

Viability And Effectiveness of Mindfulness State Measurement Methodology Using Internet of Things: Proof of Concept

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Viability and Effectiveness of Mindfulness State Measurement Methodology Using Internet of Things: Proof of Concept

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ABSTRACT

Purpose: This proof-of-concept study aimed to develop and evaluate the feasibility and preliminary efficiency of a methodology to measure the mindfulness state using a wearable device (“Cap”) capable of monitoring students’ levels of full attention by means of real-time measured heart rate variability (HRV). **Methods:** The device was developed to export the data to the user’s cell phone via Bluetooth, which in turn stores the securely accessible data in the cloud. The autonomous wearable device consists of electronic boards of the Arduino platform that, in addition to the HRV, detect the heartbeat, the external temperature of the skull surface, and head/neck movements. **Results:** Preliminary statistical data using rMSSD (root mean squared successive differences), the Poincare map, the Toronto Mindfulness Scale, the Mindful Attention Awareness Scale (MAAS) and the Philadelphia Mindfulness Scale (PMS) show that increased HRV values converge to high values for the mindfulness state when the time difference between R and R_{N+1} sample is greater than 88 ms. **Conclusion:** The device proved to be viable and potentially effective for measuring the state of mindfulness. Thus, further studies should be conducted to test it on a large scale as well as in real classroom situations.

Keywords: *Heart Rate Variability, Internet of Things, Mindfulness State, Academic Performance.*

DECLARATIONS

Funding: This research received a partial funding from high school Internacional Radial IEB, due use logo “Radial” in the Cap.

Conflict of interest: The authors have no conflicts of interest to declare.

Ethical Approval: All procedures were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1964 and its later amendments. The protocol for this study was approved by the Research Ethics Committee of the Mackenzie Presbyterian Institute under number CAAE: 38711120.8.0000.0084.

Informed Consent: Written informed consent was obtained from all the participants of this study (or their parent or legal guardian in the case of children under 16 years of age) for participation and publication of their data.

Contributions: The high school International Radial IEB, located in São Paulo, SP, Brazil, provided the pedagogical environment and the volunteer students for the tests.

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1 INTRODUCTION

The main negative element of smartphones is dependence on electronic games and social networks among children, adolescents and adults [1]. Nomophobia (an illness characterized by the fear of being without access to a cell phone, video game, or other electronic device to communicate via the Internet) generates the need to maintain social networks as a persistent, parallel world that is always active and online for as long as possible [2]. The excessive use of smartphones causes psychological and behavioral damage in individuals comparable to that of drug addicts [3] as well as causing both stress and insomnia [4] and reduced school performance in children and adolescents [5].

In schools, the use of cell phones can have a distracting effect, leading to a loss of focus or a decrease in the degree of attention during classes depending on the age of the student [6]. Therefore, the research target of this work is a concept test in the form of a wearable prototype with Internet of Things (IoT) technology, e.g., a Cap capable of preliminarily indicating the degree of attention of students during their school activities by combining the behavior of their heart rate variability (HRV) [7, 8], the effects of mindfulness intervention [9], and scales that quantify the degree of attention: the Mindful Attention Awareness Scale (MAAS) [10], Philadelphia Mindfulness Scale (PMS) [11] and Toronto Mindfulness Scale [12].

Based on the central idea of the IoT to monitor individuals' HRV, the physiological basis of the human body is the simultaneous actions of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) [13], given that both constitute the human nervous system [14, 15].

It is known that the SNS transmits messages in a bidirectional flow inside the spinal cord that can accelerate the heartbeat, dilate the bronchi of the lungs, decrease motility of the large intestine, constrict blood vessels, cause pupil dilation, initiate sweating, and increase blood pressure. The PNS, in contrast, transmits messages via the vagus nerve [16, 17], a shorter and therefore faster-acting pathway than the spinal cord [7] that seeks to balance the excesses of the SNS, i.e., by slowing the heart rate and decreasing blood pressure, adrenaline and sugar in the blood. With the actions of the SNS, especially the PNS, we can obtain HRV in milliseconds [8]. The period in milliseconds is calculated between two subsequent referential R peaks of the QRS complex wave [18]. The proposed affordable wearable device measures this time using blood oxygenation attached to the earlobe of the individual [19] and detects oxygen peaks by means of infrared reflection on the bloodstream with every pulse of the heart [20].

For a healthy individual, it is natural that the *RR* beat interval changes during daily life, either during physical activity or at rest. The lower the heart rate (HR), the higher the HRV [21]

and the greater the action of the PNS. For individuals with emotional or social disorders, such as attention deficit hyperactivity disorder (ADHD) and chronic stress, the HR is higher, and consequently, the HRV is lower [22, 23, 24].

However, if an individual practices meditation of any type, the HR is lower and the HRV is higher [25, 26]. In this study, we highlight the Western meditation practice known as mindfulness, adapted from the Vipassana practice outside of a religious context by the Zen Buddhist Jon Kabat-Zinn in 1970 [9]. Mindfulness is self-reflection with self-awareness that seeks to reduce levels of stress and anxiety by heightening conscious experience in a given moment, i.e., by intentional and effortless full attention [27, p. 1481] with the mind centered in the moment and, above all, with nonjudgmental acceptance (compassion) [28, 29].

To associate the mental health of a person with their HRV, there are previous statistical studies in the time and frequency domain [24]. With regard to time, the NN50 counts the quantity of *RR* intervals greater than 50 ms, the pNN50 calculates the percentage of NN50 on the total of *RR* intervals analyzed, the standard deviation NN50 (SDNN) is the standard deviation of the NN50, and the root mean squared successive differences (rMSSD) is related to the mental workload or the degree of activity of the parasympathetic autonomic system [21, 30]. In the frequency domain, the power spectral density of the QRS signal uses the fast Fourier transform in two groups: low frequency (LF) from 0.04 to 0.15 Hz and high frequency (HF) from 0.15 to 0.4 Hz [31]. HF corresponds to parasympathetic and vagal activity, while LF is sensitive to the two activities of the autonomic nervous system, SNS and PNS. Regardless of the domain of analysis, HRV should be observed between 0.5 and 30 minutes [32, 33].

Other studies [25, 26] present results that demonstrate increases in HRV in participants undergoing medium- and long-term training in ancient and religious Vipassana meditation (the birthplace of mindfulness) in addition to reducing stress and increasing alertness through mindfulness meditation [34, 35, 36, 25].

However, in addition to the measurement of HRV performed by the Cap, this study evaluates a methodology to measure the degree of attention of senior high students by collecting the surface temperature of the skull and head/neck movements using sensors of the Arduino family. This is followed by the presentation of the methodology.

2 METHODOLOGY

The object of study of this research was a wearable device with Internet of Things technology capable of measuring the degree of students' concentration while they were engaged in their school

activities, specifically, during a 100-minute class. The prototype testing consisted of the following steps.

First, 155 invitations were sent to students' parents with the informed consent terms attached (the invitations were sent by e-mail due to COVID-19 pandemic isolation rules). The students were regularly enrolled in senior high school at Internacional Radial IEB, located in São Paulo, SP. In parallel, informed consent was sent to the same 155 students, all of whom were under the age of 18. The project received approval from the Research Ethics Committee of the Mackenzie Presbyterian Institute under protocol number CAAE: 38711120.8.0000.0084.

The sample consisted of voluntary participation by the first 5 parents and their children who met the inclusion criteria: any color/race or sexual orientation, between 15 and 17 years old, regularly enrolled in the 1st or 2nd year of senior high school and having a cell phone with the Android system. As exclusion criteria, the student could not be under treatment with medication for heart disease, stress, depression, ADHD, anxiety, or chemical dependency, could not have ear-hole spacers installed in the lobes, and could not have more than two holes in each lobule. The students could not have any diagnosis of heart problems. Subsequently, we conducted virtual and individual interviews confirming the inclusion and exclusion criteria until we obtained the first five students, three women and two men, with an average age of 15.6 years and SD ± 0.48 years.

After the selection of the 5 eligible participants, a new collective and virtual meeting was held via Google Meet to clarify doubts and explain the objectives and benefits presented in the informed consent during the invitation. If there were any dropouts in this step, it would have been necessary to return to the previous step for replacement; however, there were no dropouts. The next step was the personal and individual delivery of each Cap kit (composed of a Cap with an Internet of Things, rechargeable 9V battery, battery recharger, USB cable and a single magnet to attach the sensor to the earlobe) in their respective homes. The kit was sanitized (using Lysoform Spray Johnson, with 99.9% efficiency against germs) and kept inside the box for 60 days. In addition to this procedure, a sachet with alcohol gel was added to the external lid of the box so that the student could sanitize his/her hands before first contact with the Cap as a way to prevent the harmful effects of COVID-19.

