Low heart rate variability is associated with a negativity valence bias in interpreting ambiguous emotional expressions

Authors: Osnes, B.[1,2], Berrefjord, S. R.[1]. Poless, P. G.[1], Sigrist, C. [3], Koenig, J.[3] & Sørensen, L.[1]

[1] Department of Clinical Psychology, University of Bergen, Norway
[2] Bjørgvin District Psychiatric Centre, Haukeland University Hospital, Bergen, Norway
[3] University of Cologne, Faculty of Medicine and University Hospital Cologne, Department of Child and Adolescent Psychiatry, Psychosomatics and Psychotherapy, Cologne, Germany

Berge Osnes, PhD (berge.osnes@uib),
Simen Røssland Berrefjord (Simen.Berrefjord@student.uib.no),
Pauline Georgees Poless (pauline_georgees@hotmail.no) MS,
Christine Sigrist (christine.sigrist@uk-koeln.de) PhD,
Julian Koenig, PhD (julian.koenig@upd.unibe.ch)
Lin Sørensen, PhD (lin.sorensen@uib.no).

Corresponding Author:
Berge Osnes
Department of Clinical Psychology University of Bergen
Bergen, Norway

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Abstract

Background: Most people tend to overstate positive aspects of their experiences, i.e., a positive valence bias. However, some people tend to have attenuated attention for negative aspects of perceived information, i.e., negative valence bias. This dispositional tendency in either valence is especially significant for emotion regulation as it influences the intensity of later stages of emotional experiences. Heart rate variability (HRV) is used as an index of emotion regulation and for the effect dispositional valence bias has on social cognition. The aim of the current study was to investigate whether a positivity or negativity bias in processing ambiguous facial expressions would predict high or lower HRV, respectively, in a healthy sample.

Methods: The Reading the Mind in the Eyes task (RMET) was presented to a sample of 128 healthy participants (*N* = 86 women participants) and resting HRV was acquired. In multiple linear regression analyses, the mean accuracy score for items with positive, negative and neutral valences were included as predictors of HRV. As a follow-up analysis, we tested whether a general tendency to interpret negative stimulus as positive, i.e., a positivity bias, predicted HRV.

Results: Higher accuracy on items with negative emotional valence predicted lower HRV. There was no association between accuracy scores on items of positive or neutral valence and HRV. Higher positivity bias predicted higher HRV.

Conclusion: The present findings suggest that a dispositional valence bias relates to levels of HRV and as such, is influenced by the functioning of the vagal system.

Keywords: Negativity bias; emotion recognition; autonomic nervous system; heart rate variability

A basic aspect of most experiences is whether they are perceived as positive or negative, hence, their valence (Barrett, 2006; Frijda, 1986; Russel, 1980). There are individual differences in the dispositional tendency and bias towards processing information positively or negatively, i.e., a valence bias (MacLeod et al., 2002; Raila et al., 2015; Scherer, 2021; Vaish et al., 2008). While most people have a bias towards positive and away from negative aspects of emotional stimuli (Pool et al., 2016), some have a bias towards focusing their attention on negative rather than positive aspects (Van Bockstaele et al., 2014; Yiend, 2010). This dispositional tendency in either valence is especially significant for emotion regulation as it influences the intensity of later stages of emotional experiences (Pool et al., 2016; Sheppes et al., 2011). A positive bias tends to associate with lower intensity of emotional experiences and thereby allow for cognitive resources for appraisal and re-appraisal of the situational context (Pool et al., 2016). On the other hand, a negative bias may induce intense negative emotions, such as anger or sadness, and lead to inadequate impulsive responses to the situation expressed in language and body signals (Scherer, 2021). Such a negativity bias and subsequent problems with emotion regulation have been shown to also influence social cognition in understanding emotional expressions in others (Vaish et al., 2008).

