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Effects of emotions on heart rate asymmetry

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Abstract

Heart rate asymmetry (HRA) is an index that accounts for an uneven contribution of decelerations and accelerations to the heart rate variability (HRV). Clinical studies indicated that HRA measures have additive clinical value over the more frequently used HRV indexes. Despite the abundance of studies on psychological influences on HRV, little is known whether psychological factors influence HRA. Based on previous research regarding HRA and stress, we expected that negative emotions compared to positive emotions would decrease the contribution of decelerations to HRV. Thirty female participants watched three clips that produced negative emotions, positive emotions, and neutral affect. Besides electrocardiogram, we measured several physiological and behavioral responses to ascertain the affective impact of the clips. Using the RR interval time series, we calculated HRV and HRA indexes. We found that HRA differentiated between positive emotions and negative emotions reactivity. Positive emotions produced a higher number of decelerations in short-term variability to the total short-term variability ($C1_d$) compared to negative emotions. Moreover, $C1_d$ correlated with subjective ratings of affect. In sum, the results of this study indicated that HRA is sensitive to psychological influences. HRA indexes are likely to contribute to a more nuanced physiological differentiation between emotions.

KEYWORDS

cardiovascular, electrodermal, emotion, heart rate, heart rate variability, respiration

1 | INTRODUCTION

Heart rate asymmetry (HRA) is a physiological phenomenon related to the different contribution of decelerations and accelerations to heart rate variability (HRV), structure, and complexity (Guzik, Piskorski, Krauze, Wykretowicz, & Wysocki, 2006; Piskorski & Guzik, 2011). Clinical value of HRA has been shown in several studies and different clinical scenarios. For instance, reduced HRA has been found in patients with Type 1 diabetes (Guzik, Piskorski, Contreras, & Migliaro, 2010), heart failure (Ricca-Mallada, Migliaro, Piskorski, & Guzik, 2012), obstructive sleep apnea (Guzik et al., 2013), and patients after myocardial infarction who are at an increased risk of premature death (Guzik et al., 2006).

Despite literature regarding effects and associations between other metrics of HRV and psychological factors (Appelhans & Luecken, 2006), no study examined psychological factors that might influence HRA. Such integration is essential given the clinical value of HRA (Guzik et al., 2012; Kovatchev et al., 2003). Furthermore, more nuanced physiological indexes are needed to differentiate between physiological emotions with a broader scope and higher precision (Kreibig, 2010). For instance, a recent meta-analysis indicated that anger and happiness are mostly differentiated by HRV indexes with little differences in hemodynamic responses (Siegel et al., 2018). In this study, we examined whether HRA structure distinguishes between positive and negative emotions. As a secondary aim, we explored how

HRA affective reactivity is related to HRV indexes and other measures of peripheral physiology. This study contributes to a more complex understanding of how psychological phenomena influence heart rate, its variability, and asymmetrical properties of the variance.

1.1 | Heart rate asymmetry

HRV is the variation in interbeat intervals (consecutive R peaks of the QRS complex) of sinus origin. HRV is modulated by several intrinsic physiological mechanisms with the strongest influence from breathing, tonic, and reflex parasympathetic and sympathetic activities, hormones, metabolites, and cytokines. HRV is often considered as an indirect and noninvasive marker of the autonomous nervous system activity. For several decades, HRV has been extensively studied in several clinical settings, and its predictive value in some groups of patients has been documented (Bauer et al., 2006; Bigger et al., 1992; Guzik et al., 2012; Nolan et al., 1998; Sassi et al., 2015; Schmidt et al., 1999; Task Force, 1996).

There are several mathematical algorithms for HRV computation based on statistical analysis (time domain), advanced spectral analysis of signals (e.g., Fourier transform and Lomb-Scargle periodograms), and nonlinear analyses (e.g., Poincaré plots). Some of the methods, such as Poincaré plots (also known as scatter plots, first return maps, or Lorenz plots; see Figure 1), have an excellent physiological explanation (Brennan, Planiswami, & Kamen, 2001).

On a Poincaré plot (Figure 1), each RR interval is represented as a point on *x* and *y* axes, where *x* represents the current duration of the RR interval (RR_n), and *y* represents the duration of the next RR interval (RR_{n+1}). The Poincaré plot of RR intervals distributed on a plane (RR_n, RR_{n+1}) shows different shapes of points. For sinus (i.e., normal) rhythm, the plots are similar to comets, and they are interpreted with the use of two perpendicular lines. The first line, called the identity line, goes across all points representing no change in the duration of consecutive RR intervals ($RR_n = RR_{n+1}$). The second line is perpendicular to the identity line, and they both cross closely to the gravity of the whole plot (centroid; i.e., where the mean of all RR_n intervals and the mean of all RR_{n+1} intervals are identical). The distribution of all points of the Poincaré plot along the identity line shows the differences between the duration of two consecutive RR intervals (i.e., $RR_n - RR_{n+1}$), and it corresponds to the fastest or the shortest possible HRV.