On the day after the delivery of the kit, another general and virtual meeting was held for training on the use of the wearable device and proper positioning of the heart rate sensor on the earlobe. The app was installed on the participant's own cell phone, and the Bluetooth connection between the cell phone and the Cap was tested to ensure its proper functioning and data storage in the researcher's Google Drive. As a complement, an online manual was available for student consultation with images and videos that reinforced the virtual training conducted directly with the researcher.

With the Cap and app developed exclusively for this research working properly at each student's

residence, a common school class was randomly defined in which the Cap would be tested. This class was from 7:30 am to 9:10 am, totaling 100 minutes of continuous monitoring during school activities. During this period, the researcher followed the procedure online, validating the *RR* interval, the external temperature of the skull surface, and head/neck movement data stored in Google Drive. According to the pedagogical scheme adopted in the school because of the COVID-19 pandemic, all 5 students entered the respective subject of their course via Google Meet (Google's video calling platform), where the students were normally organized in virtual classrooms with their respective 1st or 2nd grade classes. The 5 selected kept their cameras and microphones on during the class, and the subject teacher of each class taught the class to all students normally.

After the 100-min lesson using the Cap, the 5 students completed 3 questionnaires quantifying the degree of full attention referring to the last 100 minutes of activity. These questionnaires were completed via Google Forms. The researcher followed the completion by video call (following the same scheme of simultaneity of the 100-min class), where each student assigned a score for the questions that classified his or her own degree of attention. The MAAS [37] and PMS [38] questionnaires and their scales were validated in the Portuguese-Brazilian language. The Toronto questionnaire [12] was translated by the researchers involved in this work due to its relevance in quantifying the degree of the students' full attention in the last moments of the class.

After data collection, the researcher made correlations and statistical analyses between the *RR* intervals extracted during the 100-min class and the answers to the mindfulness scale questionnaires completed immediately after the 100-min class. It was expected that a relationship would be found between maximum HRV and the questionnaire scores.

At the end of the trials, the kits were collected by the researcher, and the participating students received their individual report with conclusions about their degree of attention. The grades are presented in the Results section.

2.1 INSTRUMENTS

2.1.1 Prototype Cap

The technology employed in the prototype was the IoT, which allows mobility, connectivity, scalability, low power consumption, intelligence, miniaturization of electronic boards, and multifunctional sensors [39, 40, 41, 42, 43, 44]. Other studies have shown the feasibility and accuracy of remotely monitoring vital signs [45, 46, 47]. With the versatility of the Internet of Things, a Cap-shaped prototype was created, with circuits fixed (sewn) on its external side.

Fig. 1 shows the Cap. The main board comes from a worldwide open platform [48, 49], model

Arduino Nano ATmega328 V3, 16 MHz clock, 31 kB flash and 1 kB EEPROM (no storage memory), powered by a 9 V rechargeable battery through the Vin pin (which in turn has an input voltage regulator that supports 7 to 20 V and provides 5 and 3.3). From the main board, the power supply is derived for the other peripheral boards, such as the sensors and the Bluetooth communication board.

The heart rate sensor is a low-cost reflected infrared oximetry sensor composed mainly of an instrumentation amplifier with no need for a symmetrical power supply. There are also some resistors and capacitors calibrated to detect, filter and compare the inputs and outputs of the amplifiers in addition to the emitting LED and a phototransistor receiver for the detection process by reflecting the infrared on the blood current with each pulse of the heart [20]. Pulse detection by oximetry is reliable for the real beats of the human heart [50].

The temperature sensor (ranging from -40 to +85°C) positioned inside the Cap is integrated with the MPU6050 gyroscope motion sensor, which is capable of determining simultaneous movements in the X, Y, and Z axes of the head and neck. Its communication with the Arduino main board is via the I2C bus.

Fig 1 Wearable Internet of Things device in the form of a data collector Cap. The heartbeat sensor attached to the orange, red and brown wire and magnet is highlighted



Source: designed by the author.

The Bluetooth board is the HC05 model of the master-slave type, with the BC417 radio chip from the British company CSR and the American telecommunications group, Qualcomm. The baud rate between the Arduino Nano main board and the Bluetooth board is 115,200 bps via the serial 232 bus. Below the 115,200b rate, there may be overlapping samples for short *RR* intervals that may generate data losses according to the tests performed.

2.1.2 App

After the beats are detected by blood oximetry, the data are transmitted via Bluetooth technology to the participating student's cell phone, which is loaded with an app developed by the researcher and receives the data from the Cap. App usability can be observed in Figure 2. This is designed so that the student pairs the Cap with his/her cell phone via Bluetooth by entering the standard code 1234 when prompted. Next, the participant opens the application, types his/her name in the "Enter your name" field, then expands a menu by clicking the "(1) Cap #" button and chooses the Cap he/she is wearing (ranging from 01 to 05). Finally, by means of a short click on the "(2) On-off" button, the app connects with the Cap. If this communication is successful, the same "(2) On-off" button turns green. The following are the screen details of the Android app. Item "(3) Calibration" on the screen, serves to calibrate the oximetry sensor and item "(4) Send data" serves to send the data to the cloud storage, which will be further processed via MATLAB. The "Exit" button kills the application.

- Cap: the Cap identification number (between 01 and 05) is loaded in front of this word when it successfully connects to the application;
- Man Icon: this icon varies between "sitting man" and "standing man", indicating whether the Cap has detected the user's head/neck movements by means of the gyroscope;
- Speaker Icon: the participant can turn the beep (which sounds synchronously with his/her heartbeat) on and off by making a quick, vertical upward movement with his/her head (i.e., turn on-off with vertical head movements);
- Thermometer Icon: indicates the external temperature of the skull surface in degrees Celsius;
- [*bmp*]: indicates the heartbeat value per minute;
- [*avg*]: indicates the moving average of heart beats per minute. This moving average is $N = 5$ samples (a simple low-pass filter that avoids high-frequency noise at detection);
- [*var*]: variability between the sample peak R_N e R_{N-1} .

These variables were recorded continuously and serially in the application in the form of a text file and separated by the preamble "P" (character 50_h of the ASCII table). Once the data were collected

by the cell phone and Cap, they were uploaded to Google Drive (via local Wi-Fi and TCP/IP protocol).

2.1.3 Questionnaires

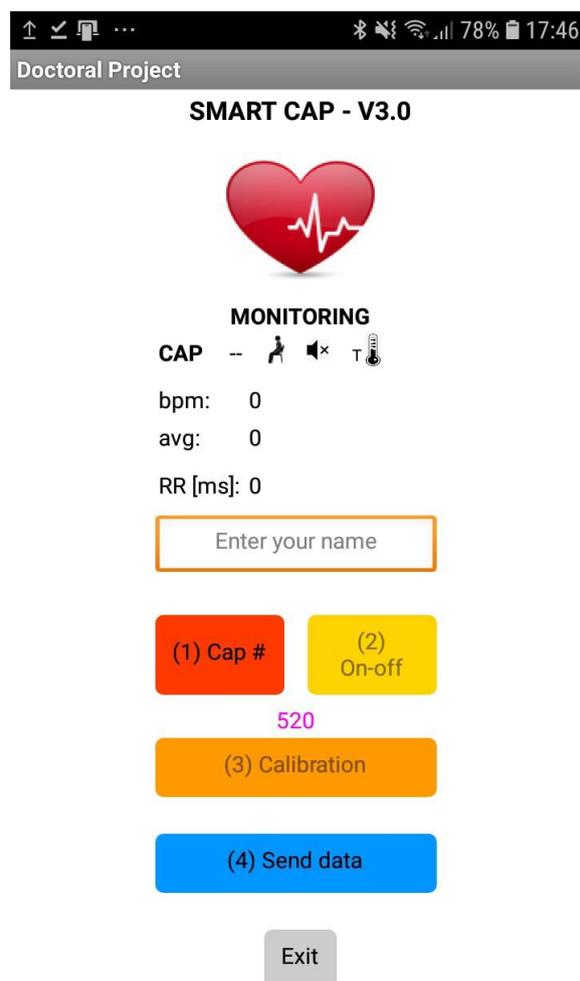
The participants completed three questionnaires after the 100-min period of HRV monitoring during school activities at home.

MAAS objectively stratifies the state of full attention in that phase of the measurement [37]. The MAAS result is obtained by adding the score attributed to each of the 15 questions, which can be between 1 and 6, and then dividing this sum by 15 to obtain the final average. The closer this average is to the value of 6, the higher the degree of full attention of the participant.