The valence bias in attention processing and the subsequent intensity, i.e., low or high arousal level, of experienced emotions both influences and is influenced by the regulation of activity in the autonomic nervous system (ANS: Dimberg et al., 2000; Glenberg et al., 2013; Niedenthal, 2007). This is mediated through the efferent and afferent parts of the ANS and the central nervous system, in particular between the limbic and prefrontal brain systems (Adolphs et al., 1994; Damasio, 2003). The vagal nerve is hypothesized to essentially influence prefrontal regulation of the limbic systems and as such, regulation of emotional perception and behavior (Thayer & Lane, 2000; Appelhans & Luecken, 2006; see also Dixon et al., 2017; Franklin & Zebrowitz, 2017; Thayer & Lane, 2009; Thayer and Ruiz-Padial, 2006). The role of the vagal nerve in emotion regulation tends to be indexed by measures of the ANS, such as using resting state heart rate variability (HRV; Appelhans & Luecken, 2006; Berntson et al., 1997; Billman, 2013; Porges, 2009; Reyes del Paso et al., 2013; Thayer & Lane, 2000, 2009). Levels of HRV have typically been shown to positively associate with both cognitive and affective flexibility and adaptive emotion regulation abilities (Ottaviani et al., 2016; Visted et al., 2017; Williams et al., 2015). Interestingly, recent studies have revealed that stimulating the vagus nerve enhances the accuracy of the perception of other people´s emotional expressions (Colzato et al., 2017; Koenig et al., 2021; Steenbergen et al., 2021). Also, higher abilities in social cognition, measured by accuracy in reading emotional facial expressions, has been shown to be associated with higher HRV in accordance with Porges' theory of HRV being essential for social engagement (Porges, 2001, 2003, 2009). However, to our knowledge, only a few studies have specifically studied the differentiation of either positivity or negativity valence bias in relation to HRV. Lischke et al. (2017) reported an association between stimuli with positive valence and high HRV, whereas Madison et al. (2021) found that lower HRV mediated a lower tendency of positivity bias in vocal emotion recognition. There is a need to study this further since internalizing (mental health) disorders typically have been associated with a dispositional negative valence bias (Gotlib & Joormann, 2010; Lembke & Ketter, 2002; Munkler et al., 2015) and lower HRV (Beauchaine & Thayer, 2015; Brown et al., 2018; Jandackova et al., 2016; Koch et al., 2019; Koenig et al., 2016). In fact, it seems that a negativity valence bias can be a risk factor for developing affective disorders (Vinograd et al., 2020).

The aim of the current study was to test if a valence bias in a healthy sample would associate with high or low resting HRV. To investigate this, we applied The Reading the Mind in the Eyes test (RMET: Baron-Cohen et al., 2001), which depicts ambiguous expressions relevant for everyday social cognition (Pahnke et al., 2020). RMET has previously been applied to investigate emotional inferences in relation to resting-state HRV (Cugnata et al., 2018; Lischke et al., 2017; Quintana et al., 2012; Varas-Diaz et al., 2017; Zammuto et al., 2021). The differences in valence across the RMET items have been categorized into positive, negative, and neutral items (Hudson et al., 2020). Lower accuracy for positive RMET items has been reported in clinical samples such as Borderline Personality Disorder (Anupama et al., 2018; Meyer & Morey, 2015; Scott et al., 2011), obesity (Caldu et al., 2019), Parkinson Disease (Yu et al., 2018), and pre-frontal lesions (Shaw et al., 2005). In contrast, enhanced performance on RMET items with negative valence have been found in samples with childhood abuse (Weinstein et al., 2016) and Major Depressive Disorder (Nejati, 2018).

We expected higher HRV to be linked to enhanced accuracy performance on RMET items with positive emotional valence, and lower HRV to be linked to enhanced accuracy performance on items with negative emotional valence, indicative of positivity and negativity bias, respectively. In addition to accuracy scores, we explored if there was a systematic preference for responding with a positive versus negative response to the items, irrespective of the correct answer. As a follow up analysis, we therefore created indexes for interpretation bias, hence, preferences for either positive or negative response alternatives. We predicted that a preference for positive response alternatives would predict higher HRV, and preference for negative response alternatives would predict lower HRV.

