Computers and Education: Artificial Intelligence 2 (2021) 100011

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.elsevier.com/locate/caeai

Artificial Intelligence in education: Using heart rate variability (HRV) as a biomarker to assess emotions objectively

Joanne Wai Yee Chung [d], Henry Chi Fuk So [b], Marcy Ming Tak Choi [a], Vincent Chun Man Yan [a], Thomas Kwok Shing Wong [c,e,*]

[a] Department of Health and Physical Education, The Education University of Hong Kong, Tai Po, New Territories, Hong Kong
[b] Department of Mathematics and Information Technology, The Education University of Hong Kong, Tai Po, New Territories, Hong Kong
[c] The Guangzhou Medical University, China
[d] School of Nursing and Health Studies, The Open University of Hong Kong, Homantin, Kowloon, Hong Kong
[e] Hong Kong Nang Yan College of Higher Education, Sham Shui Po, Hong Kong

A R T I C L E I N F O

Keywords:
HRV
Emotion
Prediction
Sadness
Happiness

A B S T R A C T

The aim of this study was to assess the emotions of happiness and sadness objectively to develop Artificial Intelligence (AI) tool in education. There were two stages in the study. The inclusion criteria for selecting participants were healthy adults in local community with no known medical diagnosis. Those with a history of mental health problems, mood disorders, and cardiovascular and pulmonary problems were excluded. At Stage 1, subjects were asked to categorize the selected video clips downloaded from YouTube into happiness, sadness, and others. The subjects in Stage 1 did not participate in Stage 2. At Stage 2, the videos were presented randomly via computer to each subject who could, immediately after he/she had watched a video clip, input his/her respective emotion ratings through a touch-screen monitor. Simultaneously his/her HRV was captured using a Polar watch with chest belt during the entire Stage 2. A total of 239 subjects participated in the study. Of them, 158 (66.1%) were female and 81 (33.9%) were male. The mean ages for females and males were 34.10 (sd = 18.11) and 37.51 (sd = 18.35) respectively. In the Partial Least Squares Discriminant Analysis (PLS-DA) model, a sensitivity of 70.7% that the model correctly identified a subject's happiness, while a specificity of 58.4% that the model correctly identified sadness. Prediction of the emotions of happiness and sadness using HRV measures was supported. HRV measures does provide an objective method to assess the emotions. Further work could be done to explore the prediction of other emotions.

1. Introduction

Emotions are a fundamental means of communication for human beings as they are gregarious in nature. All living beings, across species and culture, use emotions which are either explicitly expressed or implicitly conveyed to inform others of their feelings (Paul and Mendl, 2018). Emotions create the bonding among living beings and protect their survival (Delahaij and VanDam, 2017; English et al., 2018). Humans have emotions, be they good or bad, and these need to be communicated. Unfortunately, there are people who do not know what their own emotions are and let alone how to express them (Nuske et al., 2013; White et al., 2018). They include, inter alia, those relating to attention deficit hyperactivity disorder (ADHD), Parkinson's disease, and social-emotional agnosia that we commonly encounter in clinical, school, or community settings.

It was reported that the autonomic nervous system (ANS) functions can be evaluated by HRV (Quintana et al., 2012; Shi et al., 2017). HRV, in beat-to-beat time intervals (R-R intervals), has been hailed as a new method of assessing individuals' self-regulatory capacity and detecting their health risk in recent decades. Physiologically, HRV resembles the function of our ANS which faithfully reflects the emotions of an individual (Castaldo et al., 2015). With the physiological basis for emotions (Balzarotti et al., 2017), could emotions be assessed objectively through observing and tracking the autonomic nervous system? To enhance future research in emotions and to better monitor emotion changes in relation to emotion related interventions, the research team thus

* Corresponding author. The Guangzhou Medical University, China.
E-mail addresses: jwychung@ouhk.edu.hk (J.W. Yee Chung), hcfso@eduhk.hk (H.C. Fuk So), mtchoi@eduhk.hk (M.M. Tak Choi), cmyan@eduhk.hk (V.C. Man Yan), thomaswong@ny.edu.hk (T.K. Shing Wong).

https://doi.org/10.1016/j.caeai.2021.100011
Received 16 December 2020; Received in revised form 27 January 2021; Accepted 27 January 2021
2666-920X/© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

questions if there is any relationship between HRV and emotions, and whether HRV measures could be used objectively to assess and identify the prevailing emotions.