In contrast, the distribution of all points of the Poincaré plot along the perpendicular line shows how far the mean of the duration of two neighboring RR intervals (i.e., RR_n and RR_{n+1}) departs from this line. The identity line of the Poincaré plot separates the whole cloud of points into three sets. First, heart rate decelerations for which the duration of the current RR interval is shorter than for the next RR interval ($RR_n < RR_{n+1}$). Second, heart rate accelerations for which the duration of the current interval is longer than for the next RR interval ($RR_n > RR_{n+1}$). Third, the points placed on the identity line for which intervals are equal ($RR_{n+1} = RR_n$). The proportion of variance of decelerations to accelerations represents the phenomenon of HRA (Guzik et al., 2006). Noteworthy, points placed precisely on the identity line (two consecutive intervals of the same value) reflect the sampling frequency imprecision as it is unlikely that two intervals are identical (Piskorski & Guzik, 2011). When the sampling rate

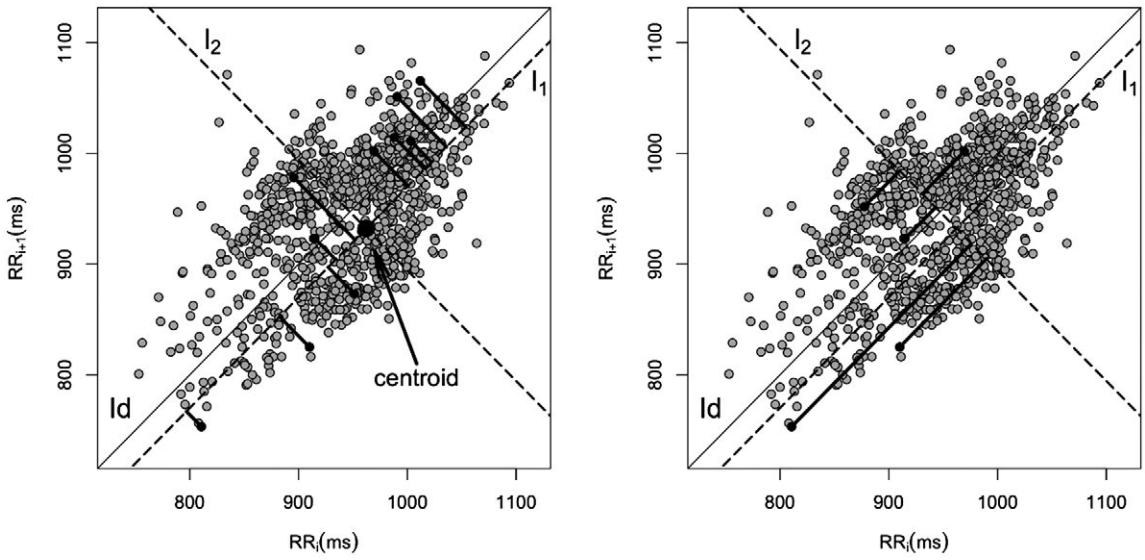

FIGURE 1 Construction of short-term (left) and long-term (right) HRA descriptors. For each panel, the distance of a few select points is marked with segments. For better presentation, the centroid and l_1 have been artificially moved away from the identity line, and thus their positions are largely exaggerated. Id = identity line; l_1 = Id-parallel centroid-crossing line; l_2 = Id-perpendicular centroid-crossing line

is higher, there are lower odds that two consecutive intervals will be classified as equal (e.g., 742 and 742 ms) despite their actual difference (e.g., 742.0 vs. 742.9 ms). Increasing measurement precision is feasible due to the increasing technical capacity of modern equipment.

HRA results from an unequal contribution of heart rate decelerations and accelerations to the variance of RR intervals (Piskorski & Guzik, 2011). More recent developments have also shown that heart rate decelerations and accelerations have a significantly different input to the structure and complexity of heart rate. For each of the above parameters, a contribution of points above the identity line (decelerations of heart rate) and of points below the identity line (accelerations of heart rate) to the heart rate variability can be calculated. In general, the asymmetry for the short-term HRV is reflected in greater contribution of decelerations, while for long-term and total variability the accelerations have larger impact—a phenomenon that shows that long-term variability prevails in the total variability of heart rate (Piskorski & Guzik, 2007, 2011). By the difference between two consecutive RR intervals, several time-irreversibility indices can be calculated that represent the proportion of accelerating or decelerating heartbeats.

There is little research on psychological phenomena that might be associated with HRA. A recent study indicated that the contribution of decelerations declines under stress (Visnovcova et al., 2014). However, no studies on the expression of HRA in relation to emotions have been published. Evaluation of the dynamic expression of asymmetrical features of cardiovascular time series related to different emotional processes is likely to provide validity of these indexes in psychophysiological research.

1.2 | A multivariate approach to the measurement of emotions

Emotions are complex phenomena that engage subjective, physiological, and behavioral responses (Gross, 2015; Levenson, 1994). Emotions optimize bodily milieu for effective responses. Whereas some theorists emphasize the coherence between these systems in affective responding (Lazarus, 1991; Levenson, 1994), others emphasize weaker than expected relationships between physiological responses and subjective or behavioral outcomes (Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005). Thus, a multivariate approach (Mauss & Robinson, 2009; Thayer & Friedman, 2000) is preferred to ascertain that significant affective responses were elicited and indicate which affective systems were significantly engaged. Moreover, a multivariate approach to physiology is particularly important because there are several components of cardiovascular arousal that have different prognostic value for the development of cardiovascular disease (Guzik et al., 2010; Hughes, 2007).