Method

Participants

Participants were recruited from the student population of the University of Bergen, and staff at the Haukeland University Hospital, using internal announcements and posters. The following exclusion criteria were applied: 1) former or current neurological conditions, 2) psychological illness, and 3) cardiac conditions. Data for the present study analyses were pooled from two studies that recorded the same experimental measure of resting HRV, used identical sampling methods, and applied the same inclusion criteria, but had different main outcome measures. All participants gave written informed consent in accordance with the Helsinki declaration and internal ethical guidelines. The protocols were approved by the regional ethics committees South-East (Study number: 2018/1554) and West (Study number: 33928). To determine whether to perform multiple linear regression including seven predictors, we estimated a priori statistical power using G*Power (Faul et al., 2009). There are no previous studies that applied a comparative multiple linear regression model. However, existing studies investigating a link between HRV and accuracy scores from the RMET (i.e., Quintana et al., 2012; Lischke et al., 2017) reported moderate effects sizes (f^2 = 0.303 and f^2 = 0.264, respectively). These studies, however, considered accuracy scores on the RMET in terms of a total score, while we considered different sub scores, separated by emotional valence. We therefore assumed a conservative, moderate effect size of f^2 = 0.15 as an estimate, and the conventional level for sufficient statistical power to be at $1\text{-}\beta = .80$, and a significance level of $\alpha = 0.05$. The power analysis revealed that a minimum total number of 103 participants would be required to achieve a significant result.

Procedure

Written informed consent was obtained from each participant prior to the experimental procedure. Upon signing the consent form, resting ECG was acquired. ECG data were acquired at approximately the same time of day, to avoid circadian HRV effects (Kim et al., 2014). Participants were asked to refrain from caffeine or nicotine on the day of the experiment, prior to participating. No participants used any psychoactive medication or medication influencing heart function.

Reading the Mind in the Eyes Test

The revised version of the RMET (Baron-Cohen et al., 2001) was digitally presented using the open source stimulus presentation software PsychoPy (Peirce et al., 2019). In total, 36 pictures of the eye region (18 men and 18 women) were presented in a fixed order (see Baron-Cohen et al. 2001).To approximate the paper and pen version of the test, visual stimuli were presented in the center of the screen, with adjectives placed at each of the four corners of each visual stimulus. The four adjectives consisted of one target and three foils (Baron-Cohen et al., 2001). Participants had to indicate which label best described the facial-emotional expression presented, by pressing the left-hand mouse button.

Accuracy scores for items of positive, neutral, and negative emotional valence

The participants' responses were analyzed separately for items of positive, negative, and neutral emotional valence, based on an empirical classification system provided by Hudson and colleagues (Hudson et al. 2020). For each of the three valence categories, RMET scores were computed as accuracy scores; that is, as the averaged sum of correct answers.

Table 1: Scoring for Interpretation indexes

Items	Item Valence	Response Valence: Positive		Response Valence: Negative	
7	Negative	apologetic*	friendly	**uneasy**	dispirited*
8		relieved	excited	**despondent**	shy
11		amused	flirtatious	**regretful**	terrified
17		affectionate	playful	**doubtful**	aghast*
27		joking	reassuring	**cautious**	arrogant
	(Scoring Positivity index)	1		0	
1	Positive	**playful**	comforting	irritated	bored
3		**desire**	joking	insisting	convinced
18		**deceive**	amused	aghast	bored
30		**flirtatious**	grateful	hostile	disappointed
31		**confident**	joking	ashamed	dispirited
	(Scoring Negativity index)	0		1	

*Note: Words in bold are target words, all other words are foils according to the original test construction. * not listed in any of the linguistic references, the frequent synonyms were applied for categorization.*

Interpretation bias: positivity and negativity indexes

As a follow-up analysis, we investigated whether there was a tendency to interpret items positively or negatively, irrespective of the correct answer, with regard to items where there was an equal positive versus negative response alternative. We categorized targets and foils, i.e., the answer alternatives, as having either a positive or negative valence using the Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2007), Affective Norms for English Words (ANEW; Bradley & Lang, 1999), and the valence rating of targets words in RMET provided by Hezel and McNally (2014). We then selected RMET items with negative valence, with an equal number of positive and negative item response alternatives (i.e., items 7, 8, 11, 17, and 27). A tendency to perceive these as more positive, that is, responding with a positive rather than negative response alternative, was scored as 1, rendering a positivity index. In contrast, the same was done for positive items, but here, negative responses were scored as 1, hence rendering a negativity index (see *Table 1*).

