Review

Wearables for Engagement Detection in Learning Environments: A Review

Maritza Bustos-López¹, Nicandro Cruz-Ramírez¹*, Alejandro Guerra-Hernández¹*, Laura Nely Sánchez-Morales², Nancy Aracely Cruz-Ramos³ and Giner Alor-Hernández³,*

¹ Instituto de Investigaciones en Inteligencia Artificial, Universidad Veracruzana, Xalapa, Veracruz 91097, Mexico; maritbustos@gmail.com (M.B.-L.); ncruzz@uv.mx (N.C.-R.); aguerra@uv.mx (A.G.-H.)
² Division of Research and Postgraduate Studies, CONACYT-Tecnológico Nacional de México/I. T. Orizaba, Av. Oriente 9 852 Col. Emiliano Zapata, Orizaba, Veracruz 94320, Mexico; laura.sm@orizaba.tecnm.mx
³ Division of Research and Postgraduate Studies, Tecnológico Nacional de México/I. T. Orizaba, Av. Oriente 9 852 Col. Emiliano Zapata, Orizaba, Veracruz 94320, Mexico; dci.ncruz@ito-depi.edu.mx
* Correspondence: giner.ah@orizaba.tecnm.mx

Abstract: Appropriate teaching–learning strategies lead to student engagement during learning activities. Scientific progress and modern technology have made it possible to measure engagement in educational settings by reading and analyzing student physiological signals through sensors attached to wearables. This work is a review of current student engagement detection initiatives in the educational domain. The review highlights existing commercial and non-commercial wearables for student engagement monitoring and identifies key physiological signals involved in engagement detection. Our findings reveal that common physiological signals used to measure student engagement include heart rate, skin temperature, respiratory rate, oxygen saturation, blood pressure, and electrocardiogram (ECG) data. Similarly, stress and surprise are key features of student engagement.

Keywords: engagement detection; learning environments; physiological signals; sensors; wearables

1. Introduction

Student engagement in the classroom is usually directly linked to the student’s perception of the pedagogical activities and strategies implemented in class. Student engagement is usually measured when teaching reading comprehension. In many cases, reading is a fundamental building block to students’ development and success both in and out of the classroom. It strengthens the brain and promotes critical thinking. Similarly, reading comprehension as a skill allows students to interpret written discourse. However, teaching reading comprehension may be a challenging task when it comes to keeping students fully engaged.

In their work, Bosch et al. [1] identified three types of student engagement: affective, behavioral, and cognitive. Current methods for monitoring engagement levels among students during educational activities usually rely on computer vision for image processing and recognition of facial expressions, gestures, postures, and eye movements. Similarly, physiological and neurological sensors attached to wearables can capture key physiological features as indicators of student engagement.

The computer vision approach allows researchers to extract valuable data on the affective, cognitive, and behavioral states of students during specific learning activities and from three channels: audio, image, and video. The data obtained from computer vision allow experts to monitor and measure to what extent students remain engaged in a particular classroom activity, initially designed to teach something. In parallel, the use of wearables in learning environments allows for detecting data of factors involved during learning experiences, such as concentration, engagement, and attitude to name but a few,
through the monitoring of physiological signals. Such data is key for teachers, as it allows them to understand why students perform in a certain way in class.

A substantial amount of scientific literature includes reviews or proposes sensors and biosensors to measure physiological variables. Castaneda et al. [2], Shabaan et al. [3], Lou et al. [4], Guo et al. [5] and Tandon et al. [6] developed their own sensors and wearable technologies for monitoring of different physiological signals. Nahavandi et al. [7] analyzed the challenges and opportunities of Artificial Intelligence (AI)-based wearable devices. In turn, researchers Reda et al. [8], Surantha et al. [9], Khoshmanesh et al. [10], Santo et al. [11], Akinosun et al. [12], DeVore et al. [13] and Burnham et al. [14] have introduced their own reviews of wearables applied to healthcare. In this perspective, some parameters used in these works are relevant for engagement in students, such as heart rate, blood pressure, postures, sleep, to mention but a few. Other researchers [15–19] have proposed works focuses on sensors and wearables for physiological and behavioral monitoring of students, eye-tracking devices for capturing student attention and understanding Engagement in Learning.

Emotional state and posture recognition have become an important topics for student engagement detection [20–25]. Additionally, contributions such as that of Salmeron-Majadas et al. [26] seek to collect and process keyboard and mouse interactions to measure how students perform during learning activities. Other works centered around student emotional state detection analyze and process signals from Electroencephalogram (EEG), Electromyogram (EMG), Electrocardiography (ECG), Electrodermal activity (EDA), heart rate variability, skin temperature, blood volume pulse, respiration, or Electrodermography (EDG)/galvanic skin response (GSR) [27–37]. Researchers [38–47] report the use of deep learning and machine learning (ML) techniques for emotion classification. Finally, other techniques rely on emotion recognition via computer vision [22,41,48–50], linguistic semantic approaches [51], and biological features [52].

Our analysis of the aforementioned works leads us to conclude that emotion recognition based on physiological signals is highly applicable to the study of student learning processes. Most of the physiological signals involved in such studies analyze and process EEG data from wearable devices such as wristbands or headbands. Other studies rely on strategies that combine facial expression recognition with the monitoring of vital signs and other factors, such as keystrokes, body movements, muscle pressure, or gesture rigidity. It also seems that Machine Learning Algorithms (MLA) and computer vision are the most common techniques to detect student emotion states and engagement through factors such as facial expressions, eye movement, and speech. Some deep-learning-based algorithms have been developed to monitor in real time emotions such as anger, disgust, fear, happiness, sadness, and surprise. These algorithms compute Mean Engagement Score (MES) by analyzing data retrieved from facial landmark detection and emotional recognition.

From this understanding, the use of information technologies for engagement level detection in different educational subjects such as Spanish, history, science, or mathematics based on innovative technologies such as the recognition of physiological signals represents an opportunity to improve the teaching–learning process.

This research has four objectives that distinguish it from similar reviews. First, we review and identify commercial and non-commercial wearables that use sensors for engagement detection. Second, we identify the common sensors attached to those wearables. We also highlight the key physiological variables involved in student engagement detection and monitoring. Finally, we review and discuss the FDA approval status of the reviewed commercial wearables.

2. Main Physiological Signals for Student Engagement Detection

The sources of data for the collection of emotional and physiological data in learning environments are diverse. According to Feidakis [53], some tools can compute physiological signal readings, whereas some others allow for observing behavioral activity. Some parameters and signals commonly used for emotion state detection and physiological
monitoring are introduced below [53]. Additionally, Figure 1 visually illustrates the body parts commonly associated to the measurement of these parameters and signals:

**Figure 1.** Physiological Variables for Engagement Detection and Associated Body Parts.

*Electroencephalography (EEG):* According to Rogers [54], EEG is a technique for registering and analyzing the brain’s electrical activity. Neurons, also referred to as brain nerve cells, produce electrical impulses that oscillate rhythmically in different patterns. An EEG is used to measure and record brain activity patterns. The instrument’s recording is called an electroencephalogram. In educational contexts, EEG measurements should provide a more objective indication of how the brain functions during learning activities over time in comparison to the think-aloud type of self-reporting technique. Additionally, EEG can distinguish between the different brain’s active states quantitatively by analyzing the wavelength band.

*Electrocardiogram (ECG):* An ECG records the natural electrical impulses that coordinate the contractions of the various parts of the heart to show the rate at which the heart beats, the rhythm of the beats (steady or irregular), and the strength and timing of the electrical impulses as they travel through the various parts of the heart [55]. In a learning environment, monitoring ECG patterns can help track students’ attention in the classroom and their cognitive activities.

*Blood Pressure (BP):* BP refers to the force of the blood pushing against the walls of the arteries. It is measured in millimeters of mercury, and it is expressed as a measurement with two numbers, one number on top (systolic), and the other one on the bottom (diastolic), as in a fraction (for instance, 120/80 mmHg). Systolic pressure is the pressure of the blood when the heart beats or contracts. Conversely, diastolic pressure is the pressure of the blood between beats; that is, when the heart relaxes [56]. According to Taj-Eldin et al. [57], measuring BP helps monitor changes in a person’s emotional state, such as stress. If a student experiences a stressful situation, the body produces hormones that temporarily increase BP.
Electromyogram (EMG): An EMG is a test that measures electrical discharges from muscles. The test is performed by placing a thin needle into a muscle and measuring its electrical activity at rest and during use [58]. Monitoring EMG signals can help identify student emotional arousal during educational activities. Measuring the movement of facial muscles through EMG provides parameters to study student behavior during interactions with dynamic visual content.

Skin temperature (ST): According to Yasuma and Hayano [59], skin temperature is measured on the surface of the human skin; thus, only skin contact is required. Furthermore, including body and peripheral temperature as a physiological parameter is useful for detecting emotions such as stress. The use of skin sensors to monitor parameters such as skin temperature facilitates emotion detection and allows researchers to measure student engagement in different educational activities, such as watching movies and role playing [60].

Galvanic Skin Response (GSR): It measures skin conductance. GSR is measured by placing two electrodes on the skin surface, namely on the fingers. One electrode applies a small amplitude alternating current into the skin, and the other is used to calculate skin impedance using Ohm’s Law given a voltage [61]. GSR is a function of skin moisture level that is related to the sweat glands. Through the sweat glands it is possible to measure emotional arousal, which leads to an increase in sweat gland activity. In the educational context, research has measured both student engagement and emotional arousal during educational activities such as reading using GSR data [62].

Photoplethysmography (PPG): According to Allen [63], PPG is a simple and affordable optical technique used to detect changes in blood volume in the microvascular bed of tissues. It is often used noninvasively for measurements on the skin surface. In educational research, PPG sensors have been useful for measuring parameters such as heart rate to detect student cognitive engagement during learning activities.

Respiratory pattern (RP), Respiratory volume (RV) and heart rate (HR): According to Braun [64], in the ventilation process that allows the movement of air into the lungs, the respiratory system has a central respiratory pacemaker within the medulla of the brainstem. Neuronal output travels from this center by the spinal cord to the respiratory muscles. The changes made by the inspiratory and expiratory muscles, as they contract and relax, cause a rhythmic breathing rate and pattern. Changes in respiratory patterns are related to positive emotions such as happiness. Some of the changes include increased variability in the respiratory pattern or decreased respiratory time. On the other hand, respiratory volume relates to the volume of gas present in the lungs at a specific time during the respiratory cycle [65]. Some lung volume parameters, such as inspiratory reserve volume, tidal volume, and expiratory reserve volume, are measured by spirometry. However, functional residual capacity, total lung capacity, and residual volume are measured by body plethysmography, nitrogen washout, and helium dilution. Finally, heart rate refers to the number of times the heart beats per minute and is used to monitor cardiac activity [57]. Even though it provides partial information on the heart’s activity, monitoring heart rate is useful for measuring student engagement in different teaching modalities. For instance, during active learning activities based both on problem-solving and peer discussion, heart rate tends to increase [66].

Facial Expression Recognition (FER): Facial expressions are changes that occur in the human face [67]. According to Dewan et al. [41], facial expressions are directly associated with perceived engagement. One of the methods for the detection of facial expressions is the analysis of facial images. Analysis methods used to extract information about engagement use geometric and holistic features. Such methods are classified in part-based and appearance-based methods. The study of FER among students is useful to identify their emotions, which helps teacher recognize whether students understand or not a given topic, for example.

Gestures and postures: According to Dewan et al. [41], gestures and posture are forms of nonverbal communication expressed by human body language. They are linked to
emotional-cognitive states that either favor or hinder learning. In their research, Dewan et al. [41] collected data from webcam video recordings, skin conductance, and Kinect depth video to infer student engagement. The analysis of gestures such as hand movements helps determine a person’s intention when performing an action, which allows teachers and experts to detect student attention or disengagement in the learning process.

