Review

Biometric Data as Real-Time Measure of Physiological Reactions to Environmental Stimuli in the Built Environment

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Abstract: The physiological and cognitive effects of environmental stimuli from the built environment on humans have been studied for more than a century, over short time frames in terms of comfort, and over long-time frames in terms of health and wellbeing. The strong interdependence of objective and subjective factors in these fields of study has traditionally involved the necessity to rely on a number of qualitative sources of information, as self-report variables, which however, raise criticisms concerning their reliability and precision. Recent advancements in sensing technology and data processing methodologies have strongly contributed towards a renewed interest in biometric data as a potential high-precision tool to study the physiological effects of selected stimuli on humans using more objective and real-time measures. Within this context, this review reports on a broader spectrum of available and advanced biosensing techniques used in the fields of building engineering, human physiology, neurology, and psychology. The interaction and interdependence between (i) indoor environmental parameters and (ii) biosignals identifying human physiological response to the environmental stressors are systematically explored. Online databases ScienceDirect, Scopus, MDPI and ResearchGate were scanned to gather all relevant publications in the last 20 years, identifying and listing tools and methods of biometric data collection, assessing the potentials and drawbacks of the most relevant techniques. The review aims to support the introduction of biomedical signals as a tool for understanding the physiological aspects of indoor comfort in the view of achieving an improved balance between human resilience and building resilience, addressing human indoor health as well as energetic and environmental building performance.

Keywords: biometric data; biosignals; non-intrusive sensing; physiological metrics; environmental stimuli; stress detection; health; comfort

1. Introduction

Urban living is on the rise. The majority of the population worldwide lives in urban areas and expectations are that the number of global urban inhabitants will grow up to two thirds in the next 30 years [1]. At the same time, research shows that people also spend a great majority of their time in closed environments made by humans; over the past few decades people on average spent between 90% and 98% of their time indoors depending on season and holiday time [2–5]. These numbers can also be expected to rise further during crisis events forcing people indoors—be it heat waves, hurricanes, or global pandemics.

The progressive detachment of humans from the natural world has proven to have a series of negative impacts on users ranging from low productivity [6], disruption of the circadian rhythm [7,8] and the hormonal system [9], resulting in diseases such as sleep disorders, immune system disorders, macular degeneration, cardiovascular diseases, diabetes and osteoporosis to cancer [10]. Furthermore, as we increasingly become an "indoor species", the indoor built environment is known to pose serious health hazard risks, commonly known as sick building syndrome (SBS) or "building-related illnesses" (BRI) [11,12]. They derive from a lack of good design and proper maintenance and the use

of new hazardous chemicals in building materials as well as in furnishings and consumer products [9]. Being largely undocumented, exposure levels to the chemicals in everyday life should seemingly increase with people spending more time indoors and air exchange rates decreasing as buildings are made more airtight to improve energy efficiency [9,12].

Achieving healthier indoor conditions also becomes relevant from the perspective of energy and environmental building efficiency, if the bigger picture of overall sustainability is considered. Not only have researchers claimed that improved indoor conditions affecting user productivity can end up with massive savings on a company's operational costs [13,14], but the overall energy use has been clearly described as a consequence of trying to attain comfort (in terms of homeostasis) [15].

Therefore, we urgently need to improve our understanding of short- and long-term impacts of the indoor environments on us, in order to not only design energy and resource efficient spaces, but also ones that improve the health and wellbeing of people [16].

1.1. Measuring Human Wellbeing and Health in Indoor Environments

Wellbeing and health are naturally related concepts. While these can be considered to consistently impact each other, they are neither synonyms nor consequent [17]. The World Health Organization (WHO) defines health as a "state of complete physical, mental and social wellbeing", in other words, a state that goes beyond the mere absence of disease [18]. While "wellbeing" is an easy concept to grasp when contextualized, it remains hard to define and predict [19]. It is widely used across a great number of disciplines, setting focus on different aspects such as physical health (absence of disease) and comfort, psychological aspects (individual internal generation of meaning and sense of self), ethical aspects, social aspects (comparison with others as a means of assessing one's own abilities and functioning), economical aspects (standard of living, the real opportunities available to individuals), etc. [19,20]. In many cases, wellbeing, wellness [21] or also subjective wellbeing (SWB) [20] are interchangeably used and measured in terms of "happiness" [19,20,22] or "life satisfaction" [20]. These concepts are not only very broad but are also to a big part based on subjective judgments of satisfaction, as well as individual aims and values, which can change over time and between contexts. This creates critical challenges in terms of measurement and comparison due to differences in type and magnitudes of the chosen parameters and experimental conditions along with notorious problems of information bias even in studies with good reliability and validity [22].

Needing more objective parameters to evaluate the quality and efficacy of wellbeing conditions and interventions, SWB has been further broken down into concepts that include more measurable and objective factors [20,22].

In general, the human reactions that can be observed in response to environmental agents can be classified into three kinds: (i) behavioral, (ii) physiological and (iii) psychological [23]. Behavioral aspects are coordinated responses of individuals or groups to internal and/or external stimuli [24] including objectively observable activities and nonconscious processes (habits) [25]. These actions, reactions, or mannerisms (habitual gestures or way of speaking or behaving [26]) mostly refer—in the context of building physics—to physical (body) actions. Physiological aspects refer to the autonomic responses of the bodily parts of an organism to a stimulus, whether as a form of homeostasis, withstanding changes in environmental conditions that are outside their optimal range [27], or to trigger a behavioral reaction in response to an immediate threat [28]. The rising availability of sensing technologies and data processing methodologies has turned biometric sensors into interesting high-precision tools to study the physiological effects of environmental stimuli on humans [29]. Psychological aspects are functional processes, operations, and changes that relate to the mental and emotional state of an individual (or a group of individuals in the case of group dynamics). Depending on what is measured and, on the methods used, different combinations of these three aspects are taken into account.

Which parameters and methods are appropriate to reliably measure the effect of environmental conditions on users?

The answer to the question is inevitably complex as it depends, among many factors, on the timeframe taken into account and the overall aim of the study. While health and psychologically oriented studies tend to focus on measuring outcomes as individual stress or satisfaction [30–34], economically oriented research tends to use more performance-based criteria focusing on productivity [35,36].

For what concerns the built environment, the significance of the environmental context and conditions in determining human health has mainly been the object of environmental psychology studies [37,38], healthcare environment design [15,38–41], and studies on sick building syndrome [15]. Research in the field of building physics on the other hand has largely focused on indoor comfort [15,16,30,42–51] and user satisfaction [30,32] as a measure of the indoor environmental conditions, and in some cases also on productivity and performance [2,14,35,52–54]. These methods follow, at heart, radically different visions of human wellbeing and/or health, and can be grouped into three major categories:

- Self-selection metrics include preference, acceptance, satisfaction and comfort;
- Performance-based metrics include attention, distractibility, productivity and mental workload;
- Physiological metrics include discomfort and stress.

1.2. Self-Selection Metrics

Self-selection refers to the act of individually opting "in or out of something (such as a group, activity, or category) in accordance with one's personality, interests, etc." [14]. The term is used in economic and social statistics referring to a type of selection bias that can arise when following rules of non-probability sampling, as decisions deriving from self-selection are the object of study [55]. By distorting the selection rules, self-selection makes determination of causation more difficult, resulting in influencing the data.

The term "self-selection" is generally not used in the field of building physics, although three main methods used to measure the quality of indoor environments (preference, satisfaction, and comfort) are overtly known to be highly subjective [22,50,56–58]. Experiments in the field of architecture largely rely on soft data assessed by questioning test subjects about their preferences, which is the case in a great majority of thermal comfort studies [6,16,30,42,50,59–62].

1.2.1. Preference, Acceptance and Satisfaction

Preference involves a choice between two or more alternatives. In preference testing, users or consumers are typically given a choice and asked to indicate their most liked option [63]. Acceptance (or liking) involves rating a specific option or aspect on a scale and can also be achieved without the need of comparing the solution with any other one [63]. What fundamentally connects preference and acceptance as measures is that none of these concepts reflect an ideal solution (the best possible), but at most an optimized solution. Both terms are largely used in business-oriented fields for consumer testing. Research in the context of the built environment also employs these terms [30] to estimate the quality of indoor environments.

Satisfaction is a more complex type of testing as it involves, from the side of the test subject, the rating of a specific option against one's individual scale of values and expectations. As compared to preference and acceptance, satisfaction does in fact reflect a positive assessment. Despite the innate complexity of the valuation method, satisfaction is a well-established metric for assessing quality in the indoor environments [32,57,64]. In building engineering, an indoor environment is generally considered acceptable when 80% of the occupants are satisfied with the conditions [58]. Occupants' environmental satisfaction is directly related to the amount of perceived comfort [32,64], and both of these aspects sequentially impact user performance [14].

All three concepts are often, and sometimes interchangeably, used in indoor environmental research to describe user feedback and assess environmental conditions. While part

of the assessment truly depends on the physical conditions of the context, a large part of the estimation is determined by individual psychological conditions.

1.2.2. Comfort

Comfort is defined as the "absence of unpleasant sensations" or as described within the most widespread definition in the field of building physics "the condition of mind that expresses satisfaction with the (thermal) environment and is assessed by *subjective* evaluation" [58]. It is therefore, by definition, a lack of discomfort: a neutral state with no stress. From a biological perspective, comfort can be effectively compared to the maintenance of homeostasis, indicating the absence of environmental stressors [15]. Comfort is broadly recognized as a multidimensional and subjective construct that varies across contexts [15] and depends on functional and environmental factors, on personal health and mood and is recognized as being highly subjective [14,15,47,65].

A large majority of comfort studies are based on the unvoiced assumption that physical health is a direct consequence of comfort. The gap existing between the definition of indoor comfort conditions and long-term health conditions however becomes apparent when looking at studies showing correlations between time spent in thermoneutral environments and the likeness of developing obesity [66–69]. Similarly, exposure to conditions outside the thermoneutral zone have shown to reduce the susceptibility to developing type 2 diabetes [70].

Measuring comfort is a difficult task. Comfort studies rely largely on self-reports and other types of user-feedback methods [6,16,30,42,50,59–62]. Though subjective measurement remains a major research method in many disciplines, the reliability of the results is contested by many authors [56]. If on one hand self-reports allow taking into account the mental state and mood of users, the data also involve a large risk of information bias [22,71]. The feedback is not only strongly influenced by the individual character of the perceived conditions, which can be minimized if analyzed over larger numbers of individuals, but psychological components are also known to consistently alter users' perceptions and thermal expectations of an environment [50,56]. Moreover, the data typically lack precision in timing, are generally not scalable and are usually difficult to reproduce [56]. Moreover, measuring comfort involves the collection of processed and combined data, such as physiological factors (thermoregulation), potentially random or non-repeating variables such as climatic behavior (subjects turn on the desk fan, wear another piece of clothing, etc.), and psychological or other highly individual factors (emotional stress levels, hormonal levels, etc.). Although current practice statistically normalizes individual differences in the datasets by collecting data on a large scale, it also involves significant physiological aspects not being easily parsed from the datasets.

1.2.3. Considerations on Self-Selection Metrics

Investigating the *perceived* indoor environmental conditions is on one hand an important task, as it takes the objective physical measures of environmental data into account, as well as the psychological mindset of the occupants [72]. However, from a health perspective, the importance of users' perception is relative for two main reasons:

1. Indoor comfort and indoor health are related concepts but refer to two essentially different timeframes. While comfort is perceived in an immediate and narrowly defined point in time, potentially changing within hours, minutes or seconds, health is the result of a multitude of actions happening over a much longer lapse of time, and can as such not be assessed by users in the present time but only retrospectively;

2. The use of self-selection measures, such as preference, satisfaction and to some degree also comfort, to determine the quality of an environment (often implying also health), is essentially driven by the idea that users are able to distinguish the conditions that are positive from those that are detrimental to their health. This is however not always the case as even in the cases where the long-term health effects of a specific action are

known, the choice between an immediate gratification (e.g., smoking) and a delayed gratification (health) is in psychological terms not always obvious [73].