Heart rate variability

ECG was recorded and digitized at 1000 Hz through an A/D converter (Biopac, MP36, Biopac system INC. Santa Barbara, CA). A simple II lead ECG set-up was applied to obtain a sufficiently clear QRS complex. ECG was sampled for a period of 5 min at rest in a supine position, with a period of 30 sec in the same supine resting position prior to data acquisition, in accordance with available recommendations (Quintana et al., 2016). The participants were asked to find a comfortable position. All heart rate data were manually inspected for artifacts, and all data sets were included. HRV analysis was performed with Kubios version 2.0 (Tarvainen et al., 2014). First, data were corrected for miss-placed R peaks manually. Then, Fast Fourier Transform (FFT) frequency bands, heart rate (HR), and the root mean square of successive differences (RMSSD) as a measure of vagally-mediated HRV were calculated. RMSSD is less affected by respiration than other HRV measures, while still being largely indicative of vagal activity (Penttila et al., 2001). ECG-derived respiratory rate was estimated with the algorithm provided by the analysis software Kubios (Tarvainen et al. 2014). Trend components were removed with the smoothness priors detrending method (λ = 500). Given that RMSSD data are typically skewed, as was the case in the present study, log-transformation was applied to approximate a normal distribution (Shaffer and Ginsberg 2017; Task Force, 1996). Other aspects that can potentially influence HRV is body mass index (BMI; height/ weight^2; Speer et al., 2021), age, gender (Voss et al., 2015), respiration frequency (Brown et al., 1993), and heart rate (HR: Billman, 2013; Gasior et al., 2016; de Geus et al., 2019; Sacha, 2014). These variables were included as co-variates in the main statistical analysis and subsequent follow-up analyses.

Statistical analysis

The open source statistical software package R (R Core Team 2020) was used for all statistical analyses. The R packages 'tidyverse' (Wickham et al. 2019) and 'psych' (Revelle 2021) were applied for data parametrization, exploration, visualization, and descriptive statistics. Inferential statistics were performed using the R package 'stats' (R Core Team, 2019). Mean differences between accuracy scores were subjected to separate one-way repeated measures ANOVAs, and subsequent pairwise comparisons were corrected using Bonferroni correction.

In the main analysis, the effect of mean accuracy score for each valence category (positive, neutral, and negative) on logRMSSD was tested simultaneously in a multiple linear regression analysis. In the analysis, potential covariates known to influence HRV included age, BMI, respiration frequency (EDR), and HR (Billman 2013; Gąsior et al. 2016; de Geus et al. 2019; Quintana et al. 2016; Sacha 2014). In the secondary follow-up analysis, the effect of positivity and negativity indexes on logRMSSD was tested simultaneously in a multiple regression analysis. As done in the main analysis, potential covariates of HRV were included in the model (i.e., age, BMI, EDR, and HR).

Data were screened for assumptions of linearity, normality, multicollinearity, homogeneity, and homoscedasticity, and all assumptions were met. No outliers were identified. Bonferroni corrections were applied for the multiple linear regression analyses."rroni correction was applied for the multiple linear regression analysis. The main model included seven predictors, which gave an alpha corrected p value (p.05/7) of 0.007. To estimate the robustness of the applied statistical model we performed a sensitivity analysis with the R package 'sensemakr' (Cinelli & Hazlett, 2020). In accordance with the suggestions outlined by Cinelli and Hazlett (2020), we applied age as a benchmark measure, since age is not related to any of the experimental manipulations and is known to have an impact on HRV (De Meersman & Stein, 2007; Voss et al., 2015).

The raw data will be retained for 5 years after publication of the research, by the decision of the reginal ethic committees, mentioned above. After this 5-year period the data will de -identified and openly accessible.

