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Smart Wearable Devices for Monitoring and Enhancing Student Engagement in Remote Learning

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Resumo

A eficácia do ensino online depende significativamente do empenho dos alunos, que é frequentemente difícil de avaliar e manter em ambientes virtuais de aprendizagem em comparação com salas de aula tradicionais. Esta dissertação investiga o uso de dispositivos *wearables* inteligentes, especificamente a plataforma BITalino, para monitorizar sinais fisiológicos, como eletrocardiograma (ECG) e atividade eletrodérmica (EDA), visando a avaliação em tempo real do empenho dos alunos durante a aprendizagem remota. Ao integrar esses sinais com uma aplicação de biofeedback personalizada, o estudo propõe um sistema inovador para fornecer feedback imediato a alunos, promovendo a autorregulação e estratégias de ensino adaptativas.

Resultados experimentais de uma amostra de 20 alunos demonstram correlações significativas entre métricas fisiológicas (e.g., variabilidade da frequência cardíaca e respostas de condutância da pele) e níveis de empenho autorrelatados, validando a eficácia do sistema. As descobertas contribuem para a tecnologia educacional ao oferecer uma solução de baixo custo, transparente e escalável para melhorar o empenho na aprendizagem virtual, com implicações para a colaboração entre humanos e tecnologia no contexto da Educação 5.0. Considerações éticas, incluindo privacidade de dados e consentimento informado, também são abordadas para garantir uma implementação responsável.

Palavras chave: *Wearables* inteligentes, Ensino remoto, Empenho dos estudantes, IoT, Análise de dados, Indústria 5.0

Abstract

The effectiveness of online education heavily depends on student engagement, which is often challenging to assess and sustain in virtual learning environments compared to traditional classrooms. This dissertation explores the use of smart wearable devices, specifically the BITalino platform, to monitor physiological signals such as electrocardiogram (ECG) and electrodermal activity (EDA) for real-time assessment of student engagement during remote learning. By integrating these signals with a custom biofeedback application, the study proposes a novel system to provide immediate feedback to students, promoting self-regulation and adaptive teaching strategies.

Experimental results from a sample of 20 students demonstrate significant correlations between physiological metrics (e.g., heart rate variability and skin conductance responses) and self-reported engagement levels, validating the system's efficacy. The findings contribute to educational technology by offering a low-cost, transparent, and scalable solution for enhancing engagement in virtual learning, with implications for fostering human-technology collaboration in Education 5.0. Ethical considerations, including data privacy and informed consent, are also addressed to ensure responsible implementation.

Keywords: Smart Wearable Devices, Remote Learning, Student Engagement, IoT, Data Analytics, Industry 5.0

United Nations Sustainable Development Goals

The United Nations Sustainable Development Goals (SDGs)¹ are 17 objectives set by United Nations member states in 2015 to promote a sustainable future. They address critical societal challenges such as poverty, inequality, and climate change. These goals are intended to guide nations in fostering economic growth, improving quality of life, and safeguarding the environment.

The present dissertation project, which explores smart wearable technology for monitoring and enhancing student engagement in remote learning, is aligned with several SDG goals, mainly the following:

- **SDG 3 - Good Health and Well-being:** Ensure healthy lives and promote well-being for all at all ages.
 - **Target 3.4:** Reduce by one third premature mortality from non-communicable diseases through prevention and treatment, and promote mental health and well-being.
- **SDG 4 - Quality Education:** Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.
 - **Target 4.1:** Ensure that all girls and boys complete free, equitable and quality primary and secondary education.
 - **Target 4.4:** Substantially increase the number of youth and adults who have relevant skills, including technical and vocational skills, for employment and entrepreneurship.
- **SDG 9 - Industry, Innovation and Infrastructure:** Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.
 - **Target 9.5:** Enhance scientific research and upgrade the technological capabilities of industrial sectors.
- **SDG 10 - Reduced Inequalities:** Reduce inequality within and among countries.
 - **Target 10.2:** Empower and promote the social, economic and political inclusion of all.

Table 1 outlines the specific contributions of this project towards the targeted SDGs and their respective targets. It details how the project aligns with these goals and describes the performance indicators and metrics that will be employed to assess the project's impact in achieving these objectives.

¹<https://www.un.org/sustainabledevelopment/sustainable-development-goals/>

Table 1: Alignment with United Nations Sustainable Development Goals.

SDG	Target	Contribution	Performance Indicators and Metrics
3	3.4	Supports student mental well-being through physiological monitoring (e.g., heart rate, EDA) and feedback, helping reduce stress and improve focus during remote learning.	Reduction in reported stress levels; increased average engagement time per session.
4	4.1	Enhances remote learning through real-time feedback and data-driven engagement strategies, supporting inclusive and effective learning.	Improved student participation and completion rates; better academic performance in remote settings.
	4.4	Fosters digital literacy and promotes use of emerging technologies in education, improving future job readiness.	Number of students using technology-enhanced learning tools; wearable platform adoption in schools.
9	9.5	Contributes to innovation in education and biofeedback by applying wearable tech in a novel academic context.	Number of publications/citations; development of research tools/platforms.
10	10.2	Bridges gaps in education for underserved students by improving access to remote, data-supported learning environments.	Lower dropout rates in underserved areas; survey data on improved access.

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“Victory is celebrated in the light, but it is won in the darkness.”

Dune Prophecy

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List of Acronyms

AE	Affective Engagement
BIDS	Brain Imaging Data Structure
BVP	Blood Volume Pulse
BLE	Bluetooth Low Energy
BP	Blood Pressure
BT	Bluetooth
CIoT	Cellular IoT
CSV	Comma-Separated Values
CWT	Continuous Wavelet Transform
COVID-19	Coronavirus Disease 2019
DAS	Direct-Attached Storage
DCT	Discrete Cosine Transform
DECEiVeR	Dataset for Emotion Classification using Electrodermal and Electrocardiogram Responses
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalogram
EMD	Empirical Mode Decomposition
EMG	Electromyography
FER	Facial Expression Recognition
FFT	Fast Fourier Transform
GPIO	General Purpose Input/Output
GSR	Galvanic Skin Response
HR	Heart Rate
HRV	Heart Rate Variability
I2C	Inter-Integrated Circuit
ICA	Independent Component Analysis
IED	Índice de Engajamento
IMF	Intrinsic Mode Functions
IoT	Internet of Things

List of Acronyms

IU	Interface do Utilizador
LBP	Local Binary Pattern
Li-Ion	Lithium-Ion
LiPo	Lithium Polymer
LTE-M	Long Term Evolution for Machines
LTP	Local Ternary Pattern
MAC	Media Access Control
MSPCA	Multi-Scale Principal Component Analysis
NAS	Network-Attached Storage
NB-IoT	Narrowband Internet of Things
NPM	Non-Physiological Metric
PCA	Principal Component Analysis
PPG	Photoplethysmography
PSD	Power Spectral Density
RMSSD	Root Mean Square of Successive Differences
RP	Respiratory Patterns
RR	Respiratory Rate
RV	Respiratory Volume
SCR	Skin Conductance Response
SDNN	Standard Deviation of NN intervals
SCL	Skin Conductance Level
SPI	Serial Peripheral Interface
SSH	Secure Shell
ST	Skin Temperature
SP	Signal Power
SpO2	Peripheral Oxygen Saturation
SVM	Support Vector Machines
UI	User Interface
UART	Universal Asynchronous Receiver-Transmitter
USB	Universal Serial Bus
WBT	Wearable Technology
WSL	Windows Subsystem for Linux

Chapter 1

Introduction

The enormous growth of online education has indeed reshaped the educational landscape, mirroring a significant shift towards accessibility and flexibility. However, as educators and researchers have articulated, this transition is not without its critical challenges. One particularly important issue is achieving effective student engagement, which is crucial for academic success. Traditional educational models enable instructors to observe real-time interactions such as body language and attentiveness, facilitating adjustments to teaching methods as necessary. In contrast, these observational opportunities diminish in virtual environments, resulting in challenges associated with monitoring and enhancing student engagement [1].

The rapid shift to remote learning, accelerated by the COVID-19 pandemic, has underscored the disparities in access to online education. Research indicates that various barriers exist, including inadequate technology, lack of stable internet access, and differing levels of digital literacy among students [2][3]. For instance, Deichakivska *et al.* highlight how adaptive learning technologies can customize educational experiences for individual students, an aspect that has become increasingly important in isolated areas [4]. Further, Demirel *et al.* argue that technological deficiencies negatively affect students' perceptions of their professional self-efficacy, emphasizing the real consequences of these access barriers on learning outcomes [5]. This sets the stage for a pressing need for innovative solutions that can help mitigate these engagement challenges and improve the overall learning experience.

Emerging technologies present novel solutions to enhance student engagement in online education. For example, wearable devices and the Internet of Things (IoT) can provide real-time metrics on student engagement indicators such as heart rate and movement, enriching the virtual learning experience significantly. Gu discusses how factors like family dynamics can restrict access to online education and exacerbate inequalities, contrasting the ideal scenario of universal educational access with the reality many students face [3]. By leveraging data analytics from these technologies, personalized interventions can be crafted, promoting a more tailored educational approach that caters to individual learner needs [6][7].

Motivated by the limitations of current online education systems, this research explores the integration of intelligent wearable technologies to enhance engagement specifically in virtual en-

vironments. The aim is to synthesize human-centric data with machine intelligence, aligning with the broader movement towards Education 5.0, which seeks to balance human creativity and technological innovation [8]. This integration emphasizes a paradigm shift from a purely efficiency-focused approach towards more ethical, personalized, and sustainable solutions, advocating for a learning environment that fosters meaningful connections between educators and learners.

1.1 Problem Description

Tracking student engagement in online learning spaces comes with enormous challenges, especially in independent study sessions where there is no live supervision or feedback from teachers.

In face-to-face classroom setups, instructors have been able to use behavioral indicators like facial expressions, body posture, or engagement to measure student engagement. In self-paced online learning, though, none of these indicators exists, and students tend to learn without enabling cameras or actually engaging with sites, thus losing the ability to monitor their attention or motivation. Current methods like quizzes or participation scores offer incomplete and lagged snapshots of engagement. Additionally, students are frequently subject to various distractions in their home environments, causing task-switching, passive learning, and disengagement. Being unable to sense and react to these patterns in real time inhibits personalized intervention and impacts learning outcomes.

Moreover, the absence of physiological or emotional feedback during independent study sessions restricts students' perception of their own mental state. Without perception, students might not be aware when they are tired, stressed, or no longer motivated.

Thus, there is a requirement for smart and non-intrusive approaches to monitor engagement continuously in autonomous learning. Such approaches are required to offer real-time feedback to allow students to self-regulate learning and permit teachers to support students on the basis of physiological evidence and not merely digital records of interaction.

1.2 Objectives

This dissertation seeks to enhance virtual learning environments by deploying wearable technology integrated with IoT sensors and data analytics to monitor and improve student engagement. The primary aim is to create a system that captures real-time physiological and behavioral data from students as they engage in learning activities. Through the design of algorithms, the study endeavors to analyze this data to provide actionable, real-time feedback to students, enabling a more dynamic and personalized educational experience.

Another central objective is to validate the system's effectiveness through targeted experiments, focusing on engagement metrics such as student performance and participation, particularly in remote self-learning environments. These experiments are designed to demonstrate the potential of the technology to support and enhance learning outcomes in settings where students often engage independently.

Additionally, the study explores the broader implications of this work for Industry 5.0, emphasizing the role of human-technology collaboration in education. By integrating wearable technology into virtual learning frameworks, the dissertation aims to contribute to a future where technology and human interaction synergize to optimize educational experiences.

1.3 Research Questions

- **RQ1:** Which physiological and behavioral metrics are most effective in assessing student engagement during remote learning?
- **RQ2:** Which algorithms are best suited for real-time analysis and feedback on student engagement, balancing accuracy and computational efficiency?
- **RQ3:** How does the implementation of wearable technology impact key indicators of engagement, such as student performance, participation, and attentiveness?
- **RQ4:** How can wearable devices be ethically designed and implemented to ensure data privacy, security, and compliance with informed consent practices?
- **RQ5:** What are the implications of integrating wearable technology into remote learning for fostering human-technology collaboration in an Industry 5.0 context?

1.4 Research Hypotheses

This dissertation investigates how physiological signals, specifically electrocardiogram (**ECG**) and electrodermal activity (**EDA**), can reflect students' emotional states and engagement during remote learning. To validate the emotion recognition approach, the study also incorporates data from the DECEiVeR dataset [9] - a publicly available reference database containing **ECG** and **EDA** signals recorded from professional actors performing predefined emotional states. This allows the comparison between real-world user data and well-labeled emotional benchmarks. Emotions are represented using the valence-arousal model, which maps affective states along two dimensions: **valence** (from unpleasant to pleasant) and **arousal** (from calm to excited). Based on this framework, and on comparisons with labeled reference datasets, the following hypotheses are formulated:

- **H1:** There is a statistically significant correlation between physiological signals, namely **ECG** and **EDA**, and self-reported engagement levels in remote learning activities.
- **H2:** Physiological features extracted from **ECG** and **EDA** signals can distinguish between emotional states across the valence-arousal space, enabling classification into high, medium, and low engagement categories.
- **H3:** The emotional mapping derived from real participant data aligns with standardized patterns, supporting the external validity of physiological-emotional associations.

1.5 Dissertation Structure

This dissertation is organized into six chapters, each addressing a specific aspect of the research:

- **Chapter 1: Introduction** – Provides an overview of the research, including the problem description, objectives, research questions, hypotheses, and the structure of the dissertation.
- **Chapter 2: State of the Art** – Reviews existing literature on emotion and learning, wearable devices, physiological signal processing (ECG and EDA), and commercial solutions for monitoring student engagement, identifying limitations and gaps in current systems.
- **Chapter 3: Proposed Solution and Implementation** – Describes the design and implementation of a low-cost system using the BITalino platform for real-time monitoring of physiological signals, including the biofeedback application and signal processing methodologies.
- **Chapter 4: Experimentation and Results** – Presents the experimental setup, data collection process, and findings from analyzing ECG and EDA signals in relation to student engagement, including correlations with self-reported data.
- **Chapter 5: Discussion** – Compares the study's results with the state of the art, discusses knowledge contributions, and addresses the research questions based on experimental findings.
- **Chapter 6: Conclusions and Future Work** – Summarizes the key findings, outlines contributions to educational technology, and proposes directions for future research, including ethical considerations and multimodal system development.

The dissertation concludes with references and an appendix containing supplementary materials, such as consent forms and detailed signal data of participants.

Chapter 2

State of the art

The development of online education has been characterized by both technological innovation and shifting educational demands. Although the COVID-19 pandemic served as a catalyst for the mass implementation of distance learning, it also manifested in serious constraints-e.g., decreased interactivity, absence of real-time feedback, and challenges in preserving learners' engagement.

Yet, these issues go beyond the pandemic situation. Asynchronous and independent study sessions are still a primary learning mode for most students in higher education. In these situations, students tend to have limited supervision, more frequent distraction, and less awareness of their cognitive or emotional status. This calls for innovative approaches to track engagement in real time and personalize learning experiences in response.

In this chapter, we discuss how physiological and behavioral data can be utilized, especially through wearable sensors, to offer a window into students' affective and cognitive engagement to enable more adaptive and personalized learning systems.

When using online learning, it is essential to follow certain measures, like setting up facilities, training with modern technology, giving teachers and students guidance, providing interactive multimedia resources that align with the existing curriculum, and making sure that an effective evaluation system is in place. It's critical to consider learning as a social and cognitive activity rather than a means of transferring knowledge. Modeling the various interactions that take place during the online learning process is just as important as modeling the content itself.

Considering the characteristics of each learning methodology, the teacher-student interactions can be divided into one of four kinds based on the dimensions of time (synchronous-asynchronous) and place (online-offline) [10], as shown in Figure 2.1. The online synchronous activities include live lectures and Q&A sessions, which offer immediate feedback. Online asynchronous tasks include posting of replies and assignments, allowing flexibility in scheduling. The offline synchronous interactions relate to face-to-face teaching and discussions that provide for direct engagement. Lastly, the offline asynchronous tasks are individual works such as material compilation and reviews. It indicates how traditional class learning and e-learning each falls into these categories, meeting different educational needs and preferences.

As a result, engagement becomes a key idea while creating and executing online learning

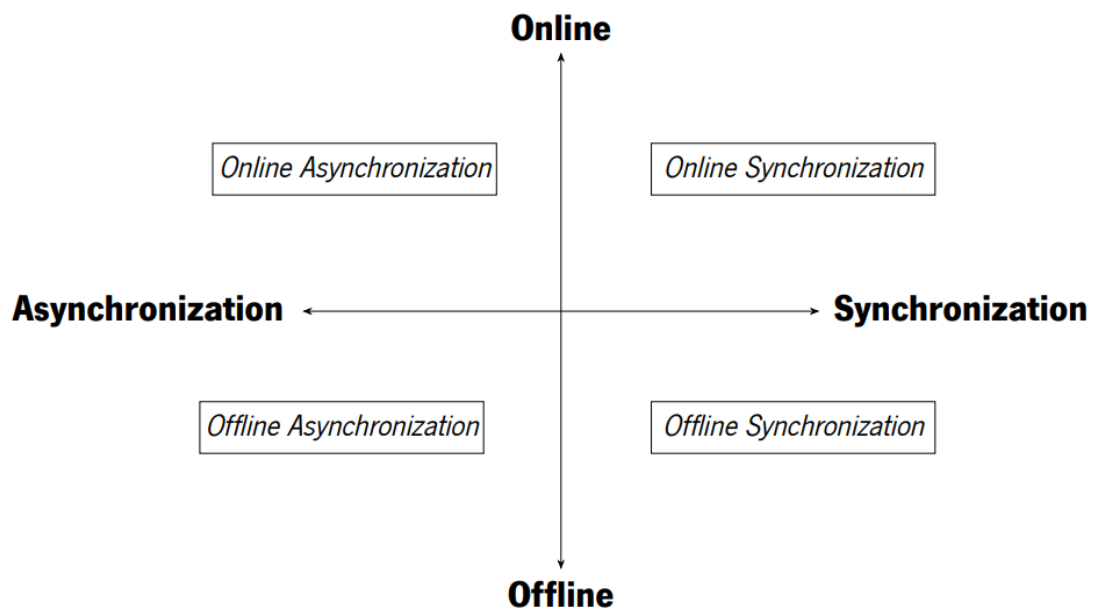


Figure 2.1: Diagram illustrating the modalities of teacher-student interactions in traditional and e-learning environments. The figure categorizes interactions into synchronous (e.g., live lectures) and asynchronous (e.g., recorded materials) formats, highlighting how each modality supports different engagement levels and educational needs in remote learning settings.

environments. Students' perception of educational activities and strategies employed in the classroom is often strongly linked to their engagement levels in the learning process. When it comes to teaching reading comprehension, assessing student involvement is a standard approach. For many learners, reading plays a pivotal role in their development and achievements both within and beyond the classroom. It promotes critical thinking and enhances cognitive abilities. Similarly, reading comprehension skills empower students to interpret written text effectively. However, sustaining their attention during reading comprehension lessons can present significant challenges.

Student engagement is typically understood across three key dimensions: behavioral, cognitive, and affective. Behavioral engagement reflects active participation in learning activities, demonstrated through involvement, persistence, and positive behavior. Cognitive engagement involves the mental effort applied to learning, characterized by deep learning, self-regulation, and comprehension. Affective engagement relates to emotional investment in the learning process, evident in positive feelings toward the learning environment, peers, and teachers, as well as a sense of belonging. These dimensions and their corresponding components are summarized in Table 2.1.

Table 2.1: Components of Engagement

Engagement	Component of Engagement
Behavioral Engagement (Action)	Participation, effort, attention, conduct
Cognitive Engagement (Thought)	Will, skills & strategies, self-regulation, deep learning
Affective Engagement (Feeling)	Positive emotion, belonging, social support, personal growth

Current approaches to monitor student engagement during educational activities often utilize computer vision to analyze images and interpret facial expressions, gestures, postures, and eye movements [11]. Additionally, wearable devices equipped with physiological and neurological sensors can collect essential physiological data indicative of student engagement. Through computer vision, insights into students' emotional, cognitive, and behavioral states can be derived during learning tasks, utilizing information from audio, image, and video sources [12]. This data aids in tracking and assessing how actively students participate in classroom activities designed to facilitate learning. Meanwhile, wearables contribute by capturing physiological signals that reveal aspects such as concentration, engagement, and attitude during learning experiences. These insights are invaluable for educators, as they provide a deeper understanding of the factors influencing students' classroom performance.

2.1 Emotion and Learning

The association between emotion and learning is extensively examined as emotion is an essential aspect of the learning process and affects students' learning outcomes [13]. Pleasant emotions, like enjoyment or pride, are positively correlated with learning, while unpleasant emotions, like frustration, are often detrimental to learning. Emotions tend to be defined on the basis of either a categorical or dimensional approach. Categorical theories differentiate between different types of emotions, e.g., the six basic emotions: fear, anger, happiness, surprise, disgust, and sadness [14].

All emotions have distinct facial expressions and action tendencies. Nevertheless, it is argued that these basic emotions have very little to do with learning. Dimensional theories of emotion do establish this correlation and characterize emotions by two or three successive factors.

Two-dimensional theories, such as the circumplex model of Russell [15], are going to be used and are defined by the characterization of emotions by valence and arousal.

Arousal is the level of physiological activation that occurs when an emotion is provoked, and valence is used to refer to the pleasantness of an emotion from positive or pleasant to negative or unpleasant.

Using Russells circumplex model, emotions can be separated into two dimensions:

- Valence (pleasantness)
- Arousal (activation level)

Based on these dimensions, four discrete emotional classes are defined:

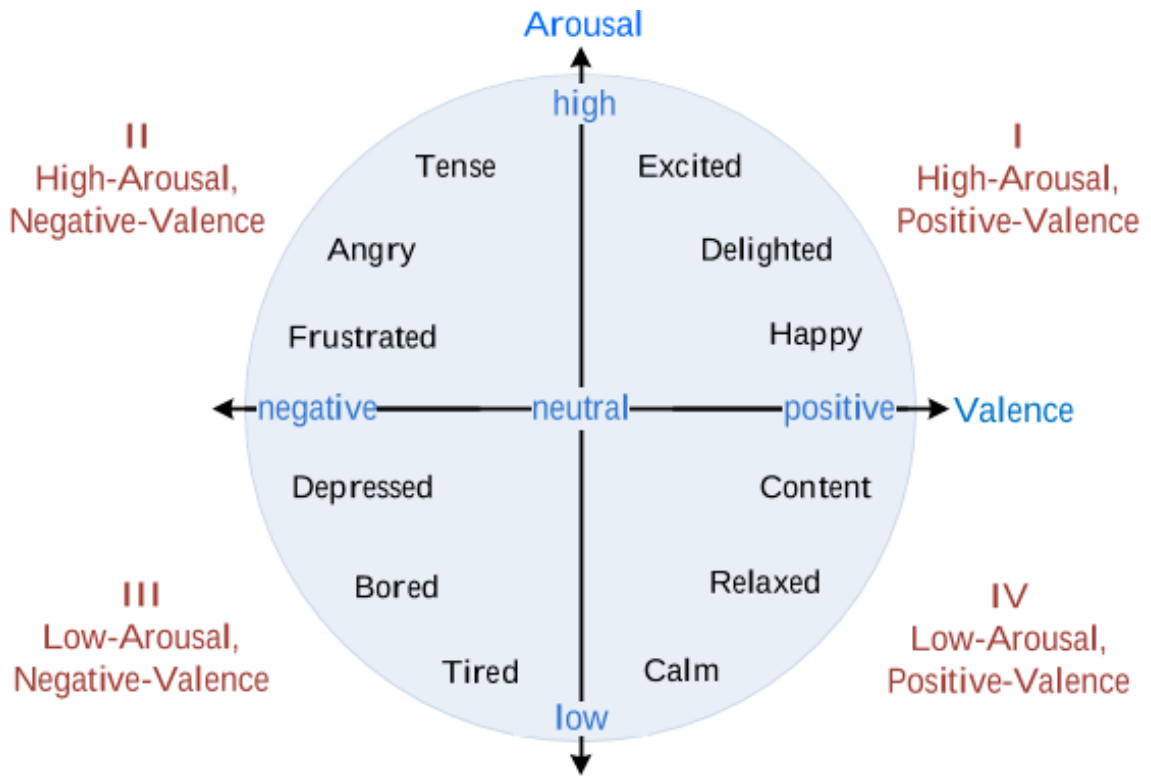


Figure 2.2: Russells circumplex model of emotion [16], mapping emotions in a two-dimensional valence-arousal space. The model divides emotions into four quadrants: high-arousal positive-valence (e.g., excited), high-arousal negative-valence (e.g., angry), low-arousal negative-valence (e.g., bored), and low-arousal positive-valence (e.g., calm).

