Follow your heart? Examining heart rate variability as a predictor of neural reactivity to social rejection - A network approach to individual differences in social threat sensitivity

Elise D. Kortink^{1,4}, Wouter D. Weeda^{2,4}, Bart Verkuil^{3,4}, Selin Topel¹, Melle J.W. van der Molen^{1,4}

¹Developmental and Educational Psychology, Institute of Psychology, Leiden University;

²Methodology and Statistics, Institute of Psychology, Leiden University; ³Clinical Psychology,

Institute of Psychology, Leiden University; ⁴Leiden Institute for Brain and Cognition

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Corresponding Author:

Elise D. Kortink, Institute of Psychology, Faculty of Social and Behavioral Sciences, Leiden University, Leiden, the Netherlands

Email: e.d.kortink@fsw.leidenuniv.nl

Phone: +31 71 527 3644

Abstract

Frontal midline (FM) theta (4–8 Hz) reactivity to unexpected social rejection seems to be an important correlate of a neural threat-detection system. Neurovisceral integration theory proposes that the functioning of such systems is indexed by heart rate variability (HRV). Here, we tested this by examining whether baseline HRV predicts FM-theta reactivity to unexpected rejection feedback. Additionally, we examined whether this alleged heart-brain connection differs based on individual differences in personality and behavioral constructs relevant to social threat sensitivity. Female undergraduates ($n = 149$; mean age = 19.7 years) performed the social-judgment paradigm, where they communicated their expectations about being liked/disliked by unfamiliar peers who had allegedly evaluated them, and received peer-feedback indicating social acceptance/rejection. We used community structure analysis to subtract subgroups, based on self-esteem, social feedback expectations, and response speed of providing expectations. Results provided evidence of two distinct subgroups: optimistic vs. pessimistic in light of social threat. Baseline HRV did not predict FM-theta reactivity to unexpected rejection, and this relationship was not modulated by the subgroups. Both subgroups showed a significant FM-theta power increase following unexpected rejection. Additionally, the optimistic subgroup was uniquely characterized by a FM-theta power increase following rejection (as against acceptance) feedback. Supporting prior studies, our results suggest that enhanced FM-theta signals the need for cognitive control when faced with unexpected outcomes, and extend this by suggesting that differences in social threat sensitivity may determine whether an outcome is deemed meaningful enough to signal the need for cognitive control.

Keywords: frontal midline theta, heart rate variability, social evaluation, cognitive control, self-esteem, network analysis

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44 Social connectedness and maintaining a positive sense of self is of paramount importance for our
45 mental health (Baumeister & Leary, 1995; Pfeifer et al., 2007). For example, being socially
46 rejected by others is not only painful (Eisenberger & Lieberman, 2004), but when experienced
47 persistently, it has also been related to various types of mental health problems such as anxiety,
48 depression, and substance abuse (Rubin, 2006). Therefore, those who are better equipped to
49 monitor and adequately respond to social threats like rejection, would have higher chances of
50 safeguarding their mental wellbeing (Baumeister & Leary, 1995). Neuroimaging studies have
51 demonstrated that processing cues that communicate social exclusion or rejection trigger a so-
52 called neural alarm system, which is involved in the fast detection and processing of various types
53 of social threat (Eisenberger & Lieberman, 2004). A central hub of this system is the dorsal anterior
54 cingulate cortex (dACC) which – together with the prefrontal cortex (PFC) – is involved in
55 cognitive and affective regulation (Thayer et al., 2012; Thayer & Lane, 2000). Not only does this
56 neural system down-regulate amygdala activity during emotional tasks, it also exerts
57 parasympathetic control over the heart by reducing heart rate and increasing heart rate variability
58 (HRV). This cortical control over the autonomic nervous system is a central premise of the
59 neurovisceral integration theory (Thayer et al., 2012; Thayer & Lane, 2000) which suggests that
60 vagally-mediated HRV reflects the interaction between brain areas involved in self-regulation
61 when faced with contextual changes. For example, higher HRV would reflect increased levels of
62 prefrontal control over limbic brain areas (Thayer et al., 2012; Thayer & Lane, 2000). In turn,

increased prefrontal control levels are associated with better ability to appraise and flexibly control behavioral responses to threatening internal and environmental changes (Thayer et al., 2012; Thayer & Lane, 2000). This dovetails with findings suggesting that higher baseline HRV is linked with better emotion regulation skills (e.g., Lane et al., 2009; Thayer & Brosschot, 2005), better cognitive performance (e.g., Hansen, Johnsen, & Thayer, 2009; Thayer, Hansen, Saus-Rose, & Johnsen, 2009), and overall better physical and mental health outcomes (e.g., Thayer & Fischer, 2013).

The aim of our study is to test whether baseline HRV is related to the neural activity evoked by the processing of social evaluative threat. Specifically, our previous studies have shown that processing of unexpected social rejection feedback is associated with a pronounced increase in EEG frontal midline (FM) theta (4 – 8 Hz) oscillations (Kortink et al., 2018; van der Molen et al., 2017, 2018). The neural sources of this EEG response comprised the dorsal medial PFC, the supplementary motor area, and the dACC. A common notion is that FM-theta oscillatory power signals the need for cognitive control during social situations involving uncertainty about actions and their possibly adverse consequences (e.g., Cavanagh & Shackman, 2015; Shackman et al., 2011). Especially the dACC, a main source of FM-theta, is involved in determining the necessity of eliciting cognitive control by means of a cost-benefit analysis (Shackman et al., 2011; Shenhav, Cohen, & Botvinick, 2016). This corresponds with findings that FM-theta is particularly increased in response to unexpected social rejection feedback (Kortink et al., 2018; van der Molen et al., 2017, 2018). Namely, unexpected rejection poses a particularly salient threat to social connectedness due to high amounts of cognitive conflict, uncertainty about what caused the rejection, and negative emotional force. Heightened FM-theta activity may brace people to

85 adaptively control their behavior to maintain or regain social connectedness and may thus be an
86 adaptive, fitting response to unexpected social rejection. If FM-theta constitutes an EEG correlate
87 of a cortical regulatory system, higher baseline HRV might predict higher FM-theta activity in
88 response to unexpected social rejection feedback. This would suggest a neurovisceral mechanism
89 governing the response to social threat by means of flexible behavioral control, through the link
90 between vagally-mediated HRV and FM-theta activity.

91 The functioning of this purported neurovisceral mechanism might depend on individual
92 differences in personality and behavioral constructs pertinent to social threat sensitivity. Among
93 the personality constructs, trait self-esteem seems particularly relevant here, since it affects how
94 people process social threat (e.g., Kashdan et al., 2014; Leary, Terdal, Tambor, & Downs, 1995;
95 Onoda et al., 2010; Somerville, Kelley, & Heatherton, 2010; vanDellen, Campbell, Hoyle, &
96 Bradfield, 2011). For example, van Dellen and colleagues (2011) examined the influence of
97 individual differences in trait self-esteem on people's responses to various types of social threat
98 (e.g., exclusion, rejection, receiving negative social feedback). Results indicated that people with
99 high self-esteem generally showed more compensating responses that minimized the direct
100 influence of the social threat on their self-feelings than people with low self-esteem (van Dellen et
101 al., 2011). This coincides with fMRI results demonstrating that people with low self-esteem show
102 heightened responsivity and sensitivity to social threat (i.e., exclusion) in brain regions associated
103 with feelings of distress (Kashdan et al., 2014; Onoda et al., 2010). In addition, people with higher
104 self-esteem tend to have a more optimistic view of their social worth, in contrast to people with
105 lower self-esteem (MacDonald, Saltzman, & Leary, 2003). Consequently, people high and low in
106 self-esteem seem to anticipate social threat differently as well. For example, in a social evaluative

context, individuals with low self-esteem expected that more people would reject them (Leary et al., 1995; Somerville et al., 2010). These personality, behavioral, and neural constructs relevant to social threat thus seem to be closely linked. Yet, examining them together to study individual differences remains uncommon.