The second questionnaire is the SMP, which also assesses the quantification of the subject's full attention state [38]. The result of the SMP is also obtained by simple average of the score of the 20 questions, which can be between 1 and 5. However, the SMP has two facets of mindfulness: acceptance and awareness (equivalent to "self-awareness" or "acting with awareness" [38]). Consequently, the SMP generates two results. The closer to the value is to 5 in each of the subgroups of 10 questions, the higher the degree for each facet.

The third and last questionnaire, Toronto [12], has 13 questions divided into two subgroups: the curiosity score with 6 questions (3, 5, 6, 10, 12 and 13) and the decentering score with 7 questions (1, 2, 4, 7, 8, 9 and 11). Both have five answer choices: "(0) not at all", "(1) a little", "(2) moderately", "(3) quite a bit" and "(4) very much". Each subgroup is added, and its average is obtained. A value closer to 4 indicates more curiosity or more decentering, respectively, the individual will be.

Fig 2 Screenshot of the Android app, developed for the purpose of this thesis



Source: Developed by the author.

2.1.4 Variables Analysis

In the area of neuroscience, four signals are observed here: BPM, *RR* interval, temperature, and head/neck movements. In the area of psychology, we use the averages of the three questionnaires: MAAS, PMS, and Toronto. Considering this, the *p-value* hypothesis test was used between rMSSD and these questionnaire averages in addition to the geometric analysis through the Poincaré map [51, 52], the histogram of the *RR* intervals and the rMSSD value [51]. An association was defined between the rMSSD (in milliseconds) of each participant and the participant's questionnaire results to support the hypothesis of measuring the degree of full attention using the Internet of Things.

Numerically, the rMSSD is equivalent to the standard deviation in the geometric analysis of

the Poincaré map.

$$rMSSD = \sqrt{\frac{\sum_{i=0}^{N-1} (RR_i - RR_{i+1})^2}{N-1}} \text{ [ms]} \quad (1)$$

The HRV analysis for the 100-min class was segmented into intervals of 15 and 30-min, based on [32], and additionally for 50 minutes on an experimental basis. Thus, the data were organized as follows:

- First half (1st P) divided into 15-, 30- and 50-min, i.e., from the 1st to the 15th minute, from the 1st to the 30th minute and from the 1st to the 50th minute;
- Second half (2nd P) or the last 50-min: from the 51st to the 65th minute, from the 51st to the 80th minute and from the 51st to the 100th minute.

Moreover, some signal enhancement techniques were adopted. The results will be discussed in the following section.

1. Noisy samples whose RR_N interval became larger than 1500 ms were truncated to this value. The same occurred for RR_N samples smaller than 250 ms. These limits were adopted because they correspond, respectively, to the largest and the smallest RR_N interval among the five participants in the observed scenario in the 100-min lesson;
2. Corrupted RR_N samples in the interpretation of the transmission byte between Cap and smartphone were recovered with the average of 4 subsequent previous samples, i.e.,

$$RR_N = \text{mean}(RR_{N-1} + \dots + RR_{N-4}) \quad (2)$$

This was necessary to avoid discarding P_N packets because the observation windows depend directly on the number of packets processed to obtain 15-, 30- and 50-min times.

3. The entire RR time signal resulting from the two previous techniques (truncation and replacement) was subjected to a moving average of $MA = 2$. This value was adopted minimally to reduce the spuriousness that borders the limits of the Poincaré maps without changing their shape (in particular, their width). It is essential to maintain “perpendicular width” of the Poincaré because it represents the individual’s HRV [51]. The geometric maintenance of the Poincaré map is important to prove the hypothesis of the degree of full attention measured through the Internet of Things.

The temperature, given in °C, was extracted from the external skull surface, on the scalp. There was no intervention to bring the sensor into direct contact with the skin, such as shaving the hair. However, the sensor remained inside the Cap, and the temperature was recorded with each heartbeat. Within the two observation windows of 15-, 30- and 50-min, the mean and standard deviation were calculated.

Regarding the head/neck movement, the physical behavior of the student was rated on a binary basis of whether the student was moving at each heartbeat. Within the intervals of 15-, 30- and 50-min, the percentage of each state was defined as still or moving.

Regarding the head/neck movement, the physical behavior of the student was binary rated as to whether or not he was moving at each heartbeat. Within the intervals of 15-, 30- and 50-min, the percentage of each state was defined: still or moving.

3 RESULTS

3.1 Treatment of Corrupted Samples

In compliance with the social isolation of the COVID-19 pandemic, the school routine of the 5 subjects took place in their own homes. Consequently, the data collection process via the Cap occurred from the students' home environment. In this research, the degree of attention during a 100-min lesson was measured.

Initially, the two correction techniques for sample data did not show significant differences between the original and the postprocessed statistical parameters. That is, neither the replacement of a given totally corrupted sample by the average of the 4 immediately preceding uncorrupted samples (Eq. 2) nor the application of the moving average (MA = 2) as a filtering technique to all samples of each subject changed the identity line of the Poincaré map (chart 3, blue and yellow diagonal), keeping it at a 45° inclination, which corresponds to the maintenance of the normal distribution with $\mu=0$ defined in [51].

The highest percentages of corrupted *RR* samples were, from subject 02 (between the 1st and 15th minute of the 1st interval) with 6.39% corrupted samples, subject 01 (between the 51st and 65th minute of the 2nd interval) with 6.27%, and subject 03 between the 1st and 15th minute of the 1st interval) with 6.20%. The cause was inadequate displacement of the oximetry sensor installed in the earlobe caused by the subject.

Calculating the average of the values in the 3rd row of Tables 2, 3 and 4, it is possible to find the average percentage of corrupted samples involving all participants:

- Windows between the 1st - 15th (1st P) and the 51st - 65th minute (2nd P): 3.8%
- Windows between 1st - 30th (1st P) and the 51st - 80th minute (2nd P): 3.6%
- Windows between the 1st - 50th (1st P) and the 51st - 100th minute (2nd P): 2.9%

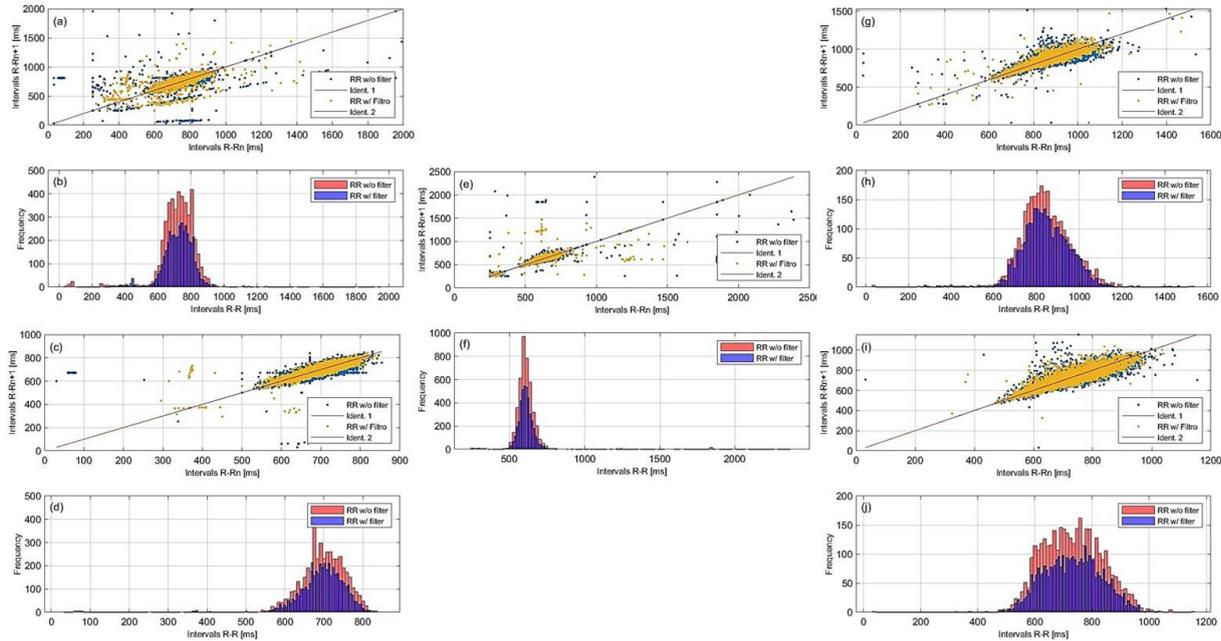
Thus, among the observation windows of 15-, 30- and 50-min, the best results considering corrupted samples, statistical values, and the scale of the questionnaires were between the 1st and 50th minute and the 51st - 100th minute of each student rather than among all of them. The 1st to 15th and 1st to 30th minute windows are presented for discussion but did not show a significant correlation between maximum HRV and the mindfulness questionnaire.

