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A Review of the Use of Wearables in Indoor Environmental Quality Studies and an Evaluation of Data Accessibility from a Wearable Device

Belal Abboushi, Sarah Safranek, Eduardo Rodriguez-Feo Bermudez, Shat Pratoomratana, Yan Chen, Michael Poplawski and Robert Davis*

Pacific Northwest National Laboratory, Richland, WA, United States

An understanding of indoor environmental quality (IEQ) and its effects on occupant well-being can inform building system design and operation. The use of wearables in field studies to collect subjective and objective health performance indicators (HPIs) from a large number of occupants could deliver important improvements in IEQ. To facilitate the use of wearables in IEQ studies, there is a need to identify which HPIs should be collected and to evaluate data accessibility from these devices. To address this issue, a literature review of previous IEQ studies was conducted to identify relationships between different IEQ factors and HPIs, with a focus on HPIs that were collected using wearables. A preliminary assessment of data accessibility from a selected wearable device (Fitbit Versa 2) was performed and documented. The review suggested the need to further investigate and collect sleep quality parameters, heart rate, stress response, as well as subjective ratings of comfort using wearables. The data accessibility assessment revealed issues related to missing data points and data resolution from the examined device. A set of recommendations is outlined to inform future studies.

Keywords: wearables, indoor environmental quality, occupant well-being, health performance indicators, data accessibility

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****Correspondence:***
Belal Abboushi
Belal.abboushi@gmail.com

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1 INTRODUCTION

The original energy crisis of the 1970s stimulated five decades of a nearly continuous focus on improving the energy efficiency of buildings. The systems used to provide heating, air conditioning, ventilation, and illumination in buildings continue to be radically transformed by this focus, along with other energy users such as appliances, water heaters, refrigeration units, computers, and other office equipment. Whereas early implementations of energy-efficient building technologies focused on achieving energy savings while maintaining some simplistic measures of performance (e.g., illuminance, temperature, humidity), today's evaluations of building performance strive to account for a more holistic set of occupant experiences.

These occupant experiences are often expressed in terms of indoor environmental quality (IEQ). As embodied in the US Green Building Council's Leadership in Energy and Environmental Design (LEED) Rating System, IEQ includes considerations of indoor air quality, thermal comfort, acoustic performance, quality interior lighting (glare control, color rendering, dimming), daylight exposure, and quality views to the outdoors (USGBC, 2021). Beyond energy savings, the justification for addressing these other attributes includes protecting occupant health; promoting occupant productivity, comfort, and well-being; reinforcing circadian rhythms; enhancing a connection to nature; and facilitating communications.

An understanding of IEQ and its effects on occupant well-being can inform building system design and operation (Bluyssen, 2013). Physical measurements of environmental attributes such as illuminance and sound levels are sometimes used to infer potential effects on occupants, but these inferences typically rely on general relationships between the IEQ measures and the occupant response. These responses can vary by building and occupant type (e.g., workers in an office may have a different response than nurses at a hospital). In field studies, subjective measures such as perceived comfort and satisfaction can be collected, but access to employees and budget constraints usually limit the ability to collect objective well-being indicators such as heart rate and activity level from occupants; these measures combined with subjective responses provide a more complete view of occupant responses to the environment.

Methods and tools that can be utilized in the field to collect both subjective and objective well-being data from many occupants have the potential to improve our understanding of the relationships between IEQ and occupant responses, and ultimately to ensure that energy-efficient building technologies achieve significant savings while supporting occupant needs. Recent studies have begun exploring the use of non-invasive wearable devices, such as smartwatches, for administering micro ecological momentary assessments (μEMAs) (Intille et al., 2016; Jayathissa et al., 2019, 2020a). These devices can also gather objective data on measures such as sleep quality, physical activity, and heart rate; collectively referred to herein as health performance indicators (HPIs) (Allen et al., 2015). While the possibility of more easily collecting these HPIs while occupants are engaged in normal activities holds great promise, it also raises new challenges related to knowing which HPIs to collect, understanding precedents for measuring HPIs using wearables, and ensuring data accessibility from wearable devices.

This article aims to answer two questions: 1) which HPIs should be collected using wearables? 2) how accessible is the data? While there are several types of wearable devices that can be worn on the wrist, chest, as a headset, or as a clip-on sensor (Piwek et al., 2016; Taub et al., 2016), in this article the focus is on wrist or chest-mounted devices that can be worn by occupants while performing daily tasks in a field setting. In **Section 2**, relationships between IEQ factors and HPIs were summarized with a focus on identifying HPIs that can be collected using wearables. Second, data accessibility from a market-available wearable device (Fitbit Versa 2) is documented. Lastly, recommendations for data collection and data accessibility verification are described. The goal is to facilitate the use of wearables in future IEQ field studies where data can be collected from a large number of participants for extended durations. This can further our understanding of dose-response relationships and interactions between IEQ factors.

2 REVIEW OF PREVIOUS STUDIES THAT EXAMINED EFFECTS OF IEQ ON WELL-BEING

Well-being is a broad construct that includes physiological, psychological, and cognitive HPIs such as stress, sleep quality, comfort and satisfaction, mood, and cognitive performance. The relationships between these HPIs and IEQ factors were examined in previous studies (Veitch et al., 2008; Allen et al., 2016; Colenberg et al., 2020) using different approaches. Some of the studies used occupant questionnaires, with or without IEQ measurements (Altomonte and Schiavon, 2013; Allen et al., 2015), while others also included objectively-measured HPIs such as heart rate variability, cortisol levels, and sleep duration (Thayer et al., 2010; Boubekri et al., 2020).

