Adaptive thresholding increases ability to detect changes in rate of skin conductance responses to
psychologically arousing stimuli

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Abstract

Psychophysicologists often record electrodermal activity (EDA) exosomatically to derive measures of slow, tonic activity—skin conductance level (SCL)—and faster, more punctate changes—skin conductance responses (SCRs). An SCR is considered relevant when its amplitude exceeds a researcher-determined threshold (e.g., 0.05 μ S), typically fixed across study participants and conditions. However, fixed SCR thresholds may detect more SCRs in samples with higher SCL because the number and amplitude of SCRs correlate positively with SCL. To address this issue, we developed a novel *fixed plus adaptive (FA)* thresholding method that adjusts SCR detection as a function of the prevailing SCL. We hypothesized greater statistical power to detect a difference in the rate of SCRs across high vs. low arousal stimuli using FA thresholding compared to fixed thresholding. Study 1 consisted of 254 young adults measured in a laboratory using wired EDA sensors during exposure to evocative images and sounds. Study 1 constituted our exploratory dataset, wherein we found an optimal FA threshold of 1.9% that maximized the ability to detect a difference in SCR rate between high vs. low arousal stimuli. Study 2 involved 20 children with autism repeatedly measured in a clinic using wireless EDA sensors during several behavioral tasks. Study 2 constituted our validation dataset, wherein FA thresholding at 1.9% increased statistical power to detect a difference in SCR rate between high vs. low arousal tasks, compared to fixed thresholding at 0.05 μ S. Future research should test for reproducibility and generalizability of our results in other tasks, samples, and contexts.

Keywords: electrodermal activity (EDA), galvanic skin response (GSR), skin conductance response (SCR), thresholding, statistical power, sensitivity, optimization, arousal

1 | Introduction

Electrodermal activity (EDA) reflects eccrine sweat gland activity controlled by the sympathetic nervous system (Boucsein, 2012; Dawson, Schell, & Fillion, 2007). Measures of EDA are widely used in studies of emotion (Bradley & Lang, 2007a), decision-making (Bechara, Damasio, Damasio, & Lee, 1999), attention or efficiency of information processing (Bradley, 2009; Spinks, Blowers, & Shek, 1985), medical symptomology such as pain (Geuter, Gamer, Onat, & Buchel, 2014) or cancer treatment side-effects (Savard, Savard, Caplette-Gingras, Ivers, & Bastien, 2013), and autism spectrum disorder (ASD) (Prince et al., 2016).

Although the number, amplitude, and rate of skin conductance responses (SCRs) are widely used electrodermal metrics, there is little consensus on optimal criteria for detecting SCRs (pp. 156, (Boucsein, 2012)). In the pre-computer era, an SCR was typically detected when a short-term (less than 1-2 seconds) deviation from the prevailing skin conductance level (SCL) occurred where the amplitude of the change exceeded a fixed threshold such as 0.05 μS (Venables & Christie, 1980) or 0.1 μS (Edelberg, 1972). Although more modern electrodermal analytic approaches typically use smaller values such as 0.01 μS (Boucsein, 2012), thresholds adopted across studies still vary due to a dearth of data-driven criteria. Some criteria informing sufficient change from the prevailing SCL to detect an SCR have been suggested, such as requiring each SCR amplitude to exceed 0.1% of the SCL at the onset of the SCR (Edelberg, 1972). However, most researchers use arbitrarily chosen fixed thresholds of 0.01 μS (e.g., (Fusar-Poli, Landi, & O'Connor, 2009; Kleckner et al., 2017; Sano, Picard, & Stickgold, 2014)), 0.02 μS (e.g., (Sjouwerman & Lonsdorf, 2018)), 0.03 μS (e.g., (Armel & Ramachandran, 2003)), or 0.05 μS (e.g., (Wood, Ver Hoef, & Knight, 2014)).

In this paper, we identify and propose a solution to the limitations that result from SCR detection procedures that use a fixed threshold. One specific problem is that individuals with higher SCL commonly have a greater number of SCRs and larger amplitude SCRs (Boucsein, Baltissen, & Euler, 1984; Venables & Christie, 1980)(for discussion, see p. 240 of (Boucsein, 2012)). Thus, the use of a fixed SCR threshold can lead to detection of more SCRs and a higher SCR rate in samples with higher SCLs because relatively small peaks will be counted as SCRs. Similarly, use of a fixed threshold can lead to detecting fewer SCRs in samples with lower SCLs, yielding floor effects. Thus, it is important to consider how to optimally detect SCRs in the context of large variations in SCL because otherwise the probability of type I and type II errors are inflated, particularly in samples with widely varying SCL. Additionally, the effects of the prevailing SCL can reduce effect sizes when comparing rates of SCRs between conditions that induce higher vs. lower arousal. Smaller effects sizes necessitate larger sample sizes to reliably observe a given effect or to test a novel hypothesis, which collectively adds unnecessary burden to research funding, staff, and participants.

We hypothesize that detecting the number or rate of SCRs using a novel *fixed plus adaptive (FA) threshold* that is proportional to the SCL at the onset of an SCR will increase the sensitivity to detect differences in the SCR rate across conditions of lower vs. higher psychological arousal. Our proposed FA threshold method is similar to Edelberg's suggestion to use a relative SCR threshold (Edelberg, 1972), but goes further by accounting for prevailing SC at the trough before onset of each SCR, not just the SC at the beginning of an entire recording epoch.

The goal of the current study is to evaluate our novel FA SCR thresholding technique to examine whether it can increase sensitivity to detect changes in SCR rate across varying experimental stimuli, tasks, conditions, and samples. We use two independent datasets analyzed

using both traditional fixed SCR thresholds and our FA thresholding technique to first explore and optimize our approach (Study 1) and then to validate it (Study 2). We also use statistical models to account for individual differences in SCR rates (mixed models with random intercepts) as well models to account for the SCR-SCL dependency (covariate adjustment by mean SCL). In Study 1 we explored and optimized FA threshold level using a dataset from 254 healthy community-recruited adults in a traditional laboratory setting, with wired recording equipment who rated their subjective arousal following exposure to standard affective images and sounds. Other data collected from this sample are reported in (Khalaf et al., under review; Wormwood et al., under review). Study 2 was used to validate the FA method using the optimal FA threshold level found in Study 1. The Study 2 dataset was comprised of 20 children with autism who participated in high-arousal social interactions and completed low-arousal puzzles while EDA was measured using wireless wrist-worn recording equipment. The initial findings from Study 2 are reported in (Jones, Carberry, Hamo, & Lord, 2017; Jones et al., in press; Jones, Southerland, et al., 2017; Jones, Tarpey, Hamo, Carberry, & Lord, 2018; Kleckner et al., 2018).

