Received: 30 October 2018 | Revised: 10 May 2019 | Accepted: 12 May 2019
DOI: 10.1111/psyp.13420

ORIGINAL ARTICLE

PSYCHOPHYSIOLOGY SPR WILEY

Changes in heart rate and skin conductance in the 30 min preceding aggressive behavior

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Funding information
De Borg and DForZo (Directie Forensische Zorg) grant

Abstract
Aggressive behavior of inpatients threatens the safety and well-being of both mental health staff members and fellow patients. It was investigated whether heart rate and electrodermal activity can be used to signal imminent aggression. A naturalistic study was conducted in which 100 inpatients wore sensor wristbands during 5 days to monitor their heart rate and electrodermal activity while staff members recorded patients' aggressive incidents on the ward. Of the 100 patients, 36 displayed at least one aggressive incident. Longitudinal multilevel models indicated that heart rate, skin conductance level, and the number of nonspecific skin conductance responses per minute rose significantly in the 20 min preceding aggressive incidents. Although psychopathy was modestly correlated with displaying aggression, it was not a significant predictor of heart rate and skin conductance preceding aggression. The current findings may provide opportunities for the development of individual prediction models to aid acute risk assessment and to predict aggressive incidents in an earlier stage. The current results on the physiological indicators of aggression are promising for reducing aggression and improving both staff as well as patient safety in psychiatric mental health institutions.

KEYWORDS
aggression, ambulatory, antisocial personality disorder, heart rate, galvanic skin response, monitoring

1 | INTRODUCTION

Aggressive behavior directed toward staff members and fellow patients in psychiatric treatment settings is a worldwide problem, as it threatens the safety and well-being of those involved (Hensel, Lunsky, & Dewa, 2013). A meta-analysis revealed that mental health nurses are three times more likely to experience physical aggression in the workplace (Edward et al., 2016) than nurses in other disciplines. Almost all psychiatric nurses experience verbal aggression on a daily basis, and about one out of every six psychiatric nurses also experiences physical aggression on an annual basis (Nijman, Bowers, Oud, & Jansen, 2005).

Not surprisingly, researchers have developed questionnaires and risk assessment tools to predict and prevent patient aggression toward nursing staff or fellow inpatients. For example, researchers have developed methods for early recognition of potential warning signs of disruptive and aggressive incidents based on observing the patient's

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behavior (Fluttert, Van Meijel, Bjørkly, Van Leeuwen, & Grypdonck, 2013). Apart from observing and interpreting patients' behaviors that are assumed to be linked to imminent aggressive incidents, there is a growing interest in the potential of predicting aggression by means of more objective physiological measurements, indicative of autonomic nervous system (ANS) functioning. Methods to assess ANS functioning consist of, but are not limited to, assessment of heart rate (HR), breathing, blood pressure, neurotransmitter levels, or skin conductance (a measure of electrodermal activity, EDA; Zygmunt & Stanczyk, 2010). EDA and HR have historically been two of the most popular measures in research focusing on ANS function (Lorber, 2004). For example, the association between EDA and aggression was studied on psychiatric wards (Kuijpers, Nijman, Bongers, Lubberding, & Ouwerkerk, 2012) and in facilities caring for people with intellectual disability disorders (Noordzij, Scholten, & Laroy-Noordzij, 2012). Besides EDA, HR is an often studied indicator of aggression, and efforts have been made to study this in a more naturalistic setting. For instance, Beauchaine, Gartner, and Hagen (2000) used a 10-s intake electrocardiogram to predict aggressive behavior based on depression scores and high heart rate variability. However, the majority of these physiological parameters have been studied in experimental and laboratory settings (Lorber, 2004), leaving the question unanswered whether physiological parameters are relevant real-time predictors of actual aggressive behavior.

As far as we know, four major systematic reviews have been performed on the associations between HR, EDA, and aggression. The most recent meta-analysis by Portnoy and Farrington (2015) reported a small summary effect size (Cohen's $d = -0.20$) between resting HR and violent behavior. An earlier meta-analysis by Ortiz and Raine (2004) reported a lower resting HR in samples of antisocial children compared to children without antisocial behavior (Cohen's $d = -0.44$) and a lower HR during a stressor (Cohen's $d = -0.76$). Lorber (2004) reported a small effect size (Cohen's $d = -0.38$) for resting heart rate in adult aggression samples. In addition, a higher HR and EDA reactivity to stimuli was observed in aggressive people. In these meta-analyses, several categories of externalizing problem behaviors were distinguished: aggression, psychopathic traits, and conduct problems. Lorber concluded that HR was mostly related to aggression, while EDA was most prominently associated with psychopathy (especially lower rest EDA and reactivity in psychopathy samples). Consensus on the exact core features of psychopathy is lacking, but psychopathy is typically characterized by problems in affective, behavioral, and interpersonal functioning, which increases the psychopath's risk for violent behavior (Sörman et al., 2016). Lastly, the fourth review by Patrick (2008) reported a higher HR and EDA reactivity to stressful events, interpersonal stressors, in particular, and in samples of hostile-aggressive adults.