With many studies on emotional experience and peripheral physiology, there is less evidence for affective facial behavior. Many studies have used electromyography (Mauss & Robinson, 2009) or manual FACS coding (facial action classification system; Ekman & Friesen, 1978) to quantify facial expression of emotions. However, with the progress of machine learning, specialized software has been increasingly accurate in detecting and quantifying facial expression of emotions (Lewinski, de Uyl, & Butler, 2014). Although the zygomaticus major used in facial electromyography is the leading facial muscle involved in positive expression (Larsen, Norris, & Cacioppo, 2003), a genuine smile involves the activity of other facial muscles (Ekman, 1992). A trained neural network used in facial expression recognition software is capable of accounting for several facial action units that are analyzed in parallel (Lewinski et al., 2014). Moreover, facial recognition software is based on the actual observable behavior rather than activity in muscles that are involved in the production of responses in facial muscles. Thus, further multivariate approaches in psychophysiology focused on physiology and behavior might capitalize on automated facial expression analysis via specialized software.

1.3 | Present study

This study aimed to examine the affective influence on HRA. Based on initial evidence regarding HRA and mental stress (Visnovcova et al., 2014), we expected that negative emotions would decrease the contribution of decelerations to the heart rate variability relative to positive emotions. Testing these hypotheses would provide more information on whether HRA indices might be relevant to psychophysiological studies. Furthermore, we aimed to explore how HRA affective reactivity is related to the reactivity in other physiological responses. We also accounted for the standard measures of autonomic modulation of the cardiovascular system, that is, parameters used to better define the current autonomic status (i.e., sympathetic predominance/suppression or parasympathetic predominance/inhibition). With these parameters as the reference measures, it would be easier to understand changes in HRA caused by negative and positive emotions.

2 | METHOD

2.1 | Participants

This study involved 30 women between the ages of 19 and 27 years old ($M = 21.26$, $SD = 2.42$). Noteworthy, with each participant responding to three stimuli, we recorded a total of 90 responses. Upon conducting a power analysis with G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009), we determined that, with the current repeated measures analysis of variance (ANOVA) design, 27 participants would provide

a statistical power of 0.95 for medium effect sizes of 0.26 (Quintana, 2017), with $\alpha = 0.05$, and correlation of $r = 0.75$ between repeated measures. This level of power is superior compared to what might be expected from a single measurement ANOVA, where each participant responds to a single stimulus. With differences in affective responding between women and men (McRae, Ochsner, Mauss, Gabrieli, & Gross, 2008; Stevens & Hamann, 2012), we invited a convenience sample of women to maintain adequate power. Women were more representative of the sampled population because they constituted the majority of undergraduate students in the social sciences department where we ran this study. Volunteers were Caucasian undergraduates from a university in Poland with their body mass index (BMI) between 17.30 and 26.51 kg/m^2 ($M = 22.01$, $SD = 2.89$). One person was excluded from the sample due to BMI > 30. Exclusion criteria were significant health problems, use of drugs or medications that might affect cardiovascular functions, prior diagnosis of cardiovascular disease, or hypertension. Participants were asked to reschedule if they experienced illness or a major negative life event. We instructed participants to avoid eating for at least 1 hr before the experiment and to refrain from physical exercise and intake of caffeine, nicotine, alcohol, or nonprescription drugs for at least 2 hr before the experiment. Each participant received a cinema ticket for their involvement. The study was approved by the Institutional Ethics Committee.

2.2 | Measures

2.2.1 | Interbeat intervals

Electrocardiogram (ECG) was recorded with BioAmp and Powerlab 16/35 AD converter (ADInstruments, New Zealand) and Ag/AgCl surface electrodes on the chest. The signal was stored on a computer with other biosignals using a computer-based data acquisition and analysis system (LabChart 8.1; ADInstruments). The signal was reduced to interbeat intervals (intervals between R peaks in the ECG waveform in ms). The ECG signal was sampled at a higher-than-usual frequency of 20 kHz because higher sampling frequency minimizes the odds that two beats will be classified as identical due to the signal resolution (Piskorski & Guzik, 2011).

2.2.2 | Heart rate asymmetry

For HRA, we calculated the mean distance, Guzik's Index (Guzik et al., 2006) of the plotted points above (decelerations) and below (accelerations) the identity line in the Poincaré plot (Figure 2). Values related to non-normal beats (e.g., supraventricular or ventricular) were removed. According to the standards on HRV, only files with less than 10% of artifacts and nonsinus beats were accepted for all analyses.

