Can Passive Measurement of Physiological Distress Help Better Predict Suicidal Thinking?

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Abstract

There has been growing interest in using wearable physiological monitors to passively detect the signals of distress (i.e., increases in autonomic arousal measured through increased electrodermal activity [EDA]) that may be imminently associated with suicidal thoughts. Before using these monitors in advanced applications such as creating suicide risk detection algorithms or just-in-time interventions, several preliminary questions must be answered. Specifically, we lack information about whether: (1) EDA concurrently and prospectively predicts suicidal thinking and (2) data on EDA adds to the ability to predict the presence and severity of suicidal thinking over and above self-reports of emotional distress. Participants ($n=25$, 56% female, M age= 33.48 years) completed six daily assessments of negative affect and suicidal thinking duration of their psychiatric inpatient stay and 28 days post-discharge, and wore on their wrist a physiological monitor (Empatica Embrace) that passively detects autonomic activity. We found that physiological data alone both concurrently and prospectively predicted periods of suicidal thinking, but models with physiological data alone had the poorest fit. Adding physiological data to self-report models improved fit when the outcome variable was severity of suicidal thinking, but worsened model fit when the outcome was presence of suicidal thinking. When predicting severity of suicidal thinking, physiological data improved model fit more for models with non-overlapping self-report data (i.e., low arousal negative affect) than for overlapping self-report data (i.e., high arousal negative affect). These findings suggest that physiological data, under certain contexts, may be useful in better predicting – and ultimately, preventing – acute increases in suicide risk. However, some cautious optimism is warranted since physiological data do not always improve our ability to predict suicidal thinking

Introduction

In recent years, wearable devices that measure physiological signals once only detectable with laboratory equipment have become increasingly more available, useable, and affordable. This has led to increased interest in using such devices to study psychological constructs of interest in the real world, such as detecting signals of distress that may predict the onset of suicidal thoughts.^{1–3} Periods of suicidal thinking can occur rapidly and be highly distressing,^{4–6} possibly escalating quickly to a level that interferes with the cognitive resources needed to ask for help or use skills learned in therapy. If a wearable monitor could passively detect this distressing state, it would provide opportunities for the deployment of *just-in-time* adaptive interventions.⁷

There is a long history of laboratory research supporting the promise of passively detecting distress that may characterize or precede periods of suicide risk. The psychological experience of distress is reliably associated with sympathetic autonomic activity. This activity can be indirectly detected by observing the small increases in perspiration that occur during an autonomic event.^{8,9} Because sweat is a good conductor of electricity, changes in skin conductance (also called electrodermal activity; EDA)¹⁰ signal when an individual is distressed. Increases in EDA are associated with laboratory-induced distress in the

form of social comparison⁹ or watching a disturbing film.¹¹ Individuals at risk for suicide exhibit increased physiological reactivity to stress (i.e., increased skin conductance)¹² and this reactivity distinguishes those who are suicidal from those who are depressed but not suicidal (for review see Sarchiapone et al.¹³). This aligns with clinical observation and increasing empirical findings that periods of high suicide risk tend to be characterized by the high arousal affective states (e.g., agitation¹⁴) that are potentially most easily detectable by monitoring autonomic activity.

Although there is optimism about the possibility of using wearable monitors to identify those at (and periods of) risk for suicidal thoughts, there are important questions that must be answered about the predictive ability of autonomic arousal before developing interventions that rely on wearable passive sensing. The goal of this study is to begin answering these questions.

Is passively detected distress associated with periods of suicidal thinking?

