The Impact of External Factors on Cardiac Parameters

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Abstract. Life in urban areas that are busy and noisy includes factors that are not usually taken into consideration when talking about a "healthy heart". Even though factors like noise, stress, or negative thoughts are ignored, they can affect vital parameters such as heart rate and heart rate variability in a bad way. At the opposite point, art, music, and cognitive activities can positively influence these parameters and improve both the well-being state and the health of a subject. This is why it is critical to continuously monitor the parameters through wearable devices. Thus, one of the goals of this paper is to observe the influence of the external factors on two parameters, heart rate and heart rate variability, by developing and using an Arduino-based device that records electrocardiographic (ECG) signals, that were first compared with the ones recorded with the Biopac system. To record the changes in the ECG signals caused by the external factors, a presentation containing four distinct tasks, besides relaxation (to establish the baseline) —visual variations, auditive variations, cognitive activities, and memories—was used. Another goal is to design and implement a graphical user interface (GUI) that is user-friendly and can help the subject to better visualize and understand the outcomes of the recordings.

Keywords: Electrocardiogram · external factors · heart rate · heart rate variability · Arduino and Matlab systems · signal acquisition and processing · statistics

1 Introduction

Unbalanced and excessive urban development degrades the quality of life in cities. The level of noise pollution rises as a result of inhabitants' growing discomfort in tandem with an increase in traffic [1]. Every day, millions of individuals endure elements including

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traffic, noise, stress, and busy lives. While it is generally accepted that factors like smoking, drinking, and so on cause a significant increase in heart rate, this study proposes to present that other factors that do not directly affect the subject—like exposure to sounds, depression, or stress—can affect heart rate and the heart rate variability in both positive and negative ways [2]. For instance, according to the European Environment Agency [3], long-term exposure to ambient noise results in 48000 new cases of ischemic heart disease and 12000 early deaths in Europe each year, and stress also represents a well-known risk factor for cardiovascular diseases [4].

The electrocardiogram (ECG) can be utilized to differentiate between the traces left by each condition. An ECG is a method for assessing the cardiac muscle and electrical activity [5]. This provides both physiological and pathological information, forming the diagnosis of the disease. Heart rate (HR) is the number of heartbeats in one minute. The HR depends on the activity at that moment. Over time, the body modifies the HR in response to emotional states and its needs for energy. HR increases when a person is stressed or anxious and decreases when a person is happy and calm. These differences in HR change the time interval between each heartbeat, meaning heart rate variability (HRV). People with high HRV are usually happier and less stressed. In general, low HRV is considered a sign of current or future health problems because it shows that the body is less resilient and struggles to handle changing situations. HRV gets lower if a person is stressed, depressed, or exposed to noise [6]. Evaluating both parameters—HR and HRV—is necessary since they indicate unique characteristics and because two individuals with the same HR may have different HRVs.

The aim of this study is to observe the influence of external factors on the HR and the HRV and to offer a personalized graphical user interface (GUI), as well as demonstrate that an Arduino-based device can achieve results comparable to those of a more sophisticated, professional device, such as Biopac, the focus nowadays being on lowbudget, small, and lightweight, wearable devices.

As mentioned before and according to studies in the field, it has been observed that external factors influence the cardiac rhythm [2]. The paper [7] has the main objective of performing an analysis of specialized literature to obtain an overview of the factors that affect HR. The main categories that stand out from this study are physiological/pathological, neuropsychological, non-modifiable, lifestyle, and environmental factors; thus, it is observed that these factors are interdependent. The study [8] had 33 healthy subjects perform emotion regulation tasks, during which they were instructed to either passively view negative images or attempt to regulate the effect elicited by the images. During the test, ECG was recorded and HRV was measured. Thus, certain conclusions were drawn related to the increase or decrease in HR depending on the subject's emotional state. The paper [9] studies the influence of music on HR as it increases it. Paper [10] emphasized the idea that, according to a recognized neuroscience explanation of emotions [11], emotion-related signals are variations in a person's visceral state, such as HR, that show how that person emotionally reacts to certain situations.

Section 1 introduced the ECG signals, the necessity of this work, and previous studies in this field. The rest of the paper is divided into two main sections, both following two directions: signal acquisition and signal processing (Fig. 1). Section 2 consists of the signal acquisition with two different devices – Arduino and Biopac – followed by the

offline signal processing and statistics based on the outcomes, and presents the materials and methods used, both hardware and software, the results of the experiment, statistics, and comparisons and discussions. In Section 3, based on the previous results, the Arduino device is developed, the signals are now analyzed in real-time, and the outcomes are displayed in a user-friendly GUI. The final conclusions of the paper are formulated in the end, and the limitations and perspectives of this study are presented.

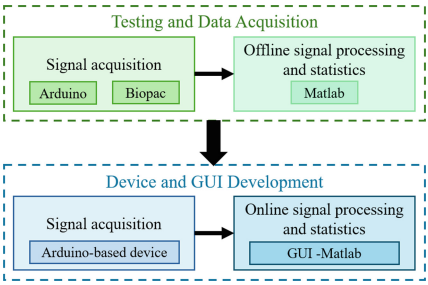

Fig. 1. The two main sections of the proposed work

2 Testing and Data Acquisition

2.1 Materials and Methods

In this stage, two different devices, Arduino and Biopac, are used to record the signals, which are then uploaded into Matlab for further analysis (offline). Subsequently, every phase will be described in detail.

Participants and Database

Ten volunteers, five of them male and five of them female, with ages ranging from 25 to 58 (Mean = 32.8, Standard Deviation = 12.43), participated in this study. They received instructions not to consume any food or coffee for two hours prior to the experiment, and they were also requested not to smoke right before the experiment because, as mentioned in other papers, quitting smoking can cause fluctuations in a smoker's heart rate. Rather, they should hydrate appropriately before.