1.1. HRV and emotions

HRV is a relevant marker reflecting the ANS activities. ANS plays a vital role in modulating heart rates and cardiac output in response to physiological and psychological stress. It comprises of two self-regulatory systems, namely the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). SNS and PNS activities are antagonistic. While an increase in SNS activities quickens heart rates, an increase in PNS activities slows down heart rates. The SNS is responsible for the fight-or-flight response in stressful situations, while the PNS is for resting and digesting in relaxed conditions. Due to the continuous antagonistic inputs from the SNS and PNS, the cardiac rhythm cyclically fluctuates slightly around the mean heart rate (Tarvainen et al., 2014). By measuring this fluctuation, the SNS and PNS activities, and their balance can be assessed since the rates and pressure intensity signals of the baroreceptors, situated in the aorta and the internal carotid arteries, will respond to the demand of the cardiac needs as a reaction to stressors experienced by the body. These responses are usually in the form of changing blood pressure levels, heart rates, and emotions, etc. As bio-signals, such responses can be measured by changes in heart beats which can be precisely represented by HRV using spectrum analysis, also referred to as frequency domain analysis. Recent neurovisceral integration model supported that HRV might be an index for the function of the medial Pre Frontal Cortex (mPFC) (Thayer et al., 2012). Emotion appraisal is a function of the mPFC and there was still controversy over using HRV to assess emotions. Emotion is a strong feeling towards a situation or an event. Feeling entails perception which is subjective. One may perceive a situation as joyful and therefore feel happy; while others may just feel the opposite and feel sad. So emotional responses may not have anything to do with the current situation. Moreover, only individuals with higher resting HRV appeared to be more trustworthy and able to produce context appropriate responses including appropriate recovery after the stressor had ended (Thayer et al., 2012).

Assessing emotions is hard in clinical settings where periodic self-reports by patients have to be obtained. Self-reporting always relies on individuals' willingness to tell and is subject to intra-subject variations in reporting due to other circumstantial factors like environment, people, situation, etc. There is an increasing interest in investigating ways to assess emotions from various fields of study such as psychology, psychiatry, mathematics, neuroscience, and nursing. Given the perception of emotions have always been subjective and there are people who cannot or do not accurately express their emotions, is there a way to assess emotions objectively? Scientists have been attempting to assess emotions objectively by sweat test (deGroot et al., 2018; Waitt and Stanes, 2015), cortisol (Peters et al., 2016), and other means (Duesenberg et al., 2016; Feng et al., 2018). The team postulated that HRV might contribute to such an endeavour because heart beats are regulated by the ANS when the balance of the body system is disrupted.

2. Method

There were two stages in the study. Stage 1 was the preparation of video clips for emotion stimulation, while Stage 2 was the main part of the experimentation. The inclusion criteria were the same for both stages. Healthy adults from the local community with no known medical diagnosis were recruited. Those with a history of mental health problems, mood disorders, and cardiovascular and pulmonary problems were excluded.

2.1. Stage 1: preparation of videos

Three members of the research team selected and downloaded relevant video clips from YouTube and categorized them by consensus into 3 emotional groups, namely, happiness, sadness, and others. In this categorization, "others" was represented the emotion other than happiness and sadness. Each video clip lasted for 5 min. There were 20 video clips in total (5 video clips per happiness and sadness emotion, and 10 video clips for others emotion). To ensure cultural relevancy, a pilot survey (n = 30) was conducted to categorize the emotions aroused by the downloaded video clips. The team recruited 30 ethnic Chinese subjects to view the clips to categorize them into happiness, sadness, and others. Only those clips with 100% agreement on happiness and sadness were used in Stage 2. As a result, 4 video clips for happiness and 5 for sadness were screened in for use in Stage 2.

2.2. Stage 2: main study

It was an experimental study. A total of 239 subjects were recruited by convenience sampling. The subjects were randomly exposed to the video clips with different emotional impact. Basing on the 90-s emotion rule (Taylor, 2006), each subject was allowed 5 min of resting time between each clip. To ensure uniformity, all subjects are required to sit upright in resting position throughout the experimentation.

2.3. Experimentation protocol

The subjects were asked to rest for 15 min after they completed the demographic questionnaire which included age, gender, and self-reports on their personality. They were then asked to randomly draw one order sequence from an envelope with different sequences of video clip presentation. There were six sequences (h.s.h.s., s.h.s.h, s.s.h.h., h.h.s.s., s.h.h.s, h.s.s.h, where 'h' was happiness and 's' was sadness.) Then a research assistant helped the subjects to put on the chest belt and the Polar watch (Polar s810) so as to record continuously their heart beat signals throughout the experiment. An electrocardiography (ECG) lasting for 10 min was recorded using the Polar watch before the first video clip was played. The subjects would then be asked to indicate their emotions (happy, sadness, others) with their intensity after watching each clip. There was a 5-min rest time in between each video. All these videos were presented and emotion ratings were entered by computer. Thus, all subjects received the same instructions under the same environment. Fig. 1 shows the sequences of the video presentations.