As mentioned above, almost all research on the association between aggression and ANS functioning was done in experimental and laboratory settings, and the most consistent findings were reported for resting HR. The aim of the current study was to investigate these associations in a naturalistic setting, namely, during day-to-day life at forensic psychiatric treatment facilities for people with mild intellectual disabilities or borderline intellectual functioning (MID-BIF). Recent technological advances allow for the continuous measurement of physiological markers like HR and EDA in real life by means of wearable sensors. In this study, it was investigated whether episodes preceding aggressive behavior differ from episodes that do not precede aggressive behavior on a physiological level. It is expected that EDA will substantially rise preceding an aggressive incident, such as has been reported in a case study by Kuijpers et al. (2012). In this pilot study, the EDA level of a patient rose significantly in the period preceding aggressive behavior on the ward, even well before the staff members noted the aggressive behavior.

Another small-scale empirical study (Nijman et al., 2014) with 47 patients also indicated that EDA does seem to rise preceding aggressive behavior (chi-square = 6.42). However, in that study, the authors did not control for an individual's baseline level or for time-of-day effects on the days that the participants did not display aggressive behavior (Nijman et al., 2014). The physiological starting values can vary between individuals, and the starting value of each preincident interval can be different from incident to incident within that individual. To overcome the baseline and time-of-day effect problems in the current study, we analyzed the period preceding aggressive behavior and controlled for between- and within-subject variance on the days that the participants did not display aggressive behavior. To our knowledge, no studies have been published on heart rate preceding aggressive behavior in psychiatric MID-BIF patients. It was expected that HR would rise preceding aggressive behavior, considering that people get aroused. Furthermore, we also included level of psychopathy as a predictor, as psychopathy is one of the most important predictors of future violence (Hare & Neumann, 2009; Lindsay et al., 2006, Lorber; 2004). In addition, the study included covariates for movement and temperature, as these are known to influence the quantity and quality of noise-free data obtained with ambulatory devices (Hu et al., 2015; Taylor et al., 2015). The following research question is addressed:

Is aggressive behavior preceded by a significant rise in HR and EDA compared to baseline levels when the client is not aggressive? And if so, over what time period do the observed rises in physiological parameters take place before the aggressive behavior is manifested?

2 | METHOD

For this observational, naturalistic study, forensic psychiatric patients with MID-BIF and a history of aggressive behavior were asked to wear a wristband that measured their HR and EDA during 5 consecutive days. The staff members were asked to score the Modified Overt Aggression Scale+ (MOAS+; see below) each time they observed any aggressive behavior. Approval for the study was granted by the scientific committee and committee of ethics of the Faculty of Social Sciences of the Radboud University at Nijmegen (ECSW2015-1901-282). This study conforms to the Declaration of Helsinki for ethical principles involving human participants. The patients are legally detained and treated in the forensic psychiatric facilities.

2.1 | Participants and setting

Before the start of data collection, an a priori power analysis was conducted based on the pilot study described earlier (Nijman et al., 2014) in which there were two groups (aggressive and non-aggressive) with three measurements (three 30-min epochs). As we had multiple dependent variables in the current study and no studies that investigated changing levels of EDA and HR preceding aggressive behavior were available at the time we designed this study, we conducted a power analysis for a repeated measures multivariate analysis of variance (RM-MANOVA) with Cohen's d of 0.52 (based on chi-square of 6.42), with two groups and three epochs. The power was set to 95% and alpha at 0.05, which indicated that at least 61 participants were needed (Faul, Erdfelder, Lang, & Buchner, 2007). As patients were invited without restrictions on the sample size, 104 patients with MID-BIF were included. As we used six epochs in the current study instead of three, a post hoc power analysis indicated that we needed 79 participants with two groups and six epochs. Four of the patients withdrew their consent before the end of the study. The remaining 100 participants were admitted in four (forensic) psychiatric hospitals located in different regions of the Netherlands that provide treatment and care to patients with MID-BIF and severe forms of aggressive behavior.

The age of the 100 participants ranged from 18 to 57 years ($M = 32.01$, $SD = 9.02$) and 68% were male. The country of birth of the sample was 69% native Dutch, 18% non-native Dutch and non-Western, and 13% was non-native Dutch, but Western. Aggressive incidents were scored with the MOAS+ (see Section 2.3 Incidents), a questionnaire that consists of scales on verbal and physical aggressive behaviors as well as auto-aggressive and sexual aggressive behaviors. For 36 out of 100 patients, the staff members reported one or more aggressive incidents, with a total of 101 aggressive incidents. Several participants were involved in multiple aggressive incidents (range 1–9 aggressive incidents per aggressive participant).

2.2 | Procedure

Initially, the participants were invited and informed about the aim of the study through email, posters, and flyers. Written informed consent was obtained for all patients after they received all necessary information on the study. Participants wore a device in the form of a wristband, called the Empatica E4 (Empatica Inc.), during the entire day, for 5 consecutive days while they were on the ward. Data were collected between May 2015 and August 2017, as the study was part of a larger longitudinal study into the use of wearable biosensors in practice (see de Looff, Didden, Embregts, & Nijman, 2019). Staff members monitored aggressive behavior while wearing watches that allowed them to time stamp the moment they observed any aggressive behavior and subsequently documented the nature and severity of the observed aggressive behavior on the MOAS+.

