

# Feelings from the heart: Developing HRV decrease-trigger algorithms via multilevel hyperplane simulation to detect psychosocially meaningful episodes in everyday life

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## Abstract

Heart rate variability (HRV) has been associated with diverse psychosocial concepts, like stress, anxiety, depression, rumination, social support, and positive affect, among others. Although recent ecological momentary assessment research devoted the analysis of cardiac-psychosocial interactions in daily life, traditional time sampling designs are compromised by a random pairing of cardiac and psychosocial variables across several time points. In this study, we present an approach based on the concept of additional heart rate and additional HRV reductions, which aims to control for metabolic-related changes in cardiac activity. This approach allows derivation of algorithm settings, which can later be used to automatically trigger the assessment of psychosocial states by online-analysis of transient HRV changes. We used an already published data set in order to identify potential triggers offline indexing meaningful HRV decrements as related to low quality social interactions. First, two algorithm settings for a non-metabolic HRV decrease trigger (i.e., the number of HRV decreases in a specified time window) were systematically manipulated and quantified by binary triggers (HRV decrease detected vs. not). Second, triggers were then entered in multilevel models predicting (lower levels of) social support. Effect estimates and bootstrap power simulations were visualized on hyperplanes to determine the most robust algorithm settings. A setting associated with 13 HRV decreases out of 29 min seems to be particularly sensitive to low quality of social interactions. Further algorithm refinements and validation studies are encouraged.

## KEYWORDS

heart rate variability, interactive ambulatory psychophysiological assessment, simulation

## 1 | INTRODUCTION

In daily life, we experience various affective states, stress and episodes of vulnerability, which might challenge wellbeing and health. However, these vulnerable states are often subtle

and less salient (Brosschot et al., 2018). Therefore, in this article we propose a simulation approach toward the development of a real-time system to identify psychosocial states associated with increased vulnerability and stress. Grounded on the concept of additional heart rate variability reductions

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(AddHRVr) developed by Brown et al. (2018; see also Verkuil et al., 2016), we advocate for a simulation approach to derive AddHRVr algorithms that could later be used to automatically trigger and identify periods of vulnerability in everyday life. Precisely, by using psychophysiological data recorded via ecological momentary assessment (EMA) we aim to demonstrate a method composed of two steps to identify patterns of metabolically independent HRV decreases that may allow conclusions about individual psychosocial states.

HRV could constitute a useful tool to identify such episodes, because it sensitively indicates a complex interplay between the autonomic and the central nervous system (for overviews, e.g., Appelhans & Luecken, 2006; Schwerdtfeger, Schwarz, et al., 2020; Shaffer et al., 2014; Thayer & Lane, 2009). Specifically, the vagus nerve as the primary parasympathetic nerve and major constituent of HRV ensures a rapid communication between the brain and the heart (~200 ms) with afferent fibers (from the heart to the brain) outweighing efferent fibers (from the brain to the heart). Hence, vagally mediated HRV could signal cognitive function, emotion regulation, and states of stress and vulnerability, among others (e.g., Schwerdtfeger, Schwarz, et al., 2020). Accordingly, several prominent theories have been developed to account for the salient role of HRV for psychosocial functioning (e.g., theory of neurovisceral integration, Thayer & Lane, 2009; polyvagal theory, Porges, 2007; vagal tank theory, Laborde et al., 2018).

Numerous empirical studies seem to support the hypothesis of a close connection between the heart and the brain and the advent of modern imaging techniques have further accelerated this field of research (e.g., Jennings et al., 2016; Keller et al., 2020; Pfurtscheller et al., 2018; Schwerdtfeger, Schwarz, et al., 2020). Of note, the root mean square of successive differences (RMSSD) and the high frequency (HF) component of the heartbeat are indicators of vagally mediated HRV (Goedhart et al., 2007; Task Force Guidelines, 1996). These measures seem to be especially sensitive to higher central nervous system (dys) function and thus, could be of special importance for psychosocial functioning (e.g., Appelhans & Luecken, 2006; Carnevali, Koenig, et al., 2018; Friedman, 2007; Gerteis & Schwerdtfeger, 2016; Schneider & Schwerdtfeger, 2020). Taken together, analyzing the rhythm of the heart may inform about the adaptive or compromised psychosocial functioning of an organism in an ever-changing environment. Thus, EMA approaches seem to be especially suited to examine associations between HRV and psychosocial concepts as they unfold in daily life.

Although the benefits of EMA are obvious, this method is limited by the sampling strategy. In principle, we can distinguish two strategies: First, a time sampling strategy allows to record both psychosocial and physiological variables randomly at certain periods in time across multiple hours

or days. Specifically, random psychosocial assessments are matched with corresponding ECG traces to allow calculating psychophysiological correlations within and between individuals. Because of the random assessments in time, this approach ensures reasonable generalizability of the findings. However, as a drawback, situations of interest such as highly stressful episodes and associated alterations in HRV might be missed by chance. This limitation can be countered by an event-sampling strategy, which requires individuals to trigger the assessment in the case of specific events or circumstances (e.g., when they feel stressed). Entries are then compared to randomly prompted assessments. Although this sampling strategy is more sensitive to salient events of interest, it is hampered by the conscious allocation of attention to the specific event, which might induce behavioral and/or cognitive adjustments and could even sensitize the individual to specific events. Furthermore, entries are dependent on subjective evaluations, thus precluding less salient encounters to be detected. Therefore, detection of such seemingly incidental episodes could be accomplished by using HRV as a trigger (see, Brown et al., 2018), which has been referred to as interactive psychophysiological assessment (Myrtek, 2004).

## 1.1 | Interactive psychophysiological assessment

Recently, mobile devices became available, which—in principle—offer the opportunity to record physiological variables and bodily movement in daily life and to interact with smartphones. This interactive psychophysiological assessment allows to identify episodes of transient bodily changes in daily life, which might signal certain psychosocial states. For example, Ebner-Priemer et al. (2012) applied this method to detect episodes of intensified and lowered physical activity and to trigger the assessment of wellbeing during such events.