It is currently unknown whether passively detected distress (i.e., increased EDA) measured with a wearable device is associated (either concurrently or prospectively) with periods of suicidal thinking. Importantly, what is found in a controlled laboratory environment – the settings used for the vast majority of such studies to date – may not be as clear in the uncontrolled environment of everyday life. For example, changes in temperature, exercise, being in a hot room, and wearing the device incorrectly can all contribute to noise and may do so to the point of degrading the validity of physiological data. Thus, even though wearable devices are becoming cheaper and easier to use, the technology is still prohibitively expensive to deploy on a large scale based on laboratory research alone. Consequently, it is important to establish whether physiological signals of distress as measured with wearable devices are associated with periods (hours and days) of suicidal thinking.

Does passively detected distress add to our ability to predict periods of suicidal thinking over and above self-reports of affect?

The “gold standard” for assessing elevations in distress associated with suicide risk involves technology like smartphone-based ecological momentary assessment (EMA) which captures self-reported affective experiences and suicidal thinking in the moment throughout the day.¹⁵ In most initial cases, wearables will not be used as a stand-alone method of detecting risk but will rather be paired with the current “gold standard” of EMA. One key step is to see whether passive detection of distress improves the concurrent and prospective prediction of periods (i.e., hours and days) of suicidal thinking beyond self-report alone. This is important from a scalability perspective because it is still cheaper and easier to deploy monitoring solutions that rely solely on self-report (though certainly, self-report monitoring may require more active engagement for patients/participants). If wearable devices do not add to what self-report can tell us, it may suggest decreased utility of using wearables when self-report is available, and participants are willing/able to respond to these questions.

The present study

In this study, we were interested in (1) the contemporaneous and prospective associations between physiological assessments of distress (i.e., EDA) and self-reported suicidal thinking as well as (2) the incremental predictive validity of physiological assessment of distress above and beyond self-report, across both the presence/absence of suicidal thinking and the severity of suicidal thinking. Since we consider the aims and analyses in this paper to be exploratory, we have few specific hypotheses. Generally, however, we expected that if passively detected physiological distress adds to our ability to predict self-reported suicidal thinking, it would be most likely to do so in cases where the self-report items do not assess states known to be strongly correlated with these same physiological metrics. For example, increases in EDA are more strongly tied to high arousal, rather than low arousal, affect.^{16,17} When self-report items assess high arousal affect, this may contribute to overlap and therefore redundancy between the self-report ratings and the physiological data. Thus, we expect passively-detected distress to improve the characterization and prediction of suicidal thinking when combined with assessments of low arousal versus high arousal affective states.

Methods

Participants

Participants were recruited from an inpatient psychiatry service from July 2019 until March 2020 at Massachusetts General Hospital as part of an IRB-approved registered clinical trial (NCT03950765) testing a novel smartphone intervention. The sample consisted of 25 adults (56% female; 44% male. *M* age = 33.48 years, *SD*=13.84 years, 19–63). The sample was 64% White, 20% Asian, 8% Black/African American, and the remaining 8% were of other or multiple ethnicities. 16% were Hispanic or Latinx. Inclusion criteria were: (1) admission due to severe suicidal thinking or a suicide attempt, (2) access to a smartphone, (3) willingness to wear the physiological monitor, and (4) absence of any factor that would preclude capacity to consent (e.g., acute psychosis, drug withdrawal), which was independently confirmed by clinical staff.

Procedures

Recruitment/consent/baseline. Eligible and interested participants provided informed consent and completed baseline measures assessing demographics, history of suicidal thoughts and behaviors, and other trait-level factors. We used only the demographic questionnaire from the baseline session in this study. Participants also were asked to install on their phone a set of apps that allowed us to send surveys and retrieve data from the wearable device.

Monitoring period. Throughout their inpatient stay and for 28 days afterwards, participants were asked to complete on their smartphone six brief surveys per day.^[i] The surveys were hosted on Qualtrics and delivered using LifeData.^[ii] The surveys were delivered at random times within pre-specified windows.^[iii] Participants also were asked to wear on their wrist the Empatica Embrace 2 (www.Empatica.com), a physiological monitoring device that assesses movement (via 3-axis accelerometer), orientation (via a

gyroscope), skin temperature, and electrodermal activity. It has been well-validated for its consumer use as an FDA-approved seizure detection device and uses similar technology and sensors as other validated^{18,19,20} research-grade wearables made by the same company.