We recently showed that a community structure detection analysis (CSA) for the combined examination of such constructs was useful to identify idiosyncratic subgroups of people that differ in their rejection-sensitive personality profiles (Kortink et al., 2018). People within these subgroups are characterized by shared construct profiles (i.e., based on similar personality and/or behavioral traits), while people from different subgroups are characterized by distinct construct profiles. A network-theoretical approach like CSA offers more detailed insight into how various traits are related within and between people. In the current study, we used CSA to identify subgroups of people differing in their self-esteem level and their behavioral responses during the ‘Social Judgment Paradigm’ (SJP; Kortink et al., 2018; van der Molen et al., 2017). This paradigm allows for studying the neural reactivity to social acceptance and rejection feedback, either congruent or incongruent with the participants prediction about the social evaluative outcome.

The current study’s first aim is to test whether baseline HRV (i.e., RMSSD and HF-HRV) predicts FM-theta reactivity to social rejection feedback. Based on prior work (i.e., Kortink et al., 2018; Shackman et al., 2011; Smith et al., 2017; Thayer et al., 2012; Thayer & Lane, 2000; van der Molen et al., 2017) we hypothesized that higher baseline HRV would predict higher FM-theta activity following unexpected rejection feedback. The current study’s second aim is to examine whether this alleged neurovisceral mechanism works differently as a function of individual differences in personality and behavioral constructs relevant to social threat sensitivity. We

anticipated to find two distinct subgroups of people: one subgroup that could be interpreted as having a more optimistic attitude in light of social threat and one that could be viewed as having a more pessimistic attitude (Kashdan et al., 2014; Leary et al., 1995; MacDonald, Saltzman, & Leary, 2003; Onoda et al., 2010; Somerville et al., 2010; vanDellen et al., 2011). We predicted that the optimistic subgroup would be characterized by relatively high trait self-esteem scores, and low percentages of expected rejection feedback (Leary et al., 1995; Somerville et al., 2010). Due to their alleged positive attitude, people in this group might feel more uncertain when deciding that someone probably does not like them. The amount of time it takes people to provide their expectation was previously proposed to be an indicator of how certain they are of this expectation, with greater uncertainty resulting in higher reaction times (Kortink et al., 2018; van der Molen et al., 2013). Therefore, we predicted that people with higher self-esteem levels would be slower in predicting social rejection than acceptance feedback (Jackson, Nelson, & Hajcak, 2016). An opposing profile was expected for the pessimistic subgroup, with relatively low trait self-esteem scores, high percentages of expected rejection feedback, and shorter response times for providing their rejection expectations than their acceptance expectations (Jackson et al., 2016; Kashdan et al., 2014; Leary et al., 1995; Onoda et al., 2010; Somerville et al., 2010; van Dellen et al., 2011). We hypothesized that participants with a socially optimistic personality profile, would probably show a more adaptive neurovisceral response to unexpected social rejection. We anticipated this to be reflected by a stronger link between HRV and FM-theta. The opposite was expected for participants with a personality profile characterized by social pessimism: we expected these participants to respond to social threat in a less adaptive way, which would be reflected by a weaker link between HRV and FM-theta (Chang et al., 2013; Kortink et al., 2018; Sakaki et al., 2016;

Shackman et al., 2011; Shenhav et al., 2016; Thayer et al., 2012; Thayer & Lane, 2000; Wei et al., 2018).

Method

Participants

Our study sample consisted of 149 participants¹. Only female participants were recruited, since prior research has unveiled that females show greater physiological reactivity to social rejection than males (Stroud, Salovey, & Epel, 2002). Participants were right-handed and had normal or corrected-to-normal vision. Exclusion criteria entailed use of psychoactive medication, extensive drug or alcohol use, neurological or psychological disorders, and brain trauma. Participant recruitment took place at or within proximity of Leiden University. Before the experiment, participants gave written informed consent. Afterwards, they received either course credits or a monetary reward. Protocols were in line with the local Ethics Committee of the Psychology Institute of Leiden University (Kortink et al., 2018; van der Molen et al., 2017) and with the Medical Ethical Review Committee of the Leiden University Medical Center (van der Molen et al., 2017).

Self-esteem level

We used the Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965) to assess

¹ The participants performed the same experimental task during two separate studies (i.e., Kortink et al., 2018; N = 78; van der Molen et al., 2017; N = 71). The recruitment process and the inclusion/exclusion criteria were equal for both samples.

participants' level of trait self-esteem. This widely used questionnaire consists of 10 items with a 4-point Likert scale, ranging from 0 ('strongly agree') to 3 ('strongly disagree'). Total scores range from 0 – 30, with higher scores referring to higher self-esteem and scores below 15 suggesting low self-esteem. Reliability and validity are sufficient, with acceptable to good internal consistency (Cronbach's alphas ranged from .77 to .88; Rosenberg, 1965).

Social Judgment Paradigm

Participants would allegedly take part in a first impressions study and were asked to send a portrait picture of themselves at least a week prior to the experiment. This picture would then supposedly be reviewed by a peer-panel from a different university in the Netherlands. Peers in this panel would indicate whether they liked or disliked the participant, based on their first impression. Participants were then invited to the lab where they viewed a portrait photo of each peer that allegedly had judged their picture. For each peer, participants indicated whether they thought the peer had previously liked or disliked them. Thereafter, 'actual' peer feedback was shown, indicating social acceptance (like) or rejection (dislike). This feedback could thus be either congruent or incongruent with participants' previous expectations. This leads to one of four conditions: expected vs. unexpected acceptance vs. rejection. In truth, this feedback was not provided by peers, but by a computer.

During the SJP, participants were presented with 160 trials, of which the first 10 were practice trials. Every trial consisted of a white fixation cross that stayed on screen for a jittered time period of 500 to 1000 ms. Thereafter, a peer photo was shown in the position of the fixation cross. Peers' facial expression was neutral (i.e., based on the Self-Assessment Manikin; Bradley

& Lang, 1994). From the start of the presentation of this peer photo, participants had 3000 ms to indicate whether they expected that this peer had liked or disliked them. They could signal their expectation by pressing one of two buttons on the armrests of their chair (left vs. right). One of these buttons indicated ‘YES’, I think this peer liked me, whereas the other indicated ‘NO’, I think this peer did not like me. The type of expectation indicated by the left/right button was counterbalanced among participants. If participants did not provide their response within 3000 ms, a message: ‘too slow’, was shown on screen for 5000 ms, before a new trial commenced. If participants communicated their expectation in time, this expectation (i.e., ‘YES’ or ‘NO’) was shown on the left side of the peer photograph for 3000 ms (fixed anticipation period). Then, the ‘actual’ feedback from the peer was shown on the right side of the photograph for 2000 ms, indicating social acceptance (‘YES’, like) or rejection (‘NO’, dislike), concluding the trial. Figure 1 shows a schematic outline of one trial.

Stimuli were presented using E-prime 2.0 software (Psychology Software Tools, 2002) on a 17-inch monitor (60 Hz refresh rate; visual angle [width x height] = 4.66° x 6.05°). Feedback was presented pseudo-randomly, so that participants got 50% social acceptance and 50% social rejection feedback.

Figure 1. Schematic outline of a single SJP trial sequence (Van der Molen et al., 2014).

Procedure

Participants were recruited based on an online self-report questionnaire that screened for inclusion and exclusion criteria and were invited to the Leiden EEG laboratory for the experimental procedure. Before the start of the experiment, participants were informed about the procedure, after which they signed an informed consent form and completed a set of self-report questionnaires, including the RSES. EEG and ECG electrodes were then placed, followed by a 5-minute resting state EEG/ECG measurement (i.e., baseline) during which participants were instructed to sit as still as possible with their eyes closed. Next, participants performed the SJP while EEG and ECG were measured. The protocol was finalized by a second 5-minute EEG/ECG resting state. Finally, electrodes were removed, followed by a debriefing and a check for belief in the cover story. In total, the experiment took approximately 2 hours.