**Eye movements:** Eye movements have been widely used to understand the emotional states of students during online educational activities [41]. In their work, Dewan et al. [41] review a series of studies in which eye movement patterns, head movements, and facial features measure the level of student engagement and concentration in online learning environments.

**Keyboard and mouse motion capture:** The mouse motion technique analyzes features such as average speed, inactivity, the orientation of mouse movements, mouse speed, acceleration, hand agitation, click coordinates, scrolling, temperature, humidity, and user keystroke intensity to detect a person’s mood. On the other hand, analyzing keyboard movements to determine student affective states or engagement implies analyzing elements such as keystroke verbosity (number of keys and blanks), keystroke time (latency measures), pause behaviors, typing speed, the number of characters typed during a 5-s interval, total typing time, and idle times [26]. Overall, the analysis of mouse and keyboard interaction patterns during tasks such as free text typing enables the study of student affective states during learning activities.

**Physiological signals detectable through the headband:** Most of the physiological signals detected through a headband use EEG with features such as Power Spectral Density (PSD), Signal Power (SP), and Common Spatial Pattern (CSP) [27]. Signals measured through a headband can help monitor student concentration during educational activities, which is in turn helpful for teachers to monitor student engagement in class.

### 3. Methods

This paper is a review of sensor technologies from the IoT perspective. We highlight how sensors attached to wearables manage to detect and monitor student cognitive engagement in learning environments through the recording and processing of physiological signals. We rely on the PRISMA [68] statement to ensure research clarity and methodological robustness.

**Inclusion and exclusion criteria.** Initially, we retrieved 4142 queries from a selected set of databases. Below, we describe the review inclusion and exclusion criteria:

**Inclusion criteria.** We searched for studies published from 2010 to 2021 on (1) engagement detection in learning environments, (2) physiological signal monitoring, (3) commercial and non-commercial wearable devices and sensors, (4) IoT wearable devices, and (5) FDA-approved medical devices.

**Exclusion criteria.** We discarded search results of researches that (1) were not written in English, (2) were presented in the form of reports and letters, (3) was not a first study, and (4) were not peer-reviewed.

**Information Sources.** The keywords of our research questions were identified and classified into two groups: computing technology and engagement detection. These areas of knowledge helped us to determine the specialty of the scientific digital library chosen as an information source. In terms of engagement detection, we relied on PubMed (3%) and Nature (19%), whereas in terms of computing technology, we chose Science Direct (9%), Wiley Online Library (7%), IEEE Xplore (1%), Hindawi (15%), Inderscience (8%), Springer Link (17%), ACM Digital Library (18%), and MDPI (3%). During federate search on Google Scholar, all these scientific libraries yielded good results. Once the libraries were selected, we retrieved relevant studies by submitting search queries to the corresponding search engines of each digital library (See Figure 2). The search was performed from January to December 2021.
**Search Strategy.** We combined keywords using Boolean-like connectives to filter the search results. The keywords of the search were extracted from the keywords that shaped the research questions. The search strategy resulted of a series of intermediate searches that led to the answer to the research question. These intermediate searches were ordered to determine the search terms to be used in the posterior queries:

1. Sensors and biosensors that measure these physiological variables;
2. FDA-approved commercial wearable devices for engagement detection in learning environments;
3. Commercially available consumer wearable devices using sensors for engagement detection in learning environments;
4. Non-commercial wearable devices using sensors for engagement detection in learning environments;
5. Physiological variables involved in engagement detection in learning environments.

Queries 3 and 4 were used to the databases. Query 3 resulted in the following search expression, which used adjacent search terms conjugated with AND and OR connectives as follows:

‘Engagement Detection’ AND ‘Learning Environments’ AND (‘Physiological Signals’ OR ‘Physiological Variables’ OR ‘Physiological Parameters’) AND (‘students’ OR ‘young people’) AND ‘wearable’.

Results showed that the physiological variables involved in the students’ emotions were the relevant search terms. Query 4 integrated these search terms into a search expression whose implementation produced new results associated with the physiological variables. Similarly, as the results of each of the queries detailed above generated new search terms, the results were progressively expanded to those that were relevant to this study. The results of the last phase of consultation included those wearable devices that contain sensors (biosensors) which measure physiological variables in students. The wearable devices included could be commercial or non-commercial and, in the first case, they could be FDA-approved or not.

**Selection process.** Three subject matter experts (SMEs) screened the abstracts and titles of the 4142 relevant papers retrieved at the search stage. Next, the information was
grouped into eight categories: wearable manufacturer, model, form factor (it refers to the size, type, and physical specifications of the device), sensors used, measured parameters, physiological signs detected, API, and FDA status. Following this first analysis 3933 papers were discarded. The remaining 209 papers became of interest for a more detailed analysis of their content. Following this second analysis, we excluded 183 more papers. Finally, only the remaining 26 papers were selected for this review. These papers came from the following digital libraries: PubMed (3), Nature (5), IEEE Xplore (2), ScienceDirect (1), MDPI (2), Springer Link (2), ACM Digital Library (4), and other sources (6). In Figure 3, the PRISMA diagram details our study search and selection strategy.

![PRISMA Flow Diagram of the Search Strategy.](image)

**Figure 3.** PRISMA Flow Diagram of the Search Strategy.

**Data collection and analysis.** We categorized relevant information from the studies and migrated it to structured tables for a thorough analysis. The database thus contained details on current commercial and non-commercial wearables and sensors for engagement detection. We did not perform a randomized controlled selection, since we found a relatively small number of wearables; only 26. Information of interest for each wearable was as follows: device manufacturer, model, form factor, sensors used, parameters measured, physiological signs being detected, API, and FDA approval status.

**4. Results**

**4.1. Study Selection**

We initially collected 4172 records across the digital libraries mentioned in the beginning of this section and listed in Figure 3. These records were then screened to assess their relevance, thus discarding 3933 of them. The eligibility of the remaining 209 records were evaluated by analyzing the relevance of their full-text content. The evaluation excluded
183 records for several reasons, including the following: (i) the papers were not written in English, (ii) they focused on topics irrelevant to the research, and (iii) they were irrelevant to the aim of the research questions. Therefore, only 26 studies were included in the review as primary researches after applying the inclusion and exclusion criteria for eligibility.

4.2. Study Characteristics

We grouped the identified wearable devices into two large categories: commercial wearables and non-commercial wearables. Commercial wearables included those being manufactured, those already found on the market, and those being in presale by the time of writing this paper. Conversely, non-commercial wearables comprised all those wearables still found at prototype phase and those reported in scientific literature but not yet being manufactured by the time of writing this paper. Reviews of each device category, including 79 wearable devices and 15 non-commercial wearable devices, are presented below.

4.2.1. Classification of Wearables for Learning Engagement Detection in Learning Environments

In terms of the biosensors comprised in the wearables, Table 1 presents our classification. This classification is based on the analyses of wearable biosensor technologies proposed by [69,70], and it groups our findings into three categories: mechanical biosensors, physiological biosensors, and biochemical biosensors. The table also lists the technologies upon which these sensors rely, their applications in engagement detection, and the types of wearables using these sensors.

| Type of Wearable Biosensor | Description | Wearable Biosensor Technologies | Wearable Device | Applications |
|----------------------------|-------------|---------------------------------|----------------|--------------|
| Mechanical (Accelerometers and motion sensors) [69,70]. | Accelerometers and motion sensors require the integration of another wearable physiological monitoring device as well as some type of computer software interface equipped with specific algorithms for signal manipulation and analysis. They are especially valuable when combined with wireless heart rate and ECG monitoring. | Accelerometer with ECG necklace Accelerometer and wireless heart rate monitor Motion sensor algorithm | Leap Motion Smartwatch Armband Headband Chest strap | Tracking gait Motion sensing |
| Physiological [69,70]. | Physiological sensors can be used for predicting obstructive sleep apnea and monitoring heart rate, oxygen saturation, heart rate variability, breathing rate, and oxygen saturation. Further, these sensors can measure stress levels and mental fatigue. | PPG ring sensor PPG biosensors with smartphones PPG ECG magnetic earring and wireless earpiece PPG biosensors with GSR | Ring Muse band S Armband Headband Smartwatch Wristband Abdominal patch Chest patch Chest strap Vest | Concentration monitoring |
| Biochemical [69,70]. | Biochemical sensors can be used for non-invasive sweat monitoring through epidermal tattoo potentiometric sodium sensors with wireless signal transduction. Further, they are used for one-point wireless ECG acquisition with flexible polydimethylsiloxane (PDMS) electrodes. | Epidermal tattoo potentiometric sodium sensor Flexible PDMS-electrode Flexible thick-film glucose biosensor Hydrogel-based (FAAM) photonic sensor Textile based patch with optical detection system Knitted fabric biocloth | | Finger and limb motion detection |

4.2.2. Commercial Wearables for Engagement Detection

Our review of commercial wearables for engagement detection comprises commercially available wearables that set monitoring metrics for detecting engagement. However, notice that most of these devices do not limit themselves to engagement detection in learn-
ing environments, as they are reported to have other applications. Our findings revealed that a wide range of commercial wearable devices for monitoring physiological parameters and detecting emotional states have applications in healthcare [70,71]. Table 2 presents our classification of commercial wearable devices for engagement detection. This classification takes into account the following aspects of each device: manufacturer, model, form factor, parameters measured, physiological signs detected, and APIs. Our most important findings concern the different wearable form factors commercially available, including armbands, chest belts, wrist monitors, chest patches, chest straps, contactless in-bed sensors, earbuds, headbands, smart rings, smartwatches, wristbands, and T-shirts. Both smartwatches and wristbands are the most common form factors among manufacturers. Examples of smartwatches include the Huawei Watch 3, Venu® Sq from Garmin, the Apple Watch Series 7, and the Samsung Gear Sport. As regards the parameters measured by these wearables, the following stand out: skin temperature, oxygen saturation, respiratory rate, heart rate, heart rate variability, blood pressure, EEG, stress levels, sleep, EMG, step tracking, and PPG. On the other hand, the most common physiological signals involved in engagement detection are stress, relaxation, surprise, postures, engagement, concentration, and laugh. Finally, each wearable relies on different type of software, which depends on the physical components of each device and the parameters that can be measured.

We can identify the contribution of the devices to assist and increase student engagement during educational activities. We found that the Chest strap, Smartwatch and Leap Motion can detect ECG signals, and their application is focused on gait tracking and motion tracking. Meanwhile, the Armband, Wristband, Ring, Abdominal patch, Headband and GSR Velcro electrodes can detect PPG and GSR signals, which have application in concentration monitoring. Furthermore, epidermal patches and textile patches can detect ECG signals in an inhaled form that facilitate the detection of movement in the extremities. Additionally, ECG signals such as heart rate or heart rate variability are associated with stress, surprise, relaxation and concentration. Meanwhile, PPG signals such as blood volume or oxygen saturation are related to stress, laughter, interest and frustration. In both cases, physiological signals allow the detection of students’ engagement in educational activities.

Most of the commercial wearables can record important physiological characteristics, such as respiratory rate, barometric pressure, posture, skin temperature, muscle movement, blood oxygenation, and heart rate to name but a few. Further, such devices usually transfer the recorded data to be processed using wireless technology. Once the data is processed, wearable users can visualize the data reports via a mobile application. As our findings revealed, commercial wearable devices are mostly smartwatches (32%). Conversely, less commonly manufactured wearables include helmets, bracelets, spoons, smart thermometers, smart sleeves, and fitness trackers (1%). Devices with 10–11% of incidence in the review include wristbands and chest patches, whereas headphones, analog watches, headbands, smart rings, earbuds, contactless in-bed sensors, and chest straps only showed 3% of incidence. Figure 4 introduces a graph for the classification of the commercial wearable form factors reported in the literature.