3. Data analysis

Descriptive statistics were used to summarise the demographic characteristics and the HRV distributions of the subjects. The R-R interval signals from the Polar watch were downloaded and relevant Low Frequency power (LF) and High Frequency power (HF) were obtained using the power spectral analysis with MATLAB. HRV parameters were then extracted. Classification methods were used to develop the model for emotion prediction. Fig. 2 summarises the extraction of HRV parameters and the HRV classification in the bio-signal processing (VanBemmel et al., 1997).

4. Results

A total of 239 subjects participated in the study. There were 186 (66.1%) females and 81 (33.9%) males. The mean ages for females and males were 34.10 (SD = 18.10) and 37.51 (SD = 18.53), respectively with 2 females and 1 male declined to respond to the question on age. Table 1 shows their self-report on personality.

Though significantly more of the females rated themselves as happy, introverted, extroverted, and cheerful than the males, the corresponding Phi coefficients were between −0.3 and +0.3 showing little or no association. In the light of this, we grouped all HRV parameters from both genders in our ensuing analysis.

The subjects had been asked to indicate their emotions with

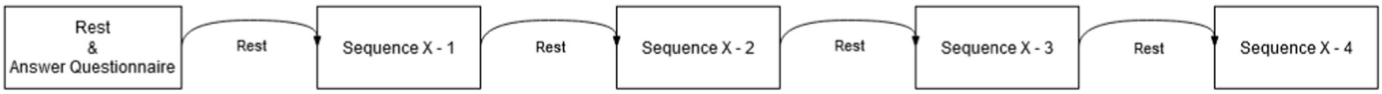

Fig. 1. Experimentation protocol.

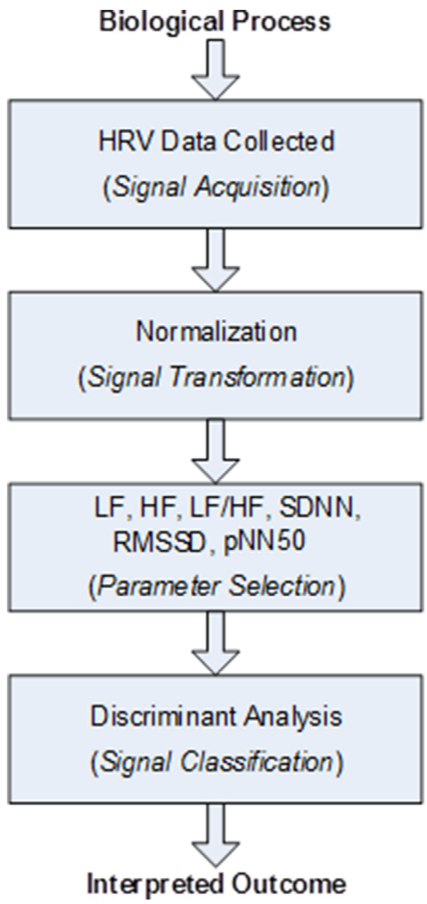

Fig. 2. HRV parameter extraction and classification process. LF, Low frequency; HF, High frequency; SDNN, Standard deviation of NN intervals; RMSSD, Root mean square of successive RR interval; pNN50, The percentage of adjacent NN intervals that differ from each other by more than 50 ms.

Table 1
Self-report on personality by gender (N = 239).

Emotion	Gender n (%)		X^2	p-value	Phi Coefficient
	Female	Male			
Calm	54 (59.3)	37 (40.7)	3.004	0.083	0.112
Friendly	109 (64.5)	60 (35.5)	0.669	0.413	0.053
Anxious	48 (68.6)	22 (31.4)	0.268	0.605	−0.033
Happy	83 (73.5)	30 (26.5)	5.158	0.023[a]	−0.147
Bad-tempered	14 (56.0)	11 (44.0)	1.273	0.259	0.073
Introverted	43 (51.8)	40 (48.2)	11.608	0.001[a]	0.220
Extroverted	71 (74.0)	25 (26.0)	4.412	0.036[a]	−0.136
Impatient	44 (71.0)	18 (29.0)	0.882	0.348	−0.061
Cheerful	82 (75.2)	27 (24.8)	7.440	0.006[a]	−0.176
Optimistic	96 (67.6)	46 (32.4)	0.350	0.554	−0.038
Pessimistic	20 (58.8)	14 (41.2)	0.939	0.333	0.063
Depressed	28 (65.1)	15 (34.9)	0.023	0.879	0.010

[a] Statistically significant ($p < 0.05$).

respective intensities, after watching each video clip, on a 0–10 (10 being the highest) visual analog scale (VAS). All of them could correctly identify the emotions carried by the videos. The VAS for happiness and sadness were 4.30 (SD = 2.23) and 5.15 (SD = 2.57), respectively.