2 | Methods

2.1 | Study 1

2.1.1 | Participants. Two hundred and sixty participants (100 males, 159 females, 1 not reported) were recruited from the greater Boston area through fliers on college campuses, advertisements on craigslist.com, and in the Metro newspaper. Participants were 18 to 65 years old ($M = 24.8$, $SD = 10.2$) with a body mass index of 15.2 to 47.0 ($M = 24.1$, $SD = 5.2$). Participants were required to be native English speakers and were excluded if they reported skin allergies, very sensitive skin, any chronic medical conditions including asthma, or a history of cardiovascular illness, stroke, or mental illness. Participants were also excluded if they were currently taking

medications to treat attention deficit hyperactivity disorder, insomnia, anxiety, high blood pressure, rheumatoid arthritis, epilepsy/seizures, cold/flu, or were taking any autonomically active medications for allergies. Eligible participants were asked to refrain from consuming caffeine, tobacco, diet pills, sleeping pills, and alcohol for 24 hours prior to the experiment. All participants provided informed consent in accordance with the Institutional Review Board of Northeastern University. Six participants were removed due to errors in data collection, yielding a final sample of 254 participants.

2.1.2 | Affective Images and Sounds Task. All Study 1 data reported herein are from an affective images and sounds task. Affective image stimuli were taken from the International Affective Image System (IAPS; (Lang, Bradley, & Cuthbert, 2008)) and affective sound stimuli were taken from the International Digitized Sound System (IADS; (Bradley & Lang, 2007b)). Sound and image stimuli were selected across a range of ratings of normative valence and arousal (Table 1). We report data from 10 stimulus blocks with each block containing 10 stimuli of similar valence and arousal. For each block, image or sound stimuli were drawn from only one of five affective categories in the following fixed order: (1) low arousal/positive; (2) high arousal/positive; (3) low arousal/neutral; (4) low arousal/negative; and (5) high arousal/negative. Five image blocks were presented first followed by five sound blocks. Each stimulus was presented for 6 sec and separated from the next stimulus by a blank screen for 200 msec (for images) or silence for 200 msec (for sounds). Stimulus blocks were separated by a random inter-trial interval of 1-6 seconds, with an additional 1-min separating the last image block from the first sound block. After each block, participants rated their current affective feelings of valence and arousal using the Self-Assessment Manikin (SAM; Bradley & Lang, 1994) to indicate how pleasant/unpleasant and how activated/de-activated they felt on a 5-point scale, with lower values indicating more unpleasant

or more de-activated affect and higher values indicating more pleasant or more activated affect. Data from two other tasks in which we presented a block of randomly presented images and a block of randomly presented sounds are not analyzed here.

2.1.3 | Procedures. All participants completed the affective images and sounds tasks during a single experimental session in which they also completed other tasks and questionnaires not relevant to the current investigation. Some participants completed this session as the second part of a two-session experiment, after having completed other unrelated low- and high-arousal tasks in the lab 1-2 weeks prior to completing this session. Participants received \$5 per half hour for their time and an additional \$10 for completing both experimental sessions.

After providing written informed consent, participants completed brief questionnaires providing health and demographic information to ensure eligibility. Height and weight were measured, and participants were instrumented with physiological sensors to record EDA as well as electrocardiography, impedance cardiography, and respiration (data from these last three measures are not reported here). Participants then sat quietly for a five-minute resting baseline. Following baseline, participants completed two experimental tasks unrelated to the current investigation. Following these tasks, electrodes for recording facial electromyography were placed (data not reported here), and then participants received instructions for the affective images and sounds tasks, the first of which was preceded by a three-minute baseline. After an additional unrelated task, all electrodes were removed, participants completed several more questionnaires, and then were debriefed and compensated for their time.

2.1.4 | EDA data collection and processing. After participants washed their hands with warm water only, we recorded EDA from the right palmar surface (i.e., from the thenar and hypothenar eminences) using disposable Ag/AgCl (11mm diameter) electrodes from Biopac

(Goleta, CA). These electrodes contain isotonic paste (0.5% chloride salt) in a 16 mm diameter, 1.5 mm deep well, and a small additional amount of isotonic electrode paste (Biopac; 0.5% saline in a neutral base) was added to the electrodes prior to placement. EDA was sampled at 1,000 Hz using BioLab v. 3.0.13 software (Mindware Technologies LTD; Gahanna, OH) and a BioNex 8-Slot Chassis (Model 50-3711-08). Raw EDA in volts was converted to μS and amplified using a gain of 100 resulting in a full-scale range of -500 to 500 μS . We used BioLab's default EDA settings, including a low-pass filter with a cutoff of 1 Hz and a moving average filter of 100 samples (0.1 sec).

EDA data were processed using Mindware Technologies EDA software (version 3.0.25) for ten 61.8-sec epochs (one for each stimulus block). All epochs were visually inspected for movement artifacts by trained scorers prior to analyses; this process did not result in any data loss. The EDA 3.0 software detects peaks using the second derivative and requires a minimum peak width of 1/5 of the sample rate to remove higher frequency (i.e., likely noise related) peaks. Then the preceding trough (onset) is identified and a trough-to-peak change (SCR amplitude) is calculated. The output of interest from this initial analysis was a list of all detected SCRs using a fixed threshold $> 0.01 \mu\text{S}$, and the following features per SCR: amplitude, SC value at the onset, and the affective category of the stimulus block during which the peak occurred. For each block, we also calculated mean SC (i.e., the mean of the entire SC, regardless of whether it was considered part of the SCL or an SCR).

2.2 | Study 2

2.2.1 | Participants. We recruited families of twenty children and adolescents (5 females, age 5-13 years, $M = 8$ years) with a confirmed diagnosis of autism spectrum disorder (ASD) made by a licensed clinician using the Autism Diagnostic Observation Schedule-2 (ADOS-2;

Lord et al. (2012)) at the Center for Autism and the Developing Brain (CADB). All caregivers provided informed consent, and children and adolescents seven years of age and older also provided assent in accordance with the Institutional Review Board at Weill Cornell Medicine.