Measures and feature creation

Affect. At each prompt, participants were presented with a list of affective state labels and a definition for each state. They were asked to rate each label in regard to the current moment on a 0 (not at all) to 10 (very much) scale. Relevant to this study were five specific negative affect states, categorized into high/low arousal based on the circumplex model of affect.^{21,22} There were three low-arousal negative affect states: (1) fatigued, (2) hopeless, and (3) burdensome and two high arousal negative affect states: (4) agitated and (5) angry.

Suicidal thinking. We used a three-item measure of suicidal thinking assessing (in the present moment) the strength of: (1) urge to die by suicide, (2) the intention to kill oneself at some point during the next day, and (3) the ability to resist the urge to die by suicide. All items were on a 0 (not at all) to 10 (very strong) scale. In line with prior EMA studies,⁵ we averaged these items to create a suicidal thinking composite with high internal consistency ($\alpha=.82$)[\[iv\]](#). The item assessing ability to resist the urge to die by suicide was reverse-coded.

Autonomic events. The Embrace records EDA at 4hz using three stainless steel electrodes mounted on the bottom of the watch case. Once these data are transferred to the server, a proprietary algorithm classifies autonomic events. Specifically, the algorithm identifies increases in skin conductance level (i.e., tonic EDA) that occur in the absence of increases in temperature and movement (since increases in temperature and movement could be signs that increased EDA is due to being in a hot room or physical activity). The algorithm removes any increase in EDA due to a potential “storm” of rapid EDA changes during sleep.^{24,25} Evaluation of this algorithm in 46 adults found high sensitivity (97%) and a low rate of false positives (0.83/day) (Matteo Migliorini, Ph.D., Empatica s.r.l., Email Communication, April 2021).

Data preparation

Physiological data were collected continuously, meaning that autonomic events could have been recorded at any time of the day. Self-report data were collected six times daily over a participant-defined 14-hour period (most participants chose a window that lasted from 9am-11pm). This means we would likely not have self-report data at or near the time of most autonomic events. To address this, we aggregated our data into two levels, hourly (i.e., within-day) and daily (i.e., between-day). Hourly data provide increased granularity and resolution (we can describe hours instead of days with suicidal thinking); however, only 26% of the autonomic events observed occurred within one hour of an EMA prompt. Daily data allowed us to use all available autonomic event data, although doing so meant that we lost some ability to determine the temporality of responses. To aggregate the data, we computed for each participant-hour[\[v\]](#) or participant-day an average of the affective states and suicidal thinking ratings

and a sum score for number of autonomic events. To adjust for between-person variability in response styles, we participant-mean centered all affective state ratings in the aggregated datasets.

Analytic strategy

Models. Because we were interested in the incremental predictive effects of physiological data over various configurations of self-report data, we tested models that included high or low arousal negative affect, with and without physiological data. We analyzed separate models with high and low arousal negative affect because doing so allowed us to test our specific hypotheses about physiological data improving the predictive ability of low arousal negative affect more than high arousal negative affect. We operationalized our outcome variable, suicidal thinking, in several ways. First, we were interested in both the presence (0, 1) and severity of suicidal thinking. Second, we were interested in both the contemporaneous (i.e., predictors and outcomes at the same timepoint) and prospective associations (i.e., suicidal thinking measured at the next assessment/day). Thus, we had four sets of analyses using combinations of binary vs. continuous data and contemporaneous vs. prospective associations. All models were multi-level models with either a normal distribution (models where severity of ideation was the dependent variable) or binomial distribution (models where presence/absence of ideation was the dependent variable) conducted in the *lme4*²⁶ R package with fixed slopes and participant-centered predictors.