A two-way ANOVA was used to examine the effect of emotions (happiness and sadness) on various HRV parameters across different time points for a subject to view a particular sequence of the videos (baseline–before watching any videos, initial 5 min—watching the first video, last 5 min—watching the last video, and after—having watched all videos) (Table 2).

Remarks: BPM (beats per minute), HF (High frequency), LF(Low frequency), SDNN (Standard deviation of NN intervals), SDSD (Standard deviation of successive RR interval differences), RMSSD (Root mean square of successive RR interval differences), pNN50 (The percentage of adjacent NN intervals that differ from each other by more than 50 ms).

The results showed the main effect of emotions on BPM, SDNN and SDSD were statistically significant ($p < 0.05$). Emotions did influence these HRV parameters. The main effect of time was statistically significant ($p < 0.05$) for HF (between the baseline and all other 3 time points, and between the initial 5 min and the last 5 min), LF (between the baseline and all other 3 time points; and between the initial 5 min and the last 5 min), SDSD (between the baseline and all other 3 time points), RMSSD (between the baseline and all other 3 time points), pNN50 (between the initial 5 min and the last 5 min), and LF/HF ratio (between the baseline and all other 3 time points); thus, time as a factor did influence these HRV parameters. The result of the effect of emotion across time was essential because it could be interpreted as a significant change in emotion across the time point. As for the existence of any interaction effects, the results showed that emotions by BPM, LF, and SDNN were all statistically significant ($p < 0.05$), implying that the effect of emotions on these parameters depended on time.

To decide on the factors to be used in classification, an exploratory factor analysis was done. Ten components showed eigenvalues greater than 1. The scree plot showed that the eigenvalues dropped off dramatically before the 6th component (Fig. 3). After Varimax with Kaiser Normalization, the components with a loading greater than 0.4 were selected for classification. The 6 components (HRV parameters) were LF, HF, LF/HF ratio, SDNN, RMSSD, and pNN50.

To increase the discriminability of the model, the following selection criteria were used for classification: (1) subjects with VAS > 0.5 for happiness or sadness; and (2) happiness or sadness with stable segments of peaks. As a result, 179 subjects met the criteria and were included in the classification process.

4.1. Classification

Partial Least Squares Discriminant Analysis (PLS-DA) was used in this classification as it is widely used in the chemometric analysis (Höskuldsson, 1988). Scientific research often involves using variables that are easily measured to explain or predict the behavior of response variables that are often much more difficult to acquire (So et al., 2013, 2019). PLS-DA is a robust method used to construct predictive models. The performance of the PLS-DA model was compared to that of the Linear Discriminant Analysis (LDA), Neural Network (NN), and Support Vector Machine Analysis (SVM). The same training and prediction sets were used for the comparison. Fig. 4 shows the building and training of the mathematical model in predicting emotions (Xp).

The 6 parameters (LF, HF, LF/HF ratio, SDNN, RMSSD, and pNN50) were used as HRV inputs for simulation. The performance of various methods can be evaluated by the sensitivity and specificity of the model. Sensitivity is a measure of the ability of the classifier to identify true happiness emotion. Specificity is a measure of the ability to identify true

Table 2
Two-way ANOVA to examine the effect of emotions (happiness and sadness) and time on HRV parameters.