2.3 | Instruments

Frequency and severity of the patient's aggressive behavior on the ward was assessed with the Modified Overt Aggression Scale plus (MOAS+; Crocker et al., 2006; Dutch translation by Drieschner, Marrozos, & Regenboog, 2013; Oliver, Crawford, Rao, Reece, & Tyrer, 2007). Subtypes of the MOAS+ are verbal aggression, physical aggression, aggression against objects, sexual aggression, and auto-aggression. The MOAS+ has four subcategories ranging from light to severe for each of the subtypes of aggression. Cohen's kappa for the MOAS ranges from 0.65 to 0.90 (Oliver et al., 2007).

Psychopathy was assessed with the Dutch version of the Psychopathy Checklist–Revised (PCL-R; Hildebrand, de Ruiter, de Vogel, & van der Wolf, 2002). The PCL-R consists of 20 items that assess the prototypical characteristics of a psychopath. Each item is scored on a 3-point Likert-type scale, ranging from 0 (*absent*) to 2 (*present*). In Europe, the cut-off score for psychopathy is set at 26 (Hildebrand, de Ruiter, & Nijman, 2004). The internal consistency of the PCL-R is high (Cronbach's alpha of 0.87); the two factors have a Cronbach's alpha of 0.83. The PCL-R has two main factors: Factor 1 reflects the affective and interpersonal features of psychopathy; Factor 2 reflects the social deviance found in psychopathy. The PCL-R was scored on the basis of the patients' files by professionals with at least a Bachelor level degree in the Behavioral Sciences, who received an official 3-day training in the administration of the PCL-R.

2.4 | Physiological assessments

The physiological parameters were obtained with the Empatica E4 (Garbarino, Lai, Bender, Picard, & Tognetti, 2014), a device in the form of a wristband that allows for measuring EDA, blood volume pulse (on which an interbeat interval and HR are based), skin temperature, and movement. Participants were asked to wear the E4 for 5 days on their nondominant hand. HR was expressed in beats per minute; Empatica uses two algorithms to detect the heartbeats based on the blood volume pulse and provides both the interbeat intervals (IBI) and a HR summary (see Empatica, 2018). The sensor used to detect blood volume pulse is a photo plethysmography sensor, which is known to be subject to missing data as a result of movement or pressure artifacts (Taylor et al., 2015). The IBI and HR data resulted in exactly the same estimates. The analysis of the SC data was based on an automated script that uses a support vector machine to classify the electrodermal data into peaks and artifacts and is based on a data set of expert labels (Taylor et al., 2015). A particular problem in ambulatory monitoring is obtaining a noise-free signal, which is difficult due to, for instance, movement, tightness of the device that is worn, or electrode attachment and placement (Hu et al., 2015; Taylor et al., 2015). As a result, ambulatory measurements may result in artifacts. The parameters that we extracted were skin conductance level (SCL) and number of peaks per minute (PPM). The threshold for the amplitude of peaks was set to a minimum rise of 0.005 μSiemens. The maximum rise time of the peaks was set to 4 s. For the calculation of the peaks, while considering the refraction period (i.e., a peak [skin conductance response] that occurred during a not-yet-completed previous peak), the end of the first peak was not to be later than the start of the next (Taylor et al., 2015). Movement was assessed with a 3-axis accelerometer and was calculated over the three axes as an indication of average movement (Rowlands et al., 2015) using the Euclidean norm, which results in

$$\text{magnitude of acceleration}_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$$

Skin temperature was measured in degrees Celsius. As mentioned before, the measurements are somewhat artifact prone, especially when worn on the wrist, possibly because considerable movements during the day can influence the quality of the recordings (Boucsein, 2012). As is standard practice, the physiological signals were both visually inspected as well as automatically checked by automated recognition software (Kleckner et al., 2017; Taylor et al., 2015) with the use of the program *eda explorer* developed by MIT (Taylor et al., 2015). We devised a batch tool with which we were able to process the data (de Looff et al., 2019). Artifacts influence the amount of data that can be used to estimate the parameters. For each file and time period, the number of artifacts was established as an indicator to retain or discard the time period for analysis. For the current study, we set the threshold for the maximum number of artifacts to 25%, which is conservative, but we also tested models with 50% and 75% artifact levels (not reported here).

The physiological data from the half-hour periods preceding the aggressive incidents were extracted. Each period was divided into six epochs of 5-min intervals. The PPM, SCL, and HR were averaged for the six 5-min periods.

For each of the 36 aggressive patients and for each of the individual incidents, we calculated a difference score between the 6*5 minute epochs preceding aggressive behavior with the mean of ~4 days of 6*5 minute epochs on non-aggressive days for PPM, SCL, and HR. The ~4 days of 6*5 epochs is such that they cover the same time of day as the 6*5 epochs preceding an aggressive incident. This was done to control and standardize for both individual baseline levels preceding an aggressive incident and time-of-day effects in the physiological parameters preceding aggressive behavior.