Comparison. To compare models, we used metrics provided by the *performance*²⁷ package. This includes measures of relative (AIC and BIC) and absolute fit (R^2 and RMSE). In many cases, these metrics are aligned but not perfectly correlated. To reconcile potential differences in model fit ranking across metrics we used the *performance* package's performance score metric which produced a weighted average of all metrics, suitable for use as an overall summary metric of model performance.

(1) Akaike Information Criterion (AIC) and (2) Bayesian Information Criterion (BIC) balances fit (i.e., minimal prediction error) with parsimony (i.e., having the fewest possible predictors) by penalizing models that have so many predictors (AIC) or data points (BIC) as to risk being overfit to the data. *AIC* and *BIC* useful to determine which model, among a group of models fit to the same data, best fits the data. A model with a relatively lower *AIC/BIC* value is better fitting than a model with a higher *AIC/BIC* value.

(3) Bayes Factor (BF) compares a set of models to a comparator. Scores of >1 indicate a model with more support than the comparison model.

(4) Marginal and conditional R^2 reflect proportion of variability in the dependent variable accounted for by the independent variables(s). Marginal R^2 considers only the effect of the fixed effects in a multi-level model. Conditional R^2 includes random effects (in this case, the difference in between-person intercepts).

(5) Root Mean Squared Error (RMSE) refers to the standard deviation of the error (i.e., deviation between observed and predicted values). Lower values indicate better fit (i.e., less error) and are in the same scale

as the dependent variable.

(6) Performance score is used to rank the performance of multiple models that takes into account multiple metrics that may not always converge on the same “best” fitting model. It is calculated by rescaling all of the other indices mentioned above from 0 to 1 and then taking the mean across all indices for each model. Thus, scores can range from 0% (all indices point to this model being the worst fitting) to 100% (all indices point to this model being the best fitting).

Results

There were 2,427 survey responses across 604 days ($M=24.16$ days, $SD=11.74$, range=3–44, compliance rate=66.98%). 1,739 autonomic events were recorded, 453 of which (26%) occurred within an hour of an EMA survey prompt.^[i]

Daily-level models

Presence/absence of suicidal thinking. The first section of **Table 1** shows contemporaneous (i.e., same day) models and the second of **Table 1** section shows prospective (i.e., next day) models using presence/absence of suicidal thinking as the outcome.. Both sets of models had the same interpretation. The models including autonomic events consistently performed poorer than the corresponding models that did not include autonomic events. See sections 1 and 2 of **Supplementary Table 1** for the individual regression results.

Severity of suicidal thinking. The third section of **Table 1** shows contemporaneous (i.e., same day) models and the forth section of **Table 1** shows prospective (i.e., next day) models using severity of suicidal thinking as the outcome. Across all models, adding autonomic events improved model fit and supported our hypothesis regarding greater relative improvements for low versus high arousal negative affect: the improvement in performance score was greater when adding autonomic events to low-arousal negative affect than it was for high arousal negative affect (contemporaneous: 24.95% improvement vs. 5.35% improvement [low vs. high, respectively], prospective: 31.90% vs. 10.25%). See sections 2 and 3 of **Supplementary Table 1** for the individual regression results.

Hourly-level models

Presence/absence of suicidal thinking. The first section of **Table 2** section shows contemporaneous (i.e., same hour) models and the second section of **Table 2** shows prospective (i.e., next hour) models using presence/absence of suicidal thinking as the outcome. Both sets of models had the same interpretation: autonomic events did not improve the fit of low arousal negative affect. Autonomic events marginally (performance score improved by 0.48%) improved the fit of contemporaneous model with high arousal negative affect. See sections 1 and 2 of **Supplementary Table 2** for individual regression results.