- **Quadrant I** (High-Arousal, Positive-Valence) - e.g., excited, happy
- **Quadrant II** (High-Arousal, Negative-Valence) - e.g., angry, tense
- **Quadrant III** (Low-Arousal, Negative-Valence) - e.g., tired, bored
- **Quadrant IV** (Low-Arousal, Positive-Valence) - e.g., calm, relaxed

The valence-arousal model, as illustrated in Figure 2.2, is a tool used to classify emotions based on their valence and level of arousal. The Valence-axis and Arousal-axis divide up the coordinate plane into four regions that refer to affective states located on the valence-arousal continuum; a person can be placed in a particular affective state that can thus be stated as follows:

$$\alpha = \begin{cases} \{\text{excited, happy, pleased, interested, convinced}\}, & \text{if } valence > 0 \wedge arousal > 0 \\ \{\text{alarmed, stressed, upset, frustrated, hostile}\}, & \text{if } valence < 0 \wedge arousal > 0 \\ \{\text{sad, depressed, bored, tired, worried, doubtful}\}, & \text{if } valence < 0 \wedge arousal < 0 \\ \{\text{sleepy, relaxed, calm, impressed, peaceful, confident}\}, & \text{if } valence > 0 \wedge arousal < 0 \end{cases}$$

Physiological arousal reflects complex unconscious body reactions. Physiological activation has been demonstrated to shift through the learning process: physiological activation increases when students first view a difficult problem and peaks when solving the solution of a problem or receiving feedback upon an answer from a student [17].

Arousal also plays a direct influence on learning itself. There must be some minimum physiological activation so that students listen to instructions or the exercises. Physiological arousal may be estimated from several modalities, such as heart rate variability (HRV), blood volume pulse (BVP), skin temperature, and EDA.

2.2 Wearable Devices

Wearable sensors have transformed into an integral part of everyday life, thanks to the technological advancement that enables the compelling interaction of humans with computers. Each one of these devices enables one person to interact with a machine through various sorts of interfaces, including desktop computers, smartphones, touch- or gesture-based systems, or even more immersive technologies like Virtual Reality and Augmented Reality.

Today, wearables are defined as small digital devices carried on the body, with most carrying wireless connectivity to exchange information. These devices are increasingly popular for use in different applications, including health monitoring, gesture recognition, entertainment, gaming, and even fashion. More recently, wearables have also found their way into education, wherein teachers and learners alike use them to enhance engagement and interaction during learning processes. Their discreet nature and placement close to the body position put wearables as promising tools for supporting learning processes. Human and animal mobility is a very important factor in the full realization of smart wearable devices, as they can collect and send data on the move while also receiving information from the Internet to help in making smarter decisions. Applications in use of smart wearables can bring efficiency and optimization to enhance quality of life and also ensure increased productivity and safety.

The development of low-power mobile networks, miniaturization of electronic devices and sensors, and the unique benefits of smart wearables have all combined to make this field progress rapidly [18].

We have seen, in the very recent past years, a rise in the number of wearable products designed for several applications, as illustrated in Figure 2.3, including smartwatches, wristbands, eyewear, headsets, ear-buds, body straps, and smart jewelry. While the first big wave in the market was fitness activity trackers, these were followed by Bluetooth headsets, smartwatches, web-enabled glasses, and eventually virtual and augmented reality headsets developed primarily for gaming, reflecting the broader evolution of wearable technology as outlined by Buruk *et al.* [19], who trace its trajectory from health-focused tools to immersive, interactive systems. The most impactful applications of wearable technology are seen in health monitoring and medical contexts, but it is notorious to affect education. The benefits of wearable IoT solutions become more apparent if integrated IoT solutions can be had.



Figure 2.3: Wearable Devices [20]

Most existing work connects wearables to the Internet in two major directions: either sending data to the cloud or a server for offline processing or offloading processing online to maximize device operation. Notably, the recent cellular IoT technology (CIoT), including Long Term Evolution for Machines (LTE-M) and Narrowband Internet of Things (NB-IoT) [21], has opened new possibilities for wearable IoT applications due to the much wider connectivity options and reduced dependency on the traditional short-range technologies of WiFi and Bluetooth.

2.2.1 Wearable Sensors for Psychophysiological Measures

The data sources for collecting emotional and physiological data are diverse. Some tools can compute physiological signal readings, while some others allow for observing behavioral activity. Some parameters and signals commonly used for emotion state detection and physiological monitoring are introduced next [22]:

- **Electrocardiogram (ECG):** ECG records the heart's electrical impulses that drive heart contractions, capturing data on rate, rhythm, strength, and timing [23]. In educational settings, educators can use ECG patterns to monitor student attention and engagement with learning tasks.
- **Blood Pressure (BP):** BP measures the force of blood against artery walls and is expressed in systolic and diastolic pressures. Systolic pressure is measured during heart contractions, while diastolic pressure reflects blood pressure when the heart is at rest [24]. Monitoring BP helps assess emotional states like stress, which may impact student engagement in classroom settings.
- **Electroencephalogram (EEG):** EEG records and analyzes the brain's electrical activity, capturing rhythmic oscillations generated by neurons, or nerve cells [25]. These patterns,

shown on an electroencephalogram, enable researchers to quantify active brain states through wavelength bands, allowing for objective studies of brain functions during learning.

- **Electromyogram (EMG):** EMG measures electrical signals from muscles [26]. By assessing facial muscle activity, EMG provides insights into students' emotional arousal and engagement, especially when interacting with dynamic visual content.
- **Skin Temperature (ST):** Skin temperature sensors measure surface temperature to detect stress and other emotional states. Changes in skin temperature can signal engagement levels during activities like watching videos or role-playing.
- **Galvanic Skin Response (GSR) or Electrodermal Activity (EDA) :** GSR or EDA measure skin conductance by tracking moisture levels linked to sweat gland activity [27]. Their readings indicate emotional arousal, useful for monitoring engagement and emotional response during tasks such as reading.
- **Photoplethysmography (PPG):** PPG detects blood volume changes in microvascular tissue, often via non-invasive measurements on the skin [28]. In educational research, PPG sensors measure heart rate to track cognitive engagement.
- **Respiratory Patterns (RP), Respiratory Volume (RV), and Heart Rate Variability (HRV):** HRV is the physiological variation of the interval between consecutive heartbeats. HRV analysis is traditionally performed on ECG signals [29]. Respiratory changes, including rhythm and volume variations, relate to emotional states, such as increased variability in positive emotional states.
- **Facial Expression Recognition (FER):** FER detects engagement levels through facial expressions by analyzing facial images for features like muscle movements. This method helps teachers gauge student understanding.
- **Gestures and Postures:** Non-verbal cues like gestures and posture are tied to cognitive-emotional states. Teachers can infer attention or disengagement levels by analyzing video and sensor data.
- **Eye Movements:** Eye movement tracking reveals students' emotional states and concentration during online learning. Patterns of eye movement, along with head and facial tracking, provide insights into engagement levels.
- **Keyboard and Mouse Motion Capture:** Analysis of keyboard and mouse interactions, such as typing speed, inactivity, and hand movements, provides indicators of student mood and engagement.
- **Headband-Detectable Physiological Signals:** Headbands often measure EEG signals like Power Spectral Density (PSD) and Signal Power (SP) to monitor concentration and provide real-time feedback on student engagement [30].

2.3 Electrocardiogram

This signal gives a comprehensive picture of the heart's electrical activity from which it's possible to extract many features of empirical and deterministic value. This work originates from ionic transmembrane fluxes in and out of myocardial cells. Sodiumpotassium ATPase pump proteins found in the cell membrane generate a potential difference, when at rest, of approximately 90 mV. These proteins keep concentration gradients in order that Na^+ is more concentrated outside and K^+ is more concentrated inside the cell and also supplying thermodynamic energy to another mechanism which has a greater concentration of Ca^{2+} in the extracellular space [31].

The cyclical selective opening and closing of these channels is what makes up the electrical action potential that travels through the tissue and, at the organ level, from region to region of the heart, causing the myocardial muscles to contract and producing the cardiac cycle and hence the electrical signal detected by the ECG. Some areas in the heart, primarily the sinus node, create this potential naturally, as a built-in pacemaker that regulates heart rate. This signal is captured through an array of usually three, four or ten electrodes placed on the skin that occur at precise locations on the chest or arms.

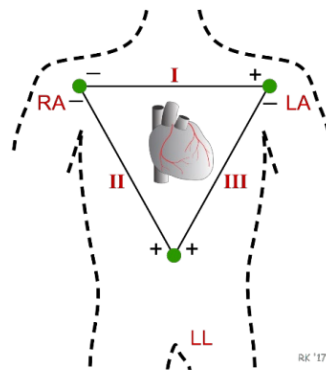


Figure 2.4: Einthoven's triangle diagram. Adapted from CV Physiology [32]

The potential difference between any two electrodes is called a lead which can also be produced from virtual electrodes that show the average of the three limb electrodes (Figure 2.4). The ECG graph shows the difference in potentials at two different leads, one closer to the source of activation than the other (referred to as endocardium and epicardium respectively). The action potential is picked up by each electrode at various times, which generate a waveform whose structures are representative of the action potential propagation and thus functional and morphological features of the heart. The investigation of the alteration of the waveform's normal morphology is the basis of the clinical use of the ECG and provides relevant information to almost all heart-related pathologies. The signal is recognized by its characteristic points *P*, *Q*, *R*, *S*, *T*, as shown next in Figure 2.5. Key features include the RR interval, from which heart rate is derived; the QRS complex, which reflects ventricular depolarization and the onset of ventricular contraction;

the PR interval; and any depression or elevation of the ST segment, which may indicate ischemia or myocardial injury.

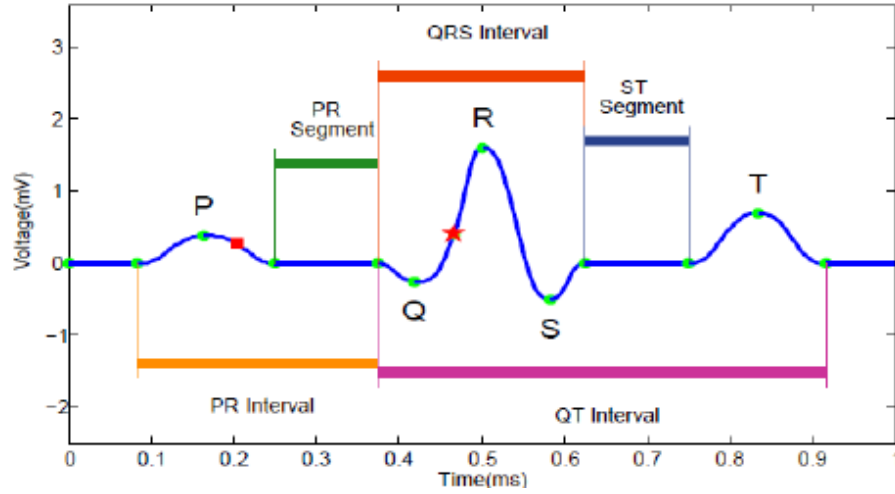


Figure 2.5: The key characteristics of the ECG and the crucial segments [33]

2.3.1 ECG for emotion detection

Emotion detection using ECG is a relatively newer approach compared to more established modalities like facial expressions or voice analysis. Nevertheless, ECG can effectively reflect emotional changes, primarily through variations in heart rate and heart rate variability. Typically, ECG-based emotion recognition follows a structured process consisting of four main steps:

1. Collecting ECG data,
2. Preprocessing the signal,
3. Extracting relevant features
4. Classifying emotional states.

2.3.1.1 Preprocessing

The ECG is usually tainted with artifacts that could make it difficult to use and apply to various tasks. The powerline interference (50-60 Hz), the electrode contact noise, nearby muscles contraction, outside electronic devices interference and motion artifacts are just a few of unwanted noise. In this way, in both handcrafted and non-handcrafted features, pre-processing can be employed to clean the ECG signal.

According to Pan and Tompkins [34], the 5-15 Hz bandpass can be used to maximise the energy of QRS. In this way, the signal is typically filtered to remove the impact of baseline wander and noise. Murugappan [35], employed 0.002 Hz and 100 Hz cut-off frequencies in a 3rd order Butterworth filter. A high-pass filter with a cut-off frequency of 4 Hz is also often used to remove

baseline wander from ECG signals. Alternatively, signal transforms can be applied for noise reduction. One effective approach is the Discrete Wavelet Transform (DWT), which decomposes the signal into multiple components while preserving both frequency and temporal information [36].

Several denoising techniques have also been explored and compared, including Independent Component Analysis (ICA), Principal Component Analysis (PCA), and Multiscale Principal Component Analysis (MSPCA). PCA is a linear statistical method that uses orthogonal transformations to generate uncorrelated variables while retaining the most significant features [37]. ICA extends this by being non-linear, identifying independent components from multivariate signals [38]. MSPCA combines wavelet decomposition with PCA to uncover relationships among variables and decorrelate them when necessary [39].

The choice of preprocessing technique depends on factors such as the type of ECG signal, acquisition settings, and characteristics in both time and frequency domains. In addition to high-pass filtering, various low-pass filters, such as elliptic, adaptive, and Butterworth are commonly used.

Some artifacts may also be removed through manual inspection, which requires expertise and careful observation. Ultimately, effective preprocessing must preserve the informative content of the ECG signal relevant to the specific application.

2.3.2 Feature-based models

Feature extraction may transform the ECG signal to a collection of meaningful and valuable features for further classification. Features can again be categorized according to the domain they are extracted as frequency or time [40].

Also, features are classified as linear or non-linear, fiducial or non-fiducial. Statistical features have taken measurements into account like the mean, variance and other computations which may consider the whole signal or even only be computed between fiducial points. Fiducial-based approaches utilize some points like P, Q, R, S, or T, considering their interval, amplitude, time, etc. Non-fiducial approaches consider the signal as a whole, or parts of it, in order to derive features related to the waveform morphology. Fiducial features are normally computed in the time domain, although there are some exceptions to frequency-fiducial approaches. Non-fiducial are generally computed in the time and frequency domains. In this subchapter, approaches are distinguished based on the domain of extracted features (time or frequency) and further investigated the fiducial and non-fiducial approaches in each.

2.3.3 Time-Domain Analysis

As previously mentioned, heart rate (HR) and HRV are the primary ECG-based indicators linked to emotional changes. Consequently, time-domain features are often derived from HRV metrics using various detection and extraction methods. Commonly used features include heart rate, R-R

intervals, R-peak values, the standard deviation of NN intervals (SDNN), and the root mean square of successive differences (RMSSD), among others.

2.3.4 Reference-Based Features

Reference-based features rely on specific landmarks or points within the ECG waveform. In the context of emotion recognition, several studies have extracted such features based on prominent ECG components, including the R peak, as well as the P and T waves.

When the heart rhythm is stable, HR can be estimated by the time interval between successive QRS complexes. Thus, detecting the QRS complex, particularly the R peak, is a common approach to acquire HRV metrics in the time domain. The R peak is relatively easy to identify due to its high amplitude, and several algorithms are available for this purpose, such as Pan and Tompkins, Hamilton, Slope Sum Function, and Christov. Although the QRS complex is a well-established marker of cardiac activation, its lack of specificity across different emotional states presents challenges in emotion classification. Nonetheless, it remains one of the most widely used sources of time-domain features in emotion analysis.

There are three analytical approaches: time-domain, frequency-domain, and statistical, that can be applied to study HRV. Time-domain features include the mean, standard deviation, and coefficient of variation of R-R intervals. Similarly, 13 HR features were found, 10 of which were time-domain metrics like the mean, median, mean absolute deviation and standard deviation of HR, as well as other HRV features such as RMSSD, average NN interval (AVNN), NN50 (the number of pairs of successive NN (R-R) intervals that differ by more than 50 ms), among others.

According to Gjoreski *et al.* [41], R-R intervals were filtered using a median filter to exclude outliers, and the cleaned intervals were used to compute time-domain features such as mean HR, mean RR, SDNN, SDSD (Standard Deviation of Successive Differences), SRR(Standard Deviation of the RR interval), RMSSD, pNN20, and pNN50. Another way can be, decompose the ECG waveform to identify the P-QRS-T complex. After detecting R peaks, Q and S points were defined as the minimum values to the left and right of R, respectively. P and T waves were located between successive QRS complexes. Based on these detections, features such as the mean, median, maximum, amplitude, and range of the R wave were extracted, along with similar measurements for the QS interval and the median amplitude of the P wave. While most studies focus on QRS amplitude, R-R intervals, and durations between successive complexes, some have also investigated QT/QTc dispersion, which has shown potential correlations with anxiety and anger.

2.3.5 Global Features

Global features analyze the entire ECG signal or its segments without relying on specific waveform landmarks. This broader approach offers greater flexibility and can be applied in both time and frequency domains. In the time domain, such features typically involve statistical metrics such as the mean, median, or variance computed over the full signal or selected segments. Techniques such

as Empirical Mode Decomposition (EMD) and Bidimensional EMD (BEMD) are also commonly used to extract global features.

According to Tivatsansakul and Ohkura [42], Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) techniques were applied to image and facial expression analysis to ECG signals. The signal was segmented into frames to extract directional and pattern-based information, achieving high accuracy in emotion recognition.

Agrafioti *et al.* [43] proposed a method to assess the oscillatory activity of the ECG signal using EMD to extract Intrinsic Mode Functions (IMFs). From these IMFs, time-domain oscillatory features were derived using local oscillation analysis.

2.3.6 Frequency-Domain Analysis

To have frequency-domain features, the ECG signals have to be transformed from the time domain to the frequency domain first. While some of these methods still rely on independent waveform landmarks, most of the frequency-domain features are computed by global methods that consider the entire signal or segments of it.

The most common approach is the use of the Fast Fourier Transform (FFT), which breaks down the signal into its constituent frequency components. From this, one may calculate features like power in particular frequency bands, very low frequency (VLF), low frequency (LF), and high frequency (HF) and their corresponding peak frequencies. One feature that is commonly used is the LF/HF ratio, traditionally linked to autonomic nervous system balance [44].

One of the best methods is by using wavelet transforms. A wavelet is a mathematical function used to analyze a signal into various frequency components, then analyze each of the components with a resolution that is matched to its scale. Wavelets have time-frequency localization, contrary to the Fourier transform, which not only indicates which frequencies are present but also when these frequencies appear in the signal. This renders wavelets highly suitable for analyzing non-stationary signals like ECG, where the time and spectral content of the signal is of interest.

DWT is most widely used with different wavelet functions like Daubechies, Symmlets, and Coiflets for ECG feature extraction. Continuous Wavelet Transform (CWT) may also be used for achieving finer time-frequency resolution. Discrete Cosine Transform (DCT) is sometimes used as another frequency domain analysis technique.

Furthermore, signal decomposition methods such as Empirical Mode Decomposition (EMD) can be coupled with frequency analysis methods such as the Hilbert Transform or Discrete Fourier Transform (DFT). Such hybrid methods enable the extraction of oscillatory features that represent the dynamics of emotional reactions at a more subtle level.

2.3.7 Non-Linear Analysis

Other than the previously discussed feature extraction techniques in both the time and frequency domains, additional methods can be applied to extract meaningful information from ECG signals.

One such method is the Poincaré Plot of RR intervals, which provides a visual and quantitative analysis of beat-to-beat variability. It is commonly used to assess HRV.

The Poincaré Plot, illustrated in Figure 2.6, displays each RR interval against the previous one, creating a scatter plot that reveals the dynamics of the heart's rhythm. The resulting point cloud is typically analyzed by measuring its geometry: the length along the line of identity, known as SD2, represents long-term variability; the width perpendicular to this line, referred to as SD1, reflects short-term variability. The ratio SD1/SD2 is also considered a valuable metric for characterizing the balance between short- and long-term heart rate fluctuations.

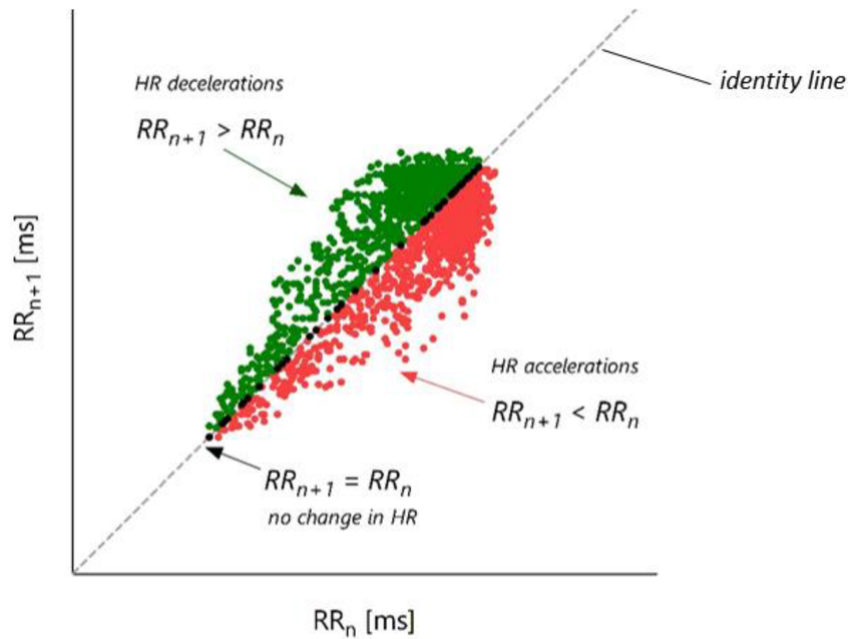


Figure 2.6: Example of the Poincaré plot of RR intervals [45]

These diverse feature categories allow ECG signals to reflect both linear and non-linear dynamics related to emotional and cognitive states.

Table 2.2 summarizes the main types of features commonly extracted from ECG data in the context of emotion recognition and engagement tracking.

Table 2.2: Summary of ECG features used for emotion recognition.

Category	Examples	Description / Application
Time-Domain	HR, RR interval, SDNN, RMSSD	Reflect HRV and autonomic regulation.
Frequency-Domain	LF, HF, LF/HF ratio, PSD	Assess the balance between sympathetic and parasympathetic activity.
Non-Linear Analysis	SD1, SD2, Poincaré plot	Characterize variability patterns beyond linear metrics.
Fiducial Features	Amplitude and duration of P, Q, R, S, T waves	Based on specific points of the ECG waveform morphology.
Global / Morphological	EMD, BEMD, LBP, LTP	Capture signal shape and oscillations without relying on fiducial points.

2.4 Electrodermal Activity

Electrodermal Activity (EDA), also known as Galvanic Skin Response (GSR), refers to fluctuations in the skin's electrical conductance, which occur in response to sweat secretion, even in very small amounts. These fluctuations can be detected by applying a constant, imperceptible voltage across the skin and observing changes in conductance [46].