Each participant in the study signed a written consent, agreeing to participate in this study, including the signal recording and the anonymous use of their responses and personal information, such as gender, age, pathologic history, and form responses. This form consists of 8 sections: the consent, some details about the subject relevant for the study (such as age or gender), the aforementioned protocol before the acquisition, and four paragraphs corresponding to the four tasks that will be later described, as well as the form. For each participant, an approximately 36-min signal is recorded, which will be split according to the protocol, as it will be further described.

Acquisition Devices and Protocol

Devices

Using two devices, an Arduino-based sensor (alongside the DataStreamer Toolbox from Excel) and the Biopac system, the signals are randomly acquired from the ten participants, storing them as .csv files for further processing in Matlab. The aim of this comparison, as we did in our previous work [12], is to see whether outcomes obtained with a less complex and less expensive device are comparable to those from a more advanced and expensive one. For a visual representation, Fig. 2 displays two signals of the same duration that were obtained using these two distinct devices; the Biopac signal has 10 times more samples than the Arduino signal, but the waveforms are similar.

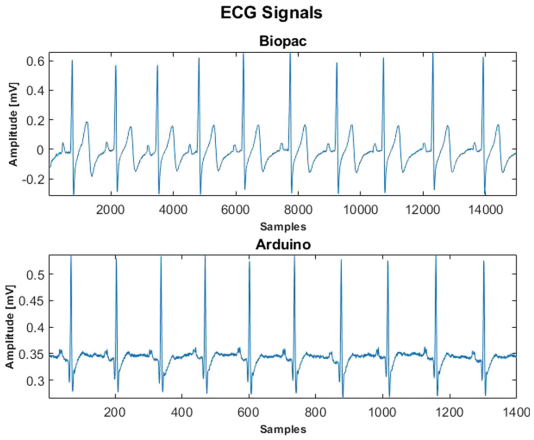

Fig. 2. A comparison between the two acquisition systems

Arduino. An Arduino Uno board, an AD8232 sensor, jumper wires, and a USB cable are the few materials required to conduct this experiment. Because it is less expensive and has enough memory and pins, the Arduino Uno board is adequate for this application. Also, the AD8232 sensor has been tested in previous studies, such as [12, 13], and it has been demonstrated to be an affordable, practical tool for recording high-quality ECG signals. Since it needs to be connected to power, ground, and an analog pin in order to read the signal, just three jumper wires are required. It is enough to use the USB cable because wireless data transfer is not required since the participants remain seated throughout the whole experiment. The sampling frequency is 200 Hz.

Biopac. The BioNomadix 2Ch Wireless ECG Amplifier (ECG2-R) module, which is a transmitter and receiver module with a simultaneous dual-channel recording feature, is used alongside the Biopac system. This feature might be helpful in other experiments, but since each participant has a unique set of answers, this experiment should be performed individually. Signals acquired with Biopac are transmitted wirelessly, with a 2000 Hz sample frequency, compared to the Arduino system.

Protocol

For better understanding, Fig. 3 illustrates all the details regarding the acquisition protocol. Since the recording is performed continuously, an automatic PowerPoint presentation is created, with a fixed duration for each slide. Every participant completes the acquisition procedure individually. The experiment is carried out in a room with a standard temperature, no external noise, and no distracting lights while the patient remains seated throughout. Additionally, the same electrode placement—Einthoven's triangle on the chest—and disposable gel electrodes are used, as well as the same acquisition protocol.

At first, during the device's calibration period, the participant receives an exhaustive description of the full process, including every task and break. The entire procedure includes an initial task (task 0) in which a 5-min signal is recorded while the patient is sitting calmly. This is followed by 4 main tasks (tasks 1-4), each of which has 2 separate 3-minute scenarios (a and b) separated by 10 seconds and a 1-minute break in between the main tasks. A ten-second introductory slide with task information is presented before each subsequent task.

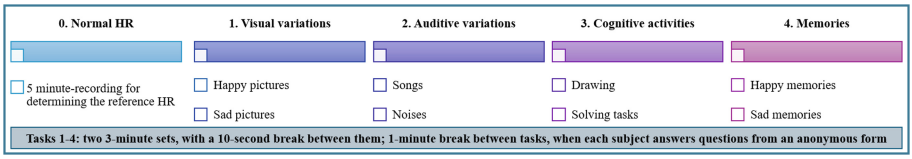

Fig. 3. The acquisition protocol with all the tasks

1. **Visual variations.** This task consists of 2 scenarios: happy pictures and sad pictures. Thirty pictures covering a variety of subjects are presented one after the other for each task (from landscapes, animals, and art, to war, pollution, and natural disasters).
2. **Auditive variations.** This task consists of 2 scenarios: songs and noises. Six distinct songs or noises (ranging from pop, rock, or classical music to alarms, sirens, and insects) are played for each task.
3. **Cognitive activities.** There are two primary objectives in this task: drawing and solving. First, the subject has to draw three distinct pictures in accordance with the term that is displayed on the slide (holiday, home, hobby). Then, he has to complete a few tasks on time, like computing, counting letters, numbers, and shapes, and responding to brief attention-getting questions.
4. **Memories.** There are two scenarios in this task: happy memories and sad memories. Three images accompanied by songs related to various themes are presented and played one after the other for every task. The images range from an airport, a beach, and a forest to a train station, a rainy day through a window, and a dark forest. The participant is required to recall six memories that bring these circumstances to mind.