The idea of an interactive ambulatory psychophysiological assessment can be dated back to the 1990s when Myrtek and Brügger (1996) used increases in heart rate to detect meaningful psychological episodes in daily life. Based on well-controlled laboratory experiments, they suggested that controlling for bodily movement and hence, metabolic demand during the recording of ambulatory heart rate would allow to estimate the amount of the so-called additional heart rate, which should mainly result from cognitive/emotional factors (see also Myrtek, 2004). It needs to be mentioned that heart rate is innervated by both the sympathetic and the parasympathetic (i.e., vagal) branches of the autonomic nervous system, which makes a thorough interpretation of heart rate increases and decreases challenging. In turn, vagally mediated HRV as a sensitive indicator of vagal innervation (e.g., RMSSD) might appear a promising alternative for an

interactive psychophysiological assessment, allowing a more rigorous interpretation, because it is based on well-founded neuropsychological theories and has been related to various psychosocial concepts (e.g., stress, anxiety, depression, worry, rumination, social support, and negative affect). Since transient HRV changes are also strongly influenced by metabolic adjustments, methods to automatically detect HRV decreases need to account for bodily movement. Such non-metabolic (additional) reductions in HRV (AddHRVr) are supposed to index psychosocial states, such as stress and vulnerability (e.g., Brown et al., 2018; Verkuil et al., 2016). Probing such an algorithm in offline-mode Verkuil and colleagues (2016) could show that prolonged metabolic-independent (hence, additional) HRV decreases were accompanied by increased feelings of worry and negative affect as assessed via smartphone (Brown et al., 2018; Raugh et al., 2019).

The general procedure of such an approach relies on a regression algorithm. In particular, while continuously recording the ECG and analyzing vagally mediated HRV (RMSSD) on a minute-by-minute basis, bodily movement is regressed on RMSSD. The general relationship between HRV and bodily movement is individually estimated during a calibration period. When the deviation of the momentary HRV from the predicted HRV reaches a pre-defined threshold (e.g.,  $2 \times SE$  of the RMSSD during calibration period), the algorithm delivers a binary trigger (Brown et al., 2018; Verkuil et al., 2016). The triggered psychosocial states may then be compared with random assessments. In order to avoid excessive alarms when individuals show frequent fluctuations in HRV, the algorithm can be set silent for a predefined period (e.g., 20 min).

It should be noted that previous research on AddHRVr mainly focused on deriving a reasonable calibration protocol to assess the individual association between HRV and bodily movement (Brown et al., 2018) and then to analyze associations with psychosocial states to evaluate the algorithm's validity (e.g., Verkuil et al., 2016). Specifically, beside standardized laboratory protocols mirroring daily life activities like sitting, cycling, climbing stairs etc., ambulatory RMSSD across a period of 24 hr seem to constitute a robust calibration procedure, which could make time-consuming laboratory approaches obsolete (Brown et al., 2018, 2020).

Although the interactive psychophysiological assessment of HRV has gained considerable interest and first steps toward its development appear promising, research is still in its infancy and there are several unresolved questions that need to be tackled. First, it should be noted that up till now this algorithm has only rarely been applied and—to the authors' knowledge—there are yet no published reports on HRV decrease algorithms working in online-mode. Second, and most importantly, the exact algorithm settings have not yet been systematically evaluated with respect to their psychosocial sensitivity. Specifically, it remains unclear how often and in which time period AddHRVr should be quantified to

sensitively index psychosocial states. Precisely, the number of meaningful RMSSD decreases (e.g., 7) in a given time period (e.g., 20 min) needs further systematic research (we refer to this as the window threshold) and these algorithm's settings (i.e., long-term vs. short-term changes in RMSSD) might be differentially sensitive to different psychosocial phenomena. Notably, Verkuil et al. (2016) used a time period of at least 7.5 min of subsequent HRV decrease segments (specifically, 15 segments of 30 s, which corresponds to 15 additional HRV decrease epochs in 15 segments) for a psychologically meaningful HRV decrease trigger (AddHRVr). When at least one AddHRVr was prevalent, the corresponding hr was classified as reflecting a meaningful decrease.

Of note, previous approaches did not examine a potential online applicability of the algorithm and different trigger characteristics were not evaluated. Hence, the aim of this study was to simulate different settings of the algorithm and to explore their respective associations with psychosocial states of vulnerability. Importantly, this study did not aim to examine the validity of such an algorithm, but to present and exemplify a toolbox that could be applied to similar EMA data sets to derive trigger algorithm settings for an interactive psychophysiological assessment. To illustrate our approach, we used an already recorded EMA data set and analyzed a cascade of multilevel models to predict the quality of social interactions in daily life by different patterns of AddHRVr.

## 2 | METHODS

### 2.1 | Participants

An already published data set was used to simulate the algorithm settings (Schwerdtfeger, Rominger, et al., 2020). In total 21 participants (9 men, 12 women) showed ECG recordings of sufficient quality (i.e., at least 50% of continuous ECG information was valid and showed no artifacts). The mean age of the participants was  $M = 22.48$  years ( $SD = 3.23$ ). The study was proved by the local ethics committee (GZ. 39/78/63 ex 2017/18).

### 2.2 | EMA design

Schwerdtfeger, Rominger, et al. (2020) applied an ecological momentary assessment (EMA) approach (time sampling) to collect data through three consecutive days between 9 a.m. and 9 p.m. Each day a maximum of 16 random prompts were delivered (with a minimum of 30 min between prompts). In total 921 prompts were available of which 560 covered social interactions during 5 min before the prompt. Participants had also the possibility to self-initialize prompts ( $k = 190$ ; 34% of all prompts with a social interaction).

## 2.3 | Material and instruments

### 2.3.1 | Perceived quality of interactions

To measure the perceived quality of social interactions, participants answered four items assessing closeness, valence, warmth, and the supportive value of a relationship during the last 5 min on a six-point Likert scale. The mean of all four items was used as a measure of the quality of the interaction ( $M = 4.37$ ,  $SD = 0.92$ ,  $\min = 1.50$   $\max = 5.75$ ). We applied Generalizability Theory Analysis (GTA; Brennan, 2001; Shrout & Lane, 2012) to analyze reliability of this composed measure and found satisfactory within-person reliability ( $R_C = .71$ ) and excellent between-person reliability ( $R_{KR} = .94$ ), thus suggesting reliable assessment of both within-person changes and interindividual differences.