In all self-selection metrics described, issues concerning potential systematic data bias have been raised. Surveys, questionnaires, and other self-reporting systems can also be argued as to discard neutrality as the subjects are made temporarily consciously aware of their surroundings when they are questioned about them. Additionally, these highly individual pieces of information pose problems with replicability, scalability and comparability of the said data.

1.3. Performance-Based Metrics

Performance-based metrics are most often aimed at measuring the efficiency of a system in economic terms, whether the outcome is expressed as environmental, financial or process excellence. Such metrics are effective to express usability and to inform key decisions [74] as they reduce complex measurements and result in a single value that can be tracked, managed, and improved. While complexity is reduced, looking only at the outcome of a network of interacting factors, it is important to keep in mind that these shortcuts can also become misleading when used for process improvement.

In the context of the built environment, performance-based metrics are used to express functionality in domains such as energy performance, indoor environmental quality, environmental impact, capital, and operating costs [75–77]. Few studies have focused on performance metrics in the occupant domain, and even those mostly focus on the built environment's qualities rather than on the effect on users [75].

Typical user-based performance metrics measure task success (binary success or level-based success), time on task (completion of a task within a time limit), error-based measure (single or multiple error opportunities), efficiency (number of actions required to complete a task, ratio of task success rate to the average time per task) and learnability (how any efficiency metric changes over time) [2,14,33,35,36,38,74,78,79].

1.3.1. Productivity

A number of studies have attempted to measure the effect of indoor environmental conditions by evaluating user performance in terms of *productivity*, mostly focusing on the thermal aspect [2,14,51,78] and on indoor air quality [14,53,78]. The underlying concept is that as environmental conditions exceed the range of comfort, the human body adapts to sustain the level of task performance. This is achieved through homeostatic adaptation on one hand and through psychological adaptive behavior (as attentional focus) on the other [51]. If the environmental conditions exceed the body's maximum range of adaptability, the attentional resources are depleted, and human performance ultimately deteriorates [51]. Assessing productivity can be achieved either using (i) subjective approaches, with self-assessing methods to rate perceived performance over a specific period of time [2]; (ii) quantifying productivity by defining a context- and content-specific ratio of output to input (ratio of company turnover to employee cost [80], individual/team performance [35,36,81], etc.) and gathering data in a real environment [14]; (iii) evaluating performance based on specifically designed tests (neurobehavioral tasks such as logical/comprehension/numerical/visual/memory etc. [82] or perceptual motor tasks [83]). The main drawbacks of assessing indoor environmental conditions by measuring productivity come from the environmental effects not being directly reflected on the subjects' task performance [84], due to partial adaptation to the stressing agents [51] and individual motivation [85], which can offset the effects on task performance. In fact, productivity is known to be influenced by many factors, among which are personal, social, organizational, and environmental factors [14].

1.3.2. Attention and Distraction

Another performance measure used is *selective attention* and its counterpart, distraction. To overcome its limited processing resources and reduce the amount of sensory information

it needs to comprehend [86], the brain uses various filtering mechanisms. It therefore constantly oscillates between states of deep focus—as we momentarily disengage from the real world when we are highly concentrated on a task [87]—and awareness of our surroundings—when we are distracted by environmental stimuli [86]. The oscillations between bursts of attention can therefore be closely linked to our behavior [88], providing indications on the effects the surrounding environments have on us. Specifically, increased cognitive engagement (attention) is known to produce decreased sensitivity to visual events [87] with slower reaction times, decreased situation awareness [89], and specific eye movements such as spontaneously closing the eyes or looking away [90]. The neural oscillations leading to selective attention, alternating periods of either heightened or diminished perceptual sensitivity, have been studied through human behavioral studies [88,91,92], but also using physiological measures as electroencephalography (EEG) [88] and oculomotor capture [87]. Researching the impact of selective attention can be a complex task, as can be seen by the multiple attempts to collect and interpret data from different sources:

- Detection of foreseeable behavior and movements in the test subjects: detection of head and neck movement using a series of sensors [93,94], detection of eye-movement data [95], gait analysis [96,97];
- Detection of specific biosignals, such as measuring cortical activity related to externally cued auditory events using event-related potentials (using EEG, electrooculogram (EOG) and electromyogram (EMG) signal extraction) [98–100] or using other measures as oculomotor control [101,102].

1.3.3. Mental Workload

Similarly to selective attention, *mental workload* or mental fatigue, defined as "the mental resources devoted to the tasks of an individual" [103], is used to measure a lack in performance typically characterized by higher error rates, decreasing efficiency and alertness, and effort disinclination [104], resulting in some cases also in detrimental health effects on long timeframes [105,106]. While measurements of productivity are limited and offset by individual motivation and ability to maintain the performance, mental workload can be assessed using physiological measures, such as electroencephalography (EEG) on subjects while being asked to perform tasks specifically designed to activate typical cognitive functions [2]. Other commonly used measures of physiological metrics include event-related potentials, magnetoencephalography, positron emission tomography, electrooculograms, cardiovascular measures, pupillometry, respiratory measures, and electrodermal measures [107].

1.3.4. Considerations on Performance-Based Metrics

Summarizing the reviewed types of performance-based metrics, only selective attention and mental workload appear to enable an objective measurement of the effect of the surrounding environment on users through the use of physiological measurements. These systems measuring cortical activity are on one hand accurate, providing a good option as a quantitative approach but present some intrinsic limitations: (i) datasets are very complex to read, and in some cases (as selective attention) do not provide a specific EEG signature; (ii) datasets can potentially be affected by many other factors [2]; (iii) the potentially high number of false positives due to interference from other body functions and movements. Reliability of the results can be theoretically achieved by adopting a multimodal approach [89], combining two or more physiological detection methods.

As far as this review could find, these methods are commonly used in the field of neuroscience [108], psychiatry [109], computer science and biomedical informatics [110], as well as architecture, computing and engineering [89], but very few attempts have been undertaken in the field of building physics [2,111].

As discussed in the beginning of the paper, another aspect that part of building physics studies focuses on, apart from comfort (or *sensation* and *preference*), is mental workload and productivity. While both terms have a similar individual complexity, they also have a

similar timeframe: both comfort and productivity are momentary states. However, these are also some of the most important factors in building operations and have a direct impact on the economy and use of resources. This argument is significant on a strategic level. While comfort studies prioritize optimizing building energy use and user satisfaction, and studies on productivity bring a more direct economic impact; both constellations forgo the health implications as they are not visible at the same timescales.

1.4. Physiological Metrics

Physiological aspects refer to the autonomic responses of the bodily parts of an organism to a stimulus, to withstand changes in environmental conditions that are outside their optimal range [27], or to trigger a behavioral reaction in response to a threat [28].

1.4.1. Discomfort

As previously discussed, comfort perception is the main key measure used in building physics to assess the quality of indoor environments, although the concept is known to be strongly impacted by psychological factors and the data are potentially biased. The sensation of *discomfort* on the other hand is the complementary entity of comfort [112] and is more broadly researched in fields such as ergonomics [112,113], medicine [114–116] and psychology [33,117,118]. Discomfort is described as a mental or physical uneasiness or annoyance [119], resulting in a natural response of avoidance or reduction in the source of the discomfort [114]. While in many studies physical discomfort is used as a synonym of pain [33,116], not every discomfort can be attributed to pain [114,115]. In most research, discomfort is identified and measured using self-report [112], assessing the severity, frequency, and duration of work-related body-part discomfort [113,116], or the observation of physiological and behavioral outcomes [114,116]. Generally, literature agrees on the subjective nature of the sensation of discomfort [114,116–118]. In physiological terms, there are no receptors to measure comfort (which is defined as lack of discomfort), while discomfort does in fact leave a mark.

1.4.2. Stress

Stress is the prototypical response to an internal or external event, force, or condition (the stressor), triggering a cascade of processes to help the body to adapt [25]. The effects are behavioral, physiological, and psychological [120], testifying how the stress experience relates both to the objective perception and the subjective evaluation of an event [56]. Physiological stress response is largely involuntary and is mediated by the autonomic nervous system (ANS) [56] as neurotransmitters and hormones signal action to the body [121]. Examples of the physiological stress response are palpitations, sweating, dry mouth, shortness of breath, fidgeting, accelerated speech, augmentation of negative emotions (if already being experienced), and longer duration of stress fatigue [25]. Although the concept is often negatively connotated, under certain circumstances, stress can also have positive adaptive effects such as arousal [56,122] and enhancing immune function (e.g., preparing the immune system for challenges such as wounds or infection) [121]. The impact on health and performance has also been shown to vary depending on the person's individual mindset regarding the stress conditions [123]. Damaging, long-term consequences of stress are essentially encountered as the reaction becomes a chronic condition [29,124–127]. Stress has been suggested to have four main components impacting health [128]: exposure, reactivity, recovery, and restoration. (i) The number of stressors experienced (exposure); (ii) the strength of the individual physiological reaction (reactivity); (iii) time of recovery from the stress reaction (recovery); (iv) healing processes of the organism (restoration), which might be hindered by the stressful condition.

In other words, stress is the physiological reaction of the body to a necessity of adaptation, triggering the body's homeostatic functions to regulate (temperature, heart activity, blood pressure, respiration, and glucose levels) [56,129,130]. As long as the range of adaptation required is within the capacity of the organism [131], the dominant perception

is of comfort. If the stimuli exceed the capacity of adaptation, the resulting sensation is of discomfort. Stress can therefore become an interesting measure in the field of building physics as a source indicator for physiological change in conditions. Especially as, contrary to the case of mental workload, stress has many known biophysical signatures, allowing for better data precision and reliability [89].

1.4.3. Considerations on Physiological Metrics

Physiological metrics appear to have a good potential to sustain the current mainstream data collection methods in the field of building engineering, potentially offering reliable and objective methods to measure environmental stressors. Specifically, recent advancements in sensing technology and time-sensitive biomedical data acquisition are opening up new possibilities to use biomedical signals as indicators of quality. The promise of parsing physiologically relevant data is that the impacts of additional variables, such as adaptive behavior, tolerance, psychology, exposure time, can be studied against a constant, in a situation where almost all other parameters vary.

1.5. Research Gap

More objective means are needed in the field of building physics to measure the effects of indoor environments on users as the mainstream parameters of indoor environmental quality, comfort, and discomfort are widely accepted as subjective sensations and data collection methods are prone to be biased. Following a review of methods to measure human wellbeing and health, the use of physiological signals to detect stress is seen as a promising alternative.

The use of these methods is however relatively new to the field of building and climate engineering, where solid theoretical foundations need to be established before being systematically used. While biosignal patterns are regularly researched for psychological, social, and mental stress conditions, comparatively few attempts were found to be made in the field of building physics to investigate the patterns of individual biosignal features triggered by stress factors originating from the built environment.

Within this context, this review reports on a broader spectrum of available and advanced biosensing techniques used in the fields of building engineering, human physiology, neurology, and psychology. The aim of this review is to offer a systematic and comprehensive insight on the current capacity to detect stress from the built environment using biosignal measures. Emphasis is put on the efficiency, robustness, and consistency of biosignals as a data source. Specifically, the paper will:

1. Review the current state of knowledge in neighboring fields of study that can be of use in the field of building physics;
2. Review the current parameters and measures used to describe indoor environments;
3. List and assess relevant biosignals highlighting their effectiveness and reliability with regard to stress detection;
4. Establish the relationship between the multitude of biosignal features and their corresponding behavior under different environmental conditions;
5. Establish reliable biosignal (and multimodal biosignal) indices that reveal the underlying physiological mechanisms of the stress response;
6. Discuss existing limits and solutions of the methods reviewed.