Severity of suicidal thinking. The third section of **Table 2** shows contemporaneous (i.e., same hour) models and the forth section of **Table 2** shows prospective (i.e., next hour) models using severity of suicidal thinking as the outcome. With only one exception, adding autonomic events improved model fit. The only exception was in the prospective models, adding autonomic events worsened model fit for the model with high arousal negative affect (25.05% poorer performance). There were mixed findings regarding our hypothesis around greater relative improvements for low vs. high arousal negative affect. Contrary to our hypothesis, adding autonomic events to the contemporaneous models improved the model with high arousal (22.92% improvement) more than the model with low arousal (16.97% improvement). In line with our hypothesis (albeit weakly) adding autonomic events data only slightly improved the prospective model with low arousal negative affect, though only slightly (2.74% improvement). See sections 2 and 3 of **Supplementary Table 2** for individual regression results.

Discussion

The study yielded several key findings. First, variability in autonomic arousal (in the form of EDA, used to identify autonomic events) was associated with periods of suicidal thinking. Second, models with *only* physiological data, however, were generally weaker than models with *only* self-report data. This may be expected given the shared method of assessment (self-report EMA) for the affective states and suicidal thinking outcomes. Third, physiological data generally added to the ability of self-report data to predict the *severity* but not the *occurrence* of suicidal thinking. It is unclear why physiological data would improve prediction of severity but not occurrence. One possible explanation may be that suicidal thoughts come and go involuntarily throughout the day (for those who have such thoughts), but when people are distressed and in a high-arousal state, those thoughts become more severe (and possibly more persistent, although we did not test that in this study). Fourth, when predicting severity of suicidal thinking, physiological data generally improved model fit more for models with less conceptually overlapping self-report data (i.e., low arousal negative affect) than for overlapping self-report data (i.e., high arousal negative affect).

Taken together, our findings suggest that physiological data are most useful in detecting severity (but not presence) of suicidal thinking when paired with self-report data. However, there are some cases where physiological data may be useful in isolation. For example, because almost 75% of the autonomic events in this study occurred outside of a time when we had self-report data, wearable devices may be particularly useful to identify periods of risk that are not otherwise captured by self-report, which can be cumbersome to complete many times per day.

Although these findings are promising for our ability to improve the prediction of severity of suicidal thinking, several challenges remain. First, our conceptualization of autonomic events used a proprietary algorithm that has only been validated in one internal study by the device manufacturer. Thus, our study was testing the validity of the algorithm to detect autonomic events just as much as it was testing the construct of autonomic arousal, although findings appear positive for both. Second, increased autonomic arousal is not an exclusive indicator of psychological distress. Autonomic arousal is non-specific to the

valence of emotion. Consequently, increased autonomic activity could also be an indication of emotion like surprise and excitement. Third, physical activity or heat also increase EDA in similar ways to the increases associated with autonomic arousal. To address both the second and third issue, work is needed to further refine the algorithm used to detect distress. Work by Wilhelm et al.²⁸ incorporates multiple data streams (e.g., accelerometer, EDA) to determine whether an increase in skin conductance is due to physiological arousal or a factor like excess movement. Finally, although we had a large number of observations per person, we had a relatively small number of participants. Future studies should replicate these initial findings in samples with more participants.

In sum, the findings here show that autonomic arousal is a potentially useful data stream to aid in the prediction of severity of suicidal thinking. These data are less useful when predicting the presence of suicidal thinking. Being able to detect the severity of distress and suicidal thinking could enable us to deliver assistance in real-time when it is needed most. This may be a useful framework for knowing which intervention to deliver at which times, for example delivering a less cognitively-taxing intervention during times of higher distress.

Declarations

Conflict of Interest Statement

There are no potential conflicts of interest to disclose.