Variables	Baseline	Initial 5 min	Last 5 min	After
BPM (Happiness) (n = 219)	77.5379 (12.6242)	76.9449 (16.1812)	77.6189 (17.2433)	77.7218 (16.0365)
BPM (Sadness) (n = 219)	77.5379 (12.6242)	75.9860 (13.1165)	75.9852 (13.0872)	75.8287 (10.7049)
HF (Happiness) (n = 219)	5.3962 (1.4590)	4.7038 (1.5852)	4.9011 (1.5844)	4.8872 (1.6080)
HF (Sadness) (n = 219)	5.3962 (1.4590)	4.9526 (1.6365)	4.9493 (1.6451)	4.8557 (1.5804)
LF (Happiness) (n = 219)	5.9540 (1.3743)	5.2942 (1.2969)	5.5503 (1.2817)	5.6044 (1.3057)
LF (Sadness) (n = 219)	5.9540 (1.3743)	5.5410 (1.3687)	5.5422 (1.3703)	5.4693 (1.3395)
SDNN (Happiness) (n = 223)	55.9723 (24.1966)	52.4531 (25.3701)	54.4573 (25.5550)	54.1753 (24.8059)
SDNN (Sadness) (n = 223)	55.9723 (24.1966)	57.2774 (27.8102)	56.9659 (27.7267)	54.0870 (25.6790)
DIST Rest (Happiness)	–	1.7168 (1.7104)	1.5133 (1.6198)	1.5540 (1.6718)
DIST Rest (Sadness)	–	1.6878 (1.7154)	1.6926 (1.7158)	1.6934 (1.7154)
SDSD (Happiness) (n = 224)	42.7541 (24.7279)	37.6098 (23.9627)	37.9253 (23.9878)	37.5748 (25.8286)
SDSD (Sadness) (n = 224)	42.7541 (24.7279)	39.9315 (28.6493)	39.9075 (28.6341)	39.7000 (28.7650)
RMSSD (Happiness) (n = 159)	42.3954 (19.7904)	36.9231 (19.7114)	36.7108 (19.9823)	36.8065 (21.8561)
RMSSD (Sadness) (n = 159)	42.1954 (19.7904)	39.3707 (26.3233)	39.3326 (26.3202)	38.9410 (26.8635)
pNN50 (Happiness) (n = 224)	0.1454 (0.1508)	0.1557 (0.1719)	0.1475 (0.1649)	0.1471 (0.1634)
pNN50 (Sadness) (n = 224)	0.1454 (0.1508)	0.1573 (0.1722)	0.1570 (0.1723)	0.1587 (0.1701)
LF/HF Ratio (Happiness) (n = 219)	1.1354 (0.2242)	1.3206 (1.2792)	1.2228 (0.4162)	1.2427 (0.4458)
LF/HF Ratio (Sadness) (n = 219)	1.1354 (0.2242)	1.2062 (0.4233)	1.2104 (0.4403)	1.1924 (0.3066)

Variables	Emotion			Time			Emotion[a]Time		
	Df	F	p-value	Df	F	p-value	Df	F	p-value
BPM	1, 218	3.974	0.047[a]	3, 654	1.506	0.224	3, 654	3.395	0.039[a]
HF	1, 218	1.437	0.232	3, 654	20.648	<0.001[a]	3, 654	2.847	0.059
LF	1, 218	0.274	0.601	3, 654	19.804	<0.001[a]	3, 654	5.725	0.004[a]
SDNN	1, 222	4.938	0.027[a]	3, 666	1.397	0.248	3, 666	5.821	0.003[a]
SDSD	1, 223	4.068	0.045[a]	3, 669	7.912	0.001[a]	3, 669	1.449	0.235
RMSSD	1, 158	3.592	0.060	3, 474	8.573	0.001[a]	3, 474	1.477	0.229
pNN50	1, 223	3.574	0.060	3, 669	3.158	0.047[a]	3, 669	2.884	0.053
LF/HF Ratio	1, 218	3.535	0.061	3, 654	4.793	0.015[a]	3, 654	1.321	0.259

[a] Statistically significant ($p < 0.05$).

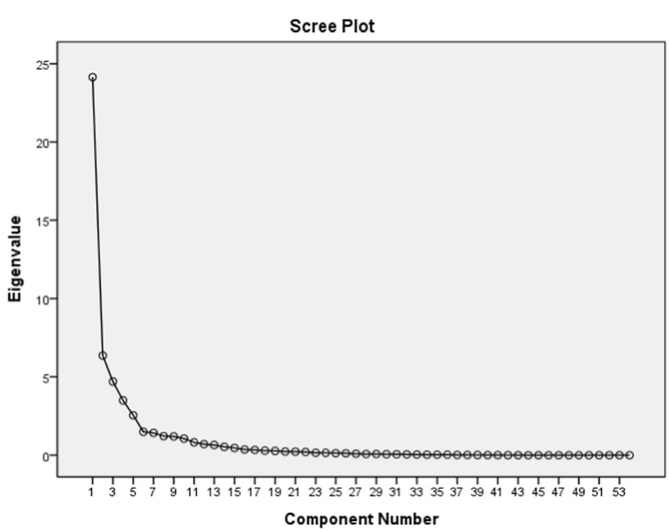

Fig. 3. A scree plot visualizing the eigenvalues (quality scores) of the components.

sadness emotion. They are defined by the following equations:

$$\text{Sensitivity} = TP/(TP + FN), \text{ and} \quad (1)$$

$$\text{Specificity} = TN/(TN + FP), \quad (2)$$

where TP, TN, FP and FN denotes the number of true positives, true negatives, false positives and false negatives respectively. Here, TP and TN refer to the correct classification of happiness and sadness respectively, whereas FP and FN refer to incorrect classification of happiness and sadness respectively.

The results were averaged over 100 runs. Ten hidden layers were used for NN training. Both linear and Gaussian Radial Basis Functions (RBF) were used for SVM training. Table 3 shows the sensitivity, specificity, and the overall classification rate of the illustrated 5 methods and PLS-DA was found to outperform the other methods.

