Creative city design / Vol. 5, No. 2, 2022, 65-80

Evaluating the Impact of Architectural Space on Human Emotions Using Biometrics Data[1]

Mahbubeh Zamani[1], Mehran Kheirollahi[2*], Mohammad javad Asghari ebrahim absd [3], Hasan Rezaee[4], Farzaneh Vafaee[5]

1. PhD Student in Architecture, Department of Architecture, Mashhad Branch, Islamic Azad University, Mashad, Iran
2. Assistant Professor, Department of Architecture, Mashhad Branch, Islamic Azad University, Mashhad, Iran
3. Associate Professor of Psychology Department, Faculty of Education and Psychology, Ferdowsi University of Mashhad, Mashhad, Iran
4. Assistant Professor, Department of Architecture, Mashhad Branch, Islamic Azad University, Mashhad, Iran
5. Assistant Professor, Neuroscience Research Center, Mashhad University of Medical Sciences, Mashhad, Iran

Submit Date: 02 April 2022, Accepted Date: 27 July 2022

ABSTRACT

Human beings respond to the architectural spaces cognitively and emotionally. Research has shown that emotional feedback affects human health and well-being. Previously, researchers used qualitative methods such as observation or interview to measure human emotions in built environments, which did not provide a clear answer to human emotional needs because of researcher's unintended bias in research results. Today, with the advancement of cognitive and behavioral sciences, architects are able to quantitatively establish the impact of the built environment on humans using biometric data and provide more accurate results. The questions raised in the research can be expressed as follows: What is effect of the built environment on human emotions? How can these effects be measured? And how can it be effective in architectural design? The aim of this study is to identify an experimental methodology using a biometric data set to measure and record human emotions, which can be used to evaluate architectural design. The present study is carried out in two steps: In the first step, the related studies of 2015-2020 were identified using the systematic review method with a specific entry and exit criteria; and in the second step, different methods and tools of measuring and recording human emotions in the environment were investigated through descriptive-analytical method and logical reasoning. The results indicate that studies in this field are divided into three main categories: evaluation through cognition and perception, evaluation through visual features and evaluation through space navigation. The study ends with considerations for implementing a comprehensive approach that uses the biometric response as an evaluative method for designs in the future research.

Keywords: *Architectural Space, Biometrics Data, Emotions, Evaluation*

1. Introduction

Architecture has different effects on human beings. So far, architectural studies have been conducted in the field of objectives and items related to structures, facilities and construction [1]. Because architecture is effective both at the cognitive level (as the processing and evaluation of perceived information) as well as the emotional level (as adaptive reactions to perceived information) [2], they act in an interrelated way. For example, lack of vegetation in the architectural space has caused stress [3-4] and this

*Corresponding author: Dr.mehrankheirollahi@gmail.com

[1] The present article is extracted from the doctoral dissertation of the first author entitled "Determining the role of the physical components of the interior residential space in the formation of emotional feelings using neuroscience (case study: contemporary architecture after the revolution)" under the supervision of Dr. Mehran Kheirollahi and Dr. Mohammad Javad Asghari Ibrahim Abad and Dr. Hassan Rezaei and Dr. Farzane Vafaee as advisors. The thesis is being completed in the architecture department of Islamic Azad University, Mashhad branch.

environmental stress has a negative impact on life expectancy [5]. Therefore, architectural space has different cognitive-emotional effects on human beings [6] and studies related to emotions have shown that architectural space also significantly affects people's sensory-motor responses [7]. Peter Zumthor also states that humans perceive architecture through emotional sensitivities [8]. Since emotions play an important role in logical decision-making, perception, learning, and other functions and affect physiological and psychological state of human beings [9], it is necessary to pay attention to the effect of architectural space on human emotions.

Previously, architects have qualitatively studied the emotional dimension of architectural space [10], which may cause bias and inadequate results in responding to human emotional needs [11]. The reason is that the placement of man in the architectural space causes changes in the human mind [12]. Researchers are now able to better understand the impact of architectural space on humans by exposing people to architectural design factors in a physical space, and by using biometric data [13].

Although the examination of the impact of space on humans is not new [14], the recording of emotions by modern tools of behavioral sciences, biometrically will provide a framework for future design and studies [15] and evaluation of these human responses can have a significant impact on architectural design as architects can change their perspective to explain the problem, new strategies and concepts [16].

So far, there has been a clear gap between the correlation between architectural space and human experience, and architectural design requires further study of human experience of architecture. For this reason, by using human biometric feedback, the quality of architectural design can be improved. So, the research questions can be expressed as follows: How does the built environment affect human emotions? How can these effects be measured? And how can it be effective in architectural design?

The present study describes the evaluation of architectural space using EBD approach and descriptive-analysis method. It also provides an overview of the biometric sensors used in architecture, and examines the Immersive Virtual Environments (IVE) used in architecture, engineering, and construction (AEC). In this regard, it reviews the existing literature focusing on the developments over the past five years that have used empirical methodologies to integrate an immersive visual system with the collection of biometric data to evaluate architectural design. Finally, it will provide a model for evaluation architecture.

2. Theoretical Foundations of the Research

2.1. The Evaluation of Architectural Design

The living environment is full of physical and non-physical components that affect human emotions [16] and there is a deep link between emotion and human well-being [17]. For this reason, architectural space has had a great impact on human well-being and in recent years, has become an important concern [18]. Considering that human beings spend an average of 87% of their time in architecture space, its impact on human beings becomes more important [19]. Therefore, architects have a great role in responding to human psychological needs in the architectural space and can use new scientific evidence to maintain well-being in the architectural space [20].

One of the challenges in evaluating the impact of architectural space on human emotions is the configuration of laboratory environments [21]. Non-invasive sensors, are devices that do not require injection or cutting [22]. There are various tools and techniques that can be used to evaluate and map human responses to different stimuli and analyze emotional, cognitive and behavioral information [23]. Small sensors can be placed on the human body to record various physiological parameters, send data to other devices [24], and allow human responses to be observed in controlled conditions [25-26]. These instruments are designed to measure changes in the human body and brain, which are used in the fields of behavioral and cognitive sciences.

In addition, the use of virtual environments (VEs) as a research tool in this field allows researchers to provide accurate evidence-based design (EBD) [27]. EBD is the process of consciously, explicitly and wisely using the best scientific evidence and experience and vital decisions. By using virtual environments, architectural spaces can be used along with tools for measuring brain and body changes, and the problem of portability of some laboratory equipment will be solved.

Methods and tools for measuring changes in the human body

Galvanic skin responses (GSR), also known as skin conduction [28], are part of electrodermal activity (EDA). This method measures the conductivity of human skin and can provide a sign of change in the human sympathetic nervous system [29]. EDA measures changes in electrodermal properties, especially electrical conductivity [30]. Therefore, it is suitable for tracking arousal [28]. This device refers to changes in sweat glands activity and reflects the intensity of the participant's emotional state, but does not specify which specific emotion is evoked [31]. EDA is also used to study attention [32].

Heart rate variability (HRV) is one of the most promising indicators of autonomic nervous system regulation [33]. HRV measures time changes between heart rates [34]. HRV variations generally occur between the two domains of time and frequency range, both of which are of clinical and cognitive-emotional significance [35]. Since human emotions vary widely from person to person and are a qualitative factor, HRV is not sufficient to measure emotions with the required degree of accuracy. The possibility of using HRV to assess human emotions has been widely discussed [36-37].

Electrocardiography (ECG) measures the electrical signal caused by the contraction of the heart muscle, which indirectly shows the blood flow inside the heart [38]. ECG sensors provide the optimal source signal for HRV analysis, but require an intrusive electrode or adhesion of conductive materials [39]. PPG sensors, integrated into wearable devices such as smart watches and telephones, are widely used to measure heart rate. To use the PPG signal to determine HRV, an accurate estimate of the time interval between successive peaks can be measured [40].

Methods and tools for measuring changes in the human brain

translate patterns of human brain activity into messages or commands in an interactive application. Brain activity processed by the BCI system is usually measured using electroencephalography (EEG) [41].