Results

Descriptive results

The final sample consisted of *N* = 128 individuals (*N* = 86 women and *N* = 42 men) and a mean age of 25.31 (SD = 7.89) years. A descriptive summary of all measures included in the statistical analyses is presented in *Table 2*. No significant differences were observed between man and women with respect to any of the measures reported. The one-way ANOVA conducted on accuracy scores revealed a significant effect of emotional valence ($F(2,254) = 36.06$, $p < .001$, $\eta^2 = .221$). Pairwise post-hoc comparisons revealed significantly higher accuracy scores for the items of neutral valence compared to both positive ($p < .001$, $d = .57$), and negative ($p < .001$, $d = .67$) valence.

Table 2: Descriptive summary of all measures included in the statistical analyses, divided by gender.

Variables	All participants (n = 128)	Women (n = 86)	Men (n = 42)	*p-value*
Age	25.31 (7,89)	25.03 (7.27)	25.88 (9.09)	0.60
BMI	23.72 (3.29)	23.40 (3.45)	24.37 (2.88)	0.10
Heart rate (Hz)	69.37 (9,66)	69.58 (9,69)	68.95 (9.71)	0.73
EDR (Hz)	0.20 (0.05)	0.20 (0.05)	0.20 (0.04)	0.46
logRMSSD	3.93 (0.62)	3.92 (0.64)	3.94 (0.59)	0.91
RMET Total	27.45 (3.43)	27.62 (3.58)	27.12 (3.13)	0.42

Note: RMET = Reading the Mind in the Eyes Test, BMI = body mass index, logRMSSD = natural logarithmic transformation of the Root Mean Square of Successive Difference, EDR = ECG-derived respiratory rate.

Main results: Accuracy scores by valence as predictors of resting HRV.

A multiple linear regression analysis was conducted to predict HRV based on RMET performance. A matrix of first-order correlations between all predictor variables included in the model can be seen in *Table S1* in the online Supplement. In the regression equation, accuracy scores separated by emotional valence (i.e., positive, negative, and neutral) were independently included as predictors of logRMSSD, alongside potential covariates of HRV (including BMI, age, EDR, and HR). The resulting overall model was significant ($F(5,120) = 18.59$, $p < .001$, $R^2 = .52$). Accuracy on RMET items of negative emotional valence was identified as a significant, negative predictor of logRMSSD ($\beta = -0.933$, $t(120) = -3.152$, $p = 0.002$), indicating that higher accuracy on RMET items of negative emotional valence was linked with lower logRMSSD (see *Figure 1A*). Accuracy scores on neither positive nor neutral valence items were significantly associated with logRMSSD (see *Table 3*). Age ($\beta = -0.023$, $t(120) = -4.176$, $p < 0.001$) and HR ($\beta = -0.040$, $t(120) = -9.245$, $p < 0.001$) were significant covariates of logRMSSD.

Table 3: Valence and logRMSSD association with RMET accuracy

Variables	**B**	**SE B**	**t**	***p***	**R^2**
Model ACC					0,52
RMET Negative	-0.933	0.29	-3.152	0.002	
RMET Neutral	-0.141	0.29	-0.511	0.610	
RMET Positive	-0.165	0.34	-0.488	0.626	
Age	-0.023	0.005	-4.176	0.000	
BMI	-0.01	0.012	-0.841	0.401	
EDR	0.142	0.877	0.162	0.871	
HR	-0.04	0.004	-9.245	0.000	

Note: RMET = Reading the Mind in the Eyes Test, ACC = accuracy scores. BMI = body mass index, logRMSSD = natural logarithmic transformation of the Root Mean Square of Successive Difference, EDR = ECG-derived respiratory rate. HR = Heart Rate

The sensitivity analysis revealed that an extreme confounder would need to explain at least 7.96% of residual variance of the treatment to account for the observed effect. An extreme confounder is defined as an unobserved variable orthogonal to all covariates that explains 100% of the residual variance of the outcome variable. In a less extreme scenario, the unobserved confounders would have to explain more than 25.39% of the residual variance of both treatment and outcome measure to bring the point estimate to 0. If sampling uncertainty is accounted for, this robustness value, a = 0.05, would be 10,56%. A confounder at least as strong as *age* can explain 17.2% of the residual variance of the outcome and 6.7% residual variation of the treatment. Hence, the point estimate, i.e., Negative, is robust to confounder as strong as age.