2.2.2 | Social Interaction and Puzzles Tasks. EDA data were collected (see section 2.2.4) during administration of a modified version of the Brief Observation of Social Communication Change (BOSCC; Grzadzinski et al. (2016)). This task consists of a 12-min examiner-child social interaction including two 5-min interactive play segments each with a standardized set of toys (Play 1 and Play 2) and two 1-minute conversations (Conversation 1 and Conversation 2) conducted in the same order (i.e., Play 1, Conversation 1, Play 2, Conversation 2). The examiner and child were seated across from each other (face-to-face) at a small table. During both Play tasks, the child was given the option to choose a single toy from a variety of standardized and developmentally appropriate options that were placed inside a box. The transition to the Conversation task was signaled by the examiner stating that it was time to clean up and then introducing an open-ended conversational topic (e.g., “I went to the park this weekend”). During the Conversation task, no toys were present on the table. After the BOSCC, participants completed the Purdue Pegboard Task (Tiffin, 1968) for 10-minutes, which was intended to be mildly frustrating for the child as it required putting small, difficult-to-grasp pegs into tiny holes as fast as possible. Next, the Puzzle task consisted of a 10-minute iPad game during which participants dragged and dropped shapes on the iPad screen to fit into a puzzle. Lastly, participants watched 10-minutes of the Pixar Short Films Collection Volume 1 (Disney/Pixar, 2007).

Analyses in the present paper focus on Conversation 1 as the high-arousal condition, as it represents face-to-face interactions without the presence of potentially arousing toys. We chose the Puzzle task as a low-arousal condition because it requires minimal cognitive demand from

participants. We obtained near identical results when Conversation 1 (results herein), Conversation 2 (not reported here), and the Pegboard task (not reported here) were selected as the high-arousal condition.

2.2.3 | Procedures. Study procedures are described in (Jones, Southerland, et al., 2017). In brief, there were three 1-hour assessment sessions at CADB: week 1, week 4, and week 8. In each session, participants were provided task instructions, followed by placement of the Q sensor device on participants by a trained researcher as described below before completing the BOSCC tasks (play and conversation), the pegboard fine motor task, the puzzle task, and watching the movie.

2.2.4 | EDA Data Collection and Processing. EDA data were obtained via the Q Sensor (Affectiva, Inc.; Waltham, MA) using methods described in (Kleckner et al., 2018). The Q Sensor uses two electrodes that are both positioned on the ventral surface of the non-dominant wrist and covered with an athletic sweatband to prevent the wearer from touching, moving, or turning off the device. The Q Sensor remained on the child's wrist for the duration of the visit. Start and end times for each behavioral task as well as Q Sensor recording start time were recorded. The Q Sensor records skin conductance, skin surface temperature, and motion data (using a 3-axis accelerometer) at either 16 Hz or 32 Hz (which varied across participants). For optimal signal quality, we recorded skin conductance using adhesive, solid conductive hydrogel Ag/AgCl electrodes that were affixed to the skin (22 mm square; model A10040-5; Vermed; Buffalo, NY).

We performed visual inspection and automated quality assessments for all EDA recordings using our freely available software (Kleckner et al., 2018), with valid data meeting the following four quality control parameters: (1) EDA range 0.05 to 60 μ S; (2) maximum slope 10 μ S/sec; (3) temperature range 30-40°C; and (4) data within 5 sec of any data point that met one of the first three rules were removed from analyses. We also computed the mean of the magnitude of

acceleration, $A_{\text{mag}} = \text{abs}(\sqrt{A_x^2 + A_y^2 + A_z^2}) - 1$ from the 3-axis accelerometers, where 1 is subtracted to remove the effect of gravity and the absolute value (abs) function is used to remove effects of directionality. We identified EDA peaks using the MATLAB *findpeaks* function, then searched for a preceding trough within 1-3 seconds of the peak to calculate a trough-to-peak change (SCR amplitude). The output of interest in the current investigation was a list of all detected SCRs (fixed threshold $> 0.01 \mu\text{S}$) and the following features per SCR: amplitude, SC value at the onset, and the task during which each peak was observed (i.e., Play 1, Conversation 1, Play 2, Pegboard, or Puzzle). We also calculated mean SC for each task. All outcomes were computed only on portions of data that passed the above EDA quality control checks.

2.3 | Application of fixed and FA SCR thresholds

In both studies, we calculated a metric—the skin conductance response amplitude percent (RAP)—that we used to assess the relative size of the SCR to be used in our FA thresholding procedure. This metric was calculated as the SCR amplitude divided by SC value at the onset. To apply our FA SCR threshold, we required that SCRs (i.e., those greater than a fixed threshold of $0.01 \mu\text{S}$) had an SCR amplitude percent greater than the selected threshold. To evaluate how our results were affected by each specific threshold, we tested 200 fixed threshold levels logarithmically spaced between 0.01 and $10 \mu\text{S}$, and 200 FA threshold levels logarithmically spaced between 0.01% and 10% .

We used data from Study 1 to explore which FA threshold value maximized the observed effect size in our comparisons of higher vs. lower arousal conditions. Specifically, we used polynomial curve fitting of plots of effect size vs. $\log_{10}(\text{threshold})$ in each of four comparisons: (1) unpleasant high arousal images vs. neutral images; (2) pleasant high arousal images vs. neutral images; (3) unpleasant high arousal sounds vs. neutral sounds; and (4) pleasant high arousal sounds

vs. neutral sounds. We obtained four FA threshold values that each maximized the effect size and averaged them to obtain a single FA threshold value used for confirmatory testing in Study 2 comparisons of FA vs. fixed thresholding at 0.05 μ S and 0.03 μ S. We also used curve fitting in the exploratory portion of Study 2 to estimate maxima of the effect size vs. $\log_{10}(\text{threshold})$ plots.

2.4 | Statistical Analyses

2.4.1 | Assessing associations between SCR amplitude and SC at onset. Because prior work suggests that SCL is positively correlated with amplitude of detected SCRs within a person (Boucsein et al., 1984; Venables & Christie, 1980), we assessed whether our data also showed a positive correlation between SCR amplitude and SCL both across and within individuals. All these analyses drew from SCRs across all conditions (Study 1: all blocks of images and sounds; Study 2: all tasks). For between-person tests, we obtained a list of each participant's SCRs ($> 0.05 \mu$ S) and calculated across-SCR mean, SCR amplitude, and mean SC value at onset (i.e., the preceding SC trough). We then used linear regression wherein each data point consisted of one participant to predict SCR amplitude using SC at onset. In Study 2, we calculated mean values across each individual's assessment session (1-3 per individual) so each data point constitutes one participant's assessment. For within-person tests, we used linear mixed regression where each data point was one SCR to predict SCR amplitude using SC at onset (fixed effect) and a random intercept that varied per individual (or per individual's session in Study 2). These two different models enable us to make inferences regarding associations between SCR amplitude and the SC at onset both at the individual level and at the group level.