In the PLS-DA model, a sensitivity of 70.7% means 70 out of 100 times the model correctly identified an individual's happiness while a specificity of 58.4% meant 58 out of 100 times, the model correctly identifies sadness. The overall classification rate of the PLS-DA model reached almost 65%, meaning that 65 out of 100 emotion classifications were correctly made.

5. Discussion

Heart beating is under a dynamic relationship with PNS and SNS. PNS predominates at time of rest and slows the heart rate to an average of 75 BPM (Shaffer & Ginsberg, 2017). The participants in this study recorded BPM at around 75 per minute and it showed, in general, they had active dynamic PNS and SNS. Happiness is seen as an SNS-dominated emotion which causes faster heart beats, i.e., a higher contribution of the ANS. Thus, the heart rate related to happiness is higher than sadness. Similar to BPM, both SDNN and SDSD are time domain measurements. It is thus reasonable to find lower SDNN and SDSD in relation to greater happiness since, mathematically, they are the results of a higher BMP. Our findings were consistent with other studies in which there were significant differences in HF and LF between happiness and sadness, while there was no significant difference in RMSSD and pNN50 (Shi et al., 2017). It has been hypothesized that lower HF reflected decreased parasympathetic activation and led to exaggerated responses to stressors and diminished emotion regulation capacity (Beauchaine and Thayer, 2015; McCraty and Shaffer, 2015). Our results demonstrated a significant interaction between the effects of emotions and time for HF and LF. But, we found that lower HF caused bigger responses in happiness than sadness. We doubted if the subjects' awareness of participating in the experiment brought about anxiety; thus, PNS was overshadowed by SNS. For LF, there was a sustainable effect during the intermediate period. This is understandable since sadness as a negative emotion will cause rumination with negative

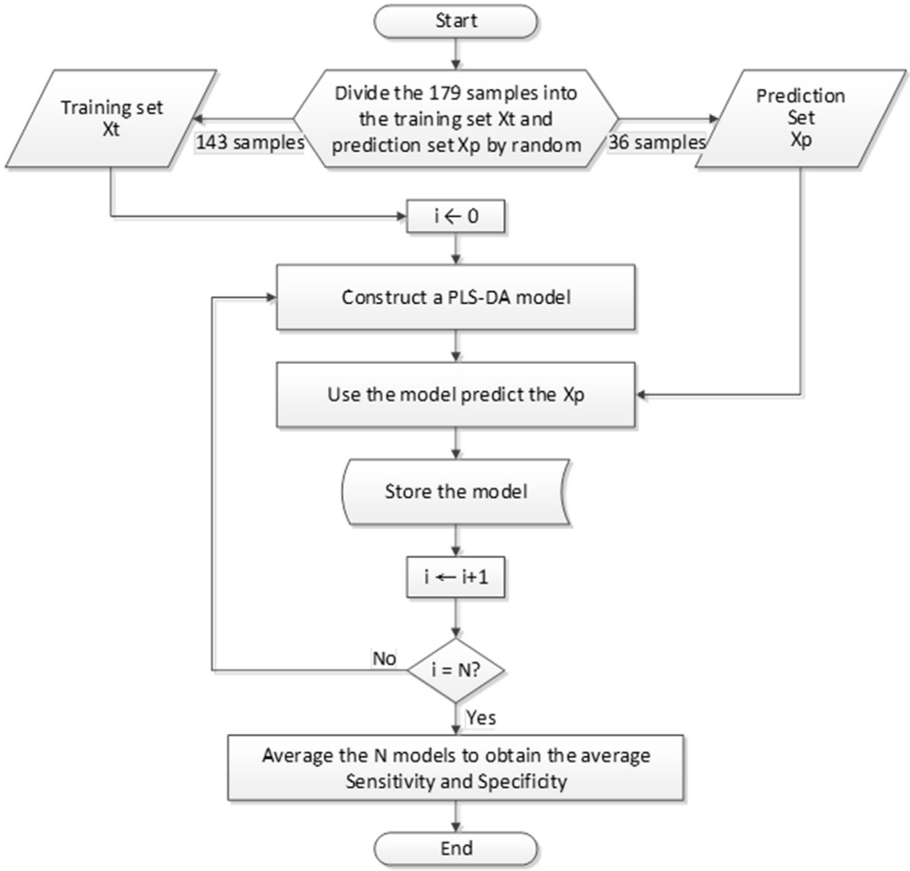

Fig. 4. Building and training of the mathematical model to predict emotions (Xp).

Table 3
Sensitivity, specificity and overall classification rate of the 5 methods.

Method	Sensitivity	Specificity	Overall
LDA	62.66%	58.29%	60.48%
NN	36.45%	76.68%	56.56%
SVM (Linear)	71.17%	46.47%	58.82%
SVM (RBF)	70.59%	49.66%	60.12%
PLS-DA	70.72%	58.36%	64.54%

appraisals.