References

1. Kessler RC. Clinical Epidemiological Research on Suicide-Related Behaviors—Where We Are and Where We Need to Go. *JAMA Psychiatry*. 2019;76(8):777-778. doi:10.1001/jamapsychiatry.2019.1238
2. Stanley B, Mann JJ. The Need for Innovation in Health Care Systems to Improve Suicide Prevention. *JAMA Psychiatry*. 2020;77(1):96-98. doi:10.1001/jamapsychiatry.2019.2769
3. Kleiman EM, Glenn CR, Liu RT. Real-time monitoring of suicide risk among adolescents: Potential barriers, possible solutions, and future directions. *J Clin Child Adolesc Psychol*. 2019;48(6):934-946. doi:10.1080/15374416.2019.1666400
4. Hallensleben N, Spangenberg L, Forkmann T, et al. Investigating the dynamics of suicidal ideation: preliminary findings from a study using ecological momentary assessments in psychiatric inpatients. *Crisis*. 2017;39(1):65-69. doi:10.1027/0227-5910/a000464
5. Kleiman EM, Turner BJ, Fedor S, Beale EE, Huffman JC, Nock MK. Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. *J Abnorm Psychol*. 2017;126(6):726-738. doi:10.1037/abn0000273

6. Czyz EK, Horwitz AG, Arango A, King CA. Short-term change and prediction of suicidal ideation among adolescents: a daily diary study following psychiatric hospitalization. *J Child Psychol Psychiatry*. 2019;60(7):732-741. doi:10.1111/jcpp.12974
7. Nahum-Shani I, Smith SN, Spring BJ, et al. Just-in-Time Adaptive Interventions (JITIs) in Mobile Health: Key components and design principles for ongoing health behavior support. *Ann Behav Med*. 2018;52(6):446-462. doi:10.1007/s12160-016-9830-8
8. van Dooren M, de Vries JJG (Gert-J, Janssen JH. Emotional sweating across the body: Comparing 16 different skin conductance measurement locations. *Physiol Behav*. 2012;106(2):298-304. doi:10.1016/j.physbeh.2012.01.020
9. Kilpatrick DG. Differential Responsiveness of Two Electrodermal Indices to Psychological Stress and Performance of a Complex Cognitive Task. *Psychophysiology*. 1972;9(2):218-226. doi:10.1111/j.1469-8986.1972.tb00756.x
10. Critchley HD. Electrodermal responses: what happens in the brain. *Neurosci Rev J Bringing Neurobiol Neurol Psychiatry*. 2002;8(2):132-142.
11. Lazarus RS, Speisman JC, Mordkoff AM, Davison LA. A laboratory study of psychological stress produced by a motion picture film. *Psychol Monogr Gen Appl*. 1962;76(34):1-35. doi:10.1037/h0093861
12. Nock MK, Mendes WB. Physiological arousal, distress tolerance, and social problem-solving deficits among adolescent self-injurers. *J Consult Clin Psychol*. 2008;76(1):28-38. doi:10.1037/0022-006X.76.1.28
13. Sarchiapone M, Gramaglia C, Iosue M, et al. The association between electrodermal activity (EDA), depression and suicidal behaviour: A systematic review and narrative synthesis. *BMC Psychiatry*. 2018;18(1):22. doi:10.1186/s12888-017-1551-4
14. Rogers ML, Ringer FB, Joiner TE. A meta-analytic review of the association between agitation and suicide attempts. *Clin Psychol Rev*. 2016;48:1-6. doi:10.1016/j.cpr.2016.06.002
15. Kleiman EM, Nock MK. Real-time assessment of suicidal thoughts and behaviors. *Curr Opin Psychol*. 2018;22:33-37. doi:10.1016/j.copsyc.2017.07.026
16. Erwin RJ, McClanahan BA, Kleinman KM. Effects of level of arousal and type of task on bilateral skin conductance asymmetry and conjugate lateral eye movements. *Pavlov J Biol Sci*. 1980;15(2):59-67. doi:10.1007/BF03003684
17. Bradley MM, Codispoti M, Cuthbert BN, Lang PJ. Emotion and motivation I: Defensive and appetitive reactions in picture processing. *Emotion*. 2001;1(3):276-298.