2. Materials and Methods

The paper explores the interaction and interdependence between (i) indoor environmental parameters affecting humans and (ii) human biosignals that respond to the environmental stressors by activating a physiological response. As such, the review was developed in subsequent phases of research and analysis. The topic is addressed from a holistic point of view, defining the relevant features through a qualitative and multidisciplinary research approach. State-of-art knowledge in the relevant fields was reviewed by

searching online available databases: ScienceDirect, Scopus, MDPI and ResearchGate and through the university libraries of the authors' home university.

A total of 246 sources were reviewed throughout this paper. A large majority of the publications, 82.5% of the total amount, were published after 2000, and 93.1% were published after 1990. Figure 1 shows a histogram based on publication years.
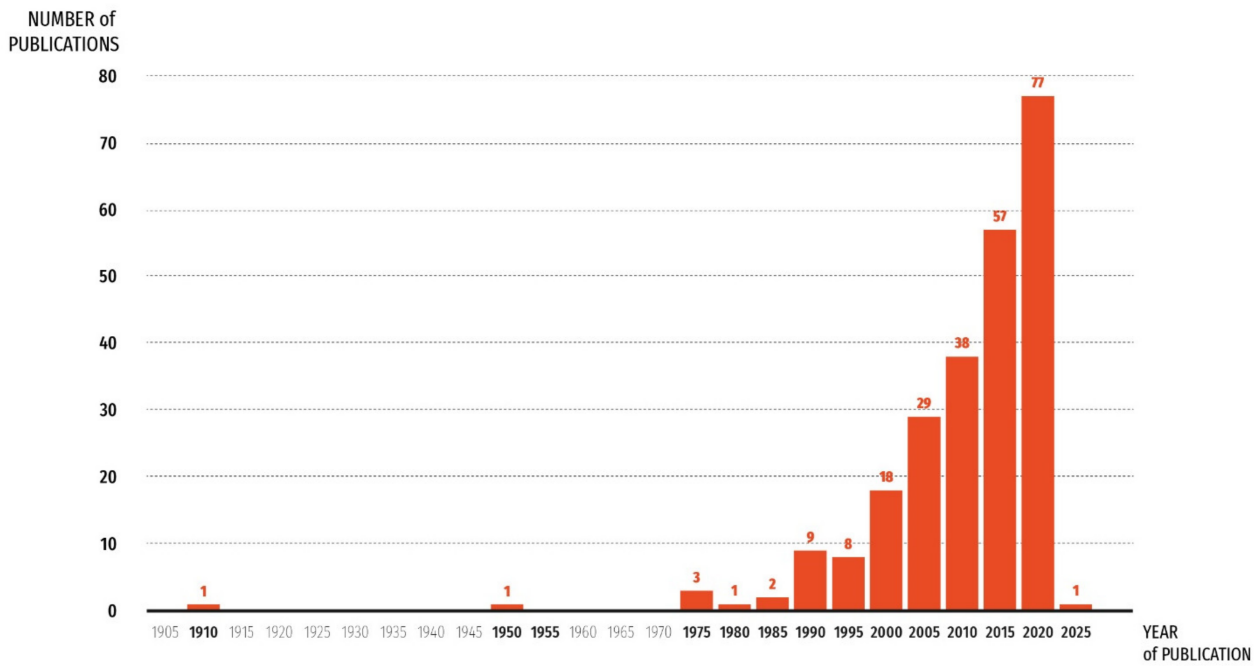

Figure 1. Histogram of publication years of sources.

Out of these 246 sources, journal papers seem to be the absolute majority when looking at the types of the publications. Figure 2 shows the breakdown of the entire bibliography based on the publication types.
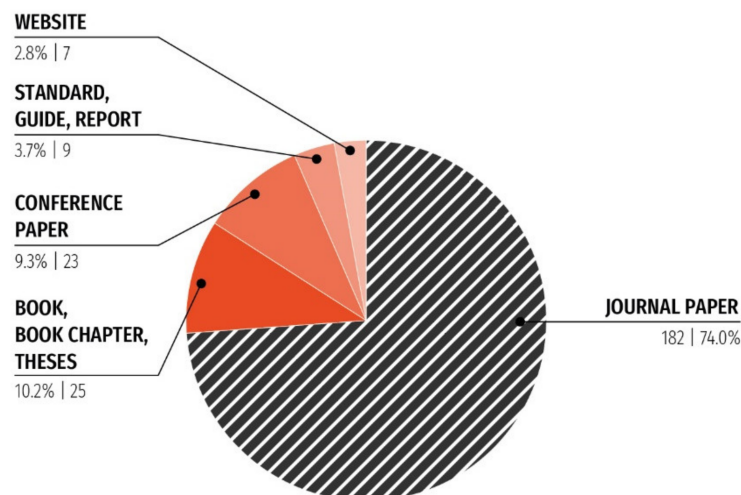
Figure 2. Breakdown of publication types.

Due to the interdisciplinary nature of the research topic and aiming to achieve a broad overview of the methods used to measure human health and wellbeing, the research reviewed appears to be extremely broad and diverse. Table A1 categorizes the publications based on their authors' original research fields and Figure 3 illustrates their distribution. As can be seen in both Table A1 (please see Appendix A) and Figure 3, nearly half of the

reviewed material comes from medical fields (general medicine, neuroscience, biomedical engineering, biology, psychology) and 31% originates from fields related to built environments (architecture, building engineering, building physics). The third prominent discipline seems to be computer sciences with 11%, including relevant sensing and data acquisition technologies or data analytics.
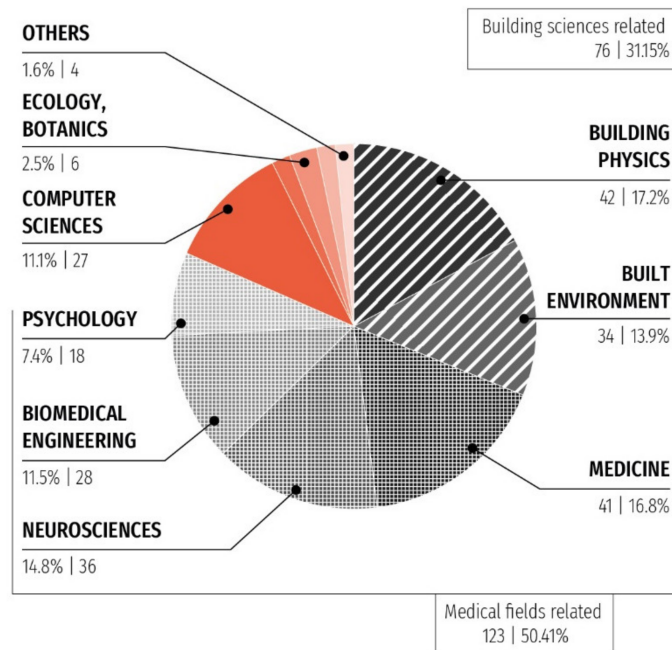

Figure 3. Distribution of main research fields of authors.

2.1. Methods for Measuring Human Wellbeing and Health in Indoor Environments

For the first step, the available methods commonly used, according to literature, to measure human wellbeing and health in the indoor environment were briefly summarized. The databases were searched with the keywords "health, well-being, indoor environment, self-selection, assessment, questionnaire, survey, satisfaction, performance, comfort, productivity, attention, mental workload, fatigue, task performance, cognitive performance, physiological, discomfort, stress, biosignal".

For this part, 157 sources were reviewed in total: 10 books, book chapters and theses, 18 conference papers, 121 journal papers, 4 standards, guides or reports and 4 websites. The publication dates range from 1950 to 2021, with 130 of the publications dated after 2000.

The majority of the research came from the fields of built environment (28/157) and indoor environment (building physics and engineering, 24/157) as well as medicine (27/157). Table A2 shows the sources used in this chapter based on the authors' main research fields in further detail (please see Appendix A).

Table A3 provides a more specific grouping for the publications contributing to the review and discussion of definitions of human aspects. "Stress" comes forward as the most repeated term amongst these publications, mostly with medical origins (25 publications out of 38) and computer sciences and engineering background (12 out of 38), with no occurrences in built environment or building engineering originated publications. However, the term "comfort" is the most common in these two fields (with 23 out of 36), with only 6 from a medical background. Finally, "health" comes forward as a shared term, as it appears in the publications from a medical background 21 times out of 36, and 14 times in the sources with a built environment background.

2.2. State of Art: Indoor Environmental Quality (IEQ) Parameters

For the second step, indoor environmental parameters typically used in the field of building physics were summarized in order to give a structured overview of the aspects that are usually taken into consideration in the design and environmental regulation of indoor spaces. The databases were searched using different combinations of keywords, such as "indoor environmental quality, IEQ, air quality, IAQ, thermal IEQ, thermal comfort, visual IEQ, visual comfort, visual health, acoustic IEQ, acoustic comfort, acoustic health, indoor health, comfort, occupant comfort, user comfort". The literature available on IEQ parameters appears to be very broad as the concepts are well-established in the field of building physics. This is the reason why the literature search was focused on identifying relevant reviews, proceeding in a second step to find specific articles that focused on single aspects of interest.

As a result, 90 sources were reviewed in total, amongst which 50 of these sources were also used in the previous summary of measures for human health and wellbeing. The search includes recent as well as well-established sources on different indoor environmental condition theories between the years 1973 and 2021, and 75 of these were published after 2000. As can be seen in further detail in Table A4, the majority of publications (72 out of 90) are journal papers (please see Appendix A).

The majority of the reviewed material came from the field of building related research and building physics (in total 58 out of 90). Table A5 shows a catalogue of IEQ-related publications reviewed in this paper, based on their authors' main research fields.

Looking at the cross relation of human factors and IEQ parameters, it seems that "health" and "comfort" come forward as frequent terms used in reviewed IEQ research, followed by "productivity", "performance, mental workload". However, comparing Table A6 to Table A3, where the sources on human aspects were categorized based on their focus, it was revealed that the literature on "stress" was the most prominent. However, in Table A6, it becomes clear that research on stress in relation to IEQ is not equally prominent; with "health" (33/90) and "comfort" (25/90) having higher priorities amongst reviewed publications on IEQ, while "stress" being found as the focus point of a single publication in this category.

Looking at the distribution of subcategories of IEQ parameters, thermal IEQ research presents itself as most prevalent, with 26 publications out of 90, while acoustic IEQ research comes last with 9 publications. Table A7 provides an overview of sources based on their relative IEQ parameter focuses.

Aspects that are relevant in terms of human health and comfort or otherwise useful for further bridging with biosensing techniques were identified and summarized. More specifically, all IEQ parameters were discussed in terms of:

- Threats to human health and wellbeing;
- Variables and sub-parameters;
- Solutions and strategies to improve the specific IEQ parameters and achieve healthy ranges for the indoor conditions;
- Parameter measurements, units in use, methods of measurement, limits to the methods.

2.3. Background Research on Physiological Signatures

For the third step, an extensive investigation of published studies on available biosensing techniques, used to measure human stress response, was performed. Broad research criteria were initially adopted in order to take into consideration a larger pool of potential biosignals. Databases were therefore scanned using different combinations of a number of keywords, among which were "biosignals, biologic signals, biomedical signals, biosensors, neurophysiology, psychophysiology, electroencephalogram (EEG), electrocardiogram (ECG), heart rate (HR), electrodermal activity (EDA), galvanic skin response (GSR), physiology of comfort, physiology of stress, stress recognition, mental workload, stress hormones", and the research was expanded to the sources cited by the selected literature. The search was subsequently narrowed down to more recent publications, focusing on research and

technologies achieved within the last 20 years (with the exception of publications that were of specific relevance).

As a result, a total of 110 publications were reviewed; the majority (78/110) being journal papers. Table A8 shows the sources based on their publication types.

When checked against the authors' main research fields (Table A9), it was clear that medical fields take the lead, followed by computer sciences and engineering in sensing and data acquisition technologies. Amongst the reviewed sources, research from built environment or building physics seems to have weak direct correlation to physiologic or biologic methods in terms of human aspects (health, comfort, wellbeing) in the context of indoor environmental quality.