2.4.2 | Testing for differences in the rate of SCRs across high vs. low arousal conditions. Our primary electrodermal metric of interest was the SCR rate (number of SCRs per minute), which is commonly used in the literature (e.g., (Gendolla & Krusken, 2001; Kleckner et

al., 2017; Posada-Quintero et al., 2018)). To test for differences in SCR rate across high vs. low arousal conditions, we ran four types of models that each predict SCR rate as a continuous linear outcome using either fixed effects (i.e., the coefficient is the same across participants) or random effects (i.e., the coefficient can differ across participants; thereby yielding a mixed effects model). We employed several statistical models of varying complexity to assess the extent to which it is important to account for between-person variability in SCL and to adjust for any correlation between SCL and SCR rate. The models were as follows. Model A used a fixed effect of condition and a random intercept. Model B used a fixed effect of condition, a fixed effect of mean SC in each condition, and a random intercept. Model C used a fixed effect of condition, a random effect of mean SC in each condition, and a random intercept. Model D (Study 2 only) used a fixed effect of condition, fixed effects of both mean SC and mean Q Sensor accelerometer magnitude in each condition, and a random intercept.

Given the common finding that higher ratings of subjectively reported arousal positively correlate with greater SCR rates (e.g., Kleckner et al. (2017)), we used three models to predict SCR rate from arousal ratings (Study 1 only). Arousal ratings (with integer values of 1-5) were treated as a continuous linear variable. Model A used arousal rating as a fixed effect with a random intercept. Model B used arousal rating as a fixed effect with a random intercept, with mean SC as a fixed effect covariate. Model C used arousal rating as a fixed effect with a random intercept, with mean SC as a random effect covariate.

We evaluated goodness-of-fit using the corrected Akaike Information Criterion (AICc), wherein a smaller number indicates better model fit. We assessed statistical power of our paired t-tests using Cohen's $d = \text{mean}(\text{RateSCR}_{\text{HighArousal}} - \text{LowArousal}) / \text{SD}(\text{RateSCR}_{\text{HighArousal}} - \text{LowArousal})$, wherein both the numerator and denominator use within-subjects change scores. We assessed the

statistical power of our mixed models using the t-ratio of the coefficient for the Condition variable (i.e., high minus low arousal) and the t-ratio of the coefficient for the Arousal Rating variable.

2.4.3 | Testing whether FA thresholding improves statistical power vs. fixed thresholding. To compare statistical power in FA vs. fixed thresholding methods in the validation portion of Study 1, we used linear regression to predict the t-ratio of the Arousal Rating variable using method (FA at 1.9% vs. fixed at 0.05 μ S or 0.03 μ S) controlling for task (IADS, IAPS), model (A, B, C), and subjects (all, responders only). We used an analogous approach for the validation portion of Study 2, using linear regression to predict the t-ratio for the Condition variable using method (FA at 1.9% vs. fixed at 0.05 μ S or 0.03 μ S) controlling for task (Conversation minus Puzzle, Pegboard minus Puzzle), session (1, 2, or 3), model (A, B, D) and subjects (all, responders only). We excluded Model C from Study 2 because it often did not converge due to its complexity. Analyses were performed using MATLAB (MathWorks; Natick, MA) and JMP Pro v.13 (SAS Institute Inc.; Cary, NC, USA).

3 | Results

In the following sections, we first demonstrate that SC values positively correlate with SCR amplitudes detected via a fixed threshold of 0.05 μ S, suggesting that analyses using SCR rates can be higher or lower depending on SCL. Next, we introduce our novel FA thresholding procedure and compare it to traditional fixed SCR thresholding in analyses of SCR rate. Study 1 data was used to explore results and determine an optimal FA threshold, followed by independent confirmatory using that optimal FA threshold in Study 2.

3.1 | SCR amplitude is positively correlated with SCL

Figure 1 shows an example SC trace wherein there are larger and more frequent SCRs detected using a fixed threshold when prevailing SCL is high. The figure shows two types of

potential errors that result, namely, detection of relatively small SCRs in the context of high prevailing SCL (lower left inset) and moderate amplitude SCRs undetected in the context of lower prevailing SCL (lower right inset). Next, we tested for a relationship between SCL and SCR amplitude across the entire dataset.

Data from both Study 1 and Study 2 show a positive association between SCL and SCR amplitude (using a fixed threshold of $0.05\ \mu\text{S}$; Figure 2), which is consistent with prior work (Boucsein et al., 1984; Venables & Christie, 1980). In regression models of Study 1 data, we observe an across-person positive association (223 individuals, $F=231$, $p<0.0001$) and a within-person positive association (4,976 SCRs, $t=10.9$, $p<0.0001$). Similarly, in Study 2 we observe an across-person positive association (45 assessments, $F=25$, $p=0.002$) and a within-person positive association (5,137 SCRs, $t=13.7$, $p<0.0001$). These results suggest that prevailing SCL and rate of SCRs are positively correlated when SCRs are counted using a traditional fixed SCR threshold of $0.05\ \mu\text{S}$.

3.3 | Exploring the effects of SCR threshold level (Study 1)

We next compare rate of SCRs (number of SCRs per minute) in normatively high vs. low arousal conditions and quantify the difference in terms of effect size (Cohen's d) for different fixed and FA thresholds. The fixed thresholding uses SCR amplitude (e.g., $0.05\ \mu\text{S}$) whereas FA thresholding uses a novel metric we call *skin conductance response amplitude percent (RAP)*, which is the SCR amplitude divided by the SC value at onset (i.e., the trough preceding the SCR peak). We hypothesized we could maximize effect size by finding an optimal SCR threshold level that was not too small—detecting excessively small peaks that are effectively noise—and not too large—missing detection of peaks that we would want to consider signal. Thus, we expected to see a peak in the plot of effect size versus threshold level; such a plot would indicate that adjusting

the threshold can increase the effect size. We used polynomial curve fitting to find the FA threshold value that maximized the observed effect size, so we could later use that optimal FA threshold in confirmatory testing with Study 2 data.