It has been hypothesized that lower HF reflected decreased parasympathetic activation that led to exaggerated responses to stressors and diminished emotion regulation capacity (Beauchaine and Thayer, 2015; McCraty and Shaffer, 2015). Our results demonstrated significant interaction effects for HF and LF between emotions and time. In addition, the findings in this study shed lights on the use of HRV as a biomarker to assess emotions (happiness and sadness) objectively. Our analyses supported that both the time domain (SDNN) and frequency domain (HF, LF) of the HRV parameters are useful in predicting happiness and sadness. Also, the classification method of the PLS-DA is a feasible process for classifying emotions. In the PLS-DA model, the sensitivity for identifying happiness and specificity for identifying sadness were at acceptable levels. Perhaps the only shortfall of the experiment was the mixed feelings of the subjects, which sometimes caused confusion about their emotion appraisals. In summary, about 2/3 of the times, the feelings of pure happiness and sadness were correctly revealed by this model. So this study can fill the knowledge gap by providing evidence to support assessing emotions (happiness and sadness) objectively using the heart rate variability (HRV) as a biomarker.

However, it is worthwhile to note that stable peaks of the R-R interval recorded by the Polar watch are crucial to the accuracy of the emotion prediction model. Unstable peaks may harm the results significantly. It is thus essential to remove ‘artifact-like’ peaks before analysis. Further work can be done in this respect.

6. Conclusion

This research suggests that using HRV as a biomarker and the PLS-DA as an emotion classifier to assess emotions is feasible. We found that LF, HF, LF/HF ratio, SDNN, RMSSD, and pNN50 are positively associated with happiness and sadness. In the future work, our team will focus on improving the model and attempting to determine some mixed and complicated emotions, such as anger, fear and surprise, etc. The findings from this study help to detect students’ emotions (happiness and sadness) during class, thus educators can adjust their teaching accordingly.

Statements on open data and ethics

The participants were protected by hiding their personal information in this study. They were voluntary and they knew that they could withdraw from the experiment at any time. The data can be provided upon requests by sending e-mails to the corresponding author.

Funding

This work was supported by Taison Digital and Ginger KT Consultancy [grant numbers RD007062017].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The study was kindly supported by Taison Digital, Ginger Knowledge Transfer Consultancy and those who participated in the study.

An abstract entitled [Deep Heart Rate Variability Analysis for VR-Learning] of this paper has been presented at International Conference on Education and Artificial Intelligence 2020, The Education University of Hong Kong, 9–11 November 2020, Hong Kong.

References

Beauchaine, T. P., & Thayer, J. F. (2015). Heart rate variability as a transdiagnostic biomarker of psychopathology. *Int. J. Psychophysiol., 98*(2), 338–350. https://doi.org/10.1016/j.ijpsycho.2015.08.004

Delahaij, R., & VanDam, K. (2017). Coping with acute stress in the military: the influence of coping style, coping self-efficacy and appraisal emotions. *Pers. Indiv. Differ., 119*, 13–18. https://doi.org/10.1016/j.paid.2017.06.021

McCraty, R., & Shaffer, F. (2015). Heart rate variability: new perspectives on physiological mechanisms, assessment of self-regulatory capacity, and health risk. *Global Advances In Health and Medicine, 4*(1), 46–61. https://doi.org/10.7453/gahmj.2014.073

Paul, E. S., & Mendl, M. T. (2018). Animal emotion: descriptive and prescriptive definitions and their implications for a comparative perspective. *Appl. Anim. Behav. Sci., 205*, 202–209. https://doi.org/10.1016/j.applanim.2018.01.008

Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. *Frontiers in Public Health, 5*, 258. https://doi.org/10.3389/fpubh.2017.00258

Waitt, G., & Stanes, E. (2015). Sweating bodies: men, masculinities, affect, emotion. *Geoforum, 59*, 30–38. https://doi.org/10.1016/j.geoforum.2014.12.001

Balzarotti, S., Biassoni, F., Colombo, B., & Ciceri, M. R. (2017). Cardiac vagal control as a marker of emotion regulation in healthy adults: a review. In *Biological Psychology* (vol. 130, pp. 54–66). Elsevier B.V. https://doi.org/10.1016/j.biopsycho.2017.10.008