2.4. Selection of Biosensing Techniques

Relevant biosensing techniques were subsequently selected from the larger pool of physiological signatures based on their relevance in the context of measuring potential indoor environmental stress sources.

Originally, the list of biosignals retrieved from the literature review was as shown below (see Figure 4):
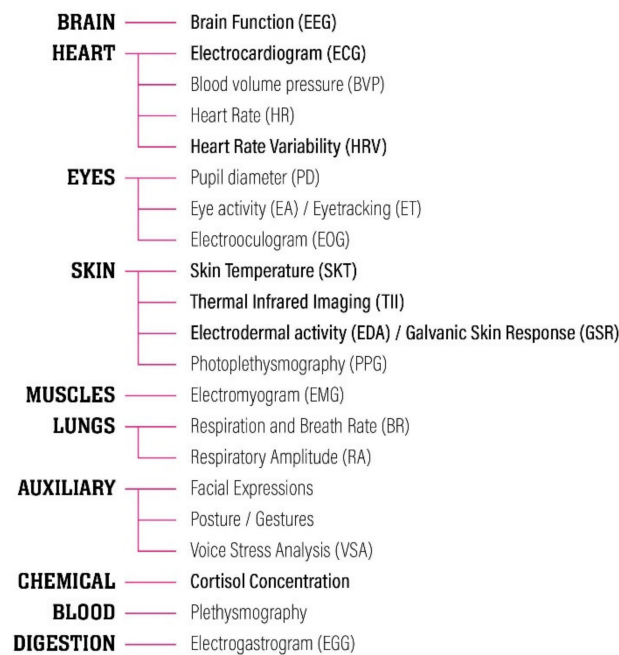

BRAIN —— Brain Function (EEG)
HEART —— Electrocardiogram (ECG)
—— Blood volume pressure (BVP)
—— Heart Rate (HR)
—— **Heart Rate Variability (HRV)**
EYES —— Pupil diameter (PD)
—— Eye activity (EA) / Eyetracking (ET)
—— Electrooculogram (EOG)
SKIN —— **Skin Temperature (SKT)**
—— **Thermal Infrared Imaging (TII)**
—— **Electrodermal activity (EDA) / Galvanic Skin Response (GSR)**
—— Photoplethysmography (PPG)
MUSCLES —— Electromyogram (EMG)
LUNGS —— Respiration and Breath Rate (BR)
—— Respiratory Amplitude (RA)
AUXILIARY —— Facial Expressions
—— Posture / Gestures
—— Voice Stress Analysis (VSA)
CHEMICAL —— Cortisol Concentration
BLOOD —— Plethysmography
DIGESTION —— Electrogastrogram (EGG)

Figure 4. List of biosignals gathered from the literature review. Biosignals marked as bold are examined in this paper.

Selected biosensing techniques were then organized according to hierarchy and relevance following their prevalence in stress literature, but more importantly in building engineering stress literature, efficacy and accuracy of the results, and robustness of the system. The selected biosensing techniques were then examined in means of their physiological processes and relevance to the stress cues as investigated in this paper.

Finally, limits and potentials of these techniques described in the literature were further mentioned and discussed for all selected biosignals.

3. Results

3.1. Indoor Environmental Parameters

The factors influencing an individual's perception of the environment of a built space include a variety of aspects characterizing on one hand the physical setting itself and on the other the person's reactions to the context. The parameters in the physical space that can

trigger a (conscious or subconscious) reaction in the users essentially include (i) environmental (air quality, climate, noise, light), (ii) functional/spatial (disturbances, interruptions, distance from work, resources, plan, layout, ergonomics) and (iii) psychological factors (privacy, territoriality, aesthetics) [35,36]. This review focuses on the factors pertaining to the physical environment, and as such only the aspects under point (i) are further explored.

The physical parameters and conditions of an indoor space are mostly straightforward and objective. These can be measured according to state-of-the-art procedures and with broadly accepted units. Ranges of acceptability for human health conditions are set through national laws and standards, although in most domains research still does not agree with precision on the ranges of acceptability and healthiness [16,47]. A common way to describe the physical indoor conditions is through the assessment of the indoor environmental quality (IEQ). This system is adopted in many green building systems—the United States Green Building Council (USGBC), the Leadership in Energy and Environmental Design (LEED) and the Comprehensive Assessment System for Building Environmental Efficiency (CASBEE) [14].

Indoor environmental quality (IEQ) describes the environmental conditions inside a building in relation to the health and wellbeing of its occupants and is determined through air quality, thermal, visual, and acoustic parameters [2,132,133]. In comparison to indoor air quality (IAQ) and thermal IEQ, both visual and acoustic IEQ have received way less attention [43], as can also be seen by the number of sources reviewed in each section (see Table A7).

3.1.1. Indoor Air Quality (IAQ)

Variables influencing indoor air quality (IAQ) include airborne contaminants from indoor and outdoor sources (gases and particles from equipment and furnishings, cleaning products, building materials, pollutants, etc.), ventilation rate, humidity and the type of indoor activities and the occupants' adaptive opportunities (manually intervening to adjust the conditions) [133]. Perceived IAQ is an umbrella of reported descriptors such as odor/smell, stuffy air, and dry and wet (humid) air [134].

The quality of indoor air has a direct impact on users' health and comfort [21,42,135]. Poor IAQ can directly cause severe respiratory and cardiovascular diseases, allergies, asthma, and sick building syndrome (SBS) [11,12,14,21]. As indoor air has been found to be in some cases up to five times as polluted as outdoor air [136] and new buildings tend to be increasingly tightly insulated from the external environment to achieve better energy balance [12,15,21], greater attention needs to be given to achieving good IAQ.

- Airborne Contaminants

Airborne contaminants from indoor and outdoor sources, such as gases and particles from equipment and furnishings, cleaning products, building materials, pollutants, etc., substantially affect IAQ. Common airborne contaminants include volatile organic compounds (VOCs, such as formaldehyde and benzene), microbiological volatile organic compounds (MVOCs), nitrogen oxides (NO and NO_2), polycyclic aromatic hydrocarbons (PAHs) and carbon monoxide (CO) [135,137]. Carbon dioxide (CO_2) is mostly not considered as a pollutant as its major source (in non-industrial indoor environments) is the human metabolism itself, but rather it is considered as a contribution to lesser air quality [53]. Finally, a great number of chemicals and materials used in everyday environments are also known to impact IAQ. A (non-exhaustive) list includes:

1. Polychlorinated biphenyls (PCBs) used in electrical equipment, caulking, paints and surface coatings;
2. Chlorinated and brominated flame retardants, used in electronics, furniture, and textiles;
3. Pesticides used to control insects, weeds, and other pests in agriculture, lawn maintenance, and the built environment;
4. Phthalates used in vinyl, plastics, fragrances, and other products;
5. Alkylphenols used in detergents, pesticide formulations, and polystyrene plastics;
6. Parabens used to preserve products such as lotions and sunscreens.

As a result of weak regulatory requirements for chemical safety testing, only limited toxicity data are available for many new chemicals that are being developed on a daily basis. Mechanisms of action, adverse effects, and dose–response relationships for many of these chemicals are poorly understood and no systematic screening of common chemicals for endocrine disrupting effects is currently underway, so questions remain as to the health impacts of these exposures [9]. Over the past 15 years, some chemical classes commonly used in building materials, furnishings, and consumer products have been shown to be endocrine disrupting chemicals, meaning they interfere with the action of endogenous hormones [9].

Solutions to contrast the accumulation of these pollutants include raising the ventilation rate, controlling or reducing indoor human activities such as smoking and cooking, and controlling the safety of building materials (paints, preservatives, etc.) and indoor elements (furniture, equipment, cleansers, etc.) [135,138]. Indoor greenery has been found to have positive biofiltering effects taking up toxic agents as benzene, formaldehyde, trichloroethylene [139], particulate matter (PM, fine solid particles suspended in a gas) [33] and CO_2 from the air during the photosynthetic process [14,78]. Additionally, studies have suggested that buildings exhibit decreasing tendencies of VOCs in indoor environments over time, which is why old buildings tend to have lower VOC levels than new buildings [14].

Measuring of IAQ is a complex task as it has many potential components [14]. The most common methods for indoor air sampling and analyses are toxic organic (TO) methods, air pollutants in indoor air IP-methods (compendium of methods for the determination of air pollutants in indoor air) and air-phase petroleum hydrocarbon (APH) methods [140]. The emission rate of air pollution is measured in olf (from "olfactory"), where 1 olf is the emission rate of pollutants from one standard person (an average adult working in a non- industrial workplace, sedentary and in thermal comfort with a hygienic standard equivalent to 0.7 baths per day) [141]. Decipol (from "pollution") is used to represent the level of perceived air quality, where 1 decipol is the pollution caused by one standard person (one olf) ventilated by 10 l/s of unpolluted air [141]. The decipol scale ranges from 0.1 decipol (outdoors in a city) to 10 decipol (sick building). [141]. The main difficulties and limits to the measurement and mapping of VOCs are linked to their very broad diversity in physio-chemical properties [14]. This entails varying degrees of sensitivity to the diverse compounds and subjective reactions in individuals, which in turn brings difficulties in developing standard measures for sampling and analysis [14].

- Ventilation Rate

Indoor spaces are ventilated to reduce contaminants in the air and exchange the exhausted indoor air. While higher ventilation rates give better IAQ values [14], they also result in thermal exchanges between indoor and outdoor areas and therefore in higher energy consumption as the air entering needs to be treated to meet the indoor thermal comfort requirements [45]. Researchers however argue that achieving better health and productivity of occupants with higher IAQ levels results in substantial financial returns in comparison to the annual energy and maintenance costs of the building [14].

The ventilation rate is expressed as the outdoor air flow into a building per unit of time divided by the number of people in the building, and thus in liters per second (l/s) per person or per square meter.

- Humidity

Recommended levels of indoor humidity are between 40 and 60% [142]. Higher rates of humidity in indoor spaces have shown to improve sleep quality and reduce effects on the vocal cord on one hand [143], but also to create unhealthy conditions that can bring microbial growth—fungal, bacterial and mold [133,142]—and affect the rate of outgassing of formaldehyde from indoor building materials, the rate of formation of acids and salts from sulfur and nitrogen dioxide, and the rate of formation of ozone [142]. Low humidity on the other hand can favor the survival and transmission of many influenza viruses as

well as aggravate the eye tear film stability and physiology, and the osmolarity of the upper airways [143]. "Dry air", which is a very common complaint in indoor spaces [134], is a sensation most likely caused by an exposure to sensory irritants such as indoor air pollutants [48,144]. Literature recommends distinguishing between elevated moisture in construction materials, elevated relative humidity (RH) resulting in condensation on surfaces, and RH in the breathing and ocular zone [143].

Relative humidity (RH) is measured as a percentage of water vapor in the room air, relative to the amount of vapor that the air could contain at a given temperature and is usually measured with a hygrometer. Absolute humidity (AH) measures the water in grams per kg of air at a defined pressure and is used in some cases for comparison and identification of associations, also considering sometimes better correlation between outdoor and indoor AH [143].

3.1.2. Thermal IEQ

Thermal comfort is one of the main factors affecting occupants' perceived environmental satisfaction [2] and IEQ-productivity belief [6], influencing their health and well-being [60,132]. Uncomfortable thermal indoor conditions have been reported to affect cognitive performance and productivity [2,14,51] and to be in extreme cases responsible for sick building flu-like symptoms (eye, nose, and throat irritation) [2]. The range of indoor temperatures deemed acceptable also has a strong bearing on building energy requirements [51]. It is therefore understandable that the opportunity of achieving important cuts in operational CO_2 emissions with the energy efficiency upgrade of the existing building stock [145] has driven much research to focus on the thermal aspect.