Brain metabolic activity is measured by a variety of methods; functional magnetic resonance imaging (fMRI), Magneto encephalography (MEG), functional near-infrared spectroscopy (fNIRS), and electroencephalography (EEG) are other types of non-invasive methods for measuring the electrical activity of the brain [42]. Functional magnetic resonance imaging (fMRI) is a non-invasive brain imaging technique [43] that indirectly measures neural activity by detecting changes in magnetic properties related to blood flow [44]. This method offers better depth structure recognition clarity than other methods [45]. EEG is a procedure that measures small electrical activities and currents that reflect brain activity on the scalp in real time [41]. This device measures the fluctuations of the electric field caused by ionic currents produced by neural activity in the brain [46]. MEG is a measure of the magnetic field produced by the electrical activity of neurons [47]. Although its infrastructure is flawed (not wearable or portable), it has advantages that make it a powerful tool for exploring the function of deeper cellular structures, such as the role of the hippocampus in cognition [48]. Similarly, stimulation of brain regions is possible using transcranial magnetic stimulation (TMS), which is used in various fields [49]. fNIRS measures changes in hemoglobin (Hb) concentrations in the brain using hb absorption spectrum in the near-infrared range [50].

Table 1: Methods and tools for measuring changes in the human brain Source: Authors

Implicit Technique	Biometric Signal Measured	Sensor	Features	Psychological or Behavioural Construct Inferred
MEG (Magnetoencephalography)	magnetic fields produced by electrical currents occurring naturally in the brain	superconducting sensors (SQUID, superconducting quantum interference device)	detect and amplify magnetic fields generated by neurons a few centimeters away from the sensors.	Characterizing brain activity related to various sensory, motor, and cognitive processes, including attention, memory, and language, in normal development [51].
EEG (electroencephalogram)	Changes in electrical activity of the brain	Electrodes placed on scalp	Frequency band power, functional connectivity, event-related potentials	Attention, mental workload, drowsiness, fatigue, arousal and valence [52].

fMRI (functional magnetic resonance imaging)	Concentrations of oxygenated vs. deoxygenated haemoglobin in the blood vessels of the brain	Magnetic resonance signal	blood-oxygen-level dependent	Motor execution, attention, memory, pain, anxiety, hunger, fear, arousal and valence [53]
fNIRS (functional near-infrared spectroscopy)	Concentrations of oxygenated vs. deoxygenated haemoglobin in the blood	Near-infrared light placed on scalp	blood-oxygen-level dependent	Motor execution, cognitive task (mental arithmetic), decision-making and valence [54]

Methods and tools for measuring Psychophysiology

In this method, facial electromyography (fEMG) and eye tracking (ET) are used [55]. Facial electromyography (fEMG) is a psycho-physiological technique used to measure the electrical potential produced by facial muscles [56]. To measure emotion-related facial expressions [57], wavy muscles are commonly used for recording [58]. These muscles are strongly influenced by emotions [59]. FEMG responses to various external emotional stimuli are well-documented [60]. Detecting and recognizing the facial expressions of emotions is an important interpersonal ability. Although individuals usually perform well in recognizing the facial expressions of basic emotions, there are significant individual differences in accuracy of judgment [61].

In addition, there is automatic image-based face recognition (face coding) [62-63]. The Facial Action Coding System (FACS) has also been studied for the predominant facial expressions during the expression of primary emotions [64]. Other studies have shown that FACS separates all visible facial movements into 44 distinct visual and descriptive muscle units [65].

Available software for the AFC can classify facial movements into emotions or cognitive states [66]. The AFC method makes it possible to analyze the expression of emotions on the face in different contexts, where the audience is examined in their environment without the hindrance of technical tools.

The criterion for eye tracking is eye movement [67]. Eye movements to some extent determine our focus voluntarily and involuntarily and are influenced by cognitive and emotional states [68]. It is also possible to plot the observed sequence and distance from the target in which the observer's eyes move from one place to another, as well as the area of interest (AOI) [69]. In eye tracking, certain parts of the goal or plan are observed that are important to the researcher. Eye movement tracking can help HCI researchers understand visual and display-based data processing, factors and factors that may affect the usability of system interfaces [70]. The recorded data can be used later to improve the design and interface. Recently, several articles and experiments in the AEC sector have examined design evaluation through eye tracking [71].

Methods and tools for measuring self-report interventions

Self-report interventions include a report of individuals' mentality and are in accordance with cognitive, emotional and behavioral dimensions [72]. Self-report questionnaires provide new opportunities for empirical studies on the nature of the mind and its relationships with other psychological structures [73]. The Self-Assessment Manikin (SAM) is a non-verbal visual assessment technique that directly measures pleasure, arousal, and mastery associated with an individual's emotional response to a wide range of stimuli [74]. The Geneva Emotion Wheel is another method of self-report of emotions that includes discrete emotional terms related to emotional families that are systematically aligned in a circle [75-76]. In general, the methods for measuring emotion changes in humans are presented in the following diagram.

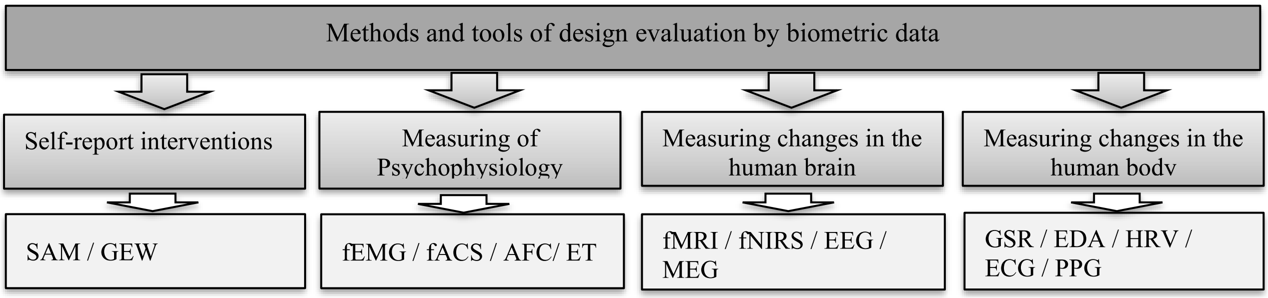


Diagram 1: Methods and tools of design evaluation by biometric data Source: Authors

2.2. Emotion

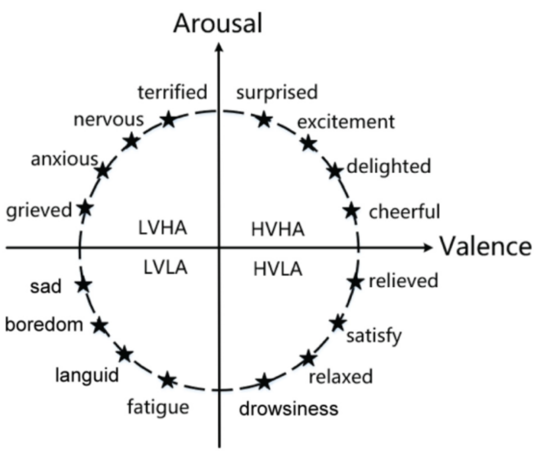
Emotion is the translation of the word "Emotion" from the Latin root “Motere” meaning to move and the addition of the prefix e gives it the implicit meaning of "moving away" [77] and literally refers to any stimulus or disturbance in the mind, feeling and state of strong mind or aroused are included [78]. Emotions include the physiological states of feelings, different human thoughts, and behaviors. Emotions have an important place in human daily life and their correct recognition is important in many areas [79].

Due to the importance of this field, in psychological studies, emotional calculations, artificial intelligence, computer vision and medical treatment, etc. have been studied extensively [80-81-82].

Psychologists believe that emotions are a mental attitude and produced by people's experience of external conditions [81]. Emotions are a constant process of mental emotions [83]. Emotions are usually associated with personality, mood and desire [84-85]. Emotions are an instinctive response by the body that may include the common effects of language, behavior, and spirit [86].