Signal Processing

After the process of signal acquisition, the signals are uploaded into Matlab as .csv files for further analysis. Additional signal filtering is not required because the signals are already filtered when they are recorded, and only the R peaks (the highest amplitude peaks) need to be detected. The signals are first divided into the corresponding tasks based on the sampling frequency and task duration, obtaining 9 signals per subject. The R peaks are then identified as local maxima (percentage of the signal's mean amplitude) separated by a minimum number of samples. The RR intervals are calculated in samples and then converted to seconds based on the location of the R peaks. The outcomes are kept if they fall within the proper range for a healthy subject (0.6 to 1.2 s); if not, they are removed as considered artifacts. The process is demonstrated using a 3.2-second Arduino-recorded signal (Fig. 4). The four R-peaks are identified first, then the three RR intervals are computed, first in samples, then converted into seconds or milliseconds (by knowing the sampling frequency), and then HR and HRV are computed. Moreover, the experiment is not affected by the acquisition equipment because both systems recorded accurate ECG signals and accurate enough data to locate the R-peaks needed to calculate the HR and HRV.

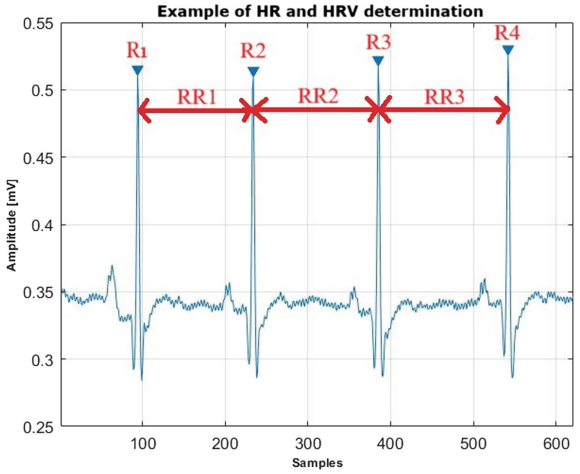

Fig. 4. An example of HR and HRV determination: R-peaks detection and RR intervals duration

Using the formula (1) and the correct RR intervals, one important parameter is computed: HR, with the mean value of the previously computed RR intervals.

$$HR = \frac{60}{RR\ intervals\ (s)} \tag{1}$$

Given that all the subjects are in good health with no history of cardiovascular diseases, the HR values are evaluated to ensure they fall within the appropriate range of 50 to 110 bpm. In the unlikely scenario that the values go outside of the range, the entire algorithm is retested with revised parameters after debugging. Then, another important parameter is HRV, computed with the method called RMSSD (Root Mean Square of

Successive Differences between each heartbeat), as Formula (2) describes. Given that all the subjects are in good health with no history of cardiovascular diseases, the HRV values are evaluated to ensure they fall within the appropriate range of 20 to 80 ms.

$$RMSSD = \sqrt{\overline{RR\ intervals^{\,2}\ (ms)}} \tag{2}$$

The values are stored for every task for each participant if they fall within the proper range, and statistics are computed to provide a more comprehensive understanding of the variations in HR and HRV. The whole algorithm is synthesized in Fig. 5.

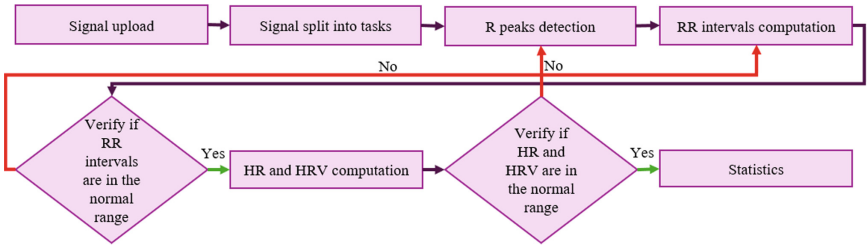

Fig. 5. The block diagram of the algorithm

2.2 Results

All the results are consolidated in Table 1, followed by separate discussions for each of the seven series of outcomes (in accordance with the procedure described previously). For the first three series, + denotes a good value and - a bad value. The notation + for differences above 0 and - for differences below 0 applies to the remaining four series and the rest of the differences in series 1-3.

Series 1: RR intervals duration. The first step is to verify if the RR interval duration is within the normal range. The RR interval lengths are determined, as was discussed in the previous section, and all participants' values, both during the relaxation state (0.66-1.09 s) and the whole experiment (0.68-1.07 s), fall within the normal range. These results were expected because the algorithm proved to be accurate, and no subjects reported having cardiovascular diseases.

Series 2: HR. Checking to determine if the HR is within the normal range is the second step. All of the individuals' computed HR values, both in the relaxation state (55-91 bpm) and during the experiment (56-89 bpm), fall within the normal range. These results were expected because the algorithm proved to be accurate, and no subject reported having any cardiovascular disease. Nevertheless, 60% of the participants had a greater HR in their relaxation state than throughout the experiment, indicating that overall, the experiment decreased their HR, as determined by calculating the difference between the HR in the relaxation state and the mean HR for the rest of the experiment.