Starting with subject “01” (male, 15 years old), Fig. 3(a) shows the sequence of the RR signal on the time axis interleaving the RR_N sample on the x-axis and with RR_{N+1} on the y-axis for the 1st to 50th minute window of the lesson without and with $MA = 2$, respectively.

3.2 Benefits of the Moving Average (MA = 2)

To better consolidate the comparison of the effect of the $MA = 2$ of subject 01 and to demonstrate the maintenance of the Poincaré standard shape, Fig. 3(a) shows the overlay between the Poincaré map without the filter effect (blue) and with the filter effect (yellow) as well as their respective histograms in Fig. 3(b), overlaid to visualize the effect of $MA = 2$. Neither graph (blue or yellow) presents significant differences in the normal distribution for moving average $MA = 2$; thus, the advantage of this low-pass filtering is the elimination of the spuriousness caused by the eventual movement of the oximetry sensor attached to the earlobe of the participant (spuriousness represented by blue points detached from the region accompanying the diagonal line of the graph). This technique seems to scientifically support the affordable oximetry sensor of the Arduino family.

Fig 3 Overlapping RR intervals of subjects 01 to 05 at 50-min with and without the effect of the MA = 2 filter. Item (a) is a subject male, 15 years old; (b) it's histogram RR intervals; (c) a subject female, 16 years old; (d) it's histogram; (e) a subject male, 16 years old; (f) it's histogram; (g) a subject female, 15 years old; (h) it's histogram; (i) a subject female, 16 years old. (j) it's histogram



Source: Elaborated by the author.

Poincaré maps of every 50-min of the remaining subjects 02 to 05 (with and without MA = 2) are organized in Fig. 3 as follows: Cap 02 (a) and (b), Cap 03 (a) and (b), Cap 04 (a) and (b) and Cap 05 (a) and (b), with the Poincaré map in (a) and the histogram in (b).

3.3 Participants' Data

Table 1 organizes the variables, their respective meanings, and the row position in which they will be presented in the other tables.

Table 1 Indices evaluated in the time domain during 100-min of class and divided into Part 1 and Part 2.

Line	Period of X minutes			Meaning
	Indices 1 st P	2 nd P		
1 st	N	-	-	No. of samples from the period package x
2 nd	μ BPM	-	-	Overall average bpm
3 rd	% RR ajust.	-	-	Percentage of the RR samples error in the period ajust
4 th	μ RR [ms]	-	-	Overall mean of RR over the entire period
5 th	SDR-R [ms]	-	-	RR standard deviation over the whole period
6 th	rMSSD [ms]	-	-	Poincaré geometric standard deviation
7 th	NN50 [N]	-	-	Number of RR intervals > 50 [ms]
8 th	pNN50 [%]	-	-	Percentage of NN50
9 th	SD1 [ms]	-	-	Perpendicular Poincaré standard deviation
10 th	SD2 [ms]	-	-	Poincaré diagonal standard deviation
11 th	SD1/SD2	-	-	How far SD1 is to SD2

12 th	Toronto C	-	-	Toronto Scale for Curiosity (0 - 4) for 1 st P and 2 nd P
13 th	Toronto D	-	-	Toronto Scale for Decentering (0 - 4) for 1 st P and 2 nd P
14 th	PMS	-	-	Philadelphia Mindfulness Scale (1-5) for 1 st P and 2 nd P
15 th	MAAS	-	-	Mindful Attention Awareness Scale (1-6) for 1 st P and 2 nd P

Initially, the information consolidated in Table 2 is the statistical data of subject 01 (male, 15 years old), 02 (female, 16 years old), 03 (male, 16 years old), 04 (female, 15 years old) and 05 (female, 16 years old). The interpretations of the values found will be discussed in Section 4 Discussion.

Table 2 Indices evaluated in the time domain during the movie for the initial 50-min period.

		50-min windows of the 1 st P and 2 nd P									
		Sub 01		Sub 02		Sub 03		Sub 04		Sub 05	
Indices		1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P
1 st	N	4327	4381	4511	4560	4361	4854	3546	3125	4107	4280
2 nd	μ BPM	86,53	85,74	90,23	91,92	87,26	97,05	70,92	62,36	82,15	85,50
3 rd	% RR	4,84	5,11	4,77	3,98	3,09	3,25	2,18	1,89	0,0	0,0
4 th	μ RR [ms]	727,89	734,25	694,65	673,17	608,13	598,46	846,26	974,96	732,84	701,37
5 th	SDR-R [ms]	95,07	83,83	57,59	62,66	74,61	64,42	109,62	138,90	98,54	91,27
6 th	rMSSD [ms]	74,01	52,13	36,31	38,75	67,71	39,21	53,99	78,39	49,53	49,57
7 th	NN50 [N]	5142	5132	5318	5427	5102	5646	2733	3683	3571	5093
8 th	pNN50 [%]	98,52	98,33	98,46	98,33	98,13	97,77	98,95	99,30	99,25	99,03
9 th	SD1 [ms]	52,43	37,07	25,90	27,59	48,22	27,86	38,64	55,45	35,27	35,20
10 th	SD2 [ms]	123,80	112,59	77,21	84,20	93,84	86,74	150,10	188,42	134,80	124,17
11 th	SD1/SD2	07,0	0,80	0,80	0,81	0,58	0,81	0,88	0,84	0,87	0,85
12 th	Toronto C*	3.67	2.83	3.00	3.17	3.33	2.00	2.83	3.50	2.17	1.50
13 th	Toronto D*	2.29	3.29	1.14	1.43	2.14	2.71	2.71	1.71	2.43	3.00
14 th	PMS**	3,40	3,40	3,40	3,40	3,20	3,20	4,20	4,20	2,70	2,70
15 th	MAAS***	2,73	2,73	4,30	4,30	2,93	2,93	3,10	3,10	3,24	3,24

*Scale from 0 to 4 for C = Curiosity and D = Decentering / **From 1 to 5 for Awareness / ***From 1 to 6

Also, in Table 2, in the 1st row, we have the N number of samples analyzed in the respective window of the lesson (Part 1 or Part 2). Dividing this N number of samples by the global average μ BPM (from the 2nd line), it is possible to find the lesson window observed in minutes, i.e., 4327 (samples)/ 86.53 (beats) = 50.0 minutes. The same can be done for any subject in that same table.

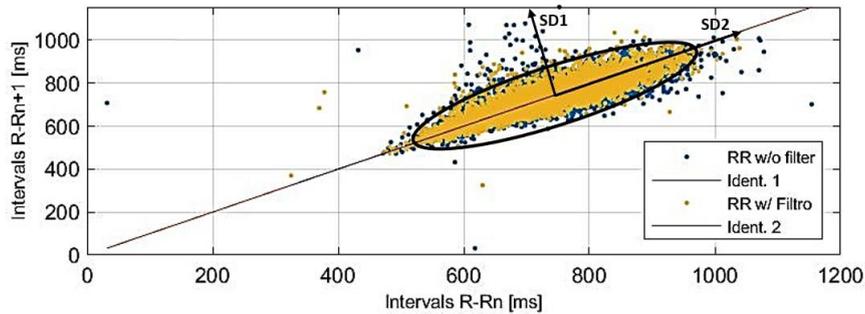
The 3rd row of the same Table 2 shows the percentage of corrupted RR samples that were adjusted following the replacement rules and $MA = 2$ previously listed in 2.1.4. In the case of subject 01, this was 4.84% corrupted samples over the total number of samples within 50 minutes of the 1st P.

The 4th row of the same table shows the global average μ RR in milliseconds; the 5th row shows its standard deviation in milliseconds (SDR-R), and the 6th row shows the most commonly used index to measure the Poincaré map dispersion, the rMSSD, in milliseconds. In the 7th row, NN50 indicates the number of adjacent RR samples with intervals greater than 50 ms over the total number of RR samples of the subject. Both rMSSD and NN50 indicate the presence of parasympathetic activity in the

individual organism by evaluating adjacent intervals [21, 30]. In the 8th row, there is the predominance percentage of NN50 intervals over the sample's universe of the first 50 minutes, which in the case of subject 01 was 98.52%.

The 9th and 10th lines show SD1 and SD2, respectively. These indices represent a qualitative analysis of the Poincaré map in geometric ellipse form [51]. Fig. 4 shows that SD1 is equivalent to the width of the scatter of points perpendicular to the identity line and behaves as an instantaneous recording index of the beat-to-beat variability [53], while SD2 appears to represent the scatter of points along the identity line and the HRV in long duration recordings. Finally, in the 11th row, we have the ratio of both (SD1/SD2) which shows the ratio between the two variations, short and long, of the *RR* intervals [54, 55].