Measurement of EDA is typically done using specialized sensors that employ electrodes to monitor the skin's electrical signal. Although this physiological process is partly involved in thermoregulation [47], a considerable body of research has linked EDA closely with emotional arousal [48]. Activation of the sympathetic nervous system in response to emotionally salient stimuli causes detectable changes in the Skin Conductance Response (SCR).

The intensity of emotional arousal, whether triggered by joy, fear, excitement, or distress, can cause a rise in eccrine sweat gland activity, leading to increased skin conductance [49]. This makes EDA a valuable measure for tracking the strength of emotional responses, though it does not differentiate between emotional types (positive or negative). Notably, the highest concentrations of sweat glands, ranging from 200 to 600 per square centimeter, are found on the palms and soles, making these regions the most common locations for EDA recordings [48, 49].

EDA responses are not under conscious control, as they are regulated by the autonomic nervous system. Because of this, EDA serves as a non-invasive, objective marker for autonomic emotional regulation [50]. It is often used to complement subjective methods such as self-reports or interviews in behavioral studies.

2.4.1 EDA Sensors

Since EDA relies on detecting ionic activity from sweat, electrodes must be both conductive and biocompatible. Modern systems typically use silver/silver chloride (Ag/AgCl) electrodes due to their reliability, affordability, and ability to provide high-fidelity signals. Some electrodes are pretreated with conductive gel to enhance signal quality, while others allow gel application as needed. Once the signal is picked up by the electrodes, it is transmitted via leads to a recording

device. Depending on the system, the signal can be stored onboard, sent wirelessly, or transmitted through a wired connection to a computer.

The electrodes are easy to apply and can measure skin conductance at sampling rates commonly ranging from 10 to 100 Hz or higher, depending on the application and the device used. For phasic EDA analysis (such as SCR detection), a sampling rate of at least 10 Hz is recommended, while higher rates (e.g., 100 Hz) improve temporal resolution and precision. The data is recorded in micro-Siemens (μS), the standard unit for conductance.

2.4.2 Characteristics of EDA Signals

EDA signals consist of two main components: a slow-changing tonic level and a faster-varying phasic component, as shown in Figure 2.7. Tonic levels reflect the overall baseline conductance, while phasic responses are rapid increases triggered by stimuli. These phasic responses typically feature a quick rise to a peak followed by a gradual return to baseline.

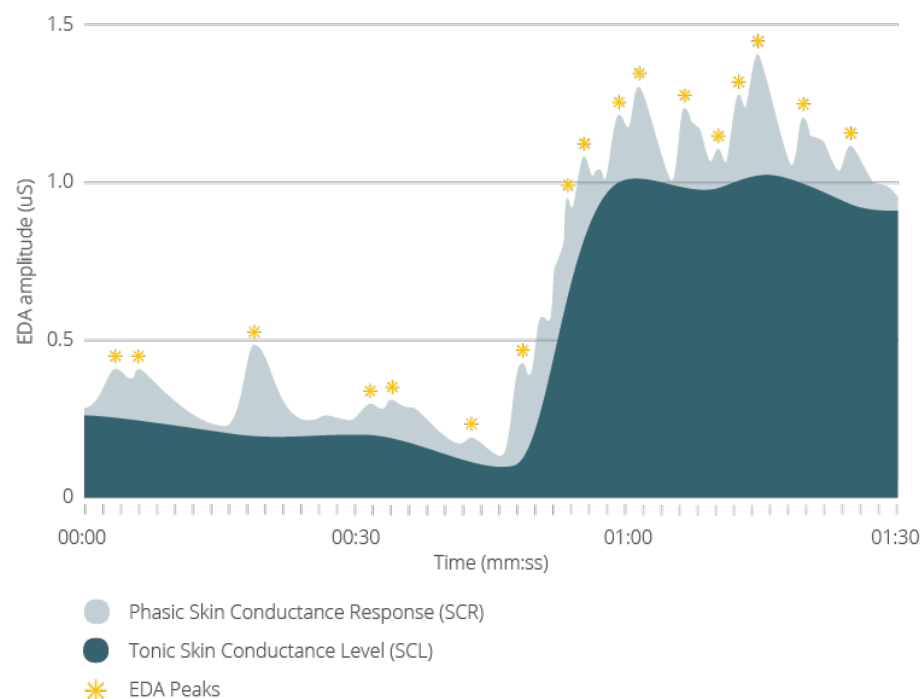


Figure 2.7: Electrodermal activity. Phasic and Tonic components [51]

By quantifying parameters like the number and amplitude of these peaks, researchers can objectively assess emotional arousal. This makes EDA an essential tool for gaining deeper insights into human emotional and cognitive behavior. Figure 2.8 illustrates examples of physiological signals, with EDA on the left and ECG on the right, demonstrating the typical structure of these data.

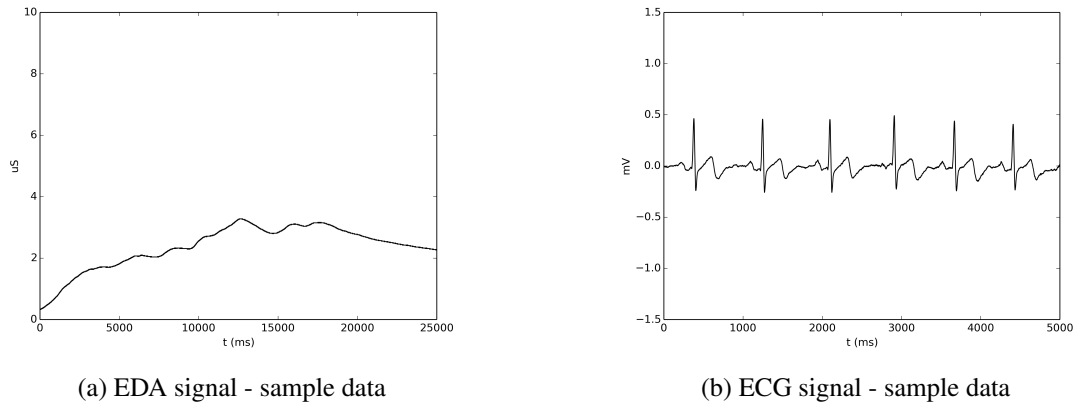


Figure 2.8: Example of sample physiological signals: EDA (left) and ECG (right).

Similarly to ECG, EDA based emotion recognition process also follows a structured pipeline consisting of four main steps:

- Collecting EDA data: Using sensors placed typically on the fingers or palm, where sweat gland density is high.
- Preprocessing the signal: Removing noise and artifacts, often through filtering or smoothing techniques.
- Extracting relevant features: Such as skin conductance level (SCL), skin conductance response (SCR), rise time, and recovery time.

2.4.3 Preprocessing and relevant features

EDA signals are often contaminated with noise and artifacts from motion, environmental changes, or sensor displacement. Consequently, preprocessing plays a crucial role in ensuring the quality and reliability of EDA data. This typically involves:

- **Filtering:** Low-pass filters are commonly used to eliminate high-frequency noise, with cut-off frequencies ranging between 1-5 Hz. High-pass filters may also be applied to remove slow-varying trends.
- **Cleaning:** Movement artifacts are addressed through visual inspection, accelerometer-based detection, or automated techniques such as Support Vector Machines (SVMs).
- **Down-sampling:** To manage data size and processing time, signals are often down-sampled to rates like 10 or 16 Hz.
- **Normalization:** Z-score normalization [52] or range correction is employed to mitigate inter-individual variability. In some cases, baseline recordings, taken during a resting period or neutral video, are used to correct individual differences.

The preprocessing strategy varies significantly depending on the device used, the setting (laboratory vs. real-world), and the signal components of interest (tonic or phasic).

2.4.4 Feature-Based Models

After preprocessing, EDA signals are transformed into meaningful quantitative measures that can support emotion classification. These features are typically categorized into two main components: tonic, represented by the Skin Conductance Level (SCL), and phasic, corresponding to the Skin Conductance Response (SCR). The extraction process commonly involves several types of features, such as:

- **Statistical measures:** including the mean, standard deviation, minimum, maximum, and range of the EDA signal within a given time window.
- **Peak-related metrics:** such as the number of SCRs detected, their frequency, amplitudes, and characteristics like onset latency and recovery time.
- **Segmented averages:** calculated across defined time intervals or specific task-related periods (e.g., every 60 seconds).

To facilitate this process, signal processing toolkits like *Ledalab* [53] and *NeuroKit2* [54] are frequently employed. These tools support both feature computation and the decomposition of EDA into its phasic and tonic elements.

2.4.5 Time-Domain Analysis

Features like the SCL and SCRs are extracted over a specified time period as part of the time-domain analysis of EDA. In order to track changes in EDA during an activity, it is common practice in the literature to divide tasks into one-minute intervals. These characteristics are commonly employed to deduce emotional fluctuations or levels of engagement during educational tasks.

2.4.6 Reference-Based Features

By contrasting task-related EDA activity with a baseline period, typically recorded during a resting or neutral state, reference-based features are obtained. This method aids in accounting for variations in tonic skin conductance among individuals. Standardized scores or difference scores between task and baseline segments are examples of common methods.

2.4.7 Global Features

Instead of focusing on individual SCR events, global features take into account the EDA signal as a whole. This involves figuring out statistical descriptors for the entire session or spotting patterns in the signal using methods like EMD, which records the signal's oscillatory components.

Despite being less common than in ECG analysis, frequency-based methods may still reveal meaningful oscillatory patterns related to stress and emotional states.

Table 2.3 presents a summary of the most commonly extracted EDA features for emotion recognition.

Table 2.3: Summary of EDA features used for emotion recognition.

Category	Examples	Description / Application
Tonic (SCL)	Mean, standard deviation	Represents the baseline skin conductance level.
Phasic (SCR)	Peak count, amplitude, latency	Indicates emotional arousal in response to stimuli.
Reference-Based	Comparison to neutral baseline	Controls for inter-individual physiological differences.
Global Features	Mean, variance of full signal	Captures overall physiological state during session.
Frequency-Domain	Fourier or Wavelet transforms	Less common; used to detect rhythmic stress-related patterns.

2.5 Supplementary Dataset Exploration

As part of the data collection process, and given the limitation of study groups, several publicly available physiological signal datasets compatible with the BITalino platform were explored. These datasets contain real-world biosignal recordings, including ECG and EDA, both of which are central to this research. After a thorough review, three datasets were identified:

- **BIRAFFE & BIRAFFE2 Datasets** [55]: Developed by researchers at AGH University and Jagiellonian University, these datasets include physiological responses recorded via BITalino (r)evolution kits to emotionally evocative stimuli such as standardized multimedia content (e.g., International Affective Picture System (IAPS) images and International Affective Digitized Sounds(IADS sounds) and affective video games. Signals are recorded at 1000 Hz and include ECG and GSR (EDA) data, along with rich metadata such as participant demographics and self-reported emotional states. These datasets provide a valuable source of multimodal emotional response patterns that could inform threshold modeling and engagement classification strategies.
- **DECEiVeR Dataset** [9]: This dataset includes ECG and EDA signals from professional actors enacting predefined emotional states such as tension, calmness, and excitement. Collected with a BITalino device and sampled at 100 Hz, it offers labeled, emotion-driven physiological responses under controlled conditions. The inclusion of both raw and processed signals, along with synchronized video, makes it particularly useful for validating emotion-related biosignal patterns.
- **PhysioNet Spider Phobia Dataset** [56]: This collection features data from individuals with a diagnosed fear of spiders, recorded while viewing fear-inducing video clips. Signals include ECG and EDA, recorded via a BITalino device at 100 Hz. This dataset is of particular interest due to its clear, stimulus-linked arousal patterns and clinical relevance, which could aid in distinguishing emotional intensity thresholds in physiological responses.

While these datasets were not initially part of the primary research design, they may serve as complementary resources for analysis and validation. Given the relatively small size and limited inter-subject variability expected from the planned data collection, it was considered to use selected data from one of these repositories. Such inclusion could enhance the robustness of the threshold determination process for physiological engagement markers.

2.6 Case Studies of Smart Wearable Devices

In all these cases each student is equipped with a wearable device that continuously collects physiological and behavioral data related to engagement. This data is transmitted to a cloud server, or locally, where it is processed and analyzed, which is illustrated in Figure 2.9. The results are then made accessible through a platform that allows the assessment via dedicated applications. The following diagram illustrates the overall architecture of this systems.

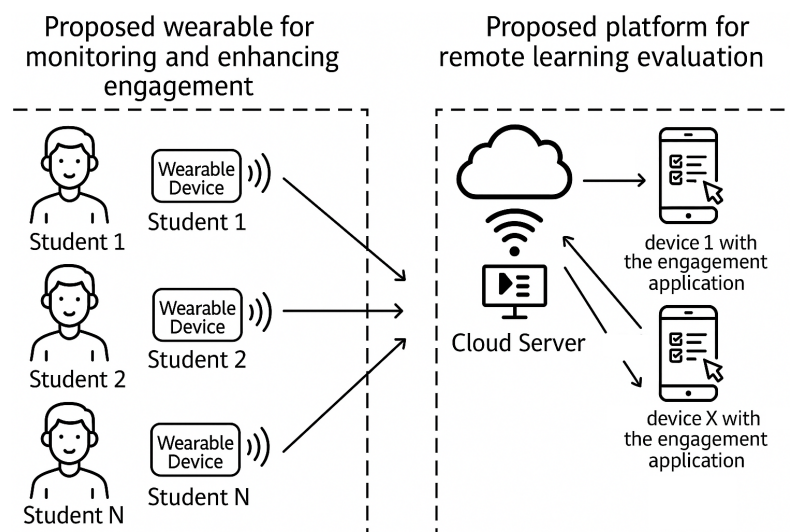


Figure 2.9: Structure of the wearable systems

A notable study from the Faculty of Pharmacy at the University of Hradec Králové, Czech Republic, investigated stress levels in a large sample of 375 pharmacy students by combining physiological data with psychological assessment tools. The researchers used HRV, a reliable physiological marker of autonomic nervous system activity, alongside the Perceived Stress Scale (PSS-10) to evaluate students' stress responses. The study revealed that pharmacy students commonly experience moderate levels of stress during their academic routine. These findings underscore the relevance of HRV-based monitoring through wearable devices as a non-invasive and scalable solution for identifying stress trends in university populations [57].

In another context, biofeedback wearables have proven effective in younger educational environments. At the Amara Berri public school in Spain, researchers implemented a study involving 585 children to assess the impact of biofeedback on stress and anxiety reduction. Utilizing the EmWave biofeedback device in conjunction with the BASC-S2 (Behavior Assessment System for

Children), the intervention demonstrated a significant reduction in stress and anxiety levels among participants. This evidence supports the integration of wearable-based biofeedback technologies as valuable tools not only for monitoring but also for actively improving emotional regulation and well-being in school-aged children [58].

Beyond psychological measures, physiological markers have also been linked to broader health behaviors, such as sleep. A study carried out in South Korea examined the association between students sleep behavior and stress levels in a group of 86 college students. The methodology included HRV analysis and salivary cortisol sampling, providing both objective and biochemical insights into stress. Results indicated that irregular or poor-quality sleep patterns were strongly correlated with elevated stress responses. These findings reinforce the multidimensional value of wearable systems, not only in real-time stress tracking but also in providing feedback on related behaviors like sleep, which can indirectly influence engagement and academic performance [59].

Affordability and accessibility remain critical factors in the broader adoption of wearable technologies in schools and universities. Addressing this, a study from China proposed a cost-effective approach to physiological monitoring through the development of an Arduino-based ECG acquisition device paired with a mobile application. The system, designed for classroom settings, was able to capture ECG data reliably and interpret stress states in real time. This research demonstrates that low-cost solutions can be effectively leveraged for stress detection and management, opening avenues for more inclusive deployment of wearable health monitoring systems across different socioeconomic educational contexts [60].

Collectively, these studies reveal a growing consensus around the utility of wearable devices for understanding and managing stress in academic environments. From validated stress biomarkers like HRV and cortisol, to user-centric feedback platforms that promote behavioral change, wearable technologies are shaping a new era of student-centered, data-informed educational support.

2.7 Commercial Solutions for Monitoring Student Engagement

Biometry devices have become increasingly significant in educational environments, offering new ways to monitor and enhance student performance, engagement, and overall well-being. Table 2.4 highlights key biometry devices used in educational contexts, detailing the type of signals they measure, the sensors involved, data storage methods, and power supply solutions.

Table 2.4: Commercial solutions and their specifications.

Device	Signals Measured	Components	Connectivity	Battery	Platform
Apple Watch	Heart rate, BP, SpO2, movement [61]	PPG, light sensor, 3-axis accel/gyro	Bluetooth	Rechargeable lithium	DAS, NAS, App
BITalino [62]	ECG, EMG, EDA, EEG	MCU, Power, EMG, EDA, ECG, accel, LED	BT 2.0 + EDR, BLE 4.1	700 mAh LiPo (rechargeable)	OpenSignals
Microsoft Band 2 [63]	ECG, temp	Optical sensor, 3-axis accel, gyrometer	Bluetooth 4.0	200 mAh Li-polymer	Not provided
NeuroSky MindWave [64]	EEG, ECG, 12-bit brainwaves, power spectrum	eSense, sensor arm	BT/BLE dual mode	AAA battery	App
OpenBCI Cyton [65]	EEG, EMG, ECG	Not applicable	BLE, USB dongle	3-6 V DC	PC, mobile
Raspberry Pi [66]	Not provided	GPIO, SSH, UART, I2C, SPI, USB, LAN, WIFI, Bluetooth	Various	Not provided	N/A
Samsung S7 Smartphone [67]	Heart rate, SpO2	SpO2, heart rate sensor	Not provided	Rechargeable Li-Ion	S-Health software

Among the wide variety of technologies, EEG became the most used non-invasive physiological measurement tool within educational research. Usually, EEG equipment is used alone but often in combination with other biometric systems, such as electrodermal activity (EDA), eye tracking, electrocardiography (ECG), electromyography (EMG), or blood pressure monitors. Mostly, applications of EEG in the classroom environment center around two main purposes: understanding students' mind states examining physiological constructs, and informing teaching through biofeedback and qualitative approaches.

Physiological responses to stress are especially useful in assessing student performance. Stress analysis is commonly carried out during examinations or tests, showing that increased levels of stress have a negative effect on academic performance and psychological health [68].

According to research, the monitoring of stress levels can improve the quality of a class by recognizing studying behavior and learning engagement patterns. Other physiological constructs like motivation, flow state, concentration, and sustained attention have also been explored, all of which are positively correlated with better educational interventions. Further, mental fatigue has been noted as a concern [69], especially in the case of long school days, in order to underline the necessity of monitoring tools for the management of students' well-being.

Wu *et al.* propose a solution utilizing the **NeuroSky MindWave**, a single-channel EEG wearable device, and algorithms like J48 decision tree analysis and logistic regression to measure and analyze real-time flow states in students. The NeuroSky MindWave records brainwave activity from the dorsolateral prefrontal cortex, focusing on attention and engagement as key flow indicators. EEG data is integrated with self-reported reflective flow experiences (SR-F), the balance of challenge and skill (BCS), and test performance metrics, momentary (MOM-tp) and overall

(OA-tp), to construct a predictive model of flow. Despite these advancements, research on EEG-detected flow states (EEG-Fs) remains underexplored [70].

Ciolacu *et al.* proposed an adaptive Education 4.0 framework using wearables, **Raspberry Pi**, and artificial intelligence for continuous assessment of personalized and technology-enhanced learning. The framework integrates IoT sensors connected to a Raspberry Pi for conducting analyses in the learning environment and student activities, while AI algorithms for early identification of at-risk students, adapting instruction. First experiments managed to prove significant for improving the level of engagement, learning performance, management of stress, by increasing self-awareness and the level of activity among students [66].

Francisti *et al.* propose a plan wherein smart wristbands and eye-tracking technologies could monitor and further improve student engagement in education. Employing IoT devices, these authors measured an **Apple smartwatch** and Tobii EyeX tracker to measure students' heart rate and eye movements, respectively, when performing time-limited quizzes to investigate how physiological responses relate to performance. Their work consequently shows proof that students who have higher heart rates before being tested tend to score lower, thus establishing that pre-test stress hits directly on the latter [71].

BITalino features a modular design with ECG, EMG, EDA, EEG, and accelerometry sensors. Hasán *et al.* present a solution to recognize student stress levels using wearable sensors during exams. In the research, it monitors ten students with BITalino devices in order to capture ECG and EDA signals. The signals are further processed and classified using machine learning algorithms. It achieved the accuracy of recognition in a range of 86-91% for three states: relaxation, written exams, and oral exams. The system can hence detect the situation of stress in real time to offer insight to develop stress-coping strategies and improve academic achievement [62].

Hafeez *et al.* propose a solution to assess the effects of stress on student exam performance using EEG signals. The study involved 14 students performing mental arithmetic tasks (MAT) under two conditions, timed and untimed. EEG data was collected to measure the power spectral density (PSD) of theta, alpha, and beta frequency bands, revealing that timed tests induced higher stress levels, which correlated with lower performance. The results highlight EEG's potential in identifying stress-induced performance degradation.

Khalid Oweis *et al.* use **Microsoft Band 2**, to capture students' GSR for analyzing their emotional and psychological states. In this research, nineteen engineering students were followed in classes for one semester, relating the obtained GSR signals to the level of their weekly activity according to surveys conducted through the Internet. One-Way Analysis of Variance and Correlation Analysis have pointed to a high intra-group significant difference and very good correlations of GSR values with activity levels, which justifies the efficiency of wearable technology in making inferences concerning students' engagement and emotional state within a learning environment [63].

Hunasgi *et al.* gives a solution to assess academic stress in dental students by measuring physiological markers such as heart rate, oxygen saturation, and stress levels using the **Samsung S7 Smartphone**, with its S-Health software.

The study monitored 70 third-year dental students during university practical exams, comparing stress levels before and after viva sessions. Results showed significantly higher stress markers in the previva stage, highlighting the impact of examination stress. The study suggests implementing stress-reduction techniques to mitigate anxiety and improve student well-being and performance in high-pressure academic environments [67].

While Table 2.4 provides a technical overview of the commercial wearable solutions available for physiological signal monitoring, it does not fully address their educational relevance. Therefore, Table 2.5 offers a critical comparative analysis of selected wearable devices with a focus on their applicability in remote learning environments. This table evaluates each device based on its technical features, estimated cost, signal measurement capabilities, demonstrated educational impact, and critical remarks regarding usability and suitability for classroom or research contexts.

Table 2.5: Comparative analysis of wearable devices for monitoring student engagement in educational settings. The table evaluates devices based on cost, signal measurement capabilities, educational impact and usability remarks.

Device	Cost (approx.)	Educational Impact	Critical Remarks
Apple Watch	High (>€300)	Correlates heart rate with performance; useful for passive monitoring.	Discreet and popular, but expensive and lacks EDA. Limited access to raw data.
BITalino	Moderate (€150 -€300)	Used in research to monitor stress and engagement with high accuracy.	Versatile and affordable, but less practical for everyday use. Ideal for labs and controlled experiments.
Microsoft Band 2	Moderate (€250 , discontinued)	Showed correlation between EDA and engagement in Engineering students.	Useful multisensor device, but obsolete. Good historical proof-of-concept.
NeuroSky MindWave	Low (€130)	Detects flow states and cognitive engagement in educational tasks.	Easy to use, but limited data and proprietary metrics. Good for demonstrations.
OpenBCI Cyton	High (>€500)	High resolution for detailed studies on attention and emotional states.	Excellent for research, but complex and uncomfortable for classroom use.

The comparative analysis in Table 2.5 highlights a trade-off between research-grade wearables (e.g., BITalino, OpenBCI) and consumer-oriented devices (e.g., Apple Watch, NeuroSky). Research tools offer richer physiological data but lack usability for everyday classroom settings, while commercial devices are more user-friendly but often restrict access to raw data and lack key sensors like EDA. No single solution fully balances accuracy, comfort, and scalability, suggesting the need for hybrid approaches and further validation of wearables in real-world educational contexts.

In teaching and learning assessment, wearable and mobile devices have been useful in giving real-time feedback. Questionnaires and biofeedback techniques have also been used in assessing lesson effectiveness and identifying cognitive misconceptions among learners. HR is another commonly used NPM (Non-Physiological Metric) within classroom settings, measured via ECG or photoplethysmography (PPG).

Although, wearables in education face challenges like heterogeneity in the devices used and diversity in data processing techniques create barriers to result comparability between studies.

2.8 Limitations of Current Systems

In spite of the encouraging progress in wearable technologies for education, current systems have several shortcomings that motivate the creation of a novel solution.

First, numerous studies use isolated physiological signals, i.e., EEG or EDA, without combining multimodal data capable of offering a more complete picture of student engagement. Second, most commercial and research-level systems do not support real-time feedback functionality personalized for both students and teachers, which hinders their everyday use in dynamic learning settings. Third, the heterogeneity of wearable devices and data processing techniques significantly complicates standardization and comparability across studies. Variations in sensor quality, data formats, sampling rates, and preprocessing algorithms, both between different brands and even between models of the same brand, make it difficult to harmonize data for large-scale or multi-study analyses [72].

Moreover, the lack of interoperability and transparency in proprietary platforms often prevents direct comparison or replication, further limiting their research utility. Fourth, most solutions rely on costly or proprietary hardware, making them less affordable for wider educational use. Last but not least, there is no customizable, open-source platform facilitating the acquisition and processing of signals like ECG for an educational environment. These shortcomings demonstrate the necessity for an inexpensive, modular, and real-time engagement monitoring system based on physiological signals like ECG and EDA proposed in this dissertation.

The proposed system addresses several of these limitations. First, by simultaneously acquiring ECG and EDA signals, it overcomes the single-modality restriction of many current solutions. Second, the desktop application delivers immediate biofeedback to learners and teachers, filling the real-time feedback gap. Third, using the open-source BITalino platform and a transparent processing pipeline promotes reproducibility and comparability across studies. Finally, the low cost of BITalino hardware meets the need for affordable solutions and avoids proprietary black-box devices.

Chapter 3

Proposed Solution

In this chapter, the solution for the proposed problem will be presented, taking into account the background and state-of-the-art analysis conducted in the previous chapters.

The proposed solution for monitoring and enhancing student engagement in remote learning environments makes use of the BITalino or BITalino (r)evolution platforms, shown in Figure 3.1, along with a standard personal computer and a user-friendly interface. The system is designed to collect physiological data during online learning activities, such as watching educational videos or participating in virtual classes, which are considered representative of remote learning contexts. Physiological signals such as ECG and EDA are widely recognized as robust indicators of attention, emotional arousal, and engagement in learning contexts. In the last section, studies demonstrated that HRV measures from ECG correlate with cognitive load and engagement, while SCRs provide sensitive markers of sympathetic activation.

BITalino was selected because it offers validated ECG and EDA modules, allowing simultaneous multimodal acquisition at a sampling rate appropriate for HRV and EDA analysis. Moreover, BITalino is low-cost, modular, and manufacturer-independent, enabling easy integration with custom software and aligning with the projects goal of developing an affordable and open solution.

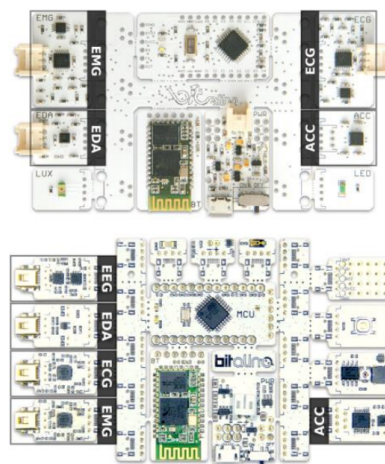


Figure 3.1: BITalino (top) and BITalino (r)evolution (bottom) platforms

Whereas the system was initially envisaged to rely on embedded platforms such as Raspberry Pi, as we are dealing with remote learning, this setup uses a regular computer to collect and process the data. The signals acquired by the BiTalino are transmitted to the computer via Bluetooth, where they can be filtered and processed. From there, the data is sent directly to the computer storage for further analysis.

While advanced features like dedicated databases, data anonymization, or role-based access control are not implemented at this stage, the system architecture leaves room for these enhancements in future developments. For now, the focus remains on capturing reliable engagement-related biosignals and making them available for analysis.

3.1 Solution Architecture

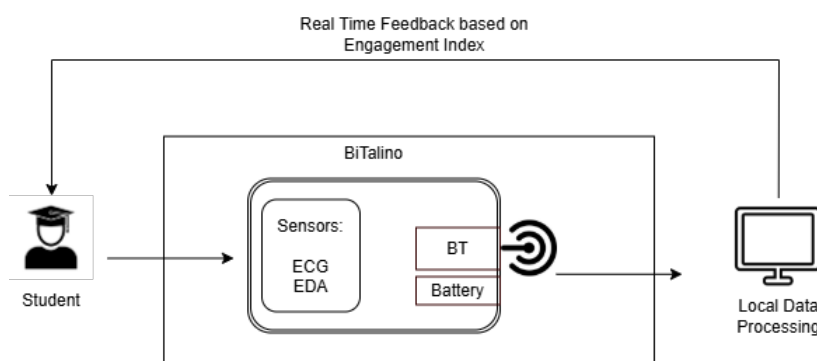


Figure 3.2: High Level Architecture

The signal acquisition flowchart presented in Figure 3.2 shows the developed system.

The student wears a BiTalino device equipped with ECG and EDA sensors which are responsible for capturing heart activity and electrodermal responses respectively both of which are reliable indicators of cognitive attention emotional arousal and engagement levels.

The BiTalino device is wireless, powered by a rechargeable battery, and transmits data via Bluetooth to a nearby computer, which acts as the local processing hub. This computer receives the raw physiological signals and performs essential preprocessing tasks such as filtering noise, correcting signal drift, segmenting relevant portions of the signal, and preparing the data for analysis. Once the data is preprocessed, it is analyzed locally using predefined algorithms to assess engagement levels, detect patterns of distraction or stress, and extract meaningful insights about the students state during the learning process. These insights are then used to trigger adaptive feedback mechanisms, such as real-time alerts, aiming to re-engage the student or support self-regulation of attention.

3.2 Methodology

In this study, physiological data are acquired using biomedical sensors in order to support the classification of emotional states based on Russells two-dimensional circumplex model, as illustrated in Figure 2.2. According to this model, emotions are represented along two axes: valence (indicating the pleasantness of an emotion) and arousal (indicating its intensity). For example, calmness corresponds to high valence and low arousal, while stress corresponds to high arousal and low valence.

The acquired signals include electrocardiogram (ECG) and electrodermal activity (EDA), which are commonly used to infer emotional states. The following subsections describe the acquisition setup and the signal processing techniques applied to each modality.

3.2.1 ECG Signal Processing

The ECG signal was acquired using the *BITalino (r)evolution* board, with the sensor connected to analog input A2. Data was collected via the *OpenSignals* software and exported in plain text format. The file includes a metadata header followed by rows of raw sample data.

3.2.1.1 Data Format and Acquisition

The exported file includes the following columns: sequence number (nSeq), digital inputs (I1, I2), digital outputs (O1, O2), and analog input A2, where the ECG signal was recorded. The data were sampled at a rate of 100 Hz, with each analog sample represented by a 10-bit resolution ADC value ranging from 0 to 1023.

3.2.1.2 ADC-to-mV Conversion

To convert raw ADC values into millivolts (mV), the following transfer function, based on the BITalino ECG sensor specifications, was used:

$$ECG(V) = \left(\frac{ADC}{2^n} - \frac{1}{2} \right) \cdot \frac{V_{CC}}{G_{ECG}} \quad (3.1)$$

$$ECG(mV) = ECG(V) \cdot 1000 \quad (3.2)$$

Where:

- ADC is the raw digital value from the analog channel (0-1023),
- $n = 10$ is the resolution of the ADC,
- $V_{CC} = 3.3\text{ V}$ is the supply voltage,
- $G_{ECG} = 1100$ is the gain of the ECG amplifier.

This conversion results in ECG values ranging approximately between **-1.5 mV and +1.5 mV**, centered around 0 mV. The offset correction ensures that the plotted signal reflects true physiological variations without artificial displacement from the midpoint of the ADC range.

3.2.2 EDA Signal Processing

The Electrodermal Activity (EDA) signal was also recorded using the BITalino system, with the EDA sensor connected to an analog channel (A3). The data were exported in the same plain text format, with raw ADC values representing skin conductance levels.

3.2.2.1 ADC-to-Microsiemens Conversion

The conversion from ADC values to skin conductance in microsiemens (μS) is defined by the following equations:

$$EDA(\mu S) = \frac{ADC}{2^n} \cdot \frac{V_{CC}}{0.132} \quad (3.3)$$

$$EDA(S) = EDA(\mu S) \cdot 10^{-6} \quad (3.4)$$

Where:

- $EDA(\mu S)$ is the EDA signal in microsiemens,
- $EDA(S)$ is the EDA signal in siemens,
- ADC is the raw digital value (0-1023),
- $n = 10$ is the ADC resolution,
- $V_{CC} = 3.3 V$ is the supply voltage.

The valid physiological output range of the sensor is between **0 μS and 25 μS** . During processing, offset correction and scaling were applied to align the signal within this range. This ensures accurate interpretation of skin conductance changes over time, which are commonly associated with autonomic nervous system activity.

3.2.3 Data Pre-processing

In addition to the raw log files obtained from the biomedical sensors, a statistical summary and feature-based annotation of the data were also generated. Feature extraction is a fundamental step in signal processing, as it allows for the reduction of data dimensionality while preserving the most relevant information for subsequent analysis.

Although this project does not involve training machine learning models, the extracted features provide a structured and interpretable representation of the biosignals, which can support further

analysis or integration with external systems. For this purpose, the BioSPPy toolbox [73] was used- a Python-based library designed for biosignal processing that integrates a range of signal processing and pattern recognition techniques.

Before feature extraction, it was necessary to apply pre-processing techniques to clean the signals and improve their interpretability. For the ECG signals, a bandpass filter was used to retain only the frequency components relevant for cardiac activity, typically within the range of 0.5-40 Hz. This filter effectively removes low-frequency drift (such as baseline wander due to respiration or electrode movement) and high-frequency noise (such as muscle artifacts). To further reduce interference, particularly from electrical mains noise common in indoor environments, a notch filter centered at 50 Hz was applied. This is a standard procedure in Europe, where power line frequencies tend to contaminate biosignals.

Following signal pre-processing, the next critical step involved identifying R-peaks in the ECG signals. R-peaks represent the dominant upward deflection in the QRS complex and correspond to the electrical depolarization of the heart's ventricles. To detect R-peaks, the Pan-Tompkins algorithm was employed through the `ecg` function of the `biosppy` library. This method is widely recognized for its robustness in ECG processing and combines several preprocessing stages (band-pass filtering, derivative, squaring, and moving window integration) with an adaptive thresholding mechanism. Unlike fixed threshold approaches, the Pan-Tompkins algorithm continuously adjusts its detection criteria based on the amplitude of recent QRS complexes and noise levels. Two core principles guided its operation in this study:

- **Adaptive thresholding:** Instead of relying on a fixed percentile of the signal amplitude, the algorithm dynamically updates decision thresholds to distinguish true QRS complexes from noise or minor fluctuations.
- **Refractory period:** A minimum interval of approximately 0.20-0.25 seconds was imposed between successive detections, corresponding to a maximum heart rate of 240-300 beats per minute. This constraint ensures that only one R-peak is detected per cardiac cycle.

Each detected R-peak was assumed to represent an individual heartbeat. By calculating the time difference between consecutive R-peaks, known as inter-beat intervals (IBIs) or RR intervals, it was possible to construct a sequence of temporal heart activity. The RR intervals were computed using the sampling rate ($f_s = 100$ Hz) as follows:

$$RR_i = \frac{R_{i+1} - R_i}{f_s} \quad (3.5)$$

From the RR intervals, the instantaneous heart rate (HR) was derived as:

$$HR_i = \frac{60}{RR_i} \quad (3.6)$$

This yields the HR in beats per minute (bpm), allowing the extraction of dynamic cardiovascular information over time.

Although the R-peak detection and HR/HRV computations were performed on the complete 15-minute signals, only the first 30 seconds of each ECG recording were plotted for visual inspection. This choice was made to improve clarity and interpretability: plotting the full-length signals (90,000 samples at 100 Hz) would result in excessively dense and visually cluttered figures. In contrast, zooming into a shorter time window allows clear visualization of the QRS morphology and confirms the validity of the peak detection method.

For EDA signals, a lowpass filter with a cutoff frequency of 5 Hz was applied. EDA signals are inherently slow-changing and reflect variations in skin conductance due to sympathetic nervous system activity. The lowpass filter helps suppress high-frequency noise, ensuring a smoother signal and facilitating the detection of key features such as SCRs.

These filtering methods were chosen for their balance between simplicity, computational efficiency, and their widespread use in physiological signal processing. By reducing noise and isolating the relevant signal components, the pre-processing stage enhances the reliability of the extracted features and ensures that subsequent analyses reflect genuine physiological activity rather than artifacts or measurement errors.

Chapter 4

Implementation

In this part of the implementation, we proceed with the data acquisition phase using physiological sensors.

4.1 Data Gathering

4.1.1 Electrode Placement for EDA

The EDA sensor measures changes in skin conductance associated with sweat gland activity, which is modulated by the sympathetic nervous system. BITalino's EDA sensor uses two measuring electrodes.

Recommended Placement: The electrodes should be placed on the anterior side of the hand, typically on two adjacent fingers, such as the index and middle fingers. This area is rich in eccrine sweat glands and yields strong EDA signals.

- **Positive Electrode (+):** Red sleeve
- **Negative Electrode (-):** Black sleeve

The position of the electrodes can be interchanged, provided the same configuration is used consistently, which can be seen in Figures [4.1](#) and [4.2](#).

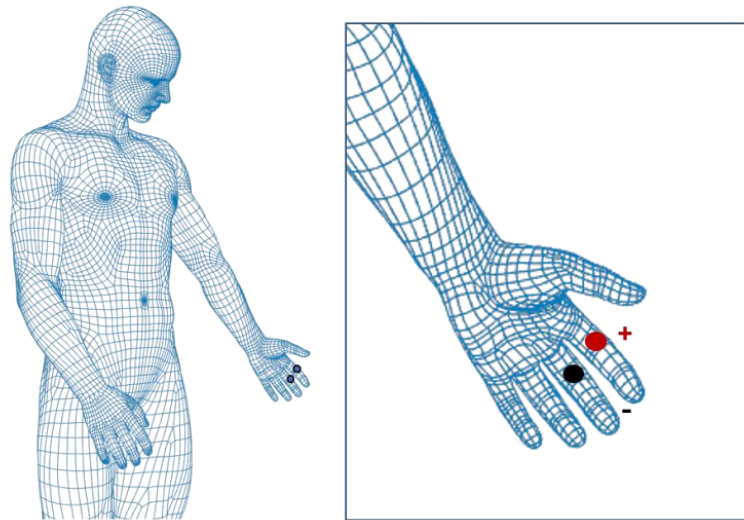


Figure 4.1: Example electrode placement on index and middle fingers for EDA acquisition [74].

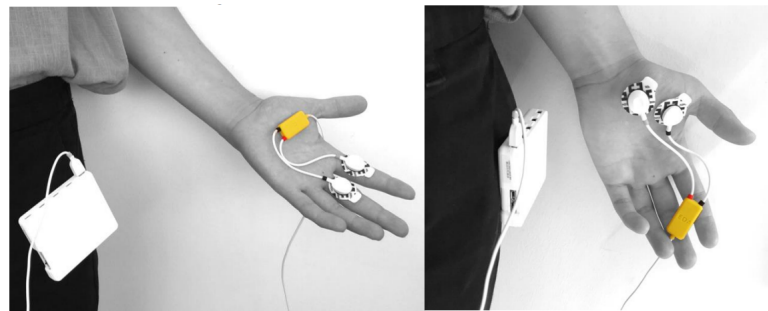


Figure 4.2: Alternative EDA electrode placements: anterior side of the hand on the index and middle finger (left) and below the thumb (right) [74].

4.1.2 Electrode Placement for ECG

The ECG sensor captures the electrical activity of the heart via a triode electrode configuration: one positive, one negative, and one reference electrode. It can be seen in Figure 4.3 and 4.4, which illustrate the electrode placements for Einthoven leads when using a short cable ECG sensor and a long cable, respectively.

Einthoven Triangle Configuration: The sensor supports standard Einthoven configurations, as shown in Table 4.1.

Table 4.1: Einthoven lead configurations for ECG electrode placement.

Lead	Positive (+)	Negative (-)	Reference
I	Left Arm (LA)	Right Arm (RA)	Left Leg (LF)
II	Left Leg (LF)	Right Arm (RA)	Left Arm (LA)
III	Left Leg (LF)	Left Arm (LA)	Right Arm (RA)

Color Coding:

- **Red sleeve:** Positive electrode (+)
- **Black sleeve:** Negative electrode (-)
- **White sleeve:** Reference electrode

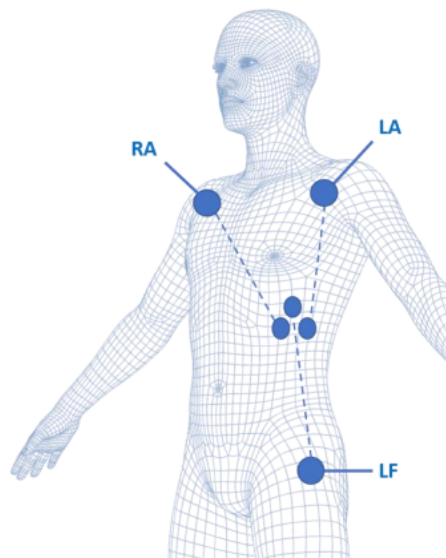


Figure 4.3: Electrode placements for Einthoven leads using short cable ECG sensor [75].

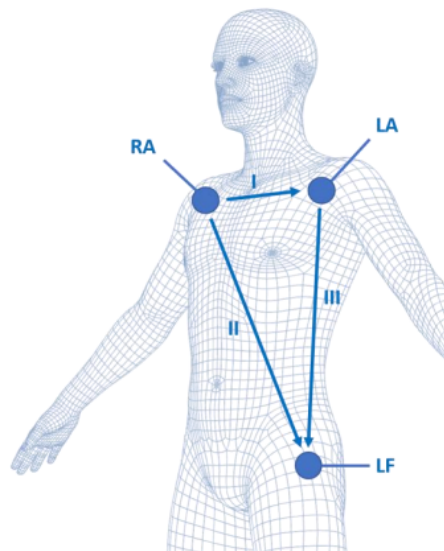


Figure 4.4: Electrode placements for Einthoven leads using long cable ECG sensor [75].

Note: A two-electrode configuration (positive and negative only) is also available for simplified applications, such as basic heart rate monitoring. However, the absence of a reference electrode may increase baseline noise.

4.1.2.1 Best Practices

- Apply electrodes on clean, dry, and unbroken skin.
- Avoid areas with excessive hair or over bony prominences.
- Ensure cables are secured to minimize movement artifacts.

After the data acquisition process begins, a Bluetooth connection must be established with the BITalino board using a socket based on its MAC address. Along with this connection, configuration parameters such as the sampling rate and the selected acquisition channels are sent to the board. The available sampling rates are 1, 10, 100, or 1000 samples per second; in this case, 100 Hz was chosen to obtain a more precise representation of the pulse waveform.

The acquisition channels specify which BITalino sensors will be activated, for this project, the ECG and EDA modules were selected. These signals are transmitted with a 10-bit resolution. Both the sampling rate and the acquisition channels are encoded into individual byte frames and sent to the board to initiate data acquisition.. Once activated, the board begins transmitting data via Bluetooth along with a timestamp.

4.1.3 Biofeedback Application Interface and Real-Time Feedback

To support the real-time monitoring and analysis of student physiological signals, a custom desktop application was developed using Python's Tkinter library for graphical interface design [76] and the BITalino API for Bluetooth communication. This application enables acquisition, filtering, and analysis of both ECG and EDA signals from the BITalino (r)evolution device and provides intuitive feedback based on physiological states.

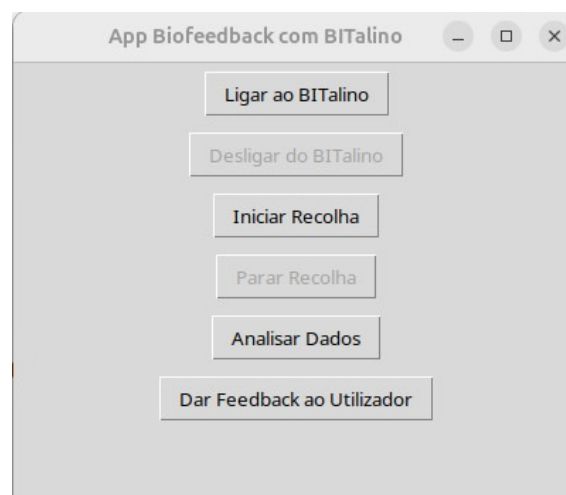
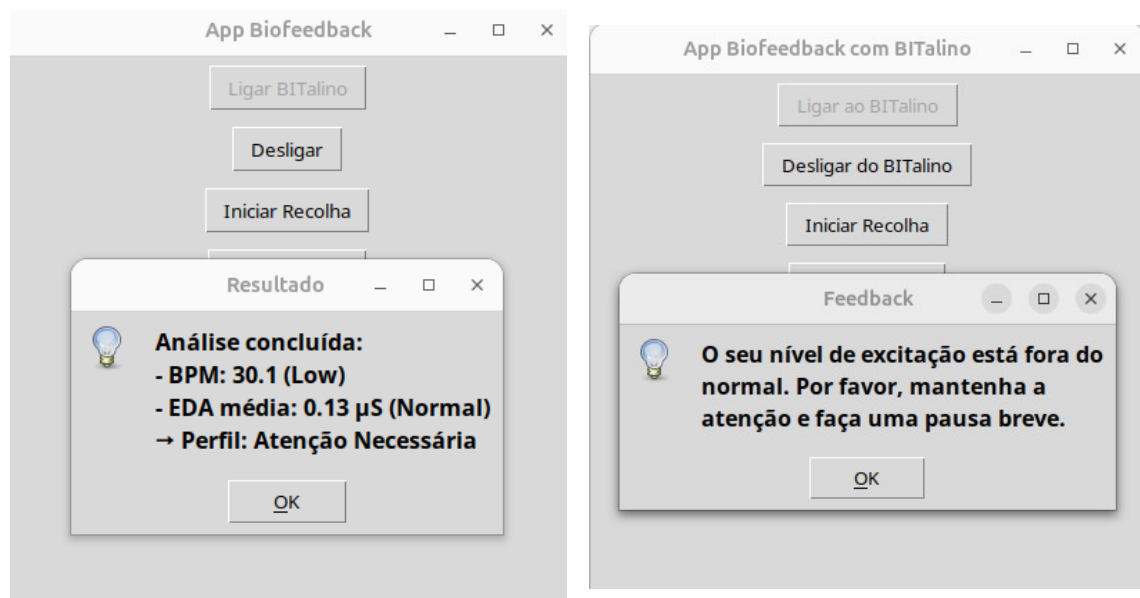


Figure 4.5: Screenshot of the biofeedback applications user interface developed using Python's Tkinter library.

The user interface includes buttons for connecting and disconnecting the BITalino device, starting and stopping signal acquisition, analyzing the collected data, and generating feedback.