Emotion Model

The emotion recognition model plays a key role in research and includes discrete and continuous models. Discrete model theory states that people's emotions are composed of the basic emotions [87]. Platchik (2001) categorizes emotions into eight basic states: love, anger, sadness, joy, expectation, hostility, fear, and surprise. All human emotions can be formed through a combination of one or more of these basic emotions [87]. Ekman et al. (1987) divide basic emotions into fear, anger, sadness, and interest [88]. Continuous model theory is a dimensional theory proposed by Lang et al. [89-90]. This theory classifies emotions based on dimensional space. Dimensional theory states that emotion is constantly changing, such as the two-dimensional emotion model of capacity and arousal and the three-dimensional emotion model of capacity, arousal, and mastery. Different emotions can be represented by different coordinate positions in the figure. Continuous model theory can divide states that are more emotional and can differentiate different emotions more intuitively.



Picture 1: Continuous model of emotion

Researchers are able to correctly judge participants' true feelings based on physiological signals. In the field of research based on physiological signals, EEG is a spontaneous and non-mental physiological signal that can objectively reflect human emotional states [91].

Thus, the diagnosis of EEG-based emotions has become an important research topic. EEG also plays a key role in the study of emotions and shows that the activity of different areas of the brain is closely related to some emotional moods [92].

Emotion Induction

In the detection of emotions, we must obtain the corresponding emotional mood EEG signals, which are several common methods of detection, such as visual induction, video induction and music induction. In visual induction, different images are used to inspire emotional moods that must have some notable emotional characteristics or create strong stimuli such as the International affective picture System (IAPS) [93]. In video induction, different types of videos are used to induce emotions. Compared to visual induction, video induction takes less time to obtain different emotions and has clearer effects [94-95-96-97]. Music induction requires a calm environment, and subjects are required to listen to different types of music. Music is then associated with related emotional moods that are acquired while listening, such as joy, peace, sadness, and so on. However, music induction is not suitable for everyone. This requires the subjects to experience the rhythm of the music carefully. For people who have little to do with music, induction of music cannot yield consistent results [98-99].

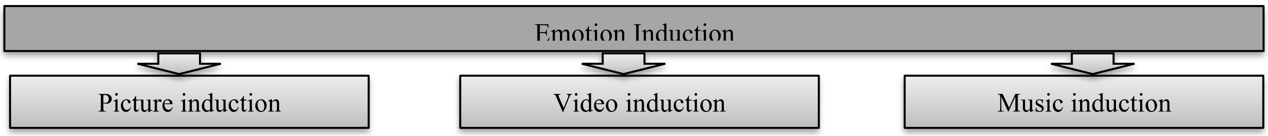


Diagram 2: Emotion Induction Source: Authors

Recently, virtual reality (VR) has been used to arouse induction. VR has grown a lot in recent years in scientific and commercial fields [100]. VR has many applications from education to health, and its new generation consists of head-mounted displays (HMDs) [101]. The scientific interest in VR is due to the fact that it provides a simulated space that creates a sense of presence in the real world [102] and allows researchers to analyze reactions to the concepts studied [103].

2.3. Virtual Reality

human behavior in fully controlled designs in vitro [104-405]. Many researchers are currently studying in this field and have created a strong and interdisciplinary society [106]. Participants will perceive a higher presence if they are emotionally aroused. In previous studies, a strong correlation has been found between arousal and presence [105]. Therefore, the user experience in virtual environments is measured by the concept of presence, which is understood as the mental feeling of "being- there" [107] and the high degree of presence makes the user feel in the real world [108], therefore a powerful tool. This has been suggested to evoke emotions [109]. In recent years, VR has been used in architecture as a framework for testing the overall validity of proposals, generating alternatives, and conceptualizing learning, teaching, and the design process [110].

3. Method and material

This research uses three methods: systematic review of existing literature, classification of architectural design evaluations in the field, experimented VEs and biometric feedback in the literature. Therefore, first, the basics are extracted from the systematic review method, and finally, using descriptive-analytical method, analyzed the data and the help of logical reasoning of the process of evaluation the architecture based on human emotions, by using biometrics data will be provided.

The literature review focuses on integrating a comprehensive visual system with the biometrics data set used to evaluate architectural design for pre- or post- occupancy. The study focused on the past five years, when research accelerated and significant development occurred. This period can be described as the new era of VR [111], where virtual reality technologies have been widely available since 2015.

The literature review focused specifically on empirical studies and was based on the following objectives: 1) Evaluating architectural design, the interior of which examines human experience, emotions, cognition. 2) Measuring biometric data using sensors. 3) Understanding human visual perception through which people are exposed to the virtual environment.

First, studies are extracted using a systematic review method. The process and criteria for defining studies have been defined as described below:

Inclusion criteria:

1) Keywords: In this regard, the keywords Virtual reality AND EEG / Biometric AND Architecture, EEG AND Virtual Reality AND Perception, Virtual reality AND EEG AND architecture / Design, Virtual reality AND EEG / Biometric AND Architecture, have been used for the search.
2) Measurement tool (using biometric data): An EEG device should be used to measure brain activity.
3) Year of publication: Due to the novelty of the subject, studies between 2015 and 2020 can be included in the study, and studies before these years were removed from the study process.

Locating studies:

First, two electronic databases (ProQuest and Scopus) were selected as valid directories for publishing experimental studies. In addition, these two databases have advanced search with the ability to modify the entry and exit criteria, which help the researcher to identify studies. Three Elsevier databases, including EMBASE, Science Direct, and Scopus, were then used for identification. Searches were examined with a set of keywords in the title, abstract, keyword, questions and hypotheses. Also, systematic review database; MEDLINE; PsycINFO and Web of Science were also examined.

Selecting studies:

Article search restrictions were set in three groups which were defined as follows: (1) Keywords related to experiments, stimuli, and design variables that are useful for finding architectural and environmental studies. (2) keywords related to "methods" for studying human emotional and neuro-physiological responses to those stimuli; and (3) keywords related to scientific terms for human response to external stimuli and various methods of revealing human conscious and unconscious processes. In each group, the "OR" function is used to expand the search result. Between groups, the "AND" function was used to limit the number of search results, and it was ensured that each search result provided at least one keyword.

Assessing study quality:

In order to evaluate the quality of work, the sources extracted by two browsers were studied independently and the reasons for their acceptance and rejection were presented. Since there were no theoretical differences between the browsers, the degree of agreement between the two browsers was determined using the Kappa (K) test and was finally approved by the expert, and ultimately all articles were approved by the authors.
After extracting the final studies, using descriptive-analytical method, they were analyzed and logical reasoning of the process of evaluating the architecture based on human emotions using biometric data was utilized.

4. Results

The results of the first step of the research, i.e., systematic review, were extracted, which are shown in the table below. All studies used the EEG device to measure human responses according to the inclusion criteria, but the type of EEg device and the number of device outputs in each study were different, as shown in the table below. In addition, the component under study also includes different species, each of which is described in the table.