Psychophysiological signal recording

EEG and ECG were recorded using a Biosemi Active Two system (Biosemi, Amsterdam, the Netherlands) at a 1024 Hz sampling rate. The active Common Mode Sense (CMS) and passive Driven Right Leg (DRL) were used to generate an electric feedback loop, replacing the ground electrode. CMS posed as an online reference. Sixty-four Ag-AgCl electrodes (10/20 placement), two mastoid electrodes and four ocular electrodes were used to record EEG data. The two mastoid electrodes were used as an offline reference. We used two ocular electrodes, below and above the left eye, to measure the vertical electro-oculogram, and two ocular electrodes at the canthus of both eyes to measure the horizontal electro-oculogram. To record ECG data, we used two electrodes, one placed underneath the right collarbone and one placed in between two ribs on the left side of the thorax.

EEG signal processing

Brain Vision Analyzer software (BVA 2.0.4; Brain Products GmbH, Munich, Germany) was used to analyze the EEG data offline. Data were down-sampled to 512 Hz and re-referenced to the mean of both mastoids. A 0.5 – 70 Hz band-pass filter of 24 dB/oct and a 50 Hz notch filter was applied. Segments of 11.5 sec time-locked to the onset of the cue (photo) were created, including a 1.5 sec pre-cue baseline. Thereafter, a baseline correction was performed using the 500 – 200 ms before the cue. Next, a semi-automatic artifact inspection was performed². An epoch was removed from analysis if it entailed artifacts other than eye blinks, such as muscular activity, drift, clipping, or if it entailed one or more invalid responses of the participant (e.g., responses that did

² We performed the semi-automatic artifact rejection using the following criteria: maximal allowed voltage step: 50 μ V/ms; maximal allowed difference (min – max) of values in intervals: 170 μ V (interval length: 200 ms); lowest allowed activity in intervals: 0.5 μ V (interval length: 100 ms).

not fall within the reaction time window or more than one response within this time window). Eye blink removal was performed using Ocular Independent Component Analysis and bad channels were corrected using spherical spline interpolation. Hereafter, a second segmentation was performed to create -4 sec to +4 sec epochs, which enclosed the feedback. Non-response trials and trials during which participants did not respond in time were excluded from further analysis.

Time-frequency power analyses

Prior to the time-frequency analysis, a Current Source Density (CSD) transformation was applied to the time series to localize the neural patterns that generate the measured EEG signal. For convolution of the single trials and extraction of the time-frequency components from the EEG time-series, a complex Morlet wavelets family was used. The Morlet wavelets can be viewed as Gaussian windowed sine wavelets:

$$\Upsilon(t, f) = A e^{-t^2/(2\sigma_t^2)} \cdot e^{i2\pi f t}$$

which stands for the complex combination with the wave function. In this function, t stands for time, and f for frequency. Frequency is increased from 0.5 to 70 Hz using 60 steps of logarithmic size. A stands for the wavelet normalization function, which ensures that the frequencies all have identical energy values (i.e., of 1), so that the signal can be compared over all frequency levels. σ_t refers to the Gaussian bell function's SD. The Morlet parameter $C = f(2\pi\sigma_t)$ defines the complex Morlet wavelets family. This parameter was set at 5 so that the time vs. frequency precision resolution could be suitably obtained. Following convolution of the single trials, time-frequency power was exported: $p(t) = (\text{real}[z(t)]^2 + \text{imag}[z(t)]^2)$. The time-frequency power was normalized with a percent-change from the -0.5 to -2 sec pre-stimulus interval baseline. Theta power at Fz was

examined, as a grand-average over participants and conditions showed that theta was strongest at this site. This procedure ensures correct site determination, whilst remaining blind for condition effects (Kappenman & Luck, 2016). All further analyses were performed on log-transformed theta power.

ECG signal processing

ECG data during the pre-SJP resting-state measurement were exported from BVA in .edf format and imported in Kubios version 2.2 (Tarvainen, Niskanen, Lipponen, Ranta-aho, & Karjalainen, 2014) to perform heart rate variability calculations. Beat-to-beat RR intervals were derived from the signal automatically and were manually examined for artifacts (e.g., motion artifacts and ectopic beats). If this resulted in > 5% data loss, the participant was excluded from further analysis. No participants were excluded due to too much data loss. Artifacts were corrected using the automatic artifact correction tool. To correct non-stationary trends in the data, the smoothness priors detrending method was used with Lambda to 500 (Tarvainen, Ranta-aho, & Karjalainen, 2002). We used the widely adopted and highly correlated root mean square of successive differences (RMSSD) and high frequency (HF) power as indices of HRV (Kleiger, Stein, & Bigger, 2005). RMSSD in ms —reflecting the beat-to-beat variance in the heart rate— was exported and used as the time-domain index of HRV. HF power (0.15 – 0.4 Hz) was used as the frequency index of HRV and was obtained using the Fast Fourier Transform (FFT) algorithm, based on the periodogram by Welch. Both HRV indices were based on 300 seconds of artifact-free heart rate data.

289 **Community structure analysis**

290 To parse subgroups from our data, we used community structure detection (Newman,
291 2006), which stems from network theory. The constructs within networks have great predictive
292 value (Haslbeck & Waldorp, 2018) making network approaches particularly useful to clarify
293 heterogeneity within psychopathology (e.g., Borsboom, 2017; Cramer et al., 2016; Fried et al.,
294 2017; Kortink et al., 2018), and for examining the etiology and treatment of mental disorders (Agid
295 et al., 2007). Network approaches to studying psychopathology suggest that disorders or co-
296 occurring symptoms might not be the effects of one common underlying cause (Borsboom, 2017).
297 Instead, the symptoms are thought to influence each other, which can be visualized as interactions
298 between nodes in a network. In such networks, the nodes indicate symptoms and the connections
299 between the nodes indicate the causal relations between the symptoms (Borsboom, 2017). In our
300 study, participants themselves form the nodes in the network (Kortink et al., 2018). The connection
301 between participants is based on similar self-esteem levels and similar behavioral responses to
302 social evaluation. The analysis aims to detect communities of people with profiles that are
303 comparable to the profiles of people within their community, but that are different to the profiles
304 from people in other communities. An algorithm is used for detecting the structure of communities
305 within the network. This algorithm depends on the modularity matrix's eigenvalues and looks for
306 the best possible modularity value to distribute the network (Newman, 2006). By means of 200
307 runs of the modularity matrix algorithm, participants in the network were assigned to communities
308 (subgroups). The strength of the community structure was determined by quality index Q .
309 Normally, Q lies between -0.5 and 1, with positive scores indicating that the community structure
310 within the network exceeds levels of chance (Newman, 2004). CSA analysis was performed using

R software version 3.3.2 (R Core Team, 2018), and was based on participants' self-reported self-esteem score, the percentage expected rejection feedback and percentage expected acceptance feedback during the SJP, and two reaction time ratio scores for providing these expectations. RT ratio 1 was calculated by dividing the average RT for rejection expectations by the average RT for acceptance expectations. Values > 1 for this ratio score indicate slower response times for rejection expectations relative to acceptance expectations, whereas values < 1 indicate faster response times for rejection expectations relative to acceptance expectations. We interpreted higher values as indicative of greater uncertainty about rejection expectations compared to acceptance expectations. RT ratio 2 was calculated by dividing the average RT for acceptance expectations by the average RT for rejection expectations. Values > 1 for RT ratio 2 indicate slower response times for acceptance expectations relative to rejection expectations and values < 1 indicate faster response times for acceptance expectations relative to rejection expectations. We interpreted the communities (subgroups of participants) as a function of the constructs included in the CSA³.