2.5 | Statistical methods

First, characteristics of patients for whom aggressive incidents were reported ($N = 36$) were compared to the patients for which no aggressive incidents were reported ($N = 64$) using independent t tests and a chi-square test.

Second, we evaluated if the physiological parameters differed in the half-hour period preceding aggressive incidents, compared to the time-matched control periods on days in which the patients did not become aggressive. The statistical model to test this was a multilevel model with epochs (Level 1) nested within the incident level (Level 2) nested within the person level (Level 3). The equations for the statistical models that were tested follow the notation by Hox, Moerbeek, and van de Schoot (2017) and are as follows:

The Level 1 model is a repeated measures model; for time point t within incident i within participant j it is given by

$$Y_{tij} = \pi_{0ij} + \pi_{1ij} * T_{tij} + \pi_{2ij} * T_{tij}^2 + e_{tij}$$

where Y_{tij} is the response variable, T_{tij} is the variable for time, and e_{tij} is the residual. We included a quadratic term for time to account for a nonlinear trend because that was suggested by our data. The baseline score π_{0ij}, linear trend π_{1ij}, and quadratic trend π_{2ij} were allowed to vary across incidents. We used temperature and movement to explain part of the between-incidence variability in baseline score (but not of variability of the linear and quadratic trend). The Level 2 model is then

$$\pi_{0ij} = \beta_{00j} + \beta_{01j} * temperature_{ij} + \beta_{02j} * movement_{ij} + u_{0ij}$$

$$\pi_{1ij} = \beta_{10j} + u_{1ij}$$

$$\pi_{2ij} = \beta_{20j} + u_{2ij}$$

All regression weights β vary between participants. The unexplained variability in baseline, linear, and quadratic trend is captured by random effects u. We use participant level predictor variables gender, PCL-R-score, and type of aggressive behavior to explain part of the baseline variability (but not of all other regression coefficients). Aggression was entered as a dummy variable for this model (0 = *verbal*, 1 = *other*). The Level 3 model is given by

$$\beta_{00j} = \gamma_{000} + \gamma_{001} * gender_j + \gamma_{002} * pcl_j + \gamma_{003} * aggression_j + v_{00j}$$

$$\beta_{01j} = \gamma_{010} + v_{01j}$$

$$\beta_{02j} = \gamma_{020} + v_{02j}$$

$$\beta_{10j} = \gamma_{100} + v_{10j}$$

$$\beta_{20j} = \gamma_{200} + v_{20j}$$

Here, the v terms are random effects at the participant level. The multilevel model is especially useful to test for effects of predictor variables at multiple levels of the model (Snijders & Bosker, 2012) and when there are missing epochs (Hox et al., 2017), as is the case in our data set. The analysis was performed with both SPSS 24 and the *nlme* package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018) in R version 3.5.1 (to check the residuals as they are not given in SPSS). We also used MLwiN version 3.03 (Charlton, Rasbash, Browne, Healy, & Cameron, 2019) to check for assumptions of normally distributed residuals on all levels of the model. Separate models were considered for each type of parameter (PPM, SCL, HR). As mentioned before, the models described in the Results section of this article were the ones fitted on the <25% artifact data, which constituted the most conservative level of thresholds. For the repeated measures, we used the final 5 min prior to the aggressive incident as the intercept ($T_{tij} = 0$). This allowed us to interpret the value of the parameters at the last epoch before aggressive behavior occurred. The 5–10 min epoch before the aggressive incident was given a value of $T_{tij} = -1$, the 10–15 min epoch before the aggressive incident was given a value of $T_{tij} = -2$, etc. (see Figures 1–3). In addition, an autocorrelation covariance structure was tested as we expected that points in time that are nearer to each other will be more correlated. The variance at the participant level turned out to be nonsignificant (e.g., the addition of a third level did not result in a significant improvement of model fit), and therefore the incidents were considered as the highest level.

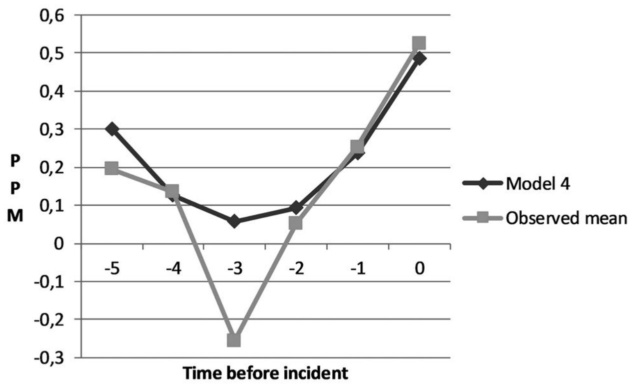

FIGURE 1 Difference scores for the 6*5 min aggressive day – epochs with the ~4 6*5 min nonaggressive days epochs. The observed means and best fit models for PPM are shown