Table 1. The outcomes of the first experiment

No.	State	Subjects				Values range	
		+		-		Range	Difference
1	**RR intervals (relaxation)**	10	100%	0	0%	0.66 - 1.09 s	0.43 s
	Mean RR intervals	10	100%	0	0%	0.68 - 1.07 s	0.39 s
2	**HR (relaxation)**	10	100%	0	0%	55 - 91 bpm	36 bpm
	Mean HR	10	100%	0	0%	56 - 89 bpm	33 bpm
	HR (relaxation vs. mean)	6	60%	4	40%	−1.25 - 2.32 bpm	3.57 bpm
3	**HRV (relaxation)**	10	100%	0	0%	29.87 - 64.92 ms	35.05 ms
	Mean HRV	10	100%	0	0%	27.03 - 53.45 ms	26.43 ms
	HRV (relaxation vs. mean)	6	60%	4	40%	−4.83 - 19.69 ms	24.53 ms
4	**HR (relaxation vs. task)**						
	relax - a1	7	70%	3	30%	−3.92 - 5.41 bpm	9.33 bpm
	relax - b1	6	60%	4	40%	−5.06 - 2.61 bpm	7.67 bpm
	relax - a2	5	50%	5	50%	−1.34 - 2.09 bpm	3.43 bpm
	relax - b2	5	50%	5	50%	−1.99 - 3.03 bpm	5.02 bpm
	relax - a3	4	40%	6	60%	−4.30 - 2.49 bpm	6.79 bpm
	relax - b3	6	60%	4	40%	−3.87 - 4.53 bpm	8.4 bpm
	relax - a4	9	90%	1	10%	−2.11 - 7.01 bpm	9.12 bpm
	relax - b4	9	90%	1	10%	−0.84 - 5.18 bpm	6.02 bpm
5	**HR (task a vs. b)**						
	task 1	3	30%	7	70%	−2.90 - 4.09 bpm	6.99 bpm
	task 2	4	40%	6	60%	−4.01 - 2.39 bpm	6.4 bpm
	task 3	6	60%	4	40%	−3.45 - 7.06 bpm	10.51 bpm
	task 4	4	40%	6	60%	−4.26 - 2.82 bpm	7.08 bpm
6	**HRV (relaxation vs. task)**						
	relax - a1	7	70%	3	30%	−14.55 - 37.69 ms	52.24 ms
	relax - b1	6	60%	4	40%	−14.36 - 30.10 ms	44.46 ms
	relax - a2	5	50%	5	50%	−29.44 - 29.99 ms	59.43 ms
	relax - b2	8	80%	2	20%	−5.52 - 12.63 ms	18.15 ms

(*continued*)

Table 1. (*continued*)

No.	State	Subjects				Values range	
		+		-		Range	Difference
	relax - a3	6	60%	4	40%	−34.53 - 28.79 ms	63.32 ms
	relax - b3	5	50%	5	50%	−21.42 - 3.97 ms	25.40 ms
	relax - a4	8	80%	2	20%	−19.51 - 23.78 ms	43.28 ms
	relax - b4	7	70%	3	30%	−6.68 - 32.20 ms	38.99 ms
7	**HRV (task a vs. b)**						
	task 1	4	40%	6	60%	−7.59 - 2.32 ms	9.91 ms
	task 2	6	60%	4	40%	−33.58 - 35.30 ms	68.88 ms
	task 3	2	20%	8	80%	−50.21 - 33.89 ms	84.10 ms
	task 4	7	70%	3	30%	−7.52 - 31.23 ms	38.75 ms

Series 3: HRV. Checking to see whether the HRV is within the normal range represents the next step. The HRV values are computed, as was explained in the previous section, and all participants had values within the normal range throughout the experiment (27.03 - 53.45 ms) and in the relaxation state (29.87 - 64.92 ms). Since none of the subjects reported having any cardiovascular disorders, these results were anticipated. Nevertheless, it can be observed that 60% of the participants had a greater HRV in their relaxation state than in the experiment, indicating that overall, the experiment decreased their HRV by computing the difference between the HRV in the relaxation state and the mean HRV for the rest of the experiment.

Series 4: HR variations between relaxation state and each scenario. In this series, the difference between HR in the relaxation state and HR in each scenario is computed. For task 1 (visual variations), 70% of the subjects had a lower HR when watching happy pictures and 60% when watching sad pictures. For task 2 (auditive variations), 50% experienced a lower HR in both scenarios (music and noise). For task 3 (cognitive activities), 40% of the subjects had a lower HR when drawing, and 60% of the subjects had a lower HR when resolving cognitive tasks. For task 4 (memories), 90% of the subjects had a lower HR in both scenarios (happy and sad memories). From these computations, it can be seen that the memories have the greatest influence over HR compared to the normal HR of a subject, decreasing it, followed by the happy pictures that also decrease the HR. Auditive factors do not follow a specific pattern, as half of the subjects experienced an increased HR and half of them decreased HR. The greatest range of values is obtained in task 1, scenario a, and task 4, scenario a (visual variations – happy pictures, cognitive activities - drawing): 9.33 bpm, 9.12 bpm, respectively.

Series 5: HR variations between tasks a and b. In this series, the difference between the HR in different scenarios of the same task is computed. For task 1 (visual variations), 70% of the subjects have higher HR when watching sad pictures. For task 2 (auditive variations), 60% of the subjects have higher HR when listening to noises. For task 3 (cognitive activities), 60% of the subjects have higher HR when drawing. For task 4 (memories), 60% of the subjects have a higher HR when thinking of sad memories. From these computations, it can be seen that the greatest difference between two scenarios of the same task is given by the visual variation, as 70% of the subjects have higher HR when watching sad pictures. Also, negative emotions (including watching sad pictures, listening to various noises, or thinking of sad memories) increase the HR, while positive emotions decrease it. Task 3 (cognitive activities) has the widest range of values, with a difference of 10.51 bpm between the maximum and the minimum values, since it is the most subjective task.