Fig 4 SD1 and SD2 dispersion on the Poincaré map.



Source: Elaborated by the author.

The 12th and 13th rows show the Toronto Scale for Curiosity and Decentering values used to quantify the degree of the subject's attention in the last class. Among the three scales adopted, curiosity showed the best relationship with rMSSD, i.e., the highest values of the Toronto Scale for Curiosity accompanied the highest values of rMSSD for the same subject in the 1st P and 2nd P windows of 50 minutes. Finally, rows 14th and 15th show the PMS and MAAS values, respectively.

The statistical data from the 30- and 15-min periods for the five subjects are shown in Tables 3 and 4 below.

Table 3 Indices evaluated in the time domain for two 30-min windows of the lesson.

		30-min period of the 1 st P and 2 nd P									
		Sub 01		Sub 02		Sub 03		Sub 04		Sub 05	
Indices		1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P
1 st	N	2609	2609	2700	2759	2599	2887	2126	2126	2463	2571
2 nd	μ BPM	87,74	85,98	91,72	90,38	86,42	102,16	72,89	63,74	82,39	85,29
3 rd	% RR	5,50	5,52	5,88	3,88	5,03	6,10	2,83	1,08	0,0	0,0
4 th	μ RR [ms]	724,24	725,12	695,46	674,67	609,26	584,06	819,23	928,90	730,47	700,24
5 th	SDR-R [ms]	98,67	102,36	58,64	67,51	89,69	55,27	102,02	123,96	98,81	83,60
6 th	rMSSD [ms]	76,28	94,90	36,92	42,65	87,47	36,13	51,71	68,35	49,19	47,02
7 th	NN50 [N]	2564	2352	2656	2723	2541	2818	2105	2111	2443	2540
8 th	pNN50 [%]	98,28	90,00	98,37	98,70	97,77	97,61	99,01	99,29	99,19	98,79
9 th	SD1 [ms]	54,13	67,12	26,56	30,54	62,36	25,79	37,14	48,34	35,15	33,58
10 th	SD2 [ms]	128,59	128,23	78,54	90,45	110,43	73,77	139,39	168,47	135,22	113,34
11 th	SD1/SD2	0,70	0,57	0,79	0,80	0,52	0,78	0,87	0,85	0,87	0,84
12 th	Toronto C*	3.67	2.83	3.00	3.17	3.33	2.00	2.83	3.50	2.17	1.50
13 th	Toronto D*	2.29	3.29	1.14	1.43	2.14	2.71	2.71	1.71	2.43	3.00
14 th	PMS**	3,40	3,40	3,40	3,40	3,20	3,20	4,20	4,20	2,70	2,70
15 th	MAAS***	2,73	2,73	4,30	4,30	2,93	2,93	3,10	3,10	3,24	3,24

*Scale from 0 to 4 for C = Curiosity and D = Decentering / **From 1 to 5 for Awareness / ***From 1 to 6

Table 4 Indices evaluated in the time domain for two 15-min windows of the lesson.

		15-min period of the 1 st and 2 nd hour.									
		Sub 01		Sub 02		Sub 03		Sub 04		Sub 05	
Indices		1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P	1 st P	2 nd P
1 st	N	1304	1304	1349	1379	1299	1443	1082	1062	1231	1285
2 nd	μ BPM	89,95	86,06	93,18	89,42	86,21	101,08	70,62	64,30	82,36	86,69
3 rd	% RR	5,33	6,27	6,39	4,15	6,20	5,71	2,83	1,08	0,0	0,0
4 th	μ RR [ms]	709,18	730,80	703,00	684,78	610,44	588,95	849,80	925,36	729,82	687,60
5 th	SDR-R [ms]	95,69	95,24	58,61	67,50	109,14	52,33	92,88	134,46	96,04	67,71
6 th	rMSSD [ms]	71,41	72,44	42,60	48,09	108,85	33,72	55,45	79,54	48,13	40,11
7 th	NN50 [N]	1275	1277	1327	1353	1275	1408	1053	1053	1218	1277
8 th	pNN50 [%]	97,78	97,93	98,37	98,11	98,15	97,57	99,15	99,15	98,94	99,38
9 th	SD1 [ms]	50,84	51,81	30,91	34,67	77,77	24,38	40,44	56,27	34,85	29,03
10 th	SD2 [ms]	125,36	25,34	76,87	88,90	133,25	69,86	124,91	181,55	131,22	91,22
11 th	SD1/SD2	0,72	0,71	0,72	0,74	0,49	0,78	0,81	0,82	0,87	0,82
12 th	Toronto C*	3.67	2.83	3.00	3.17	3.33	2.00	2.83	3.50	2.17	1.50
13 th	Toronto D*	2.29	3.29	1.14	1.43	2.14	2.71	2.71	1.71	2.43	3.00
14 th	PMS**	3,40	3,40	3,40	3,40	3,20	3,20	4,20	4,20	2,70	2,70
15 th	MAAS***	2,73	2,73	4,30	4,30	2,93	2,93	3,10	3,10	3,24	3,24

*Scale from 0 to 4 for C = Curiosity and D = Decentering / **From 1 to 5 for Awareness / ***From 1 to 6

4 DISCUSSION

The present study is considered a concept test and naturally requires further investigation. For example, the sample of subjects was reduced to five due to pandemic restrictions, and the data collection environment was not controlled due to the imposition of social distance. Factors such as these generated partial results that were not sufficient to accept a *p-value* of 5% significance.

However, the studies mathematically proved the minimum average value of the rMSSD intervals to obtain the acceptance of the hypothesis using a Z-Test. That is, for H_0 (the device - Cap - is able to measure the degree of attention) to classify a student as “concentrating on school activities” in an observation window of up to 50-min, the minimum average interval should be 88 ms.

To prove this statement, we adopted the Z-Test (Eq. 3) at 5% significance, for which the acceptable critical value should be less than 1.9599 for the variances of the rMSSD and the Toronto questionnaire presented in Table 2.

For example, consider, hypothetically, that subject 01 had obtained an average rMSSD = 133 ms in the first 50-min of the class and in the second part of the class, his/her rMSSD fell to 45 ms, i.e., the difference of 88 ms as mentioned. Considering that the two Toronto values are the same 3.67 and 2.83 for the 1st P and 2nd P trials, respectively, the Z-Test calculations would result in the following:

$$n_1 = 2, n_2 = 2 \text{ (number of tests)}$$

$$\bar{X}_1 = \frac{133 + 45}{2} = 89$$

$$\bar{X}_2 = \frac{3.67 + 2.83}{2} = 3.25$$

$$\sigma_1^2 = \frac{\sqrt{(133 - 45)^2}}{2} = 3872$$

$$\sigma_2^2 = \frac{\sqrt{(3.67 - 2.83)^2}}{2} = 0.42$$

Substituting in Eq. 3, the following result is obtained:

$$Z = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} = \frac{(89 - 3.25)}{\sqrt{\frac{3872}{2} + \frac{0.42}{2}}} = 1.94877$$

$$1.94877 < 1.9599 \text{ (} P < 0.05 \text{)}$$

Thus, H_0 would be accepted.

Although the minimum rMSSD difference of 88 ms was not reached in the small group of 5 subjects and even though these subjects are not practitioners of any meditation technique, care should be taken in affirming that higher degrees of full attention come only from groups with experience in mindfulness, which is not entirely true [56]. Undoubtedly, there are benefits of this practice, as demonstrated by [57] among other authors cited in this paper. However, this study suggests that the hypothesis tests will likely have more reliability if we employ the Internet of Things Cap on a group with experience in meditation practice and a group without experience.

In addition, the partial results indicated that the comparisons were made from subject to subject in different concentration scenarios. No statistical evidence was found to support hypothesis H_0 when comparing the rMSSD and the questionnaires among the subjects. For better statistical test results, larger and better databases should be collected from each individual subject as a kind of scenario calibration. This calibration would also involve monitoring the 50-min sleep period of each subject.

The error in the transmission of bytes via Bluetooth between the Cap and the smartphone, it does not seem to be significant given the percentage of corrections of the RR intervals presented in Tables 4, 3 and 2. However, a third Internet of Things wearable prototype is underway using the Orange Pi Zero processor with a 12-bit ADC and 1 kSP sampling rate and improvements to the smartphone app to perform and record the check-sum during data transmission. This new prototype will serve as a quality reference in sampling and signal analysis in the frequency domain (which has not yet been done). Furthermore, this new prototype should not be adopted as a mobile version of the Cap because the Orange Pi board consumes three times as much electricity as the Arduino, i.e., peaks of 315 mA during boot, average of 165 mA with the CPU processing the pulse signal, and average of 140 mA for the idle CPU not performing calculations, making it impossible to use the 9V rechargeable battery for 100-min (the time adopted in the tests of this study).