Indeed, several of the plots in Figure 3a reveal a peak, indicating that an optimal threshold can be found that maximizes effect size. Several of the curves exhibit two local maxima, but it is not clear if this is due to random variation or a genuine effect. The left portion of the plot is flat because at very liberal FA thresholds (to the left of $10^{-1}\%$), the threshold allows “detection” of all SCRs, thereby yielding identical results to those of the traditional fixed threshold of $0.01\ \mu\text{S}$.¹ With stricter FA thresholds (moving toward the right in the plot), effect sizes increase slightly starting at $\text{RAP} = 0.1\%$, peak at approximately $\text{RAP} = 0.5\text{-}6\%$, and then decrease for larger RAP values. The curve fitting indicates the optimal RAP values as 6.3% , 0.6% , 0.3% , and 0.5% for unpleasant images, pleasant images, unpleasant sounds, and pleasant sounds, respectively. This yields an across-condition optimal RAP value of 1.9% , which is shown as a vertical red line in

Figure 3a. The 1.9% value is a rough estimate given the variability in the shapes of the effect size curves plus the differences in maxima across conditions. We also show the percentage of the sample who are considered responders, exhibiting at least one SCR across all stimulus conditions. At the optimal FA threshold of 1.9% , 93% of the sample are considered responders. Finally, we show the number of SCRs from all the images or sounds. The FA threshold at 1.9% retains approximately $4,300$ SCRs, which is 53% of the $8,100$ SCRs greater than $0.01\ \mu\text{S}$ (i.e., the original set of SCRs available for FA thresholding) and 86% the number of the $4,976$ SCRs greater than $0.05\ \mu\text{S}$ (note that this 86% is not a strict subset of the SCRs found at $0.05\ \mu\text{S}$ because FA thresholding may detect SCRs with amplitudes less than $0.05\ \mu\text{S}$ as long as the SCL is low enough, e.g., below $2.6\ \mu\text{S}$ for an FA threshold of 1.9%).

For comparison, we also test a range of fixed SCR threshold levels. The plots in Figure 3b suggest that increasing fixed thresholds can increase effect sizes, perhaps except for negative sound stimuli. This effect size from the unpleasant image category was the most responsive to increases in both FA threshold and fixed threshold levels. The lower right plots show that the percentage of responders and number of SCRs is quickly reduced upon increasing the fixed threshold level by an amount that notably increases the effect size. Excluding participants is undesirable because it can reduce generalizability and power in across-participants analyses.

Next, we used linear mixed modeling to account for between-person variance in SCL (using random intercepts) and for the correlation between SCR amplitude and SCL (using covariate adjustment by mean SC). The results from these models indicate that FA thresholding at 1.9% yields equivalent performance compared to traditional fixed thresholding at 0.05 μ S and 0.03 μ S in terms of effect size and goodness-of-fit (with exception of Model B in sounds stimuli; Figure S2). We identical conclusions when excluding non-responders.

3.5 | FA SCR threshold increases correspondence of SCR rate and subjective ratings of psychological arousal (Study 1)

This analysis explores how FA thresholding affects the ability to assess the relationship between SCR rate and self-reported subjective arousal in the evocative images and sounds tasks in Study 1. We hypothesized that SCR rate more closely tracks participant ratings of arousal using FA thresholding at 1.9% (value obtained from the prior analysis) compared to traditional fixed thresholding at 0.05 μ S or 0.03 μ S. Specifically, we predicted that linear models would show increased power (t ratio), superior goodness-of-fit, and smaller standard errors using FA thresholding than fixed thresholding.

Qualitatively, Figure 4 suggests that FA thresholding at 1.9% performs slightly better than fixed thresholding at 0.05 μ S and 0.03 μ S, although all the plots are reasonably linear. The sound stimuli suggest that FA thresholding is more monotonic and linear than fixed thresholding, as the SCR rate for fixed thresholding is very similar at arousal = 1, 2, and 3, and that the SCR rate for arousal = 5 is less than for arousal = 4. By comparison, when using FA thresholding the SCR rate increases with each increment in rated arousal. For the sound stimuli, the results are more similar for FA thresholding and fixed thresholding, wherein all plots are fairly linear and monotonically increasing with the exception that the SCR rate is smaller at arousal = 5 than at arousal = 4, which is undesirable, for all methods.

Quantitatively, we see that FA thresholding has a slight advantage over fixed thresholding based on its smaller standard errors, larger t-ratios, and superior goodness-of-fit regardless of method used to account for between-person variance or covariate adjustment by mean SC (Figure S3). In statistical testing, we found FA thresholding at 1.9% to yield larger t ratios than fixed thresholding at 0.05 μ S (advantage of $M \pm SE = 0.77 \pm 0.22$ units on the t ratio; $p = 0.002$; Table 2) and at 0.03 μ S (advantage of 1.02 ± 0.26 units on the t ratio; $p = 0.009$; Table S3) adjusting for model type (A, B, C), stimulus type (sounds, images), and subjects (all, only responders). The bottom row (black) shows mean SC, another commonly used electrodermal metric, which does not relate to self-report ratings of arousal and has the largest standard errors. These results suggests that SCL does not track subjectively reported arousal as well as SCR rate, which has also been previously reported by other groups (Nagai, Critchley, Featherstone, Trimble, & Dolan, 2004)(pp. 349 (Boucsein, 2012)).

3.4 | Independently and quantitatively assessing FA thresholding vs. fixed thresholding (Study 2)

Next, we quantitatively assess FA thresholding by directly comparing results from FA thresholding at 1.9%—the value independently obtained from Study 1—and fixed thresholding at 0.05 μS and 0.03 μS —two of the most commonly used values in the literature (Boucsein, 2012). First, using Session 1 data using Model A (Table S5), we see that FA thresholding at 1.9% indicates that the high-arousal condition has a higher SCR rate with a t ratio of 2.22, which is statistically significant by traditional standards ($p = 0.041$). By comparison, fixed thresholding at 0.05 μS yields smaller and non-significant effects, with $t = 1.19$ ($p = 0.251$). These results suggest that analyses using a fixed threshold may lead to false negative results (type II errors), as the face-to-face conversation likely induces greater arousal than the puzzle task based on its greater duration of eye contact in these data (Jones, Southerland, et al., 2017) and prior demonstrations that eye contact increases SCL in children with ASD (Kylliäinen & Hietanen, 2006).