Wearable devices can be used to collect localized IEQ measurements as well as subjective and objective HPIs that traditionally have been limited to laboratory settings or a small number of participants. Some examples include measuring illuminance at the eye, CO_2 in the inhalation zone (Coulby et al., 2020; Salamone et al., 2021), EMAs, and electrodermal activity (Jayathissa et al., 2020a; Zhang et al., 2020). However, to effectively utilize wearables in IEQ studies, there is a need to identify IEQ factors and HPIs that need to be collected (Altomonte et al., 2020), explore the role of wearables for collecting these data, and discuss considerations for data collection. These issues are summarized and discussed through a literature review of previous relevant studies. Given that the focus was on the role of wearables, the review outlined in this section is not exhaustive and does not discuss all possible relationships between IEQ factors and HPIs.

2.1 Identifying Health Performance Indicators That Were Collected Using Wearables

2.1.1 Comfort Ratings

Previous studies examined occupants' comfort and satisfaction to determine comfortable and acceptable levels of different IEQ factors. A detailed questionnaire was often used at a single or few points in time to elicit responses evaluating satisfaction with various environmental factors (Choi et al., 2012a; Heinzerling et al., 2013; Elzeyadi et al., 2017; Park et al., 2019). While many IEQ factors can affect occupant's comfort, a recent analysis of a large database revealed that satisfaction levels were lowest for sound privacy, noise level, and temperature (Graham et al., 2021). While detailed questionnaires can be helpful for general evaluations and for identifying sources of discomfort, they are unlikely to capture temporal variations in comfort and satisfaction as a result of changing IEQ.

To track such variations, EMAs on smartphones or wearables can be used (Wei et al., 2014; Konis and Annavaram, 2017; de Vries et al., 2021; Peeters et al., 2021). μEMAs can provide higher granularity, response rate, and are perceived to be less distracting compared to online questionnaires or EMAs administered on smart-phones (Intille et al., 2016; de Vries et al., 2021). Jayathissa et al. (2020b) demonstrated potential for using μEMAs on a Fitbit smartwatch to record thermal, lighting, and acoustical preferences (5–15 prompts per day). These preferences can be used to identify occupant and space profiles and make comfort predictions that could potentially be used to control building systems.

2.1.2 Sick Building Syndrome Symptoms

Sick building syndrome (SBS) symptoms describe building-related symptoms experienced by building occupants that are relieved or go away after leaving the building. These symptoms can be influenced by environmental and personal factors and can be classified as (1) upper respiratory and mucosal symptoms such as dry or itchy eyes; (2) lower respiratory irritation like cough; (3) neurophysiological symptoms such as headache and mental fatigue; and (4) skin irritation symptoms like itching or reddening (Apte et al., 2000; Bluyssen et al., 2016; Sakellaris et al., 2020). Several studies associated air quality factors such as CO_2, NO_2, nicotine, particulate matter (PM), volatile organic compounds (VOCs), and microbial contamination with SBS symptoms (Erdmann et al., 2002; Menzies et al., 2003; Mitchell et al., 2007; Colton et al., 2014; Azuma et al., 2018). Additionally, air temperature and relative humidity were also linked to SBS symptoms (Arundel et al., 1986; Fang et al., 2004; Seppänen and Fisk, 2006; Wolkoff, 2017). To the authors' knowledge, previous studies have not used μEMAs to check SBS symptoms. This is expected because participants typically report the frequency of experiencing symptoms over the past month using detailed questionnaires (Apte et al., 2000).

2.1.3 Sleepiness

In addition to ratings of comfort and satisfaction, variations in sleepiness can be captured using EMAs. Generally, lighting has been shown to decrease subjective sleepiness, but this response may vary by time of the day (Vetter et al., 2021). One of the studies that had a different conclusion was a 3-weeks study where higher illuminance at the eye led to negative effects on sleepiness in the spring and no effects in the winter (Peeters et al., 2021). This study evaluated sleepiness using the Karolinska Sleepiness Scale (Åkerstedt and Gillberg, 1990) that was completed eight times a day using EMAs on mobile phones. This highlights the importance of capturing temporal and seasonal variations in sleepiness. In addition to lighting, high noise levels can affect self-reported tiredness (self-reported number of yawns in the last 10 min) and motivation, compared to low noise (Jahncke et al., 2011).

2.1.4 Sleep Quality

Previous field studies utilized wearables that track activity (actigraphs) to track sleep in relation to variations in light intensity and spectral power distribution (de la Iglesia et al., 2015; Wams et al., 2017; Cain et al., 2020; Peeters et al., 2020). For example, a study by Boubekri et al. (2020) used a wrist-worn device to track sleep duration over a week and found a significant increase of 37 min in sleep duration associated with working in an office that had optimized daylight and views, compared to roller shades. Sleep quality parameters such as duration of deep sleep, number of awakenings, sleep efficiency, and sleep onset latency—all assessed using actigraphy—can be negatively affected by other IEQ factors such as CO_2 levels (Akimoto et al., 2021) and air temperature (Pan et al., 2012; Caddick et al., 2018).