For the 15-, 30- and 50-min observation periods, the latter presented the closest results to the expected ones, as shown in Table 2. In the 6th row of this table, it is possible to find the highest rMSSD values among the observed periods (15-, 30- and 50-min), which seem to correspond to the highest sums among the questionnaires (values in bold), especially the Toronto C, which suggests quantifying the degree of full attention in a short period of time.

It is worth noting that in this pretest no mathematical association was found between rMSSD and PMS or rMSSD and MAAS. A possible justification for PMS not having achieved this association is that the author himself note its effectiveness if considered for the last week [11] and not the last hour. With regard to MAAS [56], which also did not show an association with rMSSD, the author does not specify which reference window should be considered when choosing the answers to questionnaire. This issue needs to be better investigated with a larger number of participants and more care in

phenomenology.

Another finding in this research, originally predicted in [51] and confirmed in [53], is the mathematical relationship between rMSSD and the Poincaré map. According to this author, rMSSD is numerically equivalent to the geometric width of the graph ellipse, oriented by a perpendicular line on the identity line (review Fig. 4). Initially, this width was called SD1, but it was later interpreted as short-term HRV. The width SD1 is defined mathematically as follows:

$$SD1 = \frac{rMSSD}{\sqrt{2}} \quad (4)$$

In fact, this was proven by sampling 15-, 30- and 50-min. For example, taking any rMSSD value from the 6th row of any Table 4, 3 or 2 and dividing by $\sqrt{2}$ is practically the respective value SD1 of the 9th row of the same table. Therefore, this suggest that the data presented in these tables are correct.

For the filtering technique by means of the moving average (MA = 2), care was taken not to mischaracterize the geometry of the Poincaré map and, at the same time, to remove the marginal spuriousness of the graph. Therefore, we applied the smallest possible MA (only 1 sample delay or MA = 2) where each output sample depends on the average between two adjacent input samples. Additionally, no mathematical evidence was found to support this technique. Figure 3 presents this geometric comparison (blue and yellow) of the Poincaré. The histograms had the least aggressive peaks due to the frequency damping of each sample but kept the width of their bases. This is equivalent to preserving the elliptical shape of the respective Poincaré map while minimizing the spurious shape.

5 CONCLUSIONS AND FURTHER WORKS

Measuring heart rate variability by analyzing the RR time interval of the heartbeat QRS wave complex was a challenging and functional goal. The results in Tables 2, 3 and 4 show that the Poincaré map method and the SD1 calculations are correlated geometrically and mathematically. This reproduction of results that were predicted in other articles was important in the trajectory of this research as a way to validate the operation of the prototype circuit using ArduinoTM.

However, there are new investigations to be done, such as increasing the sample rate of subjects and Caps, with one group practicing meditation and the other not.

The result of pNN50 (8th row of the tables, which corresponds to the percentage of RR intervals greater than 50 ms) suggested that all participants were active in the parasympathetic autonomic system.

Currently, no direct association was found between MAAS and PMS responses with the rMSSD values found for each subject. However, the Toronto questionnaire showed indications of success in defining the degree of short-term full attentiveness using the Cap with the Internet of Things.

Among the analyzed periods of 15-, 30- and 50-min, the latter proved to be more robust in associating rMSSD with any adopted questionnaire.

All data packages collected by the five Caps were mathematically analyzed initially in Octave and subsequently in MATLAB. The hypothesis tests were performed in Excel, but IBM SPSS was also used for comparison purposes.

For the average temperature of the skull surface, no direct relationship with the degree of attention was found. It was noted that the sensor did not reach the average human body temperature of 36°C because the scalp behaves as a poor conductor of heat. However, the tests show that the behavior of the surface temperature of the scalp during the test lesson did not vary significantly among the participants.

The monitoring of head/shoulder movements, also presented as time in the same table, did not provide evidence that relates rMSSD to the quantification of full attention by the questionnaires. However, it did produce suspicions of excessive leg movement presence while the subject was sitting focused on his/her school activity, as was the case for subject 02, who self-reported in the experimental feedback. On the other hand, subject 04 got up from her chair in the 1st and 2nd P of the class, changing her BPM at certain times (as seen in the analysis of the tachogram of Cap 04). However, this BPM change did not translate into higher or lower levels of full attention within the 50 minutes observed, proving the thesis already presented that accelerated BPM is related to the activity of the sympathetic nervous system and during this period, HRV is reduced and without focus of attention.

Poincaré maps presented the expected geometric shape (an ellipse) even with the application of the moving average ($MA = 2$). Its rMSSD width was mathematically preserved with SD1, respecting the ratio of $\sqrt{2}$ [51].

Finally, partial results seem to indicate that the minimum *RR* interval (or rMSSD) of 88 ms for the same subject allows the Cap to classify him/her as being or not being in full attention level. Further investigations in this direction will be conducted.

References

- [1] F. Picon, R. Karam, V. Breda, A. Restano, A. Silveira, D. Spritzer *et al.*, “Precisamos falar sobre tecnologia: caracterizando clinicamente os subtipos de dependência de tecnologia,” *Revista brasileira de psicoterapia*, vol. 17, no. 2, pp. 44–60, 2015.
- [2] D. M. Boyd and N. B. Ellison, “Social network sites: Definition, history, and scholarship,” *Journal of computer-mediated communication*, vol. 13, no. 1, pp. 210–230, 2007.
- [3] R. A. Sansone and L. A. Sansone, “Cell phones: the psychosocial risks,” *Innovations in clinical neuroscience*, vol. 10, no. 1, p. 33, 2013.
- [4] X. Zheng and M. K. Lee, “Excessive use of mobile social networking sites: Negative consequences on individuals,” *Computers in Human Behavior*, vol. 65, pp. 65–76, 2016.
- [5] X. Cao, A. Masood, A. Luqman, and A. Ali, “Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain- outcome perspective,” *Computers in Human Behavior*, vol. 85, pp. 163–174, 2018.
- [6] B. W. O’bannon and K. Thomas, “Teacher perceptions of using mobile phones in the classroom: Age matters!” *Computers & Education*, vol. 74, pp. 15–25, 2014.
- [7] T. Murata, T. Takahashi, T. Hamada, M. Omori, H. Kosaka, H. Yoshida, and Y. Wada, “Individual trait anxiety levels characterizing the properties of zen meditation,” *Neuropsychobiology*, vol. 50, no. 2, pp. 189–194, 2004.
- [8] D. Hagemann, S. R. Waldstein, and J. F. Thayer, “Central and autonomic nervous system integration in emotion,” *Brain and cognition*, vol. 52, no. 1, pp. 79–87, 2003.
- [9] J. Kabat-Zinn, “An outpatient program in behavioral medicine for chronic pain patients based on the practice of mindfulness meditation: Theoretical considerations and preliminary results,” *General hospital psychiatry*, vol. 4, no. 1, pp. 33–47, 1982.
- [10] K. W. Brown and R. M. Ryan, “The benefits of being present: mindfulness and its role in psychological well-being.” *Journal of personality and social psychology*, vol. 84, no. 4, p. 822, 2003.
- [11] L. Cardaciotto, J. D. Herbert, E. M. Forman, E. Moitra, and V. Farrow, “The assessment of present-moment awareness and acceptance: The philadelphia mindfulness scale,” *Assessment*, vol. 15, no. 2, pp. 204–223, 2008.
- [12] M. A. Lau, S. R. Bishop, Z. V. Segal, T. Buis, N. D. Anderson, L. Carlson, S. Shapiro, J. Carmody, S. Abbey, and G. Devins, “The toronto mindfulness scale: Development and validation,” *Journal of clinical psychology*, vol. 62, no. 12, pp. 1445–1467, 2006.