### 2.3.2 | Physiological ambulatory monitoring of ECG and bodily movement

ECG and bodily movement were recorded with the physiological ambulatory monitoring device EcgMove4 (movisens GmbH, Karlsruhe, Germany) between 9 a.m. and 9 p.m. throughout three consecutive days. The ECG signal was sampled with 12 bit-resolution and stored with 1,024 Hz. Bodily movement was recorded with 64 Hz via a 3D acceleration sampling.

### 2.3.3 | Data preprocessing

The EcgMove4 device delivers readings of several variables (e.g., HRV, movement) in real time. Relevant variables (e.g., RMSSD) are calculated in adjacent 1-min segments, which could be used for the online application of an algorithm. Therefore, we used the stored live data of the device for the simulation of the algorithm function. These stored online values are automatically scanned for artifacts by the EcgMove4 device during recording. The use of the stored live parameters is important to achieve a realistic simulation of an algorithm, which should finally work in online mode during everyday life. As a measure of HRV the established time domain measure RMSSD (ms) was used and movement was indexed by the movement acceleration (g).

### 2.3.4 | Development and simulation of an algorithm for detecting AddHRVr

In this work, we illustrate the two major steps of simulating and developing an algorithm and elaborate on how to adjust the algorithm to work in online mode. In step 1, the AddHRVr

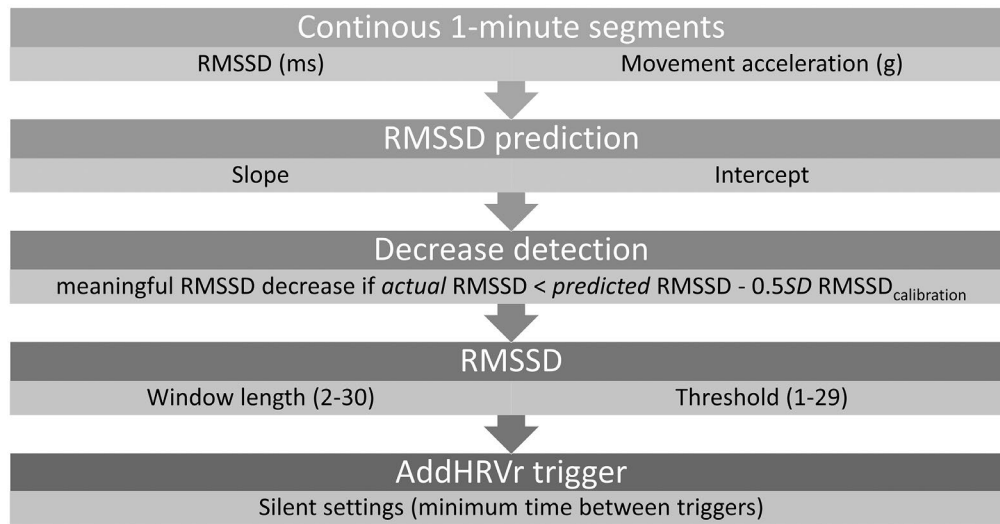
trigger was simulated at the individual level. By simulating various algorithm adjustments, we were able to determine when an algorithm would have detected meaningful HRV decreases and delivered triggers within the 3 days of recording. In step 2, these triggers were used to predict the quality of social interactions in order to evaluate their psychosocial sensitivity. By running bootstrapped multi-level analyses per algorithm setting (1,000 iterations each), predicting the quality of social interactions following a trigger (within 20 min), the power and the (unstandardized) effect size associated with a specific algorithm setting can be evaluated. Following this procedure, researchers should be enabled to select the most promising algorithm settings for an online application to predict the quality of social interactions. In the following, we will illustrate the two steps in more detail.

#### *Step 1: Simulation of individual AddHRVr triggers for each person*

Importantly, the exact definition of a meaningful HRV decrease may differ for each individual. Specifically, the association between bodily movement and HRV might differ between persons. Correspondingly, in a first step, a regression analysis predicting participants' RMSSD (ms) by movement acceleration (g) was calculated for the calibration of the algorithm (see e.g., Verkuil et al., 2016). The regression was estimated with data of the first 12 hr of recording (e.g., Brown et al., 2020). This was done via Matlab. Of note, since single artifacts might strongly bias the estimated slope and intercept of the regression analyses, a semi-automatic procedure was applied. Precisely, if a 1-min data segment showed one of the 50 highest RMSSD scores (within the 12-hr period; 720 data points) and, at the same time one of the 50 highest movement acceleration scores, it was automatically deleted, since it most likely represents an artifact. Please note in this respect that the observation of the highest RMSSD scores accompanied by the highest amount of movement within a particular person appears physiologically implausible. Then, the resulting scatter plots and regression lines were visually inspected for each participant to indicate if further outliers were present. Consequently, a few 1-min segments were deleted before calculating regression analyses ( $M = 0.90$ ,  $SD = 1.30$ ,  $\max = 4$ ).

The individual regression parameters (i.e., intercept and slope) were then used to simulate the algorithm's settings and calculate meaningful RMSSD decreases (see, Figure 1). Specifically, the continuous 1-min movement acceleration scores were used (after applying a 5-min moving maximum window) to calculate the *expected* RMSSD (due to the regression function), which was compared with the corresponding and *actual* RMSSD of this very minute. If the deviation between *actual* RMSSD and *predicted/expected* RMSSD was higher than a predefined threshold





**FIGURE 1** A schematic representation of the AddHRVr algorithm

(i.e.,  $>0.5 \times SD$  of  $RMSSD_{calibration}$ ), this 1-min segment was classified as a meaningful RMSSD decrease.

It should be noted that according to the algorithm, a 1-min segment classified as a meaningful RMSSD decrease is not considered sufficient to provoke an AddHRVr trigger. To reach a robust estimate of an AddHRVr, three further adjustment parameters are implemented in the algorithm (for algorithm illustration, see Figure 1): (a) the RMSSD window length (i.e., number of 1-min segments included), (b) the RMSSD window threshold (the number of 1-min segments, which have to be classified as a meaningful RMSSD decreases in order to provoke an AddHRVr trigger) and (c) the silent setting. Specifically, if within a predefined period of, for example, 5 min (window length), four segments are classified as significant decreases (RMSSD window threshold), an AddHRVr trigger will be provoked (i.e., 4 out of 5). Following an AddHRVr trigger, the algorithm will remain silent for a predefined time (silent setting; e.g., 20 min). The silent setting prevents the algorithm to trigger numerous prompts during a longer period of consecutive RMSSD decreases.