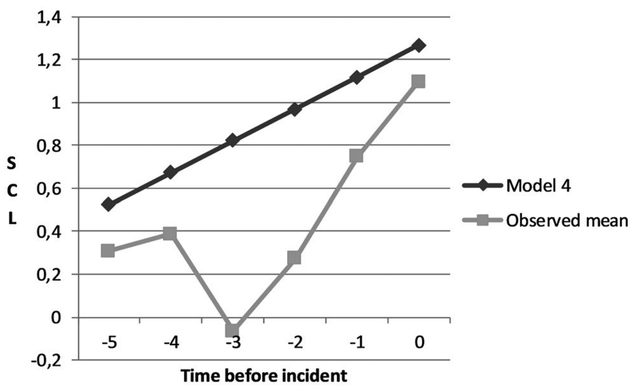

FIGURE 2 Difference scores for the 6*5 min aggressive day – epochs with the ~4 6*5 min nonaggressive days epochs. The observed means and best fit models for SCL are shown

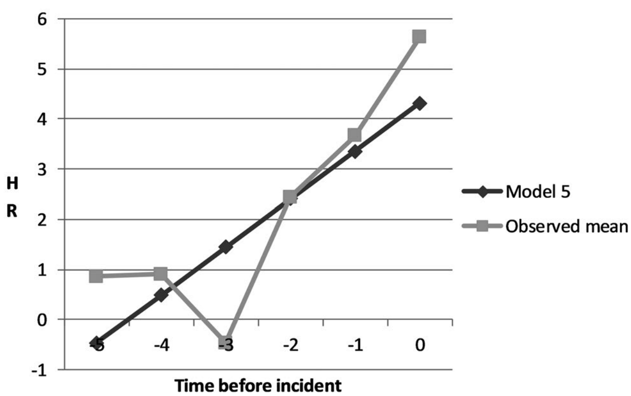

FIGURE 3 Difference scores for the 6*5 min aggressive day – epochs with the ~4 6*5 min nonaggressive days epochs. The observed means and best fit models for HR are shown

3 | RESULTS

3.1 | Type of aggressive incidents

As mentioned earlier, 36 of the 100 participants displayed one or more aggressive incidents during the study, with a total of 101 aggressive incidents. The 101 aggressive incidents of 36 patients who were involved concerned the following types of aggression (combinations of aggressive behavior were possible per incident, which occurred in 16 cases): For 78 of the 101 incidents (77.2%), staff members reported verbal aggression; in 22 (21.8%) instances, the aggression concerned property damage or aggression against objects; 6 incidents (5.9%) concerned acts of sexual aggression; and 5 incidents (4.9%) concerned physical aggression toward people. Finally, 9 incidents (8.9%) concerning auto-aggression were reported by the direct care staff on the MOAS+.

3.2 | Characteristics of the sample

The 36 aggressive participants were significantly younger than the 64 nonaggressive participants (mean ages of 28.7 and 33.9 years, respectively; $t(98) = 2.83$, $p < 0.05$; two-tailed). There were no significant differences between the aggressive and nonaggressive participants concerning gender or level of psychopathy. The mean psychopathy score of the 100 participants was 15.04 ($SD = 7.59$). As can be seen in the logistic regression in Table 1, lower PPM, SCL, and HR over the 5-day assessment period was associated with a slightly higher probability of an aggressive incident as evidenced by the negative parameter estimates; however, the estimates were nonsignificant. The mean values for the entire sample over the 5-day assessment period on the physiological parameters are presented as well. The mean values for the aggressive participants are only slightly lower for PPM ($M = 1.14$, $SD = 0.82$), SCL ($M = 1.46$, $SD = 2.35$), and HR ($M = 86.33$, $SD = 13.09$). The Poisson regression in Table 1 shows that increasing levels of PPM, SCL, and HR over the 5-day assessment period were associated with an increasing number of aggressive incidents, as evidenced by the positive parameter estimates. However, only the estimates for SCL were significant.

3.3 | Sample attrition due to artifacts and missing data

We aimed at measuring 100 participants with the Empatica E4 for 5 consecutive days. However, two of the 100 participants completed only 4 days of measurement, one participant completed 3 days, and one completed 2 days of assessment. Furthermore, data were removed for three main reasons: (a) absence of physiological data prior to aggressive behavior, (b) absence of comparison data, and (c) sensor failure. For 13 of the 101 aggressive incidents, the aggression slopes toward aggressive incidents were excluded as we did not have a full 30 min of physiological data preceding an aggressive incident (e.g., if the participant started wearing the device around 9 am and the incident occurred around 9.15 am, for instance), leaving us with 88 aggression slopes. Of the nonaggression (control) slopes derived from nonaggressive days, 11 slopes were removed because we did not have 30 min of physiological comparison data on the same time frame on a nonaggression day. Of the 345 nonaggression slopes, another 67 were excluded due to sensor failure (EDA). In addition, HR data were missing for five participants on 9 days due to sensor failures. As a result, there were 88 aggression slopes that could be compared to 278 nonaggression slopes for the within-subject comparison.