Statistical Analyses

IBM SPSS Statistics (version 24; IBM corporation, 2016) was used for the statistical analyses. Following manual inspection of the data, an outlier analysis was performed for all variables. If participants' scores deviated > 3 standard deviations from the mean for 1 or more variables they were marked as an outlier and removed from further analyses. For the on-task

³The percentage expected acceptance and rejection feedback and their associated RT ratios are inversely related to each other. Since the community detection algorithm weighs negative and positive correlations differently, including both values into the analysis adds important information. For clarity, we only mention the percentage expected rejection feedback and RT ratio score $1 - \text{rejection} / \text{acceptance}$.

behavior, we first calculated the percentages of rejection and acceptance expectancies by respectively dividing the amount of rejection and acceptance expectancies by the total amount of expectancies given during the SJP, and multiplying the outcome by 100%. The percentage acceptance expectancies indicates a bias score, suggesting either an optimism bias ($> 50\%$) or a pessimism bias ($< 50\%$; Dekkers, Van der Molen, Gunther Moor, Van der Veen, & Van der Molen, 2015; Gunther Moor, Rombouts, Crone, & Van der Molen, 2010b). We performed a one-sample t -test to check whether this bias score was significantly different from 50%. Further, we examined participants' RT scores for providing their on-task expectations. A paired-samples t -test was used to check whether speed of providing acceptance predictions was different than speed of providing rejection predictions.

Thereafter, a two-factor repeated measures ANOVA was performed on FM-theta power with Feedback Congruency (2 levels: expected, unexpected) x Valence (2 levels: acceptance, rejection) as within-subject factors to verify that FM-Theta power was highest for the unexpected rejection condition. Further, we performed separate regression analyses to examine whether RMSSD predicted FM-theta power and whether HF-HRV predicted FM-theta power. We suspected that a non-linear relationship might exist between HRV (i.e., RMSSD, HF-HRV) and FM-theta power, since the neural network that parasympathetically controls HRV can be viewed as a nonlinear dynamic structure, of which the elements are mutually interrelated (Thayer & Lane, 2000). To find the best fitting model, we therefore used a curve estimation procedure to compare both a linear, inverse, and quadratic regression model for predicting FM-theta power from RMSSD and for predicting FM-theta power from HF-HRV. Lastly, we performed Pearson product-moment correlation to explore the relations between the behavioral constructs relevant

to social threat sensitivity (i.e., self-esteem level, percentage expected rejection, RT ratio 1 – rejection / acceptance and RTs for providing rejection and acceptance expectations) and HRV responses and theta power responses respectively.

Next, subgroups derived from the community structure analysis were examined for differences on constructs relevant to social threat sensitivity (i.e., self-esteem level, percentage expected rejection, RT ratio 1 - rejection / acceptance, and RTs for providing rejection and acceptance expectations) and age, via separate independent-samples t-tests. Z-score transformations were applied to enable comparison. Moreover, separate one-sample t-tests were used to check for a significant expectation bias in each group, and paired-samples t-tests were used to check whether speed of providing acceptance predictions was different than speed of rejection predictions in each group. Thereafter, we examined the subgroups for differences on RMSSD and HF-HRV, using independent-samples t-tests. To examine whether subgroups differed on their FM-theta power response to social evaluation, a three-way mixed ANOVA was performed with Feedback Congruency (2 levels: expected, unexpected) x Valence (2 levels: acceptance, rejection) as within-subject factors and Subgroup as between-subjects factor.

Lastly, to examine whether the link between HRV (i.e., RMSSD, HF-HRV) and FM-theta power during unexpected rejection was moderated by subgroup-type, we conducted a hierarchical multiple regression analysis, including RMSSD and Subgroup into the first step and adding the interaction term between RMSSD and Subgroup in the second step of the analysis. The same analysis was performed for HF-HRV to examine whether the link between HF-HRV and FM-theta power was moderated by Subgroup. Greenhouse-Geisser correction was applied if

applicable, but uncorrected degrees of freedom are reported for clarity. To control for multiple testing, all post-hoc comparisons were Bonferroni corrected.

Results

Participant characteristics

Twenty-seven participants were excluded from analysis due to disbelief in the cover story of the SJP ($n = 10$), EEG recording problems ($n = 6$), or bad EEG data ($n = 11$). Furthermore, inspection for outliers showed that 6 participants scored > 3 standard deviations from the mean for 1 or more variables. These participants were removed from subsequent analyses, yielding a total sample of 116 participants for data analysis (age range = 18 – 24 years, $M = 19.7$, $SD = 1.48$).

Participants showed a slight positive expectation bias during the SJP. That is, they predicted to receive social acceptance feedback on 55.1% ($SD = 8.20$) of the trials, which differed significantly from 50%, $t(115) = 6.68$, $p < .001$. This corroborates findings from previous studies, showing similar positivity bias outcomes (Dekkers et al., 2015; Gunther Moor, Van Leijenhorst, Rombouts, Crone, & Van der Molen, 2010a; Van der Molen et al., 2014). Participants' speed of providing rejection predictions was not significantly different from their speed of providing acceptance predictions (mean difference = 18.4 ms, $t(115) = 1.84$, $p = .069$).

Table 1 depicts an overview of the behavioral results on the SJP and the self-reported level of self-esteem in the total participant sample⁴.

⁴ The mean self-esteem score of our sample is comparable to previously reported norm scores (e.g., $M = 19.7$, $SD = 6.63$) for the age group of 18 – 25 across demographic groups (Sinclair et al., 2010).

Table 1. Means, standard deviations (*SD*) and range (*min – max*) of trait self-esteem level and behavioral responses during the SJP (i.e., percentage of expected rejection, RT ratio 1 - rejection / acceptance, and RTs for providing rejection and acceptance expectancies).

Construct	Mean (<i>SD</i>)	Range
Self-esteem	19.9 (3.97)	12.0 – 29.0
% expected rejection	44.9 (8.20)	24.5 – 66.0
RT ratio 1 - rejection / acceptance	1.02 (0.08)	0.83 – 1.29
RT rejection expectancies (ms)	1434 (280)	630 – 2100
RT acceptance expectancies (ms)	1416 (280)	675 – 2104

HRV

Manual inspection for outliers in the ECG signal yielded an average amount of 1.24 (*SD* = 0.71) artifacts. The current sample had a mean baseline RMSSD (ms) value of 61.4; *SD* = 36.7; Range = 13.6 – 228; and a mean baseline HF-HRV (ms²) score of 2373; *SD* = 2718; Range = 93.1 – 13630. Our population's RMSSD and HF-HRV averages fall within the range of norms previously reported for healthy adults, but are on the higher side of these norms⁵. Further analyses were performed on log-transformed data (RMSSD: *M* = 3.96; *SD* = 0.56; Range = 2.61 – 5.43; HF-HRV: *M* = 7.23; *SD* = 1.10, Range = 4.53 – 9.52).

⁵ In their quantitative systematic review, Nunan and colleagues (2010) examined mean RMSSD values from 15 studies and HF-HRV values from 36 studies using short-term HRV measurements in healthy adult populations. The following norms were reported for RMSSD: *M* = 42.0; *SD* = 15.0; Range = 19.0 – 74.0, and for HF-HRV: *M* = 657; *SD* = 777; Range = 82.0 – 3630 (Nunan, Sandercock, & Brodie, 2010).

Theta power

On average, 1.24 ($SD = 0.70$) artifacts were corrected per participant. The average amount of artifact-free segments used for calculation of the FM-theta response (per condition of the SJP) is presented in Table 2.

Table 2. Average amount of artifact-free EEG segments (SD) and range ($min - max$) per condition of the SJP.