Wearable devices with healthcare applications must be approved in terms of reliability and efficiency. FDA-approved wearables for engagement detection have proved to be efficient in measuring physiological signals for detecting and monitoring engagement. Each wearable reported in the literature holds one of the four FDA statuses: approved, clear, unknown, and unapproved. Our findings indicated that 51% of the devices reported in the literature had an unknown FDA status, which is mainly due to the fact that most device manufacturers do not disclose such type of information. Conversely, 33% of the devices have a public FDA registration. This information is summarized and visually presented in Figure 5.
Table 2. Commercial Wearable Devices for Engagement Detection.

| Manufacturer       | Model                     | Form Factor   | Sensors Used                                      | Parameters                                      | Physiological Signs          | API                  | FDA       |
|-------------------|---------------------------|---------------|-------------------------------------------------|------------------------------------------------|-------------------------------|----------------------|-----------|
| Biovotion™ [71]   | Everion                   | Armband       | HR sensor, PPG sensor                           | ST, SpO2, RR, HR, HRV, Sleep                   | Stress, relaxation           | Everion device       | Approved  |
| Abbott [72]       | FreeStyle Libre           | Semi-invasive | Continuous Glucose Monitoring (CGM) sensor      | ST, BP                                         | Distress                     | Ambrosia             | Approved (2020) |
| Halo Sport [73]   | Halo Sport 2.0            | Headphones    | Electro neurostimulator                        | Neuropriming                                   |                               | Halo Sport           | Approved  |
| Scosche™ [74]     | Scosche Rhythm24          | Armband       | HR optical sensor                               | PPG, HR, HRV, cadence, step tracking, burned calories, distance, speed | Stress, postures, surprise | ScoscheSDK24 Framework | Not Approved |
| Equivital™ [75]   | LifeMonitor               | Chest belt    | ECG biosensor, HR sensor, medical-grade thermometer, and tri-axis accelerometer | ST, SpO2, RR, HR, HRV, GSR                       | Stress, engagement           | Equivital            | Approved  |
| Med/Wise [76]     | Gluco Wise B              | Clip (thumb, forefinger or earlobe) | CGM radio wave Sensor | Continuous glucose monitor (CGM) | No specified | Gluco Wise® | - |
| Biobeat™ [71]     | Biobeat™ Chest patch      | Chest patch, wrist monitor | PPG | ST, SpO2, RR, HR, HRV, BP, ECG                  | Stress, surprise             | Biobeat              | Approved (2019) |
| G-Tech Medical™   | G-Tech Medical™           | Chest patch   | EMG                                             | EMG                                            | Surprise                      | G-Tech Medical       | -         |
| Kenzen™ [83]      | Kenzen™ Chest patch       | Chest patch   | HR biosensor                                    | ECG                                            | Stress, surprise             | Kenzen™              | No Approved |
| Preventice™ [80]  | Bodyguardian Heart        | Chest patch   | Accelerometer, ECG sensor                       | ECG                                            | Surprise                      | Preventice™          | Clear (2012) |
| VitalConnect™ [81]| Vital Patch               | Chest patch   | Accelerometer, ECG sensor, thermistor           | ECG, HR, HRV, RR, ST, body posture, activity, BP, SpO2 | Stress, surprise             | VitalConnect™ website | Cleared |
| BioTelemetry™ [82]| BioTelemetry™             | Chest patch   | ECG sensor                                      | ECG                                            | Surprise                      | BioTelemetry™        | Cleared |
| Kenzen™ [83]      | Kenzen™ Chest patch       | Chest patch   | HR biosensor                                    | Sweat, HR, ST                                 | Stress, surprise             | Kenzen™              | No Approved |
| Theranica Migra™  | Theranica Migra™          | Chest patch   | EMG sensor                                      | EMG                                            | Surprise                      | Theranica            | Approved (2019) |

Notes:
- **API** refers to the application programming interface that enables communication between the device and a mobile application or cloud platform.
- **FDA** status indicates whether the device is approved by the US Food and Drug Administration.

- **Clear (2021)**: The device is approved by iRhythm™ in 2021.
- **Cleared**: The device is cleared by the FDA for marketing.
Table 2. Cont.

| Manufacturer    | Model                  | Form Factor                        | Sensors Used                          | Parameters                                                                 | Physiological Signs  | API                                           | FDA              |
|-----------------|------------------------|------------------------------------|---------------------------------------|---------------------------------------------------------------------------|----------------------|-----------------------------------------------|------------------|
| Medtronic™ [85] | Zephyr BioHarness      | Chest Strap                        | CGM sensor                            | HR, HRV, RR, body posture, activity intensity, acceleration, accelerometry, ST, burned calories, speed, distance, elevation, BP, SpO2 | Stress, surprise    | Zephyr: Developer and User Tools             | Approved (2012)  |
| Beddit™ [71]    | Beddit Sleep Monitor   | Contactless in-bed sensor          | PPG sensor                            | RR, HR, sleep measures                                                   | Stress, relaxation   | Beddit™                                       | -                |
| Beurer™ [71]    | Beurer SE80            | Contactless In-bed sensor          | Respiratory rate sensor, HR sensor    | RR, HR, sleep measures                                                   | Stress, relaxation   | Beurer™                                       | -                |
| Cosinuss™ [71]  | Cosinuss Two           | Earbud                             | HR sensor, body temperature sensor, 3D accelerometer | HR, HRV, SpO2, activity                                                   | Stress               | Cosinuss™                                     | -                |
| Yono™ [70]      | Earbud                 | Earbud                             | Thermometer                          | ST                                                                       | Stress               | Yono™                                         | -                |
| BioIntellisense™[71] | BioIntellisense Epidermal patch | Epidermal patch                     | HR sensor                            | ST, RR, HR, coughing, sneezing                                         | Stress               | BioIntellisense™                             | Approved (2019)  |
| Bose® [86]      | SoundSport ® Pulse     | Wireless headphones                | HR sensor                            | HR, PPG                                                                  | Stress               | Bose® Connect                                | -                |
| VivaLNK™ [87]   | Fever Scout            | Epidermal patch                    | ECG and HR sensors                   | ST                                                                       | Stress, relaxation, surprise | VivaLINK          | Approved (2017) |
| Vital Scout     | Epidermal patch        | ECG and HR sensors                 | HR, HRV, RR, activity, sleep, stress levels | Stress, relaxation                                                        | Stress, relaxation   | VivaLINK                                      | Approved (2019)  |
| Spire Health™ [88] | Spire Health Tag      | Fitness Tracker                    | HR, ECG, and RR sensors              | HR, RR, breathing pattern, activity                                      | Stress, relaxation, surprise | Spire Health™    | Not Approved                                |
| Muse™ [89]      | Muse S                 | Headband                           | EEG sensor                           | EEG, PPG, SpO2, breathing pattern, sleep tracking                      | Relaxation, concentration, postures, surprise, frustration, interest, laugh | Muse Developers    | -                |
| Motiv™ [90]     | Motiv Ring             | Ring                               | Accelerometer and PPG and HR sensor  | PPG, HR                                                                  | Stress, surprise     | Motiv™                                       | -                |
| Oura™ [91]      | Oura Ring              | Ring                               | Body temperature sensor, optical, infrared sensors, 3D accelerometer and gyroscope sensor | PPG, HR, HRV, ST, RR, activity, sleep                                   | Stress, surprise, relaxation | Oura Cloud API | -                |
Table 2. Cont.

| Manufacturer                  | Model            | Form Factor          | Sensors Used                                | Parameters                                                                 | Physiological Signs           | API                          | FDA             |
|-------------------------------|------------------|----------------------|---------------------------------------------|----------------------------------------------------------------------------|-------------------------------|------------------------------|-----------------|
| Komodo Technologies™ [92]     | AIO smart sleeve | Sleeve               | ECG sensor                                  | ECG, HR, HRV, activity intensity, SpO2, step tracking, distance            | Stress, postures, surprise, interest, laugh | AIO Sleeve App | No Approved    |
| Kinsa™ [71]                  | Kinsa            | Smart thermometer    | ST sensor                                   | ST                                                                         | Stress                        | Kinsa™          | Approved (2013) |
| Orpyx™ [70]                  | Surro Gait Rx    | Smartwatch, shoe insert, shoe pod | Pressure sensor | BP | Stress, surprise | Orpyx™ | -  |
| Orpyx™                        | Surro Sense Rx   | Watch, shoe insert, shoe pod | Pressure sensor | BP | Stress, surprise | Orpyx™ | Cleared        |
| Apple™ [93]                  | Watch Series 3,4,5 | Smartwatch          | Oximeter, electrical HR sensor, optical HR sensor, accelerometer, gyroscope sensor | Fitness and activity-tracking, ECG, PPG, HR, HRV, sleep quality, stress levels, RR | Stress, relaxation, postures, surprise, laugh, interest | Apple™ Developer | Approved      |
| Empatica™ [94]               | Embrace 2        | Smartwatch           | EDA sensor, peripheral temperature sensor, 3-axis accelerometer, gyroscope sensor | HR, HRV, EDA, ST, activity | Stress, engagement, laugh | Empatica™ for Developers | Approved (2018) |
| E4                            | Bracelet         |                      | PPG sensor, 3-axis accelerometer, EDA sensor (GSR Sensor), infrared thermopile sensor | BVP, GSR, SC, HR, HRV | Stress, relaxation, arousal, excitement | Empatica™ for Developers | Not Approved   |
| Fitbit™ [95]                 | Charge 4         | Smartwatch           | 3-axis accelerometer, optical HR monitor, altimeter | PPG, HR, SpO2, activity, sleep | Stress, surprise, relaxation | Fitbit™ | Not Approved   |
| Ionic                         | Smartwatch       |                      | 3-axis accelerometer, 3-axis gyroscope sensor, optical HR monitor, altimeter, ambient light sensor, vibration motor | HR, SpO2, activity, sleep | Relaxation | Fitbit™ | Approved      |
| Versa 2                       | Smartwatch       |                      | 3-axis accelerometer, optical HR monitor, altimeter, ambient light sensor, relative SpO2 sensor, built-in microphone | HR, guided breathing, SpO2, step tracking, distance, stress level, sleep | Stress, relaxation, postures, surprise | Fitbit™ | Approved      |
Table 2. Cont.