Importantly, the change of these parameters may significantly alter the characteristic of the algorithm. For example, an algorithm which fires when 4 out of 5 segments are classified as meaningful HRV decreases, detects shorter-lived effects as compared to an algorithm with a 7 out of 10 or even a 29 out of 30 setting. Hence, different algorithms are potentially associated with different alarm-rates and might differ in their psychosocial meaningfulness. Of note, although the silent setting is an important feature of the algorithm, in this demonstration we will mainly focus on the window length and window threshold, thereby fixing the silent setting at 20 min in order to keep the methodology succinct. However, we will briefly exemplify how a change in the silent setting could affect the

trigger's characteristics. We calculated the resulting trigger information (coded as 0 = absent and 1 = present) at the individual level for all combinations of RMSSD window lengths starting from 2 to 30 and RMSSD window thresholds from 1 to 29 (i.e., 1 out of 2 until 29 out of 30, thus totaling 435 different algorithm adjustments). This information was used as input for the multi-level simulation in step 2.

#### *Step 2: Simulation of the AddHRVr trigger's sensitivity to psychosocial states (quality of social interaction)*

Similar to former procedures (Brown et al., 2020; Verkuil et al., 2016), the predictive utility of an AddHRVr trigger relative to a random prompt was determined via calculating associations with the quality of social interactions assessed at the subsequent prompt following the AddHRVr trigger within 20 min. Thus, we aimed to evaluate the sensitivity of various AddHRVr algorithms by comparing the associations of AddHRVr triggers with the quality of social interactions relative to non-triggers. A reliable difference between psychosocial states associated with periods of no change in HRV and AddHRVr triggered prompts would suggest psychosocial sensitivity of the algorithm settings. Statistical evaluation was accomplished via the lme4 package (linear mixed effects modeling; Bates et al., 2015) in R (vers. 4.0.4; R Core Team, 2021).

Specifically, within 20 min preceding a prompt, the prevalence of an AddHRVr trigger was determined. The decreases identified (coded as 0 = absent and 1 = present) were subjected to a multilevel model predicting the quality of the social interaction of the subsequent prompt. In total, 435 different combinations of algorithm settings were analyzed (i.e., RMSSD window length, RMSSD window threshold) with a silent setting of 20 min. These 435 multilevel models were bootstrapped with 1,000 iterations each. For each iteration

data of 21 participants were sampled with replacement. This allowed to estimate statistical power, (unstandardized) effect sizes and confidence intervals for all combinations of the algorithm's settings. Statistical power was calculated by dividing the number of iterations with a significant effect ( $p < .05$ ) by the total number of (valid) iterations (hence, the ratio between significant effects of the quality of social interactions and total iterations). Based on this information, 3-dimensional hyperplanes were constructed visualizing the associations between the different algorithm settings (i.e., window length and threshold) and the respective predicted quality of social interactions. Figures were generated in R (plotly package; Sievert, 2020; for the R-script and data, see <https://doi.org/10.17605/OSF.IO/FMT5U>). The algorithm setting with the highest power, solid effect size (with comparably small confidence intervals), and a reasonable number of AddHRVr triggers might be favored for an online validation study.

### 3 | RESULTS

#### 3.1 | Step 1: AddHRVr trigger simulation on an individual level

Table 1 presents the descriptive statistics of the resulting individually adjusted parameters of the algorithm. Of note, all parameters showed high inter-individual variation. Accordingly, the regression analyses indicated that for some participants bodily movement (acceleration) had a low and in others a high predictive value for RMSSD.

Based on these individual algorithm adjustments, Figure 2 illustrates the distribution of the simulated AddHRVr triggers for two representative participants. Panel A depicts the AddHRVr for a short-term algorithm setting (4 out of 5) and panel B for a more long-term algorithm (29 out of 30). The number as well as the temporal distribution of triggers (green asterisks) substantially differed between the algorithm adjustments.

**TABLE 1** AddHRVr algorithm calibration: Descriptive statistics of the individual parameters for all 21 participants calculated for the first 12 hr of recording

	<i>M</i>	<i>SD</i>	<i>Max</i>	<i>Min</i>
RMSSD (ms)	42.65	18.84	92.47	15.25
Acceleration (g)	0.05	0.02	0.09	0.02
Intercept	48.73	21.12	100.00	17.09
Slope	-134.66	96.58	-12.00	-324.87
<i>r</i>	-.38	.17	-.06	-.65

On the group level, the different number of delivered AddHRVr triggers associated with varying algorithm adjustments is illustrated in Figure 3. As could be expected, short-term algorithms (yellow) were associated with a higher number of emitted triggers during the three days of recording as compared to long-term algorithms (blue). Furthermore, the silent setting seemed to have a strong impact on the total number of delivered triggers, which was significantly lower for the silent setting of 60 min (Figure 3b) as compared to 10 min (Figure 3a),  $t(434) = 25.03$ ,  $p < .001$ .