2.1.5 Stress Response

The stress response can be elicited by several IEQ factors. Thayer et al. (2010) examined two aspects of physiological stress, circadian variations in heart rate variability and morning rise in cortisol, for a group of 60 participants working in a traditional or a modern office building. They found that physical features of the work environment such as lighting, views, acoustics, and air quality may affect both physiological stress indicators. In another study, Razjouyan et al. (2020) used a chest-worn sensor to examine the effects of relative humidity in offices on the stress response. They found significant effects of relative humidity on heart rate variability indices while occupants were in the office. Participants that spent the majority of their work time with relative humidity between 30 and 60% experienced 25% less stress, compared to those that spent the majority of their time in relative humidity levels under 30%. The chest-worn sensor also estimated sleep quality, with the authors finding a significant indirect effect of relative humidity on sleep quality, mediated by the stress response.

Other studies have shown that noise levels can affect the stress response. Physiological stress (indicated by skin conductance levels) and respiratory rate increased at higher noise levels, moderated by working experience (Shafiee Motlagh et al., 2018). Furthermore, cognitive stress self-reported using the cognitive stress scale was lower in open offices in a condition with enhanced sound absorption (Seddigh et al., 2015; Colenberg et al., 2020). Other factors such as workstation type and outdoor view type were also found to affect stress response (Kaplan, 1995; Bjørnstad et al., 2015; Lindberg et al., 2018).

2.1.6 Cognitive Performance

Increased CO_2 levels can have negative physiological and cognitive effects (Azuma et al., 2018). Compared to 600 ppm, Satish et al. (2012) showed that the mean score of nine decision-making tasks dropped 12 and 51% under CO_2 levels of 1,000 and 2,500 ppm, respectively. These results are consistent with another study that found VOCs and CO_2 to be independently associated with cognitive scores (Allen et al., 2016). The mechanism by which CO_2 and VOCs affect cognitive performance remains unclear.

Lighting and access to views can affect cognitive performance. A previous study reported 26–62% higher cognitive function scores across the nine domains of the strategic management simulation test in an office with electrochromic glazing compared to roller blinds (Boubekri et al., 2020). These results are consistent with the results of another study that found improvements in working memory and inhibition in setting with electrochromic glazing or mesh shades, compared to blackout shades (Jamrozik et al., 2019). Using electric lighting only, Ru et al. (2019) found significant improvements in reaction speed at1000 lux compared to 100 lux at the eye.

It is important to note that most previous studies assessed cognitive performance using computer-based tasks. Some studies,

TABLE 1 | A summary of subjective and objective HPIs that were collected in at least one IEQ study using wearables. HPIs collected using smartphones are included for reference.

HPIs	IEQ factors	References	Wearable devices used in corresponding studies, respectively
Self-reported thermal comfort	Air temperature and relative humidity	Sanguinetti et al. (2016)[a]; Konis and Annavaram, (2017)[a]; Li et al. (2017)[a]; Jayathissa et al. (2020a)[b]; Kallio et al. (2020)[a]	Fitbit Versa
Self-reported visual comfort	Illuminance, distribution, and spectrum	Wei et al. (2014)[a]; Jayathissa et al. (2020b)[b]	Fitbit Versa
Sleepiness/ alertness	Illuminance, distribution, and spectrum	Zhang et al. (2020)[a]; Peeters et al. (2021)[a]	-
	Air temperature	Tham and Willem (2010)	-
Heart rate	Air temperature	Choi et al. (2012b)[c]	Sensor by Vernier (model HER-BTA)
	CO_2	MacNaughton et al. (2016)[b]; Azuma et al. (2018); Fisk (2019)	Basis B1 watch
Sleep quality	Air temperature	Pan et al. (2012); Caddick et al. (2018);	-
	Illuminance, distribution, and spectrum	van Bommel (2006); Boubekri et al. (2014)[b]; Boubekri et al. (2020)[b]; Caddick et al. (2018); Cain et al. (2020)[b]	Actiwatch-L Minimitter, ActiGraph wgt3x, Actiwatch Spectrum Plus/2/L
	Sound type and level	Caddick et al. (2018)	-
	CO_2	Akimoto et al. (2021)[b]; Caddick et al. (2018)	Various actigraphs were used in studies reviewed by Akimoto et al. like Fitbit Charge 2, Sensewear Armband, and Fitbit Alta 2
Stress response	Illuminance, distribution, and spectrum	Zhang et al. (2020)[b]	Empatica E4
	Air temperature	Pigliautile et al. (2020)[c]	BioHarness 3.0
	Relative humidity	Razjouyan et al. (2020)[c]	EcgMove 3
	Sound type and level	Jahncke et al. (2011); Medvedev et al. (2015)[c]; Aletta et al. (2018)	NeXus 10 device
Cognitive performance	Air temperature	Boubekri et al. (2020)	-
	Illuminance, distribution, and spectrum	van Bommel (2005); Jamrozik et al. (2019); Ru et al. (2019); Boubekri et al. (2020)	-
	Sound type and level	Kjellberg and Landström (1994); Smith-Jackson and Klein (2009); Jahncke et al. (2011)	-
	CO_2	Satish et al. (2012); Allen et al. (2016); Du et al. (2020)	-
	VOCs	Allen et al. (2016)	-
	$PM_{2.5}$	Laurent et al. (2021)[a]	-

[a]*Denotes studies that used smartphones.*
[b]*Denotes studies that used a wrist-worn device (e.g., a smartwatch) to collect HPI.*
[c]*Denotes studies that used a chest-worn device to collect HPI.*

outside the IEQ research domain, explored administering cognitive tests using wrist-mounted devices, smartphones, and tablets to overcome challenges related to administering cognitive tests in field studies and to allow for more frequent assessments of cognitive performance (Matsangas et al., 2017; Moore et al., 2017; Arsintescu et al., 2019; Koo and Vizer, 2019; Laurent et al., 2021). Currently, the use of wearables for cognitive tests limits the types of cognitive tests that can be administered, but this may change as more cognitive tests are developed for wearables.

