual analytics platform with Coordinated Multiple Views were explored for air quality visualization using geographical map, a linear timeline, a heatmap, and adjacent small multiples maps representing changes associated with timestamps (Wu et al., 2020). Several geo-visual analytics based city dashboards were compared in Jing et al. (2019) with a focus on users observation of spatio and temporal changes, but not if presented information lead to behavioral changes that caused reduction of exposure. Bachechi et al. (Kovalerchuk et al.) reviewed 6 air quality platforms across eight features and showed that only two of those platforms actually suggest actionable items general public can perform to reduce exposure. Effective communication of data collected through environmental sensing is especially important for air quality, as our olfactory systems cannot detect all air pollutants. A number of dashboards were studied in Jing et al. (2019) classified into operational, analytical and strategic dashboards from the perspective of air quality information presentation and forecasting. Although display of the air quality information can be public, intended stakeholders can be city planners, regulatory bodies, or citizens. It is very important to understand who will be the users and what is the intended outcome of the use. If general public needs to consume information presented on the dashboard it is important to present that information in a way useful for citizens. A recent study analyzed whether people noticed or used dashboards in the

first place and what attributes contribute to a higher probability of human interaction (Granderson et al., 2011).

Several methodologies have surfaced in recent years from the visual analytics community focused on the user testing of building performance dashboards. Benchmarking against the thresholds, visualizing quantities as contour (heat) maps and dashboards.

IAQ visualization with occupants text message notification resulted in improved understanding of occupants understanding of IAQ in their homes (Moore et al., 2018). Kim and Li (2020) proposed a new conceptual framework to increase IAQ awareness, and understanding of the received information that can potentially result in meaningful actions. Kim et al. (2020) designed a child-friendly interface prototypes for IAQ visualization. In the follow-up study Kim et al. (2019) reported that children assess IAQ through a sense of smell, visual cleanliness, and thermal comfort and that these aspects need to be incorporated in the visualization tool to be effective, that were incorporated in AirBuddy, app for indoor and outdoor air quality visualization (Kim et al., 2022). Kim and Paulos (2010) and Kim et al. (2013) developed IAQ visualization tool that enabled IAQ awareness increase and promoted changes in occupant behaviour that resulted in reduction of their exposure. This work showed potential that beyond increasing awareness and understanding IAQ visualization can lead to people’s behavioural changes and reduction of exposure. Some recent advancements utilized Virtual Reality to visualize IAQ (Natephra et al., 2019). Literature review of IAQ visualization proposed a framework that allows the definition of needs, assets, and appropriate tools for visualization for virus risk monitoring (Niedrite et al., 2022).

The last component of this human-system interaction is the ability of humans to give their subjective feedback information for various purposes. In the thermal comfort studies, in particular, it is well-understood that purely environmental or physiological approaches are not fully equipped for characterizing comfort conditions in urban spaces and an understanding of the dynamic “human parameter” (including the psychological adaptation, cultural and climatic history, environmental stimulation and expectations) is necessary for determining the comfort implications for the people (Nikolopoulou et al., 2001; Porter et al., 2004). However, the collection and analysis of subjective feedback is typically a tedious or expensive task. Accordingly, the integration of the momentary assessment with IoT techniques could revolutionize how the data in the built environment is tagged with information generated by occupants. Smartphone and smartwatch apps can be leveraged to create ecological momentary assessments that prompt a user to provide instantaneous feedback in an elegant and least-intrusive way (Moskowitz and Young, 2006; Jayathissa et al., 2020; Sae-Zhang et al., 2020; Quintana et al., 2021; Abdelrahman et al., 2022). An example of wearable devices that can be leveraged to create *ecological momentary assessments* that prompt a user to

TABLE 2 Summary of the key review findings.