When we analyzed the t ratios across several models and conditions, we found that FA thresholding at 1.9% yielded larger t ratios than fixed thresholding at 0.05 μS (advantage of 1.24 ± 0.14 units on the t ratio; $p < 0.0001$; Table 3) and fixed thresholding at 0.03 μS (advantage of 1.09 ± 0.13 units on the t ratio; $p < 0.0001$; Table S6) after adjusting for model (A, B, D), high-arousal task (Conversation 1 or Play 2), session (1, 2, 3), and subjects (all, responders only). These conclusions also held when considering participants' movement, as we also found superiority of FA thresholding when adjusting by per-condition mean acceleration readings from the Q Sensor (Model D) and when comparing the low-arousal puzzle task to a high-arousal play task, which involved more movement (Figure S5).

3.5 | Exploring the effects of SCR threshold level (Study 2)

In Figure 5, we explore Study 2 data to find an optimal FA threshold level. Our results suggest superiority of FA thresholding compared to traditional fixed thresholding across a broader

range of FA threshold levels (not just 1.9%). Compared to Study 1 results, Figure 5a shows that FA thresholding yields a larger increase in effect size in a pattern that replicates over the three sessions (over the course of eight weeks). The lower left plots also show that these increases in effect size do not necessarily come at the expense of removing participants from the analysis but rather by removing SCRs from the analysis, again consistent with the results from Study 1. Specifically, using an FA threshold of 1.9% retains of 1,582 (56%) of the original 2,817 SCRs $> 0.01 \mu\text{S}$ in Session 1, another 1,482 (66%) in Session 2, and 1,033 (54%) in Session 3. This is approximately 84% of the number of SCRs detected using a fixed threshold of $0.05 \mu\text{S}$.

Next we explored how effect size related to increasing fixed threshold levels. Figure 5b illustrates that for Session 1 and 2, the effect size was fairly stable across threshold levels, but for Session 3, there was a rapid decrease in effect size. The lower right plots show that these changes come at the expense of removing both participants from the analysis, which is undesirable.

4 | Discussion

This study presents and evaluates a novel fixed plus adaptive SCR thresholding technique based on RAP (SCR peak amplitude divided by SC value at onset) rather than a fixed threshold (absolute SCR amplitude) traditionally used in the literature. Our method is an extension of a prior relative SCR thresholding procedure (Edelberg, 1972) where we instead propose dynamic thresholding relative to the prevailing SCL immediately before each SCR, rather than based on a single SC value at the start of an entire recording. We demonstrate that using this FA thresholding procedure to compute SCR rates yields larger effect sizes in tests comparing normatively high vs. low arousal conditions in two distinct datasets: 254 healthy young adults wearing wired EDA sensors in a laboratory while viewing standardized evocative images and listening to standardized evocative sounds; and 20 children with ASD wearing wireless EDA sensors in a clinical setting

engaging in high-arousal social interactions and a low-arousal puzzle task with measures obtained three times across eight weeks. Study 1 data were used in an exploratory manner to optimize the FA threshold level, which we found to be 1.9%. Study 2 data were used in a confirmatory manner to validate the FA threshold independently determined in Study 1 by comparing FA thresholding at 1.9% to traditional fixed thresholding at 0.05 μ S and 0.03 μ S. Our findings suggest superiority of FA thresholding over fixed thresholding in the context of several analytical frameworks: linear mixed modeling that accounted for between-person variance in SC, plus covariate adjustment for mean SC to account for confounding by SCL, plus covariate adjustment for mean accelerometer readings from the wireless EDA sensor to account for confounding by movement. The FA threshold level that maximized effect sizes from Study 1 was to require $RAP > 1.9\%$, which resulted in approximately 85% the number of the peaks considered SCRs using a traditional fixed threshold of 0.05 μ S, or 50% of the peaks considered SCRs at 0.01 μ S. The FA threshold of 1.9% categorized more subjects as responders than the fixed threshold at 0.05 μ S (91% vs. 88% in Study 1, similar in Study 2) because FA thresholding includes small SCRs that occur as low SCL that would otherwise be excluded using a fixed threshold. Altogether, this method has identified a different set of SCRs that, in these experimental contexts, more closely relate to self-reported arousal than the set of SCRs traditionally identified in these types of analyses. This invites the hypothesis that some SCRs convey more information related to psychological arousal than other SCRs. If this hypothesis is correct, it suggests a reconceptualization of the interpretation of EDA data and SCRs more broadly.

Our FA thresholding procedure may be particularly relevant to electrodermal datasets that demonstrate a large range in SCL (e.g., (Lykken, Rose, Luther, & Maley, 1966)), including data collected in ambulatory settings wherein greater changes in sympathetic nervous system activity

can occur and more sources of noise are present (Doberenz, Roth, Wollburg, Maslowski, & Kim, 2011; Wilhelm & Grossman, 2010). We suspect our FA thresholding approach will be particularly effective for use with data from clinical trials and other randomized studies in which there are large differences in SCL across participants and contexts as afforded by ambulatory EDA devices (Goodwin, Velicer, & Intille, 2008; W. Adams et al., 2017). Indeed, our results revealed greater beneficial effects of FA thresholding in our sample of children with ASD who moved about freely during the tasks wearing wrist-based devices (Study 2) compared to the data from healthy young adults in a standardized laboratory experiment (Study 1).

This study has several notable strengths. First, we had a large sample size—254 participants in Study 1 and 20 participants with three longitudinal measures across eight weeks in Study 2—collectively increasing reliability of our findings. Second, because our results were consistent across two very distinctive studies, our conclusions should have better generalizability across diverse settings (college laboratory and outpatient clinic), populations (healthy young adults and children with ASD), tasks (standard evocative images and sounds, face-to-face social interactions, and puzzle games), recording hardware (traditional wired laboratory EDA sensors with standard isotonic electrodes and wireless EDA sensors with high-conductivity gelled electrodes), and other study-related factors that likely changed across the eight weeks of Study 2 (e.g., exact sensor placement, mood, hydration, temperature, humidity, task practice, habituation effects, etc.). Third, our approach is computationally both simple and inexpensive. The method is simple because it relies on only two EDA metrics—SCR amplitude and SC onset value—that are typically available in EDA analysis software packages. Moreover, because of its simplicity, our method can easily be used in real-time analyses of EDA data. Finally, FA thresholding increased

the number of responders in our dataset, which is helpful because the phenomenon of non-responders is an impediment to research using EDA.