2.1.7 Summary

Table 1 summarizes the studied relationships between IEQ factors and HPIs. This table does not show all possible relationships and does not suggest that a causation relationship was demonstrated, but it highlights objective HPIs that were collected using wrist or chest-mounted devices, as well as subjective HPIs that were assessed using EMAs from wearables or smartphones. Based on this table and the reviewed studies in **Section 2.1.1** through **Section 2.1.6**, a few key points can be noted:

- Wearables were used in previous IEQ studies to collect several HPIs including sleep quality, heart rate, heart rate variability, and subjective responses.
- In several cases, the same HPI is affected by multiple IEQ factors. For example, sleep quality can be affected by lighting, CO_2, noise level, and air temperature. This suggests that studies aiming to examine the effects of lighting on sleep quality should consider potential

impacts of other IEQ factors as well as possible interaction effects between the IEQ factors.

- There is a need for a more holistic research model that addresses other factors, interactions, and combined effects (Bluyssen, 2020). Other stressors that need to be addressed include psychological, work-related factors, social stressors, and personal characteristics (Bluyssen et al., 2011).
- Because of the complexity in the relationships, it is important to explore how data from wearables can augment existing data collection tools, e.g., online questionnaires, to provide a comprehensive understanding of IEQ-HPI relationships.
- Lastly, most studies did not discuss the process and criteria used for the selection of wearable devices. This information is needed to help researchers select suitable devices and effectively utilize them.

2.2 Data Collection Considerations

2.2.1 Localized IEQ Measurements

The spatial and temporal sampling resolution needed for IEQ measurements will vary based on the research questions and objectives. As discussed by Parkinson et al. (2019), spatio-temporal sampling is limited by the logistical challenges of characterizing different IEQ parameters with significant variability in time and space scales. Physical features of the space or activities of the occupants may also limit the sampling resolution of IEQ measurements as it is important to avoid any distraction or hindrance to participants. Previous studies measured IEQ data at different spatial resolutions ranging from localized measurements from wearables to point-in-time measurements using a handheld device or IEQ carts (Heinzerling et al., 2013).

Wearable devices offer the highest spatial resolution, continuously monitoring IEQ conditions experienced by individual participants as they move throughout multiple rooms or buildings (Figueiro et al., 2019; Boubekri et al., 2020; Cain et al., 2020; Peeters et al., 2020). The use of wearable devices to sense IEQ conditions provides advantages over fixed sensing stations in spaces with high spatial and/or temporal variability (Adamsson et al., 2019; Clements et al., 2019). Personal light exposure is one of the most common IEQ parameters collected via wearables, but it is also possible to measure and track temperature, relative humidity, CO_2, and sound level. One study showed that thermal comfort sensors could be placed into a small enclosure and worn on the wrist; those sensors could then control an air conditioning system based on localized comfort estimates (Feldmeier and Paradiso, 2010). Ghahramani et al. (2018) utilized a wearable sensor worn on the chest to measure sound pressure level, CO_2, illuminance, air temperature, relative humidity, and pressure. A large-scale study used sound measurements from a smart watch to examine personal sound exposures (Smith et al., 2020). Salamone et al. (2021) provided a comprehensive review of previous studies that used wearables for IEQ sensing.

Localized IEQ measurements using wearables can be directly related to other occupant-level data such as HPIs but may not be representative of ambient space-level conditions. For studies where participants spend the majority of their time in one location, like offices, a fixed monitoring station at each desk allows IEQ measurements to be captured and related to each participant (MacNaughton et al., 2016; Jamrozik et al., 2018; Clements et al., 2019). For environments where desktop monitoring stations are not feasible, a coarser approach is to use sensor stations on a mobile cart. These stations are often placed in the center of the room, capturing IEQ measurements overtime, or moved between workstations to capture point-in-time measurements of conditions participants may be experiencing (Chiang et al., 2001; Castaldo et al., 2018; Choi and Lee, 2018; Jin et al., 2018).

2.2.2 Other Data Types Needed for a Holistic Evaluation

In addition to measuring IEQ factors and HPIs, previous studies suggested other data types that need to be collected for more holistic investigations (**Figure 1**). Personal and work-related factors can directly affect or mediate effects of IEQ on occupant well-being (Veitch, 2001; Boyce, 2003; Bluyssen et al., 2011; Bluyssen, 2020). The model proposed by Bluyssen et al. (2011) considered both physical and psychosocial stressors and their effects on well-being. Many personal factors can be considered including age, gender, ethnicity, life events, body mass index, consumption of stimulants, smoking, use of medications (allergy, anxiety, melatonin, sleep), chronotype, sleep disturbances, and responsibilities outside of work. Work-related factors include workload, job type, satisfaction with work, perceived productivity, workstation type, and level of education (Bluyssen et al., 2011). These factors can be used in the inclusion or exclusion process and can aid in data analysis to account for potential confounding effects. For example, Boubekri et al. (2020) collected information on the medical status of potential participants and excluded those that had sleep apnea, chronic depression, and other health issues that may affect sleep.