- [13] D. U. Silverthorn, W. C. Ober, C. W. Garrison, A. C. Silverthorn, and B. R. Johnson, *Human physiology: an integrated approach*. Pearson/Benjamin Cummings San Francisco, 2010.
- [14] R. K. Dishman, Y. Nakamura, M. E. Garcia, R. W. Thompson, A. L. Dunn, and S. N. Blair, “Heart rate variability, trait anxiety, and perceived stress among physically fit men and women,” *International Journal of Psychophysiology*, vol. 37, no. 2, pp. 121–133, 2000.
- [15] P. Nishith, M. B. Mechanic, and P. A. Resick, “Prior interpersonal trauma: the contribution to current ptsd symptoms in female rape victims.” *Journal of abnormal psychology*, vol. 109, no. 1, p. 20, 2000.
- [16] M. M. J. De Jong and D. C. Randall, “Heart rate variability analysis in the assessment of autonomic function in heart failure,” *Journal of Cardiovascular Nursing*, vol. 20, no. 3, pp. 186–195, 2005.
- [17] J. F. Thayer and R. D. Lane, “A model of neurovisceral integration in emotion regulation and dysregulation,” *Journal of affective disorders*, vol. 61, no. 3, pp. 201–216, 2000.
- [18] H. A. J. AL-Ziarjawey and I. Çankaya, “Heart rate monitoring and pqrst detection based on graphical user interface with matlab,” *International Journal of Information and Electronics Engineering*, vol. 5, no. 4, p. 311, 2015.
- [19] C. Schulz, M. E. Kiani, and E. Mason, “Pulse oximetry ear sensor,” Mar. 11 2008, uS Patent 7,341,559.
- [20] F. Katarow, “Combination fingerprint and oximetry device,” Nov. 4 2003, uS Patent 6,643,531.
- [21] C. D. B. Luft, E. Takase, and D. Darby, “Heart rate variability and cognitive function: Effects of physical effort,” *Biological psychology*, vol. 82, no. 2, pp. 186–191, 2009.
- [22] N. Börger, J. van Der Meere, A. Ronner, E. Alberts, R. Geuze, and H. Bogte, “Heart rate variability and sustained attention in adhd children,” *Journal of Abnormal Child Psychology*, vol. 27, no. 1, pp. 25–33, 1999.
- [23] J. V. A. Silva, “Efeitos da terapia cognitivo comportamental na variabilidade da frequência cardíaca e desempenho cognitivo em crianças com tdah,” 2012.
- [24] M. R. Rukmani, S. P. Seshadri, K. Thennarasu, T. R. Raju, and T. N. Sathyaprabha, “Heart rate variability in children with attention-deficit/hyperactivity disorder: a pilot study,” *Annals of neurosciences*, vol. 23, no. 2, pp. 81–88, 2016.
- [25] J. R. Krygier, J. A. Heathers, S. Shahrestani, M. Abbott, J. J. Gross, and A. H. Kemp, “Mindfulness meditation, well-being, and heart rate variability: a preliminary investigation into the impact of intensive vipassana meditation,” *International Journal of Psychophysiology*, vol. 89, no. 3, pp. 305–313, 2013.

- [26] C. P. R. A. Teixeira et al., “Efeitos comportamentais e psicofisiológicos da meditação mindfulness no emprego de duas estratégias de regulação emocional,” 2018.
- [27] J. Kabat-Zinn, “Mindfulness,” *Mindfulness*, vol. 6, no. 6, pp. 1481–1483, 2015.
- [28] J. Shear and R. Jevning, “Pure consciousness: Scientific exploration of meditation techniques,” *Journal of Consciousness Studies*, vol. 6, no. 2-3, pp. 189–210, 1999.
- [29] N. T. Van Dam, M. Earleywine, and A. Borders, “Measuring mindfulness? an item response theory analysis of the mindful attention awareness scale,” *Personality and Individual Differences*, vol. 49, no. 7, pp. 805–810, 2010.
- [30] C. Schubert, M. Lambertz, R. Nelesen, W. Bardwell, J.-B. Choi, and J. Dimsdale, “Effects of stress on heart rate complexity - a comparison between short-term and chronic stress,” *Biological psychology*, vol. 80, no. 3, pp. 325–332, 2009.
- [31] S. Akselrod, D. Gordon, J. B. Madwed, N. C. Snidman, D. C. Shannon, and R. J. Cohen, “Hemodynamic regulation: investigation by spectral analysis,” *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 249, no. 4, pp. H867–H875, 1985.
- [32] V. Marães, “Frequência cardíaca e sua variabilidade: análises e aplicações,” *Revista andaluza de Medicina del Deporte*, vol. 3, no. 1, pp. 33–42, 2010.
- [33] J. R. P. d. Lima, “Frequência cardíaca em cargas crescentes de trabalho: ajuste sigmóide, ponte de inflexão e limiar de variabilidade da frequência cardíaca,” *São Paulo*, 1997.
- [34] S.-M. Volanen, M. Lassander, N. Hankonen, P. Santalahti, M. Hintsanen, N. Simonsen, A. Raevuori, S. Mullola, T. Vahlberg, A. But et al., “Healthy learning mind—effectiveness of a mindfulness program on mental health compared to a relaxation program and teaching as usual in schools: a cluster-randomised controlled trial,” *Journal of affective disorders*, vol. 260, pp. 660–669, 2020.
- [35] L. T. Pizutti, A. Carissimi, L. J. Valdivia, C. A. V. Ilgenfritz, J. J. Freitas, D. Sopezki, M. M. P. Demarzo, and M. P. Hidalgo, “Evaluation of breathworks’ mindfulness for stress 8- week course: Effects on depressive symptoms, psychiatric symptoms, affects, self-compassion, and mindfulness facets in brazilian health professionals,” *Journal of clinical psychology*, vol. 75, no. 6, pp. 970–984, 2019.
- [36] S. Chase-Cantarini and G. Christiaens, “Introducing mindfulness moments in the classroom,” *Journal of Professional Nursing*, vol. 35, no. 5, pp. 389–392, 2019.
- [37] V. V. d. Barros, E. H. Kozasa, I. C. W. d. Souza, and T. M. Ronzani, “Validity evidence

of the brazilian version of the five-facet mindfulness questionnaire (ffmq),” *Psicologia: Teoria e Pesquisa*, vol. 30, no. 3, pp. 317–327, 2014.

[38] A. d. C. d. Silveira, T. G. d. Castro, and W. B. Gomes, “Adaptação e validação da escala filadélfia de mindfulness para adultos brasileiros,” *Psico-USF*, vol. 17, no. 2, pp. 215–223, 2012.

[39] F. Wortmann and K. Flüchter, “Internet of things,” *Business & Information Systems Engineering*, vol. 57, no. 3, pp. 221–224, 2015.

[40] P. Suresh, J. V. Daniel, V. Parthasarathy, and R. Aswathy, “A state of the art review on the internet of things (iot) history, technology and fields of deployment,” in *2014 International conference on science engineering and management research (ICSEMR)*. IEEE, 2014, pp. 1–8.

[41] R. Khan, S. U. Khan, R. Zaheer, and S. Khan, “Future internet: the internet of things architecture, possible applications and key challenges,” in *2012 10th international conference on frontiers of information technology*. IEEE, 2012, pp. 257–260.

[42] L. Tan and N. Wang, “Future internet: The internet of things,” in *2010 3rd international conference on advanced computer theory and engineering (ICACTE)*, vol. 5. IEEE, 2010, pp. V5–376.

[43] M. Conner, “Sensors empower the” internet of things”,” *EDN (Electrical Design News)*, vol. 55, no. 10, p. 32, 2010.

[44] K. Ashton *et al.*, “That ’internet of things’ thing,” *RFID journal*, vol. 22, no. 7, pp. 97–114, 2009.

[45] B. Avitall, B. Peterson, J. Kletch, E. B. Griswold, and P. Moran, “Remote health monitoring system,” Jan. 9 2001, uS Patent 6,171,237.

[46] D. Patton, S. Switalski, D. Beaudet, R. Wien, and N. Blish, “Remote diagnostic device for medical testing,” Jan. 4 2007, uS Patent App. 11/171,671.

[47] T. Ledain, M. Brown, and K. Bailey, “Remote health-monitoring system and method,” Apr. 10 2003, uS Patent App. 10/228,034.

[48] Y. A. Badamasi, “The working principle of an arduino,” in *2014 11th international conference on electronics, computer and computation (ICECCO)*. IEEE, 2014, pp. 1–4.

[49] M. Soliman, T. Abiodun, T. Hamouda, J. Zhou, and C.-H. Lung, “Smart home: Integrating internet of things with web services and cloud computing,” in *2013 IEEE 5th international conference on cloud computing technology and science*, vol. 2. IEEE, 2013, pp. 317–320.

[50] Y. Iyriboz, S. Powers, J. Morrow, D. Ayers, and G. Landry, “Accuracy of pulse oximeters in estimating heart rate at rest and during exercise.” *British journal of sports medicine*, vol. 25, no. 3, pp. 162–164, 1991.