The present results suggest that FA thresholding increases statistical power to detect differences across people and conditions in several ways. First, our method removes the relatively smallest SCRs that would otherwise be detected using a traditional fixed threshold. In statistical terms, FA thresholding better accounts for large between-person variance, as evidenced by the fact that mixed modeling estimates of between-person variance were lower when using an FA threshold compared to a fixed threshold (Table S7). Second, FA thresholding appears to partially account for the correlation between SCR rate and SCL because covariate adjustment for mean SCL explained less variance in models that already used FA thresholding compared to models that used fixed thresholding (i.e., FA thresholds yielded slightly smaller increases in power by going from Model A to Model B than fixed thresholds did when going from Model A to Model B; Figure S2, Figure S3, Figure S4).

Taken together, FA thresholding appears to hold few disadvantages over traditional fixed thresholding. It is not more difficult or computationally complex than using a fixed threshold, and it can be used in conjunction with various analytical frameworks. We also suspect that use of FA thresholding will increase the effectiveness of other advanced approaches to analyzing SCR data, such as dictionary learning of SCRs with varying shapes (Kelsey et al., 2018; Kelsey et al., 2016).

This study has a few limitations. First, there is some variability across studies in the optimal FA threshold and there is no literature to guide selection of threshold beyond this paper. Based on Study 1 data, we found the largest effect sizes at $RAP = 1.9\%$, but this number might vary based on conditions, as we saw in Study 1 (optimal RAP ranging from 0.5-6%) and Study 2 (optimal RAP ranging from 2-5%). Moreover, the evocative stimuli in Study 1 were presented in the same

order across participants, thus confounding the affective features of the stimuli and stimulus presentation order. Nevertheless, we independently confirmed the superiority of FA thresholding in Study 2 using the 1.9% threshold found in Study 1, suggesting that even if the RAP value is not perfectly optimized for a given dataset, it can still perform better than fixed thresholding at 0.05 μS and 0.03 μS . A related limitation is that the FA threshold requires selection of a fixed threshold to build the initial list of detected peaks. Here we chose 0.01 μS as that minimal threshold because it was the smallest typically used in the literature, but future research could test other values.

A second limitation is that there may be a reduction in effect size when performing tests of individual differences, as our method reduces (accounts for) between-person variance. Indeed, reducing between-person variance might reduce power in research designs investigating individual differences (e.g., relation of EDA measures to intrinsic characteristics such as age or stable self-reported measures such as personality; for a discussion of this issue see (Birn et al., 2014)). However, our results indicate that FA thresholding is superior in tests of the relationship between SCR rates and ratings of subjectively reported arousal, which also involve between-person variance because different participants have different SCR rates and ranges of subjective arousal ratings.

Third, it is not clear whether our FA thresholding method provides a more accurate measure of increased sympathetic nervous system activity to the eccrine glands per se, or merely a stronger relationship with self-reported arousal. Moreover, it is challenging to determine whether variations in SCL are causing more vs. fewer SCRs, as small SCRs can occur at high SCL and large SCRs can occur at low SCL. In future work it could be useful to include sympathetic blockades to further test the validity of inferences using this novel FA SCR thresholding procedure compared to traditional fixed SCR thresholding. On a related point, EDA in Study 2 was recorded from the

wrist, which is thought to reflect greater thermoregulatory effects and might not map as strongly to psychological arousal (Boucsein, 2012). However, our results did show the expected relationships with tasks of varying arousal and prior research has shown that EDA from the wrist is strongly correlated with EDA from the fingertips (i.e., the gold standard location; (van Dooren, de Vries, & Janssen, 2012)).

Finally, future work should assess to reproducibility and generalizability of FA thresholding vs. fixed thresholding in other samples, contexts, and psychological tasks. Although this work contains two studies and a large sample size with repeated measures, future work should consider other stimulus types (e.g., punctate stimuli such as randomized image presentations) instead of minutes-long blocked stimuli, and other established psychophysiological phenomena such as such as habituation (e.g., reduction in SCR rate in response to repeated startle stimuli).

In sum, we make the following suggestions for use of FA thresholding. First, we reiterate standard suggestions for analyses of EDA and SCR data, whereby one uses a rigorous quality assessment procedure including visual inspection and removal of obvious movement artifact (e.g., via our freely available automated quality assessment procedure for EDA data (Kleckner et al., 2018)), followed by use of an FA threshold at 1.9% for laboratory recordings or 3.3% for ambulatory conditions with features similar to those used here. Researchers could determine their own optimal FA threshold using a small independent pilot study per the approach we used in Study 1 for paradigms with very different task features than those tested here. After applying an FA threshold, we also suggest that researchers use mixed modeling to increase statistical power and further address between-person variance (Kristjansson, Kircher, & Webb, 2007), including controlling for mean SCL as a nuisance covariate when modeling SCR rates because this further increased (or maintained) statistical power in our data (i.e., compare Models A and B in, which

adds the covariate, in Figure S2, Figure S3, and Figure S4). The results herein suggest that our novel FA SCR thresholding increases sensitivity to detect changes in SCR rate across higher vs. lower arousal conditions compared to a traditional fixed SCR threshold in data from healthy young adults and children with ASD. Future research is required to test for reproducibility and generalizability in other samples, contexts, and psychological tasks.

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Footnotes

¹More specifically, a threshold of $RAP > 10^{-2}\%$ means $SCR / SC_{\text{trough}} > 0.0001$, which allows all SCRs with amplitude $> 0.01 \mu\text{S}$ as long as $SC_{\text{trough}} < 100 \mu\text{S}$, which was always true because the maximum EDA value in the data we analyzed was $60 \mu\text{S}$.

Table 1. Mean valence and arousal of standardized images and sounds presented in Study 1.