In studies where the goal is to examine relationships between building system characteristics and occupant well-being, it is important to document general building attributes and system characteristics. Building system characteristics can be documented using existing checklists, such as the modified checklist from the Health Optimisation Protocol for Energy-efficient Buildings (HOPE) study (Cox, 2005; Bluyssen et al., 2016) and the Technical Attributes of Building Systems (TABS) survey (Aziz et al., 2010).

2.2.3 Privacy Concerns Related to Wearables

The use of wearable devices in a research study can raise privacy concerns that may affect recruitment and collected responses. Hence, it is important to develop a strategy to address privacy during early stages of research planning. Safavi and Shukur (2014) proposed a conceptual framework that included ten principles for collecting and handling health data from wearables. The principles highlight the importance of transparency in communicating study purpose, the technology used to collect data, data collection procedures, and ownership of collected data.

Paul and Irvine (2014) tested four wearable devices and found that two had policies allowing them to collect information about the user from other sources. Other issues in privacy policies were related

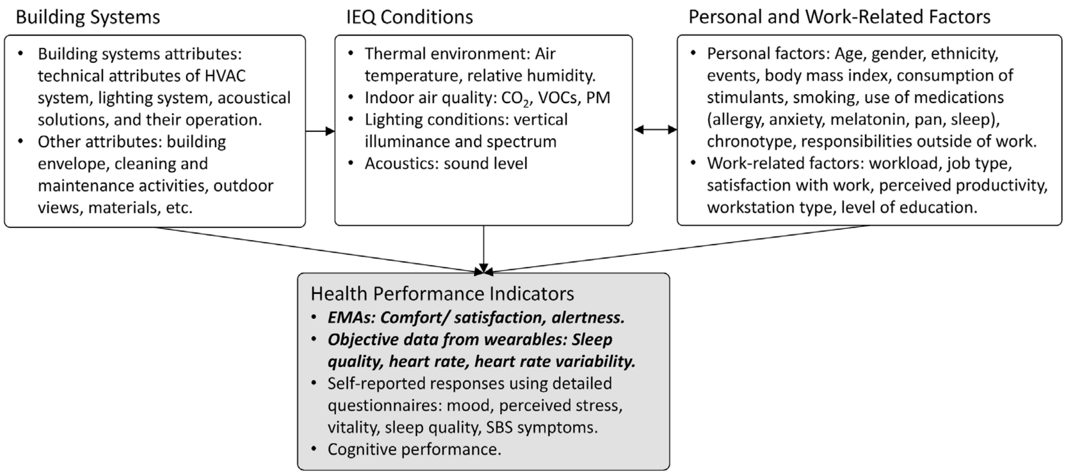

FIGURE 1 | A diagram showing four main data types that are needed for a holistic evaluation of IEQ. Bold italic font denotes HPIs that can be collected from wearables.

to data ownership, right to privacy of data, and whether device manufacturers can use collected data for commercial purposes. In a study that examined privacy concerns for wrist-mounted devices, participants were concerned about the Global Positioning System (GPS) sensor (Motti and Caine, 2015). Additionally, participants were generally concerned about these devices collecting information about them from a social network, the inability to recall and delete collected data, and having organizations or the government access the data without their awareness and consent. Fitbit's approach of using social networks, such as Facebook, to log in can lead to concerns on data breaches or misuse of user profile data (Orlosky et al., 2019). To protect the subject's privacy when publishing data, several techniques are often used such as anonymization, deidentification, and pseudonymization.

Data anonymization can be defined as an irreversible removal of the link between a subject and his/her record data (Kushida et al., 2012). This requires an a priori decision by researchers whether there would be any need in the future to link data to subjects, such as if there might be data removal requests when a subject opts out of a study. A less stringent technique is data de-identification, which is the removal or manipulation of direct and indirect identifiers such that reestablishing a link between a subject and his/her data would require a key that can be used to reverse the de-identification process (Garfinkel, 2015). De-identification can be achieved by replacing identifiers with pseudonyms or codes, or *pseudonymization* (Ren et al., 2021). For example, Kallio et al. (2020) assigned pseudonymization codes to participants that were used to log in and provide ratings of IEQ. Another study generated an ID for each participant using a cryptographic secure hash algorithm (SHA-1) using father and mother initials and months of birth (Bluyssen et al., 2016).

A complementary procedure that can be considered for certain data types from wearables is generalization, which transforms absolute data to ranges or categories. For example, age 30 can be transformed to age 25–35. Another example is location obfuscation, which is to deliberately reduce the precision of the position info. Like a circular area instead of exact geographical coordinates (Liu et al., 2018).

3 EVALUATING ACCESSIBILITY OF HPI DATA

The previous section highlighted four main HPIs that were collected in prior studies using wearables including μEMAs of comfort ratings, sleep quality, heart rate, and stress response. To ensure success in a research study that uses wearables, researchers will likely need to examine several devices to select a device that fits the needs of the study. Device selection criteria may include data accessibility, types of data generated, accuracy and validation for the population of interest, sampling frequency, as well as system integration, and scalability. Other criteria that can be considered when selecting a wearable device are device reliability over time, device malfunction, firmware updates, and the use of proprietary algorithms (de Zambotti et al., 2019).