Series 6: HRV variations between relaxation state and each scenario. In this series, the difference between the HRV in the relaxation state and HRV in each scenario is computed. For task 1 (visual variations), 70% of the subjects had a lower HRV when watching happy pictures and 60% when watching sad pictures. For task b (auditive variations), 50% experienced a lower HRV when listening to music and 80% when listening to noises. For task 3 (cognitive activities), 60% of the subjects had a lower HRV when drawing, and 50% of the subjects had a lower HRV when resolving cognitive tasks. For task 4 (memories), 80% of the subjects had a lower HRV when thinking of happy memories and 70% when thinking of sad memories. From these computations, it can be seen that the noises have the greatest influence over HRV compared to the normal HRV of a subject, decreasing it, followed by the happy images and the sad memories, which also decrease the HRV. Music and cognitive activities do not follow a specific pattern, as half of the subjects experienced an increased HRV and half of them a decreased HRV. Task 3, scenario a (cognitive activities – drawing) has the widest range of values, with a difference of 63.32 ms between the maximum and the minimum values.

Series 7: HRV variations between tasks a and b. In this series, the difference between the HRV in different scenarios of the same task is computed. For task 1 (visual variations), 60% of the subjects have a higher HRV when watching sad pictures. For task 2 (auditive variations), 60% of the subjects have a higher HRV when listening to music. For task 3 (cognitive activities), 80% of the subjects have a higher HRV when solving cognitive tasks. For task 4 (memories), 70% of the subjects have a higher HRV when thinking of happy memories. From these computations, it can be seen that the greatest difference between two scenarios of the same task is given by the cognitive activities, as 80% of the subjects have a higher HRV when solving cognitive tasks. Also, music and happy memories increase HRV. Task 3, scenario a (cognitive activities), has the widest range of values, with a difference of 84.10 ms between the maximum and the minimum values.

Given that the HR and HRV have an inverse correlation, comparing the HR and HRV results indicates that happy memories cause the HR to decrease and the HRV to increase, along with other positive emotions, while negative emotions cause the HR to increase and the HRV to decrease. Because it depends on the subject, the cognitive activities do not provide a particularly accurate discrimination between them and relaxation; yet, performing cognitive tasks increases HRV values, even though the difference in HR values is not obvious. Although there is a greater differentiation between certain tasks than

others, it is obvious that no pattern can be established since each subject should examine his personal results as the impact of external factors on HR or HRV in comparison with his regular HR or HRV is very subjective.

2.3 Form

In this section, the results of the form and the correlations of it with the signal outcomes will be discussed. The questionnaire has different types of questions: Yes / No, options, free answers, etc. The results are centralized in Tables 2 and 3.

The questions about consent, diseases, and conditions prior to the protocol (Table 2) must be completed before the experiment. As can be observed, every subject gave his consent (and also signed a written one) for the signal recording, did not eat, smoke, or drink coffee before the protocol, and hydrated properly. Ten participants, five female and five male, ages ranging from 25 to 58, took part in the study. Moreover, the subjects did not report any neurological, muscular, or cardiovascular disorders.

Table 2. Questions prior to the acquisition protocol

Question	Yes			No
Consent	10	100%	0	0%
Previous coffee consumption	0	0%	10	100%
Previously eaten	0	0%	10	100%
Previously smoked	0	0%	10	100%
Previously hydrated	10	100%	0	0%
Age	25–58			
Gender	5	50%	5	50%
Cardiovascular diseases	0	0%	10	100%
Neurological diseases	0	0%	10	100%
Muscular diseases	0	0%	10	100%

In accordance with the four tasks, the rest of the form is split into four separate sections (Table 3). For the first two tasks, 90% of the participants said that they enjoyed the happy images and the music more than the sad pictures and noises. As mentioned before, the HR and HRV values show that while negative emotions have the opposite effect, good emotions lead to an increase in HRV and a decrease in HR. Regarding the cognitive activities, as the text on the PowerPoint indicated, all the drawings covered the concepts of holidays, home, and hobbies. At least nine of the twelve questions were properly answered by every participant. Because 40% of the participants preferred the drawing activity, 40% preferred the cognitive tasks, and 20% enjoyed both activities, the preferences of the subjects could be relevant.

For this reason, Table 4 summarizes the correlation between different parameters. There is a strong inverse correlation between age and mean HR, as well as HR in the relaxation state. This means that the older a subject is, the lower the HR is. There is also a

high correlation between age and HRV in the relaxation state and lower with mean HRV. This means that the older a subject is, the higher the HRV is. There is no correlation between gender and HR, and a low correlation between gender and HRV. Between HR and favourite images or favourite sounds, the correlation is high but significantly lower in the case of HRV. However, the favourite task and the HR or HRV are quite lowly correlated.

Table 3. Questions regarding the four tasks

Question	Task a		Task b		Both		None	
Favourite images	9	90%	0	0%	0	0%	1	10%
Favourite sounds	9	90%	1	10%	0	0%	0	0%
Favourite activity	4	40%	4	40%	2	20%	0	0%
Drawings	mountain, beach, travel, family, animals, sports, painting							
No. of correct answers	9–12 / 12							
Happy memories	holidays							
Sad memories	death, loneliness, sadness							

Table 4. Correlations between different parameters

Correlations	
Between age and mean HR	−0.67
Between age and mean HRV	0.35
Between age and HR in the relaxation state	−0.67
Between age and HRV in the relaxation state	0.57
Between gender and mean HR	0.06
Between gender and mean HRV	−0.22
Between gender and HR in the relaxation state	0.09
Between gender and HRV in the relaxation state	0.35
Between favourite images and HR variations between tasks	0.51
Between favourite images and HRV variations between tasks	−0.27
Between favourite sounds and HR variations between tasks	0.41
Between favourite sounds and HRV variations between tasks	0.27
Between favourite activity and HR variations between tasks	0.33
Between favourite activity and HRV variations between tasks	−0.20

3 Device and GUI Development

3.1 Device Development

The results obtained with the AD8328 sensor having proven to be conclusive, the AD8232 sensor was paired with a data recording system via Matlab, since this software was used for signal processing. Moreover, using DataStreamer could potentially alter the quality of the recordings, as its sampling frequency was not perfectly suited to the sensor's data transmission rate, and due to the fact that it implies offline processing, since it cannot connect directly to Matlab for online processing. This third acquisition method was therefore intended to deepen the study while further validating the effectiveness of the AD8328 sensor previously demonstrated in offline signal processing by developing an online signal acquisition and processing system.