- Definition

Thermal comfort as we refer to in the field of building physics is traditionally defined through people's psychophysical responses, rather than purely biophysical processes. Thermal comfort is a subjective state of mind where each individual, influenced by physical, physiological and psychological factors, expresses a judgement of satisfaction with the thermal environment [14,47,49]. While thermal comfort is a highly subjective condition, thermal sensation is more objective and is therefore used to describe the human response to thermal comfort [146]. Other indicators used include thermal acceptability (the degree of an occupant's approval of the environment, which is subjective and directly related to the individual's expectation) and thermal preference (the expressed ideal thermal state of the environment) [30]. Variables that influence the comfort sensation are multiple. On one hand are the physical factors defining the thermal state of the environment: mean radiant temperature, relative humidity, air velocity and air temperature [14]. On the other are the factors influencing the human perception and preference towards the thermal conditions: individual factors such as age, gender sex, metabolism rate, mood, etc. [34,147]; dynamic factors such as clothing, activity patterns, posture (sedentary or steady conditions) [58]; and contextual climatic conditions as geographical factors, weather, and time of the year [14].

- Thermal Comfort Models

Achieving optimal indoor thermal comfort conditions is a complex task that has been at the center of scientific debate for about fifty years [50,62]. The outcome has been two approaches for defining thermal comfort.

The "single temperature optimum" model is based on climate chamber data, on the heat balance theory and on thermoregulation physiology [59]. This analytical model defines the predicted mean vote (PMV) index and the predicted percentage of dissatisfied occupants (PPD) through physical parameters (air temperature, mean radiant temperature, air velocity and relative humidity) and human variables (clothing insulation and activity level) [62]. Thermal comfort is therefore expressed around a single optimum temperature for any given combination of comfort parameters [148]. In this approach, any deviation from the thermal optimum anticipates a loss in comfort, performance, and productivity [51].

The "adaptive comfort" model on the other hand is based on field studies and considers that occupants' thermal acceptability, which depends on behavioral, physiological and psychological factors, influences the thermal comfort perception [14,49]. While subjects in lab conditions expect a finely controlled thermal environment, calculating the comfort predictions to a pessimistic value and are therefore less tolerant [50], in environments dependent on outdoor temperature fluctuations and passive design solutions, users accept a broader thermal comfort range [50,51]. Higher comfort and cognitive demands are also expected to be absorbed to a certain degree by the subjects with little or no deleterious effect appearing until those adaptive resources are depleted [51].

While both the "single temperature optimum" and the "adaptive comfort" models rely on thermal behavior to a certain extent, the thermoneutral zone (TNZ) describes a range of ambient temperatures where the body's core temperature can be maintained as relatively constant solely through control of dry heat loss (without regulatory changes in metabolic heat production or evaporative heat loss) [46,149]. The concept distinguishes itself from the thermal comfort models [149] as being within the thermal comfort zone does not guarantee that the body is in thermal balance at basal metabolic rate, or that it does not require heat production or heat loss to maintain the core temperature [46].

In all three concepts, the physical parameters can be measured using sensors. Subjective parameters, however, are more diverse and different methods are used to collect human responses, from complaint analyses, online surveys [14] and/or self-report. While the subjective measurement has improved greatly across several disciplines over the years, the soft data still pose problems in regard to being statistically significant, reproducible [56], or scalable.

3.1.3. Visual IEQ

Visual IEQ is affected by parameters such as daylight (in both amount and quality), the quality of views (indoors, towards the outside, introspection) and the user's opportunities to adjust these [133].

- Light

Visual comfort is generally the primary aspect considered by designers when planning the indoor light conditions and is in many cases the only aspect measured to determine visual IEQ. Visual comfort is determined by daylighting and artificial lighting levels in both amount and quality: overall luminance levels, daylight to artificial light ratio, direct sunlight, glare index, etc. It additionally depends on the type of activity performed, as different activities require different lighting levels [150].

Exposure to natural daylight is however important for more than its optical properties [44]. The intensity of the light affects human health as well as exposure to specific wavelengths, the timing, and the duration of exposure [151]. Humans have evolved by being exposed to specific amounts of natural sunlight. Spending more time indoors can therefore result in too low exposure, especially as window glasses tend to block part of the natural light spectrum [152]. Indoor sunlight can therefore not entirely substitute outdoor natural light. In terms of intensity, natural light in a minimum of 1000 lux is required for the biological rhythms of the human body to work efficiently [14], while most indoor office lighting levels for instance are around 300–500 lux [44]. In terms of wavelength, spending too much time indoors can lead to low exposure to ultraviolet (UV) radiation, which involves vitamin D3 deficiency [10]. In terms of timing, longer exposures to artificial light enriched in blue, typically irradiated from electronic screens, have been shown to affect sleep structure, particularly when exposed before bedtime [153]. Ill-timed light exposure due to the use of electrical light during periods of the day with local environmental darkness (i.e., late evening, night, early morning) has been shown to result in melatonin suppression even in settings with low light levels such as in households [10]. Melatonin is a hormone responsible for regulating the body's circadian rhythm [154,155] on which human physiological and performance aspects depend [154,156]. A multitude of disorders can emerge from the disruption of the circadian rhythm, such as sleep [153] and mood dis-

orders [157], seasonal affective disorder (SAD) [10] and shift work disorder (SWD), which create issues such as insomnia, difficulty in falling asleep, and experiencing sleepiness when it is important to be alert and productive [157].

Indoor lighting levels are mostly measured using sensors, while the glare index is mostly assessed through calculations [14]. Preferred indoor lighting settings can be assessed by comparing the lighting level and glare with occupant survey data [152].

In summary, relevant light-connected parameters to ensure good IEQ include daylight and artificial parameters in terms of quantity and quality: overall luminance levels, daylight/artificial light ratio, direct sunlight, glare index, wavelength, timing and the duration of exposure.

- Views

The quality of views impacts occupants' health and productivity in a number of ways [52]. Within the indoor environment, aesthetics and color schemes have been shown to affect human performance and productivity [14,158]. Greenery, whether in direct contact with the users [159], or indirectly spotted through windows [39,160] has therapeutic psychological and physiological restorative effects such as stress reduction, development cognitive and social skills [79]. Viewing the outdoors does not only provide contextual information such as weather, nature and surrounding activities [14].

3.1.4. Acoustic IEQ

Acoustic IEQ has high relevance in building design, and especially in offices as many tasks require noise to be kept within certain limits to enable occupants to work efficiently. Bad acoustic conditions produce psychological annoyance [161,162], fatigue and negative impact on motivation [31], anxiety with increased stress levels [163], ultimately affecting users' performance [32] and creating long term health issues [14].

Any unwanted sound is referred to as "noise" [164]. Sources of noise include external sources (traffic, the public, air traffic, machinery), internal sources such as machinery (fax machines, telephones, air conditioning systems) or from human origin (co-worker conversations, one-minute requests, etc.) [133,161].

Sound (or noise) is measured on a logarithmic arithmetic scale of decibels (dB), sound power (SWL) and sound pressure levels (SPL) [14]. The effect of variations in acoustic sensations in users' productivity has been directly compared to those of changes in thermal sensation, whereas a temperature change of 1 °C supposedly has the same effect as a change in noise of 2.6 dB [61]. The typical sound range in an air-conditioned office is between 45 dB and 70 dB [165,166].

Reducing acoustic discomfort can be achieved in a number of ways depending on the source of noise and the context: adding external (building envelope) [14] or internal building elements (internal partitions, sound absorbing materials, modifying sound reverberation time) [167], modifying the internal layout (from open office plans to cubicle/cellular office arrangements) [14], using a white noise generator [168] and introducing vegetation to promote reflection, dispersal, absorption or interference with the sound waves [78,169].

3.2. Biosignals
3.2.1. Definitions and Classifications

Living organisms, depending on their complexities, are made of several dynamic biologic systems. In human beings, some of these systems can be listed as the nervous system, cardiovascular system, musculoskeletal system, or the immune system [170]. These systems are responsible for dedicated physiological processes, such as blood circulation, breathing, digesting, etc. These processes result in changes within themselves, their immediate environment and/or their input/outputs in forms of voltage, pressure, chemical concentration, temperature, etc. These physical attributes can be measured by several means and are collectively called biosignals.

Biosignals (short for biologic signals or biomedical signals) are signals that are used to extract information on a biologic system to be examined [171]. In biomedical applications, they are a critical part of diagnosis [172]. The signal source can be at the molecular, cell, systemic or organ level. Extraction of a biosignal can go from something as simple as a physician feeling the pulse of a patient to understand the heart rate, to the use of an electrocardiogram or to measure the electrical activity of the heart more precisely and continuously, with the help of electrodes placed on the chest, arms, and legs. Overall, biosignals can be:

1. Spatial (mono-dimensional biosignals, e.g., electrocardiogram (ECG) associated with heart muscle contractions measures heart activity by detecting changes);
2. Temporal (two-dimensional biosignals, e.g., functional magnetic resonance changes associated with blood flow imaging (fMRI, functional magnetic resonance imaging measures brain activity by detecting); or
3. Spatio-temporal (three-dimensional biosignals, e.g., a medical ultrasound movement by detecting changes in the reflection of measured surfaces or internal organs structural sound waves on the tissues) records of a biological event [173].

Biosignals can be categorized in several ways: by their existence (permanent, i.e., EEG, ECG vs. induced, i.e., plethysmography, where an artificial current is induced in the tissue), by the observed time-frame changes (dynamic, i.e., heart rate or static, i.e., core temperature) or by their physical nature [174]. The latest is the most frequent classification method, categorized and elaborated as follows:

1. Bioelectric signals: Bioelectric signals are the most common and well-known biosignals. Bioelectric phenomena have had scientific value for the past 200 years in terms of modern medicine [175]. They convey the electrical activity created by nerve and muscle cells. Well known examples can be listed as electroencephalogram (EEG), electrocardiogram (ECG), electroretinogram (ERG), electrooculogram (EOG), electrogastrogram (EGG), electroneurogram (ENG), electromyogram (EMG), galvanic skin response (GSR) [176].
2. Bioimpedance signals: Bioimpedance signals are useful for estimating body composition through the amount of electric impedance passing through the body. Using bioimpedance signals, parameters can be figured such as: body cell mass, extracellular mass, fat-free mass, fat mass or total body water [177,178].
3. Biomagnetic signals: Several organs produce weak magnetic fields, as a result of their electric activity. For instance, the source for the magnetocardiogram (MCG) or magnetoencephalogram (MEG) is the electric activity of the cardiac muscle or nerve cells, respectively, as it is the source of the electrocardiogram (ECG) and electroencephalogram (EEG) [175].
4. Biomechanical signals: Results from the mechanical functions of the body, such as pressure, tension, motion. Examples can be listed as blood pressure data, human movement data via accelerometer sensors in Parkinson's disease patients, gait, balance and pose (Parkinson's disease, mobile applications, fitness). Biomechanical signals are particularly of interest in sports science, or physical rehabilitation processes [179].
5. Bioacoustic signals: Several physiological activities make noise and can be captured as acoustic data when amplified. Examples are cardiac sounds (phonocardiography) to examine heart valves' closure strength and stiffness, recording snoring in order to investigate sleep apnea, listening to respiratory sounds to detect pulmonary disorders. Apart from the medical field, use of bioacoustic data had been an important tool for animal researchers, identifying animal behavioral patterns [180,181].
6. Biochemical signals: Provide information about concentration of various chemical agents in the body. Common examples are glucose level data for diabetes control, blood oxygen level data for asthma, obstructive pulmonary disease, or heart and kidney failure detection. Biochemical signals, in general, are deemed as amongst the highest accuracy signals to detect stress levels in the human body, particularly via urine, saliva, or blood samples [182].

7. Bio-optical signals: Bio-optical signals are naturally occurring or induced optical functions of the examined biologic system. Examples of use include estimating blood oxygenation by measuring transmitted vs. backscattered light from a tissue, using dye dilution and monitoring the bloodstream to observe cardiac output, or controlling fluorescence characteristics of the amniotic fluid to acquire information about the health of the fetus [171].

