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INTEGRATION OF HUMAN WELL-BEING IN DIGITAL CONSTRUCTION PROCESSES AND DIGITAL TWINS: A SYSTEMATIC REVIEW OF STRESS DETECTION PARAMETERS AND TOOLS TO SUPPORT HUMAN-CENTRIC CONSTRUCTION PROCESSES

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SUMMARY: *The increasing digitalization of the construction industry, driven by Building Information Modeling (BIM) and the rise of digital twins, necessitates a holistic approach to worker well-being. Understanding how digital tools and processes, including BIM-based workflows and digital twin applications, impact the psychological and physiological states of construction workers is crucial for improving safety, productivity, and overall job satisfaction. This study integrates construction practices and neuroscience by systematically reviewing quantitative parameters and tools for assessing worker well-being within various digital construction workflows, with a specific focus on BIM and digital twin applications. We identify key stress detection parameters (e.g., EDA, HRV) and tools from medical research applicable to construction management for enhancing worker well-being and mitigating risks. A comprehensive literature review synthesizes findings from multiple disciplines, focusing on stress detection techniques and their application in optimizing digital construction processes, specifically within BIM-driven projects and the development and utilization of digital twins. Results highlight stress detection parameters and tools offering valuable insights into worker experience, emphasizing the need for both qualitative and quantitative measures in project management, particularly within the context of BIM and digital twin technologies. A holistic, interdisciplinary approach merging ergonomics, neuroscience, and construction methodologies is crucial for enhancing worker experience in increasingly digitalized construction environments. Integrating stress detection technologies into construction management processes, especially those leveraging BIM and digital twins, is essential for promoting worker well-being and safety, while acknowledging limitations in current systematic research. Future exploration includes developing human-centered digital tools within BIM and digital twin workflows and applying medical findings to improve construction workflows. This research aims to inspire construction professionals to prioritize worker well-being and adapt their methodologies to address the unique challenges of digital transformation in the industry, leveraging the potential of BIM and digital twins to create safer and more productive work environments.*

KEYWORDS: *Neuro-Design, Digital Construction, Well-Being Assessment, Human-centric design, BIM.*

REFERENCE: *Vito Getuli, Eleonora D'Ascenzi & Irene Fiesoli (2024). Intertwining digital design and neuroscience: a systematic review of quantitative parameters and tools for assessing user well-being in immersive experience. Journal of Information Technology in Construction (ITcon), Special issue: 'Managing the digital transformation of construction industry (CONVR 2023)', Vol. 29, pg. 1257-1274, DOI: 10.36680/j.itcon.2024.056*

1. INTRODUCTION

The increasing digitalization of the construction industry, accelerated by the COVID-19 pandemic and driven by technologies such as Building Information Modeling (BIM) and digital twins, necessitates a critical reassessment of the relationship between workers and their built environment. While the importance of quality workspaces has long been recognized, the pandemic highlighted a global dissatisfaction with existing conditions (Melone and Borgo, 2020; Amerio et al., 2020; Alraouf, 2021). Advanced technologies offer opportunities to improve worker well-being and optimize construction processes; however, current Building Information Models (BIM) and digital twin applications primarily rely on ontologies mapping building data (.ifc) and sensor data (e.g., SOS ontology). These models, while comprehensive in representing building systems and sensor networks, typically lack the integration of human-centric data to assess occupant comfort and well-being. This critical gap highlights the need for a deeper investigation into the impact of digital tools on workers' conscious and unconscious responses.

The increasing use of BIM and digital twins in construction projects necessitates a careful consideration of how these technologies affect workers' well-being (Getuli et al., 2019). While the importance of user experience and well-being has been traditionally acknowledged, few studies have evaluated these aspects through scientific well-being detection within the context of digital construction workflows. Despite significant advancements in medical research on stress detection, the application of these findings in construction design and management remains limited. This gap is particularly significant given the rising prevalence of stress as a major contributor to reduced productivity and efficiency in modern workplaces (Feng et al., 2021; Attallah, 2020). The challenge lies in effectively identifying and addressing stress even when workers are unaware of their own high-stress levels (Sağbaş et al., 2020). The development of real-time stress detection methods is crucial for improving worker health and safety (Getuli et. al, 2014, 2018, 2020, 2023).

Neurodesign principles offer a valuable framework for investigating the effects of environmental factors and biometric parameters on worker behavior in digital construction environments. While interest in the impact of digital design on public health is growing, a significant research gap persists (Burton et al., 2011). This research systematically reviews state-of-the-art tools and quantitative parameters for assessing well-being and stress detection within digital construction workflows, specifically focusing on the integration of human-centric data into BIM and digital twin models. This systematic review will identify key technologies and parameters suitable for application in construction design and management. The aim is to integrate findings from various disciplines (environmental psychology, medicine, construction, and design) for the development of a holistic framework and a better understanding of how human factors can be considered in BIM-driven and Digital Twin-enabled construction processes to improve the overall well-being of construction workers.

This research employs a systematic literature review to identify state-of-the-art tools and quantitative parameters for assessing worker well-being and stress detection within digital construction workflows, with a specific focus on applications within BIM and digital twin environments. The review begins with an extensive literature search across three primary scientific databases: Scopus, Web of Science, and PubMed. These databases were selected for their comprehensive coverage of peer-reviewed journals and conference proceedings in relevant fields, including environmental psychology, ergonomics, medicine, construction, architecture, and design. The search was not limited to recent publications to maximize inclusiveness and obtain a broader understanding of existing research.

The search strategy involved a multi-stage process. First, the research scope was defined, and relevant keywords were identified. This was followed by an initial screening of search results, focusing on articles directly related to well-being and stress detection within the context of digital construction processes. A subsequent in-depth analysis of selected articles was conducted, using a qualitative approach to identify the most significant and representative studies for further analysis. The analysis focused on identifying the main well-being detection techniques and tools employed in research across relevant disciplines and assessing their potential application to construction, particularly in relation to BIM and digital twin technology. This systematic analysis investigates the applicability of stress detection tools currently used in medicine to the evaluation of worker well-being in digital construction settings.

2. APPLIED METHODOLOGY

The research methodology, summarized in Figure 1, comprises two main phases: data gathering and analysis of relevant literature. The initial phase involved a comprehensive literature search across three primary databases (Scopus, Web of Science, and PubMed) to identify relevant studies on stress detection techniques and tools filtering those than that can be applied to the construction industry, suitable for assessing worker well-being within the context of increasingly digitalized construction workflows, specifically within BIM and digital twin environments. This interdisciplinary search spanned environmental psychology, ergonomics, medicine, construction, architecture, and design literature to capture a wide range of perspectives and methodologies.

The subsequent phase involved a systematic review and analysis of the selected articles, focusing on techniques and parameters relevant to the assessment of worker well-being. This process involved a detailed qualitative analysis of the articles, identifying and categorizing the most significant and representative studies, ultimately leading to a synthesis of findings and the identification of key parameters and tools for future implementation in the construction industry. The analysis specifically explored how established stress detection techniques and parameters from medical research can be applied to assess worker well-being in BIM-driven and digital twin-enabled construction projects.

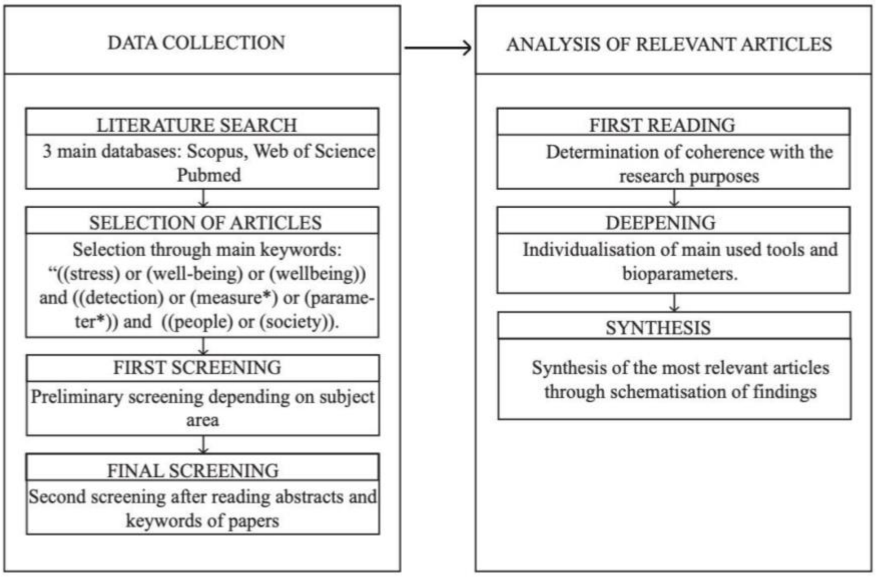

Figure 1: Systematic process of literature review.

2.1 Data collection

To identify relevant literature on stress and well-being detection methods applicable to the construction industry, a systematic search was conducted across three major databases: *Scopus*, *Web of Science*, and *PubMed*. These databases were selected for their comprehensive coverage of peer-reviewed journals and conference proceedings relevant to the interdisciplinary nature of this research, spanning environmental psychology, ergonomics, medicine, construction, architecture, and design. The search was not limited by publication date to ensure the inclusion of a wide range of relevant studies, maximizing the comprehensiveness of the review.

The search strategy employed a multi-stage process. Initially, the research scope was clearly defined, focusing on the identification of methods for detecting stress and well-being indicators. A set of keywords was then developed, encompassing terms related to "well-being," "stress," "detection," "measurement," and "construction," alongside synonyms and related terms to ensure a comprehensive search. Search fields were set to "title" and "topic" using Boolean operators to combine keywords and refine results. The search results were limited to peer-reviewed papers and conference proceedings published in English and Italian, further narrowing the focus to areas directly relevant to the research objectives (architecture, design, engineering, psychology, medicine, and sociology), while explicitly excluding irrelevant fields (e.g., agricultural research).

This initial search yielded 397 articles. A preliminary screening was conducted within the databases to filter out irrelevant articles based on title and abstract. Subsequently, a manual review of the remaining articles was undertaken by the authors to ensure alignment with the research objectives and to exclude articles that, while meeting the initial search criteria, did not fully address the research questions. This rigorous multi-stage approach ensured the selection of high-quality, relevant studies for the in-depth analysis presented in this research.

A filtering process have beeen done, Papers in peer-reviewed articles and conference proceedings focused on the proposed theme, this process included the removal of irrelevant articles, duplicates as well as dissertations and theses.

This preliminary review has been implemented by the reading of abstracts and the keywords of the remaining papers. In this case, the filtering criteria have been the following:

- Although the filtering of the selection area, searches still show the use of the keywords in different settings or with other meanings.
- Although the keywords refer to the macro area of research, they were not the focus of the main addressed issue

After applying these filtering criteria, the total number of relevant publications was quite low compared to the first total shown by the selected databases (see Table 1).

Table 1: Total number of manually reviewed articles.

Database	Total	Total after 1st screening
Wos	98	71
Scopus	48	5
Ebsco	152	5
Total	298	83

Following the initial screening, 298 articles remained for in-depth analysis, ultimately leading to the selection of 83 articles that provided the most relevant and representative insights into stress detection and well-being assessment methods in the construction industry context. While this subset does not represent the entirety of the relevant literature, it constitutes a robust and representative sample for this study.

To gain a comprehensive overview of the research landscape and identify key themes, a keyword analysis was performed using the *Voyant Tool Software*[1] software on the keywords extracted from the selected articles. Figures 2, 3, and 4 visually represent the most frequent keywords identified in each of the three databases (*Web of Science*[2], *Scopus*[3] and *Pubmed*[4]). These visualizations use a network graph representation, where nodes represent keywords and links represent the co-occurrence of keywords within the articles. The size of each node reflects the frequency of the keyword, while the color indicates automatic clustering based on semantic similarity. This technique provides insights into the key themes and concepts explored within the selected literature. Note that the visualizations are presented separately for each database due to limitations within the software, which prevented the integration of data across all three sources.

The keyword analysis revealed a cluster of highly interconnected terms related to stress detection, including "stress detection," "sensor," "quality," "mental health," "feasibility," "stress level," "reliability," "database," "validity," "parameter," and "value." Further analysis revealed related terms such as "galvanic skin response," "electrocardiogram," and "heart rate variability," providing a granular view of the specific parameters and measurement techniques discussed in the literature. The co-occurrence network of these keywords highlights the central themes of this study and provides a valuable context for the subsequent in-depth analysis of selected methodologies.

[1] https://www.vosviewer.com

[2] https://access.clarivate.com/login?app=wos&alternative=true&shibShireURL=https:%2F%2Fwww.webofknowledge.com%2F%3Fauth%3DShibboleth&shibReturnURL=https:%2F%2Fwww.webofknowledge.com%2F&roaming=true

[3] https://www.scopus.com/search/form.uri?display=basic#basic

[4] https://pubmed.ncbi.nlm.nih.gov

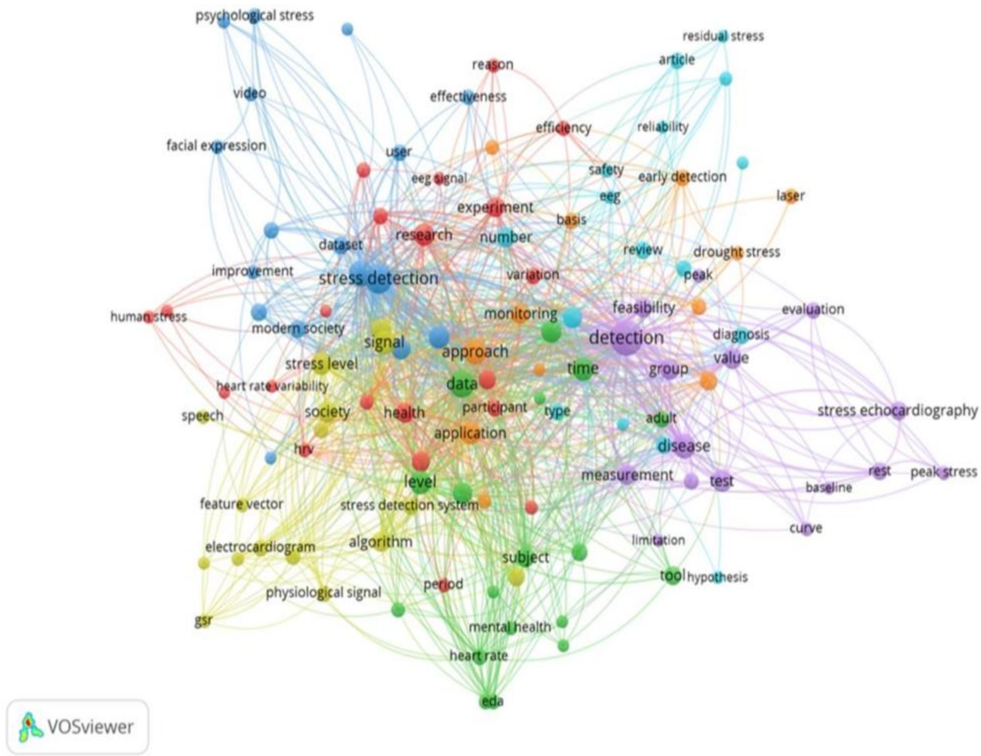

Figure 2: Web of Science keywords.

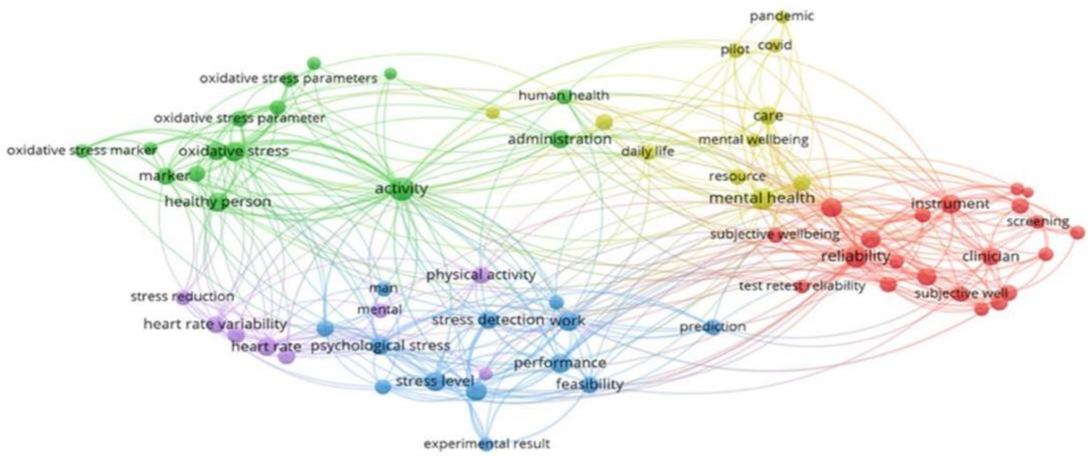

Figure 3: Pubmed keywords.

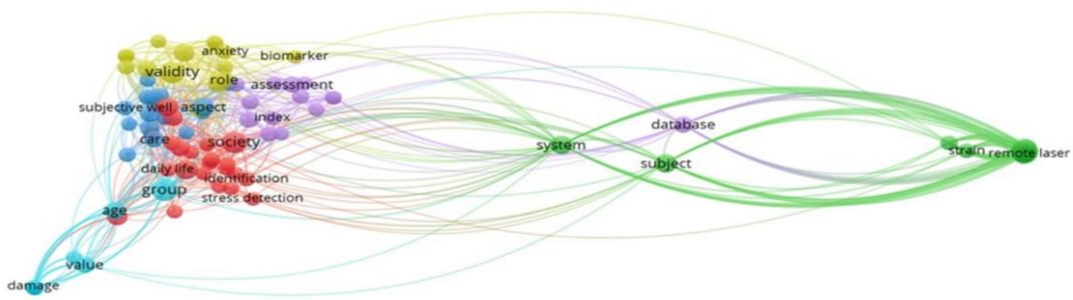

Figure 4: Scopus keywords

2.2 Analysis of relevant articles

Table 2: Main stress detection tools and stress parameters according to reviewed articles. Part one.

AUTHORS	STRESS DETECTION TOOL							STRESS PARAMETERS											
	WEARABLE	SMARTPHONE	MACHINE LEAR.	HEASET	SENSORY	VIDEO TOOL	OTHERRS	EDA	HRV	EEG	EMG	CORTISOL	TEMPERATURE	PD	BR	SENSORY	FACIAL MUSCLE	OTHERS
Debard et al. 2020	√							√	√									
Zhang et al. 2020						√												√
Attallah 2020	√									√								
Maheshwaran et al. 2020							√					√						
Sağbaş et al. 2020		√														√		
Delmastro et al. 2020	√		√					√	√									
Anusha et al. 2020	√		√					√										
Rachakonda et al. 2019	√		√										√					√
Feng et al. 2021							√		√									√
Liao et al. 2018							√		√									
Abdi et al. 2018							√	√	√					√	√			√
Li et al. 2018			√			√											√	
Minguillon et al. 2018	√						√	√	√		√							
Affanni et al. 2018							√	√										
Liu et al. 2018					√			√										
Healy et al. 2018			√			√											√	
Elzeiny et al. 2018						√	√	√	√				√			√		
Mozos et al. 2017	√		√					√	√							√		√
Mozos et al. 2017	.						√											√
Vildjiounaite et al. 2017	√	√																√
Vildjiounaite et al. 2017	√				√			√	√									
Acerbi et al. 2017	√		√					√	√									
Tillotson 2017	√						√	√	√									√
Kostopoulos et al. 2017					√													√
Zalabarria et al. 2017					√				√						√			
Pandey et al. 2016					√			√	√									
Zhao et al. 2016							√											√
Abburi et al. 2016			√				√											√
Kalas et al. 2016							√			√								
Kalimeri et al. 2016	√						√	√		√								
Reanaree et al. 2016	√			√			√		√	√								√
Vries et al. 2015	√						√	√	√						√			
Bin et al. 2015					√		√	√	√				√					
Ghaderi et al. 2015					√			√	√		√				√			
Salazar-Ramirez et al. 2014					√			√	√									
Lin et al. 2014							√											√
Vizer et al. 2009			√				√											√
Ruzanski et al. 2005							√											√
Rani et al. 2002	√		√						√									
Pu et al. 2020							√					√						
Sriramprakash et al. 2017					√			√	√									
Qiao et al. 2017							√					√						√

Table 2: Main stress detection tools and stress parameters according to reviewed articles. Part two.

AUTHORS	STRESS DETECTION TOOL							STRESS PARAMETERS										
	WEARABLE	SMARTPHONE	MACHINE LEAR.	HEASET	SENSORY	VIDEO TOOL	OTHERRS	EDA	HRV	EEG	EMG	CORTISOL	TEMPERATURE	PD	BR	SENSORY	FACIAL MUSCLE	OTHERS
Kikhia et al. 2016	√							√										
Burton et al. 2011							√											√
Pascoe et al. 2017							√	√	√			√						√
Uem et al. 2016	√						√	√	√							√		
King et al. 2002							√					√						
Sharma et al. 2012	√						√		√	√				√			√	√
Wells et al. 2014							√					√						

Following the initial selection, 83 articles were thoroughly analyzed to identify the most significant and representative studies. This in-depth, qualitative analysis aimed to provide a comprehensive review of the existing literature and to present a detailed overview of the subject matter. This research focused on two key aspects which are of primary importance in digtial processes: *Stress Detection Tools* and *Stress Parameters*. Stress Detection Tools refer to the specific instruments and technologies used to collect data related to well-being and stress. Stress Parameters, on the other hand, encompass the physiological and psychological indicators used to quantify deviations from a state of well-being and, primarily, to measure stress levels.

After an initial reading, a second phase focused on identifying the main well-being detection techniques and parameters described in the selected literature.

To pinpoint the most commonly used tools, a comprehensive review was conducted to identify the most recurrent parameters and well-being measurement tools across various fields. This involved a careful and thorough reading of the shortlisted articles, leading to a synthesis of the most relevant findings and a schematization of the key results. The authors employed a systematic categorization of the identified techniques, aiming to gain a clear understanding of the overall landscape before undertaking a more detailed investigation of individual subcategories. This process enabled the identification of most techniques and parameters prior to focused analysis.

This careful review revealed a crucial insight: while direct well-being measurement is often challenging from a purely medical perspective, deviations from a state of well-being, specifically through stress recognition, can be quantified. Consequently, the categorization of the reviewed articles (Table 2) presents a codification of well-being based on the analysis of stress recognition indicators, as identified in scientific studies.

After identifying the most frequently used techniques via keyword analysis, a synthesis of the findings was undertaken. This resulted in the grouping of methodologies into two main categories: stress detection tools and stress detection parameters. Each category was then further classified into subcategories based on the specific techniques employed, leading to a multi-level classification. This approach provided a clear summary of the deployed tools and identified trends, highlighting the most frequently used techniques while minimizing less common ones. This classification acknowledges that multiple categories may overlap due to the multi-parametric nature of much of the research. A detailed description of the main technologies and well-being measurement tools is provided in the following section.

3. LITERATURE REVIEW FINDINGS

This section presents key findings from the literature review, focusing on stress detection parameters and tools applicable to enhancing worker well-being within the context of the increasingly digitalized construction industry. While the impact of the built environment on well-being is widely acknowledged, and smart technologies are increasingly prevalent, research directly applying these advancements to assess and improve the health and well-being of construction workers remains limited. This study addresses this gap by focusing on the application of established stress detection techniques and parameters from psychological and medical research to the construction sector. The following discussion highlights key parameters and tools identified as having potential use in the design, management, and evaluation of construction projects, particularly within the context of BIM and digital twin technologies. However, it acknowledges limitations arising from inconsistencies between the methodologies developed within the medical field and their direct applicability to the construction industry, as detailed below.

3.1 Identification of the main stress detection parameters for stress detection to be implemented for evaluating immersive experience

The following sub-paragraph outlines the output of the research investigation through a brief synthesis of the main techniques adopted for stress detection. As follows, 10 kinds of stress detection adopted data have been identified as well as 6 main techniques to collect them. The following list represents the techniques most used in medicine and psychology for which exist technology and techniques that could be used also in immersive environments for planning process, management and control of virtual reality setting, as well as the detection of quality experience (Figure 5).

3.1.1 Electrodermal activity (EDA)

Electrodermal activity (EDA), also known as galvanic skin response (GSR) or skin conductance (SC), is a physiological measure reflecting the activity of the sweat glands and providing an objective index of emotional arousal and stress. EDA measures changes in skin conductance due to sweat production, which is directly related to the sympathetic nervous system's activity. Higher EDA values generally correspond to increased arousal, anxiety, or stress. The measurement is based on the principle that sweat glands are controlled by the sympathetic nervous system, which is activated during stress responses.

Increased sweat gland activity leads to increased electrical conductivity of the skin, which can be measured using non-invasive sensors. EDA's non-invasive nature makes it a particularly useful tool for studying stress and emotional responses in various settings, and it has been widely used in numerous studies employing wearable devices (Acerbi *et al.*, 2017; Anusha *et al.*, 2020; Debard *et al.*, 2020; Delmastro *et al.*, 2020; Kalimeri and Saitis, 2016; Minguillon *et al.*, 2018; Mozos *et al.*, 2017) or embedded sensors (Affanni *et al.*, 2018; Sriramprakash *et al.*, 2017; Zalabarria *et al.*, 2017). While generally considered a reliable indicator of stress, it's important to note that EDA can also be influenced by other factors, such as temperature and hydration, requiring careful consideration of these variables in the interpretation of results.

3.1.2 Heart Rate Variability (HRV)

Heart Rate Variability (HRV) is defined as the standard deviation of the intervals between successive heartbeat signals. It reflects the body's ability to adapt to stress and changing environmental conditions by assessing the dynamics of the autonomic nervous system. A higher HRV is generally associated with good health and psychological well-being, while a lower HRV may indicate stress or overload. HRV can be easily monitored using wearable devices, sensors, or traditional electrocardiogram (ECG) systems. Recent studies have even explored the combination of HRV data with social media microblogs to gather real-time information about well-being (Acerbi *et al.*, 2017; Debard *et al.*, 2020; Rani *et al.*, 2002) or other monitoring tools with specific sensors (Mozos *et al.*, 2017; Reanaree *et al.*, 2016; Sriramprakash *et al.*, 2017; Zalabarria *et al.*, 2017)(Mozos et al., 2017)(Feng *et al.*, 2021).

3.1.3 Electroencephalogram (EEG)

Electroencephalogram (EEG) is a technique used to detect and monitor real-time stress levels in daily life by utilizing specific headsets equipped with electrodes that measure electrical activity in the brain. This non-invasive technique (when using scalp surface electrodes) allows for the assessment of stress through the analysis of brainwave patterns. Numerous studies have demonstrated the correlation between EEG signals and stress levels, employing various devices ranging from traditional electrodes to helmets designed for EEG monitoring (Attallah, 2020; Elzeiny & Qaraqe, 2018; Kalas & Momin, 2016; Reanaree et al., 2016) (Kalimeri and Saitis, 2016). Although from a medical point of view it could be a non-invasive method thanks to the use of scalp surface, from a perspective of stress monitoring, on the contrary, it is quite intrusive since it requires the use of electrodes.

3.1.4 Electromyogram (EMG)

Electromyography (EMG) is a technique used for measuring the electrical activity of muscles, which can provide valuable insights into muscle response and tension. By assessing the electrical signals generated when muscles contract, EMG serves as a potential indicator of stress levels in individuals. When a person experiences stress, muscle tension often increases, which can be detected using EMG sensors placed on the skin over the targeted muscles. This method has been employed in various studies to analyze real-time stress responses, making it a useful tool for understanding how physical and psychological stressors impact muscular activity (Elzeiny and Qaraqe, 2018; Ghaderi *et al.*, 2015; Minguillon *et al.*, 2018).

While EMG can be a powerful tool for stress detection, its application in built environments poses certain challenges. The dynamic nature of construction sites—with constant movement and noise—can interfere with EMG readings, making it difficult to isolate muscle activity related to stress from other muscular movements. Despite these challenges, EMG remains a promising method for monitoring physical tension and stress in various settings, including workplaces.

3.1.5 Cortisol

Cortisol is a steroid hormone produced by the adrenal glands, playing a critical role in regulating various bodily functions, including metabolism, immune response, and, importantly, the body's reaction to stress. Often referred to as the "stress hormone," cortisol is released in response to stressful situations and helps prepare the body for a "fight or flight" response by increasing glucose availability, enhancing brain function, and modulating immune responses. Its levels fluctuate throughout the day, typically peaking in the morning and gradually declining throughout the day. Salivary cortisol is commonly used as a biomarker for measuring stress levels, as it provides a non-invasive means of assessing cortisol concentrations in the body.

Researchers often analyze salivary samples to determine cortisol levels, which can offer insights into a person's stress load and overall emotional well-being. While salivary cortisol assessment is widely used in medical and psychological research (Pascoe *et al.*, 2017; Qiao *et al.*, 2017; Wells *et al.*, 2014) , its application in built environments -such as workplaces or construction sites- presents specific challenges. Collecting saliva samples typically requires controlled settings and appropriate timing to ensure accuracy, making it less practical for real-time stress monitoring in dynamic environments.

3.1.6 Human Body Temperature

Body temperature is a critical physiological parameter that can reflect an individual's physical and mental state. It is generally maintained within a narrow range in healthy individuals, typically around 98.6°F (37°C). Variations in body temperature can indicate different levels of stress, as the body often reacts to stressors—both physical and psychological—through thermoregulation. When a person experiences stress, their body may exhibit changes in temperature due to hormonal responses, increased metabolic activity, and alterations in blood flow. Research has shown that measuring changes in body temperature can provide insights into stress levels. Higher body temperatures may be associated with elevated stress due to increased metabolic processes, while lower temperatures could indicate relaxation or reduced stress.

Various methodologies exist for detecting changes in body temperature, including contact sensors that measure temperature directly through skin contact and non-contact sensors that gauge surface temperature from a distance via infrared technology. Many studies detect stress through this method by means of contact sensors ((Bin *et al.*, 2015; Rachakonda *et al.*, 2019) or non-contact sensors ((Elzeiny and Qaraqe, 2018). The ability to monitor body temperature provides a valuable means of assessing stress, as it correlates with other physiological responses to stressors, offering a comprehensive view of an individual's well-being. By analyzing temperature data, researchers and health professionals can gain a deeper understanding of the relationship between physiological states and stress levels.

3.1.7 Pupil diameter

Pupillometry is the measurement of pupil size and reactivity, serving as a vital index for investigating various psychological phenomena and emotional states. The diameter of the pupil can indicate an individual's level of arousal, cognitive load, and emotional response, providing insights into their well-being. Pupils can undergo two primary changes: dilation, known as mydriasis, and constriction, referred to as miosis. When an individual experiences stress, the body activates the sympathetic nervous system as part of the fight-or-flight response. This activation often results in mydriasis, or pupil dilation, as the body prepares for heightened alertness and awareness of potential threats. Changes in pupil size can be measured using specialized equipment, allowing researchers to analyze pupil reactivity as an indicator of stress levels.

Various studies have effectively employed pupillometry to assess stress responses, showcasing its potential as a reliable tool in psychological and physiological research (Al Abdi *et al.*, 2018; Gunawardhane *et al.*, 2013). By monitoring pupil size and its fluctuations in response to different stimuli, pupillometry provides valuable data on the relationship between physiological states and emotional well-being, offering a non-invasive means of studying stress and other psychological conditions.

3.1.8 Breathing rate

Breathing rate, or the number of breaths taken per minute, is a vital physiological parameter that can provide insights into an individual's stress levels. Under normal conditions, the average breathing rate for adults is approximately 12 to 20 breaths per minute. However, this rate can be significantly altered by psychological stress and emotional responses.

When a person experiences stress, the respiratory pattern may change, often becoming shallower or more rapid, a phenomenon known as hyperventilation. During hyperventilation, the breathing rate can increase to between 25 and 40 breaths per minute, which may lead to feelings of anxiety or panic. This change in breathing patterns can be reliably captured using wearable devices equipped with sensors designed to monitor respiratory function (Can *et al.*, 2019; Mozos *et al.*, 2017) or through specialized tools that measure respiratory activity (Al Abdi *et al.*, 2018). By assessing breathing rate and patterns, researchers can gain valuable insights into an individual's stress responses and emotional states. This biomarker is not only useful for understanding stress-related health issues but can also inform interventions aimed at promoting relaxation and well-being.

3.1.9 Sensor data (accelerometer and gyroscope)

Sensor data obtained from accelerometers and gyroscopes can serve as valuable indicators of stress levels in individuals. An accelerometer is a device that measures linear acceleration, providing real-time information about motion, position, and orientation. It can capture data related to physical activity, posture, and movement patterns.

When applied in the context of stress monitoring, accelerometers can help identify changes in activity levels that may be associated with stress responses. For instance, increased agitation, fidgeting, or less movement may indicate heightened stress. Research has shown that analyzing accelerometer data can provide insights into how stress manifests physically, thus enabling a better understanding of its impact on an individual's behavior (Debard *et al.*, 2020; Sağbaş *et al.*, 2020).

Gyroscopes, on the other hand, measure angular velocity and orientation, allowing for a more comprehensive analysis of motion dynamics. By combining data from both accelerometers and gyroscopes, researchers can gain a detailed understanding of how stress influences both physical activity and body movement patterns. These sensors, when integrated into wearable devices, create opportunities for continuous monitoring and real-time feedback regarding an individual's stress levels based on their physical activity profile.

3.1.10 Real-time Video-Facial Muscle Detection

Video-facial muscle detection is an innovative technique that leverages machine learning models, particularly support vector machines (SVM), to identify and classify facial expressions associated with stress. This approach analyzes the movements and contractions of facial muscles through video data, enabling the detection of subtle changes that may indicate an individual's emotional state. Facial expressions are a significant indicator of psychological well-being, and certain muscle movements can be closely correlated with stress responses. By employing advanced algorithms, researchers can train machine learning models to recognize specific facial muscle patterns that correspond to various stress levels. For instance, furrowing of the brow, tightening of the jaw, or other facial cues may be analyzed to determine whether a person is experiencing stress.

The integration of facial muscle detection with deep learning techniques enhances the accuracy and reliability of stress detection systems. Deep learning algorithms can automatically learn and extract features from video data without the need for extensive manual feature engineering, improving the overall efficiency of the classification process. This can lead to quicker and more accurate assessments of an individual's stress levels based on their facial expressions. Using video-facial muscle detection as a stress monitoring tool opens up new possibilities in various contexts, from healthcare to workplace environments, where understanding emotional well-being is crucial. This non-invasive method can provide real-time insights into stress responses, helping individuals and organizations implement timely interventions to manage stress effectively. (Healy *et al.*, 2018; Zhang *et al.*, 2020).

3.1.11 Others

Moreover, other studies focus on hand movements (Reanaree *et al.*, 2016), tweeting content (Zhao *et al.*, 2016) keyboard typing (Sağbaş *et al.*, 2020; Vizer *et al.*, 2009) and audio detection (Abburi et al., 2016).

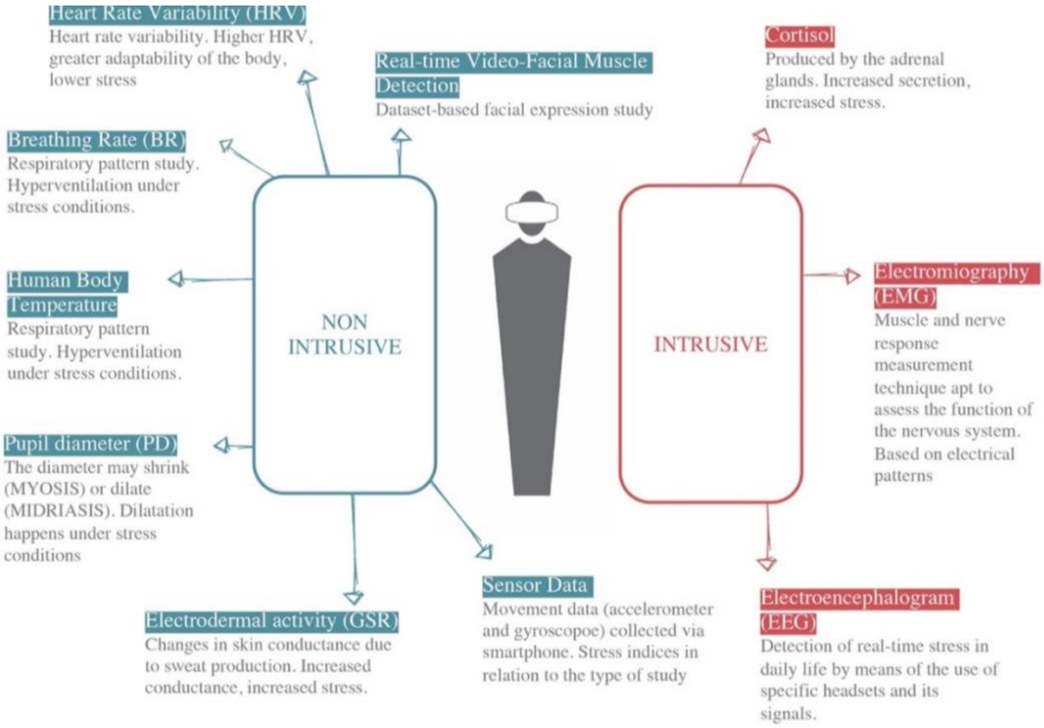

Figure 5: Non-intrusive and intrusive parameters for evaluating immersive experience.

3.2 Identification of the main adopted techniques for stress detection to be implemented for evaluating immersive experience

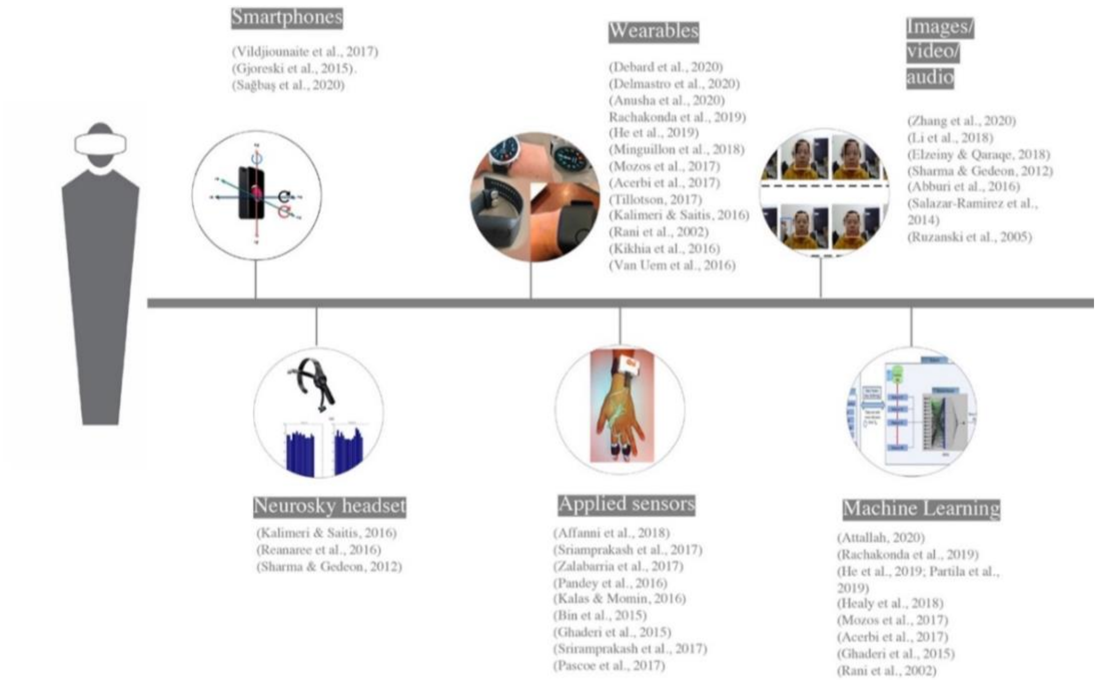

Figure 6: The main techniques adopted to detect well-being variables.

In this section the main techniques used for collecting stress detection's parameters have been outlined and synthesised as schematically reported. As mentioned in the previous paragraph, several parameters could be analysed for stress detection purposes and along this line, the main adopted techniques to detect (sometimes even simultaneously) well-being variables have been analysed (Figure 6).

Among others, it is worth mentioning:

3.2.1 Wearable devices

Wearable devices have emerged as powerful tools for stress detection, primarily due to their versatility, non-intrusiveness, and accessibility. These devices, designed to be worn on the body, include a variety of sensors capable of monitoring physiological parameters such as heart rate variability (HRV), electrodermal activity (EDA), breathing rate (BR), and hand movement. Their ability to collect and analyze real-time data makes them particularly suited for daily stress detection studies. (Anusha *et al.*, 2020; Debard *et al.*, 2020; Delmastro *et al.*, 2020; Mozos *et al.*, 2017)

The widespread availability of these devices has contributed to their popularity among consumers and researchers alike, as they can be easily integrated into everyday life, promoting regular monitoring of stress levels. Many wearable devices are designed to be user-friendly and can seamlessly fit into a person's routine, often resembling everyday accessories like watches or fitness trackers. In addition to more common physiological metrics, some advanced wearable systems are capable of collecting electrocardiogram (ECG) measurements. Notable examples include systems like Biopac MP150, MP35, and Shimmer Sensing 3 (Can *et al.*, 2019), which provide more comprehensive physiological data for stress analysis. These capabilities enable users and researchers to monitor health and stress indicators that can be correlated with emotional states and stress responses.

The non-invasive nature of wearable devices allows for continuous monitoring without significant disruption to the user's daily activities; in some instances, these devices may be worn without the user's explicit awareness. This feature is particularly beneficial for longitudinal studies and ongoing stress management initiatives, as it enables unobtrusive data collection over extended periods. Overall, wearable devices represent a promising advancement in stress detection technology, facilitating better understanding and management of stress in various contexts.

3.2.2 Smartphones

Smartphones have emerged as common unobtrusive devices capable of collecting a wide range of physiological and behavioral data, making them valuable tools for stress detection. Equipped with various sensors and functionality, smartphones can extract multiple features that contribute to understanding an individual's stress levels. Some of the key data points that smartphones can collect include: Accelerometer Data (This measures motion and can help assess physical activity levels and movement patterns); Audio Classification (Smartphones can analyze audio data to detect speech patterns and emotional tone, which may provide insights into stress-related vocal stress); Call Time and Duration (Data on the frequency and duration of calls may reflect social interactions, which can be correlated with stress levels); Light Sensor Data (Changes in ambient light conditions can affect mood and stress, and this data can be measured through smartphones); GPS Information (Location tracking can highlight changes in environment and context related to stress); Screen Mode Changing Frequency (Monitoring how often users switch their screens on and off may correlate with attentional demands and stress); Video Data (Capturing videos can be used for facial recognition and analysis of emotional expressions); Wi-Fi Connections (Frequency and patterns of connectivity can provide additional contextual information regarding a user's social environment).

Research has shown that there is a significant correlation between stress levels and the various data collected through smartphones (Gjoreski *et al.*, 2015). However, a study by Can et al. (2019) revealed low classification accuracy in stress detection when relying solely on smartphone data. This finding emphasizes the need for adopting a more integrated approach to stress monitoring. By combining smartphone data with additional data from wearable devices, researchers and practitioners can achieve a more comprehensive and accurate understanding of stress levels, leading to more effective stress management strategies.

3.2.3 Machine learning

Machine learning, a subset of artificial intelligence, plays a crucial role in processing and analyzing the vast amounts of data generated by wearable devices and smartphones. As these devices capture continuous streams of physiological and behavioral data, such as heart rate, breathing rate, and galvanic skin response, the challenges associated with big data arise. The integration of machine learning techniques enables researchers and practitioners to extract meaningful insights from this complex data landscape, facilitating more accurate stress detection and analysis (Delmastro *et al.*, 2020; Sağbaş *et al.*, 2020).

The continuous flow of data generated by wearables and smartphones not only necessitates algorithmic calculations to manage and analyze usage behaviors but also requires the application of sophisticated machine learning algorithms to derive reliable categorizations and identify patterns. Common classifiers used in this context include K-nearest neighbor (KNN) and support vector machines (SVM) (Ghaderi *et al.*, 2015), which can effectively classify and predict stress levels based on the collected bio-parameters.

Additionally, advancements in machine learning have led to the development of specialized models focused on emotion detection through human facial recognition. These models leverage deep learning techniques to analyze facial expressions and micro-expressions, providing a nuanced understanding of an individual's emotional state (Healy *et al.*, 2018). By combining data from various sources and employing machine learning algorithms, researchers aim to improve the accuracy and reliability of stress detection systems, ultimately enhancing interventions and support for individuals experiencing stress.

3.2.4 Neurosky headset

The Neurosky headset is a wearable device designed to monitor and record the electrical activity of the brain using electroencephalography (EEG) technology. This headset employs electrodes to capture brain wave patterns, allowing for real-time monitoring of neurological activity associated with various mental states, including stress. By analyzing these electrical signals, the Neurosky headset provides valuable data regarding cognitive functions, emotional responses, and overall brain activity.

EEG measurements produced by the Neurosky headset can help identify stress-related brain wave patterns, enabling researchers and practitioners to gain insights into how stress impacts cognitive processes and emotional regulation. The headset is particularly useful in environments where traditional methods of stress assessment may be impractical, offering a non-invasive way to investigate the neurophysiological aspects of stress.

In addition to its standalone capabilities, the Neurosky headset can be complemented by other devices, such as an intelligent watch made using Arduino technology. This integration allows for the collection of additional physiological data, creating a more comprehensive assessment of an individual's stress levels as it combines both brain activity and other biometric measurements (Reanaree *et al.*, 2016). The synergy between the Neurosky headset and supplementary wearable devices enhances the potential for more effective real-time stress monitoring and analysis.

3.2.5 Applied sensors

A number of applied sensors for Galvanic Skin Response (GSK), Electrocardiogram (ECG), Electroencephalogram (ECC) are available on the market. Differently from wearable and smartphones, these applied sensors are invasive, and the user is conscious of being under observation without specifically knowing the reason why. Although these kinds of applied sensors are different from each other, they can collect multiple signals or one single bio-parameter. At the same time, they can be both easily be portable and/or not movable (Attallah, 2020; Kalimeri and Saitis, 2016; Minguillon *et al.*, 2018; Pandey *et al.*, 2016).