| Manufacturer | Model          | Form Factor | Sensors Used                      | Parameters                 | Physiological Signs | API                  | FDA |
|--------------|----------------|-------------|-----------------------------------|----------------------------|---------------------|----------------------|-----|
| Gyenno [96]  | Gyenno Spoon   | Spoon       | Accelerometer                     | No specified              | Stress              | Gyenno               | -   |
| Gl Logic [97]| AbStats        | Abdominal device | Vibration sensor, acoustic sensor | A telemetry monitor       |                     | Gl Logic             | -   |
| Garmin™ [98]| Fenix 5        | Smartwatch  | HR sensor                         | HR, SpO2, activity, sleep| Stress, relaxation  | Garmin™ Connect Developer |   |
|              | Forerunner 945 | Smartwatch  | HR sensor                         | HR, SpO2, RR, activity, sleep | Stress, relaxation | Garmin™ Connect Developer |   |
|              | Venu           | Smartwatch  | Pulse oximeter, HR sensor         | HR, SpO2, RR, activity, sleep | Stress, relaxation | Garmin™ Connect Developer |   |
|              | Vivoactive 4   | Smartwatch  | Pulse oximeter, HR sensor         | HR, SpO2, RR, activity, sleep | Stress, relaxation | Garmin™ Connect Developer |   |
|              | Vivomove 3     | Smartwatch  | Pulse oximeter, HR sensor         | Step tracking, sleep quality, HR, stress levels, body composition, SpO2, intensity minutes, details of physical activity, breathing frequency | Stress, relaxation, postures, surprise | Garmin™ Connect Developer |   |
| Holter [75]  | Stat-On™       | Portable sensor | ECG sensor                         | HR, HRV                   | Stress              | No specified         | -   |
| Honor™ [99]  | Honor Watch Magic 2 | Smartwatch  | Accelerometer, gyroscope, optical HR sensor, ambient light measurement, barometer | HR, stress levels, sleep quality, distance, speed, SpO2 | Stress, relaxation, surprise | Huawei™ Developers | -   |
| Huawei™ [100]| Huawei Watch fit | Smartwatch | 6-axis IMU sensor (accelerometer sensor, gyroscope sensor), Optical HR sensor, capacitive sensor | HR, SpO2, sleep quality, stress levels, step tracking, distance | Stress, relaxation, postures, surprise | Huawei™ Developers | -   |
|              | Band 6         | Smart Watch | Accelerometer, three electrodes, ECG sensor, barometric altimeter | ECG, SpO2 | Stress, relaxation, postures, surprise | Huawei™ Developers | -   |
| Manufacturer          | Model                  | Form Factor      | Sensors Used               | Parameters                              | Physiological Signs                          | API                               | FDA |
|-----------------------|------------------------|------------------|---------------------------|-----------------------------------------|----------------------------------------------|------------------------------------|-----|
| Mobvoi™ [101]         | TicWatch Pro 2020      | Smartwatch       | HR sensor                 | HR, step tracking                       | Stress, postures, surprise                  | Mobvoi™ Developers                | -   |
| LifeBeam [102]        | LifeBeam DIY kit       | Helmet           | Optical sensor            | HR, blood flow, and oxygen saturation   |                                               | LifeBeam                          | -   |
| Kuaiwear Kuai [103]   | KUAI-Sport Headphones  | Headphones       | HR sensor and accelerometer | HR                                      | Stress                                      | No specified                      | -   |
| Omron™ [104]          | Heart Guide            | Smartwatch       | Accelerometer, PPG HR and oscillometer | PPG, HR, BP, ECG, step tracking, distance | Stress, postures, surprise, laugh, interest | OMRON API for Developers          | Approved (2019) |
| OnePulse™ [105]       | OnePulse™              | Smartwatch       | ECG sensor                | HR, activity, sleep patterns             | Stress, relaxation, surprise                | Not specified                     | Approved |
| Samsung™ [106]        | Samsung™ Gear Sport    | Smartwatch       | Accelerometer, Gyro Sensor, Barometer, HR monitoring sensor | HR, step tracking, sleep quality         | Stress, relaxation, postures, surprise     | Samsung™ Developers               | -   |
| Samsung™ [107]        | Samsung™ Galaxy Watch Active 2 | Smartwatch   | Accelerometer, barometer, gyroscope sensor, HR sensor | HR, sleep quality, stress levels, BP, distance, step tracking | Stress, relaxation, postures, surprise     | Samsung™ Developers               | -   |
| SmartMonitor™ [105]   | SmartMonitor™          | Smartwatch       | Accelerometer             | Detects repetitive shaking motions, HR, activity | Stress, surprise                            | SmartMonitor™                     | -   |
| Verily Life Sciences™ [107] | Verily Study Watch | Smartwatch       | CGM sensor                | Wireless monitor for pulse, HR, ECG, ST  | Stress, surprise, laugh, interest           | Verily                            | Approved (2019) |
| Viatom Technology™ [105] | Viatom Checkme O2     | Smartwatch       | Oximeter, HR sensor      | HR, ECG, SpO2, activity tracker, ST, sleep monitoring | Stress, relaxation, surprise, laugh, interest | Viatom                           | Approved |
| Withings™ [108]       | Withings™ ScanWatch    | Smartwatch       | ECG, oximeter            | ECG, HR, SpO2, step tracking, distance, sleep quality | Stress, relaxation, postures, surprise, laugh, interest | Withings™ Developer               | Approved |
| Move ECG              | Analog watch           |                  | Heart rate sensor, 3-axis accelerometer, 3-axis gyroscope sensor | HR, ECG                                | Stress                                      | Withings Developer               | -   |
| Xiaomi™ [109]         | Huami Amazfit Health Band | Smartwatch   | ECG sensor, pedometer    | HR, movement tracking                    | Stress, postures, surprise                  | Mi Developer                      | Approved (2019) |
Table 2. Cont.

| Manufacturer                  | Model                        | Form Factor     | Sensors Used                        | Parameters                                      | Physiological Signs                      | API             | FDA               |
|-------------------------------|------------------------------|-----------------|-------------------------------------|------------------------------------------------|-------------------------------------------|-----------------|------------------|
| Mi Smart Band 5               | Smartwatch                   | ECG sensor      | HR, sleep quality, step tracking, stress level, BP | Stress, relaxation, postures, surprise         | Mi Developer                          | Not Approved    |                  |
| Sensoria™ [110]               | T-Shirt Short Sleeve + HRM   | T-Shirt         | HR monitor                          | HR, speed, distance, step tracking             | Stress, postures, surprise              | Sensoria™ Platform | -                |
| Ambiotex™ [111]               | Ambiotex Smart Shirt         | T-Shirt         | ECG and HR sensors                  | Stress level, ECG, HR, HRV, step tracking      | Stress, postures, surprise, laugh, interest | Ambiotex™       | -                |
| Tempdrop™ [70]                | Tempdrop™ Underarm armband   | Thermometer     | ST                                  | Stress                                          | Tempdrop™                               | -               |                  |
| Carré Technologies™ [112]      | Hexoskin Smart Garments      | Vest            | ECG sensor                          | ECG, HR, HRV, RR, stress level, effort, fatigue, activity intensity, acceleration, step tracking, sleep quality, SpO2 | Stress, relaxation, postures, surprise, laugh, interest | Hexoskin Developers | -                |
| Nuubo™ [113]                  | Nuubo Wearable ECG           | Vest            | ECG sensor                          | ECG                                            | Surprise, laugh, interest               | Nuubo™ Wearable ECG | Approved         |
| Zoll™ [114]                   | Lifevest                     | Vest            | Temperature sensor                  | ECG                                            | Surprise, laugh, interest               | Lifevest        | Approved (2018)  |
| AliveCor™ [115]               | Kardia Band                  | Wristband       | Electrodes                          | ECG                                            | Surprise, laugh, interest               | AliveCor™       | Approved (2019)  |
| Ava Science™ [70]             | Ava Wristband                | Wristband       | 2-wavelength optical PPG sensor     | EDA, PPG, HR, ST                               | Stress, surprise, engagement, laugh     | Ava             | Approved         |
| Sentio Solutions™ [70]        | Feel                         | Wristband       | EDA, PPG, HR, and skin temperature sensors | EDA, PPG, HR, ST                               | Stress, surprise, engagement, laugh     | Feel            | -                |
| iHealth™ [116]                | Wireless Blood Pressure Monitor | Wristband       | Oscillometer                        | BP, HR                                         | Stress, surprise                       | iHealth™        | Approved         |
| MOCACARE™ [117]               | MOCACuff                     | Wristband       | HR sensor                           | BP, HR, SpO2                                   | Stress, surprise                       | Mocacare™      | -                |
| Wavelet™ [105]                | Biostrap Wristband           | Wristband       | 3-axis accelerometer 3-axis gyroscope sensor | HR, HRV, SpO2, RR, in-depth sleep tracking | Stress, relaxation, postures, surprise | Biostrap        | -                |
| WHOOP™ [71]                   | WHOOP Wristband              | Wristband       | HR sensor                           | RR, HR, HRV, EDA, sleep                        | Stress, engagement, laugh              | WHOOP™         | -                |

Abbreviations: SpO2: Oxygen saturation; BP: Blood pressure; HR: Heart rate; HRV: Heart rate variability; EEG: Electroencephalogram; ECG: Electrocardiogram; PPG: Photoplethysmography; EMG: Electromyography; EDA: Electrodermal Activity; GSR: Galvanic Skin Response; RR: Respiratory rate; ST: Skin temperature.
Figure 4. Incidence of Commercial Wearable Form Factors in the Literature.

Figure 5. FDA Approval Status of Commercial Wearables for Engagement Detection.
As regards the physiological signals involved in engagement detection, our findings indicate that most of the commercial wearables can detect more than physiological signal simultaneously, especially surprise, stress, interest, relaxation, and laugh. Table 3 summarizes our findings of the commercial wearables reported in the literature with respect to both the physical signs being monitored and the FDA approval status of each device.

Table 3. Main Physiological Signals for Engagement Detection.

| Physiological Signal | FDA-Approved Devices | Non-FDA Devices | Total |
|----------------------|----------------------|-----------------|-------|
| Distress             | 1                    | 0               | 1     |
| Stress               | 22                   | 39              | 61    |
| Relaxation           | 10                   | 19              | 29    |
| Sleep disorders      | 1                    | 0               | 1     |
| Postures             | 4                    | 14              | 18    |
| Surprise             | 23                   | 25              | 48    |
| Concentration        | 0                    | 1               | 1     |
| Frustration          | 0                    | 1               | 1     |
| Interest             | 11                   | 6               | 12    |
| Laugh                | 10                   | 6               | 16    |
| Emotional arousal    | 0                    | 1               | 1     |
| Excitement           | 0                    | 1               | 1     |

Figure 6 graphically illustrates the distribution of the commercial wearables reported in the literature with respect to the physiological signals for engagement detection.

Figure 6. Correspondence between Commercial Wearables and Physiological Signals for Engagement Detection.

As our findings indicate, several commercial wearables reported in the literature can detect more than one physiological signal simultaneously, especially surprise, stress, interest, relaxation, and laugh, through monitoring techniques for respiratory rate, oxygen saturation, blood pressure, and heart rate.
4.2.3. Non-Commercial Wearables for Engagement Level Detection

Non-commercial wearables for engagement detection are mostly developed for research purposes or are still at the development phase of the manufacturing cycle. Table 4 summarizes our review of non-commercial devices for emotion and engagement detection. The table highlights the key characteristics of each wearable, which are also listed below:

- **Aim**: Physiological signal(s) monitored by the wearable.
- **Device type**: Form factor of the device (e.g., smartwatch, bracelet, headband).
- **Function**: Brief description of the device’s functionality.
- **Sensors**: Sensor technologies used to record physiological signal data.
- **Real-time monitoring capability**: Whether the device can monitor physiological signals in real time.
- **Educational environment**: Type of educational environment where the wearable has been implemented.

### Table 4. Non-Commercial Wearables for Engagement Detection.

| Aim                                                                 | Device Type | Function                                                                                                 | Sensors                                                                 | Real-Time Monitoring Capabilities | Educational Environment |
|----------------------------------------------------------------------|-------------|----------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-----------------------------------|-------------------------|
| Physical exertion, health, and heart function monitoring; tracking an individual’s performance and exertion level [118]. | Patch       | It consists of a patch that includes a sensor to measure a biochemical (lactate) and an electrophysiological (electrocardiogram) signal to monitor physical exertion, health, and heart. The patch can recognize emotions such as stress and anger. | Lactate sensor, electrophysiological sensors                          | Yes                               | Unstated                |
| Skin temperature measuring [119].                                    | Patch       | The patch detects multimodal biosignals, measures skin temperature with a sensitivity of 0.31 Ω/°C, skin conductance with a sensitivity of 0.28 µV/0.02 µS, and pulse wave with a response time of 70 msec. | ST, skin conductance, and pulse wave sensors                          | Yes                               | Unstated                |
| Heart rate monitoring [120].                                         | Scarf       | It helps users to reflect on their emotional state, modify their affective state, and interpret the emotional states of other people. The design of SWARM is based on a scarf so that people with different disabilities have access to this type of technology. SWARM can detect emotions such as stress, sadness, calm, happiness, and excitement. | Biosensors                                                              | Yes                               | Unstated                |
| Aim | Device Type | Function | Sensors | Real-Time Monitoring Capabilities | Educational Environment |
|-----|-------------|----------|---------|-----------------------------------|-------------------------|
| Heart rate and skin conductance monitoring [121]. | Scarf | It is a design of a wearable device based on a scarf form factor. The device features color-changing and olfactory properties to affect people’s emotional state. The wearable comprises two sensors: a heart rate sensor and a skin conductance sensor. When changing color and emitting an odor, the scarf potentiates positive emotions and reduces negative ones. | HR and EDA sensors | Yes | Unstated |
| Blood volume pulses and muscle contraction monitoring [122]. | Glove | It is an emotion recognition framework using machine learning of physiological patterns. The framework relies on a PPG sensor for heart rate monitoring, an EDA sensor, a skin temperature sensor, and an EMG sensor. The proposal focuses on the preprocessing of emotion recognition and supports the recognition of emotions such as happiness, anger, fear, disgust, and sadness. | PPG and EMG sensors | Yes | Unstated |
| Physiological arousal detection and monitoring [123]. | Gloves, bracelet | The device monitors the student’s psychological and physical condition using heart rate, skin conductivity, and respiration sensors. The data obtained are sent to an assistive host to process, analyze, and evaluate student moods and stress levels. | HR sensor, EDA sensor, respiratory rate sensor | Yes | Mobile |
| Detection of eye movements, eyes closed, and teeth clenching [124]. | Eyeglasses | AttentivU is a device that monitors physiological data to measure the engagement and enhance learning activities using silver electrodes. The data collected by the device can be processed in real time or sent to a separate computer. | EEG sensor or electrooculography (EOG) | Yes | Unstated |
Table 4. Cont.