All of these types of biosignals have different levels of sensitivity, accuracy, timescale, and types of dedicated sensors [183]. The use of these sensors suggests another important classification relevant to the focus of this research: the level of invasiveness. This factor is mainly critical in order to eliminate any psychological bias on one hand, by ensuring that the test subjects are not aware of the experiment, but also relevant due to the applicability of the biosensing experiments outside laboratory environments on the other.

The level of invasiveness is a direct correlation between the biosignal sensor and its relation to its biologic host; naturally, the least invasive biomedical data collection methods would be through the use of no contact sensors at all (i.e., thermal infrared imaging). Minimally invasive methods can be directly in contact with the skin (i.e., measurements obtained through biopotential electrodes such as electrocardiogram, electroencephalography, electrodermal activity), whereas the most invasive methods would implement sensors within the body (i.e., rectal, oral thermometers), puncturing the skin (i.e., use of needle electrodes for electromyographic signal acquisition) or even surgically placing the sensor (i.e., a blood pressure sensor placed in an artery, vein, or in the heart) [29].

3.2.2. Use of Biosignals in the Field of Building Engineering

The human body constantly tries to self-regulate against environmental changes, trying to keep the state of homeostasis and, as defined by Selye [184], stress is "a state of biological activation triggered by the person interacting with external agents that force her or his capacity to adapt". According to Schneiderman et al. [130], following a stressful event, a cascade of changes in the nervous, cardiovascular, endocrine, and immune systems take place. As previously discussed, these changes are traceable and quantifiable through sensing of biosignals.

Stress literature is well researched and has a long history. From a medical point of view, it goes back to the beginning of the 20th century [185] and gained even more traction in fundamental and clinical neuroscience research in the 50s, after Hans Selye's stress theory [186]. Since then, stress has been a research topic in many specific fields such as psychology, economics, ergonomics, sociology, endocrinology, complementary medicine, animal breeding, etc. It has been a research topic in the domain of building physics as well, regarding occupant stress (mental or physical, in terms of *thermal stress, heat stress* or *cold stress*), as reviewed in the first chapter.

However, the use of biosignals as part of stress-research is relatively new, even more so in the field of building engineering. As indicated in Section 2, Materials and Methods, the list of publications researched for this review mostly tried to correlate IEQ parameters to comfort sensation and mental workload, while none, to our knowledge, investigated a long-term effect.

3.2.3. Limitations

Albeit promising, the use of biosignals in the field of building engineering has still several limitations, most of which pose setbacks for robust real-world applications so far. The majority of the studies using biosignals have been conducted in test chambers, laboratories or well-controlled environments, and the gap in research to transfer the know-how from the lab setting to real-world conditions still exists [120]. While this approach is beneficial in establishing working protocols with minimal noise and more comparable data, it is also well-known that people's tolerance limits may drastically vary from test environments to real-world settings in which there will be many unforeseen stressors, influencing the overall stress [122,187]. However, both the sensing and data analysis

technologies are rapidly developing, and the possibility of the use of biosignals to further develop our know-how in realistic settings does not seem unrealistic.

The following are the most critical obstacles, according to our literature review.

1. Technical problems

   a. Noise:

   The physiological processes that produce biosignals, most of the time, cannot be reduced to an unequivocal course of events. Motion of the entire body, or parts of it, creates noise in the data. While there are several methods to improve signal-to-noise ratio, and higher performing sensors already eliminate noise to a certain degree, this still poses a problem. While de Santos et al. [188] remarks that "the subjects were strongly indicated not to move during the experiment procedure, in order to avoid noise in physiological signal acquisition", it significantly deviates from a realistic setting, ergo realistic conclusions, since it not only is irrational to expect test subjects to be that restricted while doing their mundane tasks, it is also effective on the strain this command causes on the subjects, meaning the results will not be representative for real-world settings.

   Similarly, Schmidt et al. [189] states that certain biosignals, such as electrooculography or electromyogram, are prone to producing a lot of noise in real world settings, and therefore are not very suitable for any use outside the laboratory conditions.

   b. Level of invasiveness, mobility, or wearability of sensors:

   The last decade has seen a great development in wearable technologies. The wearables used in the field can be watch-like, chest-belt, stationary devices, or recently flexible sensor patches and sensors that can be integrated into fabric. These technologies offer an increased wearing comfort, potential new measurement positions, and are less intrusive [189]. Even biochemical signals such as saliva and sweat, which are sought after as direct stress measurements, can be analyzed non-invasively through recently developed wearable electrochemical sensors [190].

   However, there are still problems associated with mobile technologies: once stationary devices, EEGs now have mobile alternatives with wearable headsets, with wireless data transfer technology. Nevertheless, they are still not fully unobtrusive; in some experiments, it was reported that continuous wearing of said headset caused headaches [2], making it less suitable for prospective long-term experiments in real settings.

   c. Accuracy of sensors:

   Another topic with mobile and wearable sensors as an emerging concern has been the level of accuracy that can be obtained during the testing period [191]. Continuing with the example of mobile EEGs, mechanical setbacks still exist; several studies [192,193] have explored the drop in signal quality and accuracy after a certain time of usage, due to sweat on the skin changing the bioimpedance of electrodes.

2. Problems with data acquisition:

   Depending on country-specific regulations, data privacy is strictly controlled and regulated. This means that data collection methods, particularly when video and/or speech recording is involved, might have to be modified or restricted accordingly [29].

3. Need for self-reporting:

   Sharma and Gedeon [194] and Hernandez et al. [195] state that most methods that use biosensing techniques (alone or in combination) still use questionnaires to validate induced stressors. This eliminates the potential avoidance of psychological bias in the resulting data. On the other hand, Hernandez et al. [196] suggests that self-reports, when used as ground-truths, result in more accurate stress detection in person-specific models.

4. Need for multi-modal biosignals for better insight:

   Generally speaking, multimodal systems perform better when compared to the accuracy reached by unimodal systems [197]. However, Kyriakou et al. [120] make a critical

point by stressing the importance of combining the appropriate signals and signal processing algorithms. A multimodal data collection is also practical in order to study the cross-modal effects that one can expect to observe in a real-world setting [198].

Thereby also increasing the applicability problems parabolically, making it even more complicated under the real-world conditions.

3.2.4. State of the Art

In this chapter, relevant biosignals used to assess environmental stressors in the built environment are reviewed and classified. While there is a plethora of biosignals, the ones presented in this chapter are selected on the basis of their occurrence in stress studies directly related to IEQ parameters.

The presented biosignals are simply classified regarding their position in the human body.

- Brain: Electroencephalogram (EEG)

Since the early 20th century [199,200], brain activities can be recorded by electrodes. The system is called electroencephalogram, or EEG for short; by "electro = electrical", "encephalo = brain" and "gram = record" and used for brain function study [201]. EEG is the electrical recording of brain activity, represented as voltage fluctuations resulting from ionic current flows within the neurons of the brain [202]. EEG records brain activity at the millisecond level, and therefore is considered to be a strong tool to provide a direct measure of the dynamic interaction between the brain and other stimuli in real-time [203]. It is considered to be a non-invasive method as it can be recorded by electrodes of varying numbers placed on the scalp. However, the level of obtrusiveness can be discussed.

The amplitude of the EEG signals ranges between 10–200 V, with a frequency falling in the range 0.5–40 Hz. There are five frequency bands:

1. Delta (γ): 0.5–4 Hz in frequency. Delta waves are the slowest EEG waves, normally detected during deep and unconscious sleep.
2. Theta (θ): 4–8 Hz in frequency. Theta waves are observed during some states of sleep and quiet focus.
3. Alpha (α): 8–12 Hz in frequency. Alpha waves originate during periods of relaxation with eyes closed but still awake.
4. Beta (β): 12–25 Hz in frequency. Beta waves originate during normal consciousness and active concentration and are associated with increase in alertness and arousal.
5. Gamma (γ): above 25 Hz in frequency. Gamma waves are known to have stronger electrical signals in response to visual stimulation [202,204,205].

It is also important to note that the precise range assigned to these bands can vary across studies [206] but apart from the exact thresholds, the classification stands.

The importance of these bands is that they are associated with particular cognitive processes. For example, Nyhus and Curran [207] states that theta and gamma bands are correlated to memory processes such as retrieval and encoding, Jensen et al. [208] mentions the connection between alpha and gamma waves and visual processing and Doesburg et al. [209] addresses the whole scalp gamma frequency synchronization in association with consciousness. According to Hamid et al. [210], the presence of stress has been considered to be responsible for an increase in the EEG beta band power.

EEG is a spatio-temporal biosignal, meaning the data not only vary with time but also in location. Where the signal originates at or the comparison of activities in different hemispheres can carry valuable information. An example relevant to stress studies is frontal alpha asymmetry (FAA), which is defined as "the difference between right and left alpha activity over frontal regions of the brain" [211]. It is speculated that the greater left frontal activity is associated with reacting to positive stimuli while the greater right frontal activity is associated with the tendency to withdraw from responding to negative stimuli. The extent of asymmetry has been suggested to vary under conditions of chronic stress and alpha asymmetry is suggested as a potential biomarker for stress classification [212].

Another use of spatial EEG data is when mental workload or performance are presented as evaluation parameters. In task-based experiments, the researchers look at the frontal lobe since as mental demand increases, so does the theta band activity [105]. By recording and comparing the rise in activity, it is possible to quantify the physiological impact of the stressor on the human body. The use of EEG signal to identify attention and distraction is relatively common, as seen in distraction studies in the automotive industry [89,98].

There are methods reported quantifying human acute stress in response to induced stressors (such as impromptu speech, examination, mental task, public speaking, and the cold pressor test) using EEG signal recordings, but the literature lacks a classification of long-term stress using EEG [212]. Even more so, very few of the acute stressors in the literature are related to IEQ parameters (i.e., [2]).

However, studies exist outside the realm of building physics, as [213] study the EEG signals of cold and warm sensation on skin, using 15 healthy subjects. During the experiments, subjects were partially exposed to a temperature range of 14 to 48 °C, with different intervals and intensities. While the temperatures, particularly in the warmer range, are not usual from an IEQ point of view, the study provides valuable insight as to how brain activities react to thermal stimuli.

Finally, it is worth mentioning that EEGs, similar to many other biosensing methods, are prone to noise and artefacts that may obscure the data and their interpretation. These artefacts may be caused by the test subjects' movement (eye movements, shivering, coughing, hiccupping, breathing) or due to the faults in the equipment (electrode popping, cable movements, electrical or electromagnetic interferences) [214].

- Heart: Electrocardiogram (ECG) and Heart Rate Variability (HRV)

An electrocardiogram (ECG) measures the electrical manifestation of the ionic potential of the heart, via numerous electrodes placed on the body surface near to the particular organ (e.g., chest, hands, and legs) [215].

Each cardiac cycle in the ECG is characterized by successive waveforms, known as P wave, QRS complex (including Q, R and S waves occurring in rapid succession) and T wave (Figure 5). These waveforms represent the depolarization and repolarization activities in the heart's cells of atrium and ventricle [216].
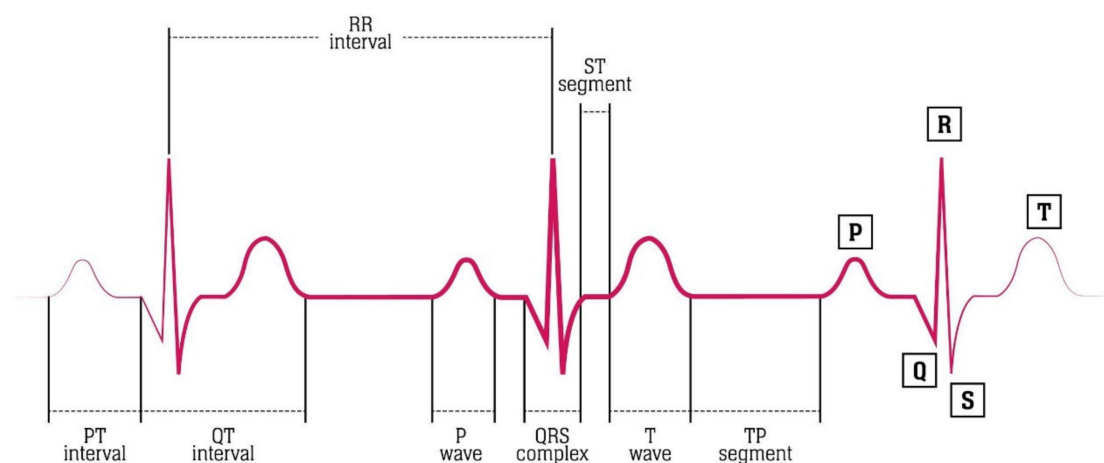

Figure 5. A typical electrocardiogram (ECG) signal that includes three heartbeats and the information lying in the P, Q, R, S, and T waves [after 215].