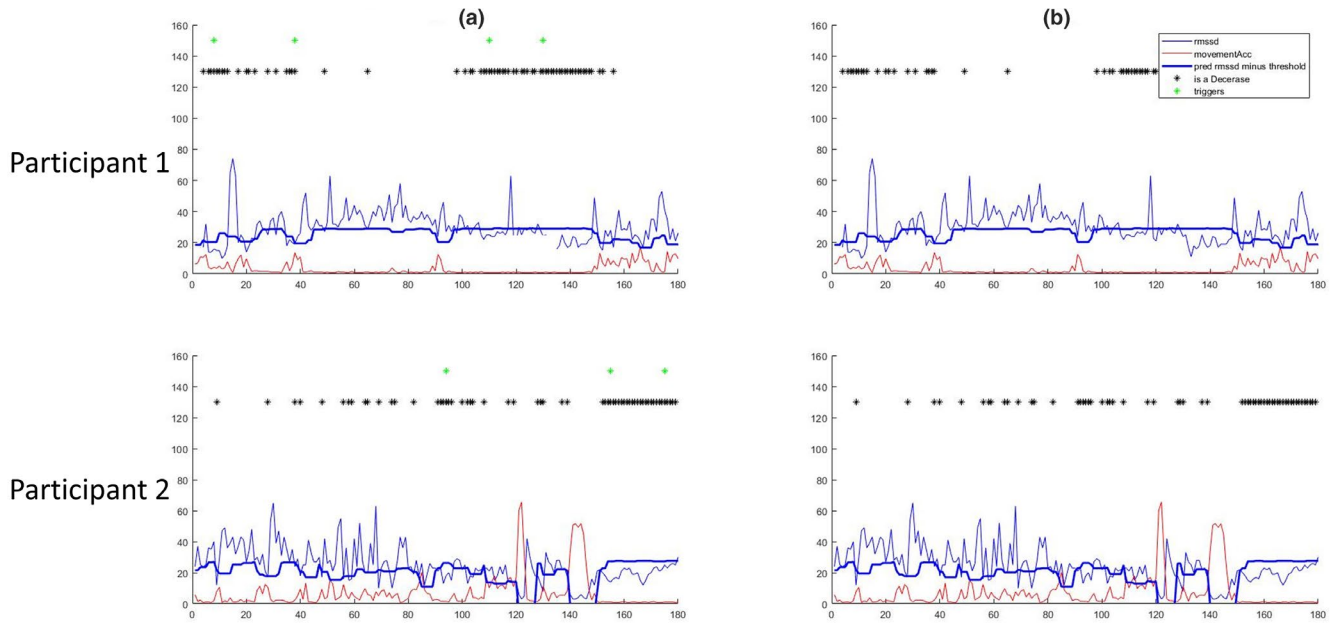
#### 3.2 | Step 2: Simulation of the trigger's sensitivity to psychosocial states

The prediction of the perceived quality of social interactions varied as a function of the algorithms' settings. In order to derive the most sensitive algorithm setting for predicting the quality of social interactions, all 435 bootstrap simulations were inspected for the highest power (Figure 4a; see URL the electronic supplement for an interactive 3D illustration), which was observed for the algorithm setting with 13 out of 29 (silent setting of 20 min). The respective power to detect episodes of low social quality interactions was 0.814 (see, Table 2 for algorithm adjustments with similar power scores). Of note, the simulation suggests that some algorithm settings showed similar properties and could also be favored for an online validation study.

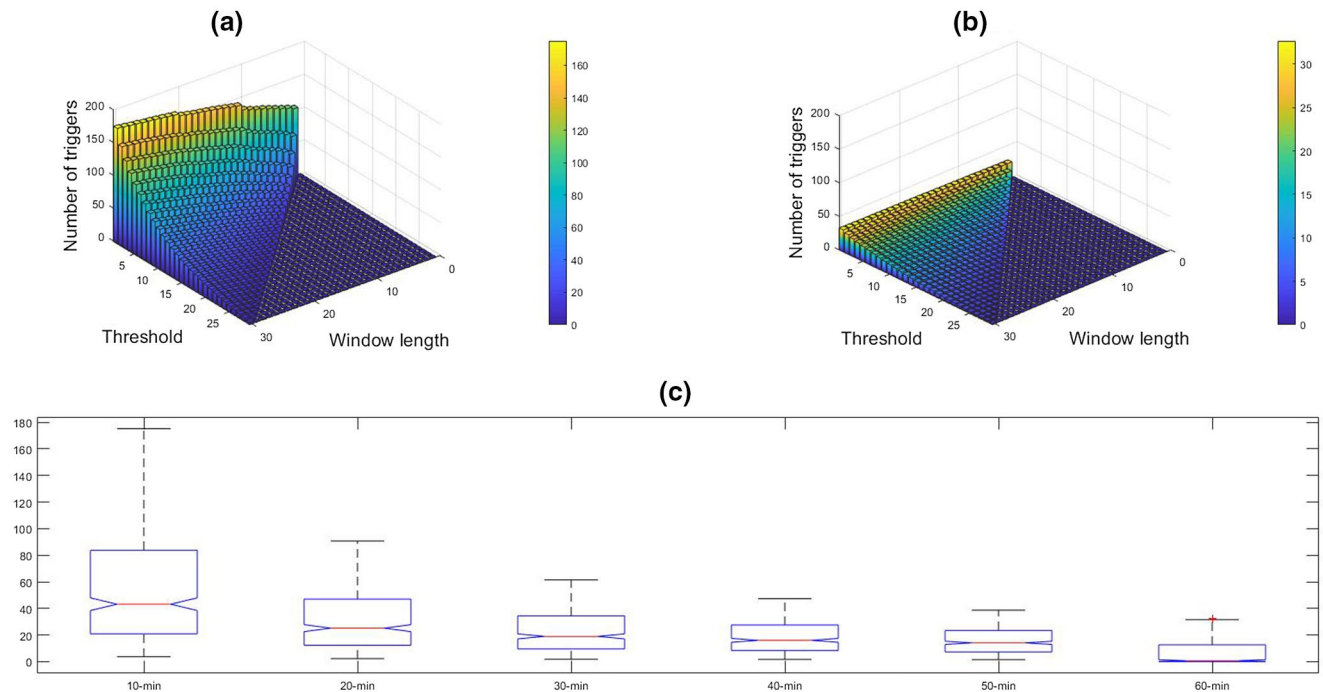
Analyzing other properties of the algorithms' settings, it was found that effect estimates and the number of triggers were comparable between the five settings with the highest power (see Table 2). With an effect size of  $b = -0.29$  (for 13 out of 29), AddHRVr triggers could predict lower quality of social interactions (specifically, a decrease trigger relative to a non-trigger was associated with a decline in the rated quality of social interactions of 0.29 on a six-point Likert scale). The total number of delivered triggers was 498 for a 13 out of 29 setting, thus indicating that on average each participant would have received about 7.90 triggers per day, in case an interactive psychophysiological ambulatory assessment would have been conducted with these settings. The mean effect estimates (and confidence intervals) for all simulated algorithm adjustments with a silent setting of 20 min are illustrated in Figure 4b (see the electronic supplement for an interactive 3D illustration).