	Urban scale	Building scale	Personal scale
Measured quantities	<ul style="list-style-type: none"> ● Tair, RH, MRT, Vair, CO, NO₂, SO₂, PM_{2.5}, PM₁₀, O₃, except Pb all aspects required by NAAQS 	<ul style="list-style-type: none"> ● Tair, RH, CO, CO₂, NO₂, SO₂, PM_{2.5}, PM₁₀, O₃, TVOC overall as a mixture of all constituent gases 	<ul style="list-style-type: none"> ● Environmental: T, RH, CO₂, PM, TVOC, NO₂, O₃ biometrix, location
The key objectives	<ul style="list-style-type: none"> ● Mapping of air quality and thermal environment (general public, urban planners, policy makers) ● Identification of air pollution hotspots 	<ul style="list-style-type: none"> ● Characterize building performance ● Validate compliance with thermal environmental requirements (e.g., ASHRAE Standard 55) ● Validate compliance with indoor air quality requirements (e.g ASHRAE Standard 62.1 and 62.2) 	<ul style="list-style-type: none"> ● Measure personal thermal/air pollution exposures ● Momentary perception assessment thermal/air quality ● Crowdsourcing for pollution hotspot identification ● Crowdsourcing for thermal environment identification
Novelty and improvements compared to established methods	<ul style="list-style-type: none"> ● Significantly reduced size of stationary sensing ● Mobile sensing mounted on the vehicles ● Crowdsourcing of information from different sources ● Increased measurement granularity ● Low cost and accessible ● Information used by general public ● Improve 2D and 3D air quality mapping 	<ul style="list-style-type: none"> ● Non intrusive measurement method ● Continous characterization of thermal environment and indoor air quality ● Increased measurement granularity ● Reduced cost of indoor environment characterization 	<ul style="list-style-type: none"> ● Adequate personal thermal exposure representation ● Adequate personal air pollution exposure representation ● Momentarily assessment of thermal comfort ● Momentarily assessment of perceived ambient and indoor air quality
Technical and scientific challenges to be addressed	<ul style="list-style-type: none"> ● Optimal spatial sensor granularity and placement across different urban typologies ● Field calibration of low-cost sensors ● Quality control of converging crowdsourcing data with stationary measurement stations ● Development of low-cost Pb sensor to fully represent air pollution matrix proposed by NAAQS ● Calibration of low-cost measurement in the field ● Inclusion as standard measurement technique ● Methods for environment description ● Low-cost wind speed data accuracy improvement ● Combining data from scales to better design and operate buildings ● Understanding environmental exposures and it's relationship to human health including full set of environmental factors that influence it ● Development of personalized thermal comfort model ● Development of personalized exposure model 	<ul style="list-style-type: none"> ● Validation of existing sensor placement strategies ● Standards for sensor accuracy, repetability and reliability ● Development of calibration and drift correction methods ● Development of velocity sensors ● Development of sensors for characterication of radiant heat exchange ● Frequency of data collection ● Develop sensor naming schema to automate data analysis ● Accuracy of sensing network vs. accuracy of a single sensor ● Development of capability to measure individual VOC ● Understand if proxy sensing can be upscaled and under which conditions 	<ul style="list-style-type: none"> ● Development and validation of sensor placement methods ● Standards for sensor measurement accuracy, sensitivity, selectivity and drift ● Calibration methods ● Converging multiple data streams to understand relationship between exposure and behaviour ● Scalability of momentary feedback
Obstacle for multiscale convergence	<ul style="list-style-type: none"> ● Traditional lack of data integration and interoperability in the building industry ● Differentiation between standards and guidelines used in design and operation that provide market forces for integration ● Lack of standardized naming and unifie meta-modeling schemas ● Strong separation of research fields driven by funding sources and publishing communities 		

provide instantaneous feedback in an elegant way (Moskowitz and Young, 2006; Sae-Zhang et al., 2020; Quintana et al., 2021; Abdelrahman et al., 2022). An example of using smartphone apps is discussed by Liu et al. (2018) where subjects are prompted by their cell phone (through a text reminder) to take an online survey and report their “right now” thermal comfort as often as possible.

7 Discussion

The current review covers the implementation of IoT environmental sensing on urban, building, and personal scales from the data convergence point. We have identified scientific and engineering advancements and challenges on each scale and between the scales. The state-of-the-art knowledge, current gaps, and necessary research directions are below. The results are summarized in Table 2.

There are several commonplace issues for each scale. On all three scales, there is a need to develop guidelines on what to measure, where and with what density to place sensors, how frequently we need to collect data, what is required accuracy, and how to utilize the collected dataset to consider data convergence. On urban and building scales, several air pollution and thermal environment sensors have reached acceptable performance, sensors for some of the sensors needs to be developed to capture a sufficient number of air pollution indicators and some air pollution sensors require accuracy and reliability improvements. IoT sensors for thermal environment characterization need the development of capabilities to measure air velocity and radiant aspects of heat exchange at a large scale and at a low cost. All the listed developments are necessary to advance and upscale adoption of this new technology.