Studies using the heart as a biosignal data source either use heart rate, or heart rate variability. Heart rate is the measurement of heart beats per minute (bpm), while heart rate variability is the fluctuation of the length of consecutive heartbeat intervals [217], also known as R-R intervals [218] or N-N intervals.

These intervals are not periodic; however, the variation is not random either. The oscillations of a healthy heart are deemed complex and dynamically changing, depending on the "extrinsic protocols imposed on the heart" [219], since the cardiovascular system plays a vital role in reacting to stressors and maintaining the state of homeostasis [220]. Due to this reason, HRV is not only a factor of the heart, but also a rich data source with information on actions of the nervous system in response to stress factors [221].

Accordingly, the use of HRV signals plays a vital role in stress assessment research [183], with several studies being published not only generally in stress literature, but also in the field of building engineering, since the actions of the nervous system in the control of cardiac activities are sensitive to changes in temperature.

As Yao et al. [201] explains, environmental temperature can have an impact on the vagal and sympathetic nerve activity; as under thermally uncomfortable situations, sympathetic activity prevails, while in comfortable situations, the vagal activity overcomes. In humans, the vagus nerve is for the protection of the body, while the sympathetic nerve is triggered for stress response, including thermal stress. Thermoregulation of the human body as a system is controlled by the sympathetic nerve.

The way activities of vagal or sympathetic nerves are presented in HRV are via high or low frequency components. The vagus nerve is thought to excite the high frequency (HF) component of HRV while the low frequency (LF) is thought to be of both. As a result, any physiological reaction concerning thermoregulation triggers the use of a sympathetic nerve, resulting in a higher LF power and lower HF power, and the ratio of LF/HF increases. For this reason, studying the LF/HF ratio data becomes a reliable parameter to understand thermal sensation and physiological comfort in humans [222].

Studies conducted by [201,222–224] have all come up with similar results, contributing to the findings that "higher LF/HF yields unpleasant thermal sensation and discomfort". In Nkurikiyeyezu et al. [225], the researchers had 17 subjects doing light office work under cold, neutral, and hot environments while collecting data on statistical, spectral, and nonlinear HRV indices. With help from machine learning classification algorithms, the study concludes that it is possible to predict people's thermal states in a reliable manner, which was found to be up to 93.7% accuracy. There are no real-world studies on IEQ parameters so far; however, experiments focusing on mental stress using HRV data exist with varying success rates [226,227].

- Skin: Skin Temperature (SKT), Thermal Infrared Imaging (TII), Electrodermal activity (EDA)/Galvanic Skin Response (GSR)

Human skin is a significant source of data when it comes to understanding physiological reactions of the body in relation to its environment. It is the primary sensory organ and anatomical interface the humans have with their immediate environments. The sensations on the skin reflect both the biological processes happening intrinsically, or how the body is impacted by the outer stimuli [228]. To illustrate the skin's adaptability, the operational temperature ranges can be compared. As previously mentioned, the core of the human body requires a rather narrow temperature range, between ~36 to ~40 °C, with normal core temperature being ~37 °C, and it has been established that the skin temperature can vary between ~15 to ~42 °C without sensation of pain [228].

Similar to HRV, skin is part of the thermoregulation system, which is part of the autonomic nervous system (ANS). Therefore, skin-originating biosignals (skin temperature, electrodermal activity or galvanic skin response, photoplethysmograms) can provide variable insights on ANS activity [229].

Amongst these biosignals, skin temperature has been the one investigated most extensively, as it provides a direct understanding in human thermal sensation and comfort estimation, while the sensors are quite inexpensive [230]. Use of contact thermometers to acquire skin temperature has proven successful as seen in [231–235], constant thermocouples in different forms and both in real-world and laboratory settings seem to function and the results seem to be good indicators in predicting thermal sensation. However,

thermocouple sensors require electrodes on the skin, making the data collection process slightly obtrusive [188,230].

As an alternative, sensing skin temperature remotely is a method being utilized by several researchers. Infrared imaging technologies are widely available today, and medical infrared has utilized the heat signature of skin to map skin temperature since the 1960s [171]. Current technology presents low-cost no-contact and non-intrusive sensors; however, there are reported application problems: Li et al. [230] states infrared thermometers have a handicap of having such narrow field of views, meaning the thermometers need to be placed very close (few centimeters) to the test subjects. Alternatively, the use of thermographic (thermal) cameras can be placed away from test subjects, while in that case, data accuracy significantly drops in comparison to thermocouple sensors or even infrared thermometers. Nevertheless, with correct data analysis methods, improved data still seem to have been proven to be a robust alternative for real-time thermal comfort detection and even prediction.

One final biosignal of interest uses the skin's thermoregulatory response as the data source. Electrodermal activity (EDA), also known as galvanic skin response (GSR), measures the changes in electrical properties of the skin caused by eccrine sweat gland activity, which is a key factor in the thermoregulatory process [236]. The idea dates back to the very beginning of the 20th century to Carl Jung, who for the first time mentioned electrodermal activity in connection to emotions in a psychoanalysis book [237].

Several studies successfully link EDA data to stress detection and quantification [238–240]. Recently, the use of wearables is becoming more reliable in the field, leading the way to long-term EDA monitoring as well [240].

- Chemical: Cortisol

There are two main pathways in the human body to relay the stress from the brain to the body. The first way is via the sympathetic nervous system, through which cardiovascular and skin-related biosignals were used as stress signifiers. The second way is through the hypothalamic–pituitary–adrenal (HPA) axis, the hormonal route. Stress triggers the HPA axis, a neuroendocrine system that regulates central and peripheral homeostatic adaptive responses to stress [126,129,241,242].

Biochemical samples, primarily urine, saliva, and blood samples, and particularly analysis of hormones such as cortisol and alpha-amylase, are amongst the primary measures used to identify the impacts of stress on the body in conventional psychology methods and long-term stress studies [183,212,243].

While these analyses are deemed to provide high accuracy in stress detection, data collection can pose difficulties in regard to the intrusiveness of obtaining the samples, or the time interval of the data acquisition. Additionally, Lee et al. [244] stress the importance of the timing of the sampling, as cortisol levels in blood also vary diurnally, increasing during early morning and decreasing towards the night. Another important aspect is that while the biochemical signals from fluid analysis may correlate with acute stress, to understand the long-term chronic stress impacts some researchers have suggested looking at extraction of cortisol from hair fibers [245]. In order to overcome the limitations of the intrusive nature of data collection, the use of wearables in the forms of sweat patches, wristbands, or epidermal sensors is becoming more available. As Seshadri et al. [190] remark, while this enables researchers to collect biologic data continuously and is truly non-intrusive, the majority of these devices are only available as market products and have not been clinically tested and validated yet.

4. Discussion

4.1. Summary and Research Gap

Our understanding of indoor environmental quality is as good as the methods we use to assess it. A brief review of the state-of-the-art has highlighted how little consensus there is concerning the actual measures used, both between radically different fields and within fields of research. Recurrent criticisms are mostly focused on two main aspects:

(i) the effect against which quality (or lack thereof) is measured; (ii) the reliability of the collected data. In the first case, human health and wellbeing are commonly implied to be the end-objective, whether the effects measured vary broadly and include self-selection, performance-oriented or physiological metrics. The use of different measures raises on one hand questions concerning their relevance and appropriateness in reflecting health parameters; on the other, it makes comparisons between studies very difficult. In the second case, the importance of taking into account psychological and individual factors in the equation is on one hand underlined by many researchers as not being adequately considered; on the other hand, these components are widely accepted as having a strong potential for data bias.

This gap in terms of measuring efficiency substantially affects the mental framework of all professionals dealing with the built environment, from designers to policymakers, with end effects not only on human health and wellbeing, but also on the overall energetic and environmental building performance.

Within this context, recent advancements in sensing technology and time-sensitive biomedical data acquisition have opened up new possibilities to use biomedical signals as an increasingly reliable objective methodology to measure environmental stressors. The promise of parsing *physiologically* relevant data is so that the impacts of additional variables, such as adaptive behavior, tolerance, psychology, exposure time, can be studied against a constant, in a situation where, as previously explained, almost all other parameters vary. The use of these methods is however relatively new to the field of building and climate engineering, where the established scientific practice largely uses self-selection or performance-based assessments (questionnaires and interviews) to measure the quality range of measured indoor conditions.

The main hypothesis supported by this paper is that introducing data collection based on biomedical signals to measure human stress in indoor environments has the potential to give new insights, more data reliability and enable comparisons between studies in the field of building physics. Hence, the review aims to contribute with a systematic and comprehensive insight on the current capacity to detect stress from the built environment using biosignal measures, in order to set a foundation for the development of this method of data collection in the field of building physics.

4.2. Approach

This paper reviews the state-of-the-art knowledge concerning (i) indoor environmental parameters affecting humans in terms of IEQ and (ii) human biosignals that respond to the environmental IEQ stressors and the physiological response they activate, and then maps the interaction and interdependence between the two. More than 240 scientific publications were analyzed, published between 1906 and 2021, dealing with topics ranging from built indoor environment, medicine and neuroscience, biomedical engineering, sensing technology, psychology, ecology, and economy.

4.3. Main Findings

Indoor environmental parameters commonly used in building engineering and indoor climate research were reviewed. Indoor environmental quality (IEQ) is determined by assessing air quality, thermal, visual, and acoustic parameters. Although the use of these parameters is well-established throughout the reviewed literature, this brief review was necessary in order to establish a common ground between current practice and the introduction of biosignal measures. This will allow bridging the new methods introduced and the state-of-art knowledge on the features of the indoor environment affecting humans, but also to set a basis for comparison with the existing research in the field.

Moreover, discussing IEQ from a health-oriented rather than a comfort-oriented perspective, relevant sub-parameters were identified, which are, in the current state of research, not taken into consideration. This is the case of visual IEQ, where the range of the natural

light spectrum should be taken into consideration also for its health-related properties (as to trigger the production of vitamin D) rather than only for its optical properties.

Parallelly, human biosignals were reviewed. Biosignal definitions and classifications were introduced in order to provide a systematic framework for professionals dealing with the built environment. The physical nature as well as the level of invasiveness of the biosignals are discussed. The physical nature of biosignals directly relates to the physical IEQ aspects of the indoor environments, while the invasiveness of the technology enables an easy and unbiased data collection that does not interfere with the study subjects' behavior patterns or awareness of being observed.

Successively, the review reported on the main limitations connected to the use of biosignal measures, being mainly of technical nature (noise, wearability, and accuracy), country-specific legal issues involved with data collection and storage and the use in some contexts of self-reporting as validation. The necessity of relying on multimodal data acquisition is also highlighted as a possible limit; however, if systematically integrated in the research method, it remains a valid method for cross validating the acquired data. The possibility of performing this kind of analysis can therefore also be seen as a strength, yielding potentially high quality and complete sets of data.

Finally, the review reports on the specific biosignals that relate to the IEQ parameters. These are classified into four categories depending on the biophysical aspect measured: brain, heart, skin and chemical.

4.4. Limitations

The introduction of biosignals as measures of indoor environmental quality still appears to have a number of limitations, in spite of the potential benefits highlighted by this review.