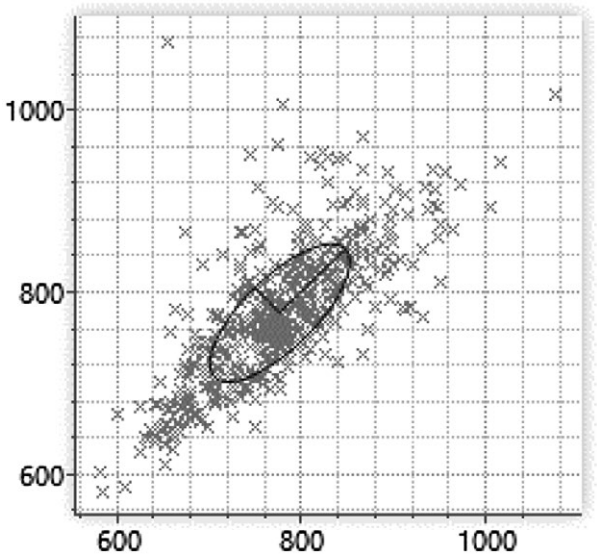

FIGURE 2 Example of an HRV Poincaré plot for one study participant. Each RR_n (x axis) interval is plotted against the subsequent interval RR_{n+1} (y axis). The semi-minor axis of the ellipse represents short-term variability, and the semi-major axis of the ellipse represents long-term variability

All recordings satisfied this criterion. For HRV, we calculated the power of low (LF) and high (HF) frequency and their ratio (LF/HF), which reflect tonic sympathovagal influences. We computed the contribution of heart rate decelerations to the short-term ($C1_d$) and long-term ($C2_d$) variability, which are measures of heart rate asymmetry (Piskorski & Piskorski, 2011). $C1_d$ and $C2_d$ are presented as ratios. Thus, $C1_d$ and $C2_d$ do not have any specific measurement unit. The variances that form the ratio are calculated in ms^2. For HRA, we used the mathematical method of the averaged Lomb periodograms that provides indexes of short-term (SD1) and long-term (SD2) variability (Guzik & Piskorski, 2011).

$$C1_d = \frac{SD1_d^2}{SD1^2}, C1_a = \frac{SD1_a^2}{SD1^2}$$

$$C2_d = \frac{SD2_d^2}{SD2^2}, C2_a = \frac{SD2_a^2}{SD2^2}$$

We present indexes for decelerations ($C1_d$ and $C2_d$) but not for accelerations ($C1_a$ and $C2_a$) because the contribution of accelerations and decelerations is perfectly inversely correlated (i.e., the more decelerations, the fewer accelerations).

$$C1_d + C1_a = 1$$

In sum, the combined HRV and HRA analysis of time series offered an in-depth insight into the heart action dynamic.

2.2.3 | Skin conductance

Electric skin conductance levels were sampled with the GSR Amp (ADInstruments) at 1,000 Hz and reported in microsiemens (μS). We used electrodes with a contact area of 8 mm diameter filled with a TD-246 sodium chloride skin conductance paste. We attached them with adhesive collars and sticky tape to the medial phalanges of digits II and IV of the left hand. Skin conductance is a measure of sympathetic arousal and is related to affective processing (Nagai, Critchley, Featherstone, Trimble, & Dolan, 2004; Waugh, Thompson, & Gotlib, 2011).

2.2.4 | Fingertip temperature

The temperature was measured with a temperature probe attached to Thermistor Pod (ADInstruments) at the distal phalange of the V finger of the left hand, sampled at 1,000 Hz, and reported in degrees Celsius. This measure is an indicator of sympathetic activity that results in peripheral vasoconstriction (Kistler, Mariauzouls, & von Berlepsch, 1998). Finger temperature tends to increase in favorable circumstances and decrease in threatening situations (Rimm-Kaufman & Kagan, 1996).

2.2.5 | Respiration

We measured abdominal and chest circumference changes during respiration with two piezo-electric belts Pneumotrace II (UFI, USA). The abdominal and chest signals were averaged. The number of respiration cycles was computed with Cyclic Measurements module in LabChart 8.1.9 (ADInstruments). The number of respiration cycles per minute provided the respiration rate. Respiratory rate increases in response to positive and negative emotions (Kreibig, 2010; Siegel et al., 2018). The increased respiration rate results from sympathetic activation and/or vagal withdrawal (Larsen et al., 2003).

2.2.6 | Facial electromyography

We recorded the activity in zygomaticus major, which is a facial muscle activated to pull lip corners during smiling (Larsen et al., 2003). The target sites of the skin of the left side of the face were cleaned with the Nuprep abrasive gel. A pair of 4-mm shielded Ag/AgCl electrodes filled with the Ten20 conductive paste were placed and secured using adhesive collars and sticky tape. Following Fridlund and Cacioppo's (1986) guidelines, the two electrodes of a pair were placed at a distance of about 1.5 cm over muscle regions associated with emotion expressions. The ground electrode was placed on the forehead. The electromyography (EMG) signal was recorded with a 30-Hz to the 400-Hz band-pass filter, rectified and smoothed online using a 500-ms time constant.