Arguably, a critical requirement for considering the use of a wearable device in a research study is data accessibility, which can be particularly challenging from consumer-grade devices that are typically intended for general tracking. Different devices may offer different access options that may require further effort or affect data resolution. Generally, previous IEQ studies that used wearables did not report device selection process and how data accessibility was verified prior to start of study. While most manufacturers clearly state data access options, some may require technical implementations such as the use of authentication (i.e., OAuth) and/or user/key management, and some may have reliability issues such as dropped data points.

Several wearable devices were used in previous studies, as shown in **Table 1**. Out of these devices, Fitbit Versa allowed for administering μEMAs. While this model is currently obsolete, its successor Fitbit Versa 2 can also be used with the *Cozie* clockface

TABLE 2 | A summary of wearable devices that were considered for the data-accessibility investigation.

Device	Measured quantities	Calculated metrics	Communication	Battery life	Notes
Fitbit Versa 2	Device orientation, heart rate, oxygen saturation, skin temperature variation	Sleep quality parameters (sleep onset, sleep offset, duration, duration of sleep phases), physical activity, off-wrist detection, breathing rate, heart rate variability, resting heart rate	Bluetooth	6 days	This model can be used to administer EMAs using Cozie clockface. A software development environment is available. Compatible with multiple smartphones
Fitbit Sense	Device orientation, heart rate, oxygen saturation, skin temperature variation, GPS	In addition to those measured by Fitbit Versa 2, this model assesses heart rhythm and electrodermal activity	Bluetooth	6 days	A software development environment is available. Compatible with multiple smartphones
Apple Watch SE (GPS + Cellular)	Heart rate, GPS, device orientation, oxygen saturation	Sleep quality parameters, physical activity, heart rate variability, irregular heart rhythm detection	Bluetooth, Wi-Fi, cellular	18 h	Software development environment
ActiGraph wGT3X-BT	Ambient lighting, off-wrist detection	Sleep quality parameters, physical activity	USB connection might be needed to download data	25 days	Research-grade device; can be worn on wrist; waist, ankle, or thigh
Actiwatch Spectrum PRO	Ambient lighting	Sleep quality parameters, physical activity, off-wrist detection	Data only accessible via USB cable	50 days	Research-grade device; allows for collecting subjective numerical ratings
Fatigue Science Readiband	Body motion	Sleep quality parameters (92% accuracy), fatigue, alertness score	Bluetooth	30 days	Wireless data syncing feature in field settings. Does not collect other HPIs
Polar H10	Electrocardiogram	-	Bluetooth	400 h	Does not collect other HPIs. Chest-worn sensor may not be practical in field studies

FIGURE 2 | An example of questions used in the data accessibility evaluation.

to prompt μEMAs (Jayathissa et al., 2020a). Additionally, Fitbit Versa 2 collects sleep quality, heart rate, physical activity, and the companion phone application calculates metrics such as heart rate variability, resting heart rate, and breathing rate. The advantages and drawbacks of other devices that we reviewed are shown in **Table 2**. Some devices did not collect heart rate, had a short battery life that makes it inadequate for IEQ field studies, or device cost was high limiting the ability to deploy it to a large number of participants in a field IEQ study. Research-grade devices tended to require a wired connection via to retrieve data which make them more appropriate for laboratory studies.

The Fitbit Versa 2 collects the needed HPIs and may be appropriate for IEQ field studies. To explore data access options, accessible data types, and identify potential issues that might be encountered when using this device, a preliminary assessment of data accessibility from this device was conducted. Data accessibility was the only topic being explored; this study did not investigate any hypotheses related to the collected data.

3.1 Evaluation Method

Three Fitbit Versa 2 devices (Version 35.72.1.15; 9/2021) were acquired and worn by three of the authors for 2 weeks. During this period, these three participants volunteered to complete daily μEMAs using the *Cozie* clockface which included default questions about participant's overall comfort, thermal comfort, satisfaction with lighting, noise, and location (indoor/outdoor). **Figure 2** shows example questions from the *Cozie* question

A Data format for µEMAs using *Cozie*

µEMAs responses


```
"startFeedback": "2021-05-27T00:05:39.908Z",
"heartRate": 54,
"comfort": 10,
"thermal": 9,
"testing": 10,
"light": 9,
"noise": 9,
"indoorOutdoor": 11,
"responseSpeed": "3.3",
"endFeedback": "2021-05-27T00:05:43.209Z",
"bodyPresence": true,
"restingHR": 46,
"BMR": 1507,
"voteLog": 18,
"lat": 45.5,
"lon": -122.6,
"user_id": "User1",
"experiment_id": "AzureTest",
"id": "2deb4115-9f5c-4fe5-b4c0-d48b3a11ec56"
```


B Sleep Data from Fitbit Versa 2

Time spent in each sleep stage


```
"summary": {
        "deep": {
          "count": 4,
          "minutes": 46,
          "thirtyDayAvgMinutes": 0
        },
        "light": {
          "count": 19,
          "minutes": 133,
          "thirtyDayAvgMinutes": 0
        },
        "rem": {
          "count": 8,
          "minutes": 81,
          "thirtyDayAvgMinutes": 0
        },
        "wake": {
          "count": 21,
          "minutes": 40,
          "thirtyDayAvgMinutes": 0
```


FIGURE 3 | Example µEMA responses and ancillary data from the Cozie clockface **(A)**, and sleep quality data **(B)**.

library as presented on the device (Jayathissa et al., 2020b). Each question could be answered by selecting one of two or three responses that were presented on the watch screen. The three authors that participated were working remotely during the 2-week test period. Each participant received a Fitbit Versa 2 a few weeks before the test period to become familiar with the device. The characteristics of the device are shown in **Table 2**. During the testing period, they were asked to complete as many µEMAs as possible while their phones were connected to internet via Wi-Fi or a cellular service.