TABLE 1 Regression with PPM, SCL, and HR as predictors and aggressive incident (logistic) and number of aggressive incidents (Poisson) as outcome variable for the 5-day assessment period

	b (CI)	*SE* B	*p*	*M*	*SD*
Logistic					
Constant	−1.38 [−1.80, −0.98]	0.21	<0.001		
PPM (μS)	−0.13 [−0.43, 0.15]	0.15	0.38	1.21	0.80
Constant	−1.46 [−1.75, −1.18]	0.15	<0.001		
SCL (μS)	−0.05 [−0.17, 0.06]	0.06	0.40	1.63	2.17
Constant	−0.25 [−2.32, 1.81]	1.05	0.81		
HR (BPM)	−0.01 [−0.04, 0.01]	0.01	0.22	87.47	9.67
Poisson					
Constant	−0.89 [−1.13, −0.67]	0.12	<0.001		
PPM (μS)	0.15 [−0.00, 0.29]	0.08	0.05		
Constant	−0.80 [−0.96, −0.65]	0.08	<0.001		
SCL (μS)	0.05 [−0.00, 0.10]	0.03	0.04		
Constant	−1.49 [−2.62, −0.36]	0.58	<0.001		
HR (BPM)	0.09 [−0.00, 0.02]	0.01	0.17		

Note: *SE*, standard error; *M*, mean; *SD,* standard deviation. $N = 100$.

3.4 | Associations of the physiological parameters with aggression

As can be seen in Table 2, after applying the 25% threshold, 285 epochs of 32 patients remained for analysis. The models based on <25% are presented.

The bivariate correlations for all variables are given in Table 3, with the observations representing a mix of multiple participants and each participant supplying multiple epochs. PPM and SCL were significantly positively correlated, which indicates that PPM rises as the SCL increases—which is expected, as a skin conductance response is defined by a sudden increase in SCL (Boucsein, 2012). Temperature was positively correlated to PPM, and movement was positively correlated to SCL and HR. Furthermore, aggression that went beyond exclusively verbal aggression was positively correlated to PPM, temperature, and the PCL-R score.

In Figures 1–3, the gray square lines represent the observed means, while the black diamond lines represent the means as estimated from the best fitting regression models in the development of the number of PPMs, SCL, and the HR preceding aggressive incidents, compared to the means found for these parameters on nonaggressive control periods. On the horizontal axis, the 5-min epochs before aggression was observed are depicted. Note that the PPM, the SCL, and the HR show a consistent rise on average preceding the aggressive behavior from 20 min before aggression was reported. The rise (note that this is a difference score) in the SCL in the 5 min before aggressive behavior became manifest was 1.15 µSiemens on average (see Figure 2). Considering that the mean difference score was 0.45 µSiemens (Table 3) and the overall mean was 1.63 µSiemens (Table 1), this increase in the SCL seems substantial. The HR increased over the 20 min preceding aggression with an average total of about six beats per minute in the epoch prior to the aggressive behavior (Figure 3).

As mentioned before, in the multilevel analyses, the person level models did not substantially add explained variance, and therefore the incidents were considered as the highest level. Separate models for the average PPM, the average SCL, and average HR were fitted. The models under the <25% artifact thresholds for PPM, SCL, and HR are presented in Table 4. The best fitting models were selected on the basis of the Akaike information criterion (AIC) indices as not all models were nested, and hence we could not rely on the deviance test only. For all three physiological markers, we started out by fitting a random intercept model (i.e., a model without predictors). Next, a linear effect of time was added, together with multiple polynomials, as the shape of the trajectory of change in the physiological parameters toward aggressive incidents was unknown. Figures 2 and 3 depict the models with a linear increase across time for SCL (Model 4) and HR (Model 5) that provided the best fit for these variables. The best fitting model for PPM was a model with a quadratic function of time where a decrease in PPM is followed by an increase (Model 4) for the entire half hour preceding aggressive behavior.

Temperature and movement were expected to have an influence on the physiological measures, and thus these effects were considered as time-varying predictors in the third model. Movement turned out to be a significant predictor only for the HR marker but not for PPM and SCL. Both a random intercept and random slopes with an autocorrelation covariance structure for all markers were tested (ARH [Autoregressive] covariance, as we expected the points in time that are nearer to each other to be more correlated). For both PPM and SCL, this improved the model but not for HR. Finally, the residuals were tested at each level for normality; only for SCL were the

TABLE 2 Number of available participants, incidents, and epochs

Artifact threshold level	25%	50%	75%
No. of available participants	32	32	33
No. of available incidents	66	77	78
No. of available epochs	285	367	421

TABLE 3 Correlations, intraclass correlations (ICC), and descriptive statistics of study variables

	Gender	PPM	SCL	HR	Temperature	Movement	PCL-R	ICC	*M*	*SD*
PPM	−0.05							0.48	0.15	1.54
SCL	−0.05	0.51**						0.88	0.45	2.85
HR	0.06	0.06	−0.07					0.37	2.17	13.49
Temperature	−0.16*	0.18**	−0.05	−0.02				0.92	0.11	4.16
Movement	−0.10	0.07	0.14*	0.17**	0.01			0.49	0.15	1.86
PCL-R	−0.08	0.03	0.04	0.06	0.10	−0.10			13.61	5.77
Aggression (dummy, 0 = verbal, 1 = other)	−0.08	0.21**	0.05	−0.08	0.19**	0.02	0.26**		0.37	0.48

Note: PCL-R, Psychopathy Checklist–Revised; PPM, peaks per minute; SCL, skin conductance level; HR, heart rate; *M*, mean; *SD*, standard deviation. $N = 285$ epochs.