2.2.7 | Facial behavior

We recorded facial expressions of each participant continuously using an HD camera mounted on the top of the PC screen. The video data were analyzed using facial expression analysis software, Quantum Sense (Quantum CX, Poland). This software uses a neural network to detect and classify facial expressions by comparing the target face against the prototypical expression of basic emotions (Ekman, 1992). We focused on the happiness expression (smile) because it yields the highest accuracy for facial emotion recognition (Den Uyl & van Kuilenburg, 2005). Smiling was quantified on a scale from 0 to 1 with higher values representing stronger expressions (Den Uyl & van Kuilenburg, 2005). Computerized solutions are valid and offer perfect reproducibility compared to the manual coding of facial expression of emotions by human coders (Chentsova-Dutton & Tsai, 2010; Stanko-Kaczmarek & Kaczmarek, 2016).

2.2.8 | Emotional valence

The valence of the emotional experience was reported by the participants continuously with a Response Meter (ADInstruments) on a scale from 1 (*extremely negative*) to 10 (*extremely positive*). Participants were asked to adjust the scale position as often as necessary so that it always reflected how they felt at a given moment. The signal was sampled at a rate of 1,000 Hz by Powerlab 16/35 (ADInstruments) and further reduced using LabChart 8.19 software (ADInstruments). Electronic rating scales collect reliable and valid emotion ratings (Ruef & Levenson, 2007).

2.2.9 | Subjective experience

Participants reported basic emotions (Ekman, 1992) that they experienced while watching the clips: happiness, fear, sadness, anger, disgust, and surprise (Stephens, Christie, & Friedman, 2010). They used a scale presented on the PC screen and developed within E-Prime (Psychology Software Tools, Inc., USA). The intensity scale ranged from 1 = *not at all* to 7 = *extremely*.

2.3 | Physiological reactivity

For each physiological measure, we calculated the difference between baseline and the activity measured at the stage of stimuli presentation (Christenfeld, Glynn, & Gerin, 2000).

The levels for each measure were averaged over the reactivity period, and the score of the baseline level was subtracted. This calculation is mathematically equivalent to computing the area between the reactivity curve and the resting level. Using difference scores is a standard strategy for the study of autonomic responses to psychological factors (Monfort et al., 2014; Peters, Reis, & Jamieson, 2018).

2.4 | Emotion elicitation

We selected stimuli from a validated emotion-eliciting video clips database (Schaefer, Nils, Sanchez, & Philippot, 2010). We selected a clip from the movie "The Professional" (the villain and his team kill the protagonist's family) for negative emotions (anger), a clip from "A Fish Called Wanda" (one of the characters is found naked by the owners of the house) for positive emotions (amusement), and "Three Colours: Blue" (people in everyday situations) for the neutral condition. The clips were 3 min long, and each clip was preceded by a 3-min baseline. Each participant watched three clips. The order of presentation was counterbalanced across participants.

2.5 | Procedure

Upon arrival, volunteers signed a written informed consent. Biosensors were attached, and participants received information on how to use the rating scale dial for continuous assessments of affect. Then, participants watched the videos. After each clip, they reported discrete emotions that they felt while watching the clip.

2.6 | Analytical strategy

To test the hypotheses that emotions influence HRA, we conducted a repeated measures ANOVA with emotions (positive vs. negative) as a within-subject factor because participants watched each of the clips presented in a counterbalanced order. To capture positive emotions and negative emotions reactivity, we subtracted reactivity scores taken during the neutral clip from reactivity scores for positive and negative clips. Analyses were performed with SPSS 21.0 (IBM, USA). We applied the false discovery rate (FDR) correction for hypotheses testing (Benjamini & Hochberg, 1995). To balance the Type I error and Type II error, exploratory comparisons unrelated to HRA testing were presented with standard p values.

In addition to HRA reactivity differences across conditions, we also examined the linear relationship between HRA reactivity and affective and physiological reactivity scores. Using multilevel modeling, we accounted for the hierarchical structure of the data that resulted from two measurements for each participant. In multilevel models, the responses from participants were conceptualized as the sum of fixed and random effects. The fixed effects are of primary interest, whereas random effects contribute to the covariance structure that makes the results more accurate. The data were conceptualized as a two-level model. At Level 1, we regressed the outcomes (Y), that is, HRA reactivity parameters $C1_d$ or $C2_d$, on each predictor (X). Because responses were nested within individuals, we added participants at Level 2 of the model to account for random effects in intercepts (β_{0j}) and slopes (β_{1j}). All predictors were group centered because our interest was in the relationship between Level 1 variables (Enders & Tofighi, 2007).

$$\text{Level 1} \quad y_{ij}(Y) = \beta_{0j} + \beta_{1j}(X) + r_{ij}$$

$$\text{Level 2} \quad \beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

We reported intraclass correlation coefficients (ICC) for both outcome variables. For $C1_d$, the ICC value (0.27, $p < 0.05$) necessitates multilevel analysis; for $C2_d$, not (0.039, $p > 0.05$). We performed multilevel analyses for clarity. For each outcome, we calculated 11 models (i.e., one for each predictor). We accounted for FDR for each outcome, so the denominator in calculation of cutoff p values was equal to 11.