After several promising preliminary tests, a complete and compact solution for HR and HRV analysis was developed, based on this acquisition method. The goal was to provide the user with a direct and autonomous evaluation of these two parameters by offering a PowerPoint presentation for recording stimuli, as well as a dedicated GUI, developed with Matlab App Designer and directly linked to this new acquisition method. The hardware specifications of this solution can be found in Table 5, as well as the circuit and the connections in Fig. 6.

Table 5. List of components of the developed ECG signal recording device

Component	Connection	Role
Arduino UNO	All	Controls all components
Resistors	Buzzer, Push Button	Regulate current
LEDs + 220 Ω Resistors	PB3, PB4, PB5	Indicates recording phases
Passive Buzzer	PB1	Emits sound signals
Push Button + 1kΩ Resistor	PD4	Initiates recording cycles
ECG AD8232	PC0	Records ECG signals

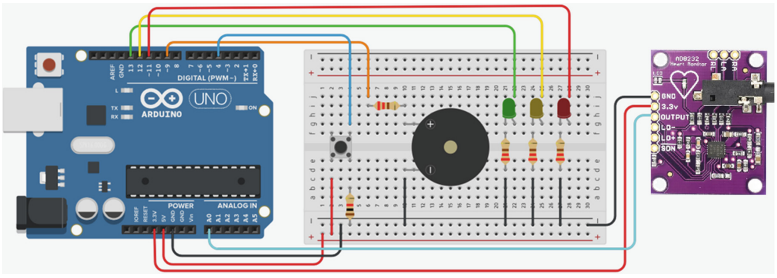

Fig. 6. Diagram (Tinkercad) of the implemented ECG signal recording device

The ECG sensor electrodes must be arranged in a triangular configuration (Einthoven's triangle) on the user, with two electrodes attached to the arms and the third on the right ankle or on the chest. The arms-and-ankle arrangement was finally chosen for this part after several successful tests, due to its practicality and showing similar results as the chest configuration [12, 13], avoiding the need for participants to undress or feel uncomfortable and enabling the recordings anywhere, anytime. Moreover, good contact between the electrodes and the skin is essential to ensure signal quality; that is why before each recording, the skin is disinfected with sanitary alcohol.

The implementation of auditory and visual alerts, such as LEDs and a buzzer, aims to guide the user throughout the recording process, as shown in Fig. 6. Additionally, the push button allows the users to switch between the different system states (Initialization, Visualization, and Recording) by following the instructions provided in the protocol displayed in the GUI. Integrating this button ensures complete user autonomy in controlling the recording, particularly by enabling navigation between the necessary windows for the recording process (Matlab application and PowerPoint presentation), allowing the user to start both the recording and the presentation simultaneously by pressing the button at the same time.

System Behaviour During a Recording Session

Step 1: Power-up and Standby Mode. The device is connected to its power source, usually through a USB cable to the computer. During this phase, the red LED is on, indicating that the system is in standby mode. No data is transmitted at this stage. The system is ready to receive instructions from the user via the push button.

Step 2: Sensor Placement and Initialization. Once the button is pressed, the yellow LED lights up. The device can send data in visualization mode to allow for sensor calibration and an initial check of the signal quality before starting the recording. Raw sensor data is continuously transmitted to the PC via the serial connection.

Step 3: Start of Recording. When the user presses the push button again, the system switches to recording mode, and the green LED lights up. The Arduino sends a specific frame to Matlab via the serial connection to indicate the beginning of data collection. From this point, the sensor data is continuously transmitted and recorded by Matlab. A sound signal is emitted by the buzzer to confirm the start.

Step 4: Ongoing Recording. For about 36 minutes, the device records the participant's ECG signals. The data is saved in real-time in a vector. The user can monitor the live data display through the Matlab console and ensure the recording is running smoothly. If any issues arise, the process can be manually interrupted by pressing the push button, which returns the system to its initial state (red LED on).

Step 5: End of Recording. At the end of the recording period, the system automatically returns to standby mode. The green LED turns off, and the red LED lights up again. A double sound signal is emitted to indicate the end of the session. Matlab saves the collected data in a *.csv* file. The system returns to its initial state (red LED on).

Participants and Database
Since there was a high correlation between age and HR and HRV, especially HR, six participants of the same age (21-23 years, Mean = 22.17, Standard Deviation = 0.69) were chosen. However, there was no correlation between gender and HR and a lower correlation between gender and HRV, so both genders were chosen (three feminine, three masculine). There was not a high correlation between the answers from the form and the values, so the form was not included anymore in this part. As the previous participants, they also received instructions not to consume any food or coffee for two hours prior to the experiment, were requested not to smoke right before the experiment, and were advised to hydrate properly. All of them signed the written consent, agreeing to participate in this study, including the signal recording and the anonymous use of their personal information (gender and age). All the experiments were conducted in the same conditions as the previous ones. A 36-min signal was recorded from each participant, which was split according to the same protocol as the one described before.