| Aim                                                                 | Device Type | Function                                                                                                                                                                                                 | Sensors                                                                 | Real-Time Monitoring Capabilities | Educational Environment |
|---------------------------------------------------------------------|-------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-------------------------------|-------------------------|
| Monitoring of physiological characteristics related to heart rate, oximetry, skin temperature, and GSR [125]. | Patch       | The proposal uses an Arduino board to obtain physiological signals from the user and connected sensors to acquire data on skin temperature, GSR, pulsmeter, and a respiratory rate sensor. The data is processed using Matlab. | ST sensor, oximeter breath-flow rate sensor, HR sensor, GSR sensor    | Yes                           | Unstated                |
| Heart rate monitoring [126].                                        | Shirt       | The prototype is based on an Arduino Uno board to which is connected a pulse sensor that uses infrared light to detect user heart rate.                                                                   | Pulse sensor                                                          | Yes                           | Unstated                |
| Human physical activity monitoring [127].                           | Shirt       | SensVest is a wearable prototype to monitor physical aspects. The device includes a series of sensors that allow the recording of different data related to human performance to improve the understanding of scientific concepts in students. | HR sensor, ST sensor, accelerometer                                   | Yes                           | Unstated                |
| Heart rate and breathing rate monitoring [128].                    | Patch       | The device obtains an ECG tracing using two electrodes in symmetrical positions on the user’s body and a third ground electrode placed next to one of the sensing electrodes. | Electrodes, ECG sensor                                               | Yes                           | Computer video          |
| Heart rate variability monitoring, skin temperature measuring [129]. | Wristband   | n-Gage is a system that evaluates the engagement levels of behavioral, emotional, and cognitive students. The system detects the student’s physical and physiological signals and environmental changes in the educational environment. | EDA sensor, accelerometer, ST sensor                                  | Unstated                      | Unstated                |
| EDA and pulse rate monitoring [130].                               | Patch       | The proposal measured and recorded electrodermal activity, pulse rate, and facial recognition during an e-learning session to determine the level of student engagement. The data collected were analyzed using software developed with Matlab. | EDA sensor, HR sensor                                                 | Yes                           | E-learning              |
Table 4. Cont.

| Aim                                      | Device Type | Function                                                                 | Sensors                                                                 | Real-Time Monitoring Capabilities | Educational Environment |
|------------------------------------------|-------------|--------------------------------------------------------------------------|------------------------------------------------------------------------|-----------------------------------|-------------------------|
| Upper body pressure distribution [131].  | Chair       | While students perform e-learning reading activities, the student's upper body pressure is recorded using a chair with a pressure mat. The data is processed using classifiers. | Pressure mat                                                               | No                                | E-learning              |
| Feet posture and movement detection [132]. | Insole      | This platform contains an insole with ground contact force (GCF) plantar pressure sensors. In addition, a microcontroller with WIFI technology collects the data and sends it to a database to be analyzed by a Human Activity Recognition classifier. | Accelerometer, gyroscope sensor, magnetometer, barometer, and range finder sensors | Yes                              | No specified            |

Non-invasive sensors are common in the monitoring of physiological parameters during educational activities. Further, physiological parameter monitoring is relevant to research efforts that seek to develop and implement appropriate techniques for identifying student engagement in the teaching–learning process. Figure 7 introduces a graphic representation of our classification of non-commercial wearables for engagement detection with respect to their form factor.

![Figure 7. Classification of Non-Commercial Wearables by Form Factor.](image)

Regarding to the contribution of non-commercial devices to assist and increase student engagement during educational activities, patches can detect signals such as ST, GSR, EDA, and ECG whose application is related to monitor the variation of the electrical properties of the skin through sweat. Meanwhile, Scarf can detect HR and EDA signals related to skin conductance monitoring. Gloves can detect PPG, EMG, HR, EDA, and RR signals...
related to monitor muscle contraction and physiological excitation. Regarding the Shirts, they can detect HR, ST, and ECG signals applied for performance monitoring associated with comprehension.

Under this context, EDA signals such as skin conductance are associated with stress and distress. While, HR signals are associated with stress, sadness, calmness, happiness, and excitement. EMG, RR, and PPG signals are related to happiness, anger, fear, disgust, and sadness. Moreover, all the detected physiological signals can identify the level of engagement of the students.

Table 5 summarizes our findings on the real-time monitoring capability of non-commercial wearables for engagement detection. As can be observed, 87% of these wearables reported in the literature can transmit physiological data in real time to other external devices for processing. Conversely, merely 13% of the wearables lack such real-time monitoring capability.

Table 5. Non-Commercial Wearables for Engagement Detection with Real-Time Monitoring.

| Real-Time Monitoring | No. of Devices | Percentage |
|----------------------|----------------|------------|
| Yes                  | 13             | 87%        |
| No                   | 2              | 13%        |

Table 6 summarizes our findings with respect to the main physiological signals involved in engagement detection in the case of non-commercial wearables. The majority of the non-commercial wearables reported in the literature can monitor two or more signals simultaneously.

Table 6. Physiological Parameters for Engagement Detection by Non-Commercial Wearables.

| Target Parameter             | No. of Devices | Percentage |
|------------------------------|----------------|------------|
| Heart Rate                   | 11             | 73%        |
| Skin Temperature             | 5              | 33%        |
| Skin Conductance             | 4              | 27%        |
| Electrodermal activity       | 4              | 27%        |
| Respiratory Rate             | 2              | 13%        |
| Pulse Wave                   | 1              | 7%         |
| Oxygen Saturation            | 1              | 7%         |

Our findings revealed that heart rate is a key parameter measured by non-commercial wearables to detect and monitor student engagement during educational activities. Other important parameters include skin temperature, skin conductance, and electrodermal activity. Similarly, most of the reviewed devices primarily aim at improving student engagement levels during educational activities and thus academic performance.

5. Discussion

5.1. Challenges and Trends of Wearables for Engagement Detection

Even though technological progress has paved the way for the application of sensing technologies in educational research, further efforts are still needed.

- Engagement detection proposals need to increase the number of physiological signals being monitored.
- Despite having the ability to record physiological data in real time, some wearable devices still lack mechanisms for analyzing and processing such data.
- It is important improve technical aspects of the wearables, such as battery performance and device intercommunication for data transfer.
- Engagement research is a notorious opportunity in educational research, since physiological data analysis and processing techniques can be more efficient than other techniques, such as surveys, even though they cannot always speed up findings.
• Technological trends point toward the design of non-invasive, comfortable wearable devices, and thus provide manufacturers with a great opportunity to explore the efficiency and suitability of new materials and device shapes. A clear example of this is how sensors have been innovatively incorporated into chair and insole designs. Such designs explore the suitability of measuring relatively uncommon parameters, such as pressure on some parts of the body.

The main trends for engagement detection can be classified according to the methods for detecting students’ engagement. These methods can be:

1) Automatic: sensor data analysis, log-file analysis and computer vision techniques.
2) Semi-automatic: engagement tracing.
3) Manual: Observational check-list and self-reporting.

We believe the recent trends are focused in developing new computer vision techniques for detecting facial expressions, gesture, posture and eye movement. For example, for gesture and posture have been developed such as Muse S band [133], Everion [134], Zephyr BioHarness [135], Xiaomi Mijia [136]. Muse S band can monitor Heart rate, EEG, PPG, posture, sleep level, Respiration Rate and Relax indicator. Everion device can identify Activity (move) indicator, Electrodermal activity/galvanic skin response, Heart rate, Respiration Rate, Sleep indicator, Relax indicator and Blood Oxygenation (SpO2). Chest Strap Zephyr BioHarness can measure Heart rate, body posture, activity intensity and SpO2. Xiaomi Mijia can monitor Heart rate, ECG, movement, Respiration Rate.

For facial expression and eye movement, smart glasses have been developed such as Oculus Quest Pro, iMotions Eye Tracking Glasses, Google Glass, Apple Glass and Tobii Pro Glasses 2, and eye tracking devices such as EyeTribe [137]. Oculus Quest Pro can be used to eye and face-tracking. iMotions Eye Tracking Glasses can be used to Track eye position, Facial Expression Analysis and movement to access visual attention in real time. Google Glass uses motion and voice recognition to process commands from the wearer and also operate the device with eye movements. Apple Glass can identify gestures and facilitate controls with eye movements. Tobii Pro Glasses 2 can be used to analyze human behavior in real time using eye tracking. EyeTribe Tracker allows controlling applications with user’s sight on desktop and tablet computers.

Additionally, with regards to sensor data analysis, embedded machine learning is used for interpreting data in Internet-of-Things applications. In this context, machine learning sensing capabilities are encapsulated in separate hardware components outside the central embedded processor and application code. Machine Learning (ML) is a subcategory of the Artificial Intelligence that refers to the process by which computers develop pattern recognition, or the ability to continuously learn and make predictions based on data, then make adjustments without being specifically programmed to do it.

5.2. Emerging Solutions

As wearable device technology progresses, solutions emerge to address common problems, such as battery performance, device size, and device shape. Graphene sensors are a clear example of innovative technological development. The use of graphene in wearable technology is an important contribution to the development of wearable devices for monitoring physiological, data such as brain signals. The recording of frequency levels using platinum and iridium electrodes is typically above 0.1 Hz, whereas graphene-based sensors could record brain signals below 0.1 Hz, thus increasing the amount of data that can be processed and improving brain-related research and its application in medicine. The use of graphene also has a positive impact on the battery performance of devices such as smartphones, since graphene is highly conductive [138].

Finally, device portability, versatility, simplicity, and real-time monitoring capabilities are important opportunities for improvement in sensing technology and ML techniques. ML techniques can process large volumes of data, and their application in biosensors can improve the monitoring of vital signs involved in the diagnosis of cardiovascular diseases, such as arrhythmias and coronary syndromes. As a key advantage, biosensor technology is
cloud-compatible, which facilitates sensor signal processing and data storage. Further, it is easy to monitor health outside a clinical setting. The advantages of using biosensors and ML techniques mostly contribute to transforming raw data into understandable information, which in turn improves the performance of biosensors currently used for health monitoring, disease diagnosis, treatment evaluation, and food safety [138].

5.3. Limitations

This research has five main limitations. First, our review did not include a comparative analysis of the efficacy and reliability of the reviewed wearables in educational contexts. Second, we did not analyze to what extent each wearable actually contributes to increased student engagement during educational activities. Similarly, this research did not examine mobile applications for physical sign monitoring, since the non-commercial wearables reported in the literature were rarely linked to a mobile application for processing the data. Additionally, we did not analyze the usability aspects of the wearable devices or their user acceptance. Finally, our analysis of FDA approvals is partially incomplete, since most wearable manufacturers do not disclose such information publicly.

This review can be used by software engineers, developers, and computer scientists to develop mobile applications, educational platforms, or software to detect student engagement using physiological sensors and wearable devices. These systems can help improve the teaching–learning process to opportunistely detect parameters such as frustration, boredom, stress, concentration, or distress that allow teachers to develop new learning strategies or improve existent.

6. Conclusions

This research is a review of current wearables used in educational environments for detecting and measuring student engagement in learning activities. Each device reported in the literature measures and analyzes different parameters, such as heart rate, skin temperature, EEG, ECG, respiratory rate, oxygen saturation, and blood pressure. Commercially available wearables for engagement detection are usually linked to a compatible mobile application to store and process physiological data in real time. In the educational domain, wearables and sensors for physiological signal monitoring can be used to identify the parameters that are key to student engagement detection during educational activities. The physiological signals being measured by a device strongly depend on the type of device. Wearable form factors such as smartwatches, chest patches, and wristbands are the most prominent in the market. As for non-commercial devices, the most cited form factors are patches (33%), shirts, gloves, and scarfs (13% of occurrence each).

The fact that wearables usually support real-time monitoring of physiological signals allows researchers to expand scenarios for data collection beyond the classroom and provides education experts with opportunities to redesign and propose meaningful teaching–learning methods and strategies. We consider our review of FDA approval status as a point of reference to judge both the reliability of the reviewed wearables in terms of data accuracy and their acceptance by users. In this sense, 33% of the wearables reported in the literature have been approved by the FDA, 7% hold a Clear status, 10% have not been approved yet, and 51% maintain an unknown FDA status.

The scope of this research only covers the analysis of wearable devices currently available for student engagement detection during learning activities. Our review is not an analysis of the efficiency of such devices in terms of increased student engagement, nor is it a comparative analysis of the most suitable parameters for engagement detection. To conclude, we list relevant findings of this review:

- In total, 32% of the commercial wearable devices reviewed are smartwatches.
- In total, 40% of the commercial wearables have either an approved FDA status or a clear status.
- Engagement detection wearables commonly assess student physiological signals such as stress and surprise through physiological signals.
• Heart rate stands as the most prominent physiological signal measured by commercial devices.
• Patches are the most common form factor of non-commercial wearables for engagement detection.
• In total, 73% of the non-commercial devices reported in the literature support real-time physiological signal monitoring.
• Physiological signals commonly recorded by non-commercial devices are related to heart rate, skin temperature, skin conductance, EDA, respiratory rate, pulse wave, and oxygen saturation.

Author Contributions: Conceptualization, M.B.-L., N.C.-R., G.A.-H. and L.N.S.-M.; Data curation, N.A.C.-R. and G.A.-H.; Formal analysis, G.A.-H., N.C.-R. and M.B.-L.; Funding acquisition, G.A.-H., A.G.-H. and N.C.-R.; Investigation M.B.-L., N.C.-R. and L.N.S.-M.; Methodology, A.G.-H. and N.C.-R.; Project administration, G.A.-H.; Resources, G.A.-H.; Software, M.B.-L., L.N.S.-M., N.C.-R. and A.G.-H.; Supervision, N.A.C.-R., M.B.-L. and N.C.-R.; Validation, N.C.-R., A.G.-H., G.A.-H. and M.B.-L.; Visualization, L.N.S.-M. and N.A.C.-R.; Writing—original draft, M.B.-L., N.C.-R. and L.N.S.-M.; and Writing—review and editing, G.A.-H., N.C.-R. and A.G.-H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Mexico’s National Council of Science and Technology (CONACYT) through postdoctoral grant 7403-2020 for research project titled Emotion Detection in Learning Environments through a Multimodal Approach using Artificial Intelligence.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Acknowledgments: This research was sponsored by Mexico’s National Council of Science and Technology (CONACYT) and Mexico’s Secretariat of Public Education (SEP) through the PRODEP program. The authors also thank to Universidad Veracruzana (UV) and Tecnológico Nacional de México (TecNM) for supporting this work.

Conflicts of Interest: The authors declare no potential conflict of interest with respect to the publication of this research.

References
1. Bosch, N.; D’Mello, S.K.; Baker, R.S.; Ocumpaugh, J.; Shute, V.; Ventura, M.; Wang, L.; Zhao, W. Detecting student emotions in computer-enabled classrooms. In Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, New York, NY, USA, 9–15 July 2016; pp. 4125–4129. Available online: https://pinigel.com/papers/bosch-pp-ijcai16-camera.pdf (accessed on 15 December 2021).
2. Castaneda, D.; Esparza, A.; Ghamari, M.; Soltanpur, C.; Nazeran, H. A review on wearable photoplethysmography sensors and their potential future applications in health care. Int. J. Biosens. Bioelectron. 2018, 4, 195–202. [CrossRef] [PubMed]
3. Shabaan, M.; Arshid, K.; Yaqub, M.; Jinchao, F.; Zia, M.S.; Bojja, G.R.; Ifikhar, M.; Ghani, U.; Ambati, L.S.; Munir, R. Survey: Smartphone-based assessment of cardiovascular diseases using ECG and PPG analysis. BMC Med. Inform. Decis. Mak. 2020, 20, 177. [CrossRef] [PubMed]
4. Lou, Z.; Wang, L.; Jiang, K.; Wei, Z.; Shen, G. Reviews of wearable healthcare systems: Materials, devices and system integration. Mater. Sci. Eng. R Rep. 2019, 140, 100523. [CrossRef]
5. Guo, Y.; Liu, X.; Peng, S.; Jiang, X.; Xu, K.; Chen, C.; Wang, Z.; Dai, C.; Chen, W. A review of wearable and unobtrusive sensing technologies for chronic disease management. Comput. Biol. Med. 2021, 129, 104163. [CrossRef] [PubMed]
6. Tandon, A.; De Ferranti, S.D. Wearable Biosensors in Pediatric Cardiovascular Disease: Promises and Pitfalls Toward Generating Actionable Insights. Circulation 2019, 140, 350–352. [CrossRef]
7. Nahavandi, D.; Alizadehsani, R.; Khosravi, A.; Acharya, U.R. Application of artificial intelligence in wearable devices: Opportunities and challenges. Comput. Methods Programs Biomed. 2022, 213, 106541. [CrossRef] [PubMed]
8. Reda, A.; El-Safty, S.A.; Selim, M.M.; Shenashen, M.A. Optical glucose biosensor built-in disposable strips and wearable electronic devices. Biosens. Bioelectron. 2021, 185, 113237. [CrossRef]
9. Surantha, N.; Atmaja, P.; David; Wicaksono, M. A Review of Wearable Internet-of-Things Device for Healthcare. Procedia Comput. Sci. 2021, 179, 936–943. [CrossRef]
10. Khoshmanesh, F.; Thurgood, P.; Pirogova, E.; Nahavandi, S.; Baratchi, S. Wearable sensors: At the frontier of personalised health monitoring, smart prosthetics and assistive technologies. Biosens. Bioelectron. 2021, 176, 112946. [CrossRef]
11. Santo, K.; Redfern, J. Digital Health Innovations to Improve Cardiovascular Disease Care. *Curr. Atheroscler. Rep.* 2020, 22, 71. [CrossRef]

12. Akinosun, A.S.; Polson, R.; Skeete, Y.D.; De Kock, J.H.; Carragher, L.; Leslie, S.; Grindle, M.; Gorely, T. Digital Technology Interventions for Risk Factor Modification in Patients with Cardiovascular Disease: Systematic Review and Meta-analysis. *JMIR mHealth uHealth* 2021, 9, e21061. [CrossRef] [PubMed]

13. DeVore, A.D.; Wosik, J.; Hernandez, A.F. The Future of Wearables in Heart Failure Patients. *JACC Heart Fail.* 2019, 7, 922–932. [CrossRef] [PubMed]

14. Burnham, J.P.; Lu, C.; Vaeger, L.; Bailey, T.C.; Kollef, M.H. Using wearable technology to predict health outcomes: A literature review. *J. Am. Med. Inform. Assoc.* 2018, 25, 1221–1227. [CrossRef] [PubMed]

15. Wang, Y.; Lu, S.; Harter, D. Multi-Sensor Eye-Tracking Systems and Tools for Capturing Student Attention and Understanding Engagement in Learning: A Review. *IEEE Sens. J.* 2021, 21, 22402–22413. [CrossRef]

16. Apicella, A.; Arpaia, P.; Proslone, M.; Improta, G.; Moccaldi, N.; Pollastro, A. EEG-based measurement system for monitoring student engagement in learning 4.0. *Sci. Rep.* 2022, 12, 5857. [CrossRef] [PubMed]

17. Lu, Y.; Zhang, S.; Zhang, Z.; Xiao, W.; Yu, S. A framework for learning analytics using commodity wearable devices. *Sensors* 2017, 17, 1382. [CrossRef] [PubMed]

18. Kapoor, A.; Picard, R.W. Multimodal affect recognition in learning environments. In Proceedings of the 13th Annual ACM International Conference on Multimedia, Singapore, 6–11 November 2005; pp. 677–682. [CrossRef]

19. Sameiro, M.; Santos, O.C.; Salmeron-Majadas, S.; Boticario, J.G. Towards Emotion Detection in Educational Scenarios from Facial Expressions and Body Movements through Multimodal Approaches. *Sci. World J.* 2014, 2014, 484-783. [CrossRef]

20. Monkaresi, H.; Bosch, N.; Calvo, R.A.; D’Mello, S.K. Automated Detection of Engagement Using Video-Based Estimation of Facial Expressions and Heart Rate. *IEEE Trans. Affect. Comput.* 2017, 8, 15–28. [CrossRef]

21. Angeline, R.; Nithya, A.A. A Review on Multimodal Online Educational Engagement Detection System Using Facial Expression, Eye Movement and Speech Recognition. *Turk. J. Comput. Math. Educ.* 2021, 12, 2013–2022. [CrossRef]

22. Murshed, M.; Dewan, M.A.A.; Lin, F.; Wen, D. Engagement Detection in e-Learning Environments using Convolutional Neural Networks. In Proceedings of the 2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PCim/CBDCom/CyberSciTech), Fukuoka, Japan, 5–8 August 2019. [CrossRef]

23. Abdellaoui, B.; Moumen, A.; Idriess, Y.E.B.E.; Remaida, A. Face Detection to Recognize Students’ Emotion and Their Engagement: A Systematic Review. In Proceedings of the 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCs), Kenitra, Morocco, 2–3 December 2020; pp. 1–6. [CrossRef]

24. Salmeron-Majadas, S.; Santos, O.C.; Boticario, J.G. An Evaluation of Mouse and Keyboard Interaction Indicators towards Non-intrusive and Low Cost Affective Modeling in an Educational Context. *Procedia Comput. Sci.* 2014, 35, 691–700. [CrossRef]

25. Wei, Y.; Wu, Y.; Tudor, J. A real-time wearable emotion detection headband based on EEG measurement. *Sens. Actuators A Phys.* 2017, 263, 614–621. [CrossRef]

26. Anil Kumar, K.M.; Kiran, B.R.; Shreyas, B.R.; Sylvester, J.V. A Multimodal Approach to Detect User’s Emotion. *Procedia Comput. Sci.* 2015, 70, 296–303. [CrossRef]

27. Fernández-Caballero, A.; Martínez-Rodrigo, A.; Pastor, J.M.; Castillo, J.C.; Lozano-Monasor, E.; López, M.T.; Zangroniz, R.; Latorre, J.M.; Fernández-Sotos, A. Smart environment architecture for emotion detection and regulation. *J. Biomed. Inform.* 2016, 64, 55–73. [CrossRef]

28. Egger, M.; Ley, M.; Hanke, S. Emotion Recognition from Physiological Signal Analysis: A Review. *Electron. Notes Theor. Comput. Sci.* 2019, 345, 35–55. [CrossRef]

29. Costa, A.; Rincon, J.A.; Carrascosa, C.; Julian, V.; Novais, P. Emotions detection on an ambient intelligent system using wearable devices. *Future Gener. Comput. Syst.* 2019, 92, 479–489. [CrossRef]

30. Salama, E.S.; El-Khoribi, R.A.; Shoman, M.E.; Shalaby, M.A.W. A 3D-convolutional neural network framework with ensemble learning techniques for multi-modal emotion recognition. *Egypt. Inform. J.* 2020, 22, 167–176. [CrossRef]

31. Zhang, J.; Yin, Z.; Chen, P.; Nichele, S. Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. *Inf. Fusion* 2020, 59, 103–126. [CrossRef]

32. Dominguez-Jiménez, J.A.; Campo-Landines, K.C.; Martínez-Santos, J.C.; Delahoz, E.J.; Contreras-Ortiz, S.H. A machine learning model for emotion recognition from physiological signals. *Biomed. Signal Process. Control* 2020, 55, 101646. [CrossRef]

33. Bulagang, A.F.; Weng, N.G.; Mountstevens, J.; Teo, J. A review of recent approaches for emotion classification using electrocardiography and electroderegraphy signals. *Inform. Med. Unlocked* 2020, 20, 100363. [CrossRef]

34. Dzedzickis, A.; Kaklauskas, A.; Bucinskas, V. Human Emotion Recognition: Review of Sensors and Methods. *Sensors* 2020, 20, 592. [CrossRef]

35. Raheel, A.; Majid, M.; Anwar, S.M. DEAR-MULSEMEDIA: Dataset for emotion analysis and recognition in response to multiple sensorial media. *Inf. Fusion* 2021, 65, 37–49. [CrossRef]
38. Kanjo, E.; Younis, E.M.G.; Ang, C.S. Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection. Inf. Fusion 2019, 49, 46–56. [CrossRef]

39. Sánchez, F.L.; Hupont, I.; Tabik, S.; Herrera, F. Revisiting crowd behaviour analysis through deep learning: Taxonomy, anomaly detection, crowd emotions, datasets, opportunities and prospects. Inf. Fusion 2020, 64, 318–335. [CrossRef]

40. Bhardwaj, P.; Gupta, P.K.; Panwar, H.; Siddiqui, M.K.; Morales-Menendez, R.; Bhak, A. Application of Deep Learning on Student Engagement in e-learning environments. Comput. Electr. Eng. 2021, 93, 107277. [CrossRef]

41. Dewan, M.A.A.; Murshed, M.; Lin, F. Engagement detection in online learning: A review. Smart Learn. Environ. 2019, 6, 1–20. [CrossRef]

42. Henrie, C.R.; Halverson, L.R.; Graham, C.R. Measuring student engagement in technology-mediated learning: A review. Comput. Educ. 2015, 90, 36–53. [CrossRef]

43. Kasatkina, D.A.; Kravchenko, A.M.; Kupriyanov, R.B.; Nekhorosheva, E.V. Automatic engagement detection in the education: Critical review. J. Mod. Foreign Psychoal. 2020, 9, 59–68. [CrossRef]

44. Altuwairqi, K.; Jarraya, S.K.; Allinjawi, A.; Hammami, M. Student behavior analysis to measure engagement levels in online learning environment. Signal Image Video Processing 2021, 15, 1387–1395. [CrossRef]

45. Liao, J.; Liang, Y.; Pan, J. Deep facial spatiotemporal network for engagement prediction in online learning. Appl. Intell. 2021, 51, 6609–6621. [CrossRef]

46. Altuwairqi, K.; Jarra, S.K.; Allinjawi, A.; Hammami, M. Student behavior analysis to measure engagement levels in online learning environment. Signal Image Video Processing 2021, 15, 1387–1395. [CrossRef]

47. Hasnine, M.N.; Bui, H.T.; Tran, T.T.T.; Nguyen, H.T.; Akçapınar, G.; Ueda, H. Students’ emotion extraction and visualization for engagement detection in online learning. Procedia Comput. Sci. 2021, 192, 3423–3431. [CrossRef]

48. Vanneste, P.; Oramas, J.; Verelst, T.; Tuytelaars, T.; Raes, A.; Depaepe, F.; Van den Noortgate, W. Computer vision and human behaviour, emotion and cognition detection: A use case on student engagement. Mathematics 2021, 9, 287. [CrossRef]

49. Hasnine, M.N.; Bui, H.T.; Tran, T.T.T.; Nguyen, H.T.; Akçapınar, G.; Ueda, H. Students’ emotion extraction and visualization for engagement detection in online learning. Procedia Comput. Sci. 2021, 192, 3423–3431. [CrossRef]

50. Panicker, S.S.; Gayathri, P. A survey of machine learning techniques in physiology based mental stress detection systems. Biocybern. Biomed. Eng. 2019, 39, 444–469. [CrossRef]

51. Panicker, S.S.; Gayathri, P. A survey of machine learning techniques in physiology based mental stress detection systems. Biocybern. Biomed. Eng. 2019, 39, 444–469. [CrossRef]

52. Peñalver, M.; Sales, N.; Macías, F.L.; Hupont, I.; Tabik, S.; Herrera, F. Revisiting crowd behaviour analysis through deep learning: Taxonomy, anomaly detection, crowd emotions, datasets, opportunities and prospects. Inf. Fusion 2020, 64, 318–335. [CrossRef]

53. Feidakis, M. A Review of Emotion-Aware Systems for e-Learning in Virtual Environments. In Sensors 2018, 18, 4271. [CrossRef] [PubMed]

54. Health, Electrocardiogram. Available online: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/what-is-blood-pressure (accessed on 15 November 2021).

55. Health, Electrocardiogram. Available online: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/what-is-blood-pressure (accessed on 15 November 2021).

56. Health, Electrocardiogram. Available online: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/what-is-blood-pressure (accessed on 15 November 2021).

57. Taj-Eldin, M.; Ryan, C.; O’Flynn, B.; Galvin, P. A Review of Wearable Solutions for Physiological and Emotional Monitoring for Lectures and Workshops. Sensors 2017, 17, 107277. [CrossRef]

58. Healthwise Staff. Electromyogram. 2021. Available online: https://www.cigna.com/es-us/individuals-families/health-wellness/hw/lectures-workshops/ (accessed on 25 September 2021).

59. Yasuma, F.; Hayano, J. Respiratory Sinus Arrhythmia: Why does the heartbeat synchronize with respiratory rhythm? Chest 2004, 125, 683–690. [CrossRef]

60. Jamal, S.K.M.; Kamioka, E. Emotions detection scheme using facial skin temperature and heart rate variability. MATEC Web Conf. 2019, 277, 02037. [CrossRef]

61. Villarejo, M.V.; Zapirain, B.G.; Zorrilla, A.M. A Stress Sensor Based on Galvanic Skin Response (GSR) Controlled by ZigBee. Sensors 2012, 12, 6075–6101. [CrossRef] [PubMed]

62. McNeal, K.S.; Spry, J.M.; Mitra, R.; Tipton, J.L. Measuring Student Engagement, Knowledge, and Perceptions of Climate Change in an Introductory Environmental Geology Course. J. Geosci. Educ. 2014, 62, 655–667. [CrossRef]

63. Allen, J. Photoplethysmography and its application in clinical physiological measurement. Physiol. Meas. 2007, 28, R1–R39. [CrossRef]

64. Braun, S.R. Respiratory Rate and Pattern. In Clinical Methods: The History, Physical, and Laboratory Examinations, 3rd ed.; Walker, H.K., Hall, W.D., Hurst, J.W., Eds.; Butterworths: Boston, MA, USA, 1990. Available online: https://www.ncbi.nlm.nih.gov/books/NBK365/ (accessed on 15 December 2021).

65. Physiopedia, Lung Volumes. 2021. Available online: https://www.physio-pedia.com/Lung_Volumes (accessed on 25 September 2021).

66. Darnell, D.K.; Krieg, P.A. Student engagement, assessed using heart rate, shows no reset following active learning sessions in lectures. PLoS ONE 2019, 14, e0225709. [CrossRef]
67. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int. J. Surg.* 2021, 88, 105906. [CrossRef] [PubMed]

68. Seshadri, D.R.; Davies, E.V.; Harlow, E.R.; Hsu, J.J.; Knighton, S.C.; Walker, T.A.; Voos, J.E.; Drummond, C.K. Wearable Sensors for COVID-19: A Call to Action to Harness Our Digital Infrastructure for Remote Patient Monitoring and Virtual Assessments. *Front. Digit. Health* 2020, 2, 8. [CrossRef]

69. Tamsin, M. Wearable Biosensor Technologies. *Int. J. Innov. Sci. Res.* 2015, 13, 697–703.

70. Dunn, J.; Runge, R.; Snyder, M. Wearables and the medical revolution. *Pers. Med.* 2018, 15, 429–448. [CrossRef]

71. Seshadri, D.R.; Davies, E.V.; Harlow, E.R.; Hsu, J.J.; Knighton, S.C.; Walker, T.A.; Voos, J.E.; Drummond, C.K. Wearable Sensors for COVID-19: A Call to Action to Harness Our Digital Infrastructure for Remote Patient Monitoring and Virtual Assessments. *Front. Digit. Health* 2020, 2, 8. [CrossRef]

72. Boscari, F.; Galasso, S.; Acciaroli, G.; Facchinetti, A.; Marescotti, M.C.; Avogaro, A.; Bruttomesso, D. Head-to-head comparison of the accuracy of Abbott FreeStyle Libre and Dexcom G5 mobile. *Nutr. Metab. Cardiovasc. Dis.* 2018, 28, 425–427. [CrossRef] [PubMed]

73. NeuroInstitute. Halo Sport 2.0. 2019. Available online: http://www.neuroinstitute.mx/index.php/tienda/halo-sport (accessed on 4 November 2021).

74. Scosche. *Socoshe Rhythm24 Waterproof Heart Monitor Armband; Socoshe*: Oxnard, CA, USA, 2021.

75. Akintola, A.A.; Van De Pol, V.; Bimmel, D.; Maan, A.C.; Van Heemst, D. Comparative Analysis of the Equivital EQ02 Lifemonitor with Holter Ambulatory ECG Device for Continuous Measurement of ECG, Heart Rate, and Heart Rate Variability: A Validation Study for Precision and Accuracy. *Front. Physiol.* 2016, 7, 391. [CrossRef] [PubMed]

76. GlucoWISE. Imagine Living a Healthier Life with Glucowise®. Available online: http://gluco-wise.com/ (accessed on 28 July 2021).

77. G-Tech Medical. G-Tech Medical. 2021. Available online: http://www.gtechmedical.com/ (accessed on 27 November 2021).

78. Health Care Originals. ADAMM-RSM-SM: Health & Wellness—Health Care Originals. 2021. Available online: https://www.healthcareoriginals.com/professional/health-wellness/ (accessed on 27 November 2021).

79. iRhythm. Uninterrupted Ambulatory Cardiac Monitoring. 2021. Available online: https://www.irhythmtech.com/ (accessed on 27 November 2021).

80. Preventice. Listens to the Beat—Preventice Solutions. 2021. Available online: https://www.preventicesolutions.com/patients/body-guardian-heart (accessed on 27 November 2021).

81. VitalConnect. VitalPatch—VitalConnect. 2021. Available online: https://vitalconnect.com/solutions/vitalpatch/ (accessed on 27 November 2021).

82. ePatch. ePatch—BioTelemetry, Inc. 2021. Available online: https://www.gobio.com/clinical-research/cardiac-safety/epatch/ (accessed on 27 November 2021).

83. Kenzen. KENZEN|KENZEN. 2021. Available online: https://kenzen.com/author/kenzen/page/5/ (accessed on 27 November 2021).

84. Medical Device Network. Nerivio Migra Wearable Neurostimulation Device, USA. 2021. Available online: http://medicaldevice-network.com/projects/nerivio-migra/ (accessed on 27 November 2021).

85. Medtronic. ZephyrTM Performance Systems|Performance Monitoring Technology. 2021. Available online: https://www.zephyranywhere.com/ (accessed on 3 December 2021).

86. Bose Corporation. Audífonos Inalámbricos SoundSport Pulse. 28 July 2021. Available online: https://www.bose.mx/es_mx/products/headphones/earbuds/soundsport-wireless-pulse.html?ProductTabs_tab4&v=soundsport_pulse_wireless_power_red (accessed on 3 November 2021).

87. VivaLink. Wearable Products. 2021. Available online: https://www.vivalink.com/wearable-products (accessed on 27 November 2021).

88. Wearable Tech. Spire Health Tag Review. 2021. Available online: https://www.wearabletech.com/health-products/smartsensors/spire-health-tag-review-6541 (accessed on 27 November 2021).

89. Muse. MuseTM—Meditation Made Easy with the Muse Headband. 2021. Available online: https://choosemuse.com/ (accessed on 27 November 2021).

90. Motiv. Motiv Ring | 24/7 Smart Ring | Fitness + Sleep Tracking | Online Security Motiv Ring. 2021. Available online: https://www.motiv.com/ (accessed on 27 November 2021).

91. Oura. Oura Ring: Accurate Health Information Accessible to Everyone. 2021. Available online: https://ouraring.com/ (accessed on 27 November 2021).

92. Komodo. AIO Smart Sleeve—HRV Monitor of the Year|Best Fitness Tracker. 2021. Available online: https://komodotec.com/ (accessed on 27 November 2021).

93. Apple. Apple. 2021. Available online: https://www.apple.com/ (accessed on 27 November 2021).

94. Empatica. Empatica|Medical Devices, AI and Algorithms for Remote Patient Monitoring. 2021. Available online: https://www.empatica.com/en-int/embrace2/ (accessed on 27 November 2021).

95. Fitbit. Sitio Oficial de Fitbit Para Smartwatches, Pulseras de Actividad, Monitores Deportivos y Mucho Más. 2021. Available online: https://www.fitbit.com/global/es/home (accessed on 27 November 2021).

96. Gyenno Spoon. Gyenno, 28 July 2021. Available online: https://www.gyenno.com/spoon-en.html (accessed on 31 October 2021).

97. Spiegel, B.M.R.; Kaneshiro, M.; Russell, M.M.; Lin, A.; Patel, A.; Tashjian, V.C.; Zegarski, V.; Singh, D.; Cohen, S.E.; Reid, M.W.; et al. Validation of an Acoustic Gastrointestinal Surveillance Biosensor for Postoperative Ileus. *J. Gastrointest. Surg.* 2014, 18, 1795–1803. [CrossRef] [PubMed]
98. Garmin. Garmin | Mexico. 2021. Available online: https://www.garmin.com/es-MX/ (accessed on 28 May 2021).
99. Honor. Catálogo de Productos y Lista de Precios HONOR | HONOR México. 2021. Available online: https://www.hihonor.com/mx/products/?categories=wearables (accessed on 27 November 2021).
100. Huawei. HUAWEI Wearables—HUAWEI México. 2021. Available online: https://consumer.huawei.com/mx/earwearables (accessed on 28 May 2021).
101. Mobvoi. TicWatch Smartwatch / Audio | Mobvoi. 2021. Available online: https://www.mobvoi.com/la/types/smartwatches (accessed on 27 November 2021).
102. Lazersport. Lazer LifeBEAM Cycling Helmet Heart Rate Monitor | Lazer Sport Helmets. 2021. Available online: https://lazersport.us/products/lifebemaidiykit (accessed on 5 November 2021).
103. Kickstarter. P. KUAL—World’s First Multiport Biometric Headphones by Kuaicwear—Kickstarter. 2021. Available online: https://www.kickstarter.com/projects/532598250/kual-worlds-first-multiport-biometric-headphones (accessed on 4 November 2021).
104. Omron. Wrist Blood Pressure Monitor & Watch | HeartGuide by OMRON. 2021. Available online: https://omronhealthcare.com/products/heartguide-wearable-blood-pressure-monitor-bp8000m/ (accessed on 27 November 2021).
105. Code, R. Wearable technology in healthcare. Nat. Biotechnol. 2019, 37, 376. [CrossRef]
106. Samsung. Samsung Gear Sport—Características, El Mejor Precio y Opiniones | Samsung España. 2021. Available online: https://www.samsung.com/es/gear-sport/highlights/ (accessed on 28 May 2021).
107. Verily. Advancing Health Outcomes Through Technology, Data Science, and a Team of Experts across Clinical Research, Care, and Devices | Verily Life Sciences. 2021. Available online: https://verily.com/ (accessed on 27 November 2021).
108. Withings. Hybrid Smartwatch with ECG, Heart Rate & Oximeter—ScanWatch | Withings. 2021. Available online: https://www.withings.com/de/en/scanwatch (accessed on 27 November 2021).
109. Xiaomi. Xiaomi Smartwatch Mi Band 5 Versión Global—Xiaomi Store México. 2021. Available online: https://www.xiaomi-store.mx/products/mi-band-5 (accessed on 27 November 2021).
110. Sensoria. Sensoria Fitness: Motion and Activity Tracking Smart Clothing for Sports and Fitness. 2021. Available online: https://store.sensoriafitness.com/ (accessed on 27 November 2021).
111. Ambiotex. Smart-Tech—Ambiotex—EN Wearable for a Better Body Understanding. 2021. Available online: https://www.ambiotex.com/en/smart-tech/ (accessed on 27 November 2021).
112. Hexoskin. Available online: https://www.hexoskin.com/ (accessed on 11 November 2021).
113. Nuubo. Nuubo. 2021. Available online: https://www.nuubo.com/en-us (accessed on 27 November 2021).
114. Zoll. ZOLL LifeVest Wearable Defibrillator | ZOLL Medical Corporation. 2021. Available online: https://lifevest.zoll.com/ (accessed on 28 May 2021).
115. AliveCor. AliveCor. 2021. Available online: https://www.alivecor.com/ (accessed on 27 November 2021).
116. iHealth. iHealth Feel Wireless Monitor—iHealth Labs Inc. 2021. Available online: https://ihealthlabs.com/es/products/ihealth-feel-wireless-monitor (accessed on 27 November 2021).
117. Mocacare. MOCA Cuff—Wrist Blood Pressure Monitor. 2021. Available online: https://www.mocacare.com/mocacuff/ (accessed on 27 November 2021).
118. Imani, S.; Bandodkar, A. J.; Mohan, A. M. V.; Kumar, R.; Yu, S.; Wang, J.; Mercier, P. P. A wearable chemical–electrophysiological hybrid biosensing system for real-time health and fitness monitoring. Nat. Commun. 2016, 7, 11650. [CrossRef] [PubMed]
119. Yoon, S.; Sim, J.; Cho, Y.-H. A Flexible and Wearable Human Stress Monitoring Patch. Sci. Rep. 2016, 6, 23468. [CrossRef]
120. Williams, M. A.; Roseway, A.; O’Dowd, C.; Czerwinski, M.; Morris, M. R. SWARM: An actuated wearable for mediating affect. In Proceedings of the 9th International Conference on Tangible, Embedded, and Embodied Interaction, Stanford, CA, USA, 15–19 January 2015; pp. 293–300. [CrossRef]
121. Guo, C.; Chen, Y. V.; Qian, Z. C.; Ma, Y.; Dinh, H.; Anasingaraju, S. Designing a Smart Scarf to Influence Group Members’ Emotions in Ambience: Design Process and User Experience. In Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Cham, Switzerland, 2016; Volume 9738, pp. 392–402. [CrossRef]
122. Hui, T. K.; Sherratt, R. S. Coverage of Emotion Recognition for Common Wearable Biosensors. Biosensors 2018, 8, 30. [CrossRef]
123. Trmcic, B. R.; Stanojevic, G.; Sapic, R.; Labus, A.; Bogdanovic, Z. Wearable solution for assessing physiological arousal towards students’ interest and engagement in the classroom. In Proceedings of the The 11th International Conference on Virtual Learning, Craiova, Romania, 29 October 2016.
124. Kosmyna, N.; Morris, C.; Sarawgi, U.; Nguyen, T.; Maes, P. AttentivU: A Wearable Pair of EEG and EOG Glasses for Real-Time Physiological Processing. In Proceedings of the 2019 IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Chicago, IL, USA, 19–22 May 2019. [CrossRef]
125. Rodríguez-Arce, J.; Lara-Flores, L.; Portillo-Rodriguez, O.; Martinez-Méndez, R. Towards an anxiety and stress recognition system for academic environments based on physiological features. Comput. Methods Programs Biomed. 2020, 190, 105408. [CrossRef]
126. Norooz, L.; Mauriello, M. L.; Jorgensen, A.; McNally, B.; Froehlich, J. E. Body Vis: A new approach to body learning through wearable sensing and visualization. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Korea, 18–23 April 2015; pp. 1025–1034. [CrossRef]
127. Theodoros, N. A.; James, F. K.; Chris, B.; Antony, S. Wearable Technologies in Education: The Lab of Tomorrow Project. Teach. Prof. Dev. 2005, 163, 163–169.
128. Kanna, S.; Von Rosenberg, W.; Goverdovsky, V.; Constantinides, A.G.; Mandic, D.P. Bringing Wearable Sensors into the Classroom: A Participatory Approach [SP Education]. *IEEE Signal Process. Mag.* 2018, 35, 110–130. [CrossRef]

129. Gao, N.; Shao, W.; Rahaman, M.S.; Salim, F.D. n-Gage: Predicting in-class Emotional, Behavioural and Cognitive Engagement in the Wild. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2020, 4, 1–26. [CrossRef]

130. Al-Alwani, A. A Combined Approach to Improve Supervised E-Learning using Multi-Sensor Student Engagement Analysis. *Am. J. Appl. Sci.* 2016, 13, 1377–1384. [CrossRef]

131. Nomura, K.; Iwata, M.; Augereau, O.; Kise, K. Estimation of Student’s Engagement Using a Smart Chair. In Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers, Singapore, 8–12 October 2018; pp. 186–189. [CrossRef]

132. André, R.D.P.; Raposo, A.B.; Fuks, H. A Platform for Assessing Physical Education Activity Engagement. In *Advances in Intelligent Systems and Computing*; Springer: Cham, Switzerland, 2019; Volume 903, pp. 271–276. [CrossRef]

133. Rajavenkatanayanan, A.; Babu, A.R.; Tsiakas, K.; Makedon, F. Monitoring task engagement using facial expressions and body postures. In Proceedings of the 3rd International Workshop on Interactive and Spatial Computing, Richardson, TX, USA, 12–13 April 2018; pp. 103–108. [CrossRef]

134. Haveman, M.E.; van Melzen, R.; Schuurmann, R.C.; El Moumni, M.; Hermens, H.J.; Tabak, M.; de Vries, J.-P.P. Continuous monitoring of vital signs with the Everion biosensor on the surgical ward: A clinical validation study. *Expert Rev. Med. Devices* 2021, 18, 145–152. [CrossRef] [PubMed]

135. Nazari, G.; Bobos, P.; MacDermid, J.C.; Sinden, K.E.; Richardson, J.; Tang, A. Psychometric properties of the Zephyr bioharness device: A systematic review. *BMC Sports Sci. Med. Rehabil.* 2018, 10, 6. [CrossRef] [PubMed]

136. Zaman, S.U.; Tao, X.; Cochrane, C.; Koncar, V. Smart E-Textile Systems: A Review for Healthcare Applications. *Electronics* 2022, 11, 99. [CrossRef]

137. Moldovan, O.; Ibáñez, B.; Deen, M.J.; Marsal, L.F. Graphene electronic sensors—Review of recent developments and future challenges. *IET Circuits Devices Syst.* 2015, 9, 446–453. [CrossRef]

138. Zhang, K.; Wang, J.; Liu, T.; Luo, Y.; Loh, X.J.; Chen, X. Machine Learning-Reinforced Noninvasive Biosensors for Healthcare. *Adv. Healthc. Mater.* 2021, 10, 2100734. [CrossRef]