For each outcome, we calculated the (a) null model (no predictor, no multilevel structure), (b) model with the predictor but not multilevel, (c) model with random intercepts, and (d) model with random intercepts and slopes. Comparison of the nested models for each predictor revealed that random slopes did not improve the models (except valence). On the other hand, the model with random intercepts and slopes for heart rate produced a singularity. Therefore, for both outcomes, we reported parameters from the models with random intercepts only. Analyses were performed with *R* 3.0.2 environment (R Development Core Team, 2014) using *R* package nlme (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017).

3 | RESULTS

As expected, participants reported more happiness while watching the positive clip and more negative emotions (disgust, fear, anger, sadness) while watching the negative clip (Table 1). Continuous rating of affect throughout the clips indicated that participants experienced more positive affect and smiled more during the positive clip compared to the negative clip (Table 2). The effect for other expressions was not

TABLE 1 Differences in felt emotions for the movie clips

	Clip								
	Neutral (A)		Positive (B)		Negative (C)				
	M	*SD*	*M*	*SD*	*M*	*SD*	*F*	η^2	Post hoc
Happiness	2.55	1.97	5.90	2.21	1.90	1.32	45.47^{***}	0.62	$B > A^{***}$, $B > C^{***}$
Sadness	2.76	1.98	1.28	0.65	4.66	2.44	32.45^{***}	0.54	$C > A^{***} > B^{***}$
Fear	1.93	1.46	1.52	1.24	4.66	2.55	33.85^{***}	0.55	$C > A^{***}$, $C > B^{***}$
Surprise	2.14	1.88	5.93	2.51	4.83	2.27	22.52^{***}	0.47	$B > A^{***}$, $C > A^{***}$
Anger	1.38	0.98	1.21	0.62	4.38	2.87	29.80^{***}	0.52	$C > A^{***}$, $C > B^{***}$
Disgust	1.21	0.49	2.62	2.14	5.97	2.64	49.07^{***}	0.64	$C > B^{***} > A^{***}$

Note. Post hoc tests with Bonferroni correction.
$^{***}p < 0.001$; *df* (2, 56).

TABLE 2 Effects of elicited emotions on affect, expression, and physiology

	Emotion						
	Positive (B)		Negative (C)				
	M	*SD*	*M*	*SD*	*F*	*p*	η^2
Hypothesized							
$C1_d$	2.47	7.78	−0.05	9.95	5.27^{*}	0.02 [0.058]	0.16
$C2_d$	1.29	8.56	3.52	9.72	1.78	0.19 [0.19]	0.06
Explorative							
fEMG [mV]	0.15	22.53	−3.02	23.43	0.83	0.37	0.03
Smile [EI]	0.12	0.22	0.02	0.16	12.95^{***}	<0.01	0.32
Valence [LSP]	0.51	2.00	−1.39	2.13	13.11^{***}	<0.01	0.32
FT [°C]	0.19	0.94	0.18	0.58	0.02	0.91	0.01
SCL [μS]	0.36	0.62	0.26	0.49	0.74	0.40	0.03
RESP [b/min]	0.77	2.93	0.94	2.80	0.08	0.78	0.01
HR [bpm]	−2.02	5.16	−1.92	6.24	0.03	0.86	0.01
HF [ms^2]	88.44	502.55	−91.16	633.25	3.84^{a}	0.06	0.12
LF [ms^2]	275.45	842.51	−101.84	1262.50	5.27^{*}	0.03	0.16
LF/HF	0.46	1.03	0.13	1.18	2.89^{a}	0.10	0.09

Note. Square brackets present FDR corrected *p* values. *df* = 1, 28; fEMG = facial electromyography (zygomaticus major); FT = finger temperature; SCL = skin conductance level; RESP = respiratory rate; HR = heart rate; HF = high frequency HRV; LF = low frequency HRV; $C1_d$ = contribution of decelerations to short-term heart rate variability (HRA); $C2_d$ = contribution of decelerations to the long-term variability (HRA); EI = expression intensity; LSP = Likert scale points.
$^{a}p < 0.10$; $^{*}p < 0.05$; $^{***}p < 0.001$.

significant, all *p*s > 0.05. The difference in expression was not detectable via facial EMG. In sum, our method produced expected affective differences in experience and expression across the conditions.

Participants responded with a higher $C1_d$ HRA reactivity to the positive clip compared to the negative condition (Table 2). However, this difference should be interpreted with caution, because it was marginally significant ($p = 0.058$) after FDR correction. There was no significant effect on $C2_d$. Furthermore, explorative analyses indicated that elicited positive emotions produced higher levels of LF HRV. This indicates that elicited emotions produced significant effects on HRV as well as HRA (i.e., increases in long-term variability and increases in the contribution of decelerations to the short-term heart rate variability, $C1_d$).

Finally, we found that individuals with a higher contribution of decelerations to the short-term variability ($C1_d$) had higher levels of valence and LF HRV (Table 3). Higher contribution of long-term decelerations ($C2_d$) was related to lower LF HRV and a lower LF/HF.