- [51] P. Kamen and A. M. Tonkin, "Application of the poincaré plot to heart rate variability: a new measure of functional status in heart failure," *Australian and New Zealand journal of medicine*, vol. 25, no. 1, pp. 18–26, 1995.
- [52] M. Brennan, M. Palaniswami, and P. Kamen, "Do existing measures of poicare plot geometry reflect nonlinear features of heart rate variability?" *IEEE transactions on biomedical engineering*, vol. 48, no. 11, pp. 1342–1347, 2001.
- [53] A. B. Ciccone, J. A. Siedlik, J. M. Wecht, J. A. Deckert, N. D. Nguyen, and J. P. Weir, "Reminder: Rmssd and sd1 are identical heart rate variability metrics," *Muscle & nerve*, vol. 56, no. 4, pp. 674–678, 2017.
- [54] U. R. Acharya, K. P. Joseph, N. Kannathal, C. M. Lim, and J. S. Suri, "Heart rate variability: a review," *Medical and biological engineering and computing*, vol. 44, no. 12, pp. 1031–1051, 2006.
- [55] F.-X. Gamelin, S. Berthoin, and L. Bosquet, "Validity of the polar s810 heart rate monitor to measure rr intervals at rest." 2006.
- [56] J. MacKillop and E. J. Anderson, "Further psychometric validation of the mindful attention awareness scale (maas)," *Journal of Psychopathology and Behavioral Assessment*, vol. 29, no. 4, pp. 289–293, 2007.
- [57] M. M. P. Demarzo, S. Andreoni, N. Sanches, S. Perez, S. Fortes, and J. Garcia-Campayo, "Mindfulness-based stress reduction (mbsr) in perceived stress and quality of life: an open, uncontrolled study in a brazilian healthy sample," *Explore: The Journal of Science and Healing*, vol. 10, no. 2, pp. 118–120, 2014.

Figures



Figure 1

Wearable Internet of Things device in the form of a data collector Cap. The heartbeat sensor attached to the orange, red and brown wire and magnet is highlighted Source: designed by the author.

SMART CAP - V3.0



MONITORING

CAP --

bpm: 0

avg: 0

RR [ms]: 0

Enter your name

(1) Cap #

(2) On-off

520

(3) Calibration

(4) Send data

Exit

Figure 2

Screenshot of the Android app, developed for the purpose of this thesis Source: Developed by the author.

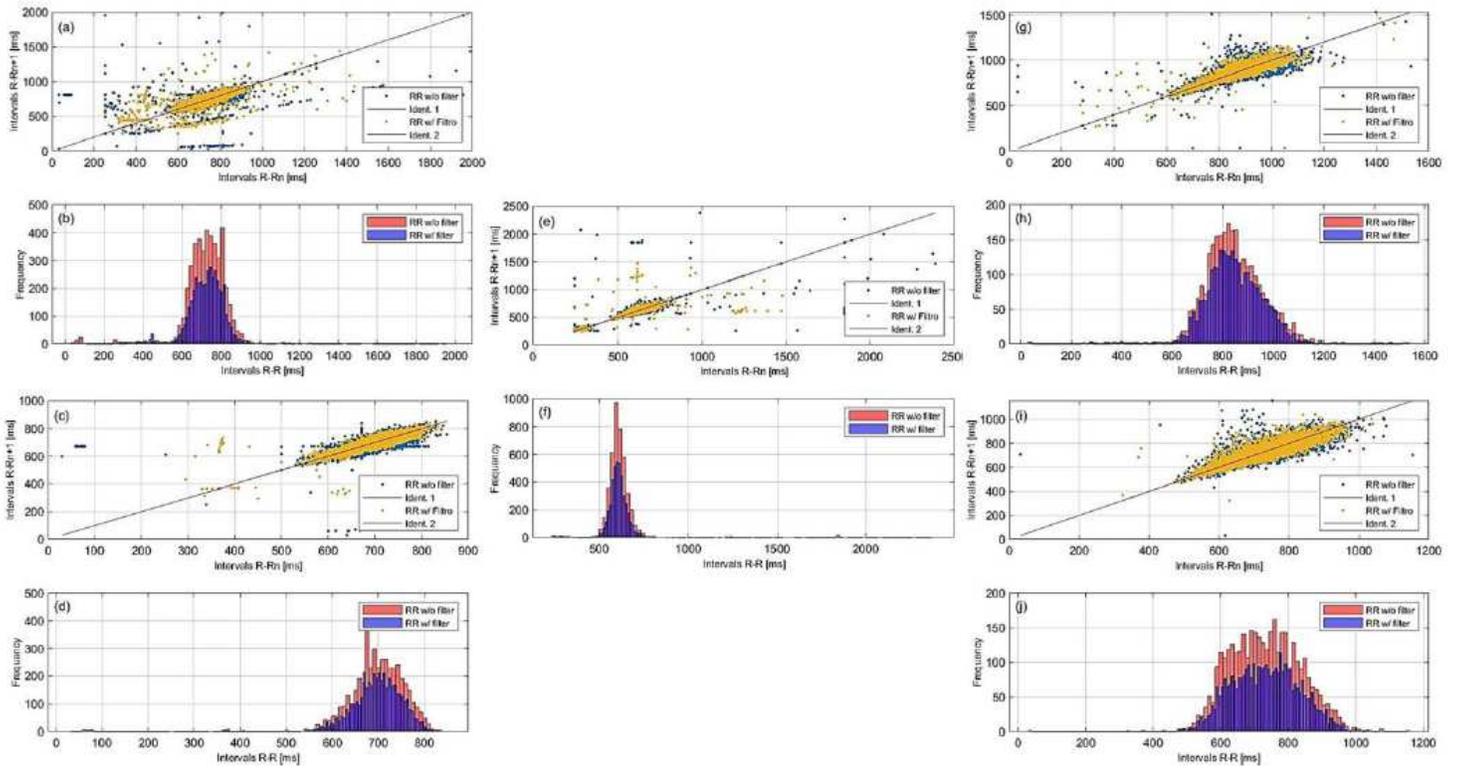


Figure 3

Overlapping RR intervals of subjects 01 to 05 at 50-min with and without the effect of the MA = 2 filter. Item (a) is a subject male, 15 years old; (b) it's histogram RR intervals; (c) a subject female, 16 years old; (d) it's histogram; (e) a subject male, 16 years old; (f) it's histogram; (g) a subject female, 15 years old; (h) it's histogram; (i) a subject female, 16 years old. (j) it's histogram Source: Elaborated by the author.

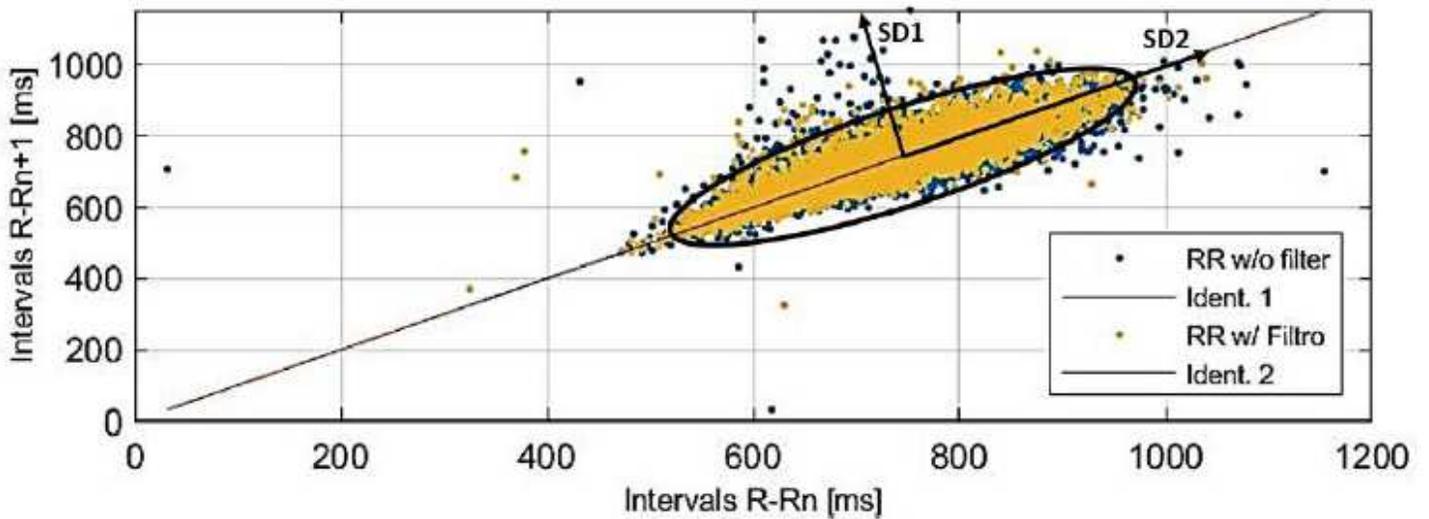


Figure 4

SD1 and SD2 dispersion on the Poincaré map. Source: Elaborated by the author.