Fear-related psychophysiological patterns are situation and person dependent: A Bayesian
model comparison approach.

Kieran McVeigh^{1*}

Ian R. Kleckner²

Karen S. Quigley^{1,3}

Ajay B. Satpute¹

¹Department of Psychology, Northeastern University, 360 Huntington Ave, 125 NI, Boston, MA
02115

²University of Maryland, Baltimore, Baltimore, MD, USA

³VA Bedford Healthcare System, Bedford, MA, USA

*Corresponding author (email: mcveigh.k@northeastern.edu)

Abstract:

Classical accounts of emotion often assume that fear triggers a single specific autonomic response pattern. This assumption underlies attempts to generalize research findings on fear across experimental paradigms, individuals, and even species. Alternatively, constructionist theoretical accounts suggest that the relationship between fear and autonomic activity will depend on the situation and/or person. This theoretical account suggests that autonomic activity cannot serve as a proxy for subjective experiences of fear because the mapping between autonomic activity and subjective experience depends on the context and individual. Here, we examined variability in the relationships between fear and skin conductance response rates (SCR rate) and fear and heart period (the inverse of heart rate), across three distinct fear-evoking situations. Bayesian model comparison showed strong support in favor of situation- and person-dependency in the relationship between fear and each of these measures of autonomic activity (Akaike Weights > .999). The findings are more consistent with a constructionist theoretical account than with a classical account. The results further call into question the assumption of generalizability of autonomic-subjective mappings during fear inductions across paradigms, individuals, and species, and suggest adopting a more contextualized approach for understanding the autonomic correlates of fear.

Keywords: fear, autonomic activity, skin conductance, heart rate, psychophysiology

Introduction

Fear is a powerful emotion that extends into practically every aspect of social life including politics (Glassner 2010; Dowler 2003; Altheide 2006), public health (Consedine et al. 2004; Tannenbaum et al. 2015; Witte and Allen 2000; Harper et al. 2020), mental illness (Kessler et al. 2005; Merikangas et al. 2010), jurisprudence (Alvarez and Buckley 2013; O'Driscoll 2008; Torres, Cannito-Coville, and Rodriguez 2017), risk perception (Fredrickson 2013; Parker and Isbell 2010; Angie et al. 2011; Hartley and Phelps 2012; Lerner and Keltner 2001; Wake, Wormwood, and Satpute 2020), and even creative thinking (Baas, De Dreu, and Nijstad 2008; Fredrickson 2013).

Despite its importance to society, there remains considerable debate regarding its underlying nature (Davis, 1992; Fanselow & Pennington, 2018; Mobbs et al., 2019). While there is agreement that fear involves both a subjective experience component or the feeling of fear, and a visceromotor component, such as cardiac and electrodermal responses driven by the autonomic nervous system, it remains unclear how these two components relate with one another. In other words, is there a particular autonomic response profile for fear that generalizes across individuals and situations as has been assumed within classical emotion approaches, or are fear-related autonomic responses variable, and dependent on the situation and the person? Contrary to classical models, constructionist models of emotion propose the latter view suggesting that fear refers to an emotion category that is composed of heterogeneous instances (Barrett, 2014, 2017; Quigley & Barrett, 2014; Satpute & Lindquist, 2019). For example, fear involving social encounters, spiders, or heights may involve different patterns of autonomic responses for a given individual due to their differential learning history with similar stimuli across situations and the need for different patterns of action that depend upon the circumstances. From this view the association between autonomic changes during an instance of fear will be structured by context and individual (Hoemann et al., 2020; Quigley & Barrett, 2014; Siegel et al., 2018).

Currently, it remains unclear whether classical or constructionist models best account for the relationship between fear experience and autonomic activity. A recent comprehensive meta-analysis involving 111 effects sizes from 47 studies with >4000 participants found, on the one hand, that fear was reliably associated with increased electrodermal activity and heart rate when summarizing findings across dozens of studies (Siegel et al., 2018; also see Cacioppo et al., 2000; Stemmler, 2004; Kreibig, 2010), but on the other hand, that effect sizes were also highly variable across studies and also that those autonomic changes were not specific to fear (Siegel et al., 2018, see also Quigley & Barrett, 2014). Constructionist theory suggests this variation in the relationship between fear and autonomic activity across studies is due to situational and individual factors. However, it is difficult to examine these variables using meta-analysis since it relies on findings from prior work that are reported in the aggregate. Perhaps as a consequence, moderators that could explain heterogeneity in effect sizes were not identified in previous meta-analytic studies, and so the underlying causes of variability remain unclear.

The aim of our study was to address the constructionist hypothesis that variation in the relationship between subjective fear and measures of autonomic activity, including heart rate and electrodermal activity, depends on the situation and person. Doing so requires an experimental paradigm in which each person experiences fear multiple times across a variety of different situations, and a modeling approach that enables assessing different potential inferences about the degree to which and how these variables contribute to the overall relationship. Several studies have examined how autonomic measures correlate with subjective fear across multiple trials for each participant (Beckers et al., 2013; Boddez et al., 2013; Taschereau-Dumouchel et al., 2020), however, they did not examine whether these relationships depended on the context or person. Other studies have shown that autonomic responses during various emotion inductions vary across contexts when averaging across individuals (Shenhav & Mendes, 2014; Stemmler, 2004) or across individuals (Hodes et al., 1985; Stemmler & Wacker, 2010; Van Diest et al., 2009). These studies do suggest that variation by context and person matter, however, none of them modeled the relationship between fear and autonomic activity at the level of each situation and participant.

To address this gap and formally test the constructionist hypothesis, we implemented a fully within-participant design in which participants were induced to experience fear across three distinct situations. Participants were exposed to multiple brief fear-evoking video clips involving heights, spiders, and social content. We selected these situations because they span a wide range of situational features and yet still consistently evoke feelings of fear (Öhman & Mineka, 2001). For example, although fear is often conceptualized as occurring in predator-prey contexts (LeDoux, 2014; Mobbs et al., 2019; Scarantino, 2018), fear of heights is also a powerful, and survival-relevant experience, and yet involves no predator. Fear of spiders and fear during social encounters also each have their own unique situational features. We parametrically varied stimulus intensity within each context to ensure that differences across contexts were not just due to differences in induction intensity. For example, some heights videos evoked higher levels of subjective fear (e.g., walking along the edge of a sheer cliff) while other heights videos evoked little to no subjective fear (e.g., walking down a set of stairs). The same within-condition parametric variation in fear was introduced for stimulus contexts involving social stimuli and involving spiders. Subjective fear and autonomic measures of heart period and skin conductance response rate were obtained in response to each video. Of note, these two autonomic measures are perhaps the two most commonly used measures of autonomic activity when studying fear (and are often assumed to be the most robust, too - Siegel et al., 2018). We then examined the relationship between subjective fear with each autonomic measure, and tested the degree to which it varied by situation and person.

To compare the classical and constructionist theoretical approaches, we used a Bayesian model comparison approach. This approach determines the relative support for compared models from given the data, by balancing the amount of variance explained against the model complexity (Vehtari et al., 2017; Wagenmakers & Farrell, 2004). To test our question we compared a range of linear regressions which assumed different degrees of variation between the autonomic activity and fear experience, at the individual and situation level. The most general model (as suggested by many classical approaches to emotion) that assumes consistency in the relationship between instances of fear and skin conductance responses, or

instances of fear and heart rate, is a simpler model that would have tremendous explanatory power, if supported. However, our question is whether taking into account the situation and the person provides greater explanatory power that justifies the added complexity. Bayesian model comparison formalizes the tradeoff between complexity and explanatory power by penalizing models that have more parameters. In doing so, this approach enables more specific inferences to be drawn about the support for tested models than are possible with a simple null-hypothesis significance testing approach. Notably, null-hypothesis significance testing has been used in virtually all prior studies that attempt to map instances of fear to either skin conductance responses or heart rate responses. Further, these studies typically only provide evidence consistent with the theoretical model being tested, rather than comparing competing models (Hoemann et al., 2020).

If the Bayesian model comparison shows the classical approach model is optimal, then our study would indicate the relationship between subjective fear, skin conductance response, and heart rate is consistent across situations and individuals. Alternatively, if, as we predict on the basis of constructionist approaches, these relationships vary significantly by the situation and person, then our study would indicate that the classical approach model is not optimal which would emphasize the need for research to focus on individual and situational factors that shape the relationship between autonomic responses and subjective experience. If so, our approach will reveal whether variation depends only on the situation, the person, independently on both, or on a hierarchical relationship between the two. Of note, constructionist models are underspecified on this point; here, our approach provides a framework to organize how variation is structured by situations and individuals.

Method

2.1 Participants

Participants (N = 110) were recruited from introductory psychology classes at Northeastern University (mean age 20.68; age range 18-33; 70 female, 0 non-binary) and consented to study procedures. Because our interest concerns the relationship between subjective fear and autonomic responses in the neurotypical population, participants with a history of mental illness or use of psychoactive medications were excluded. Participants were also excluded if they were not fluent in English or used medications for cold/flu in the prior 24 hours due to potential influence on autonomic activity. From this initial sample we excluded participants with incomplete data (~80% of this data loss was due to failed bluetooth connections in our physiological recording devices; more details are included in section 2.6). These exclusions left us with a sample of 96 participants with complete EDA data (mean age =19.91, range 18-33; 52 female; 0 non-binary), and 94 participants with complete ECG data (mean age=19.93 53 range 18-33 female 0 non-binary). Participants received course credit for participating in the study. Study procedures were approved by the Northeastern University Institutional Review Board (NU IRB# 18-02-20) .

2.2 Stimuli

This study required developing a novel stimulus set in which stimuli were chosen such that the subjective fear ratings of the videos parametrically varied within three distinct situations. We used thirty six, twenty second-long videos evenly divided between content related to spiders, heights, and social situations. Videos were shot from an immersive first-person perspective and depicted real or naturalistic footage. Videos were extensively normed online ($N > 100$ per video; results from norming analysis and video descriptions are available at <https://github.com/ABS-Lab/AffectiveVideosRatings>). Videos from each type of content were selected to evoke a wide range of fear responses (i.e. from little or no fear to very high fear) based on normative ratings. Of note, normative ratings were only used for stimulus selection. Subjective fear ratings from each participant were used for regression analyses.

2.3 Task

To acclimate to the task, participants were provided with three practice trials, one from each category (spider, heights, social) using a separate set of videos. Practice trials used videos with an average normative fear rating across the videos in the stimulus set. The experimental video trials were organized into three, twelve-trial blocks. Each block consisted of four videos from each content category, presented in pseudorandom order. A one-minute break was provided after each block of videos.

At the beginning of each trial, practice and otherwise, participants were shown a video category cue (the word “spiders”, “heights”, or “social”) for four seconds followed by an interstimulus interval of a fixation cross, and then an approximately twenty-second video from the corresponding category. The cue was provided to reduce any extraneous effects due to semantic and perceptual updating that otherwise typically occurs at the onset of any stimulus. The cue period was also introduced to address other research questions regarding expected fear. Thus, after the fixation cross, participants indicated their expected fear and current anxiety on a sliding scale anchored from “low” to “high”. Due to a coding error, the duration the fixation cross was presented for was jittered ($M=3.75$ seconds) prior to most videos, but was fixed at eight seconds before height videos. This coding error precludes the ability to examine effects related to expected fear during the fixation period. The present set of analyses focused on the video watching period (not on the fixation period). Nonetheless, we conducted several analyses to ensure that the lengthier fixation time did not influence the results (see supplemental material: Tables S1-4). The video was then shown, and participants were instructed before watching to immerse themselves in the situation depicted in the video as much as possible. After each video, participants rated their fear, anxiety, arousal, and

valence during the video. Fear, anxiety, and arousal were rated on a continuous scale anchored from “low” to “high”. Valence ratings were anchored from “unpleasant” to “pleasant”. At the end of each trial, a fixation cross was displayed for eight seconds to allow any skin conductance responses during the trial to resolve. Continuous self-report ratings were recorded on a decimal scale [0.00, 1.00].

2.4 Physiological Recordings

EDA and ECG, respiration were recorded using two Shimmer Sensing (Dublin, Ireland) recording devices. EDA was collected at 128 Hz with a Shimmer 3 GSR+ device. ECG and respiration were sampled at 256 Hz on the same Shimmer ECG/EMG device. Manual inspection revealed extensive noise in the respiratory data, therefore it was not analyzed. All samples were streamed over Bluetooth to ConsensusPro Shimmer’s data acquisition software. EDA activity was recorded from the thenar and hypothenar eminences of the left hand using disposable Ag/AgCl 1.5” X 1” EDA electrodes containing isotonic paste (Mindware Technologies, Westerville, OH). To collect the ECG, we used pregelled- Ag/AgCl sensors (Biopac Systems Inc. Goleta, CA) in a modified Lead II configuration. The respiratory waveform was derived from the measurements using the Shimmer Sensing software, however as noted, due to noise, it was not analyzed in this study.

2.5 Procedure

Upon providing consent, participants washed their hands without soap and let them air dry after which EDA and ECG sensors were placed. Demographic and personality surveys were then administered. Peripheral physiological signals were recorded during a 5-minute baseline task during which a fixation cross was presented. After this baseline, the experimenter explained the experimental task to the participant and answered any questions. Participants then completed the practice trials to get acquainted with the task and mitigate any autonomic changes associated with the novelty of performing the task. The experimenter then dimmed the lights, initiated the experimental task, and left the room. Upon completion, the experimenter removed the sensors and debriefed the participant.

2.6 Physiological Data Pre-processing and Dependent Measure Extraction

ECG and EDA data were cleaned using custom Matlab scripts. EDA data was filtered with a 1 Hz low-pass filter and the EDAQA toolbox (I. R. Kleckner et al., 2018) was then used to remove additional segments of noise in the data. Consistent with the recommendations in the EDAQA tool box, noise was defined as any signal change faster than 10 μ S/sec, signal less than .05 μ S or signal greater than 60 μ S. The Matlab script then ran the findpeaks algorithm on the cleaned EDA data with the amplitude

threshold for findpeaks set at a very minimal $.01\mu\text{S}$ threshold to detect any possible peaks. Trained research assistants manually inspected and corrected the data for any misidentified peaks. After this initial detection step, we then used an adaptive thresholding technique which was designed to address the problem that a fixed SCR threshold can arbitrarily eliminate the detection of smaller SCRs in individuals with lower tonic skin conductance levels (SCL) (Kleckner et al., 2021). Thus, adaptive thresholding can provide greater sensitivity to phasic changes in EDA for individuals with widely varying SCL. This technique calculates the magnitude of peak values as a percent change in signal from the local minimum (onset) of a possible SCR and the local maximum at the peak. It outputs a percent signal change for each peak identified in the previous peak identification step. SCRs were defined as occurring if they involved at least a 3% change between the local minimum and local maximum. We chose 3% after pilot testing 1, 3, 5, and 10% all of which yielded similar results¹. We extracted the rate of SCRs during the periods of interest. After identifying all peaks above threshold in a period of interest, we divided the total number of peaks in the period by the total duration of the period to get the rate of SCRs per second. Subsequent analyses were conducted using this rate of SCRs/second.

For ECG data, the script first runs a “findpeaks” algorithm to identify the R-spikes in the ECG waveform. Following automated peak-picking, trained research assistants then inspected and manually corrected the detection of R waves in the ECG. For analysis, heart period was calculated (instead of heart rate) because it scales more linearly with changes in autonomic activity across different basal heart periods (Berntson et al., 1993). Heart period for each epoch of interest (inverse of heart rate) was calculated as the mean interbeat interval between successive R waves within the epoch.

Finally we calculated change scores for both SCR rate and HP for each trial's video watching period trial. We calculated change scores for SCR rate by subtracting each participant's average SCR rate in the baseline task from their SCR rate during each video watching period. We used this same method for calculating HP change scores. Trials with missing physiological data (e.g., due to loss of bluetooth signal from the acquisition devices) and trials in which the signal noise, such as movement artifacts) prevented automatic or manual identifications of features of interest (i.e., R-waves) were excluded. After this exclusion criteria participants for whom there were less than 12 trials of complete data were excluded entirely from the analysis. The final sample included SCR data for 90 participants (mean age = 20.00; 57.6% female; 0 non-binary), and HP data from 87 participants (mean age = 19.93; 60.8% female; 0

¹ Of note, using a fixed peak thresholded at $.01\mu\text{S}$ had no impact on the pattern of results (Supplemental table 5).

non-binary). