APPLICATION OF SMART TECHNOLOGIES FOR ASSESSING USERS' WELL-BEING FOR IMMERSIVE DESIGN STRATEGIES: A STATE-OF-THE-ART REVIEW

Eleonora D'Ascenzi, Vito Getuli & Irene Fiesoli
University of Florence, Florence

ABSTRACT: *As never before, during the COVID-19 pandemic, the effectiveness of the digital design strategies on the user's well-being has been questioned. However, a research branch astride digital design and neuroscience able to overcome net discipline borders to analyse users' well-being seems to be lacking. Today mainly qualitative data are used in the design field for the investigation of users' quality experience. Although fundamental, they also have great disadvantages such as unanswered questions, unconscientious responses, and respondents' biases. As such, a systematic state of art review is presented to find methodologies and tools currently used in medicine to identify the impact of digital design strategies (XR) on users' well-being through quantitative and objective data. The main technologies used for this purpose have been synthesized in a schematic chart by reporting the principal related biometric data (skin conductivity, heart rate metrics and breathing rates), as well as other technologies such as video/images/audio analysis based on sensors and machine learning to reach out mass numbers. In conclusion, gaps and future applications of this innovative approach within the virtual environment have been identified by the authors.*

KEYWORDS: *extended reality, virtual reality, neuro-design, digital design, immersive experience, user experience, well-being assessment*

1. INTRODUCTION

In these current times and especially within the COVID-19 frame, we are witnessing design calling itself under question by focusing on the redefinition of the relationship between users and spaces. Although the importance of quality space has been considered a central point in design planning, the current pandemic is indeed pointing out a global dissatisfaction in this regard (Melone & Borgo, 2020) (Amerio et al., 2020) (Alraouf, 2021). Concurrently, in this perspective, the advanced technologies - such as eXtended Reality (XR)- are increasingly used to early acknowledge people responses in terms of spaces' satisfaction. However, in this regard, is it possible to take a step back and understand the impact that such immersive technologies have on users' conscious and unconscious responses? We're witnessing an increasing digitization both in our daily lives and in the working environment to such an extent that the virtualisation of the spaces -for knowing the customer satisfaction in advance as well as for creating an alternative world- is becoming an increasingly debated issue. For this reason, it becomes critical and extremely relevant to understand what impacts immersive spaces have on people's well-being. Although the importance of user experience in terms of well-being has been traditionally recognised, few studies have been conducted in the evaluation through scientific wellbeing detection in virtual spaces. Furthermore, despite the medical concurrent and ongoing findings for stress investigation, the implications of these results appear to struggle to be applied in digital design and in design in general. In this sense, medicine is today perfecting an ongoing and relevant theme of stress detection analysis since increasingly stress is becoming a serious problem for users' productivity and efficiency in modern society (Feng et al., 2021) (Attallah, 2020). Although stress is one of the major contemporary problems, it is difficult for people to perceive even if they are subject to high stress levels or not (Sağbaş et al., 2020) and for this reason the research field is working on a method that is able to return real-time stress detection. The role of neurodesign should be able to spotlight and investigate not only the effects of environmental factors on people's behaviour but also study user's biometric parameters, to inform contemporary digital design. However, even if today there is an increasing and updated interest on the influence of the digital design on public health, there is at the same time a significant lack of research (Burton et al., 2011). The research methodology has been conducted through a systematic state of the art tools for well-being and stress detection in order to define the main technologies to use for future applications within the immersive digital design.
The methodological review begins with an extensive literature search to attain the desired research items, namely the well-being detection techniques and tools and it ends, through its synthesis, with the interpretation of the most relevant articles. To obtain pertinent articles on the topic, "Scopus", "Web of Science" and "Pubmed" were used as the primary scientific search engines. In order to collect the most used techniques for people well-being by overcrossing net disciplines boundaries through a interdisciplinary approach, the choice fell to these three databases due to their huge coverage of peer-reviewed journals and conference proceedings in environmental psychology, medicine, construction, architecture and design. The time span for publication was not restricted to

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recent times due to the willingness to maximise the inclusiveness of the searched items and obtain a wider possible framework. The first step of the literature research has been identified with the definition of the research scope and identification of keywords.
After that, a short listing of the most relevant articles on the theme have been pursued by accurately analysing them for the research purposes, in order to identify the most significative and representative studies. To provide a comprehensive review of the existing literature, this research led to an in-depth study and qualitative analysis of the contents, to present the main analysis carried out on the subject theme. As such, after a first reading of the articles, a deepening phase with the gathering of the main used techniques for well-being detection for evaluating immersive experience was collected. Thus, stress detection tools currently used in medicine have been investigated to understand if could be possible to apply these for well-being evaluation in the frame of immersive digital environment.

2. LITERATURE REVIEW FINDINGS

This section aims at providing an in-depth discussion of the important findings of the reviewed literature with the aim to underline the well-being measurement techniques to be exploited in construction.
The organisation of this section is twofold: first, it presents a collection of stress detection parameters; then, it provides insights regarding the tools to detect stress. Despite the extensive acknowledgment of the impact of the built environment on users' well-being and the recent advancement of smart technologies, just a limited attention has been dedicated to digital design studies of the consequences of immersive environments on the health of occupants. Furthermore, to validate virtual spaces, even a more restricted consideration has been dedicated to the application of smart technologies derived from different research areas. Thus, a focus on the implementation of operating procedures for assessing health and well-being were analysed and reported in the present paragraph by especially referring to psychological and medical research sphere that could be employed in construction and occupancy evaluation. However, not all the initially founded methods have been reported due to the inconsistency between the encountered medical techniques and the application in the digital immersive design field. The below-listed stress detection parameters and tools have been investigated due to their possible use for design research purposes.

2.1 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 (Fig.1)

(1) Electrodermal activity (EDA)

Electrodermal activity (EDA) also known as Galvanic Skin Response (GSR) or Skin Conductance (SC) is an objective tool of stress indication. EDA measures the changes in conductance at the skin surface due to sweat production that is representative of the intensity of our emotional arousal. It could be considered as a non-intrusive control tool, and for this reason it has been used in many studies thanks to the use of wearable devices (Acerbi et al., 2017; Anusha et al., 2020; Debard et al., 2020; Delmastro et al., 2020; Kalimeri & Saitis, 2016; Minguillon et al., 2018; Mozos et al., 2017) or embedded sensors (Affanni et al., 2018; Sriramprakash et al., 2017a; Zalabarria et al., 2017) able to detect it.

(2) Heart Rate Variability (HRV)

While Heart Rate is the average number of beats in a minute, Heart Rate Variability (HRV) is defined as the standard variation of inter-beat intervals (Elzeiny & Qaraqe, 2018). HRV could be considered a biometric parameter upon which to determine people's stress conditions. Thanks to the use of a tool able to detect heart signals, HRV could be easily collected through wearable devices (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., 2017b; Zalabarria et al., 2017)(Mozos et al., 2017) or a traditional ECG. HRV could be also combined with social media microblogs (Feng et al., 2021).

(3) Electroencephalogram (EEG)

Electroencephalogram (EEG) is a tool to detect real-time stress in daily life by means of the use of specific headsets and its signals. Many studies analyse stress levels thanks to the use of brain electrodes in this technique (Attallah, 2020; Elzeiny & Qaraqe, 2018; Kalas & Momin, 2016; Reanaree et al., 2016) and helmet(Kalimeri & 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.

(4) Electromyogram (EMG)

Electromyography (EMG) could be considered as another stress alarm system. EMG measures muscle response for evaluating electrical activity. It is not easy to apply this method for stress detection in a built environment. Several studies use this method for real-time detection of stress levels (Elzeiny & Qaraqe, 2018; Ghaderi et al., 2015; Minguillon et al., 2018).

(5) Cortisol

Cortisol is a hormone made by the adrenal glands that control mood and fear, and it is one of the most used biomarkers for stress levels. Salivary cortisol increases the brain's use of glucose and is one of the most indicative factors which can analyse stress level. It could be measured by means of pipettors although it is not the most suitable for the built environment even if it is one of the most used in medicine as demonstrated through the huge usage (Pascoe et al., 2017; Qiao et al., 2017; Wells et al., 2014).

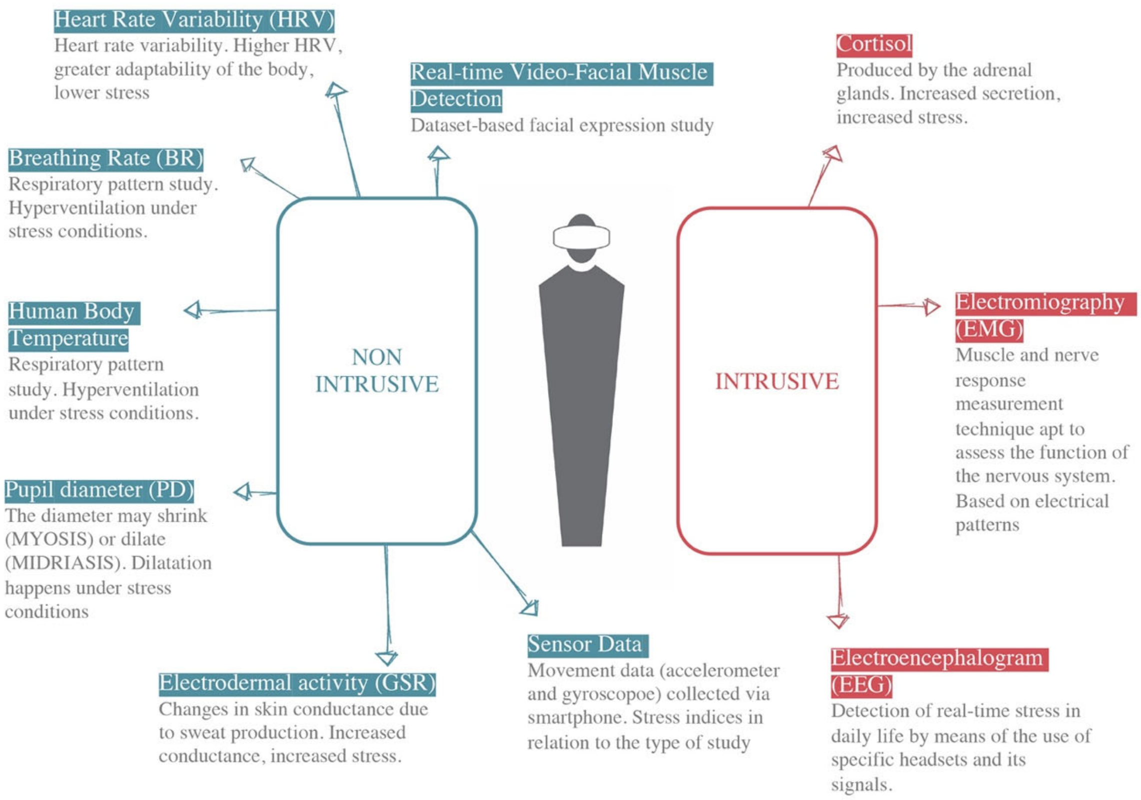

Fig. 1: Non-intrusive and intrusive parameters for evaluating immersive experience

(6) Human Body Temperature

The temperature of the human body could be one of the main data factors upon which it is possible to study stress. According to Rachakonda et al. (2019), in fact variation in body temperature is indicative of the physical and mental condition of people within a specific value range to identify high, medium and low stress. 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 & Qaraqe, 2018).

(7) Pupil Diameter

Pupillometry is a primary index to investigate psychological phenomena. The diameter of the pupil reflects the correlation between its dimension and a human's well-being. The pupil can expand (this phenomenon is called mydriasis) or shrink (in this case it is defined as miosis). When the human body is under stress it induces mydriasis and hence pupil dilatation that can be measured through accurate tools that have also been used in the analysis of stress detection (Al Abdi et al., 2018; Gunawardhane et al., 2013).

(8) Breathing Rate

Another stress biomarker response is given by Breathing Rate. The respiratory pattern can be altered by stress and it can easily be measured with wearable devices(Can et al., 2019; Mozos et al., 2017) or specific tools (Al Abdi et al., 2018). If hyperventilation occurs (around 25/40 breathes per minute) the subject can be considered to be under stress.

(9) Sensor data (accelerometer and gyroscope)

Another index of stress can be indicated through data obtained by accelerometers and gyroscopes. The accelerometer sensor gives real-time information about motion and the related stress interpretation of data as shown in some research projects (Debard et al., 2020; Sağbaş et al., 2020).

(10) Real-time Video-Facial Muscle Detection

Video-Facial Muscle Detection demonstrates how a bespoke machine learning support vector machine (SVM) can be utilized to provide quick and reliable classification. Facial Muscle Detection Algorithm, machine learning and deep learning are today increasingly used for detecting stress (Healy et al., 2018; Zhang et al., 2020a).

(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).

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

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 (Fig.2).
Among others, it is worth mentioning:

(1) Wearable devices

Wearable devices are the tools most used to detect stress due to their versatility as well as their non-intrusiveness. Moreover, these kinds of instruments are accessible to all and for this reason they can be easily chosen for daily stress detection studies (Anusha et al., 2020; Debard et al., 2020; Delmastro et al., 2020; Mozos et al., 2017). In regard to physiological data collected, the majority presented on the market are able to detect HRV, EDA, BR, hand movement. Moreover, some smart wearable systems can collect ECG measurement such as Biopacs MP150, MP35 and Shimmer Sensing 3 (Can et al., 2019). Due to their non-invasiveness, they are sometimes employed without the user being aware of it.

(2) Smartphones

Among the unobtrusive devices for ten collections of physiological data, the common smartphone should be mentioned. Multiple features can be extracted from smartphones such as: accelerometer, audio classification, the time and duration of calls, light sensor data, gps information, screen mode changing frequency, videos, wi-fi conversations and so on (Gjoreski et al., 2015). The correlation between stress and collected smartphone data produces significant results. However, according to Can et al. (2019) the low classification of accuracy highlighted by Gjoreski, suggested the importance of adopting an integrated method with the support of the use of wearables and to not rely just on smartphones.

(3) Machine learning

Wearable devices as well as smartphones generate a massive amount of data to be processed, which sometimes necessarily requests the support of machine learning techniques, a branch of artificial intelligence. The issues of the big data generated, as well as their continuous flow demand algorithmic calculation for combining usage behaviours and collected data (Delmastro et al., 2020; Sağbaş et al., 2020). To provide a reliable categorisation, bio-parameters such as Breathing Rate, Galvanic Skin Response and Heart Rate are usually collected and analysed by machine learning systems via the main common classifiers such as K-nearest neighbour (KNN) and support vector machine (SVN) (Ghaderi et al., 2015). Moreover, in the scientific literature, new models for machine learning have been created specifically for detecting emotions through human face recognition (Healy et al., 2018).

(4) Neurosky headset
Stress detection can also be analysed through an intrusive wearable device, namely the EEG Neurosky headset which is a tool to monitor and record the electrical activity of the brain via electrodes placed in the headset. According to Reanaree et al. (2016) the Neurosky Headset could also be complemented by an intelligent watch made by Arduino that has been used in his project (Reanaree et al., 2016).

(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 & Saitis, 2016; Minguillon et al., 2018; Pandey et al., 2016).

(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., 2020b).

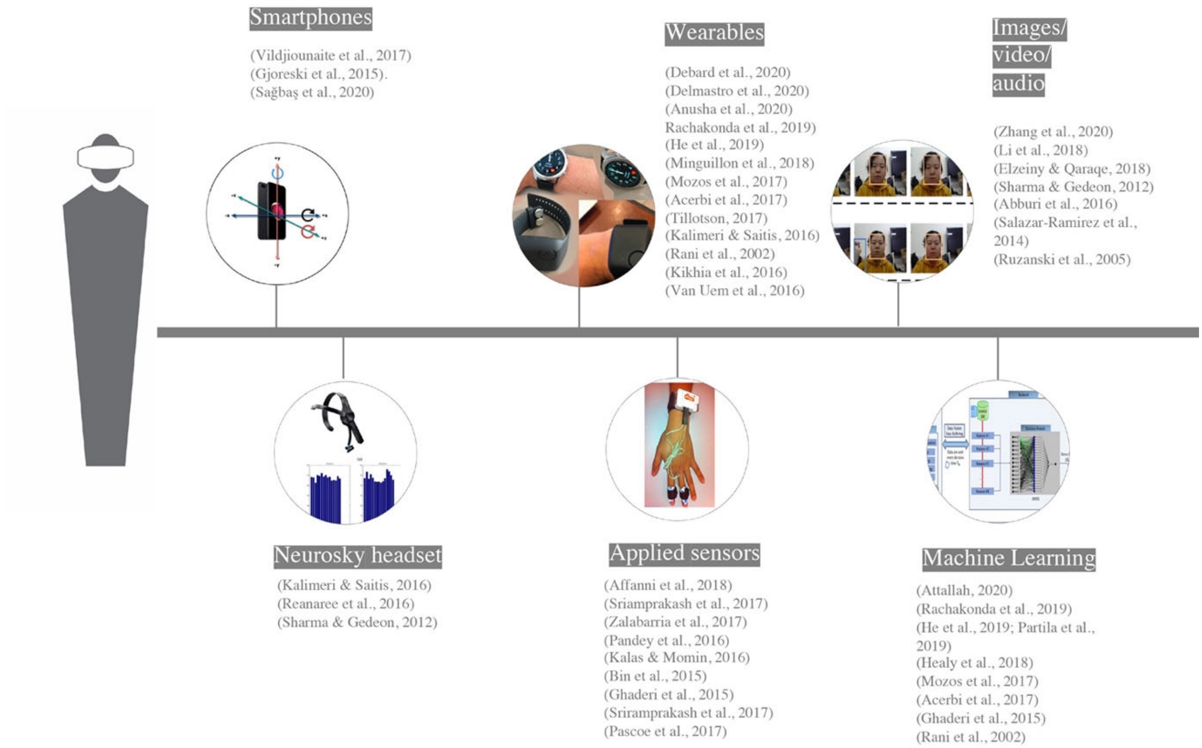

Fig. 2 Non-intrusive and intrusive techniques for evaluating immersive experience

3. DISCUSSION
In order to use them for future applications within the analysis of wellbeing in the digital immersive field, the present review summarizes the main technologies used in medicine. This investigation aims to disseminate tools and methodologies to make designers conscious of the actual impact of the digital environment in daily life and to

encourage planners to better design spaces by bearing in mind the impact of immersive environment on the users' well-being. To address this, a holistic approach is required since the comprehension of the high potential of a interdisciplinary concept that moves from the medical field to design is crucial. Based on the lessons learned from the COVID-19 pandemic, the role of this integrated approach is to provide an informational method that could reduce the gap between architects, engineers, and designers in regard to the expressed or unexpressed responses of users in terms of digital impact of immersive environments. As such, this review investigates the stress bio-parameters to be adopted in immersive digital design to outline possible indicators of high-quality satisfaction for new digital environments, by using not only qualitative data such as interviews and self-reported evaluation, but also quantitative data given by body feedbacks that inform through their unconscious responses. In this paper, the authors have reported two macro areas, namely stress bio-parameters and the related tools, to be applied in design as possible well-being indicators. The most recurring stress parameters as well as the main tools embraced in other fields, have been reported to give a complete overview of the current usage from which digital immersive design could extrapolate the non-invasive techniques with which to ascertain the impact of design strategies on the user's satisfaction. Our body is affected by the choice and design strategies adopted by virtual reality architect, engineers, and designers. There must be a scientifically recognised method to evaluate their implications for users' well-being that goes beyond the traditional qualitative data susceptible to respondents' bias. Choosing the most appropriate tool depends on the availability of resources, targets, and specific research purposes. Some advanced techniques such as video and picture analysis through machine learning, if properly used, could be beneficial for reaching out to the well-being analysis of a mass numbers of users. Therefore, the measurement of eye-pupil diameter and facial muscle movements are required for this type of analysis. It is different in the case of the analysis of a small number of users where artificial intelligence is not required. In this case, the analysis of Heart Rate Variability, Electrodermal Activity and Breathing Rate could be considered as the most informative techniques since, even an ordinary wearable can easily acquaint stress levels. However, adopting a transdisciplinary approach in which these technologies could be supplied to more deeply, investigation of the relationship between users and the built environment is advisable. Although it is widely recognized that human beings respond cognitively, emotionally and physiologically to the built environment, on the other hand, interdisciplinary studies of the physiological well-being connected to immersive environments seem to be lacking, underlining a gap that if investigated could be promising for construction. In this regard, an arising field called "neuroarchitecture/neuro design" is raising the question of how architecture can benefit from its intersection with neuroscience. However, so far, few scientific practical studies have been pursued. For this reason, this conceptual model based on the adoption of practical methodologies represents a central challenge of the present time and is expected to help the digital design researchers to integrate well-being medical analysis into the design evaluation process. Therefore, the authors attempt to improve this conceptual model in future case studies.

4. CONCLUSION AND FUTURE DEVELOPMENTS

The ongoing debate about the increasing digitisazion has raised people's awareness of the impact of the new immersive technologies. Although there is ample evidence in the scientific literature on how the living and working environment impact the psychophysiological states of the users, and despite a recent and ever-growing awareness, only limited attention has been paid to systematic research to find a quantitative tool for the detection of the effect of the virtual space characteristics on the psycho-physiology and perception of the users. The lack of a quantitative approach to evaluate users' impact should be filled by the ability to adapt medical technologies to compelling digital design requirements. Despite growing interest in research into crossing findings from different investigation fields, the application of medical results in digital environment field seems to be defective as demonstrated in the present literature. However, focusing on the trending results could help to explore promising eXtended Reality areas. Thus, by moving forward to the concept of virtual environment design, the questioning of digital spaces should be fundamental to tackle real human well-being intended as mental and emotional health, especially in these current times where the world "metaverse" is increasing advancing. Until today the use of new technologies has been focused on physical built environment rather than on eXtended Reality spaces.

Advanced research and interventions are necessary to deeply investigate the relationship between users and immersive environments. Currently, as far as we know at the time of writing, the use of bio-parameters in digital design is limited to few experimental trials mainly related to marketing field and not yet validated and introduced in the design practice as a validation method for immersive quality analysis. Therefore, if these technologies could be implemented and correctly integrated in digital design, the role of neuro-design would be enhanced. Medicine has a huge potential to inform design, and the impact of medical findings could be applied in digital design. A holistic and interdisciplinary approach could be largely adopted by opening the door to the fruitful pollination of different research fields with a clear goal: to design high quality digital environment place for wellbeing and the high-quality experience of the users. Following this, the authors have identified the applications within eXtended

Reality where the well-being analysis by using stress detection can make the best impact: real-time responsive design based on a human-centric approach; users' well-being monitoring in immersive environments; eXtended Reality "certification" based on human perception; education tools for designers and users to sensitize them to the impact of digital design on users' wellbeing; critical evaluation of extended reality design; real-time interpretation systems which arrange immersive experience variables such as illumination, length of experience, quality of design and so on. This conceptual framework aims to help, during the design process to ensure the proper attention to users' well-being. In short, there is a long road to travel, and much work needs to be done. This review is expected to help designers to rethink the impact of the digital environment in the light of the tangibility of objective and measurable data based on the well-being of users. The COVID-19 pandemic forces us to be aware of digital design implications. For an optimal design experience, our article directs a spotlight on the need for the adoption of medical techniques to evaluate the physical and mental users' well-being of the growing and ever evolving use of eXtended Reality.

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