18. McCarthy C, Pradhan N, Redpath C, Adler A. Validation of the Empatica E4 wristband. In: *2016 IEEE EMBS International Student Conference (ISC)*. ; 2016:1-4. doi:10.1109/EMBSISC.2016.7508621
19. Regalia G, Onorati F, Lai M, Caborni C, Picard RW. Multimodal wrist-worn devices for seizure detection and advancing research: Focus on the Empatica wristbands. *Epilepsy Res.* 2019;153:79-82. doi:10.1016/j.eplepsyres.2019.02.007
20. Gouverneur P, Jaworek-Korjakowska J, Köping L, Shirahama K, Kleczek P, Grzegorzec M. Classification of Physiological Data for Emotion Recognition. In: Rutkowski L, Korytkowski M, Scherer R, Tadeusiewicz R, Zadeh LA, Zurada JM, eds. *Artificial Intelligence and Soft Computing*. Lecture Notes in Computer Science. Springer International Publishing; 2017:619-627. doi:10.1007/978-3-319-59063-9_55
21. Russell JA. A circumplex model of affect. *J Pers Soc Psychol.* 1980;39(6):1161-1178. doi:10.1037/h0077714
22. Watson D, Tellegen A. Toward a consensual structure of mood. *Psychol Bull.* 1985;98(2):219-235. doi:10.1037/0033-2909.98.2.219
23. Nezlek JB. A practical guide to understanding reliability in studies of within-person variability. *J Res Personal.* 2017;69:149-155. doi:10.1016/j.jrp.2016.06.020
24. Regalia G, Gerboni G, Migliorini M, et al. Sleep assessment by means of a wrist actigraphy-based algorithm: agreement with polysomnography in an ambulatory study on older adults. *Chronobiol Int.* 2021;38(3):400-414. doi:10.1080/07420528.2020.1835942
25. Sano A, Picard RW, Stickgold R. Quantitative analysis of wrist electrodermal activity during sleep. *Int J Psychophysiol Off J Int Organ Psychophysiol.* 2014;94(3):382-389. doi:10.1016/j.ijpsycho.2014.09.011
26. Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. *J Stat Softw.* 2015;67(1):1-48. doi:10.18637/jss.v067.i01
27. Lüdtke D, Makowski D, Waggoner P. *Performance: Assessment of Regression Models Performance*; 2019. <https://CRAN.R-project.org/package=performance>
28. Wilhelm FH, Pfaltz MC, Grossman P, Roth WT. Distinguishing emotional from physical activation in ambulatory psychophysiological monitoring. *Biomed Sci Instrum.* 2006;42:458-463.

Tables

Table 1. Model information and model comparison statistics for daily-level data, ordered by performance

1. Presence/Absence of SI, Contemporaneous Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
Low arousal neg. affective states	237.58	259.43	1023.02	.96	0.02	0.50	99.95%
Low arousal neg. affect + autonomic events	239.40	265.62	46.25	.96	0.02	0.50	77.45%
High arousal neg. affective states	255.81	273.29	1.00	.94	0.02	0.54	38.24%
High arousal neg. affect + autonomic events	257.33	279.18	0.05	.93	0.02	0.54	32.59%
Autonomic events only	264.72	277.83	0.10	.91	0.00	0.56	1.14%

1. Presence/Absence of SI, Prospective Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
Low arousal neg. affective states	223.43	244.54	9470.50	.93	0.01	0.53	99.50%
Low arousal neg. affect + autonomic events	225.23	250.56	4493.17	.93	0.01	0.52	79.97%
High arousal neg. affective states	231.72	248.61	1.00	.92	0.00	0.54	29.99%
High arousal neg. affect + autonomic events	233.59	254.70	0.09	.92	0.01	0.54	27.90%
Autonomic events only	234.55	247.22	0.14	.91	0.00	0.55	0.72%