Condition	Mean (SD)	Range
Expected acceptance (Yes-Yes)	37.2 (7.12)	21.0 – 53.0
Unexpected Rejection (Yes-No)	35.7 (7.54)	18.0 – 56.0
Unexpected acceptance (No-Yes)	29.0 (7.09)	14.0 – 45.0
Expected Rejection (No-No)	30.6 (7.95)	13.0 – 48.0

The repeated-measures ANOVA on FM-theta power generated a main effect of Congruency, $F(1, 115) = 8.04, p = .005, \eta_p^2 = 0.065$, as well as a main effect of Valence, $F(1, 115) = 9.99, p = .002, \eta_p^2 = 0.080$, which were included in a significant Congruency x Valence interaction, $F(1, 115) = 16.0, p < .001, \eta_p^2 = 0.12$. Post hoc comparisons revealed that theta power was significantly highest in the unexpected social rejection condition (Yes-No) relative to all other conditions (Yes-Yes, $p < .001$; No-Yes, $p < .001$; No-No, $p < .001$). Theta results are depicted in Figure 2.

Feedback-related theta power at Fz

B. Time-frequency power

Figure 2. Theta power (4 – 8 Hz) at the Fz site. A: FM-theta power was significantly highest for the unexpected rejection condition compared to the other feedback conditions (i.e., Yes-Yes = expected acceptance; Yes-No = unexpected rejection; No-Yes = unexpected acceptance; No-No = expected rejection). The error bars indicate standard error of the mean. B: The time-frequency plot displays this significant FM-theta power increase during the unexpected rejection condition.

HRV – theta power association

Visual inspection of the relationship between RMSSD and FM-theta power and of the relationship between HF-HRV and FM-theta power via separate scatterplots (visible in Figure 3) revealed a possible nonlinear relationship. However, the separate curve-estimation procedures revealed that neither RMSSD nor HF-HRV significantly predicted FM-theta power during the unexpected social rejection condition; RMSSD: Linear: $R^2 = 0.00$, $F(1, 114) = 0.01$, $p = .93$, Inverse: $R^2 = 0.00$, $F(1, 114) = 0.01$, $p = .92$, Quadratic: $R^2 = 0.01$, $F(2, 113) = 0.20$, $p = .82$; HF-HRV: Linear: $R^2 = 0.00$, $F(1, 114) = 0.03$, $p = .87$, Inverse: $R^2 = 0.00$, $F(1, 114) = 0.01$, $p = .92$, Quadratic: $R^2 = 0.01$, $F(2, 113) = 0.38$, $p = .68$. An overview of the regression equations is depicted in Appendix 1.

438

439 **A. RMSSD vs. FM-Theta**

B. HF-HRV vs. FM-Theta

440 **Figure 3.** A. Scatterplot of log transformed RMSSD (x -axis) vs. FM-theta power during the unexpected rejection
441 (Yes-No) condition (y -axis), showing a possible Quadratic relationship. B. Scatterplot of log transformed HF-HRV
442 (x -axis) vs. FM-theta power during the unexpected rejection (Yes-No) condition (y -axis), showing a possible
443 Quadratic relationship.

444

445 **Correlations between EEG, ECG, and behavioral constructs**

446 Table 3 shows the correlations between theta power responses, HRV responses, and
447 constructs relevant to social threat sensitivity. Following Bonferroni correction, a strong
448 significant correlation for RMSSD and HF-HRV remained, which corroborates previous findings
449 (Kleiger et al., 2005). Again, the expected relation between RMSSD and FM-theta following
450 unexpected rejection feedback was not found, but interestingly, we did observe a negative
451 correlation between both HRV-measures and FM-theta following expected acceptance feedback.
452 The higher someone’s resting HRV, the lower their FM-theta response following expected social
453 acceptance feedback. Further, we found a negative association between FM-theta following
454 expected rejection feedback and self-esteem, indicating that lower self-esteem scores were linked

with higher FM-theta power responses to expected rejection feedback. Additionally, a significant negative relationship between self-esteem and percentage expected rejection was found, as well as a negative relationship between percentage expected rejection and RT ratio 1 – rejection / acceptance, indicating that participants who expected less rejection feedback, tended to take longer when providing their rejection expectations compared to their acceptance expectations. Lastly, a positive correlation between RT for rejection expectancies and RT for acceptance expectancies was found.

Table 3. Pearson product-moment correlation matrix of HRV responses (i.e., RMSSD and HF-HRV), theta power responses (per condition) and the constructs relevant to social threat sensitivity.

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Theta Yes – Yes	–										
2. Theta Yes – No	0.16	–									
3. Theta No – Yes	0.29**	0.50**	–								
4. Theta No – No	0.22*	0.58**	0.51**	–							
5. RMSSD	-0.23*	0.01	-0.11	-0.02	–						
6. HF-HRV	-0.24*	0.02	-0.11	0.04	0.95**	–					
7. Self-esteem	0.19*	-0.08	-0.15	-0.20*	0.03	0.04	–				
8. % expected rejection	-0.14	0.02	0.04	-0.13	0.13	0.10	-0.27**	–			
9. RT ratio 1 – rejection / acceptance	-0.09	0.02	-0.05	0.13	-0.01	0.03	0.15	-0.49**	–		
10. RT rejection expectancies	0.01	-0.03	0.03	-0.03	0.10	0.09	0.03	-0.09	0.20*	–	
11. RT acceptance expectancies	0.04	-0.03	0.05	-0.09	0.13	0.10	-0.01	0.11	-0.18*	0.93**	–

* indicates a significant ($p < .05$) correlation between variables. ** indicates a significant ($p < .01$) correlation between variables

Community-derived subgroups

The community structure analysis yielded 3 subgroups within our dataset. The modularity quality index ($Q = 0.62$) showed that these subgroups differed above chance level. Q-values above 0.40 are thought to indicate completely distinct subgroups (Fortunato & Barthélemy, 2007), suggesting that the found subgroups in our sample do not overlap. Figure 4 depicts the profile scores of the three subgroups on the constructs relevant to social threat sensitivity (i.e., self-esteem, percentage expected rejection, and RT ratio 1 – rejection / acceptance). An overview of the mean scores and standard deviations for these constructs per subgroup is shown in Table 4. Since the third subgroup ($n = 5$) was significantly smaller than the first ($n = 57$) and second ($n = 54$) subgroup, the third subgroup was excluded from further analyses.

Figure 4. Community-derived subgroups based on the following constructs relevant to social threat sensitivity: trait self-esteem, % expected rejection and acceptance, and RTs for providing these expectations (i.e., RT ratio 1 - rejection / acceptance and RT ratio 2 - acceptance / rejection). Only the constructs of self-esteem, % expected rejection and RT

ratio 1 - rejection / acceptance are presented on the x -axis for clarity. Participants' profile scores are presented on the y -axis (z scores). The first subgroup ($n = 57$), hereafter labeled the optimistic subgroup, is indicated in green, the second subgroup ($n = 54$), hereafter labeled the pessimistic subgroup, is indicated in red, and the third subgroup ($n = 5$) is indicated in black.

Table 4. Means and standard deviations (SD) of self-esteem level and behavioral responses during the SJP (i.e., percentage expected rejection, RT ratio 1 -rejection / acceptance, and RTs for providing acceptance and rejection expectancies) for the optimistic subgroup ($n = 57$) and the pessimistic subgroup ($n = 54$). * indicates a significant difference between the two subgroups ($p < .001$).

Construct	Subgroup	Mean (SD)	Range
Self-esteem*	Optimistic	21.1 (3.90)	13.0 – 29.0
	Pessimistic	18.2 (3.49)	12.0 – 25.0
% expected rejection*	Optimistic	38.4 (4.80)	24.5 – 47.6
	Pessimistic	51.4 (5.49)	42.8 – 66.0
RT ratio 1 - rejection / acceptance*	Optimistic	1.06 (0.07)	0.93 – 1.29
	Pessimistic	0.96 (0.06)	0.83 – 1.12
RT rejection expectancies (ms)	Optimistic	1480 (283)	630 – 2100
	Pessimistic	1387 (279)	871 – 1977
RT acceptance expectancies (ms)	Optimistic	1395 (277)	675 – 2050
	Pessimistic	1444 (290)	838 – 2104

Subgroup 1, hereafter labeled the optimistic subgroup (mean age = 19.98), scored relatively high on self-esteem and expected a relatively small amount of rejection feedback. In fact, this subgroup showed a positive expectation bias during the SJP: they predicted to receive social acceptance feedback on 61.7% ($SD = 4.80$) of the trials, which differed significantly from 50%,

$t(56) = 18.3, p < .001$. Additionally, they were significantly slower when providing their rejection relative to acceptance predictions (mean RT difference = 85.5 ms, $t(56) = 7.5, p < .001$; RT ratio 1 - rejection / acceptance was above 1).

In contrast to the optimistic group, subgroup 2, hereafter labeled the pessimistic subgroup (mean age = 19.36), scored relatively low on self-esteem. Additionally, people in the pessimistic subgroup expected a relatively great amount of rejection feedback. No significant expectation bias was found for this group. They expected to receive social acceptance feedback on 48.6% ($SD = 5.49$) of the trials, which did not differ significantly from 50%, $t(53) = -1.92, p = .06$. Lastly, opposite to the optimistic subgroup, the pessimistic group was significantly faster when providing rejection relative to acceptance predictions (mean difference = 57.02 ms, $t(53) = 5.2, p < .001$; RT ratio 1 - rejection / acceptance was below 1).

Further examination for differences on the constructs relevant to social threat sensitivity via independent-samples t-tests showed that the two subgroups differed significantly on self-esteem: mean difference = 2.85, $t(115) = 4.0, p < .001$, percentage of expected rejection: mean difference = 13.09, $t(115) = 13.4, p < .001$, RT ratio 1 - rejection / acceptance: mean difference = 0.10, $t(115) = 8.5, p < .001$. The subgroups did not differ in their RTs for providing rejection expectations: mean difference = 92.8 ms, $t(115) = 1.7, p = .09$, nor in their RTs for providing acceptance expectations: mean difference = 49.7 ms, $t(115) = 0.9, p = .36$. Differences between subgroups are visualized in Figure 5. Lastly, the optimistic subgroup was significantly older (mean age = 19.98; $SD = 1.63$) compared to the pessimistic subgroup (mean age = 19.36; $SD = 1.23$): $t(115) = 2.3, p = .027$, although this significance was lost after correcting for multiple comparisons.

Figure 5. Visual representation of differences in self-esteem level and behavioral responses during the SJP (i.e., the percentage of expected rejection, RT ratio 1 - rejection / acceptance, and RTs for providing acceptance and rejection predictions) between the optimistic subgroup ($n = 57$) and the pessimistic subgroup ($n = 54$). * indicates a significant ($p < .001$) mean difference. The error bars indicate standard error of the mean.

HRV per subgroup

The one-way ANOVA showed that the community-derived subgroups did not differ significantly on baseline RMSSD, $F(1, 115) = 1.24, p = .27$, nor HF-HRV, $F(1, 115) = 0.60, p = .44$. Mean RMSSD and HF-HRV scores and standard deviations per subgroup are shown in Table 5. Both raw and log-transformed scores are presented for clarity.

Table 5. Means, standard deviations (*SD*), and range for baseline HRV (i.e., RMSSD and HF-HRV) per community-derived subgroup: optimistic ($n = 57$) and pessimistic ($n = 54$).

Construct	Subgroup	Mean (<i>SD</i>)	Range
Raw RMSSD	Optimistic	55.8 (30.5)	13.6 – 166.8
	Pessimistic	64.3 (36.8)	13.6 – 198.9
Log-transformed RMSSD	Optimistic	3.89 (0.52)	2.61 – 5.12
	Pessimistic	4.01 (0.58)	2.61 – 5.29
Raw HF-HRV	Optimistic	2109 (2490)	93.1 – 11470
	Pessimistic	2497 (2633)	103.7 – 12307
Log-transformed HF-HRV	Optimistic	7.13 (1.08)	4.53 – 9.35
	Pessimistic	7.29 (1.12)	4.64 – 9.42

Theta power per subgroup

A three-way mixed ANOVA was used for comparing our two subgroups on differences in their FM-theta response to the four social feedback conditions. The ANOVA yielded a significant three-way interaction between Subgroup $\times$ Congruency $\times$ Valence, $F(1, 115) = 6.07, p = .015, \eta_p^2 = 0.05$. For post-hoc testing, Bonferroni correction was applied, leading to acceptance of a p -value of .025. Post-hoc examination of the two-way interaction effects of Congruency $\times$ Valence within each subgroup, revealed a significant interaction effect of Congruency $\times$ Valence in the pessimistic subgroup, $F(1, 53) = 20.2, p < .001, \eta_p^2 = 0.28$, but not in the optimistic subgroup, $F(1, 56) = 1.77, p = .19, \eta_p^2 = 0.03$. For the pessimistic subgroup, no significant main effects were found (Congruency: $F(1, 53) = 3.42, p = .07, \eta_p^2 = 0.06$; Valence: $F(1, 53) = 3.78, p = .06, \eta_p^2 = 0.07$). Further pairwise comparisons revealed that for participants in this group FM-theta power was significantly highest in the unexpected rejection condition (Yes-No) relative to all other

543 feedback conditions (Yes-Yes, $p < .001$; No-Yes, $p = .004$; No-No, $p < .001$). For the optimistic
544 group, no main effect of Congruency was observed ($F(1, 56) = 5.02, p = .03, \eta_p^2 = 0.08$), but there
545 was a significant main effect of Valence $F(1, 56) = 5.62, p = .02, \eta_p^2 = 0.09$. This indicated that
546 FM-theta power was higher when participants in the optimistic subgroup received rejection
547 relative to acceptance feedback. Although no main effect was found, pairwise comparisons were
548 performed to enable further clarification of the neural responses in both subgroups. These revealed
549 that in the optimistic subgroup – similar to the pessimistic subgroup – FM-theta power was
550 significantly highest in the unexpected rejection condition (Yes-No) relative to all other feedback
551 conditions (Yes-Yes, $p < .02$; No-Yes, $p = .001$; No-No, $p = .003$). Results of post-hoc examination
552 of the interaction effects of Congruency $\times$ Valence and the main effect of Valence in each subgroup
553 are visible in Figure 6.

Figure 6. Theta power (4 – 8 Hz) at the Fz site. The optimistic subgroup is presented in green ($n = 57$) and the pessimistic subgroup is presented in red ($n = 54$). A: FM-theta power change for each of the different feedback conditions (Yes-Yes = Expected acceptance; Yes-No = Unexpected rejection; No-No = Expected rejection; No-Yes = Unexpected acceptance), per subgroup. B: FM-theta power change in each Valence condition (i.e., Acceptance vs. Rejection), per subgroup. * indicates a significant ($p < .025$) mean difference, ** indicates a significant ($p < .001$) mean difference. The error bars indicate standard error of the mean.

HRV – theta power association as a function of subgroup

To examine whether the relationship between RMSSD and FM-theta and between HF-HRV and FM-theta varied as a function of subgroup, separate hierarchical regression analyses were performed. In the first step RMSSD and Subgroup were included to predict FM-theta during unexpected social rejection. Together, these two variables did not account for a significant amount

of variance in FM-theta power, $R^2 = 0.00$, $F(2, 115) = 0.02$, $p = .98$. Adding the interaction term of RMSSD x Subgroup to the regression model did not significantly improve the prediction model: $R^2 = 0.00$, $F(3, 115) = 0.01$, $p = .91$. The RMSSD-FM-theta relationship thus did not differ as a function of subgroup. Similarly, for HF-HRV, the analysis showed that HF-HRV and Subgroup did not account for a significant amount of variance in FM-theta power for the Yes-No condition, $R^2 = 0.00$, $F(2, 115) = 0.02$, $p = .98$. Adding the interaction term of HF-HRV x Subgroup to the regression model did not significantly improve the prediction model: $R^2 = 0.00$, $F(3, 115) = 0.03$, $p = .87$, indicating that the HF-HRV-theta relationship also did not differ as a function of subgroup.

Discussion

Recent evidence suggests that FM-theta reactivity to unexpected social rejection is an important correlate of a neural system focused on social threat detection and processing (Kortink et al., 2018; van der Molen et al., 2017). The neurovisceral integration theory proposes that the functioning of such neural threat processing systems is indexed peripherally by HRV (Smith et al., 2017; Thayer & Lane, 2000). Here, we tested this notion for the first time by examining whether baseline HRV (i.e., RMSSD and HF-HRV) predicts FM-theta reactivity to unexpected social rejection feedback. Additionally, our goal was to examine whether this alleged heart-brain connection differs as a function of individual differences in social threat sensitivity. The social judgment paradigm was used to elicit feelings of social rejection, and community structure analysis was used to subtract subgroups from our data based on personality and behavioral constructs related to social threat sensitivity (i.e., self-esteem, percentage of expected rejection and acceptance peer-feedback, and reaction time for providing these expectations). In contrast to our

hypothesis, baseline HRV did not predict FM-theta reactivity to unexpected rejection feedback. The community structure analysis revealed two opposing, completely distinct subgroups in our data, which we interpreted as 1) optimistic in light of social threat 2) pessimistic in light of social threat. These subgroups did not differ significantly in baseline HRV, nor did the HRV-FM-theta relationship differ as a function of subgroup. Interestingly, the subgroups did show some differences in their FM-theta responses to social evaluation: the optimistic subgroup showed a significantly higher FM-theta response to social rejection relative to social acceptance feedback whereas no such difference was observed in the pessimistic subgroup. When further examining the interaction between expectedness and valence of the feedback, FM-theta power was significantly highest for the unexpected rejection condition relative to all other conditions. This effect was similar for both subgroups. Together, our results suggest that individual differences in personality and behavioral constructs relevant to social threat sensitivity modulate FM-theta reactivity to social evaluation to some extent, and highlight the value of network-theoretical approaches for increasing our understanding of heterogeneity within broad concepts like social threat sensitivity.

Firstly, the anticipated predictive effect of baseline HRV on FM-theta reactivity to unexpected social rejection feedback was not found. This seems especially remarkable in light of previous findings regarding HRV, FM-theta and social threat. Particularly, the FM-theta response to unexpected social rejection seems to form an important correlate of the neural social threat-detection system (Kortink et al., 2018; van der Molen et al., 2017, 2018), which involves prefrontal control of cognitions and emotions (Eisenberger & Lieberman, 2004). According to the NVI theory, this prefrontal control is reflected by HRV (Thayer et al., 2012; Thayer & Lane, 2000), so

610 that lower levels of HRV would indicate poorer prefrontal control. This seems to dovetail nicely
611 with studies linking decreased baseline HRV to poorer emotion regulation (e.g., Lane et al., 2009;
612 Thayer & Brosschot, 2005) and to various types of psychopathology, amongst which social anxiety
613 disorder (Chalmers et al., 2014). Together, this seems to advocate that HRV should be related to
614 people's neural and behavioral responses to social threat, making our lack of finding such a link
615 all the more surprising. The alleged HRV-FM-theta link could potentially have been masked by
616 the lack of extreme scores in our sample. Our sample consisted of female undergraduate students
617 without (sub)clinical psychopathological symptoms. Although their scores on personality and
618 behavioral measures differed enough to identify clear subgroups in our data, these subgroups did
619 not significantly differ in their baseline HRV scores, nor in their FM-theta response to social
620 rejection feedback. This may explain the lack of predictive value of baseline HRV on FM-theta
621 reactivity to unexpected social rejection feedback, and why no influence of subgroup on this
622 relationship was found. Alternatively, the relationship of HRV and FM-theta may be better tracked
623 by a design that allows for examining event-related changes in HRV. For example, Gunther-Moor
624 et al., (2010) found significant transient heart rate slowing in response to unexpected social
625 rejection during the SJP. This was proposed to reflect responsivity of the autonomic nervous
626 system to unexpected rejection, suggesting that event-related HRV may be influenced by
627 unexpected rejection directly. Subsequent studies could shed more light on this notion by
628 examining event-related changes in HRV in the relationship with FM-theta responsivity to
629 rejection. Additionally, the design of the SJP could be modified to examine repeated effects of
630 acceptance versus rejection (e.g., in block-designs), because this should increase distress in
631 response to the threat of social disconnection (Cristofori et al., 2013; Crowley, Wu, Molfese, &

Mayes, 2010; Van Noordt, White, Wu, Mayes, & Crowley, 2015). Lastly, our HRV measurements showed some limitations, which might have impacted our results. Firstly, HRV is influenced by diet (e.g., caffeine and alcohol), sleep, and physical and mental stress. We did not check for, nor were able to control for the influence of such possibly confounding factors, which may have played a role in our student population. On a related note, we are unsure whether our found HRV scores were compliant with norms for short-term HRV measurements in females aged 18-25, since to our knowledge, no norm-scores for this population exist. However, HRV was repeatedly found to decrease with age, with younger people showing higher HRV scores (Kuo et al., 1999; Migliaro et al., 2001; Sinnreich, Kark, Friedlander, Sapoznikov, & Luria, 1998). This could partly explain the relatively higher RMSSD and HF-HRV findings in our younger adult population, compared to the norms of broader adult populations (e.g., Nunan et al., 2010). Lastly, HRV was repeatedly found to be influenced by gender (Nunan et al., 2010; Verkuil et al., 2015; Voss, Schroeder, Heitmann, Peters, & Perz, 2015). For instance, sadness was associated with higher circadian HRV in females, but not in males (Verkuil et al., 2015). More generally, it was suggested that for females parasympathetic tone is often more dominant over sympathetic tone, while the opposite is often found in males (Voss et al., 2015). Future studies should take this into account.

Secondly, in line with our expectations, the CSA revealed the following two subgroups in our data: one subgroup (consisting of 57 participants) that could be interpreted as more optimistic in light of social threat, characterized by relatively high self-esteem, low percentages of expected rejection and higher RTs for rejection than acceptance predictions; and another subgroup (consisting of 54 participants) that could be viewed as more pessimistic in light of social threat, characterized by relatively low self-esteem, high percentages of expected rejection and higher RTs

for acceptance than rejection predictions (Kashdan et al., 2014; Kortink et al., 2018; Leary et al., 1995; Onoda et al., 2010; Somerville et al., 2010; van der Molen et al., 2013; van Dellen et al., 2011). Results further indicated that the optimistic subgroup showed a significant positive expectation bias during the SJP. On average, people in this group expected to be liked by 61.7% of the peers, which differed significantly from 50%. This corroborates previous studies using the SJP, which found positivity biases in healthy populations similar to ours (Dekkers et al., 2015; Gunther Moor et al., 2010a; Van der Molen et al., 2014). In contrast, people in the pessimistic subgroup did not show a positivity bias during the SJP. They expected 48.6% of the peers to like them. This estimation of likeability was similar to the actual proportion of likes received during the task (i.e., 50%). These results tie in well with previous findings of an inflated pattern of estimated likeability in people with high self-esteem, as opposed to a more realistic self-view in people with low self-esteem (Brockner & Lloyd, 1986; Leary & Baumeister, 2000; Leary et al., 1995; Somerville et al., 2010). The two opposing construct-profiles of this optimistic and pessimistic subgroup also match the sociometer theory, which suggests that self-esteem can be viewed as an indicator of self-perceived social inclusionary status (Leary & Baumeister, 2000). That is, people who generally assume that other people will accept them, usually score high on self-esteem, whereas people who generally assume that others will reject them, usually score low on self-esteem (Leary & Baumeister, 2000; Leary et al., 1995). In the current study, people in the optimistic subgroup scored relatively high on self-esteem and may therefore assume that others will often accept them, as signaled by the positive expectation bias during the SJP. This optimistic attitude may also have caused them to feel more uncertain when deciding someone probably did not like them. That uncertainty about the prediction may explain why the optimistic subgroup

needed more time to provide their rejection predictions compared to their acceptance predictions (Kortink et al., 2018; van der Molen et al., 2013). In contrast, our pessimistic subgroup scored lower on self-esteem, although still above the clinical threshold of the self-esteem questionnaire (i.e., <15; Roth, Decker, Herzberg, & Brahler, 2008). People in the pessimistic subgroup may therefore generally assume more rejection by others, which may have caused the absence of a positivity bias during the SJP. Their less optimistic attitude may, in turn, have caused them to feel more uncertain when deciding someone probably liked them. This uncertainty about acceptance predictions may explain why they needed more time to provide their acceptance compared to their rejection predictions.

At the neural level, our subgroups showed some similarities and some differences in their feedback-dependent FM-theta power responses. Both subgroups showed a similar significant FM-theta power burst following unexpected rejection, which was significantly highest compared to the other feedback conditions. This matches previous results showing similarly enhanced FM-theta reactivity to unexpected rejection in people differing in personality constructs relevant to social evaluation (e.g., attachment style and fear of negative evaluation; Kortink et al., 2018). This FM-theta response was suggested to be automatized and fitting, assuming it signals the need for cognitive control when faced with unexpected rejection, a particularly salient threat to social connectedness (Kortink et al., 2018; van der Molen et al., 2017). Indeed, unexpected social rejection may be so universally threatening that it evokes the need for control, irrespective of apparent individual differences in social threat sensitivity. Possibly, the FM-theta response to unexpected rejection only differs in people who show more extreme individual differences in constructs relevant to social threat sensitivity (e.g., clinically low self-esteem). Future studies

should test this notion by including participants with more extreme scores on the currently studied constructs and by studying clinical populations including psychopathology related to social threat sensitivity (e.g., social anxiety).

Despite their similar neural response pattern to the four feedback conditions, the two subgroups did show distinct neural responses to the valence of the feedback. That is, only the optimistic subgroup showed a significantly higher FM-theta response to social rejection compared to social acceptance feedback. Since people in the optimistic subgroup expected more acceptance than rejection from others, receiving rejection feedback may have been especially valent for them. In other words, their more optimistic view of how others perceive them may be especially challenged by rejection feedback. The increased FM-theta response to rejection feedback may therefore signal a greater need for control. In their meta-analysis, Cavanagh and Shackman (2015) indeed suggested that when faced with unexpected outcomes, enhanced FM-theta power signals the need for some form of mental, emotional and/or behavioral adaptation (Cavanagh & Shackman, 2015). Either to avoid similar future outcomes when negatively valenced or to increase the likelihood of similar future outcomes when positive valenced. The FM-theta signal tends to be especially heightened in response to negatively valenced outcomes, as well as surprising outcomes (Cavanagh & Shackman, 2015). The current results both support and add to these findings by suggesting that individual differences in social threat sensitivity (or one's 'personal context', if you will) may determine whether the unexpected outcome is deemed especially meaningful to signal the need for cognitive control. That is, although unexpected rejection feedback seemed to be equally threatening for both subgroups when compared to the other feedback conditions, rejection feedback seemed to be more valent than acceptance feedback for the optimistic subgroup

only. Possibly, being rejected was especially meaningful to this group, because it challenged their self-perception to a greater extent, leading to more surprise and an increased need for adaptive control of their feelings and behavior (e.g., to deal with the negative surprise and adapt their expectations in the future). Since FM-theta power predicts future behavior (e.g., higher FM-theta power was found to predict increased avoidance of punishment cues on subsequent trials; Cavanagh & Shackman, 2015), future studies could modify the design of the SJP to examine if enhanced FM-theta reactivity predicts people's feedback-expectations on future trials.

In conclusion, baseline HRV did not predict FM-theta reactivity to unexpected rejection feedback in young female adults, nor did individual differences in social threat sensitivity influence this alleged neurovisceral relationship. Future studies should provide further insight into the existence of this relationship. For example, by using a more heterogeneous sample with more extreme scores on the currently studied constructs, or by examining the link between event-related HRV and the FM-theta response to social rejection. Furthermore, using a data-driven, network-theoretical approach we were able to show that people with opposing personality- and behavioral profiles also differed in their neural responses to social evaluation. In particular, FM-theta power was most enhanced following unexpected rejection feedback for people with a profile suggestive of a more optimistic outlook on social threat. This effect was similar for people with a profile suggestive of a more pessimistic outlook on social threat. However, only the people with a more optimistic profile showed enhanced FM-theta power following rejection feedback compared to acceptance feedback, irrespective of Congruency. Our results support previous research proposing that enhanced FM-theta power signals the need for cognitive control when faced with unexpected negative outcomes, and add essential new insight by suggesting that individual differences in

742 social threat sensitivity may determine whether an outcome is deemed meaningful enough to signal
743 the need for cognitive control.

744

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747

Appendix 1

Table 1. Equations of the plotted regression models (i.e., linear, inverse, and quadratic) for predicting FM-theta power during the unexpected rejection condition from RMSSD and from HF-HRV, respectively.

Model	Variable	B	Se B	β	t	p
Linear	RMSSD	0.00	0.02	0.01	0.09	.93
Inverse	RMSSD	0.04	0.35	0.01	0.11	.92
Quadratic	RMSSD	-0.14	0.23	-0.55	-0.61	.54
	RMSSD ²	0.02	0.03	0.56	0.62	.53
Linear	HF-HRV	0.00	0.01	0.02	0.17	.87
Inverse	HF-HRV	0.05	0.56	0.01	0.10	.92
Quadratic	HF-HRV	-0.10	0.11	-0.72	-0.84	.40
	HF-HRV ²	0.01	0.01	0.74	0.86	.39

* indicates a significant ($p < .05$) improvement to the model.

A.

B.

Figure 1. A. Scatterplot of RMSSD (x -axis) vs. FM-theta power during the unexpected rejection (Yes-No) condition (y -axis), including the regression models examined (linear, inverse, quadratic). B. Scatterplot of HF-HRV (x -axis) vs. FM-theta power during the unexpected rejection (Yes-No) condition (y -axis), including the regression models examined (linear, inverse, quadratic).

Declarations

One of the two projects was partly funded by the Research Profile Area: Health, Prevention, and the Human Life Cycle of Leiden University (van der Molen et al., 2017). No funding was received for conducting the other project (Kortink et al., 2018). The authors have no relevant financial or non-financial interests to disclose. Protocols of both studies were approved by the local Ethics Committee of the Psychology Institute of Leiden University (Kortink et al., 2018; van der Molen et al., 2017). Ethics approval numbers: CEP 5215123733 (Kortink et al., 2018); CEP 9240101255 (van der Molen et al., 2017). And with the Medical Ethical Review Committee of the Leiden University Medical Center (van der Molen et al., 2017); approval number: P12.061. Informed consent was obtained from all individual participants included in the study. The data and materials, as well as the CSA code used in the current study are available upon request with the corresponding author. None of the experiments were preregistered.

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