### 4 | DISCUSSION

The aim of this study was to demonstrate a simulation approach to derive the settings of an AddHRVr trigger algorithm to index meaningful psychosocial states (in our example, low quality of social interactions) in daily life that should



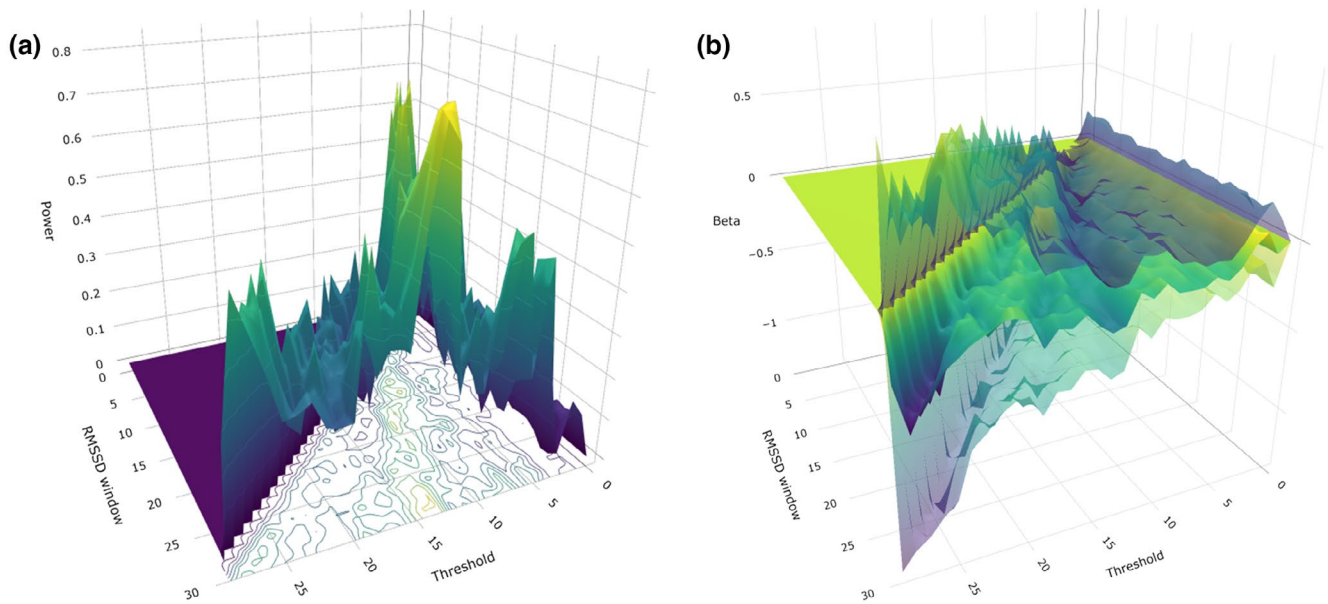
**FIGURE 2** Example of a simulation for two participants. The algorithm was run with a window threshold of 4 and a window length of 5 (i.e., 4 out of 5; panel A) and 29 out of 30 (panel B) with a silent period of 20 min in between. The figure illustrates an observation time of 3 hr. The x-axis depicts minutes and the y-axis RMSSD. The red line represents the amount of movement, the blue line is the actual RMSSD and the bold blue line represents the estimated threshold (predicted RMSSD - 0.5 × SD RMSSD<sub>calibration</sub>). Green asterisks indicate AddHRVr triggers and the black asterisks indicates a 1-min segment with the actual HRV being lower than the predicted threshold



**FIGURE 3** Number of AddHRVr triggers for different algorithm settings. A represents the number of triggers with a silent setting of 10 min and B with a silent setting of 60 min. C shows the mean number of triggers for 6 different silent settings of the algorithm (from 10 to 60 min)

further be validated in future interactive psychophysiological ambulatory assessment studies. The proposed methodological approach aims to obtain individual algorithm settings in a first step and to analyze their psychosocial sensitivity in a

second step via systematic simulations along two dimensions (window length and RMSSD window threshold). In the current example, we arrived at an algorithm specifying 13 out of 29 min-segments with AddHRVr exceeding an individually



**FIGURE 4** Panel A illustrates the power for each of the 435 bootstrapped multi-level analyses using the algorithm settings of RMSSD window length ( $x$ -axis) and window threshold ( $y$ -axis; i.e.,  $y$  out of  $x$  to be a trigger; see URL for an interactive 3D illustration). Panel B illustrates the corresponding effect estimates and confidence intervals derived from bootstrap simulations (1,000 samples with  $n = 21$ ; for an interactive 3D illustration see URL). The silent setting of both figures was fixed at 20 min

**TABLE 2** Order of algorithm setting with respect to power estimates

Order	Window threshold	Power	Effect estimate <sup>a</sup>	CI low (2.5%)	CI high (97.5%)	Total triggers	Triggered prompts
1	29/13	0.814	-0.29	-0.53	-0.07	498	112.33
2	29/14	0.806	-0.30	-0.54	-0.07	445	102.34
3	28/13	0.806	-0.30	-0.55	-0.07	481	107.93
4	30/14	0.792	-0.29	-0.54	-0.05	466	107.95
5	27/13	0.786	-0.28	-0.52	-0.06	467	106.19

Note: Total triggers = number of triggers delivered at the specific algorithm settings, triggered prompts = number of prompts classified as a triggered prompt, i.e., trigger within 20 min before prompt, total prompts = 560.

<sup>a</sup>Unstandardized effect estimate  $b$ .

determined predefined threshold of predicted RMSSD. These algorithm settings were sensitive to comparably low levels of the perceived quality of social interactions in everyday life, thus supporting previous evidence for lower HRV when individuals experience compromised social interactions (e.g., Eisenberger & Cole, 2012; Shahrestani et al., 2015). It should be noted though that the prolonged HRV decreases could have been accompanied by other negative feeling states (e.g., stress, rumination, episodes of anger), which in turn might have impacted social interactions at a later time point. Thus, based on the simulations of this study we can predict low quality social interactions by preceding AddHRVr, but are not yet able to determine the exact mechanism or directionality of this relationship.