Urban scale air quality and thermal environment management through IoT sensing is a promising line of research and innovation. Recent advances in IoT sensing and information technologies offer an opportunity to create insights from many urban environmental measurements at reduced cost and effort. On an urban scale, stationary and mobile sensors (vehicles, smartphones, portable, wearable) are used to characterize the environment. Presently, worldwide legislation linking urban air pollution and heat levels, population exposures, and health outcomes do not sufficiently consider data collected by low-cost IoT sensors. To be incorporated into existing guidelines for urban climate characterization and ultimately legislation, it is necessary to set the right set of indicators which is supported by optimal monitoring guidelines that contain information about what/how to measure, how often, and where, and minimal data quality standards as well as how to utilize the acquired dataset.

Building scale IoT sensing is gaining traction through requirements of building certification schemes. The low-cost IAQ sensors need development to capture air pollutants of concern (e.g., individual VOCs, formaldehyde, ultrafine

particles, various inorganic gases, etc.). The development of indexes for building benchmarking considering continuous monitoring capabilities represents areas with the highest research priorities. Proxy sensing is a promising emerging field that maps environmental signatures to different activities, with insufficiently understood scalability at this point.

Contrary to the conventional sensing units, which were often initiated from the research domain and later entered the commercial market, the wearable IoT movement is primarily led by the commercial sector with research trying to catch up. Personal scale sensing enables refined assessment of environmental exposures and development of relevant models, but a number of questions regarding the hardware, accuracy, measurement location considering personal air pollution cloud or thermal boundary layer and data convergence need to be resolved first.

Converging data of different types and from different sources represent a challenge that a few studies attempted to address. Developing practical frameworks to enable data integration is a research and engineering priority centered around the practical application of scaling data convergence. The development of standardized naming schemas is necessary. The current literature review identified a significant disconnect between each scale and significant inter-scale data underutilization. Traditional inter-scale differentiation is strongly supported by academic research with only a few studies that show how data from one scale can promote a more efficient operation related to another scale. Privacy, security, and liability are issues of concern, although more detail analysis was outside the scope of the current review. Some recent studies and sensing guidelines suggest that IAQ data should be communicated to people, but it is still not known what the most efficient ways are to present data and what behavioral outcomes they might produce. While there are immediate opportunities to enhance the uptake of IoT sensing technologies across cities, buildings, and humans by overcoming data, technological, and research silos, fundamental scientific and engineering developments are still necessary.

On the scientific forefront, the most important path forward is development of personal thermal comfort and air pollution exposure models that will provide deeper understanding of how environment impacts health, productivity and comfort. One of the major issue is basic understanding of what quantities we need to include into personalized thermal comfort model that will enable proper mapping of comfort as a state of mind and measurable thermal parameters both environmental and biometric. Another extremely important scientific issue is understanding relationship between air pollution exposure and human health and productivity. This area has received significant attention over the years, linking large scale population health survey to remote air quality stations. Personal sampling and manual association of other types of data to the measured exposure dataset is a tedious process are resulted in limited data sets. We

are still missing full understanding of the set of air pollutants and their respective concentrations that have acute and chronic health effects and how to link personalized exposure to health impacts. These are the two most significant advancement that will require technology enabled advancements in science because we need ability to generate large data sets. Personal exposure and thermal comfort models represent a paradigm shift and their development should be one of the scientific priorities. A wide range of data analytics, machine learning, and statistical methods are being developed to support the use of generated data sets.

At the engineering forefront, converging occupant feedback and environment characterization on urban, building, and personal scales will help us to tune building operation setpoints to maximize the thermal comfort of a particular occupant cohort and reduce their exposures.

Author contributions

JP—concept creating, writing, reviewing and leading the process. NN—concept creating, writing, reviewing.

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CM—concept creating, writing, reviewing. FM—concept creating, writing, reviewing. JL—writing, reviewing. DL—concept creating, writing, reviewing.

Conflict of interest

JP was employed by Delos Living LLC.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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