Two aspects of data accessibility were evaluated: checking µEMAs for missing responses, and verifying the resolution of sleep, heart rate, and physical activity data. µEMA responses from each participant were assigned unique consecutive numbers, *i.e.*, count. A missing count number indicates a missing response that was inaccessible. Fitbit data resolution was checked by directly querying the data using device API or web API (Fitbit, 2021).

All data from the three Fitbit devices were collected in a JavaScript Object Notation (JSON) file format and forwarded to a serverless function hosted on Azure cloud computing services. The serverless functions were Python scripts that checked incoming data for correct source, structure, and organization. Incoming data were passed to an Azure CosmoDB database, which could be accessed by the authors. The data were saved in a nested JSON format where higher levels have generic and wide-reaching descriptors while low levels are composed of specific and limited descriptors. The descriptors were formatted in a *key-value* paradigm structure (i.e., participant-name). The overall data collection structure allowed for each data source to collect their data independently and forward it to the same cloud service.

3.2 Preliminary Results

The three participants completed 50, 56, and 57 µEMAs. The responses consisted of a numerical value for each response and did not require any post processing as shown in the example in **Figure 3** and in Jayathissa et al. (2020b). The percentage of accessible EMAs were 88, 89, and 96.5%, respectively. In general, out of the 163 µEMAs that were completed using the *Cozie* clockface, 149 (91.4%) were accessible. This led to the conclusion that some of the µEMAs were being dropped. This issue could be due to the Fitbit not syncing the responses with the mobile device causing the dropped responses. One potential solution is to send reminders to participants asking them to maintain a connection between the wearable and mobile phone to regularly sync their responses. Given that responses were stored locally on the device then uploaded to the server, it is unlikely that the missing responses are due to the use of Wi-Fi versus cellular internet connection. GPS data were not accessible if a participant did not carry their phone at the time of completing a µEMA, this is because the Fitbit Versa 2 did not have a dedicated GPS sensor and used GPS data from the connected phone.

The Fitbit Versa 2 provided sleep quality, heart rate, and physical activity data in their respective metrics and did not require any post processing (Fitbit, 2021). We found that the resolution of sleep and heart rate data was limited when accessed directly using the device API, compared to the web API. Using the device API, sleep data were binary indicating whether a person was asleep or not at the time of the query. Similarly, heart rate data were only for one point in time. The Web API provided sleep duration and time spent in each sleep stage in minutes as shown in **Figure 3**. Heart rate time-series data were collected at about 10-s intervals. Physical activity data from the Web API were daily summaries as well as minutes spent in each activity level (sedentary, light activity, fairly active, and very active). Physical activity data could not be accessed using the device API. Other metrics that were displayed in the Fitbit app like heart rate variability and breathing rate were not accessible from either access option.

Due to the nature of internet-capable devices and services, their software is subject to being updated partway through an experiment (Woolley et al., 2019; Chinoy et al., 2021; de Zambotti et al., 2019). This can cause unnoticeable to disruptive changes that can affect the consistency of measurements. This issue was not evaluated and warrants further investigation. The evaluation of data accessibility and resolution that we conducted focused on understanding device capability. A case study evaluation of wearables for a specific use case was outside the scope of the current investigation but important to explore in future studies.

4 RECOMMENDATIONS

The recommendations in this section are based on the literature review (**Section 2**) as well as the preliminary device assessment (**Section 3**). It is important to note that the recommendations are intended to be a starting point for researchers and are expected to be informed by specific research questions, research setting(s), study design, participant demographics, wearable device capabilities, along with other practical considerations for field studies.

4.1 Data Types That Should Be Collected

To help evaluate effects of IEQ factors on occupant well-being, we recommend collecting subjective ratings of comfort via µEMAs, sleep quality parameters (sleep onset, sleep offset, sleep duration, and sleep efficiency), heart rate, and stress response as indicated by heart rate variability or skin conductance. Collecting these HPIs can help understand the mechanisms by which IEQ factors affect well-being. For example, Razjouyan et al. (2020) found indirect effects of relative humidity on sleep quality mediated by stress responses. It is important to note that each one of these HPIs can be influenced by several IEQ factors (**Table 1**). Therefore, we strongly recommend recording all related IEQ factors. This can help better quantify direct and indirect effects as well as interactions between different IEQ factors.