3.2 GUI

The final step was to integrate everything into a GUI called *appECG*: the app is launched, the signals are recorded with the proposed Arduino-based device in real-time or have been recorded previously, and after the recording/uploading process, the outcomes are computed (following the same signal processing algorithm as previously described) and displayed. The entire app flow is presented in Fig. 7. As it can be seen, there are three pages containing buttons with different functions and a "Back" button available all the time. In the beginning, the first page has two buttons. If the user presses the "Start a new session" button, a new recording will start. The instructions for the hardware and software will be provided and displayed for the user. After that, he has to decide on a number for his upcoming recording. The next two buttons remain disabled until the recording is over. If the "Upload an old session" button is pressed or when the recording is over, the two other buttons appear. The user can choose any signal from the database by pressing the "Previous results" button, but if he presses the "Newest results" button, the most recent stored signal from the database is automatically uploaded. The last page is the main one, which contains several features and displays the outcomes immediately after the signal has been uploaded. In the upper left corner, a random section of the signal is plotted, alongside the mean HR of the recorded signal. Two tabs can be found in the upper right corner; in the "Relaxation vs. task" tab, the difference between the HR or HRV during the relaxation phase and the HR or HRV during a task is computed, while in the "Task a vs. task b" tab, the difference between the HR or HRV during both tasks of the same phase is computed. According to the scale below, the dot's colour represents the size of the difference. A switch button in the centre of the page enables the display of either the HR and HRV values' graphs or some essential HR and HRV information.

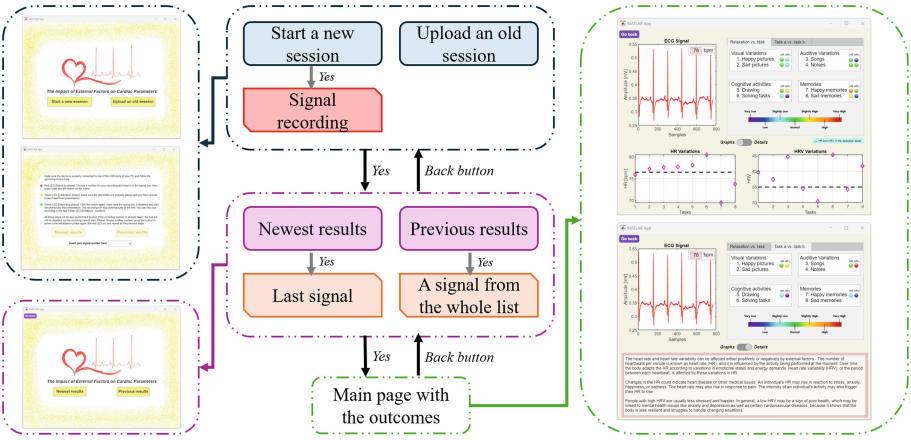

Fig. 7. Diagram of the designed GUI

3.3 Results

In this step, all the results are summarized from the *appECG*. In the same way as before, the outcomes are consolidated in a table (Table 6), and there will be separate discussions for each of the seven series of outcomes. For the first two series, + denotes a good value and - a bad value. For the rest of the five series, the notation + is for differences above 2, 0 is for the differences between -2 and 2, and – is for differences below -2. However, the results that are displayed to the subject are more specific, with a colour assigned to each interval, as presented in Fig. 8. Based on the colour, the subject can identify the problems and can also read some details that are written below. For the example presented in Fig. 7, The 1-5 tasks did not increase the HR compared to the relaxation HR. While task 6 increased the HR, tasks 7 and 8 decreased it in comparison with the HR in the relaxation state. Furthermore, there is a big change in HR when the subject is performing tasks 7-8 (the sad memories increase HR), and also the HR is higher when solving tasks than drawing. The HRV values vary more. When listening to songs or solving tasks, the HRV increases considerably, but it decreases when drawing. The most significant change appears between the 5-6 tasks.

Series 1: Mean HR. In the first series, the mean HR is checked to be within the normal range. All of the individuals' HR falls within the normal range (66-79 bpm). These results were expected because the algorithm proved to be accurate before, and no subject reported any cardiovascular disease.

Series 2: HR and HRV in the relaxation state. All of the individuals' HR and HRV fall within the normal range in the relaxation state, as can be also observed in the graphs (dotted lines).

Series 3: Overall values. In the case of variations between relaxation state and each task, the HR was the same in almost half of the cases (46%), and the other half was approximately split between lower and higher, while HRV varied in most of the cases (almost half lower (42%) and half higher (50%)). With 67% of the HR being the same

Table 6. The outcomes of the second experiment

No.	State	Subjects					
		+		0		-	
1	**Mean HR: 66–79 bpm**	6	100%			0	0%
2	**HR (relaxation)**	6	100%			0	0%
	HRV (relaxation)	6	100%			0	0%
3	**Overall HR (relaxation vs. task)**	16	33%	22	46%	10	21%
	Overall HRV (relaxation vs. task)	24	50%	4	8%	20	42%
	Overall HR (task a vs. b)	6	25%	16	67%	2	8%
	Overall HRV (task a vs. b)	10	42%	5	21%	9	38%
4	**HR (relaxation vs. task)**						
	relax - a1	3	50%	3	50%	0	0%
	relax - b1	2	33%	4	67%	0	0%
	relax - a2	2	33%	2	33%	2	33%
	relax - b2	2	33%	2	33%	2	33%
	relax - a3	1	17%	3	50%	2	33%
	relax - b3	1	17%	4	67%	1	17%
	relax - a4	2	33%	2	33%	2	33%
	relax - b4	3	50%	2	33%	1	17%
5	**HR (task a vs. b)**						
	task 1	1	17%	4	67%	1	17%
	task 2	1	17%	5	83%	0	0%
	task 3	3	50%	2	33%	1	17%
	task 4	1	17%	5	83%	0	0%
6	**HRV (relaxation vs. task)**						
	relax - a1	4	67%	0	0%	2	33%
	relax - b1	3	50%	0	0%	3	50%
	relax - a2	1	17%	1	17%	4	67%
	relax - b2	2	33%	0	0%	4	67%
	relax - a3	2	33%	0	0%	4	67%
	relax - b3	4	67%	0	0%	2	33%
	relax - a4	4	67%	1	17%	1	17%
	relax - b4	4	67%	1	17%	1	17%