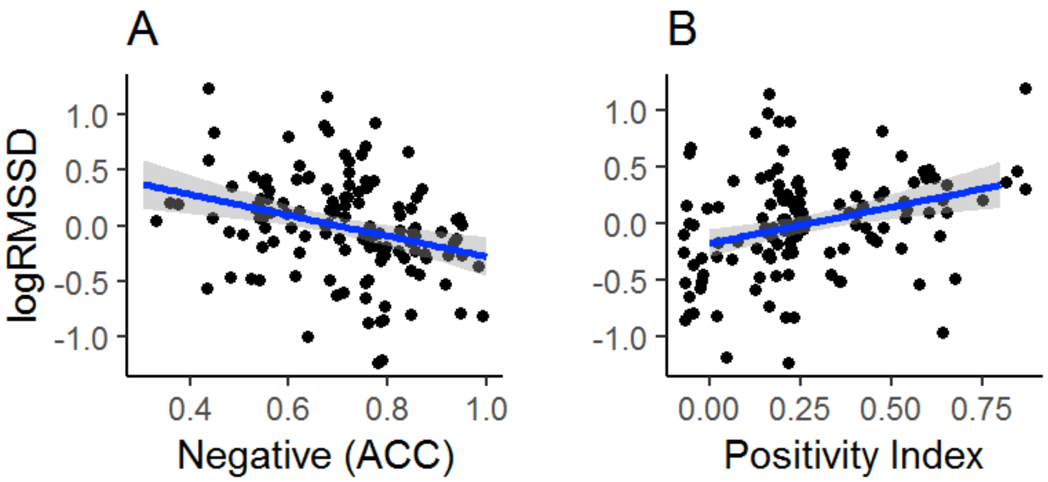

Figure 1: Scatterplot on the relation of significant predictors of logRMSSD. A: Illustration of the significant relation between accuracy in RMET for items with negative valence on logRMSSD. B: Illustration of the significant relation between the positivity index on logRMSSD. Y axes represent logRMSSD when controlled for the effect of age and heart rate, i.e., residual scores. ACC = accuracy scores of RMET items with negative items. logRMSSD = natural logarithm of Root mean square of the successive differences.

Follow-up analyses: Indexes of positivity and negativity bias as predictors of HRV.

The indices of positivity and negativity bias that were additionally derived were subjected to a multiple linear regression model with logRMSSD as the dependent variable, including potential covariates of HRV in line with the main analysis (i.e., BMI, age, EDR, and HR). The resulting overall model was significant ($F(4,120) = 18.59$, $p < .001$, $R^2 = .51$). The index of positivity bias was significantly and positively linked with logRMSSD, ($\beta = 0.670$, $t(120) = 3.425$, $p < 0.001$). This indicates that choosing more positive over negative items (assumed to be indicative of a positivity bias) was associated with higher logRMSSD (see *Figure 1B*). In contrast, the index of negativity bias was not significantly linked with logRMSSD ($\beta = -0.052$, $t(120) = -0.237$, $p = 0.812$) in this model. Again, age ($\beta = -0.022$, t(120) = -4.280, p < 0.001), and HR ($\beta = -0.041$, t(119) = -10.152, $p < 0.001$) were significant covariates of logRMSSD.

Table 4: Follow-up analysis. Valence indexes and logRMSSD

Variables	**B**	**SE B**	**t**	***p***	**R^2**
Model					0.51
Positivity index	0.67	0.2	3.31	0.001	
Negativity index	-0.033	0.132	-0.251	0.802	
Age	-0.022	0.005	-4.3	0.000	
BMI	-0.01	0.012	-0.811	0.419	
EDR	0.487	0.875	0.557	0.578	
HR	-0.04	0.004	-9.696	0.000	

Note: BMI = body mass index, logRMSSD = natural logarithmic transformation of the Root Mean Square of Successive Difference, EDR = ECG-derived respiratory rate. HR = Heart Rate

Discussion

The aim of the current study was to test if a valence bias, indexed by level of accuracy for visual stimuli with negative versus positive valence, was associated with low or high HRV. In accordance with our hypothesis, we found that higher accuracy on negative items was linked with lower HRV. However, contrary to our expectations and previous findings (Lischke et al., 2017), we did not find a statistically significant relationship between HRV and accuracy on positive items. Valence bias was further explored by applying a positivity index, indicating a tendency to interpret negative stimulus as positive. The tendency to interpret negative visual stimuli as more positive was associated with higher HRV. There was, however, no association between the negativity index and HRV.

The current findings are in accordance with a recent study, reporting an association between low HRV and processing visual stimuli with negative valence (Mantantzis et al., 2018). Mantantzis et al., 2018 reported that higher levels of HRV in older adults was negatively associated with gaze preference for angry faces, but there were no associations with happy faces. Together, ours and the findings reported by Mantantzis et al. (2018) suggest that a negativity bias is associated with lower vagal (parasympathetic) inhibitory control of the inter-beat-intervals of the heart, indexed as low HRV. This is in accordance with theories of low HRV as a marker of problems with social cognition (Porges, 2003), poorer emotional regulation (Appelhans and Luecken, 2006) and psychopathology (Beauchaine and Thayer, 2015). Of relevance to our findings, higher accuracy of negative items has been shown in samples with psychopathology and traumatic life experiences (Nejati, 2018; Weinstein et al., 2016), conditions associated with low HRV (Koch et al., 2019; Koenig et al., 2016; Sigrist et al., 2021; Stone et al., 2018).

The relation between the positivity index and higher HRV, from our exploratory follow-up analysis, is in line with a recent study by Madison et al. (2021). They found that higher HRV mediated a greater positivity bias in the recognition of emotional vocal stimuli. The overall response tendency of interpreting emotional expressions in the current study as positive most likely influenced lower accuracy on negative valanced items. Higher levels of HRV would then be linked with a tendency to experience situations and social interactions more optimistically and interpret them more positively (Schwerdtfeger & Gerteis, 2014).

RMET has been applied in previous studies that show some conceptual overlap with the current study (Lischke et al., 2017; Quintana et al., 2012), and a strength of the test is that the displayed expressions are representative of everyday expressions (Pahnke et al., 2020). However, the RMET has not been constructed with the aim to examine the effect of emotional valence. Post-hoc categorization of RMET items based on emotional valence therefore results in a slightly unbalanced number of items for the different valence categories (Hudson et al., 2020; Kynast & Schroeter, 2018), which is a limitation of the present study. Future studies are encouraged to apply an experimental design with a balanced number of positive and negative items and response alternatives.

The current study revealed that a negativity bias, measured as enhanced accuracy for visual stimuli of negative emotional valence, predicts low HRV. On the other hand, high HRV was associated with a tendency to interpret negative visual stimuli more positively, and as such, less accurately. Also, the current study indicates that valence biases as part of social cognition and emotion regulation are related to the functioning of the vagal system (Ottaviani et al., 2013; Visted et al., 2017; Williams et al., 2015; Porges, 2003; Thayer & Lane, 2000; Appelhans & Luecken, 2006). Future studies including diverse samples across the spectrum of psychopathology and across the lifespan are warranted to replicate and extend the present findings.

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Supplement

Table S1. Matrix of first-order correlations of all predictor variables included in the main multiple linear regression analysis.

Variable	1	2	3	4	5	6	7	8
(1) logRMSSD	-							
(2) RMET Negative	-0.28*	-						
(3) RMET Neutral	-0.04	0.14	-					
(4) RMET Positive	-0.15	0.18*	0.14	-				
(5) Age	-0.17	-0.22*	-0.05	0.27	-			
(6) BMI	-0.19*	-0.02	-0.03	-0.03	0.14	-		
(7) EDR	-0.08	-0.07	-0.05	-0.16	-0.17	0.16	-	
(8) HR	-0.63**	0.19*	-0.02	-0.02	-0.15	0.16	0.24*	-

Note: RMET = Reading the Mind in the Eyes Test, ACC = accuracy scores. BMI = body mass index, logRMSSD = natural logarithmic transformation of the Root Mean Square of Successive Difference, EDR = ECG-derived respiratory rate. HR = Heart Rate