During the acquisition phase, the application collects ECG (via analog input A2) and EDA (via analog input A3) signals at a sampling rate of 100 Hz. This rate is adequate for ECG analysis, allowing precise detection of R-peaks, and more than sufficient for EDA, where lower sampling rates (10–32 Hz) are typically acceptable. Higher rates, such as 1000 Hz, were intentionally avoided as they would unnecessarily increase data volume, processing time, and noise without improving signal quality for the intended analyses. These signals are preprocessed in real-time using bandpass and low-pass filters, respectively, to remove noise and highlight relevant features.

After the data is collected, the system automatically extracts heart rate (via peak detection on the ECG) and computes the mean EDA. Based on this information, a simple classification is performed. Heart rate is categorized as *Low*, *Normal*, or *High*, while EDA is categorized as *Normal* or *High*, based on heuristic thresholds. A combination of these results allows the system to infer the students biofeedback profile, categorized either as **Calm State** or **Needs Attention**.



Physiological Analysis Result Window

Immediate Feedback Window to the User

Figure 4.6: Feedback Windows

A simple rule-based threshold method was used to classify physiological states, specifically, heart rate values below 60 bpm were considered low, values between 60 and 100 bpm were considered normal, and values above 100 bpm were classified as high. For EDA, values equal to or greater than $8.5 \mu\text{S}$ were flagged as high, while values below this threshold were deemed normal. Based on the combination of these two indicators, a classification was assigned: if both HR and EDA were within normal ranges, the system labeled the state as *Estado Calmo* (Calm State); otherwise, it triggered an *Atenção Necessária* (Attention Required) alert.

This analysis is followed by real-time feedback to the student, shown via a dialog box in the application. If elevated physiological arousal is detected (e.g., high heart rate or increased skin conductance), the user receives a recommendation such as: “*High level detected! Take a*

break.” Conversely, if the physiological signals are within normal ranges, a motivational message is shown: *“Signals normal. Keep going!”*

This biofeedback mechanism supports the goals of this dissertation by providing learners with real-time awareness of their physiological state during remote learning sessions. It promotes self-regulation and enables early detection of stress or disengagement, which are crucial for maintaining high levels of engagement in virtual environments.

4.2 Feature Selection

In this study, physiological data are acquired using biomedical sensors in order to support the classification of emotional states based on Russells two-dimensional circumplex model, as illustrated in Figure 2.2. According to this model, emotions are represented along two axes: valence (indicating the pleasantness of an emotion) and arousal (indicating its intensity). For example, calmness corresponds to high valence and low arousal, while stress corresponds to high arousal and low valence.

To define and validate the emotion recognition method from physiological signals, this study employed the DatasEt aCting Emotions Valence aRousal (DECEiVeR dataset) [77], which was designed to capture deliberately elicited emotional states through internal input. The dataset involved 11 professional Portuguese actors who portrayed five target emotions—neutral, calm, tiredness, tension, and excitement—using mental imagery instead of external stimuli. This approach aimed to enhance ecological validity while maintaining experimental control. Data collection occurred across two sessions, spaced fifteen days apart, resulting in approximately seven hours of multimodal physiological recordings.

The recordings included EDA, ECG, respiration (PZT), facial electromyography (EMG), and accelerometer (ACC) data. ECG was collected using a standard Lead II configuration, and EMG was measured from the corrugator supercilii and zygomaticus major muscles. Acquisition was performed using BITalino hardware with an R-IoT module for wireless transmission and was recorded via custom software in MaxMSP.

For the scope of this study, only the EDA and ECG signals were retained. The remaining signals were excluded to streamline the analysis pipeline. The selected signals underwent preprocessing and feature extraction using the BioSPPy library.

The selection of specific features from ECG and EDA signals was grounded in their well-documented relevance in the literature for emotion and engagement recognition, as detailed in Sections 2.3 and 2.4. ECG-derived features were selected due to their established sensitivity to autonomic nervous system dynamics and ability to effectively capture variations in physiological arousal, attention, and emotional states, which are critical dimensions in engagement monitoring.

Similarly, EDA features were chosen to reflect both tonic and phasic components. These metrics provide a reliable measure of sympathetic nervous system activation and are widely used to quantify emotional arousal. The features used for emotion classification and their physiological interpretations are listed in Table 4.2.

To model **arousal**, features reflecting **sympathetic nervous system activity** were selected:

- **Mean heart rate**: increases with emotional and physiological arousal.
- **SCR count**: represents the frequency of sympathetic responses. Although EDA was normalized, SCR peaks were still detectable and serve as relative indicators of arousal.

Arousal index (sympathetic activation):

$$\text{Arousal}_i = \text{mean}(z_{\text{HR},i}, z_{\text{SCR_Count},i}) \quad (4.1)$$

Both features are direct readouts of sympathetic activation. SCR frequency scales almost linearly with sudomotor bursts, while HR rises whenever sympathetic drive increases (or parasympathetic braking is released). By normalizing first, each marker contributes on the same statistical scale; taking their mean produces a noise-reduced composite that tracks physiological arousal.

To model **valence**, features related to **parasympathetic regulation** and emotional balance were used:

- **Sample entropy (SampEn)** of ECG: reflects system adaptability and is linked to positive affect.
- **Poincaré plot metrics (SD1, SD2)**: capture short- and long-term HRV dynamics, associated with emotional regulation.
- **Reciprocal LF/HF ratio**: higher values of this ratio suggest greater parasympathetic activity and are often associated with positive valence and relaxed emotional states.

Valence index (parasympathetic–sympathetic balance):

$$\text{Valence}_i = \text{mean}(z_{\text{SampEn},i}, z_{\text{SD1},i}, z_{\text{SD2},i}, z_{1/\text{LF/HF},i}) - \text{mean}(z_{\text{HR},i}, z_{\text{SCR_Count},i}) \quad (4.2)$$

Higher values of *SampEn*, *SD1*, *SD2*, and *1/LF HF* reflect stronger parasympathetic influence which is an autonomic profile consistently associated with positive affect, social engagement, and better emotional regulation. Subtracting the sympathetic average, operationalizes the classic *sympatho–vagal balance* principle [78]: **positive valence** emerges when vagal activity outweighs sympathetic drive, whereas **negative valence** arises when the opposite is true.

Table 4.2: Selected features for emotion classification and their physiological–emotional interpretations.

Feature	Dimension	Physiological Meaning	Emotional Relation
mean_hr	Arousal	Cardiac activation (sympathetic tone)	$\uparrow \text{HR} \Rightarrow \uparrow \text{Arousal}$
SCR_count	Arousal	Sympathetic burst frequency	$\uparrow \text{SCRs} \Rightarrow \uparrow \text{Arousal}$
sd1, sd2	Valence	Short/long-term HRV geometry (relaxation)	$\uparrow \text{SD1/SD2} \Rightarrow \uparrow \text{Valence}$
sampen	Valence	HRV complexity (emotion regulation)	$\uparrow \text{SampEn} \Rightarrow \uparrow \text{Valence}$
1/LF_HF	Valence	Vagal dominance (lower stress burden)	$\uparrow (1/\text{LF}/\text{HF}) \Rightarrow \uparrow \text{Valence}$

All physiological features were first normalized to the range $[-1, 1]$ according to the equation 4.3 to ensure comparability across participants and mitigate inter-subject variability. Then, the data was segmented based on emotion labels (*neutral, calm, tiredness, tension, excitement*), and the mean of each feature was computed per segment.

$$x' = 2 \cdot \frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \quad (4.3)$$

, where $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of feature x , respectively.

This transformation ensures that each feature is rescaled to lie within the interval $[-1, 1]$, enabling cross-subject comparability and equal contribution from features with different physical units or scales.

Each emotional condition was reduced to two composite scores representing the level of arousal and valence based on the normalized physiological features:

The average normalized arousal and valence values per emotional category were computed and summarized, in the Table 4.3, as follows:

Table 4.3: Mean arousal and valence for each emotional condition.

Emotion	Arousal (z)	Valence (z)
CALM	−1.00	+0.12
EXCITE	+0.77	+0.75
NEUTRAL	+0.16	0.00
TENSION	+0.56	−0.64
TIRED	−0.61	−0.33

4.3 Preliminary Data Analysis and Interpretation

The feature values presented in the following tables were obtained through preprocessing and statistical analysis of physiological data collected of the dataset used. For both features, a CSV file containing ECG and EDA metrics was loaded and grouped by emotion using Python's `pandas` library. The mean values for each emotion category were calculated using `groupby()` and exported to an Excel file for verification.

For ECG, the dataset provided normalized values in the range $[-1, 1]$, lacking the original voltage scale in millivolts (mV). Despite the absence of absolute amplitudes, the temporal morphology of the ECG signal was preserved, which allowed accurate detection of R-peaks. This enabled reliable computation of heart rate (HR) and HRV metrics, such as RMSSD and SDNN, which can be seen in Table 4.4. Since these features are based on the timing between heartbeats (RR intervals), they remain physiologically valid even when derived from a normalized ECG.

For EDA, the available data was also already normalized to a range between -1 and 1 , and did not retain the original units of skin conductance in microsiemens (μS). As such, features that depend on absolute amplitude—such as mean EDA, standard deviation, or SCR amplitude—do not reflect physiological magnitudes and were excluded from interpretation. However, temporal and shape-based features such as the number of skin conductance responses (SCR count) were still considered valid, as they depend on signal dynamics rather than, as presented in Table 4.5. Despite the absence of calibrated EDA values, relative changes and temporal dynamics were preserved, allowing the use of certain features for modeling sympathetic activation.

This dual-modality analysis served two purposes: (1) to identify key physiological features for emotion classification using BITalino recordings, and (2) to model emotions in the valence–arousal space by linking these features to underlying psychophysiological mechanisms.

Table 4.4: ECG characteristics extracted for each emotion.

Emotion	Mean HR	SDNN	RMSSD	PNN50	LF	HF	LF/HF Ratio	SampEn	SD1	SD2
CALM	75.36	65.57	62.76	10.34	2002.31	1390.90	1.85	1.02	44.38	79.39
EXCITE	82.47	109.16	117.99	18.84	6438.76	5793.08	3.28	1.01	83.43	128.07
NEUTRAL	76.95	53.35	52.66	8.25	1257.34	983.34	2.40	1.25	37.24	64.35
TENSION	84.62	73.74	76.16	10.02	2127.40	1824.20	3.62	0.90	53.85	87.29
TIRED	80.41	85.76	87.16	11.60	4002.14	2772.64	2.73	0.92	61.63	103.07

Table 4.5: SCR count per emotion (normalized EDA).

Emotion	SCR Count
CALM	10.09
EXCITE	36.55
NEUTRAL	14.91
TENSION	26.09
TIRED	20.64

Notably, **EXCITE** learning periods showed the highest average HR (~ 82.5 bpm) and significant HRV (RMSSD ~ 118 ms), alongside elevated skin conductance responses (SCR count ~ 36) which indicates strong physiological arousal.

By contrast, **CALM** periods had lower HR (~ 75.4 bpm) and far fewer SCR peaks (~ 10), consistent with a relaxed, less aroused state. Intermediate conditions like **NEUTRAL** and **TENSION** fell between these extremes: for instance, “Tense” moments showed a moderately high HR (~ 84.6 bpm) and a negative valence rating (-0.64 on a normalized scale), suggesting stress or anxiety with relatively high arousal. Interestingly, **TIRED** states showed a moderate HR (~ 80.4 bpm) but

notably high HRV (RMSSD ~87 ms) and many SCRs (~20), which may reflect fluctuating attention or stress as fatigue set in. These physiological patterns align with prior findings; for example, active, cognitively engaging tasks tend to raise students heart rates, and spikes in EDA correlate with moments of heightened engagement or cognitive load.

In the following steps, physiological data will be collected. These signals will be processed using the same pipeline and feature set, and then compared to the results presented here. The goal is to assess whether emotional and engagement-related patterns observed in educational settings align with those seen in the structured DECEiVeR dataset.

Chapter 5

Experimentation and Results

This chapter describes the process of experimentation and findings thereof in the scenario of measuring student engagement in online learning processes.

5.1 Objectives and Hypotheses

The primary objective of the experiment is to evaluate the capability of the BITalino platform to monitor physiological signals (ECG and EDA) and correlate these with self-reported engagement levels during remote learning tasks. The study seeks to validate the system's ability to detect variations in student engagement, provide real-time feedback, and contribute to personalized learning experiences in virtual settings. The following hypotheses guide the experimental design:

- **H4:** HRV features, including SDNN, RMSSD, and Poincaré plot metrics (SD1, SD2), differ significantly between high-engagement tasks (e.g., coding, quizzes) and low-engagement tasks (e.g., video watching, reading), reflecting distinct levels of cognitive and emotional involvement.
- **H5:** EDA is higher in high-arousal conditions (e.g., time-constrained quizzes, interactive coding tasks) compared to low-arousal conditions (e.g., passive video watching), indicating increased sympathetic nervous system activation.
- **H6:** Self-reported engagement, measured through valence and arousal scores on a 1–9 scale, correlates positively with physiological indices such as HR, HRV metrics, and SCR count, supporting the alignment of subjective and objective measures of engagement.

These hypotheses test the system's ability to differentiate engagement levels and validate its potential for real-time biofeedback in remote learning environments.

5.1.1 Participants

The experiment involved 20 undergraduate students from diverse academic backgrounds, aged 21–25 years (mean age = 23.0, SD = 1.0). The sample included participants from disciplines such

as Electrical Engineering, Psychology, Architecture, Medicine, Veterinary Medicine, Mechanical Engineering, Computer Science, Social Communication, and Business Administration. All participants had prior experience with remote learning platforms and no self-reported cardiovascular or neurological conditions that might affect physiological signal quality. Each individual gave informed consent (see Appendix A) and participated in ECG and EDA data acquisition using wearable sensors.

5.1.2 Hardware Setup

The BITalino (r)evolution platform was used to acquire ECG and EDA signals at a sampling rate of 100 Hz, sufficient for accurate R-peak detection in ECG and capturing EDA dynamics. The hardware configuration included:

- **ECG Sensor:** Configured with a three-electrode setup using Einthoven leads, as referenced in Table 4.1
- **EDA Sensor:** Electrodes were placed on the index and middle fingers of the non-dominant hand, a region rich in eccrine sweat glands, as shown in Figures 4.1 and 4.2.
- **Connectivity:** Signals were transmitted via Bluetooth Low Energy (BLE) to a laptop running the biofeedback application developed with Python's Tkinter library (Appendix A.2). Initial BLE pairing occasionally introduced minor latency (<50 ms), which stabilized after connection and did not impact data quality.

5.2 Data Collection Protocol

The data collection procedure consisted of 15-minute sessions, during which ECG and EDA signals were recorded simultaneously, followed by self-reported assessments. The protocol was as follows:

1. **Preparation:** Participants were briefed on the study's purpose and provided informed consent (Appendix A). Electrodes were applied according to the specified placements, and the BITalino device was paired with the laptop.
2. **Task Execution:** Participants performed their assigned task (video watching, reading, coding, or quiz) for 15 minutes. ECG (via analog input A2) and EDA (via analog input A3) signals were collected at 100 Hz using the biofeedback application.
3. **Self-Assessment:** Immediately after the task, participants completed a digital self-assessment questionnaire (Appendix A) to report valence (1 = extremely unpleasant, 9 = extremely pleasant) and arousal (1 = very calm, 9 = very activated) levels.
4. **Synchronization:** Physiological and self-reported data were synchronized using participant IDs and timestamps. ECG and EDA signals were stored as CSV files, and self-reported data were exported to Excel for analysis.

The table below outlines the experimental conditions for each participant:

Table 5.1: Summary of participant demographics and data collection activities for 20 students during remote learning tasks. Each participants age, study area, and activity are listed, with ECG and EDA signals recorded for 15 minutes.

ID	Age	Area	Activity Description	ECG	EDA
1	23	Electrical Engineering	Watching a tutorial video	✓	✓
2	23	Psychology	Reading a scientific article	✓	✓
3	23	Electrical Engineering	Attending a live Zoom lecture	✓	✓
4	24	Architecture	Completing an online quiz	✓	✓
5	23	Medicine	Watching a medical case study video	✓	✓
6	23	Veterinary Medicine	Reading academic papers	✓	✓
7	23	Mechanical Engineering	Participating in a virtual lab simulation	✓	✓
8	23	Computer Science	Coding along with a recorded lecture	✓	✓
9	21	Social Communication	Analyzing a multimedia presentation	✓	✓
10	25	Business Administration	Reading a business case study	✓	✓
11	20	Mathematics	Solving problem sets in an online platform	✓	✓
12	22	Education	Watching a teacher training webinar	✓	✓
13	22	Philosophy	Reading a philosophical essay	✓	✓
14	22	Cybersecurity	Doing a CTF challenge	✓	✓
15	24	Medicine	Giving a remote presentation to an audience	✓	✓
16	23	Biomedical Engineering	Watching a VR-assisted live surgery	✓	✓
17	21	Architecture	Collaborating in a real-time group work	✓	✓
18	24	Political Science	Watching legislative debates on YouTube	✓	✓
19	23	Philosophy	Reading dense legal documents silently	✓	✓
20	22	Marketing	Waiting in a virtual lobby for feedback	✓	✓

5.2.1 Design of the Self-Assessment Questionnaire

Participants were asked to complete a short questionnaire immediately after each activity (e.g., video, quiz, reading task). The questionnaire included:

- A unique participant identifier (ID).
- Description of the activity.
- Valence: rated on a 9-point Likert scale (1 = very unpleasant, 9 = very pleasant).
- Arousal: rated on a 9-point Likert scale (1 = very calm, 9 = very excited).

The responses were then normalized to the range $[-1, 1]$ to align with the physiological feature scales and enable visual and statistical comparison in the Valence–Arousal plane. Higher valence indicates a more positive experience, while higher arousal reflects greater physiological and emotional activation.

To estimate engagement levels, an index was computed by summing the normalized valence and arousal values derived for each session:

$$\text{Engagement Index (EI)} = \text{Valence}_{[-1,1]} + \text{Arousal}_{[-1,1]}$$

This index, ranging from -2 to $+2$, serves as a coarse but interpretable proxy for overall engagement, under the assumption that emotionally positive and highly arousing experiences are indicative of greater cognitive and affective involvement. It was used both for descriptive analysis and for comparison with physiological engagement estimates. Based on this value, sessions were categorized into low, medium, or high engagement, as shown in Table 5.2.

Table 5.2: Engagement index and classification for each participant

ID	Valence	Arousal	Index	Engagement
1	0.25	-0.25	0.00	Medium
2	-0.25	-0.50	-0.75	Low
3	0.00	0.25	0.25	Medium
4	0.50	0.50	1.00	High
5	0.25	0.00	0.25	Medium
6	-0.50	-0.75	-1.25	Low
7	0.75	0.75	1.50	High
8	0.00	-0.25	-0.25	Medium
9	0.25	0.25	0.50	Medium
10	-0.25	-0.50	-0.75	Low
11	-0.75	0.50	-0.25	Medium
12	-0.25	0.25	0.00	Medium
13	1.00	1.00	2.00	High
14	1.00	1.00	2.00	High
15	0.75	0.75	1.50	High
16	0.50	0.50	1.00	High
17	0.25	0.25	0.50	Medium
18	-0.25	-0.50	-0.75	Low
19	-0.50	-0.75	-1.25	Low
20	-0.25	-0.50	-0.75	Low

Engagement levels were classified using a heuristic thresholding of the engagement index, where:

- **Low:** $\text{Index} \leq -0.5$
- **Medium:** $-0.5 < \text{Index} < 1.0$
- **High:** $\text{Index} \geq 1.0$

These thresholds were empirically chosen to distribute participants across engagement bands while preserving interpretability. However, future work may employ data-driven approaches such as k-means clustering or Gaussian Mixture Models to refine classification boundaries based on physiological distributions.

5.2.2 Metrics

The experiment utilized a combination of physiological and subjective metrics to assess engagement, defined as follows:

- **Dependent Variables:**

- **Mean Heart Rate (HR):** Calculated from ECG R-peak intervals, reflecting sympathetic activation.
- **HRV Metrics:** SDNN, RMSSD, SD1, and SD2, derived from time-domain and Poincaré plot analyses, indicating autonomic regulation and engagement levels.
- **Mean Tonic EDA:** Represents baseline SCL, associated with sustained arousal.
- **SCR Count:** Number of phasic skin conductance responses, indicating transient arousal events.
- **Engagement Index (EI):** Computed as the sum of normalized valence and arousal scores from self-reports, ranging from -2 to $+2$:

$$EI = \text{Valence}_{[-1,1]} + \text{Arousal}_{[-1,1]}$$

EI serves as a proxy for overall engagement, assuming that positive valence and high arousal indicate greater cognitive and affective involvement.

- **Independent Variables:**

- **Task Type:** Video watching, reading, coding, or quizzes, expected to influence engagement levels.
- **Self-Reported Engagement Level:** Valence and arousal scores, categorized into high, medium, and low engagement bands based on the 1–9 scale.

- **Control Variables:**

- **Time of Day:** Sessions were conducted between 9 AM and 6 PM to minimize circadian rhythm effects.
- **Electrode Positioning:** Standardized placements were verified before each session to ensure signal consistency.
- **Participant Fatigue:** Participants were instructed to avoid caffeine or strenuous activity 2 hours prior to the experiment to control for physiological variability.

Participants self-reported arousal and valence scores from the questionnaire (Appendix A) were used as the ground truth to validate the systems engagement measurements. These scores, rated from 1 to 9, were mapped to High, Medium, and Low engagement categories using Russells circumplex model. For example, high engagement was assigned when arousal and valence were

both 6 or higher, medium for scores between 3 and 5, and low for arousal or valence of 3 or less. This mapping matches the Engagement Index in the data, where scores of 1 or more indicate High engagement, between -1 and 1 indicate Medium, and -1 or less indicate Low. These categories were used to check if the physiological measurements (like heart rate and EDA) accurately reflect engagement.

Also, informal feedback on the Tkinter-based biofeedback user interface, collected from participants during the experiments, highlighted its simplicity and ease of navigation, although they recommended increasing text size for better readability and enhancing the clarity of visual feedback for engagement levels. This methodology establishes a rigorous framework for the experimentation described in this chapter, ensuring that the results are grounded in a systematic and reproducible approach.

5.3 Results and Discussion

To analyze correlations between subjective reports and objective physiological measures, each physiological sample was matched with the corresponding self-report entry using the participant ID. The final dataset includes features such as:

- ECG: mean heart rate, SDNN, RMSSD, sample entropy, SD1, SD2
- EDA: mean EDA, SCR count, mean SCR amplitude, EDA entropy

To understand the relationship between physiological activity and emotional experience, a correlation matrix was computed using features extracted from ECG and EDA signals. As shown in Figure 5.1, strong positive correlations were observed among the time-domain HRV features, such as SDNN, RMSSD, SD1, and SD2, confirming internal consistency of these metrics.

To understand the relationship between physiological activity, emotional dimensions, and engagement, a correlation matrix was computed using features extracted from ECG and EDA signals. As shown in Figure 5.1, strong positive correlations were observed among the time-domain HRV features (SDNN, RMSSD, pNN50, and sample entropy), confirming their internal consistency.

The results show that ECG-derived HRV features are also positively associated with both the Engagement Index and self-reported emotional states. In particular, SDNN and RMSSD demonstrate the strongest correlations with engagement ($r \approx 0.55$ - 0.58 , $p < 0.05$), as well as with both valence and arousal. Mean heart rate, on the other hand, shows only weak and non-significant correlations with engagement and emotions ($r \approx 0.10$ - 0.17).

Electrodermal activity exhibits mixed associations. SCR count shows no meaningful relationship with engagement ($r \approx 0.13$) and only weak, non-significant links with valence and arousal. The mean amplitude of SCRs is negatively correlated with arousal ($r \approx 0.52$, $p < 0.05$), suggesting that higher phasic sympathetic responses may not align with sustained engagement. These findings indicate that autonomic variability, rather than tonic heart rate or phasic EDA responses, provides the most reliable physiological indicators of student engagement.

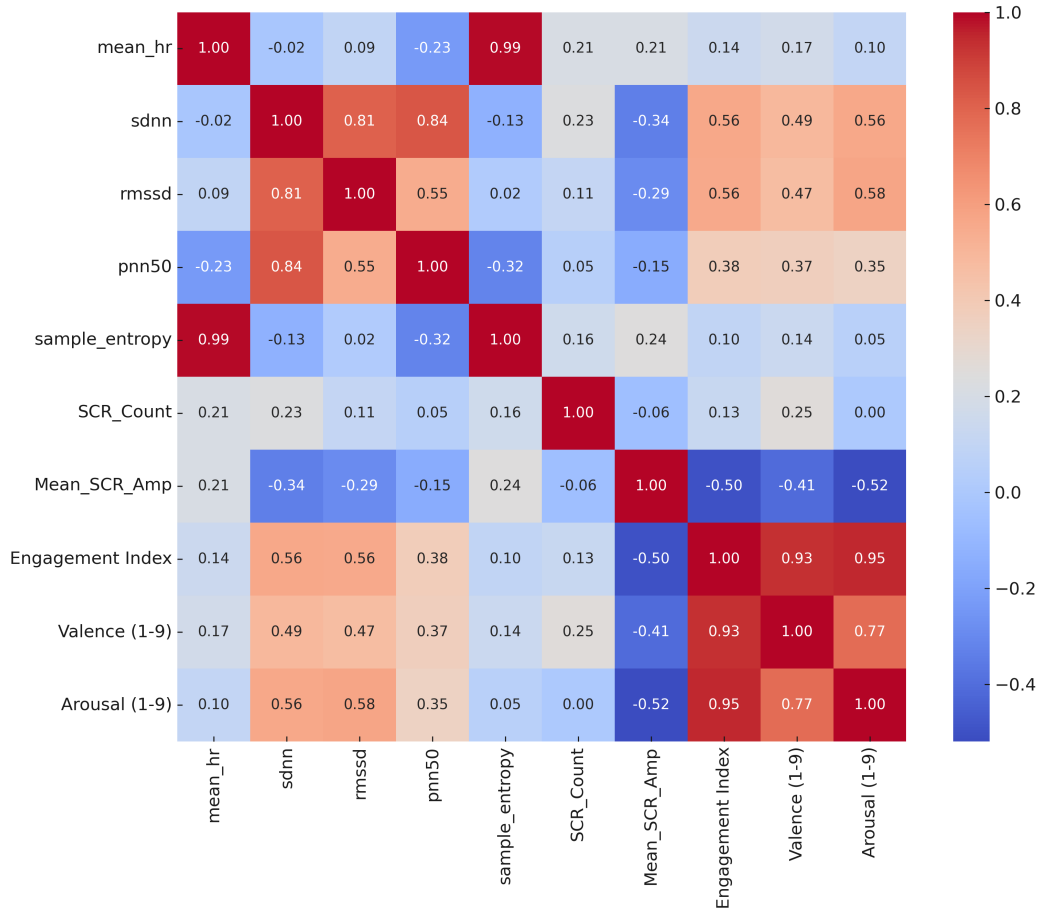


Figure 5.1: Heatmap of Physiological Features and Emotional Dimensions

Altogether, the observed pattern suggests that engagement is marked by enhanced parasympathetic modulation and stable physiological regulation, rather than heightened sympathetic arousal. This aligns with the notion of a calm focus or eustress-like state, where students maintain attention and alertness without excessive physiological stress. The findings support H1, confirming that ECG-derived features, particularly HRV metrics, correlate with self-reported engagement. H2 is only partially supported: while HRV features (SDNN, RMSSD, pNN50) significantly distinguish emotional states across the valence-arousal space, electrodermal measures show weak or negative associations. Regarding H3, the results suggest a refined view: engagement is not characterized by elevated arousal alone but rather by a nuanced interplay of autonomic balance, where parasympathetic variability plays a central role.

5.3.1 Data Overview

Each student completed a 15 min session of mixed learning tasks (video-watching, problem-solving, reading, etc.) and then rated arousal on a 1-9 scale (1 = very calm; 9 = highly excited). Table 5.3 summarizes self-reports and physiological means. Across the students, HR ranged from ~ 70 – 109 BPM (mean = 86.1), tonic EDA from ~ 2.6 – $14.9 \mu S$ (mean = 7.41), and SCR counts

from 39-195 per session. An unexpected pattern emerged when analyzing HRV in relation to self-reported arousal levels.

Contrary to the typical association between high arousal and reduced HRV due to sympathetic dominance, the data revealed that HRV actually increased with arousal. Specifically, participants in the high-arousal group exhibited substantially higher SDNN values (mean ~ 91 ms) compared to those in the low-arousal group (mean ~ 56 ms). This suggests that certain high-arousal states were not purely stress-related (fight-or-flight) but instead reflected dynamic or positively engaging experiences.

Furthermore, the nature of the task significantly influenced physiological responses. Activities involving public speaking or competitive challenges elevated all measured metrics, including heart rate, skin conductance, and HRV, indicating heightened emotional and physiological activation. In contrast, solitary reading tasks were consistently associated with lower physiological activity, reflecting a more passive and less arousing engagement profile. These findings underscore the importance of task context when interpreting physiological data related to arousal and engagement.

Table 5.3: Data table presenting self-reported arousal levels (1-9 scale) alongside physiological metrics (mean heart rate, mean EDA, SCR count) for 20 students during remote learning tasks. Higher arousal scores correlate with increased SCR counts and mean EDA, indicating physiological activation. The table highlights task-specific patterns, with interactive tasks showing higher arousal than passive reading.

Student	Arousal (1–9)	Mean HR (BPM)	Mean EDA (μ S)	SCR (count)
1	4	91.2	12.60	156
2	3	78.6	2.69	50
3	6	74.1	9.26	78
4	7	89.9	7.42	95
5	5	90.5	6.33	70
6	2	69.7	5.36	195
7	8	80.6	7.01	73
8	4	80.7	6.51	118
9	6	78.9	14.88	110
10	3	77.0	7.96	94
11	7	76.4	5.39	39
12	6	103.5	9.77	125
13	9	98.4	8.64	188
14	9	76.4	2.57	95
15	8	105.3	9.77	156
16	7	86.7	7.86	154
17	6	81.7	10.28	68
18	3	84.2	3.98	135
19	2	108.8	5.00	66
20	3	88.8	4.92	138

There were exceptional cases that deviate from group trends, potentially reflecting individual physiological traits or context-specific reactions to their assigned activities:

Student 6 reported low arousal (2/9) but exhibited the highest SCR frequency (195). Despite a calm self-assessment, the student was reading academic papers, an activity that can trigger frequent electrodermal responses due to cognitive load or sustained attention, even in the absence of overt emotional stimulation. This suggests underlying mental effort or highly attentive, not consciously perceived as arousal.

Student 14, who reported maximum arousal (9/9), showed the lowest mean EDA ($2.57 \mu S$) across the cohort. This subject was engaged in a competitive quiz, indicating psychological excitement that was not reflected in skin conductance, consistent with low-responder EDA profiles individuals whose sweat gland activity shows minimal variation even under stress.

Student 19 reported low arousal (2/9) but had the highest mean heart rate (108.8 BPM). While reading a scientific article, the elevated HR could indicate cognitive effort, stress, or individual cardiovascular reactivity, despite the absence of perceived excitement. This mismatch suggests the mental demand of the task may not have been consciously recognized as arousing.

Student 20, also in the low arousal group (3/9), showed elevated HR (88.8BPM) and a high number of SCRs (138) while waiting for personalized feedback. This pattern suggests anticipatory anxiety, a common physiological state characterized by heightened sympathetic activity despite minimal conscious emotional arousal.

5.3.2 Statistical Analysis

To evaluate differences in physiological signals across learning contexts, independent two-sample Welch t-tests were conducted using SciPy to compare HR, heart rate variability (SDNN, RMSSD), SCR count, and Mean EDA between interactive tasks (e.g., quizzes, virtual labs; $n = 7$) and passive tasks (e.g., watching videos, reading; $n = 13$). Pearson correlations were then used to assess relationships between these physiological metrics and self-reported Valence and Arousal scores from the Valence-Arousal Questionnaire (Appendix A).

As illustrated in Table 5.4, no significant differences were observed between interactive and passive tasks for any physiological metric (all $p > 0.15$). For example, RMSSD values were numerically higher during interactive tasks ($M = 74.8$ ms) than passive tasks ($M = 47.9$ ms), but this difference did not reach statistical significance ($t = 1.58$, $p \approx 0.16$). Similarly, mean HR, SDNN, SCR count, and Mean EDA all showed non-significant group differences.

Correlational analysis revealed a different pattern. HRV features (SDNN, RMSSD) exhibited significant positive correlations with both Valence and Arousal ($r \approx 0.470.58$, $p < 0.05$), indicating that greater autonomic variability is associated with more positive and more activating emotional states. In contrast, mean HR showed only weak, non-significant associations ($r \approx 0.100.17$, $p > 0.45$). Electrodermal measures displayed inconsistent results: SCR count showed no correlation with Arousal ($r \approx 0.00$, $p \approx 0.99$), and Mean EDA also did not exhibit significant associations with Valence or Arousal ($p > 0.30$).

Table 5.4: Two-sample t-tests and Pearson correlations. Values marked with * are $p < 0.05$.

Test Type	Metric	Comparison / Variable	Statistic	p-value
T-test	Mean HR	Interactive vs. Passive	-0.57	0.58
T-test	SDNN	Interactive vs. Passive	1.31	0.21
T-test	RMSSD	Interactive vs. Passive	1.58	0.16
T-test	SCR Count	Interactive vs. Passive	-1.56	0.14
T-test	Mean EDA	Interactive vs. Passive	0.72	0.49
Pearson	Mean HR	Valence	0.17	0.46
Pearson	Mean HR	Arousal	0.10	0.67
Pearson	SDNN	Valence	0.49	0.03*
Pearson	SDNN	Arousal	0.56	0.01*
Pearson	RMSSD	Valence	0.47	0.04*
Pearson	RMSSD	Arousal	0.58	0.01*
Pearson	SCR Count	Valence	0.25	0.28
Pearson	SCR Count	Arousal	0.00	0.99
Pearson	Mean EDA	Valence	0.24	0.30
Pearson	Mean EDA	Arousal	0.24	0.32

Overall, these findings indicate that HRV metrics, particularly SDNN and RMSSD, are the most reliable physiological correlates of both valence and arousal in learning contexts. Mean HR and electrodermal activity, by contrast, did not provide consistent indicators of engagement or emotional state.

Chapter 6

Discussion

6.1 Comparison with the State of the Art

The results obtained in this study align with several key findings discussed in Chapter 2, while also revealing important nuances. Mean tonic EDA showed a clear and statistically significant relationship with self-reported arousal, reinforcing its role as a reliable indicator of sympathetic activation. **H4** and **H5** were fully supported, confirming the efficacy of HRV and EDA metrics in distinguishing engagement and arousal levels across tasks. **H6** was partially supported, highlighting the need for further investigation into valence-related physiological correlates.

Time-domain HRV features such as SDNN and RMSSD also distinguished arousal levels, higher values were observed in the high-arousal group. This direction, while differing from stress, based HRV reductions reported in clinical settings, aligns with research linking elevated HRV to states of active engagement or excitement. In contrast, raw heart rate did not vary significantly across arousal levels, consistent with its known susceptibility to confounding factors such as posture, fitness, or cognitive load.

SCR frequency, though elevated in some high-arousal cases, showed no consistent relationship with subjective arousal across the sample. This variability suggests that SCR count may reflect individual sensitivity or stimulus dynamics rather than overall arousal intensity. Together, these patterns confirm the value of multimodal physiological monitoring while also emphasizing the importance of contextual and individual differences when interpreting engagement-related responses.

Cross-validation with the DECEiVeR dataset further reinforced the robustness of the physio-emotional associations. The mapping of collected participant data into the valence-arousal space showed structural similarities with labeled patterns from the DECEiVeR benchmark, especially in high-arousal and low-valence regions associated with cognitive stress or challenge. This alignment strengthens the external validity of the proposed classification approach.

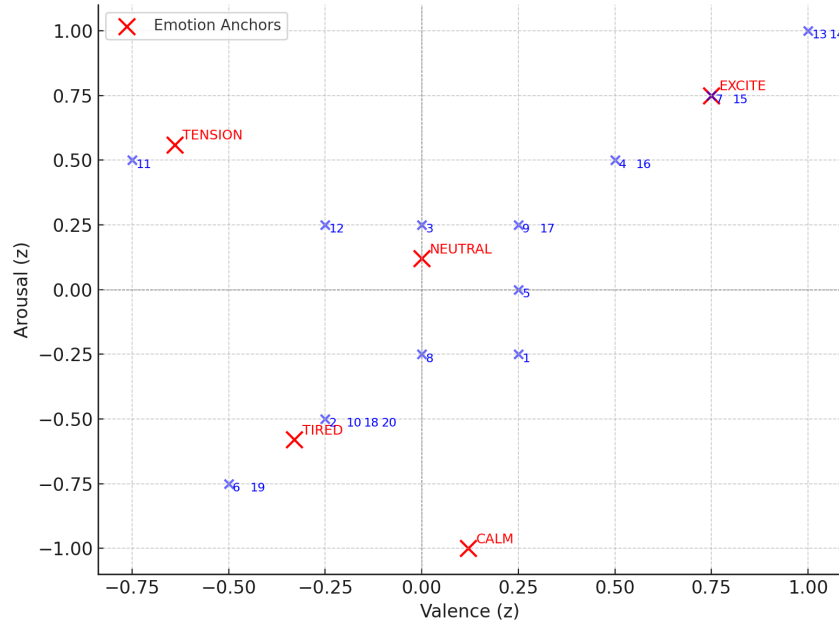


Figure 6.1: Scatter plot mapping participants emotional responses in the valence-arousal space, derived from ECG and EDA signals, compared to DECEIVeR datasets anchor emotions (e.g., excited, calm).

The graph in Figure 6.1 illustrates how participants emotional responses (derived from ECG and EDA signals) are spread across the valence-arousal space relative to the five anchor emotions. We see that participants do not cluster at a single point; instead, they span all four quadrants and the center.

Notably, several participants lie near the extremes corresponding to Excite (top-right quadrant, positive valence and high arousal) and Tired (bottom-left quadrant, negative valence and low arousal). A smaller number of points appear near the Tension anchor (top-left, high arousal but negative valence) and near Calm (bottom-right, low arousal but positive valence). Very few points are exactly at the Neutral center, though a couple of participants are fairly close to neutral. This distribution suggests that during remote learning sessions, participants experienced a range of emotional states, from engaged excitement to boredom or fatigue, rather than a uniform response.

In summary, the physiological signals (EDA and ECG) were highly consistent with the positions on the valence-arousal plane:

- High arousal anchors (Excite, Tension) corresponded with intense sympathetic nervous system activity - evidenced by frequent SCRs and elevated heart rates.
- Low arousal anchors (Calm, Tired) corresponded with lower overall activation - fewer skin conductance fluctuations and, often, more normalized or lower heart rates.
- Valence (positive vs negative) did not affect the quantity of arousal signals but did show up in patterns of heart activity: negative-valence (unpleasant) states leaned towards stress-like

cardiac profiles (lower HRV), whereas positive-valence states maintained healthier variability or quicker recovery from spikes. This reflects how our interpretation of a high arousal event (exciting vs. threatening) can modulate the physiological impact.

The use of self-reported arousal and valence scores as ground truth is consistent with engagement patterns in the DECEIVR dataset, which also uses arousal and valence, supporting the validity of the approach.

6.2 Limitations of the Study

Despite the promising outcomes, several limitations must be acknowledged that may affect the generalizability and practical deployment of the proposed system.

Foremost among them is the fact that the comparatively small and homogeneous sample restricts the statistical power and external validity of the results. A larger and more varied pool of participants would be required to confirm the engagement classification thresholds and improve the solidity of the predictive models. Also the study did not employ advanced classification, regression, or decision rule models to predict engagement levels, limiting the predictive power of the system. Future work should incorporate machine learning techniques to enhance engagement inference.

Second, despite attempts to mimic real study conditions, the experiments took place in controlled settings, which might not capture the dynamics of real-world learning environments. Environmental noise, multitasking, or emotional changes, which are natural in everyday learning environments, are not addressed and might affect physiological signals and engagement.

Third, the use of self-reported questionnaires to annotate engagement brings in an inherent level of subjectivity. Although the questionnaire was painstakingly crafted to map to the valence-arousal space, personal variations in self-perception and interpretation can influence labeling accuracy, with the possibility of introducing bias into the ground truth.

Technically speaking, Bluetooth connection, while popular, has restrictions in terms of transmission range and stability. In a multi-user environment or where there are sources of interference, there can be degradation or interruption of the signal, resulting in loss of data or delay in feedback transmission. These problems are more evident in large classrooms or remote locations.

In addition, wearability and ease of use are necessary for long-term acceptance. Sensors like BITalino need precise electrode positioning and physical contact with the skin, which can be seen as intrusive or unpleasant with extended or active use. This can degrade user compliance and the quality of the data obtained. Finally, battery life imposes a practical constraint. While the devices employed provide rechargeable batteries, their autonomy might not be enough for full-day continuous monitoring, needing periodic recharging that breaks data recording and restricts scalability.

In conclusion, in order to make the system suitable for real-life educational environments, future efforts must overcome the following limitations by investigating more ergonomic wearable

form factors, incorporating more robust wireless standards (e.g., BLE 5.0 or Wi-Fi options), and employing power-saving hardware and software techniques.

6.3 Knowledge Contributions

This dissertation advances the fields of educational technology and affective computing through the development and evaluation of a novel approach to monitor and enhance student engagement in remote learning environments using low-cost wearable devices. The key contributions are detailed below, encompassing the prototype system, data collection efforts, exploratory data analysis, and their role in shaping future research directions aligned with the principles of Education 5.0.

6.3.1 Development of a Low-Cost, Transparent Prototype System

A primary contribution of this work is the design and implementation of a biofeedback system based on the BITalino (r)evolution platform, capable of acquiring and processing ECG and EDA signals to infer student engagement in real-time. Unlike commercial wearable devices, such as the Apple Watch (see Table 2.4), which often rely on proprietary algorithms, this system offers full transparency in signal processing, feature extraction, and emotion classification. The user interface, developed using Python's Tkinter library, delivers intuitive feedback, such as “Calm State” or “Attention Required,” based on physiological thresholds ($HR > 100$ bpm; $EDA > 8.5 \mu S$). This functionality supports students in self-regulating their attention during remote learning tasks, enhancing their metacognitive awareness.

The BITalino platform, with an approximate cost of €150 compared to over €300 for commercial alternatives, significantly reduces barriers to adoption in resource-constrained educational institutions. Its modular and open-source design facilitates reproducibility and customization, enabling adaptation for various contexts, such as monitoring stress during examinations or engagement in collaborative learning activities. This contribution not only advances the practical application of wearable technology in education but also supports scalability and accessibility in virtual learning environments.

6.3.2 Comprehensive Data Collection in Real-World Educational Settings

This study contributes a unique dataset comprising physiological and self-reported emotional data from 20 students engaged in diverse remote learning activities, including watching tutorials, reading, and interactive tasks. The dataset includes over 300 minutes of ECG and EDA recordings, collected over 15-minute sessions, alongside self-assessment questionnaires capturing valence and arousal levels (see Appendix A). This resource provides a robust foundation for analyzing engagement dynamics in virtual settings, where traditional observational methods are often impractical.

The data collection methodology, outlined in Chapter 5, adheres to best practices for electrode placement (e.g., Einthoven leads for ECG, finger placement for EDA) and employs Bluetooth-based signal acquisition to ensure data quality in remote setups. By integrating subjective self-reports with objective physiological metrics, the dataset enables cross-validation of engagement indicators, addressing a gap in prior studies that typically focus on a single modality. This contribution facilitates future research into multimodal engagement models and provides baseline data for comparison with public datasets, such as DECEIVER, enhancing the study's external validity.

6.3.3 Exploratory Analysis of Physiological-Emotional Correlations

The exploratory data analysis presented in Chapter 2 offers novel insights into the relationships between physiological signals (e.g., mean heart rate, SCR count, HRV) and emotional states within the valence-arousal framework. Key findings include a significant correlation between mean tonic EDA and self-reported arousal, with higher SCR counts indicating elevated emotional activation during interactive tasks compared to passive reading. Additionally, lower HRV was observed in high-arousal, low-valence states, reinforcing the applicability of the valence-arousal model in educational contexts.

The analysis employed normalization and feature selection to mitigate inter-subject variability, ensuring reliable emotion classification. The alignment of participant data with DECEIVER's emotion anchors (Figure 6.1) validates the system's ability to map physiological signals to standardized emotional patterns. These findings contribute to affective computing by demonstrating the efficacy of low-cost wearables for real-time engagement monitoring, offering a scalable alternative to resource-intensive modalities like EEG or computer vision.

6.3.4 Foundation for Future Research

This work establishes a foundation for future investigations by identifying limitations and proposing avenues for improvement (Section 6.2). The emphasis on multimodal systems, integrating physiological, behavioral, and contextual data, highlights the potential for enhanced classification accuracy. The dataset and methodology provide a starting point for longitudinal studies exploring engagement dynamics over extended periods or across diverse populations. Furthermore, the open-source code for the biofeedback application (Appendix A) enables researchers to extend the system, incorporating advanced machine learning models or more ergonomic wearable designs, such as wrist-based sensors.

By aligning with Industry 5.0 principles, which prioritize human-technology collaboration, this dissertation paves the way for adaptive learning systems that dynamically adjust content based on real-time engagement levels. The demonstrated feasibility of physiological monitoring in educational settings opens opportunities for developing intelligent tutoring systems, enhancing personalized learning experiences in virtual environments.

6.4 Addressing the Research Questions

Table 6.1: Research Questions and Key Findings

RQ	Research Question	Key Findings
RQ1	Which physiological and behavioral metrics are most effective in assessing student engagement during remote learning?	ECG-based features such as SDNN and RMSSD, together with EDA metrics like SCR amplitude and count, reliably reflected emotional arousal and engagement.
RQ2	Which algorithms are best suited for real-time analysis and feedback on student engagement, balancing accuracy and computational efficiency?	Peak detection, then feature normalization and threshold-based classification in the valence-arousal space.
RQ3	How does the implementation of wearable technology impact key indicators of engagement, such as student performance, participation, and attentiveness?	The system revealed positive correlations between physiological features and self-reported engagement, indicating improved focus and awareness among students during remote activities.
RQ4	How can wearable devices be ethically designed and implemented to ensure data privacy, security, and compliance with informed consent practices?	All data were anonymized and stored locally, with informed consent obtained. Future versions could enhance privacy by adding encryption and differential privacy mechanisms.
RQ5	What are the implications of integrating wearable technology into remote learning for fostering human-technology collaboration in an Industry 5.0 context?	The system illustrates a form of human-machine collaboration where physiological data supports personalized feedback and learner empowerment, aligning with Industry 5.0 principles.

Chapter 7

Conclusions and Future Work

In the context of this dissertation, a physiological monitoring approach using wearable sensors was developed and evaluated to detect student engagement during remote learning activities. The results obtained in this study reveal a promising alignment between physiological signals and self-reported emotional states, particularly along the arousal dimension.

Additionally, the proximity between participant data and emotional anchors from the DE-CEiVeR dataset reinforces the external validity of the proposed methodology. This finding indicates that physiological features collected using low-cost wearable systems can approximate patterns observed in standardized emotional databases, validating the approach in real-world learning contexts.

Despite these encouraging results, several limitations must be acknowledged. First, the sample size was relatively small and homogeneous, consisting of only twenty students with similar academic backgrounds and age range, which limits the generalizability of the findings. Second, the learning activities were conducted in a semi-structured and relatively short setting that does not fully reflect the complexity of real-world educational environments. Each data collection session lasted approximately fifteen minutes. Although sufficient to capture meaningful physiological activity, this duration may not represent typical study sessions, where engagement naturally fluctuates over longer periods due to fatigue, distraction, or task complexity. Longer-term studies are needed to capture the temporal dynamics of engagement in a more realistic educational context.

Furthermore, an inherent limitation of physiological signals is their ambiguity. High arousal may not always indicate engagement or interest, it may also reflect negative affective states such as stress, anxiety, or confusion. As such, physiological signals alone may not provide a complete or reliable picture of a learner's cognitive and emotional state. This suggests a need for the development of multimodal systems that combine physiological data with contextual, behavioral, or interaction-based indicators to enhance classification accuracy and interpretability.

From an ethical standpoint, the use of wearable sensors in education raises important concerns, especially because physiological data are highly personal and sensitive. Therefore, their collection and processing must be governed by clear ethical guidelines like informed consent. Moreover, engagement monitoring tools should be employed as supportive instruments to foster self-awareness

and improve learning experiences, rather than as surveillance or punitive mechanisms. Transparent communication with students about the goals, scope, and limitations of these systems is essential to ensure trust, fairness, and responsible deployment.

Overall, this dissertation offers a solid foundation for the design and validation of physiological engagement monitoring systems. The combination of wearable sensor data with emotional self-reporting, benchmarked against established datasets, represents a significant step toward intelligent, ethical, and responsive educational technologies.

The main contributions of this dissertation can be summarized as follows:

- **Physiological Monitoring Framework:** Design and implementation of a system that collects ECG and EDA signals from wearable devices during remote learning tasks.
- **Engagement Estimation Pipeline:** Development of a signal processing and feature extraction pipeline that correlates physiological features with self-reported emotional states.
- **Comparison with Reference Dataset:** Integration of participant data with the DECEiVeR dataset to assess external validity and proximity in the valence-arousal space.

7.1 Future Work

It is hoped that future research will extend development from the foundation laid in this work by exploring several key directions to enhance utility and scalability:

1. **Integration with Learning Management Systems (LMS):** Incorporating the wearable engagement tracking system into commonly used LMS platforms (e.g., Moodle, Canvas, Google Classroom) would enable a direct link between learning content and real-time engagement feedback. This integration can support adaptive content delivery, personalized remediation strategies, and centralized data management.
2. **Inclusion of Additional Biosignals:** While the present study focused on ECG and EDA, other physiological signals such as EEG, PPG, and PZT would offer complementary insights into emotional and cognitive states. In particular, EEG could provide valuable information about cognitive workload and attentional states, augmenting the autonomic indicators already employed.
3. **Real-Time Classification Models:** The development and validation of lightweight machine learning models capable of detecting attention in real-time is a crucial next step. These models must balance predictive accuracy with computational efficiency to ensure deployment feasibility on resource-constrained wearable devices or mobile applications.
4. **Broader Dataset Coverage:** Future studies should include a larger and more diverse participant pool to enhance the generalizability of results. Additionally, longitudinal data collection across extended learning sessions may offer deeper insights into the temporal dynamics of engagement.

Although the developed system monitors physiological engagement markers and computes a real-time Engagement Index, it does not yet incorporate an automatic closed-loop feedback mechanism. Future iterations should aim to deliver timely, personalized cues such as visual or haptic signals to re-engage learners when disengagement is detected. This would enable a fully closed-loop architecture capable of dynamically supporting attention and cognitive effort.

In summary, this dissertation provides the foundation for ethical, data-informed engagement tracking in distance learning, with promising implications for adaptive learning, mental health services, and inclusive pedagogical design.

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Appendix A

Appendix

A.1 Valence Arousal Emotion Self-Report Questionnaire

ID Number:

Activity / Session:

Consent to Provide Physiological Data:

I acknowledge that I have been informed about the purpose of this study and the use of wearable sensors to collect physiological data, including Electrocardiogram (ECG) and Electrodermal Activity (EDA). I understand that my data will be treated confidentially and used solely for academic research purposes. I voluntarily agree to participate and allow the collection and analysis of my physiological signals.

Instructions: Please indicate how you felt during your task by rating each item using the 1-9 scale.

- For **Valence**, 1 means *extremely unpleasant* and 9 means *extremely pleasant*.

- For **Arousal**, 1 means *very calm or drowsy* and 9 means *very activated or energized*.

Part 1: Valence (Pleasure - Displeasure)

Item	1	2	3	4	5	6	7	8	9
Unhappy - Happy	☐	☐	☐	☐	☐	☐	☐	☐	☐
Sad - Joyful	☐	☐	☐	☐	☐	☐	☐	☐	☐
Displeased - Pleased	☐	☐	☐	☐	☐	☐	☐	☐	☐
Miserable - Content	☐	☐	☐	☐	☐	☐	☐	☐	☐
Negative - Positive	☐	☐	☐	☐	☐	☐	☐	☐	☐

A.2 Implementation of the BITalino-Based Biofeedback App

Listing A.1: Versão unificada da aplicação de Biofeedback com Tkinter e BITalino

```

1 import tkinter as tk
2 from tkinter import messagebox
3 import numpy as np
4 import datetime
5 import os
6 import threading
7 from scipy.signal import butter, filtfilt, iirnotch
8 from bitalino import BITalino
9 import biosppy
10
11 os.makedirs("dados", exist_ok=True)
12
13 # Parâmetros
14 MAC = "98:D3:31:B1:83:E0"
15 FS = 100
16 HR_MIN = 60
17 HR_MAX = 100
18 EDA_MIN = 4.0          # Limite mínimo em  $\mu S$ 
19 EDA_LIMIAR = 8.5       # Limite máximo em  $\mu S$ 
20 DURACAO_MIN = 1.0      # Duração mínima em segundos
21
22 # Estado
23 ligado = False
24 dispositivo = None
25 dados = np.array([])
26 ativo = False
27
28 def filtro_ecg(signal):
29     b, a = butter(2, [0.5/(FS/2), 40/(FS/2)], btype='band')
30     ecg_filtrado = filtfilt(b, a, signal)
31     b_notch, a_notch = iirnotch(50/(FS/2), 30)
32     return filtfilt(b_notch, a_notch, ecg_filtrado)
33
34 def filtro_eda(signal):
35     b, a = butter(2, 5/(FS/2), btype='low')
36     return filtfilt(b, a, signal)
37
38 def escala_ecg(raw, vref=3.3, ganho=1.1, offset=1.5):
39     # Conversão para mV
40     return ((raw / 1024.0) / ganho) * vref - offset) * 1000
41
42 def escala_eda(raw, ganho=0.132, offset=0.0):

```

```
43     return raw * ganho + offset
44
45 def avaliar(bpm, eda):
46     # Estado cardíaco
47     hr = "Normal"
48     if bpm < HR_MIN:
49         hr = "Baixo"
50     elif bpm > HR_MAX:
51         hr = "Alto"
52
53     # Estado EDA
54     if eda < EDA_MIN:
55         eda_estado = "Muito Baixo"
56     elif eda >= EDA_LIMIAR:
57         eda_estado = "Elevado"
58     else:
59         eda_estado = "Normal"
60
61     alerta = hr != "Normal" or eda_estado != "Normal"
62     return hr, eda_estado, "Requer atenção" if alerta else "Estável",
        alerta
63
64 def conectar():
65     global ligado, dispositivo
66     if ligado:
67         messagebox.showinfo("Status", "Já conectado.")
68         return
69     try:
70         dispositivo = BITalino(MAC)
71         ligado = True
72         btn_conectar.config(state=tk.DISABLED)
73         btn_desconectar.config(state=tk.NORMAL)
74         messagebox.showinfo("Status", "Conectado com sucesso.")
75     except Exception as e:
76         messagebox.showerror("Erro", str(e))
77
78 def desconectar():
79     global ligado, dispositivo
80     if dispositivo:
81         try:
82             dispositivo.close()
83         except:
84             pass
85     ligado = False
86     dispositivo = None
```

```

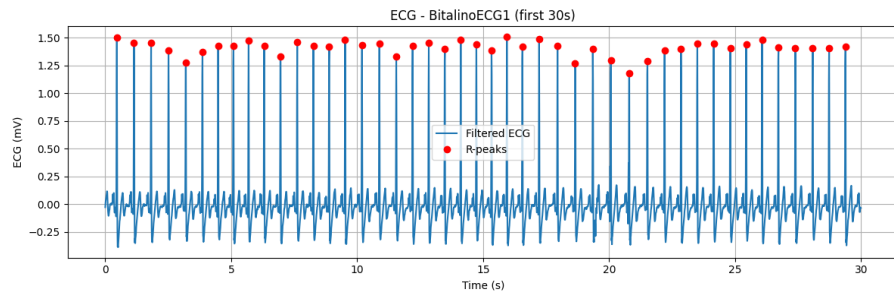
87     btn_conectar.config(state=tk.NORMAL)
88     btn_desconectar.config(state=tk.DISABLED)
89     messagebox.showinfo("Status", "Desconectado.")
90
91 def iniciar():
92     global ativo, dados
93     if not ligado:
94         messagebox.showwarning("Erro", "Conecte o BITalino.")
95         return
96     ativo = True
97     dados = np.array([])
98     btn_iniciar.config(state=tk.DISABLED)
99     btn_parar.config(state=tk.NORMAL)
100    threading.Thread(target=recolher, daemon=True).start()
101
102 def parar():
103     global ativo
104     ativo = False
105
106 def recolher():
107     global dados, ativo
108     try:
109         dispositivo.start(FS, [2, 3])
110         buffer = []
111         while ativo:
112             buffer.append(dispositivo.read(100))
113         dispositivo.stop()
114         if buffer:
115             bruto = np.vstack(buffer)
116             tempo = np.arange(len(bruto)) / FS
117             ecg = filtro_ecg(escala_ecg(bruto[:, 2]))
118             eda = filtro_eda(escala_eda(bruto[:, 3]))
119             dados = np.column_stack((tempo, ecg, eda))
120             nome = datetime.datetime.now().strftime("dados/sessao_%Y%m%d_%H%M%S.csv")
121             np.savetxt(nome, dados, delimiter=",", header="tempo,ecg(mV),eda(tS)")
122         except Exception as e:
123             messagebox.showerror("Erro", str(e))
124             dados = np.array([])
125         finally:
126             btn_iniciar.config(state=tk.NORMAL)
127             btn_parar.config(state=tk.DISABLED)
128             ativo = False
129

```

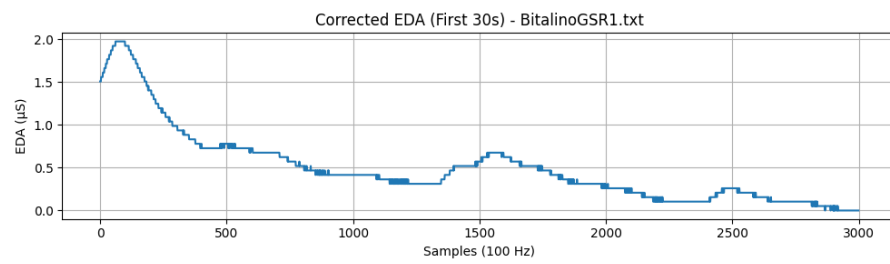
```
130 def analisar():
131     global dados
132     if dados.size == 0:
133         messagebox.showwarning("Aviso", "Sem dados.")
134         return None
135     t, ecg, eda = dados.T
136     dur = t[-1] - t[0]
137     if dur < DURACAO_MIN:
138         messagebox.showwarning("Aviso", f"Duração insuficiente ({dur:.2f}s
139                                     ).")
140         return None
141     # --- BioSPPy Pan-Tompkins ---
142     out = biosppy.signals.ecg.ecg(signal=ecg, sampling_rate=FS, show=False
143                                   )
144     rpeaks = out['rpeaks']
145     if len(rpeaks) < 2:
146         messagebox.showwarning("Aviso", "Não foram encontrados picos R
147                                     suficientes.")
148         return None
149     # BPM = número de batimentos no intervalo
150     bpm = (len(rpeaks) / dur) * 60.0
151
152     # EDA médio
153     eda_media = np.mean(eda)
154
155     estado_hr, estado_eda, perfil, alerta = avaliar(bpm, eda_media)
156
157     texto = f"BPM: {bpm:.1f} ({estado_hr})\nECG em mV\nEDA média: {
158             eda_media:.2f} tS ({estado_eda})\nPerfil: {perfil}"
159     messagebox.showinfo("Resultado", texto)
160     return alerta
161
162 def feedback():
163     alerta = analisar()
164     if alerta is None:
165         return
166     mensagem = "Alerta: Faça uma pausa!" if alerta else "Tudo normal.
167                                     Continue assim!"
168     messagebox.showinfo("Feedback", mensagem)
169
170 # Interface
171 app = tk.Tk()
```

```
170 app.title("Monitor Fisiológico")
171 app.geometry("380x400")
172
173 btn_conectar = tk.Button(app, text="Conectar", command=conectar)
174 btn_desconectar = tk.Button(app, text="Desconectar", command=desconectar,
    state=tk.DISABLED)
175 btn_iniciar = tk.Button(app, text="Iniciar", command=iniciar)
176 btn_parar = tk.Button(app, text="Parar", command=parar, state=tk.DISABLED)
177 btn_analisar = tk.Button(app, text="Analisar", command=analisar)
178 btn_feedback = tk.Button(app, text="Feedback", command=feedback)
179
180 for botao in [btn_conectar, btn_desconectar, btn_iniciar, btn_parar,
    btn_analisar, btn_feedback]:
181     botao.pack(pady=5)
182
183 app.mainloop()
```

A.3 ECG and EDA Signals (First 30 Seconds)

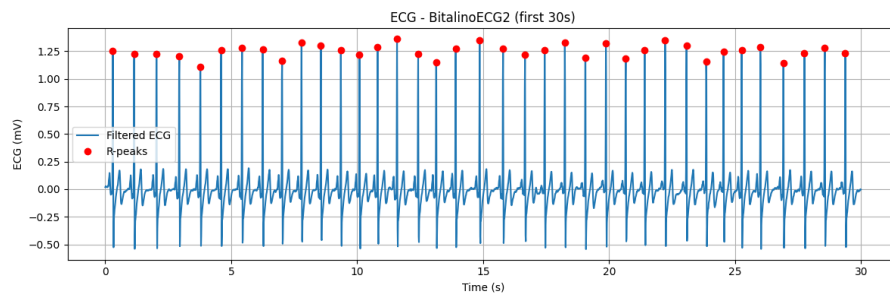


ECG - Participant 1

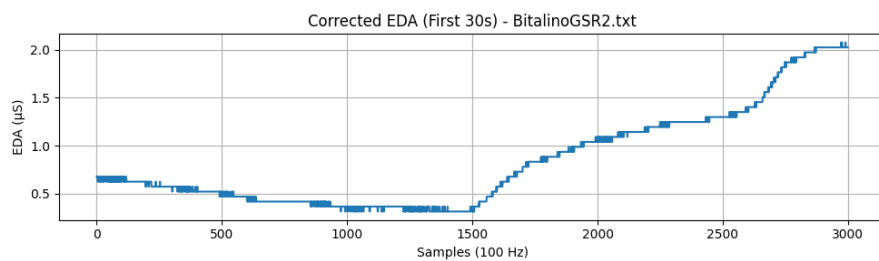


EDA - Participant 1

Figure A.1: Physiological signals (ECG and EDA) for Participant 1.



ECG - Participant 2



EDA - Participant 2

Figure A.2: Physiological signals (ECG and EDA) for Participant 2.

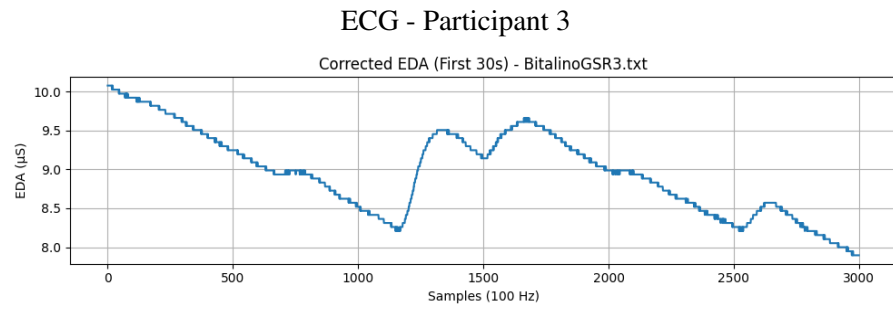
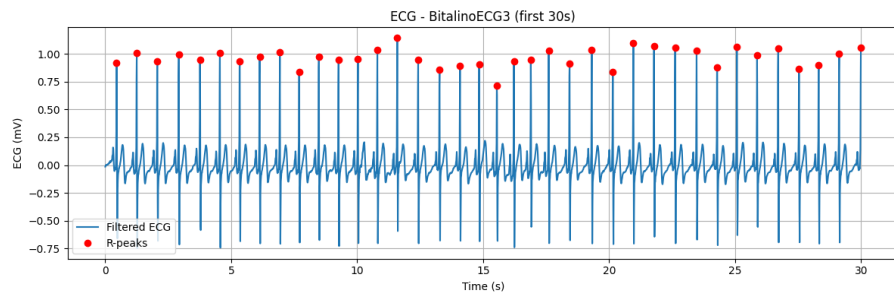


Figure A.3: Physiological signals (ECG and EDA) for Participant 3.

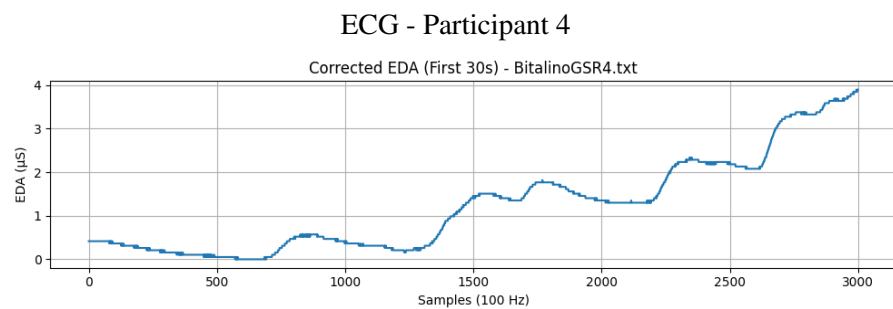
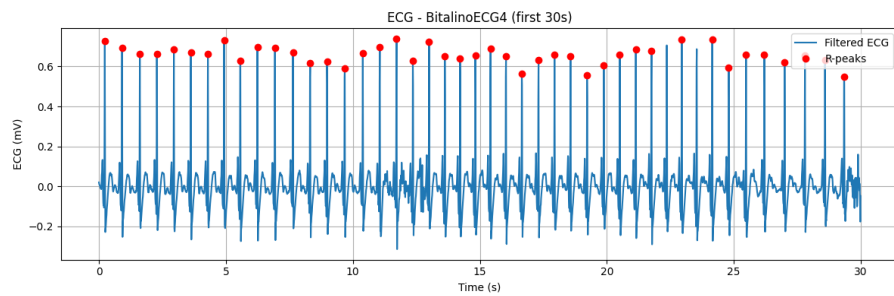
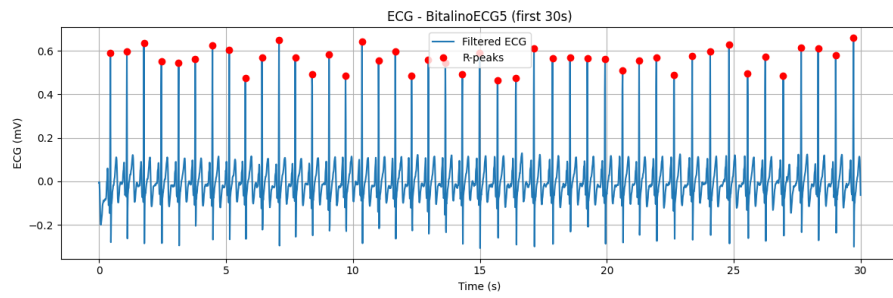
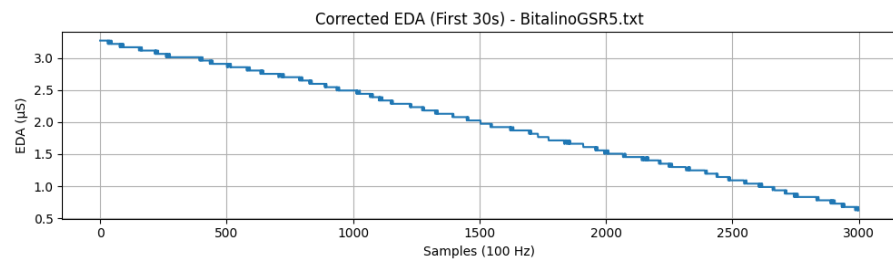


Figure A.4: Physiological signals (ECG and EDA) for Participant 4.

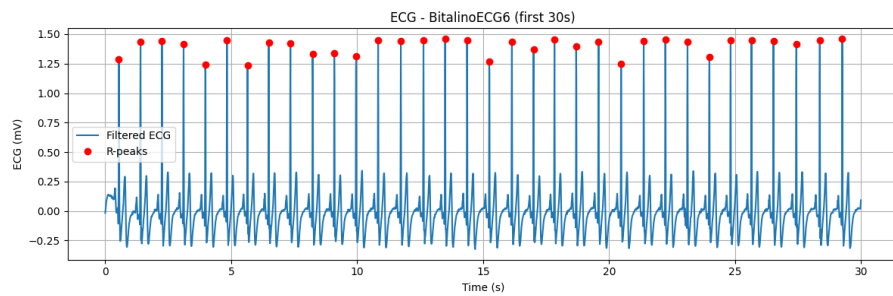


ECG - Participant 5

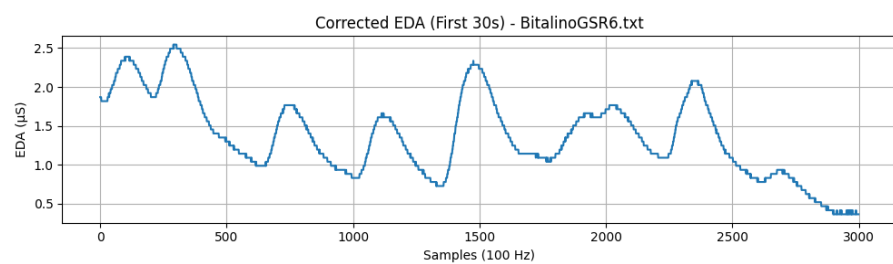


EDA - Participant 5

Figure A.5: Physiological signals (ECG and EDA) for Participant 5.

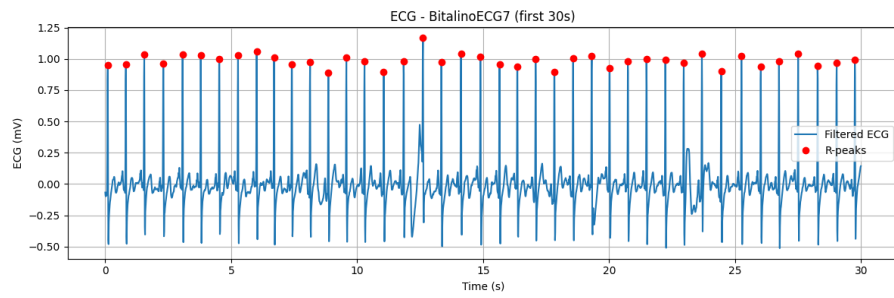


ECG - Participant 6

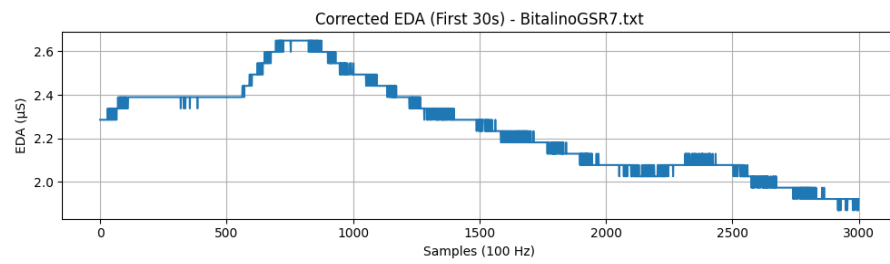


EDA - Participant 6

Figure A.6: Physiological signals (ECG and EDA) for Participant 6.

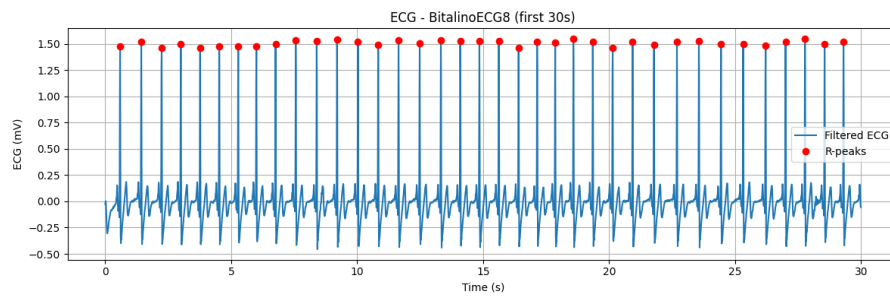


ECG - Participant 7

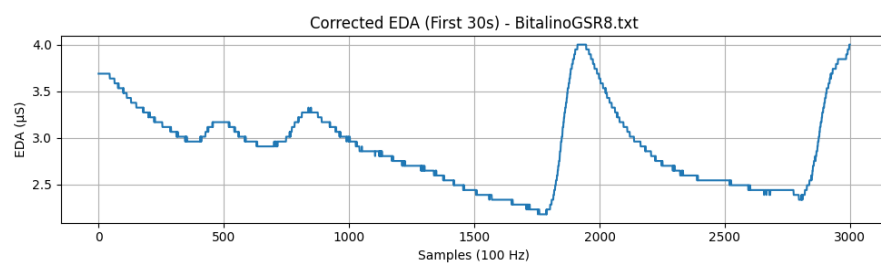


EDA - Participant 7

Figure A.7: Physiological signals (ECG and EDA) for Participant 7.

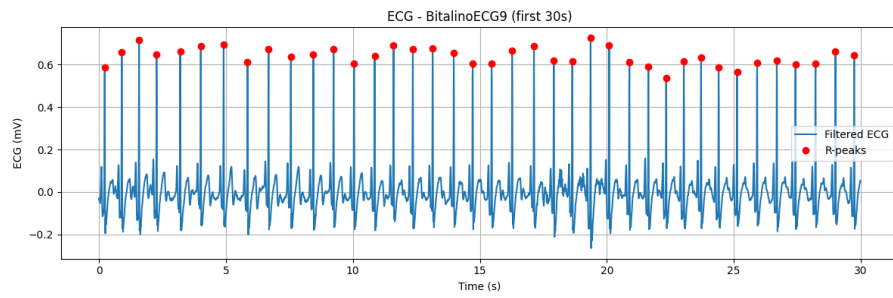


ECG - Participant 8

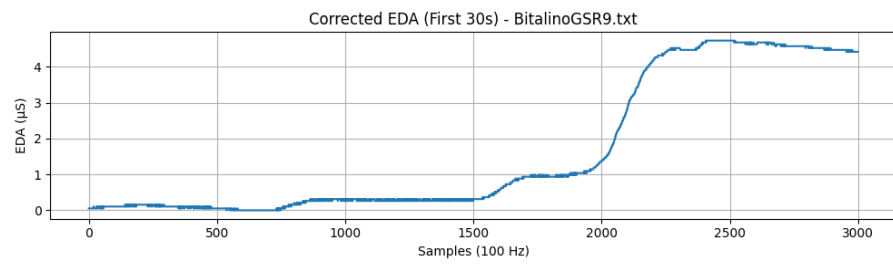


EDA - Participant 8

Figure A.8: Physiological signals (ECG and EDA) for Participant 8.

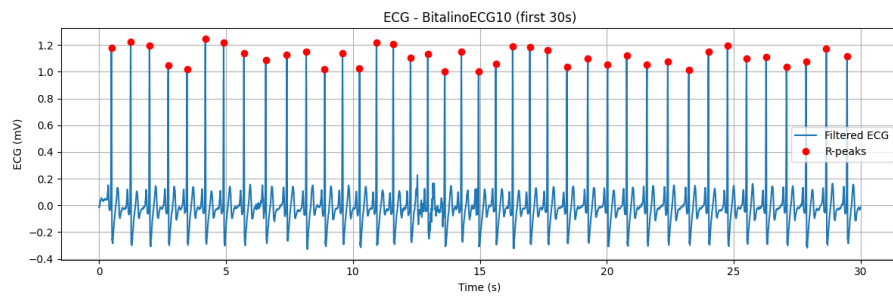


ECG - Participant 9

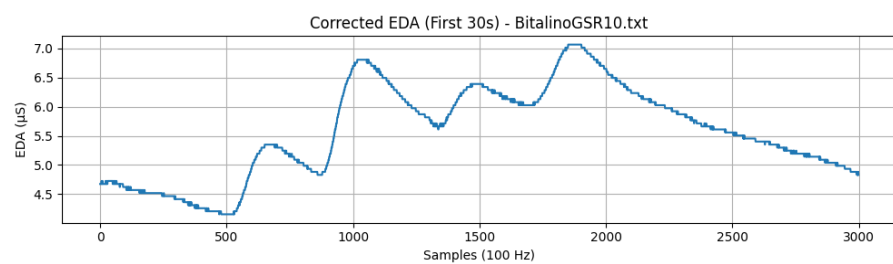


EDA - Participant 9

Figure A.9: Physiological signals (ECG and EDA) for Participant 9.

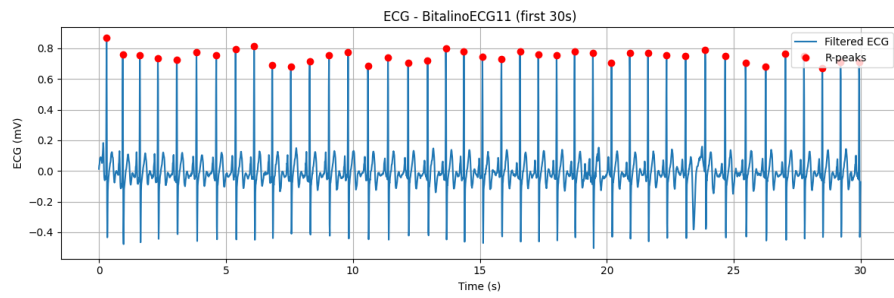


ECG - Participant 10

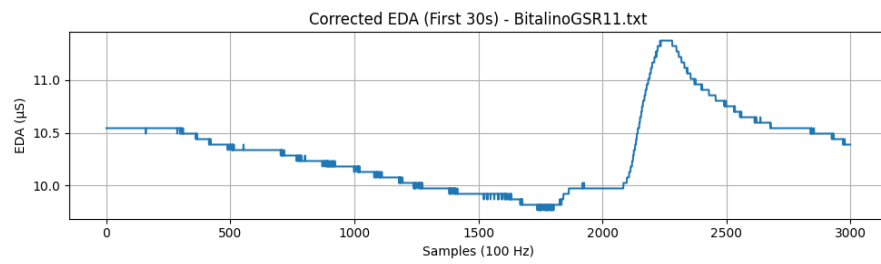


EDA - Participant 10

Figure A.10: Physiological signals (ECG and EDA) for Participant 10.

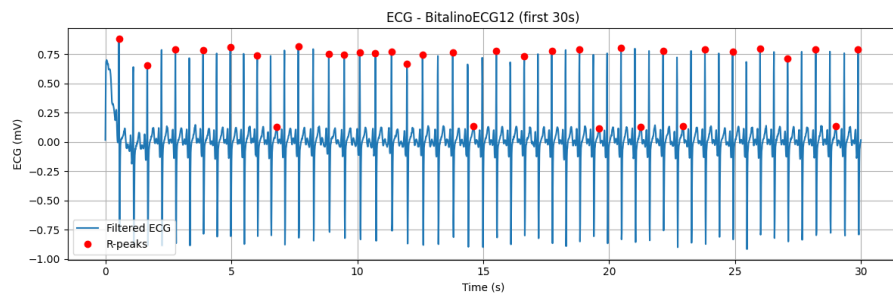


ECG - Participant 11

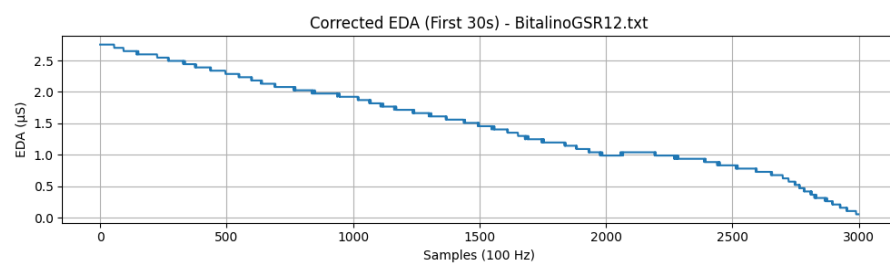


EDA - Participant 11

Figure A.11: Physiological signals (ECG and EDA) for Participant 11.

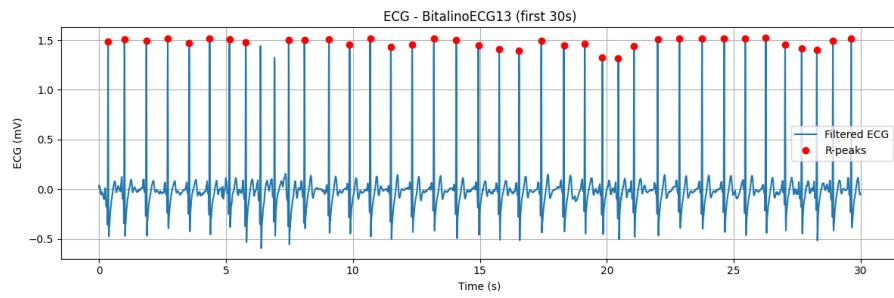


ECG - Participant 12

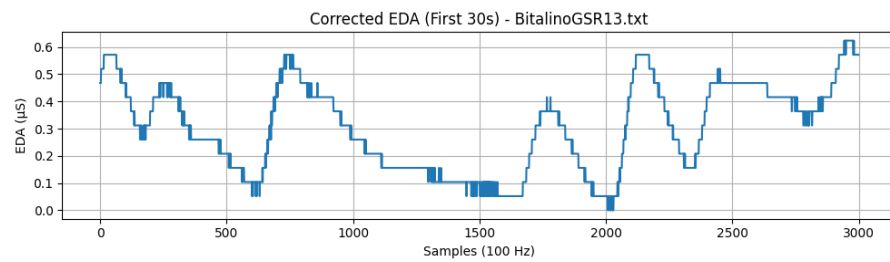


EDA - Participant 12

Figure A.12: Physiological signals (ECG and EDA) for Participant 12.

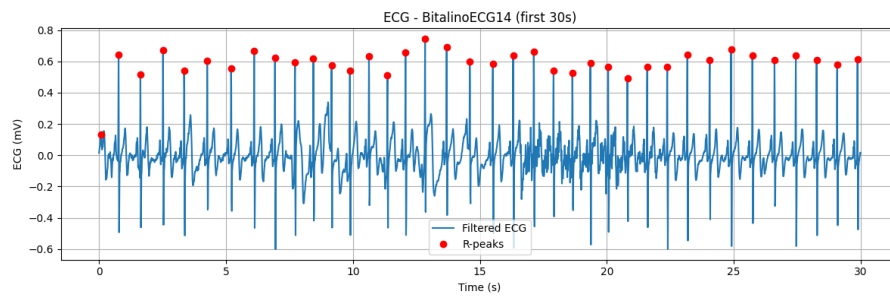


ECG - Participant 13

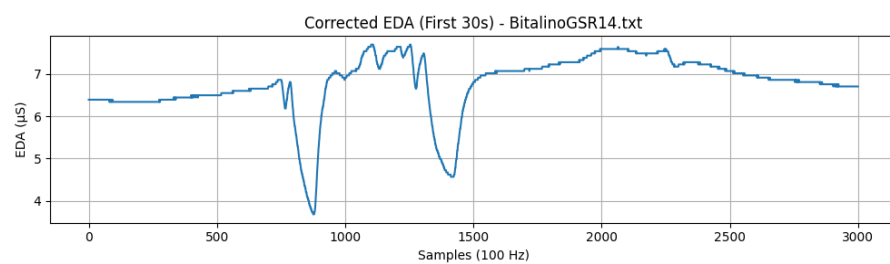


EDA - Participant 13

Figure A.13: Physiological signals (ECG and EDA) for Participant 13.

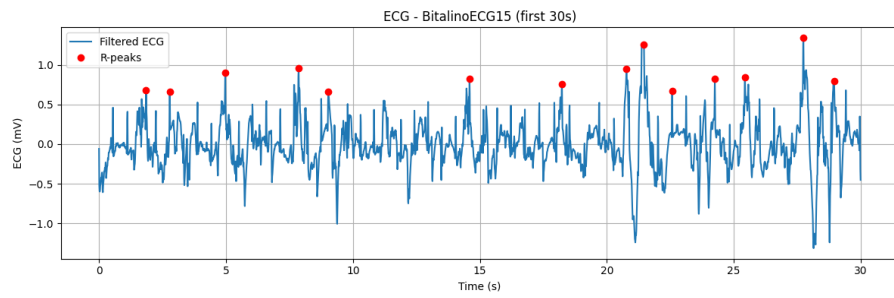


ECG - Participant 14

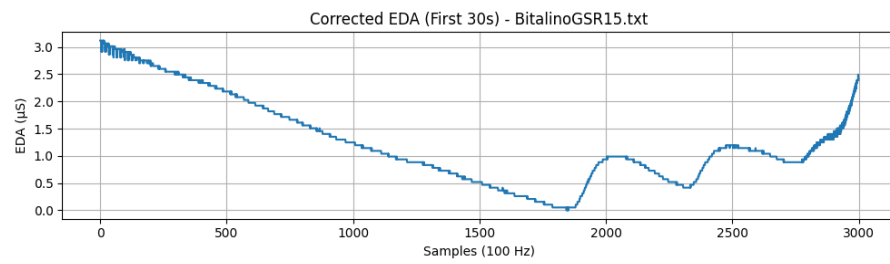


EDA - Participant 14

Figure A.14: Physiological signals (ECG and EDA) for Participant 14.

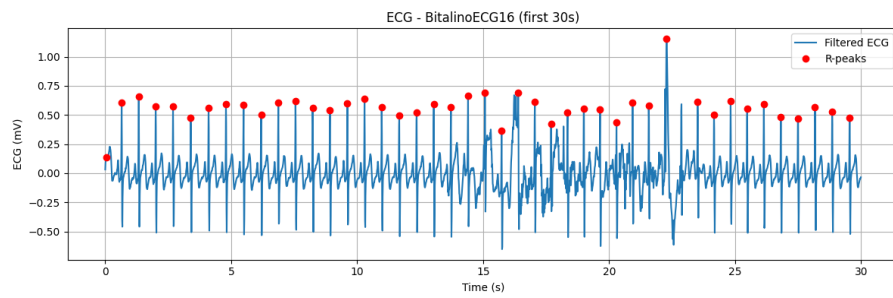


ECG - Participant 15

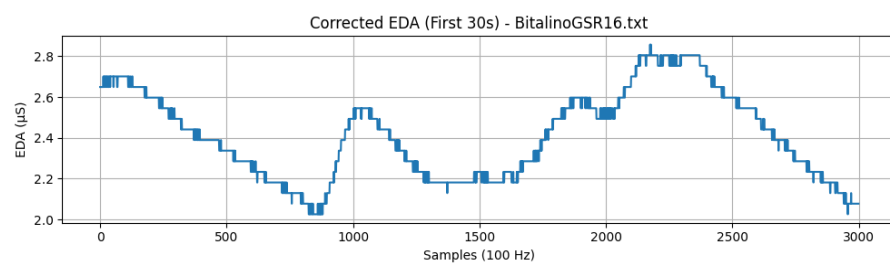


EDA - Participant 15

Figure A.15: Physiological signals (ECG and EDA) for Participant 15.

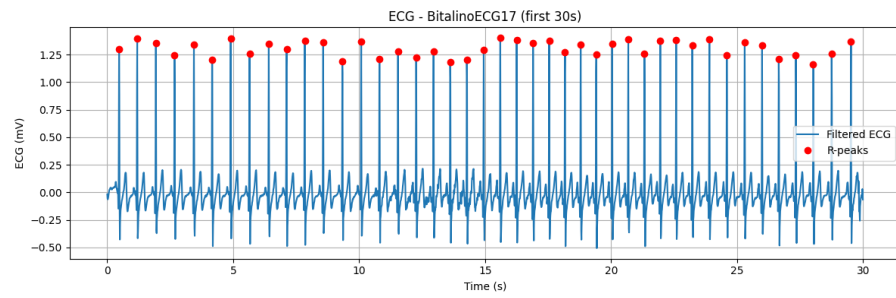


ECG - Participant 16

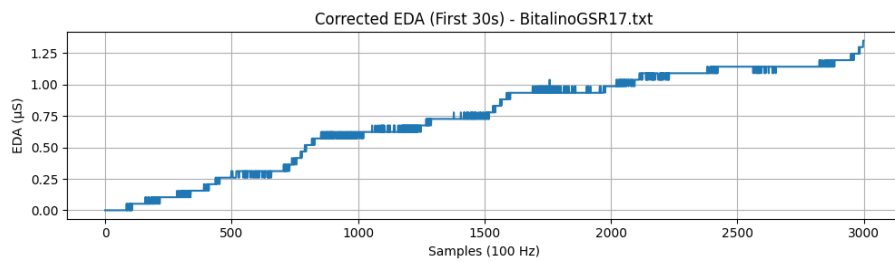


EDA - Participant 16

Figure A.16: Physiological signals (ECG and EDA) for Participant 16.

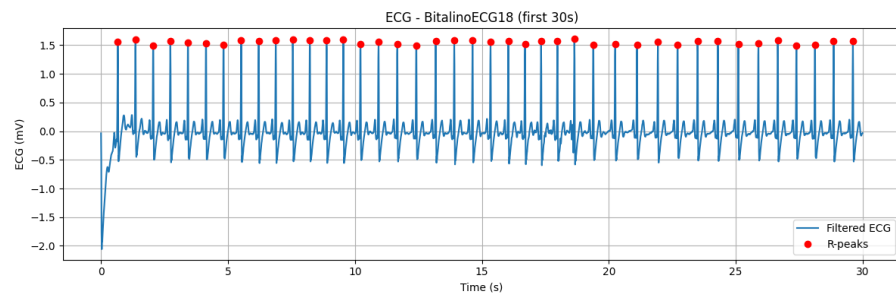


ECG - Participant 17

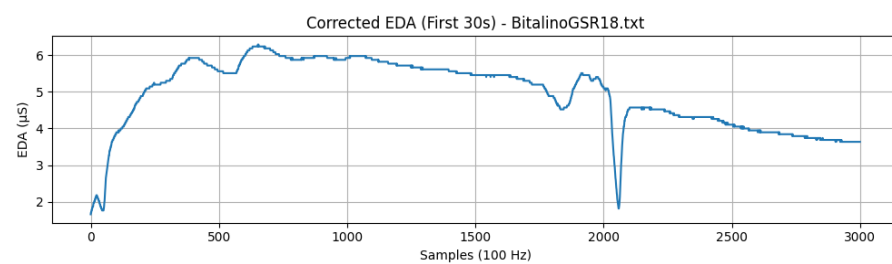


EDA - Participant 17

Figure A.17: Physiological signals (ECG and EDA) for Participant 17.

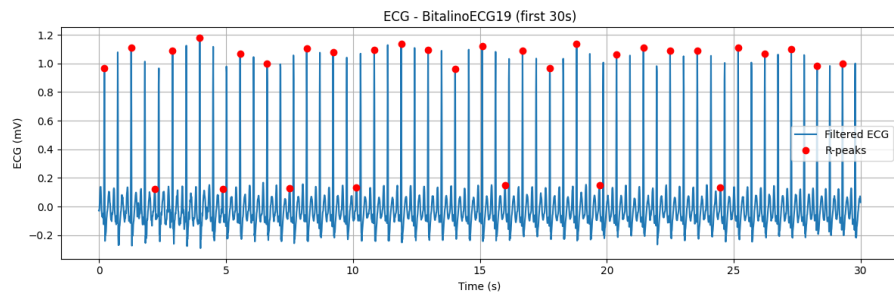


ECG - Participant 18

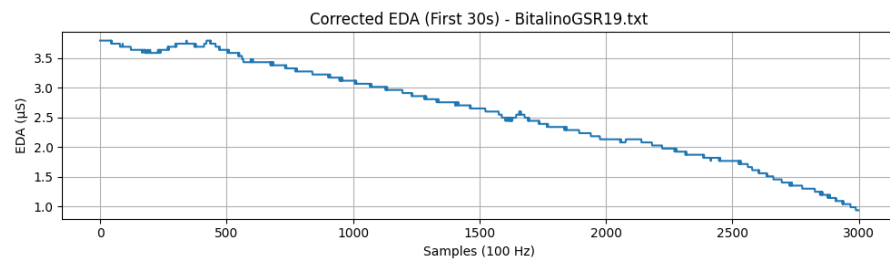


EDA - Participant 18

Figure A.18: Physiological signals (ECG and EDA) for Participant 18.

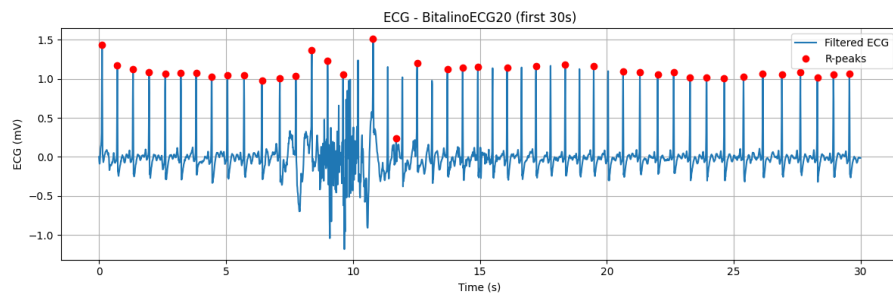


ECG - Participant 19

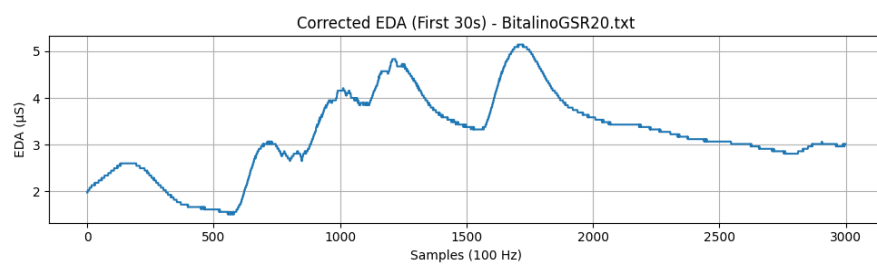


EDA - Participant 19

Figure A.19: Physiological signals (ECG and EDA) for Participant 19.



ECG - Participant 20



EDA - Participant 20

Figure A.20: Physiological signals (ECG and EDA) for Participant 20.