3.2.6 Images/video/ audio capturing tools

Other fundamental tools to be considered other than smartphones are video, audio and image-capturing devices. Among them, especially used for reaching out to a large number of people rather than to an individual person, are video cameras and contact-free camera sensors. By guaranteeing a cost-effective system, these are the most frequently used tools to detect users' facial expressions (Abburi et al., 2016; Zhang et al., 2020).

4. CONCLUSION AND DISCUSSIONS

In order to utilize stress detection parameters for future applications within the analysis of well-being in building design, construction and management; this review summarizes the main technologies used in medicine. This investigation aims to educate designers about the actual impact of the digital environment on daily life and to encourage planners to create spaces that enhance users' well-being by considering the implications of digital environments. To achieve this, a holistic approach is essential, as understanding the high potential of an interdisciplinary concept that bridges the medical field and design is crucial. Based on lessons learned from the COVID-19 pandemic, the role of this integrated approach is to create a comprehensive methodology that can bridge the gap between architects, engineers, and designers regarding the expressed or unexpressed responses of users to the digital impact of their environments. This review investigates stress bio-parameters that could be adopted in digital design to establish indicators of high-quality satisfaction for new environments. It emphasizes not only qualitative data, such as interviews and self-reported evaluations, but also quantitative data derived from physiological feedback that reveals unconscious responses. The authors have reported two main areas: stress bio-parameters and associated tools that can serve as potential well-being indicators in design. The most common stress parameters and corresponding tools used in other fields have been presented to provide a complete overview of the current practices which digital design can incorporate, particularly non-invasive techniques for assessing the impact of design strategies on user satisfaction.

Our bodies are influenced by the choices and design strategies employed by architects, engineers, and designers. There is a need for scientifically recognized methods to evaluate the implications of design for users' well-being, especially those that extend beyond traditional qualitative data, which may be subject to respondents' bias. The choice of the most suitable tool depends on the available resources, target demographics, and specific research objectives. Advanced techniques, such as video and image analysis through machine learning, can be beneficial for analyzing well-being in large populations. Thus, measurements of pupil diameter and facial muscle movements are essential for this type of analysis. For smaller sample sizes, where artificial intelligence may not be necessary, techniques such as Heart Rate Variability (HRV), Electrodermal Activity (EDA), and Breathing Rate (BR) can be more informative, as even ordinary wearables can easily monitor stress levels. It is advisable to adopt a transdisciplinary approach in which these technologies facilitate a more profound investigation into the relationship between users and the built environment.

While it is widely recognized that human beings respond cognitively, emotionally, and physiologically to the built environment, interdisciplinary studies focusing on physiological well-being in relation to immersive design seem to be lacking. This gap, if addressed, could prove promising for the construction industry. Emerging fields such as "neuroarchitecture" or "neuro design" are exploring how architecture and enginerring studies can benefit from its intersection with neuroscience. Therefore, the adoption and implementation of practical methodologies in this conceptual model represents a central challenge for contemporary building design and construction. It is expected to assist digital design and construction researchers in integrating medical analyses of well-being into the design and process.

In this sense the authors has identified a number of implications in cosntruction design and management where the introduction of stess detection can support more effective human centric digital processes:

- **Design Phase**: During the design process, integrating stress bio-parameters, such as Heart Rate Variability (HRV) and Electrodermal Activity (EDA), enables architects and designers to create spaces that not only fulfill aesthetic and functional criteria but also enhance user well-being. By analyzing user feedback through physiological measures, designers can identify stressors in specific layouts and materials and adapt the design to promote comfort and reduce stress.
- **Construction Phase**: In the construction phase, wearable devices that monitor stress levels in real-time can be invaluable for ensuring worker safety and health. Project managers can utilize data from these devices to identify stress patterns among workers, allowing them to implement supportive measures such as workload adjustment, breaks, or mental health resources. Understanding the physiological responses of workers helps create safer, more supportive work environments, ultimately leading to increased productivity.
- **Management Phase**: Building management systems can benefit from continuous monitoring of occupants' stress levels using embedded sensors. Stress data can inform adaptive control systems that adjust environmental factors—such as lighting, temperature, and air quality—to optimize comfort for building users. Regularly assessing stress levels can ensure that the building environment remains conducive to the well-being of its occupants (Bruttini et al. 2023).
- **Post-Occupancy Monitoring**: Post-occupancy evaluations utilizing stress detection technologies can yield insights into long-term user experiences within the built environment. By analyzing changes in stress indicators over time, facility managers can assess the effectiveness of design interventions and make data-driven adaptations to further enhance occupant satisfaction.

- **Integration with Digital Twins**: The concept of digital twins—virtual representations of physical structures—can leverage stress detection parameters to simulate and analyze how different design scenarios impact user experiences over time. By incorporating physiological data into digital twin models, stakeholders can forecast potential stress points and make informed design adjustments ahead of construction, leading to better outcomes.

In this sense, the use of *Building Information Models* (BIM) could provide a robust framework for integrating stress detection parameters and technologies into the construction design and management process which are based on BIM Data. Infact, after this extented analysis the authors belive that by incorporating real-time physiological data into the BIM workflow, various benefits can be realized as syntetyzed int he following point:

- **Enhanced User-Centric Design**: Integrating stress parameters within BIM allows for predictive modeling that anticipates how design changes could affect occupant well-being. Architects can modify layouts or material selections based on real-time stress data, ensuring that designs promote a conducive environment for users.
- **Dynamic Simulation of Stress Responses**: BIM can facilitate dynamic simulations that incorporate stress indicators, enabling stakeholders to visualize the impacts of design decisions on user stress levels throughout different phases of the building lifecycle. This capability allows for preemptive adjustments that enhance occupant satisfaction.
- **Improved Construction Management**: During the construction process, integrating wearables into the BIM framework allows project managers to monitor workers' health and stress levels alongside project timelines and resource allocation. This data can lead to more informed decisions related to workforce management, potentially minimizing stress-related injuries and improving productivity.
- **Adaptive Building Systems**: Through the integration of stress detection technologies with BIM, building management systems can be developed that dynamically adapt to occupant stress levels. This means that facilities can respond proactively to changes in environmental conditions that may affect well-being, aligning with the real-time needs of occupants.
- **Comprehensive Data Analysis and Reporting**: Utilizing BIM to aggregate data from stress detection technologies allows for comprehensive analyses that identify trends over time. Facility managers can use this information to make continuous improvements and support policies that prioritize occupant health and well-being.

By embracing these technologies and integrating them with BIM, the construction industry can foster a more holistic and user-centric approach to building design and management. This not only enhances the quality of life for occupants but also leads to a more sustainable and successful built environment.

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