Importantly, this study aimed to provide a tool that could be useful to derive the most sensitive settings for

a psychosocially meaningful AddHRVr trigger. While previous research used preset algorithm settings and was mainly concerned with the calibration protocol (e.g., Brown et al., 2018, 2020), we applied an exploratory approach to determine which algorithm settings are particularly sensitive to psychosocial states (in this case, the perceived quality of social interactions). It should be noted though that the derived settings in this study could differ in other populations and particularly, for other psychosocial concepts (e.g., worry, rumination, anger, fear). Thus, it seems mandatory to validate the findings in subsequent research and to analyze the specificity of the algorithms' settings. Below we first provide some ideas on the validation of these algorithms, before turning to further algorithm refinements and the algorithms' specificity.



## 4.1 | Toward the validation of algorithm settings

In principle, different validation approaches could be applied. First, offline validation studies could be carried out in the same study sample (within-person) by deriving the algorithm settings in a subset of recording days (e.g., first 3 days) and evaluating the performance of the AddHRVr algorithm on the subsequent days (e.g., days 4–6). This would allow to evaluate the robustness of the algorithm in the same sample, thus ensuring internal validity. A second approach would be to derive the settings in one study sample and to evaluate the algorithm's performance in a different sample offline. Certainly, this approach would ensure generalizability of the AddHRVr algorithm settings to other populations, but its success depends on the representativeness (and situational diversity) of the original sample.

Importantly, the functioning of the algorithm in online mode must be considered the gold standard of validation. Hence, the AddHRVr algorithm should be implemented in the ambulatory recording device, which will then emit an acoustic signal via the smartphone whenever AddHRVr with the pre-specified characteristics is detected. The subjective ratings following this alarm would then be compared to ratings following random prompts. It should be emphasized though that the selection of algorithm settings via the suggested simulation approach needs careful consideration. Specifically, a transfer from an offline identified algorithm setting to an online tool should account for the respective ambulatory setting. For example, an AddHRVr trigger with high power that is emitted quite frequently (due to its short-lived characteristic) might be unsuitable for individuals who have a dense working schedule and thus would require a comparably long silent setting. Thus, we argue that while the outlined two-step simulation approach derives quantitative evidence for the most sensitive settings, it needs to be matched with qualitative decision rules (e.g., considering the study's settings and compliance of the participants).

We are convinced that developing such HRV decrease algorithms that work in online mode would strongly stimulate electronic and mobile health interventions (e.g., via slow breathing exercises). Providing just in time interventions whenever a trigger of a meaningful HRV decrease is emitted would allow for a personalized, tailored approach that could help individuals withstanding periods of cardiac (and psychosocial) episodes of vulnerability.

## 4.2 | Trigger refinements

### 4.2.1 | Adjusting the magnitude of AddHRVr

It is important to note that within this demonstration we relied on a magnitude of change from the predicted value of 0.5

*SD*. Although it is reasonable to assume that a comparably strong HRV decrease (e.g., 1 *SD*) should be more informative regarding psychosocial states, an overly high threshold could be too restrictive, thus allowing only most severe (and hence, rather seldom) events to be detected. Likewise, a lower threshold could be less meaningful with respect to psychosocial events. It should also be noted that most studies on HRV and psychosocial concepts suggested rather moderate associations. Taken together, although a *SD* of 0.5 seems like a good starting point for identifying meaningful AddHRVr, we would recommend simulating the magnitude of change as well in order to evaluate its sensitivity to diverse psychosocial states.

### 4.2.2 | Static algorithm—Dynamic algorithm?

Importantly, the AddHRVr algorithm used in this demonstration (and in previous approaches as well!) represents a static approach. Thus, the evoked trigger responds whenever RMSSD meaningfully declines below an individually determined basal value obtained during a calibration protocol. Although a static algorithm could constitute a simple and powerful tool to detect meaningful HRV decreases from an individual set-point, it cannot account for dynamic changes from moment to moment (e.g., when HRV is declining from an elevated level) or for circadian changes. Hence, dynamic algorithms constitute promising alternatives, since they can adapt to individuals' momentary HRV via moving average windows and signal deviations thereof. Of note, we ran the same simulation procedure presented in this study with a dynamic algorithm, thereby adjusting the intercept of the regression by the mean of RMSSD recorded throughout the last 10 min. However, the setting simulation of this dynamic algorithm reached only a low maximum power estimate of 0.61 with the setting 24 out of 30 (see, URL for the simulation of a dynamic AddHRVr algorithm with a silent setting of 20 min). It remains to be studied under which circumstances more sophisticated dynamic algorithms could outperform static algorithms in the accuracy of the prediction of meaningful psychosocial states. Certainly, in addition to the other parameters dynamic algorithms offer another array for systematic simulation by varying the time interval of the moving average (e.g., between 5 and 20 min).

### 4.2.3 | Accounting for the silent setting

For reasons of parsimony, in this simulation approach we held the silent setting of the algorithm constant at 20 min. A silent setting of 20 min seems quite reasonable and corresponds to a maximum of 36 triggers in a 12 hr-period. In online mode, such a setting could be intermixed with random

prompts, thus ensuring a time-sensitive assessment of psychosocial states. It should be noted though that the silent setting could be adjusted as well and the systematic manipulation of the silent setting could substantially alter the response characteristic of the algorithm (see, for example, our results on the frequency of triggers in Figure 3). For a further evaluation, we additionally calculated the statistical power for algorithm adjustments with a silent setting of 60 min (see URL). This analysis showed a maximum power of 0.876 for the algorithm setting 14 out of 28. Importantly, 97.73% of these trigger associated-prompts were also detected by a setting 13 out of 29 (with 20 min silent setting) reported in the results section. However, considerably less triggers were delivered with a silent setting of 60 min (i.e., 199 in total corresponding to 3.16 per day and participant). This finding suggests that while different algorithm settings might be associated with similar psychosocial phenomena, they show different response characteristics. This overlap of evoked triggers between different algorithm settings might argue for an over-specification of the algorithm, since changes in different algorithm parameters are associated with similar changes in trigger characteristics. A reduction of parameters with similar effects on the algorithm's functioning might be worthwhile to consider and can be derived from simulation approaches as outlined above.

#### 4.2.4 | Accounting for body position and respiration

Because RMSSD is sensitive to body position, future algorithms could also be calibrated to handle periods of lying or sitting differently than periods of standing and walking. Even more, other confounds, like breathing and/or speaking patterns could be controlled for as long as a reliable and, for the participant, convenient assessment is guaranteed. Of note, these adjustments might change the evoked trigger characteristics considerably, which asks for continued simulation and validation of each algorithm. In the following, we will concentrate on the impact of body position, because reliable assessment of breathing (via the electrocardiogram-derived respiration; EDR) was compromised. We suggest to use elastic belts to sensitively track thoracic movements in future research, which however, are not yet implemented in the movisens EcgMove4 device.