Castaldo, R., Melillo, P., Bracale, U., Caserta, M., Triassi, M., & Pecchia, L. (2015). Acute mental stress assessment via short term HRV analysis in healthy adults: a systematic review with meta-analysis. In *Biomedical Signal Processing and Control* (vol. 18, pp. 370–377). Elsevier Ltd. https://doi.org/10.1016/j.bspc.2015.02.012

deGroot, J. H. B., vanHoutum, L. A. E. M., Gortemaker, I., Ye, Y., Chen, W., Zhou, W., & Smeets, M. A. M. (2018). Beyond the west: chemosignaling of emotions transcends ethno-cultural boundaries. *Psychoneuroendocrinology, 98*, 177–185. https://doi.org/10.1016/j.psyneuen.2018.08.005

Duesenberg, M., Weber, J., Schulze, L., Schaeuffele, C., Roepke, S., Hellmann-Regen, J., Otte, C., & Wingenfeld, K. (2016). Does cortisol modulate emotion recognition and empathy? *Psychoneuroendocrinology, 66*, 221–227. https://doi.org/10.1016/j.psyneuen.2016.01.011

English, L. H., Wisener, M., & Bailey, H. N. (2018). Childhood emotional maltreatment, anxiety, attachment, and mindfulness: associations with facial emotion recognition. *Child Abuse Neglect, 80*, 146–160. https://doi.org/10.1016/j.chiabu.2018.02.006

Feng, H., Golshan, H. M., & Mahoor, M. H. (2018). A wavelet-based approach to emotion classification using EDA signals. *Expert Syst. Appl., 112*, 77–86. https://doi.org/10.1016/j.eswa.2018.06.014

Höskuldsson, A. (1988). PLS regression methods. *J. Chemometr., 2*(3), 211–228. https://doi.org/10.1002/cem.1180020306

Nuske, H. J., Vivanti, G., & Dissanayake, C. (2013). Are emotion impairments unique to, universal, or specific in autism spectrum disorder? A comprehensive review. *Cognit. Emot., 27*(6), 1042–1061. https://doi.org/10.1080/02699931.2012.762900

Peters, A. T., VanMeter, A., Pruitt, P. J., Briceño, E. M., Ryan, K. A., Hagan, M., Weldon, A. L., Kassel, M. T., Vederman, A., Zubieta, J. K., McInnis, M., Weisenbach, S. L., & Langenecker, S. A. (2016). Acute cortisol reactivity attenuates engagement of fronto-parietal and striatal regions during emotion processing in negative mood disorders. *Psychoneuroendocrinology, 73*, 67–78. https://doi.org/10.1016/j.psyneuen.2016.07.215

Quintana, D. S., Guastella, A. J., Outhred, T., Hickie, I. B., & Kemp, A. H. (2012). Heart rate variability is associated with emotion recognition: direct evidence for a relationship between the autonomic nervous system and social cognition. *Int. J. Psychophysiol., 86*(2), 168–172. https://doi.org/10.1016/j.ijpsycho.2012.08.012

Shi, H., Yang, L., Zhao, L., Su, Z., Mao, X., Zhang, L., & Liu, C. (2017). Differences of heart rate variability between happiness and sadness emotion states: a pilot study. *J. Med. Biol. Eng., 37*(4), 527–539. https://doi.org/10.1007/s40846-017-0238-0

So, C. F., Choi, K. S., Chung, J. W. Y., & Wong, T. K. S. (2013). An extension to the discriminant analysis of near-infrared spectra. *Med. Eng. Phys., 35*(2), 172–177. https://doi.org/10.1016/j.medengphy.2012.04.012

So, C. F., Choi, K. S., Wong, T. K. S., & Chung, J. W. Y. (2019). Deep learning analysis for blood glucose monitoring using near infrared spectroscopy. *Biomedical Journal of Scientific & Technical Research, 21*(3), 15865–15871. https://doi.org/10.26717/bjstr.2019.21.003599

Tarvainen, M. P., Niskanen, J. P., Lipponen, J. A., Ranta-aho, P. O., & Karjalainen, P. A. (2014). Kubios HRV - heart rate variability analysis software. *Comput. Methods Progr. Biomed., 113*(1), 210–220. https://doi.org/10.1016/j.cmpb.2013.07.024

Taylor, J. B. (2006). *My Stroke of Insight : a Brain Scientist's Personal Story*. Penguin Group.

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. *Neurosci. Biobehav. Rev., 36*(Issue 2), 747–756. https://doi.org/10.1016/j.neubiorev.2011.11.009

VanBemmel, J., Musen, M., & Helder, J. (1997). *Handbook of Medical Informatics*. Springer-Verlag. https://www.researchgate.net/publication/229125225_A_Handbook_of_Medical_Informatics.

White, S. W., Abbott, L., Wieckowski, A. T., Capriola-Hall, N. N., Aly, S., & Youssef, A. (2018). Feasibility of automated training for facial emotion expression and recognition in autism. *Behav. Ther., 49*(6), 881–888. https://doi.org/10.1016/j.beth.2017.12.010