1. Severity of SI, Contemporaneous Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
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Low arousal neg. affect + autonomic events	2473.50	2504.09	564.49	.82	.06	1.75	100.00%
Low arousal neg. affective states	2482.48	2508.70	56.28	.81	.05	1.78	75.05%
High arousal neg. affect + autonomic	2492.53	2518.75	0.37	.81	.05	1.79	69.59 %
High arousal neg. affective states	2494.91	2516.76	1.00	.80	.05	1.81	64.24%
Autonomic events only	2598.69	2616.17	0.00	.76	.01	1.99	0.00%

1. Severity of SI, Prospective Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
Low arousal neg. affect + autonomic events	2059.58	2089.13	89.90	.83	.04	1.59	100.00%
Low arousal neg. affective states	2067.96	2093.29	11.24	.81	.03	1.62	68.10%
High arousal neg. affect + autonomic	2074.14	2099.47	0.51	.82	.03	1.63	64.58%
High arousal neg. affective states	2077.02	2098.13	1.00	.81	.03	1.65	54.33%
Autonomic events only	2126.35	2143.24	0.00	.79	.01	1.74	0.00%

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, RMSE = Root Mean Squared Error. Bayes factor reference model was the model with high-arousal negative affect states.

Table 2. Model information and model comparison statistics for hourly-level data, ordered by performance

1. Presence/Absence of SI, Contemporaneous Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
Low arousal neg. affective states	904.73	933.39	8.66x10 ¹⁴	0.94	0.02	0.59	99.73%
Low arousal neg. affect + autonomic events	905.20	939.59	3.89 x10 ¹³	0.94	0.02	0.59	83.02%
High arousal neg. affect + autonomic events	978.05	1006.71	0.10	0.92	0.01	0.62	31.50%
High arousal neg. affective states	979.25	1002.18	1.00	0.92	0.01	0.62	31.02%
Autonomic events only	1028.19	1045.39	0.00	0.92	0.00	0.64	0.00%

1. Presence/Absence of SI, Prospective Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
Low arousal neg. affective states	255.60	277.20	0.15	.95	.00	0.55	73.85%
High arousal neg. affective states	256.12	273.40	1.00	.95	.00	0.55	56.78%
Low arousal neg. affect + autonomic events	257.28	283.20	0.01	.95	.00	0.55	54.21%
Autonomic events only	256.91	269.87	5.82	.94	.00	0.56	40.80%
High arousal neg. affect + autonomic events	257.98	279.58	0.05	.95	.00	0.55	32.64%

1. Severity of SI, Contemporaneous Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
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High arousal neg. affect + autonomic events	9506.82	9541.21	59.13	.80	.02	1.87	97.00%
Low arousal neg. affect + autonomic events	9502.15	9542.27	34.69	.81	.02	1.86	93.02%
Low arousal neg. affective states	9490.10	9524.47	0.23	.81	.02	1.87	76.05%
High arousal neg. affective states	9493.14	9521.79	1.00	.80	.02	1.87	74.08%
Autonomic events only	9679.81	9702.73	0.00	.79	.00	1.96	0.00%

1. Severity of SI, Prospective Analyses

Model	AIC	BIC	Bayes Factor	Cond. R ²	Marg. R ²	RMSE	Performance Score
High arousal neg. affective states	9520.71	9549.37	1.00	.80	.02	1.88	86.05%
High arousal neg. affect + autonomic events	9509.93	9544.32	0.07	.80	.02	1.87	61.00%
Low arousal neg. affect + autonomic events	9504.52	9544.65	0.01	.81	.02	1.86	59.40%
Low arousal neg. affective states	9517.92	9552.31	0.05	.80	.02	1.87	56.66%
Autonomic events only	9715.51	9738.44	0.52	.78	.00	1.96	22.99%

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, RMSE = Root Mean Squared Error. Bayes factor reference model was model with all self-report included

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AutonomicEventsSupplementalTables.docx](#)