Block	Stimuli	Category	Mean valence	Mean arousal
1	Images	Pleasant low arousal	7.43	3.73
2	Images	Pleasant high arousal	7.21	6.58
3	Images	Neutral low arousal	5.10	3.27
4	Images	Unpleasant low arousal	3.82	3.56
5	Images	Unpleasant high arousal	2.04	6.67
6	Sounds	Pleasant low arousal	6.70	4.75
7	Sounds	Pleasant high arousal	6.74	5.95
8	Sounds	Neutral low arousal	5.11	4.79
9	Sounds	Unpleasant low arousal	4.16	5.45
10	Sounds	Unpleasant high arousal	2.44	7.18
Mean valence and arousal ratings are from 1-9 where 1 is most unpleasant, 9 is most pleasant, and 1 is lowest arousal and 9 is highest arousal. Ratings in the table were obtained by averaging across the 10 stimuli in each block using the ratings in the manuals for the International Affective Image System (Lang et al., 2008) and the International Digitized Sound System (Bradley & Lang, 2007b).				

Table 2. Study 1 statistical comparison of power (t-ratios) using FA thresholding at 1.9% vs. fixed thresholding at 0.05 μ S using linear regression of SCR rate using Arousal Rating.

Term	Estimate	SE	DF	t Ratio	p-value	Lower 95%	Upper 95%
Intercept	2.65	0.27	18	9.92	<.0001*	2.09	3.21
<u>Method</u> : FA 1.9% - Fixed 0.05 μ S	0.77	0.22	18	3.54	0.0024*	0.31	1.23
<u>Model</u> : A – C	-0.11	0.27	18	-0.41	0.6883	-0.67	0.45
<u>Model</u> : B – C	0.18	0.27	18	0.66	0.5172	-0.38	0.74
<u>Task</u> : Sounds – Images	-0.44	0.22	18	-2.01	0.0594	-0.90	0.02
<u>Subjects</u> : All – Responders	1.70	0.22	18	7.8	<.0001*	1.24	2.16

Larger estimates indicate greater statistical power (t-ratio) associated with that variable's level.

Source data in Table S1.

Identical conclusions were obtained using a fixed threshold of 0.03 μ S, see Table S3.

Table 3. Study 2 statistical comparison of FA thresholding at 1.9% vs. fixed thresholding at 0.05 μ S using linear regression of SCR rate using Condition (high arousal conversation or play minus low arousal puzzle).

Term	Estimate	SE	t Ratio	p-value	Lower 95%	Upper 95%
Intercept	1.43	0.20	7.26	<.0001*	1.04	1.83
<u>Method</u> : FA 1.9% - Fixed 0.05 μ S	1.24	0.14	8.89	<.0001*	0.96	1.52
<u>Model</u> : A – D	-0.73	0.17	-4.26	<.0001*	-1.07	-0.39
<u>Model</u> : B – D	0.22	0.17	1.27	0.2084	-0.12	0.56
<u>Tasks</u> : (Convo1-Puzzle) – (Play2-Puzzle)	-0.15	0.14	-1.05	0.2997	-0.43	0.13
<u>Subjects</u> : All – Responders	-0.37	0.14	-2.66	0.0099*	-0.65	-0.09
<u>Session</u> : 1 – 3	1.13	0.17	6.6	<.0001*	0.79	1.47
<u>Session</u> : 2 – 3	0.50	0.17	2.9	0.0051*	0.15	0.84

Larger estimates indicate greater statistical power (t-ratio) associated with that variable's level.

Source data in Table S4.

Identical conclusions were obtained using a fixed threshold of 0.03 μ S, see Table S6.

Figure 1. Example time course showing that higher prevailing SCL is associated with larger short-term fluctuations in SC. Blue circles indicate rapid SC fluctuations greater than 0.05 μS , i.e., SCRs. The bottom left panel shows a portion of data with higher SCL during which there may be some spurious SCRs shown by the red arrows. The bottom right panel shows a portion of data with lower SCL in which deflections that could be potential SCRs were not detected.

Figure 2. Positive associations between SCR amplitude and SC value at onset in two studies, both across individuals and within individuals. (a) The Study 1 across-individuals analysis, wherein each data point averages over all SCRs larger than 0.05 μS for a single healthy adult in the evocative images and sounds tasks. There are 223 individuals in total who each had at least one SCR. (b) The Study 2 across-individual assessments analysis, wherein each data point averages over all SCRs larger than 0.05 μS for a single child with ASD at one of their three assessment sessions. (c) The Study 1 within-individuals analysis, wherein each data point is a single SCR. There are 4,976 SCRs in total. (d) The Study 2 within-individual assessments analysis, wherein each data point is a single SCR. There are 5,137 SCRs in total. In all cases, data shown passed manual visual inspection and automated quality assessments. All these analyses drew from SCRs across all conditions (Study 1: all blocks of images and sounds; Study 2: all tasks).

Figure 3. In the exploratory portion of Study 1, we determined the optimal FA threshold level using curve-fitting to maximize effect sizes comparing the SCR rate during high vs. low arousal images and sounds in 254 healthy adults. Each figure shows two sets of data: unpleasant high arousal stimuli minus neutral low arousal stimuli (thick line) and pleasant high arousal stimuli minus neutral low arousal stimuli (thin lines). The vertical red line in (a) shows the optimal FA threshold level of 1.9% found by averaging each of the four optimal FA threshold levels. The lower plots show the percentage of the sample that are responders—who exhibited at least one SCR across all conditions at the given threshold—and the number of SCRs across all stimuli.

Figure 4. FA thresholding (red solid line) yields slightly smaller error bars and more monotonic increases in rate of SCRs across arousal ratings compared to traditional fixed thresholds of 0.05 μS (middle dark blue dashed line) and 0.03 μS (upper light blue dotted line) and compared to a widely used non-SCR metric from EDA: mean SC (bottom, black). Each of the 254 participants contributed five data points (X, Y pairs) to each subplot (i.e., 5 arousal ratings plus EDA data). The error bars are standard errors. The x-axis values are jittered to avoid overlapping error bars.

Figure 5. In Study 2, among 20 children with ASD, FA thresholding (a, red) yields higher effect sizes than traditional fixed thresholding (b, blue) in comparisons between high vs. low arousal tasks: a face-to-face conversation vs. puzzle. Results are consistent with and extend results from Study 1, suggesting consistency over the three sessions over eight weeks (thin, thicker, and thickest lines). The vertical red line in (a) shows the optimal threshold value 1.9% found in the exploratory portion of Study 1. Study 2 was treated as confirmatory and the effect size curves here did not influence or inform the optimization of FA threshold values found in Study 1. The lower plots show the percentage of the sample that are responders—who exhibited at least one SCR across all conditions at the given threshold, and the number of SCRs across all stimuli. For the exploratory

portion of Study 2, each effect size trace was curve-fitted to determine the FA threshold value that maximizes the effect size.