*Correlation is significant at the 0.05 level (two-tailed); **Correlation is significant at the 0.01 level (two-tailed).

TABLE 4 Fitted models at the <25% threshold level for PPM, SCL, and HR

	Model 1: Random intercept		Model 2: Random intercept with linear effect of time		Model 3: Incident level predictors		Model 4: Random slope for time (ARH covariance)		Model 2a: Random intercept with linear and quadratic effect of time	
PPM	**Parameter**	***SE***	**Parameter**	***SE***	**Parameter**	***SE***	**Parameter**	***SE***	**Parameter**	***SE***
Fixed										
Mean/intercept	0.23	0.16	0.30	0.19	0.48*	0.22	0.49	0.26	0.49*	0.21
Time			0.03	0.04	0.35*	0.15	0.30*	0.14	0.31*	0.15
Quadratic time					0.07*	0.03	0.05*	0.03	0.06*	0.03
Temperature					0.04	0.04				
Movement					0.09	0.05				
Random										
VAR(e(ij))	1.34	0.13	1.34	0.13	1.27	0.13	0.97	0.11	1.32	0.13
VAR(u(0j))	1.25	0.30	1.24	0.30	1.20	0.31	2.63	0.70	1.22	0.30
VAR(u(1j))							0.22	0.14		
COVAR							0.00	0.00		
ARH var							0.80	0.10		

	Model 1: Random intercept		Model 2: Random intercept with linear effect of time		Model 3 Incident level predictors		Model 4: Random slope for time (ARH covariance)	
SCL	**Parameter**	***SE***	**Parameter**	***SE***	**Parameter**	***SE***	**Parameter**	***SE***
Fixed								
Mean/intercept	0.91*	0.41	1.23**	0.43	1.26**	0.46	1.27*	0.48
Time			0.13**	0.05	0.14**	0.05	0.15*	0.06
Temperature					0.01	0.07		
Movement					−0.01	0.06		
Random								
VAR(e(ij))	1.57	0.15	1.51	0.15	1.63	0.16	1.22	0.14
VAR(u(0j))	10.71	2.00	10.76	2.00	11.60	2.26	13.52	2.91
VAR(u(1j))							0.11	0.05
COVAR								
ARH var							0.60	0.19

(Continues)

TABLE 4 (Continued)

HR	Model 1: Random intercept		Model 2: Random intercept with linear effect of time		Model 3: Incident level predictors		Model 4: Random slope for time (ARH covariance)		Model 5 with fixed movement	
	Parameter	*SE*	Parameter	*SE*	Parameter	*SE*	Parameter	*SE*	Parameter	*SE*
Fixed										
Mean/intercept	2.12	1.37	4.55*	1.73	4.52*	1.81	4.18*	1.59	4.13*	1.70
Time			0.99*	0.43	0.94*	0.45	0.95*	0.44	0.96*	0.43
Temperature					0.05	0.33				
Movement					1.07*	0.52	1.15*	0.51	1.22*	0.51
Random										
VAR(e(ij))	124.62	13.32	121.32	12.95	120.76	13.64	118.80	14.26	119.58	12.80
VAR(u(0j))	71.63	23.15	72.26	22.99	70.22	24.16	48.51	33.08	67.54	22.01
VAR(u(1j))							0.43	1.97		
COVAR										
ARH var							−0.69	2.80		

Note: $N = 285$.

*Effect is significant at the 0.05 level (two-tailed); **Effect is significant at the 0.01 level (two-tailed).

residuals not normally distributed, and therefore the results must be interpreted with caution (Maas & Hox, 2004). The best fitting models are presented in Figures 1–3 for the three physiological parameters by the black diamond lines.

4 | DISCUSSION

Support for our hypothesis that EDA, both in terms of the PPM and the SCL (Kuijpers et al., 2012; Nijman et al., 2014) as well as HR, would increase preceding aggressive incidents comes from both the fitted multilevel models and visual inspection of the observed means. The graphs of the observed means indicate that the increases take place from about 20 min before aggressive behavior is observed by staff members. These findings are promising in the sense that methods may be developed with which possible aggressive behavior may be prevented and the potential negative consequences of aggressive behavior could be limited. Such prediction methods may give nursing staff a warning signal that a patient is getting more aroused and that the likelihood of aggressive behavior is increasing. As far as we know, this is the first large-scale naturalistic study that shows that increases of EDA and HR precede the overt behavioral manifestations of aggressive behavior of forensic psychiatric patients, controlling for within-subject variation.