Table 2: Results research
Source: Authors

	Author(s), Year	Architectural Context	Experiment Methodology/ Case-study	Measurement	Monitoring technology
1	Djebbara et al. (2019)	Architectural Affordances	Virtual Designed Interior Environment	Early sensory brain activity Subjective and behavioural data	EEG, 64 channels,MoBI setup and EEG amplifier ANT eegoSports with Zotac gaming computer

2	Ergan et al. (2019)	Human experience in Architectural space	Virtual Designed Interior Environment	Sense of stress and anxiety through BSN	EEG, 14 channels. GSR PPG (HRV) fEMG Eye-tracking
3	Hermund, Jensen, and Klint (2019)	Emotion Evaluation during the architectural experience	Virtual BIM Model	Stress, engagement, interest, excitement, focus and relaxation.	EEG, five-channel, EMOTIV Insight.
4	Higuera-Trujillo et al. (2019)	Stress Evaluation in Virtual Environment	Virtual hospital waiting room Interior	levels of presence in CESS from the SUS questionnaire stress psychological metrics and their relationships in CESS	EEG, ten channels, b-Alert x10. EDA (Shimmer 3GSR+ device) HRV (b-Alert x10 device)
5	Simon and Hu (2019)	Perception and Emotion response to design in the early design phase	Virtual Designed Interior	a data-driven approach for design evaluation users' preference and emotional state: engagement, focus, interest, stress, or relaxation.	EEG, five channels, EMOTIV Insight
6	Zou, Yu, and Ergan (2019)	Architectural Design futures impact on human performance using machine learning	Virtual Experimental Office Design	Working motivation due to the influence of the presence of colour coding, the texture of surfaces, proportional space layout, and logical connection between sequenced space	EEG, 14 channels Eye-tracking
7	Erkan (2018)	Wayfinding Behaviour in Architectural Space	Virtual Experimental Design	effect of educational status, gender, age, and ceiling height in way finding	EEG, one channel, NeuroSky MindWave
8	Kalantari et al. (2018)	Stress Evaluation in Educational setting	Physical vs Virtual comparison of the environment	Performance assessment in cognitive tasks	EEG, 57 electrodes, EOG, four electrodes, EKG, 2 Electrodes GSR Accelerometer
9	Banaei et al. (2017)	Architectural Interior forms	Virtual Designed Interior Environment	impact of interior forms on the brain Stroop test for attention and involvement with the tasks	EEG, 128 electrodes. Mobile Brain/Body Imaging (MoBI) setup.
10	Sharma et al. (2017)	Landmark in wayfinding	Virtual Experimental Design	Behavioural measurements for solving the maze	EEG, 64 channel, ANT Neuro
11	Shemesh et al. (2016)	Human reaction to Architecture	Virtual designed Hall	measure human reactions to the examined spaces	EEG, 14 channel, EMOTIV
12	Tommaso et al. (2016)	Architectural Wayfinding with event-related	Virtual Designed Interior	colour and luminance change of target place	EEG, 57 electrodes.

		response		age-related cognitive changes	
13	Vecchiato et al. (2015)	Architectural Perception	Virtual Experimental Design	Familiarity, Novelty, Comfort, Pleasantness, Arousal, and Presence	EEG, 24 channel, 19 disposed of, EBneuro. EDA (SCL), NeXus-4. HR

From the evaluation point of view, studies include different types, which can be divided into three categories. The first category is related to user behavior related to spatial aspects such as geometry, area and visual features. The second category of human behavior is in buildings with special functions such as educational, office, residential, health care and sports. The final category is the study of human navigation and perception during the navigation of the architectural space. The following diagram categorizes the studies.

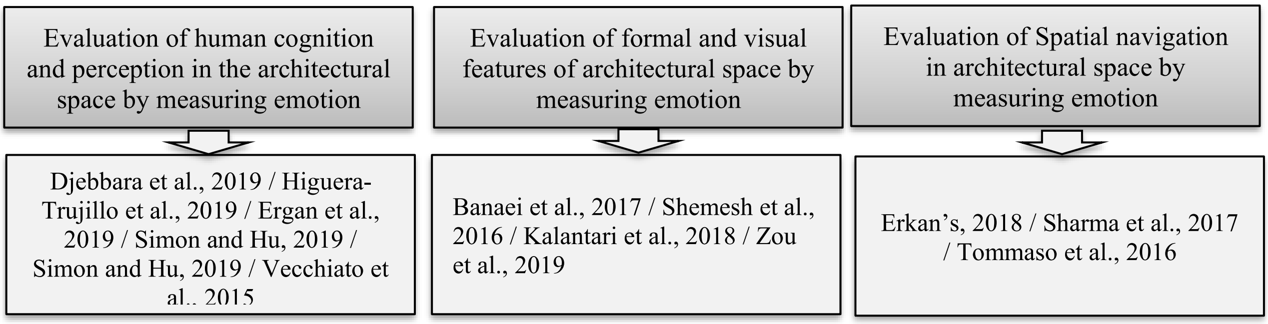


Diagram 3: Classification of studies Source: Authors

3.1. Components studied

Research in this field has studied various components of architecture, each study using the EEG tool as the most powerful device to detect. brain activity to evaluate the architectural space. The following table presents the components of each study based on the three categories.

Table 3: Evaluation of architectural space Source: Authors

evaluation	Author, year	Study component
Evaluation of human cognition and perception in the architectural space by measuring emotion	Djebbara et al., 2019	Assessed the perception of the constructed space under the influence of cost and the brain prediction process
	Higuera-Trujillo et al., 2019	Combined multisensory study of a measurable synergistic effect at the level of neurophysiology with design strategies for stress reduction
	Ergan et al., 2019	Investigated the relationship between two architectural spaces with numerical stress reduction in different situations
	Simon and Hu, 2019	Investigated the relationship of a positive emotional state of brain waves compared to a higher design score
	Vecchiato et al., 2015	Investigated how pleasant perceptions of VEs are in areas of the brain dedicated to spatial-spatial processing
Evaluation of formal and visual features of architectural space by measuring emotion	Banaei et al., 2017	Investigated the effect of right corner space and architectural space curve on emotions
	Shemesh et al., 2016	Investigated human arousal in curved and right-angled spaces with different heights
	Kalantari et al., 2018	Investigated human responses to physical and virtual repetitions and feedback to change VE characteristics
	Zou et al., 2019	Investigated work motivation in relation to the effect of color coding, surface texture and space arrangement as well as independent component analysis for classifying EEG signals
Evaluation of Spatial navigation in	Erkan's, 2018	Investigated the effect of gender, age and level of education on cognitive processing, the relationship between form perception (height of space) and spatial perception (object matching)

architectural space by measuring emotion	Sharma et al., 2017	Explained the responsibility of areas of the brain that are exposed to sights during routing in mazes
	Tommaso et al., 2016	Assessed the reliability of event-related potentials (ERPs) obtained in VR to test age-related cognitive changes

Studies in addition to the EEG device for evaluation have used other methods to supplement and confirm the extracted information. These methods, which are usually qualitative ones, have been used to assess the self-awareness of the audience, to confirm the reliability of the data of biometric devices.

Table 4: Qualitative research methods in studies Source: Authors

Type of qualitative research method	Studies
SAM test	Djebbara et al., 2019 / Banaei et al., 2017
questionnaires	Vecchiato et al., 2015 / Kalantari et al., 2018 / Erkan's, 2018 / Ergan et al., 2019 / Higuera-Trujillo et al., 2019

In evaluating the design of architectural space, the number of study populations is not the same. Because a clear framework for this type of evaluation has not yet been defined, many differences in the selection of the statistical. population of the study are evident. Also, the statistical population of men and women did not have a specific proportion. In the table below, the statistical population of each study is specified separately.

Table 5: Participant Total in studies Source: Authors

evaluation	Author, year	Participant Total	Male	Female	Average Age
Evaluation of human cognition and perception in the architectural space by measuring emotion	Djebbara et al., 2019	20	11	9	28.1
	Higuera-Trujillo et al., 2019	24	13	11	37
	Ergan et al., 2019	40	22	11	NA
	Simon and Hu, 2019	8	6	2	NA
	Vecchiato et al., 2015	12	7	5	26.8
Evaluation of formal and visual features of architectural space by measuring emotion	Banaei et al., 2017	15	8	7	28.6
	Shemesh et al., 2016	NA	NA	NA	NA
	Kalantari et al., 2018	NA	NA	NA	NA
	Zou et al., 2019	34	NA	NA	NA
Evaluation of Spatial navigation in architectural space by measuring emotion	Erkan's, 2018	343	NA	NA	35.85
	Sharma et al., 2017	35	30	5	24.75
	Tommaso et al., 2016	22	13	9	25

5. Discussion

Studies in this field are of great value and importance. This is because they have provided a new way to evaluate the design of architectural space, and their results can be used for design to be the best response to human emotions. The results of each study are presented below.