4 | DISCUSSION

In this study, we aimed to provide evidence that psychological factors influence HRA and that the use of HRA indexes is useful in the psychophysiological literature. We found the first evidence that the number of decelerations in short-term variability to the total short-term variability ($C1_d$) was influenced by emotions. This effect was parallel to other responses in HRV (higher levels of LF HRV for positive emotions). Moreover, we observed linear relationships between $C1_d$ and valence suggesting that individuals who reported more positive affect also exhibited higher levels of $C1_d$. Furthermore, $C1_d$ correlated with another well-established HRV index, (i.e., LF HRV). We found less evidence for the affective effects and correlations of $C2_d$. This index reflecting decelerations in long-term variability was correlated with lower LF HRV and LF/HF. However, it was not related to nor dependent on emotions. In sum, these findings suggest that HRV and HRA are correlated yet distinct metrics in cardiovascular physiology and that $C1_d$ is related to affective processing. The general validity of the findings was corroborated by the fact that the effects followed authentic changes in affective experience and behavior as indicated by continuous subjective ratings and facial expressions.

The $C1_d$ index provided additional information that might help to interpret the psychophysiological processes within the participants experiencing and expressing emotions. Elicited positive emotions generated higher levels of LF HRV, a finding consistent with previous studies where participants watched comedy clips (Sakuragi, Sugiyama, & Takeuchi, 2002). Although positive emotionality has been related to the higher activity of the vagal nerve marked by HF HRV (Oveis et al., 2009), there are physiological responses in amusement that engage the sympathetic system such as laughter. Laughing requires a considerable (up to 20% compared to baseline) mobilization of energy (Buchowski et al., 2007). A series of brief exhalations is engaged in the laughter production followed by a short and deep inhalation (Ruch & Ekman, 2001). These effects suggest a stronger metabolic

TABLE 3 Relationship between HRA indexes and physiological, behavioral, and subjective responses (multilevel parameters)

Predictor	*B* (*SE B*)	*t*	*p*	Intercept (*SE*)	Variance of intercept	*SD* of intercept (95% CI)
fEMG [mV]	0.03 (0.06)	0.42	0.68	−3.61(0.79)	7.58	2.75 (1.39, 5.46)
Smile [EI]	−8.25 (7.77)	−1.06	0.29	−3.61 (0.79)	8.07	2.84 (1.46, 5.54)
Valence [LSP]	1.16 (0.41)	2.82	<0.01[a]	−3.61 (0.79)	9.72	3.12 (1.88, 5.18)
FT [°C]	0.02 (1.55)	0.01	0.99	−3.61 (0.79)	7.52	2.74 (1.37, 5.47)
SCL [μS]	−0.91 (1.95)	−0.47	0.64	−3.61 (0.79)	7.59	2.76 (1.39, 5.46)
RESP [breaths/min.]	−0.51 (0.35)	−1.44	0.16	−3.61 (0.79)	8.21	2.86 (1.54, 5.34)
HR [bpm]	0.61 (0.38)	1.62	0.12	−3.61 (0.79)	8.38	2.89 (1.58, 5.32)
HF [ms^2]	0.004 (0.002)	1.84	0.77	−3.61 (0.79)	8.59	2.93 (1.63, 5.29)
LF [ms^2]	0.003 (0.001)	3.03	0.01[a]	−3.61 (0.79)	9.94	3.15 (1.92, 5.17)
LF/HF	1.29 (1.10)	1.17	0.25	−3.61 (0.79)	7.98	2.83 (1.48, 5.38)
$C2_d$	−0.23 (0.12)	−1.89	0.07	−3.61 (0.79)	8.65	2.94 (1.64, 5.28)
fEMG [mV]	−0.04 (0.09)	−0.44	0.66	3.94 (0.89)	1.82	1.35 (0.03, 71.06)
Smile [EI]	−7.79 (10.79)	−0.72	0.48	3.94 (0.89)	3.49	1.87 (0.20, 17.23)
Valence [LSP]	−1.21 (0.63)	−1.92	0.06	3.94 (0.89)	4.09	2.02 (0.33, 12.45)
FT [°C]	1.64 (2.21)	0.74	0.46	3.94 (0.90)	2.08	1.44 (0.04, 54.95)
SCL [μS]	0.03 (2.82)	0.01	0.99	3.94 (0.89)	1.68	1.30 (0.01, 144.60)
RESP [breaths/min]	0.83 (0.50)	1.65	0.11	3.94 (0.89)	3.51	1.87 (0.22, 16.13)
HR [bpm]	−1.01 (0.53)	−1.91	0.07	3.94 (0.89)	4.06	2.01 (0.32, 12.66)
HF [ms^2]	−0.006 (0.003)	−1.86	0.07	3.94 (0.89)	3.19	1.99 (0.30, 13.17)
LF [ms^2]	−0.006 (0.001)	−4.46	<0.01[a]	3.94 (0.89)	10.28	3.21 (1.70, 6.07)
LF/HF	−5.58 (1.23)	−4.53	<0.01[a]	3.94 (0.89)	10.43	3.23 (1.73, 6.04)
$C1_d$	−0.48 (0.26)	−1.89	0.07	3.94 (0.89)	4.02	2.00 (0.31, 12.83)

Note. fEMG = facial electromyography (zygomaticus major); FT = finger temperature; SCL = skin conductance level; RESP = respiratory rate; HR = heart rate; HF = high frequency HRV, LF = low frequency HRV, $C1_d$ = contribution of decelerations to short-term heart rate variability (HRA); $C2_d$ = contribution of decelerations to the long-term variability (HRA); EI = expression intensity; LSP = Likert scale points; DV = dependent variable; *Df* = 28.