(*continued*)

Table 6. (*continued*)

No.	State	Subjects					
		+		0		-	
7	**HRV (task a vs. b)**						
	task 1	2	33%	1	17%	3	50%
	task 2	3	50%	1	17%	2	33%
	task 3	3	50%	1	17%	2	33%
	task 4	2	33%	2	33%	2	33%

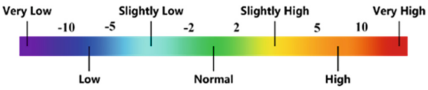

Fig. 8. Colour map and the corresponding values

and 25% being higher in task a, there was no greater HR variation between tasks a and b. However, the HRV variations were nearly evenly distributed between lower and higher, with less equal values across the two tasks (21%).

Series 4: HR variations between relaxation state and each scenario. In this series, the difference between HR in the relaxation state and HR in each scenario is computed. For task 1, no subject had a higher HR than in the relaxation state, just lower or the same, when watching happy pictures. No subject had a higher HR than in the relaxation state when watching sad pictures, but more than half had the same HR (67%). In task 2, in both cases, the values are evenly split. Task 3 shows the same HR values as in the relaxation state in half or more than half of the cases. In task 4, when thinking of sad memories, half of the subjects experienced a lower HR, but when thinking of happy memories, the values are evenly split.

Series 5: HRV variations between relaxation state and each scenario. In this series, the difference between HRV in the relaxation state and HRV in each scenario is computed. For task 1, no participant had the same HRV as in the relaxation state. More participants had a lower HRV when watching happy pictures (67%), but when watching sad pictures, the values are equally split between lower and higher values. For task 2, more than half of the participants had a higher HRV than in the relaxation state when listening to both songs and noises (67%). For task 3, more than half of the participants had a higher HRV than in the relaxation state when drawing (67%), and more than half lower when solving tasks. No participant had the same HRV as in the relaxation state. In both cases of task 4, the subjects had a lower HRV than in the relaxation state (67%).

Series 6: HR variations between tasks a and b. More than half of the subjects had the same HR values in both tasks (67%) when watching pictures, and half of them had a higher HR when drawing. Almost all of them (83%) had the same HR values in both tasks when listening to songs or noises and thinking of memories.

Series 7: HRV variations between tasks a and b. Half of the subjects had higher HRV values when watching sad pictures, listening to songs, and drawing. When thinking of memories, the values were equally split.

From these computations and from the previous results, it can still be seen that a pattern cannot be established, since the influence of external factors on HR or HRV compared to the normal HR or HRV of a person is very subjective. However, a difference between some tasks can be observed, so each subject should trace his individual variations, which is exactly the purpose of *appECG.*

4 Conclusions

In this paper, the design and development of an Arduino-based device that records ECG signals that are then analyzed in real-time is proposed, and the outcomes are displayed in the *appECG* GUI. The initial step was observing how external factors influence both HR and HRV, and in the end, it was proven that two individuals with nearly the same HRs have different HRVs, so it is important to consider both parameters. Even though some differences in HR and HRV were identified between certain tasks, it was concluded that these factors have different influences on the HR and HRV values depending on each individual, leading to the necessity of developing a user-friendly application that offers personalized outcomes for each user. At the same time, another primary purpose was to demonstrate that, given the current emphasis on low-cost, lightweight, wearable devices, an Arduino-based device could provide results that are as satisfactory as a more professional system—Biopac. The fact that both systems acquired qualitative ECG signals and accurate, adequate information to identify the R-peaks necessary for computing HR and HRV demonstrated that the experiment was not influenced by the acquisition equipment.

Both the Arduino device and GUI are very intuitive due to the features that guide the hardware part (LEDs, buzzer, button) and the instructions displayed in the GUI, colour maps and graphs. There are a few hardware resources at a relatively low cost, the connections are not complex, and the software requires little memory and runtime. The fact that everything is compatible with Matlab software is a big advantage since the whole process is straightforward and does not need to include other software.

The database dimension was one of the paper's limitations. In further research, the database should be expanded to include signals from groups of patients of different ages or other criteria that could be correlated with HR and HRV. It might also focus on particular aspects (e.g., if certain musical genres have an impact on HR and HRV). Furthermore, the development of a large database may offer better resources for ultimately identifying particular statistical patterns. Given that every subject is in good condition, this introduces another limitation. Different diseases can be investigated in the future to see how they affect HR and HRV. Evaluating additional factors such as caffeine or alcohol consumption, smoking, and physical activity offers a different perspective. The following goal is to turn the proposed method into a wearable, encapsulated, customized device that can monitor HR and HRV continuously and display the data in a mobile application, like the one presented in [14]. There will also be additional options for the device, such as fitness tracking, traffic flow estimation, and driving mode detection based on ECG signals. However, it is crucial to secure any application that stores medical information to prevent unauthorized access to that data [15, 16].

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