Psychopathy was not a predictor of HR or EDA in any of the fitted models (Hare & Neumann, 2009; Lorber, 2004; Ortiz & Raine, 2004). A possible reason for this nonexpected finding is the use of patient files. Normally, psychopathy scores are calculated based on an entire interview and are preferably scored by two trained professionals (Hildebrand et al., 2004), which was not feasible in our study. A second reason for the nonfinding is the level of psychopathy in our sample. Only six participants met the European criteria for psychopathy (≥26; Hildebrand et al., 2004), although this conclusion should be considered with care as the PCL-R was scored by only one professional. Also, adding the person level variables did not explain any variance. This might be due to a low number of incidents within a person or due to a small sample size (Hox et al., 2017).

One of the strengths of the current study is that we were able to control and standardize for both individual baseline and time-of-day effects, as this was a limitation in a recent study (Nijman et al., 2014). Time-of-day effects might be of influence due to fixed day schedules or circadian rhythms of the individuals. We could have opted for including a prestimulus baseline by including a seventh epoch (minute 30–35 preceding aggressive behavior), which would have resulted in standardization of individual baseline but not for time-of-day effects. This was important, as EDA in general tends to increase during the day (e.g., as a result of becoming tired or stressed) and because people have different baseline values for the physiological parameters that were studied (Boucsein, 2012; Kamath, Watanabe, & Upton, 2016). In addition, we were also able to correct our models for movement and temperature, which is known to increase HR and EDA (Garbarino et al., 2014; Kreibig, 2010).

There are a number of other limitations of the current study that need to be addressed. First, we had substantial data loss for varying reasons. For instance, of the original 101 aggressive incidents, only 66 were included in the final analysis (<25%) due to artifacts, lack of comparison slopes, or sensor failure. The high number of artifacts in the data poses a threat to the amount of data that can be used (Taylor et al., 2015). Therefore, further methods have to be developed aiming at increasing the reliability and validity of the physiological assessments in real-life situations. Second, the form of aggressive behavior often concerned exclusively verbal aggression and, to a lesser extent, physical aggression, as was expected (Nijman et al., 2005). We were unable to investigate the effect of more detrimental and presumably more arousing incidents involving physical aggression due to a lack of enough such incidents. In the current study, no inclusion criterion on the historical number and type of aggressive behavior of the included patients was determined. In future studies, it may be preferable to investigate more aggression-prone, high-risk patients, as this might increase the risk for physical aggression. However, it is worth noting that, even with a high number of verbal aggressive incidents, we found rising levels of physiological parameters toward aggressive behavior.

Third, the level of aggregation was set a priori. The data were analyzed by aggregating 5-min epochs, which already is a narrower time interval than previous studies (Kuijpers et al., 2012; Melander, Martinsson, & Gustafsson, 2017; Nijman et al., 2014; Noordzij et al., 2012). For future studies, it may be interesting to add every minute to the equation. This could be especially important for trying to devise real-time aggression monitoring algorithms.

Fourth, the staff members that scored the aggressive incidents had a watch with which they could time stamp the moment of aggression. However, it would be even better if we had visual or audio data on the aggressive incidents as to increase the validity of the scoring, although the collection of such data does raise ethical problems.

Fifth, the power analysis that was conducted before the study indicated that we needed 61 participants; although 100 patients were included in the study, we have only 36 patients that displayed aggressive behavior during the study. Therefore, the current study might be underpowered, and the results have to be interpreted with care. We need larger sample sizes to replicate the current results and be able to find effects of time and other predictor variables with higher probability.

Finally, we are aware that the choices that we made influenced the fitted models. We tried to be as rigorous as possible, but we could have made other choices. Our results, for instance, show that the chosen level of artifact correction influences the fitted models. However, when we repeated the analyses using more lenient artifact rejection thresholds (data not shown), the direction of the associations remained relatively stable, albeit not all significant. This suggests that even data with an extensive amount of artifacts could be useful to obtain estimates, but further investigation is warranted.

The results of the current study indicate that there are significant rises in the physiological parameters preceding aggressive behavior, controlling for within-subject variation. The current results are promising for early detection and prevention of aggression and improving both staff as well as patient safety in psychiatric mental health institutions. However, larger sample sizes are necessary to replicate the current study results and deploy multilevel modeling and machine learning to increase the accuracy of the predictions.

ACKNOWLEDGMENTS

This research was funded by a grant from De Borg and DForZo (Directie Forensische Zorg). De Borg is a collaboration of four mental health organizations for the clinical treatment of people with behavioral and mental disorders and mild intellectual disabilities or borderline intellectual functioning. DForZo is part of DJI (Dienst Justitiele Inrichtingen) and is responsible for executing detention sentences on people that are sentenced by the justice system. The authors have no conflict of interest to declare. We would like to thank Simone Vreeke, Maarten Regenboog, Jessie Veenhoven, Isabel Marrozos, Dave Gerritsen, and Ellis Steffens for their help in collecting the data.

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How to cite this article: de Looff P, Noordzij ML, Moerbeek M, Nijman H, Didden R, Embregts P. Changes in heart rate and skin conductance in the 30 min preceding aggressive behavior. *Psychophysiology*. 2019;56:e13420. https://doi.org/10.1111/psyp.13420