Evaluation of human cognition and perception in the architectural space by measuring emotion

In different functions of architectural space, structural features and elements such as color, light, texture, layout and sound affect emotions and evoke different feedbacks. In sports space research, considering the three important spaces of the foyer, the dressing room and the fitness room, it is found that no brainwave pattern explicitly corresponds to the characteristics of the similar action space, i.e., passing through the foyer and through the small corridor to the dressing room. This means that understanding architecture is a completely individual experience [112].

In office spaces, color, texture and layout affect human performance. The use of wood texture in the office space reduces work-related fatigue [113-114]. The use of vegetation, images and music and soothing scents in therapeutic spaces, reduces stress and anxiety. This means that the perception of space is related to the senses of sight, hearing and smell [115]. Details such as the type and number of windows, colors and materials used in the educational space affect the level of learning [116]. Also, changing architectural features can reduce human stress in the educational environment [114]. The type of arrangement of educational space also has an effect on reducing stress [117].

Evaluation of formal and visual features of architectural space by measuring emotion

The rectangular geometries of the architectural space evoke less satisfaction and excitement in architectural experiments, while the more curved spaces report more comfort and convenience [118]. There is also a tendency for non-designers to have a curved space, while humans with a design background are more interested in sharp and angled spaces [119]. Being in a space with a modern and advanced empty design causes a sense of familiarity, freshness, comfort, pleasantness, arousal and presence, and modern furniture in a larger room creates a sense of comfort in humans [120].

Evaluation of Spatial navigation in architectural space by measuring emotion

Spatial navigation is guided by cues that affect spatial-visual features. Signs help architects and designers in spatial navigation. The results show that navigation behaviors are related not only to the personal and social characteristics of users but also, to the design characteristics of a space. In addition, the results of the study show that age, gender and education also directly affect routing behaviors. In addition to design features, signs can also affect users' perception of a built-in space as they move through it. The left hemisphere regions of the brain play an important role in connecting object location memory to self-centered and allocentric spatial interactions [121]. Color in architectural space is also a characteristic goal that differentiates old and young people in navigation [122].

Evaluation model of architectural space design based on biometric data

Biometric measurement mainly provides quantitative data, which allows architects to make decisions based on human emotions in design. Advances in technology and the use of EEG devices play an important role in the provision of biometric data. In the meantime, there are other devices for recording human responses that measure changes in other parts of the body. These devices also help architects to evaluate the design of architectural space. And all of them can be used.

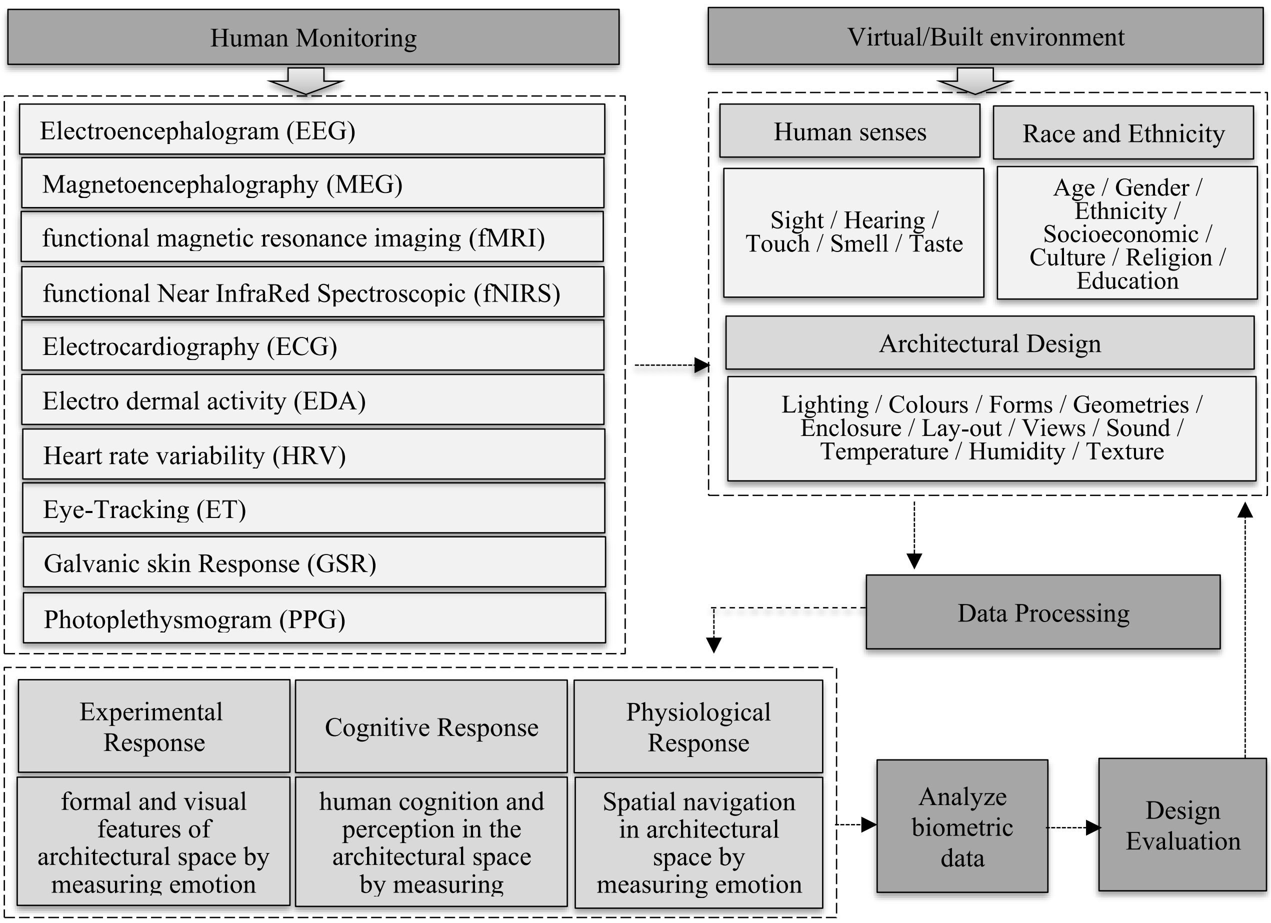


Diagram 4: Architectural space evaluation process Source: Authors

As mentioned before, the evaluation of emotional effects can be divided into three general categories: cognition and perception, visual architectural features, and space navigation. Therefore, architects must first determine the field of study to evaluate the space. Architecture also has various features such as form, geometry, area, design, color, facade, sound, light, temperature, humidity, materials, texture, etc., each of which is first received by one of the senses and then perceived. Therefore, the type of architectural feature and the recipient's senses must be specified. In any study, the statistical population should be identified in terms of age, gender, nationality, culture, etc. because they are very important and affect the results of the study. After testing and extracting biometric data, the architect can analyze the architectural space by analyzing them. The process of evaluating the design of architectural space based on biometric data is presented in the diagram 4.

6. Conclusion

The application of cognitive and behavioral sciences in architecture is increasing as they examine the impact of architectural space on humans. One of the important issues in this field is the study and measurement of emotion. In the past, the impact of space on humans was done through qualitative methods such as observation, interview and questionnaire. But today, with the advancement of technology, tools have emerged that can measure human emotional and mental reactions in the architectural space. These tools can be divided into two or three categories of tools for measuring changes in the brain, body and physiological changes, as well as the new self-reporting tools. With the advent of these new sciences and tools, human responses, especially excitement, can be converted to biometric and quantitative data, in order to obtain more accurate results from these effects.

In evaluating the architectural space in the field of cognitive and behavioral sciences, these tools can be used to obtain biometric data. Research in this field shows the effect of architectural space on emotions in terms of human cognition and perception, formal and visual characteristics and navigation in space.

The results of studies indicate that research in this area is limited. Also, the articles did not have a common and structured methodology, which is due to the complexity of the research process, the adoption of multidisciplinary approaches and technological dependencies. In addition, due to limitations in real space, simulated space in VR virtual reality glasses has been used in studies which necessitates more cooperation of architects with technology experts to bring the tested virtual space closer to the real space. In the process of studies, it has been necessary to use new medical tools to record biometric data from a protected space so that no sound, light or foreign object will distort the study.

Despite all these limitations and complexities of this method, it is necessary to understand that biometric data show more accurate and objective results of human emotions in space. This paper presented a model for the process of evaluating the design of architectural space based on biometric data and clarified the importance of using this method. Although research in this field is limited and is considered a nascent science, the knowledge produced by this research helps to meet the cognitive-emotional needs of users. The successful architects of the future are those who can make good use of these tools and methods.

Reference

1. Williams Goldhagen, S. (2017). Welcome to Your World: How the Built Environment Shapes our Lives; HarperCollins: New York, NY, USA.
2. Ledoux, J.E. (2008). Cognitive-Emotional Interactions in the Brain. Cogn. Emot. 3, 267–289.
3. Glass, D.C., Singer, J.E. (1972). Urban Stress: Experiments on Noise and Social stressors; Academic Press: New York, NY, USA.
4. Ulrich, R.S. (1979). Visual landscapes and psychological well-being. Landsc. Res. 4, 17–23.
5. Glaser, R., Kiecolt-Glaser, J.K. (2005). Stress-induced immune dysfunction: Implications for health. Nat. Rev. Immunol. 5, 243–251.
6. Ulrich, R.S. (1984). View through a window may influence recovery. 224, 224–225.
7. Banaei, M., Ahmadi, A., Gramann, K., Hatami, J. (2019). Emotional Evaluation of Architectural Interior Forms Based on Personality Differences Using Virtual Reality. Frontiers of Architectural Research, no. xxxx.
8. Zumthor, P. (2006). Atmospheres: Architectural Environments, Surrounding Objects. Conceptual Models in Exploration Geochemistry: Australia.
9. Picard, R.W. (1997). Affective Computing; MIT Press: Cambridge, MA, USA.
10. Cross, N. (1982). Designerly ways of knowing. Des. Stud. 3, 221–227.
11. Tversky, A., Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. 185, 1124–1131.
12. Ladouce, S., Donaldson, D. I., Dudchenko, P. A., & Ietswaart, M. (2017). Understanding Minds in Real-World Environments: Toward a Mobile Cognition Approach. Frontiers in Human Neuroscience, 10.Kalantari, Saleh, D. Ph, Jun Rong, and Jeffrey Neo. 2020. "Virtual Environments for Design Research : Lessons Learned From Use of Fully Immersive Virtual Reality in Interior Design Research".
13. Northoff, G. (2010). Humans, Brains, and Their Environment: Marriage between Neuroscience and Anthropology?. 65, 748–751.
14. Higuera-Trujillo, J.L., Llinares Millán, C., Montañana i Aviñó, A., Rojas, J.C. (2020). Multisensory stress reduction: A neuro-architecture study of paediatric waiting rooms. Build. Res. Inf. 48, 269–285.
15. Leeuwen, J.P.V., Harry, W. (1997). Architectural Design-by- Features, no. August: 97–115.
16. Kopec, D., Alan, D., Szenasy, SS. (2017). Health and Well-Being for Interior Architecture. New York: Routledge, Taylor & Francis Group.
17. Eberhard, J.P. (2009). Applying Neuroscience to Architecture. 62 (6): 753–756.
18. Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P. Tsang, A.M., Switzer, P., Behar, J. V., Hern, S. C., Engelmann, W. H. (2001). The National Human Activity Pattern Survey. Lawrence Berkeley National Laboratory. 11 (3): 231–252.
19. Mcintosh, A.R., Nafisa M.J. (2017). Application of Neuroscience Principles for Evidence-Based Design in Architectural Education. Journal of Young Investigators. 33 (4): 71–76.
20. Gerald, F., Von Der Heyde, M., Heinrich H.B. (2005). An Empirical Approach to the Experience of Architectural Space in Virtual Reality-Exploring Relations Between Features and Affective Appraisals of Rectangular Indoor Spaces. Automation in Construction. 14 (2 SPEC. ISS.): 165–172.
21. Bandodkar, Amay J., and Joseph Wang. 2014. "Non-Invasive Wearable Electrochemical Sensors: A Review." Trends in Biotechnology 32 (7): 363–371.
22. Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. Cognition & Emotion, 23(2), 209–237.
23. Khan, R. A., & Pathan, A.-S. K. (2018). The state-of-the-art wireless body area sensor networks: A survey. International Journal of Distributed Sensor Networks, 14(4), 155014771876899.
24. Fairhall, S.L., Ishai, A. (2008). Neural correlates of object indeterminacy in art compositions. Conscious. Cogn. 17, 923–932.
25. Ishai, A., Fairhall, S.L., Pepperell, R. (2007). Perception, memory and aesthetics of indeterminate art. Brain Res. Bull.73, 319–324.
26. Kalantari, S., Tripathi, V., Rounds, J.D., Mostafavi, A., Snell, R., & Cruz-Garza, J.G. (2021). Evaluating Wayfinding Designs in Healthcare Settings through EEG Data and Virtual Response Testing. bioRxiv.
27. Benedek, M., Christian K. (2010). A Continuous Measure of Phasic Electrodermal Activity. Journal of NeuroscienceMethods. 190 (1): 80–91.
28. Shi, Y., Natalie, R., Ronnie, T., Eric, C., Fang, C. (2007). Galvanic Skin Response (GSR) as an Index of Cognitive Load. Conference on Human Factors in Computing Systems – Proceedings. 2651–2656.
29. Boucsein,W. (2012). Electrodermal Activity, 2nd ed.; Springer Science & Business Media: Newbury Park, NY, USA; London, UK; New Dehli, India.
30. Ohme, R., Michal, M., Beata, P-L. (2011). Biometric Measures for Interactive Advertising Research. Journal of Interactive Advertising. 11 (2): 60–72.
31. Raskin, D.C. (1973). Attention and Arousal. In Electrodermal Activity in Psychological Research; Prokasy, W.F., Raskin, D.C., Eds.; Academic Press: London, UK. 123–156.
32. Pinheiro, N., Couceiro, R., Henriques, J., Muehlsteff, J., Quintal, I., Goncalves, L., & Carvalho, P. (2016). Can PPG be used for HRV analysis? 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Goldman, M. Principles of Clinical Electrocardiography; LANGE: Los Altos, CA, USA, 1976.
33. Berntson, G.G., Bigger, J.T., Eckberg, D.L., Grossman, P., Kaufmann, P.G., Malik, M. (1997). Heart rate variability: Origins, methods, and interpretive caveats. Psychophysiology. 34, 623–648.
34. Williams, D. P., Cash, C., Rankin, C., Bernardi, A., Koenig, J., & Thayer, J. F. (2015). Resting heart rate variability predicts self-reported difficulties in emotion regulation: a focus on different facets of emotion regulation. Frontiers in Psychology, 6.
35. Ferdinando, H., Esko, A. (2014). Emotion Recognition by Heart Rate Variability. Australian Journal of Basic and Applied Science. 8 (14): 50–55.
36. Brás, S., Ferreira, J. H. T., Soares, S. C., & Pinho, A. J. (2018). Biometric and Emotion Identification: An ECG Compression Based Method. Frontiers in Psychology, 9.
37. Davila, M. I., Lewis, G. F., & Porges, S. W. (2017). The PhysioCam: A Novel Non-Contact Sensor to Measure Heart Rate Variability in Clinical and Field Applications. Frontiers in Public Health, 5.
38. Alqaraawi, A., Alwosheel, A., & Alasaad, A. (2016). Heart rate variability estimation in photoplethysmography

signals using Bayesian learning approach. Healthcare Technology Letters, 3(2), 136–142.
39. Lotte, F., Bougrain, L., & Clerc, M. (2015). Electroencephalography (EEG)-Based Brain-Computer Interfaces. Wiley Encyclopedia of Electrical and Electronics Engineering, 1–20.
40. Crosson, B., Ford, A., McGregor, K. M., Meinzer, M., Cheshkov, S., Li, X., … Briggs, R. W. (2010). Functional imaging and related techniques: An introduction for rehabilitation researchers. The Journal of Rehabilitation Research and Development, 47(2), vii.
41. Mier, W., Daniela, M. (2015). Advantages in Functional Imaging of the Brain. Frontiers in Human Neuroscience. 9 (MAY): 1–6.
42. Soares, J.M., Magalhães, R., Moreira, P.S., Sousa, A., Ganz, E., Sampaio, A., Alves, V., Marques, P., Sousa, N. (2016). A hitchhiker's guide to functional magnetic resonance imaging. Front. Neurosci. 10, 515.
43. Thibault, R.T., MacPherson, A., Lifshitz, M., Roth, R.R., Raz, A. (2018). Neurofeedback with fMRI: A critical systematic review. Neuroimage.172, 786–807.
44. Cohen, M.X. (2017). Where Does EEG Come from and What Does It Mean? Trends Neurosci. 40, 208–218.
45. Singh, S.P. (2014). Magnetoencephalography: Basic Principles. Annals of IndianAcademyof Neurology. 17 (SUPPL. 1): 1–2.
46. Pu, Y., Cheyne, D.O., Cornwell, B.R., Johnson, B.W. (2018). Non-invasive investigation of human hippocampal rhythms using magnetoencephalography: A review. Front. Neurosci. 12, 273.
47. Valero-Cabré, A., Amengual, J.L., Stengel, C., Pascual-Leone, A., Coubard, O.A. (2017). Transcranial magnetic stimulation in basic and clinical neuroscience: A comprehensive review of fundamental principles and novel insights. Neurosci. Biobehav. Rev. 83, 381–404.
48. Quaresima, V., Marco, F. (2019). Functional Near-Infrared Spectroscopy (FNIRS) for Assessing Cerebral Cortex Function During Human Behavior in Natural/Social Situations: A Concise Review. Organizational Research Methods. 22 (1): 46–68.
49. Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., Yger, F. (2018). A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update. J. Neural Eng. 15, 31005.
50. Gruzelier, J.H. (2014). EEG-neurofeedback for optimising performance. I: A review of cognitive and a_ectiveoutcome in healthy participants. Neurosci. Biobehav. Rev. 44, 124–141.
51. Thibault, R.T., MacPherson, A., Lifshitz, M., Roth, R.R., Raz, A. (2018). Neurofeedback with fMRI: A critical systematic review. Neuroimage. 172, 786–807.
52. Naseer, N., Hong, K.-S. (2015). fNIRS-based brain-computer interfaces: A review. Front. Hum. Neurosci. 9, 3.
53. Duchowski, A. (2003). Eye tracking Methodology: Theory and Practice; Springer Science & Business Media: London, UK.
54. Read, Glenna L. (2017). Facial Electromyography (EMG). The International Encyclopedia of Communication Research Methods, no.1–10.
55. Ekman, P., Friesen, W.V. (1971). Constants across cultures in the face and emotion. J. Pers. Soc. Psychol. 17, 124–129.
56. Sato,W., Fujimura, T., Suzuki, N. (2008). Enhanced facial EMG activity in response to dynamic facial expressions. Int. J. Psychophysiol. 70, 70–74.
57. Wolf, K., Mass, R., Ingenbleek, T., Kiefer, F., Naber, D., Wiedemann, K. (2005). The facial pattern of disgust, appetence, excited joy and relaxed joy: An improved facial EMG study. Scand. J. Psychol. 46, 403–409.
58. Boxtel, A.V. (2010). Facial EMG as a Tool for Inferring Affective States. Proceedings ofMeasuring Behavior. (24–27): 104–108.
59. Künecke, J., Hildebrandt, A., Recio, G., Sommer, W., & Wilhelm, O. (2014). Facial EMG Responses to Emotional Expressions Are Related to Emotion Perception Ability. PLoS ONE, 9(1), e84053.
60. Andreani, S., Sayegh, A. (2018). Urban attractors, physical proximity and states of mind: Measuring dynamic experiences in varying typologies of the built environment. In Proceedings of the 2018 ANFA Conference; The Academy of Neuroscience for Architecture: La Jolla, CA, USA.10–11.
61. Suurenbroek, F., Spanjar, G. (2018). (Eye)tracking users' patterns: Visual experience and choice behavior in transition zones of Amsterdam- Southeast. In Proceedings of the 2018 ANFA Conference; The Academy of Neuroscience for Architecture: La Jolla, CA, USA. 176–177.
62. Ekman, P., & Friesen, W.V. (1978). Facial action coding system: a technique for the measurement of facial movement.
63. Ekman, P., Erika, R. (2005). What the Face Reveals. What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS).
64. Lewinski, P., Tim M., Den, U., Crystal, B. (2014). Automated Facial Coding: Validation of Basic Emotions and FACS AUs in Facereader. Journal of Neuroscience, Psychology, and Economics. 7 (4): 227–236.
65. Duchowski, A. (2003). Eye tracking Methodology: Theory and Practice; Springer Science & Business Media: London, UK.
66. Schofield, C.A., Johnson, A.L., Inhoff, A.W., Coles, M.E. (2012). Social anxiety and difficulty disengaging threat: Evidence from eye-tracking. Cogn. Emot. 26, 300–3011.
67. Duchowski, A.T. (2017). Eye TrackingMethodology. Eye TrackingMethodology.
68. Poole, A., Linden J.B. (2005). Eye Tracking in Human-Computer Interaction and Usability Research: Current Status and Future Prospects. United Kingdom: Psychology Department, Lancaster University. 211–219.
69. Afrooz, A., David, W., Michael, N. 2014. Way-Finding Improves VisualMemoryfor Built Environments. CEURWorkshopProceedings 1241. 57–61.
70. Stein J., Bennett D., Coen C., Dunbar R., Goodwin G., Husain M., Mann E., Morris J., Rolls E., Taylor JSH., Walsh V. (2016). "Spirituality." The Curated Reference Collection in Neuroscience and Biobehavioral Psychology. 1–6.
71. Baer, R. A., Smith, G. T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using Self-Report Assessment Methods to Explore Facets of Mindfulness. Assessment, 13(1), 27–45.
72. Tsonos, D., & Kouroupetroglou, G. (2008). A Methodology for the Extraction of Reader's Emotional State Triggered from Text Typography. Tools in Artificial Intelligence.
73. Sacharin, V., Schlegel, K., & Scherer, K. R. (2012). Geneva emotion wheel rating study. Unpublished manuscript.
74. Scherer, K.R. (2005). What Are Emotions? And How Can They Be Measured? Social Science Information. 44 (4): 695–729.

75. Golman, D. (2002). Primal Leadership: Realizing the power of Emotional Intelligence, Boston, MA: Harward Business School Publishing.
76. Schultz, D. (1976). Theories of Personality, Monterey, California: Brooks/Cole Publishing Company.
77. Liu, H., Zhang, Y., Li, Y., Xiangyi, K. (2021). Review on Emotion Recognition Based on Electroencephalography, Front Comput Neurosci. 15:758212.
78. Ramirez, P. M., Desantis, D., and Opler, L. A. (2010). EEG biofeedback treatment of ADD. A viable alternative to traditional medical intervention? Ann. N. Y. Acad. 931, 342–358.
79. Xin, H., Jingjing, C., and Fei, W. (2019). Ten challenges for EEG-based affective computing. Brain Sci. Adv. 5, 1–20.
80. Fürbass, F., Kural, M. A., Gritsch, G., Hartmann, M., and Beniczky, S. (2020). An artificial intelligence-based EEG algorithm for detection of epileptiform EEG discharges: Validation against the diagnostic gold standard. Clin. Neurophys. 131:32.
81. Cabanac, M. (2002). What is emotion? Behav. Proc. 60, 69–83.
82. Kumar, J., and Kumar, J. (2015). A machine learning approach to classify emotions using GSR[J]. Adv. Electr. Electron. Eng. 2, 72–76.
83. laza-Del-Arco, F. M., Martín-Valdivia, M., Urea-López, L., and Mitkov, R. (2019). Improved emotion recognition in Spanish social media through incorporation of lexical knowledge. Future Generat. Comp. Syst. 2019:34.
84. Behm, D., Whittle, J., Button, D., and Power, K. (2002). Intermuscle differences in activation. Muscle Nerve 25, 236–243.
85. Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots. New York, NY: Nature Publishing Group.
86. Ekman, P., Friesen, W. V., and O'Sullivan, M. (1987). Universals and cultural differences in the judgments of facial expressions of emotion. J. Personal. Soc. Psychol. 53:712.
87. Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (1990). Emotion, attention, and the startle reflex. Psycholog. Rev. 97, 377–395.
88. Russel, J. A. (2003). Core affect and the psychological construction of emotion. Psycholog. Rev. 110, 145–172.
89. Mohamed, H., Zaidan, B., and Zaidan, A. A. (2018). A Systematic Review for Human EEG Brain Signals Based Emotion Classification, Feature Extraction, Brain Condition, Group Comparison. J. Med. Syst. 42:162.
90. Niemic, C. (2004). Studies of Emotion: A Theoretical and Empirical Review of Psychophysiological Studies of Emotion. J. Undergr. Res. 1, 15–18.
91. Constantinescu, A. C., Wolters, M., Moore, A., and Macpherson, S. E. (2017). A cluster-based approach to selecting representative stimuli from the International Affective Picture System (IAPS) database. Behav. Methods 49, 896–912.
92. Soleymani, M., Asghari-Esfeden, S., Pantic, M., and Yun, F. (2014). Continuous emotion detection using EEG signals and facial expressions, in 2014 IEEE International Conference on Multimedia and Expo (ICME) (Chengdu, China: IEEE Press).
93. Huo, X. Q., Zheng, W. L., and Lu, B. L. (2016). Driving fatigue detection with fusion of EEG and forehead EOG. In Procceeding of the International Joint Conference on Neural Networks IEEE (Shenzhen).
94. Zheng, W. L., and Lu, B. L. (2016). A Multimodal Approach to Estimating Vigilance Using EEG and Forehead EOG. J Neural Eng. 14:026017.
95. Hu, W., Huang, G., Li, L., Zhang, L., Zhang, Z., and Liang, Z. (2020). Videotriggered EEG-emotion public databases and current methods: A survey. Brain 6, 255–287.
96. Soleymani, M., Caro, M. N., Schmidt, E. M., Sha, C.-Y., and Yang, Y.-H. (2013). "1000 songs for emotional analysis of music," in Acm International Workshop on Crowdsourcing for Multimedia ACM (Orlando, FL) 1–6.
97. Greco, A., Valenza, G., Citi, L., and Scilingo, E. P. (2017). Arousal and Valence Recognition of Affective Sounds based on Electrodermal Activity. IEEE Sensors J. 2017, 1–1.
98. Cipresso, P., Chicchi, I.A., Alcañiz, M., Riva, G. (2018). The Past, Present, and Future of Virtual and Augmented Reality Research: A network and cluster analysis of the literature. Front. Psychol. 9, 2086.
99. Castelvecchi, D. (2016). Low-cost headsets boost virtual reality's lab appeal. Nature. 533, 153–154.
100. Giglioli, I.A.C., Pravettoni, G., Martín, D.L.S., Parra, E., Alcañiz, M. (2017). A novel integrating virtual reality approach for the assessment of the attachment behavioral system. Front. Psychol. 8, 1–7.
101. Kwartler, M. (2005). Visualization in support of public participation. In Visualization in Landscape and Environmental Planning: Technology and Applications; Bishop, I., Lange, E., Eds.; Taylor & Francis: London, UK. 251–260.
102. Picard, R.W. (2003). Affective Computing: Challenges. Int. J. Hum. Comput. Stud. 59, 55–64.
103. Diemer, J., Alpers, G.W., Peperkorn, H.M., Shiban, Y., Mühlberger, A. (2015). The impact of perception and presence on emotional reactions: A review of research in virtual reality. Front. Psychol. 6, 1–9.
104. Cipresso, P., Giglioli, I.A.C., Raya, M.A., Riva, G. (2018). The Past, Present, and Future of Virtual and Augmented Reality Research: A network and cluster analysis of the literature. Front. Psychol. 9, 2086.
105. Slater, M.; Wilbur, S. (1997). A Framework for Immersive Virtual Environments (FIVE): Speculations on the Role of Presence in Virtual Environments. Presence Teleoperators Virtual Environ. 6, 603–616.
106. Heeter, C. (1992). Being There: The Subjective Experience of Presence. Presence Teleoperators Virtual Environ. 1, 262–271.
107. Alcañiz, M., Baños, R., Botella, C., Rey, B. (2003). The EMMA Project: Emotions as a Determinant of Presence. PsychNology J. 1, 141–150.
108. Portman, M.E., Natapov, A., Fisher-Gewirtzman, D. (2015). To go where no man has gone before: Virtual reality in architecture, landscape architecture and environmental planning. Comput. Environ. Urban Syst. 54, 376–384.
109. Jerald, Jason. (2015). The VR Book. The VR Book.
110. Hermund, A., Morten M.J., Lars S.K. (2019). The Neurological Impact of Perception of Architectural Space in Virtual Reality Virtual Reality with Building Information Modelling and EEG, 1–10.
111. Zou, Z., Semiha, E. (2019). Where Do We Look? An Eye-Tracking Study of Architectural Features in Building Design. Advances in Informatics and Computing in Civil and Construction Engineering, no. January.
112. Ergan, S., Radwan, A., Zou, Z., Tseng, H., & Han, X. (2019). Quantifying Human Experience in Architectural Spaces with Integrated Virtual Reality and Body Sensor Networks. Journal of Computing in Civil Engineering, 33(2), 04018062.
113. Higuera-Trujillo, J. L., Llinares Millán, C., Montañana i Aviñó, A., & Rojas, J.-C. (2019). Multisensory stress

reduction: a neuro-architecture study of paediatric waiting rooms. Building Research & Information, 1–17.

114. Kalantari, S., Contreras-Vidal, J. L., Smith, J. S., Cruz-Garza, J., & Banner, P. (2018). Evaluating educational settings through biometric data and virtual response testing. In M. Del Signore, A. J. Wit, & P. Anzalone (Eds.), Recalibration on Imprecision and Infidelity - Proceedings of the 38th Annual Conference of the Association for Computer Aided Design in Architecture, ACADIA 2018 (pp. 118-125).
115. Madlen, S., Ming, H. (2019). Mind the Perception and Emotional Response to Design : Emerging Methodology. 507–14.
116. Banaei, M., Hatami, J., Yazdanfar, A., Gramann, K. (2017). Walking Through Architectural Spaces: The Impact of Interior Forms on Human Brain Dynamics. Frontiers inHumanNeuroscience. 11, 1–14.
117. Shemesh, A., Talmon, R., Karp, O., Amir, I., Bar, M., & Grobman, Y. J. (2016). Affective response to architecture – investigating human reaction to spaces with different geometry. Architectural Science Review, 60(2), 116–125.
118. Vecchiato, Giovanni, Gaetano Tieri, Andrea Jelic, Federico De Matteis, Anton G. Maglione, and Fabio Babiloni. 2015. “Electroencephalographic Correlates of Sensorimotor Integration and Embodiment During the Appreciation of Virtual Architectural Environments.” Frontiers in Psychology 6 (DEC),
119. Sharma, G., Kaushal, Y., Chandra, S., Singh, V., Mittal, A. P., & Dutt, V. (2017). Influence of Landmarks on Wayfinding and Brain Connectivity in Immersive Virtual Reality Environment. Frontiers in Psychology, 8.
120. De Tommaso, M., Ricci, K., Delussi, M., Montemurno, A., Vecchio, E., Brunetti, A., & Bevilacqua, V. (2016). Testing a novel method for improving wayfinding by means of a P3b Virtual Reality Visual Paradigm in normal aging. SpringerPlus, 5(1).