4.2 Administering µEMAs on Wearables

Administering µEMAs on comfort ratings on a smartwatch is recommended because it can help improve completion and compliance rates while reducing perceived distraction, compared to EMAs administered on a smartphone (Intille et al., 2016). It is important to note that standardized questionnaires such as Karolinska Sleepiness Scale will need to be adapted and validated for use on a wearable device. The frequency and timing of µEMA prompt are dependent on the research questions, design, and setting. For example, a study examining changes in reported comfort in a research setting with high temporal variability in IEQ conditions may have a higher number of prompts compared to another study conducted in a research setting with fairly stable conditions (Clements et al., 2019). It is important to note that there is no agreed-upon maximum number of µEMA prompts acceptable. Generally, we recommend up to five prompts a day to reduce participation burden (Burke et al., 2017), which may affect wearable device compliance over the course of a study (Mundnich et al., 2020).

4.3 Localized IEQ Measurements Using Wearables

Wearable sensors can be used to capture localized IEQ measurements. The location of the wearable sensor should be carefully considered as it may affect the performance of the device and usability of collected data. For example, to address the non-image-forming effects of light, vertical illuminance and spectrum are best measured using a wearable sensor placed close to the eye (Aarts et al., 2017; Peeters et al., 2021). Wearable light sensors should be placed on the front of the participant's torso within approximately 20 cm from the chin (Cain et al., 2020), in a location that will not be blocked by clothing or hair. We do not recommend wrist-worn devices for measuring light exposure as they can be easily covered by clothing and may not provide an accurate representation of light at the eye of the occupant (Figueiro et al., 2013).

4.4 Techniques to Protect Participant's Privacy

When wearables are used in an IEQ study, it is important to develop a strategy and implement techniques to protect the privacy of participants. A pseudonymization technique can be used for its flexibility, as used by Bluyssen et al. (2016). For example, it allows researchers to identify a participant to delete all or part of their data after data collection had ended. Another technique that is particularly useful for GPS data is generalization, which can help identify a participant's general location, e.g., to determine if a participant was in or out of the office (Liu et al., 2018). These two techniques can facilitate recruitment by alleviating privacy concerns and reducing the ability to re-identify participants from IEQ sensors and wearable data.

4.5 Evaluating Data Accessibility From a Wearable Device

While **Table 2** shows several criteria that can be considered when selecting a wearable device, our assessment (**Section 3**) was limited to exploring data accessibility. Different platforms may have one or several options for accessing the data. If a system offers multiple data access options, it should be considered that the accuracy and precision of the data may differ depending on the access method. Some examples of the different ways data can be accessed include raw sensor values, web API, data forwards, bulk FTP downloads, web dashboards, and csv file download. Researchers and investigators should be aware that data points may be dropped or go missing throughout an experiment. For example, a device that is reliant on a smartphone connection for internet access may be susceptible to dropping data at multiple points in the chain of communicating data points to the investigator.

To verify data accessibility, we recommend first exploring the various access options the device provides. Manufacturer's documentation and previous studies that used the same device can be a good place to start. While a literature review can aid in determining the specifications of a system, real-world implementations can reveal unforeseen issues. Therefore, we also recommend testing sample devices prior to the start of a study. This testing can help assess data accessibility by determining whether all data types were accessible at the desired resolution, and whether any data points were lost.

5 CONCLUSION

HPIs that were collected using wearables and are relevant to IEQ factors include comfort ratings, sleep quality parameters, heart rate, and stress response. Our review showed that each one of these HPIs can be affected by multiple IEQ factors. Hence, ideally, all relevant IEQ factors should be monitored to better quantify their direct and indirect effects as well as any potential interactions. Similarly, monitoring multiple HPIs is highly advantageous to help identify the mechanisms by which IEQ factors affect different HPIs. For example, to determine whether effects of relative humidity on sleep quality are mediated by stress response as explored by Razjouyan et al. (2020).

The evaluation of data accessibility from the Fitbit Versa 2 with *Cozie* clockface proved helpful as we found that some μEMA data were lost and that there were differences in data resolution depending on how the data were collected. Conducting a similar evaluation is recommended prior to research or operational deployment to identify potential issues and, if possible, mitigate them (e.g., choose a data collection option that provides necessary resolution) or develop methods for limiting their impact on data usage (e.g., collect more than the minimum data required for analysis to improve resiliency against data loss). Based on the results of this work, future IEQ research studies that utilize wearables are encouraged to report and discuss device selection process and data accessibility challenges, and propose best practices for human subject recruitment, human subject engagement and compensation, study duration, and data analysis.

If data accessibility and other challenges can be overcome, the use of wearables might be extended beyond research studies to use in building system control. For example, subjective alertness response data might be used in control strategies that adjust light color and intensity to improve alertness. Such closed-loop systems could provide continuous refinements that are customized to the actual building occupants, rather than based on recommended practices or estimates of "average" occupant needs. As a result, these systems might deliver significant improvements to occupant well-being and reductions in energy use as compared to standard practices.

AUTHOR CONTRIBUTIONS

All authors contributed to the writing and reviewing of this manuscript. BA managed the study and contributed to study conceptualization. RD and MP contributed to study conceptualization and provided mentorship and supervision. All the authors have read and agreed to the published version of the manuscript.

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NOMENCLATURE

API application programming interface

FTP file transfer protocol

GPS global positioning system

HPIs health performance indicators

IEQ indoor environmental quality

EMAs ecological momentary assessments

JSON javascript object notation

LEED leadership in energy and environmental design

PM particulate matter

SBS sick building symptoms

VOCs volatile organic compounds