[a]Significant after controlling for false discovery rate.

demand that seemed to be the case for participants responding to the positive stimuli.

Findings regarding the effects of emotions on HRA and the relationship of HRA with other physiological indexes can be interpreted together. For individuals who experience positive emotions, decelerating capacities are prioritized, whereas for negative emotions, accelerations are prioritized. The heart decelerating effects seem to correspond well with the soothing function of positive emotions (Levenson, 1999). In contrast, the accelerating effects correspond with the function of negative emotions that produce stress responses, which promote physiological mobilization (Mendes & Park, 2014). Thus, using HRA might be considered a novel approach to the analysis of soothing and mobilizing physiological responses.

Before we conducted the primary analyses, we used a multilayer approach to test whether the experimental situation produced meaningful emotional responses. We found responses in cognitions and facial behavior that were in line with expectations. This finding corroborated the validity of further physiological analyses. Additionally, it serves as an argument for the validity of the database that we used in psychophysiological research (Schaefer et al., 2010). Noteworthy, we detected increases in happiness expression via facial recognition software but not with the facial EMG of the zygomaticus major. Although the zygomaticus major is the leading facial muscle involved in positive expression, a genuine smile involves activity of other facial muscles (Ekman, 1992). A trained neural network used in facial expression recognition software accounts for several facial action units analyzed in parallel (Lewinski et al., 2014). This may suggest that facial recognition methods might be an adequate substitute for facial EMG to account for smiling in psychophysiological research.

There are limitations to this study. First, the sample size did not allow for reliable detection of small effects. This suggests that effects of a smaller magnitude might have been undetected, but also that the effects we observed to be significant might have been unusually exaggerated examples of the phenomena under scrutiny. Given that psychophysiological effects are often weak (e.g., due to the imperfection of noninvasive recording methods), a larger sample might allow detecting more effects of emotions on HRA. Second, a larger and more diverse sample would allow broader generalizability of the findings. For instance, only women participated in the current study. Some previous studies revealed no differences in the influence of affective factors on HRV between women and men (e.g., McCraty, Atkinson, Tiller, Rein, & Watkins, 1995; Rainville, Bechara, Naqvi, & Damasio, 2006). Yet, women differ from men in levels of some baseline HRV indexes (Liao et al., 1995), and their HRV is influenced by female hormones cycles (Bai, Zhou, & Li, 2009; Vallejo, Márquez, Borja-Aburto, Cárdenas, & Hermosillo, 2005). Moreover, the results might be different for older participants, because cardiovascular efficiency changes with age (Mitchell et al., 2004) and for obese individuals with reduced HRV (Yadav et al., 2017). HRV is also likely to differ across ethnic groups (Choi et al., 2006). Accounting for these differences in future studies on HRA might increase the scope of generalizability. Third, we analyzed short recordings. Although the length of the recordings met recommendations for HRV analysis (Task Force, 1996), longer recordings might provide more robust material for reliable estimation of variability—and long-term variability, in particular. Fourth, we used only one clip for positive emotions and one clip for negative emotions. We aimed to compare anger against amusement, due to an increased focus on the differences between these two emotions (Harmon-Jones & Gable, 2018). There are, however, meaningful physiological differences within the group of negative emotions and within the group of positive emotions (Kreibig, 2010; Shiota et al., 2017; Siegel et al., 2018). Other differences might result from comparisons between other positive and negative emotions. Finally, the affective movie clip for anger produced a mix of discrete negative emotions. The participants in our study responded with more anger as we intended, but also with more fear, sadness, and disgust to the clip compared to the neutral material. This limitation was likely to occur because affective movie clips often produce complex emotional responses (Schaefer et al., 2010). The findings should be interpreted with caution as far as the effects of discrete emotions are concerned.

In conclusion, we found that HRA analysis is emotion sensitive and captures influences that provide additional information compared to other HRV metrics. This is an argument for the use of HRA indexes in affective psychophysiological studies. Our findings suggest that accounting for the contribution of decelerations and accelerations to the total HRV is likely to generate new questions regarding the relationship between heart action and emotional processing. For instance, given that decelerating capacity of the heart is related to better health outcomes (Guzik et al., 2010; Ricca-Mallada et al., 2012), other studies on HRA might focus on more comprehensive understanding which physiological effects of positive emotions contribute to the facilitation of healthy physiological responses (Pressman, Jenkins, & Moskowitz, 2019). Other uses for HRA might be examined in future psychophysiological studies (e.g., focused on cognition, motivation, and behavior). It is imperative for the development of psychophysiology to test new metrics in the pursuit of an increasingly in-depth and multilayer view of studied phenomena.

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