Defining the metrics of environmental quality remains a complex task due to a number of intrinsic complexities:

a. Multifaceted conditions of the indoor environment (temperature, light, air quality, humidity, etc.);
b. Elaborate human psychophysiological reactions affecting the regulation of environmental conditions for conditioned buildings (individual preferences, personal methods of adaptive behavior, i.e., different levels of clothing, different body mass index (BMIs), different sense of comfort, etc.);
c. Complex human psychophysiological reactions to the environmental conditions (stress, health, wellbeing, etc.);
d. The many-to-many relationships between the factors mentioned above, and finally;
e. The above-mentioned relationships being dependent on time factors (expectations changing together with the outdoor conditions and changing of the seasons, history of individual acclimatization, time of exposure to certain climatic conditions, etc.).

Additionally, a lack of knowledge and training from the side of building professionals in terms of the medical and technical background necessary to correctly use some biosensor measures, to collect and to interpret the data is a main limit to the effective use of these technologies. This problem is especially evident with some biosignals, such as the EEG, where possibly specialists from other fields need to be involved. Although the interdisciplinarity of these types of studies has the potential to contribute with innovative practices and relevant findings, it poses important limits in terms of time and resources that can discourage the use of these methods in regular ordinary research.

Finally, the study has addressed "indoor environments" as a whole, not distinguishing further between the type of environments, in the aim of presenting the method as an overarching tool that can be successively adapted to more specific case-studies. From the analysis of the reviewed literature, a great majority of the research has up to today focused on office spaces, a few on housing indoors and another few on healthcare contexts.

Intrinsic limitations of the review itself, in spite of the high interdisciplinarity of the sources reviewed, might come from the authors having similar cultural and professional

backgrounds. Additionally, the studies reviewed were exclusively written in the English language, with the potential exclusion of relevant sources published in other languages.

4.5. Future Directions

This review aims to set a foundation for the introduction of biosignals for the assessment of environmental parameters in the built environment, but is in that sense only a first step within a long process. Follow-up studies to effectively establish the biosignal data collection methods into current practice include:

1. The application of the identified biosignal measures in indoor environmental research, specifically starting with their use in test chamber lab experiments before staging exploratory studies in real-life indoor contexts and outdoor environments;
2. Parallels with the existing research in the field of comfort studies need to be further deepened, both in order to use stress research with biosignals to support comfort studies and to build up knowledge concerning stress related biosignals supported by the existing knowledge from comfort studies;
3. Implications in terms of building energy efficiency and indoor health are other parallel lines of research that open up, aiming to update the existing design practice as well as building regulations.

4.6. Conclusions

This review has highlighted how the relationship between daily human indoor habitats and human health needs to be researched further. While in current practice, comfort studies prioritize optimizing building energy use and user satisfaction, and studies on productivity bring a more direct economic impact, both constellations forgo the health implications as they are not visible at the same timescales. In other words, a balance needs to be found between the right dose of a higher overall human resilience and building resilience [246].

The use of biosignal measures to detect environment-related stress conditions is put forward as a promising and reliable method to effectively focus on short and long-term human health aspects. The review is a first stage within a longer process of translation of a method that is already established in other fields of study using stress research in the context of the built environment.

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Abbreviations

AH	absolute humidity
ANS	autonomic nervous system
APH	air-phase petroleum hydrocarbon
BMI	body mass index
BRI	building-related illnesses
BVP	blood volume pressure
ECG	electrocardiogram
EDA	electrodermal activity
EEG	electroencephalogram
EGG	electrogastrogram
EMG	electromyogram
ENG	electroneurogram
EOG	electrooculogram
ERG	electroretinogram
GSR	galvanic skin response
HF	high frequency
HPA	hypothalamic–pituitary–adrenal
HR	heart rate
HRV	heart rate variability
IAQ	indoor air quality
IEQ	indoor environmental quality
IP	air pollutants in indoor air
LW	low frequency
MCG	magnetocardiogram
MEG	magnetoencephalogram
MVOC	microbiological volatile organic compounds
NO	nitrogen oxides
PAH	polycyclic aromatic hydrocarbons
PCB	polychlorinated biphenyls
PMV	predicted mean vote
PPD	predicted percentage of dissatisfied occupants
RH	relative humidity
SAD	seasonal affective disorder
SBS	sick building syndrome
SKT	skin temperature
SPL	sound pressure levels
SWB	subjective wellbeing
SWD	shift work disorder
SWL	sound power
TNZ	thermoneutral zone
TO	toxic organic
TTI	thermal infrared imaging
VOC	volatile organic compounds

Appendix A

Table A1. Sources based on their main research fields.

Origin	Number (Total: 246)	References
Building physics	42	[9,11,13,21,32,39,48,53,61,71,72,112,132–137,140,141,143,144,146–148,150,153,154,156,161–199,201,226,230,246].
Medicine	41	[3–5,7,10,19,20,31,38,40,62,65–70,73,79,90,98,107,114–116,121,122,124,127,142,149,151,152,155,162,184,219,222,241–245].

Table A1. *Cont.*

Origin	Number (Total: 246)	References
Neurosciences	36	[21,28,86,88,91,92,101,102,104–106,108,125,126,128,129,157,185–188,192,193,196,198,200,203,205–209,214,216,220,221].
Built environment	34	[1,2,6,14–17,30,42–47,49–52,57–60,64,74–77,81,82,85,103,111,131,145].
Biomedical engineering, biology	28	[24,29,95,138,170–183,195,204,215,217,218,223,227,228,231,232].
Computer sciences, engineering	27	[56,89,93,94,96,97,110,120,189–191,194,197,202,210,212–225,229,233–236,238–240].
Psychology	18	[8,22,25,37,38,63,87,99,100,109,117,118,123,125,126,130,158,160,211,237].
Economy, business	4	[35,36,55,80].
Ecology, botanics	6	[12,27,33,78,159,169].
Ergonomics	4	[34,83,84,113].
Others	4	[18,26,54,119].

Table A2. Sources about comfort, wellbeing, stress, and other definitions, based on their main research fields.

Origin	Number (Total: 157)	References
Built environment	28	[2,6,14–17,30,42,43,46,47,49–51,57,59,60,64,74–77,81,82,85,103,111,131].
Medicine	27	[3,7,19,20,31,38,40,62,65,66,73,79,90,98,107,114–116,121,122,124,127,149,151,184,222,241–243].
Building physics	24	[9,11,13,32,39,48,53,61,71,72,112,134,141,147,148,150,156,161,166–168,199,201,246].
Neurosciences	24	[21,28,86,88,91,92,101,102,104–106,108,125,126,128,129,157,185,186,188,189,196,205,206].
Computer sciences, engineering	17	[56,89,93,94,96,97,110,120,190,191,194,210,224,234,235,238,240].
Psychology	13	[8,22,25,37,38,63,87,100,117,118,123,125,126,130,158].
Biomedical engineering, biology	9	[24,29,95,183,195,223,227,228,231].
Economy, business	4	[35,36,55,80].
Ergonomics	4	[34,83,84,113].
Others	3	[26,54,119].
Ecology, botanic	2	[33,159].

Table A3. Sources about human aspects, categorized based on their focus.

Terms	Number (Total: 157)	References
Stress	38	[29,56,65,110,120–130,183–186,188–191,194–196,210,224,227,234,235,238,240–243].
Comfort	36	[15,16,30,34,35,42,43,46–51,57,59,61,62,66,71,72,111–119,131,147–149,159,201,222,223,231,246].
Health	36	[3,8,9,13,15–17,19,38,39,48,53,66,79,82,114–116,121,124,126–130,134,151,156,157,168,190,199,241–243,246].
Performance	21	[2,31,53,74–77,82–84,103–107,111,120,122,161,190,206].
Behaviour	17	[16,23,24,28,49–51,55,71,112,113,117,125,131,147,150,246].
Attention	16	[86–98,100–102,206].
Productivity	14	[13,14,33,35,36,76,77,79–81,85,89,158,168].
Wellness, wellbeing	13	[19,20,22,37,38,40,82,84,118,158,187,205,243].
Preference	8	[6,7,55,60,61,63,111,166].
Satisfaction	3	[30,32,64].

Table A4. Sources about indoor environmental quality (IEQ), based on their publication types.

Type	Number (Total: 90)	References
Books, book chapters, theses	6	[36,52,74,76,146,156].
Conference paper	5	[50,51,77,110,226].
Journal paper	72	[2,4,5,8,9,11–16,21,31–33,35,42,44–49,53,60–62,66–71,75,78,79,81–83,108,111,131–135,137–139,141–144,150,152–155,158,159,161,162,165–167,169,199,225,228,230,232,233].
Standards, guides, reports	6	[10,58,136,148,149,164].
Website	1	[145].

Table A5. Sources about IEQ, based on their main research fields.

Origin	Number (Total: 90)	References
Building physics	34	[9,11,13,21,32,48,53,61,71,132–137,139–141,143,144,146,148,150,153,154,156,161,164–167,199,226,230].
Built environment	24	[2,14–16,42,44–47,49–52,58,60,74–77,81,82,111,131,145].
Medicine	15	[4,5,10,31,62,66–70,79,142,152,155,162].
Ecology, botanics	5	[12,33,78,159,169].
Biomedical engineering, biology	3	[138,228,232].
Computer sciences, engineering	3	[110,225,233].
Psychology	2	[8,158].
Economy, business	2	[35,36].
Neurosciences	1	[108].
Ergonomics	1	[83].

Table A6. Focus points of the publications on IEQ.

Terms	Number (Total: 90)	References
Health	33	[4,8–10,12,13,15,16,21,48,53,66–70,78,79,82,134,135,138,139,142–144,153–156,162,164,199].
Comfort	25	[15,16,35,42,44–51,58,61,62,66,71,111,131,148,159,165,225,226,230].
Productivity	12	[13,14,33,35,36,52,76–79,81,158].
Performance	11	[2,31,53,74–77,82,83,111,161].
Behaviour	8	[16,49–51,71,78,131,150].
Preference	5	[60,61,111,132,166].
Wellness, wellbeing	2	[82,158].
Stress	1	[110].
Satisfaction	1	[32].

Table A7. Types of IEQ parameters in publications on IEQ.

Parameter	Number (Total: 90)	References
Thermal	26	[2,42,45,46,48,50,51,58,62,66–71,83,111,131,146,148,199,225,226,228,230,232,233].
Indoor air quality	19	[5,9,11,12,42,45,50,53,77,135,137–144,165].
IEQ	18	[13–16,21,32,36,47,49,52,60,75,76,78,79,82,132,133].
Visual	12	[8,33,44,150,152–156,158,159,199].
Acoustic	9	[31,61,161,162,164–167,169].

Table A8. Sources about physiologic signatures, based on their publication types.

Type	Number (Total: 110)	References
Books, book chapters, theses	13	[116,170,171,173–176,180,182,196,198,203,237].
Conference paper	17	[29,95,98,110,121,172,179,181,194,195,210,226,234–236,238,239].
Journal paper	78	[7,8,17,28,56,65–70,86–88,91,99,101,102,104,105,108,109,120,122,142,149,151,163,177,178,183,185,187–193,197,199–202,204–209,211–225,227–233,240–245].
Standards, guides, reports	2	[10,107].

Table A9. Sources about physiologic signatures, based on their main research fields.

Origin	Number (Total: 110)	References
Neurosciences	27	[28,86,88,91,101,102,104,105,108,185,187,188,192,193,196,198,200,203,205–209,214,216,220,221].
Biomedical engineering, biology	26	[29,95,170–183,195,204,215,217,218,223,227,228,231,232].
Medicine	23	[7,10,65–70,98,107,116,121,122,142,149,151,219,222,241–245].
Computer sciences, engineering	22	[56,110,120,189–191,194,197,202,210,212,213,224,225,229,233–236,238–240].
Psychology	6	[8,87,99,109,211,237].
Building physics	5	[163,199,201,226,230].
Built environment	1	[17].

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