In order to evaluate the impact of posture on our findings, we conducted a series of follow-up simulations to predict social interaction quality by AddHRVr, thereby controlling for body position (measured via accelerometers within the EcgMove4 device). Specifically, we analyzed only segments with an upright position (without lying) and applied this setting to our simulations. Findings of step 1 simulations are depicted in the Supporting Information Table S1. The

results of step 2 simulations are illustrated in the Supporting Information Table S2 (see, URL for an interactive 3D illustration of power estimates and URL for effect estimates and confidence intervals). Importantly, the general pattern of findings did not change, thus suggesting a relatively minor influence of body position in the current research context. However, future research should strive to implement those potential confounds in the individually determined algorithm settings (simulations in step 1), because for some individuals the impact of breathing or body position on RMSSD could be stronger as compared to other individuals.

### 4.3 | Trigger specificity: Different AddHRVr algorithms for different psychosocial concepts?

The aim of this research was to demonstrate a feasible approach to derive settings for an AddHRVr algorithm, which could be further used in an interactive psychophysiological ambulatory assessment of HRV. In doing so, we used an already available data set and hypothesized, in accordance with previous theorizing and empirical reports (e.g., Eisenberger & Cole, 2012; Porges, 2007; for a meta-analysis, see Shahrestani et al., 2015), that HRV reductions in everyday life could be associated with low quality social interactions, among others. It is important to note that other research associated perseverative cognition (worry, rumination; e.g., Chalmers et al., 2016; Kocsel et al., 2019; Ottaviani, 2018; Verkuil et al., 2016; Williams et al., 2017), anxiety (e.g., Friedman, 2007), depression (e.g., Dell'Acqua et al., 2020; Koch et al., 2019; Schwerdtfeger & Friedrich-Mai, 2009), or stress (e.g., Kim et al., 2018) with decreased HRV. It is not clear yet if these phenomena share the same or different patterns of (momentary) HRV reductions. It should also be noted that more activated/arousal-related positive (motivational) states could be accompanied by HRV-reductions in everyday life as well (e.g., Schwerdtfeger & Dick, 2019; Schwerdtfeger & Gerteis, 2014). Hence, the sensitivity and specificity of each algorithm setting remains to be elucidated in future research. In particular, the following questions should be tackled: Are short-lived AddHRVr triggers associated with different psychosocial phenomena as compared to rather long-term triggers? Should the algorithm threshold (i.e., the magnitude of change from the predicted value) be adjusted depending on the psychosocial variables studied?

Furthermore, we want to encourage the development of algorithms capable of detecting meaningful increases in HRV, independent of movement patterns (i.e., AddHRVi). Elevated vagally mediated HRV has been associated with resilience and psychosocial resources (e.g., An et al., 2020; Carnevali, Thayer, et al., 2018; Gerteis & Schwerdtfeger, 2016; Koenig, 2020; Perna et al., 2020;

Schwerdtfeger & Scheel, 2012; for an inverse association on a within-person level, see however, Schwerdtfeger & Dick, 2019), which should complement the automated detection of HRV decreases. This way HRV decrease triggers could not only be compared to random prompts, but be contrasted with HRV increase triggers to maximize effects. It should be noted though that HRV increase algorithms could be more complex. Specifically, a transition from movement to rest is surely accompanied by increased HRV, which however might not be relevant for psychosocial concepts (not to mention the strong impact of respiration). Hence, an HRV increase algorithm would need to account for body position and possibly respiration or speaking patterns.

Irrespective of further research agenda described above, interactive psychophysiological ambulatory assessment could considerably advance our understanding of psychophysiological linkage in general and psychophysiological inference in particular. In this respect, Cacioppo and Tassinari (1990) distinguished psychophysiological variables as outcomes (many psychosocial phenomena linked to a particular physiological variable within a specific context), marker (a one-to-one relation between a psychosocial and a physiological variable within a specific context), concomitant (many psychosocial phenomena linked to a physiological variable irrespective of the context), and as invariant (one-to-one correspondence between a psychosocial and a physiological variable irrespective of the context). HRV-derived triggers in ambulatory assessment could be considered outcomes, markers, concomitants, or even invariants of a psychosocial state, which however, depends on further systematic research aiming to analyze the trigger's specificity and contextual sensitivity.

#### 4.4 | Conclusions

Can we detect meaningful psychosocial episodes by an online analysis of HRV? Probably so, but what sounds as quite an easy and pragmatic question imposes great methodological challenges. This study aimed to present a two-step simulation approach to derive algorithm settings for AddHRVr triggers, thus contributing to the further development of an interactive psychophysiological ambulatory assessment approach. The proposed method first aims to derive meaningful algorithm settings for each individual and, in a second step, to use the derived triggers as predictors of momentary psychosocial states in everyday life. As a result, a multidimensional hyperplane can be constructed (and verified by bootstrap simulations), which may inform about the most sensitive algorithm settings for a particular psychosocial state. In the discussion section, we elaborated on the validation of these settings, proposed further refinements (i.e., adding more dimensions and potential

confounds to the simulation approach) and argued for the need to analyze the algorithms' specificity. We hope that the toolbox presented in this report will be applied to other data sets as well and that future research will let us know if and to what extent different psychosocial states could be reliably detected/predicted by transient changes in momentary HRV in daily life.

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#### AUTHOR CONTRIBUTIONS

**Andreas Richard Schwerdtfeger:** Conceptualization; Methodology; Project administration; Resources; Supervision; Writing-original draft; Writing-review & editing. **Christian Rominger:** Conceptualization; Data curation; Formal analysis; Methodology; Software; Validation; Visualization; Writing-original draft; Writing-review & editing.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

**TABLE S1** AddHRVr trigger calibration: Descriptive statistics of the individual parameters for all 21 participants calculated for the first 12 hr of recording when periods of lying were excluded

**TABLE S2** Order of algorithm setting with respect to power estimates, when periods of lying were excluded

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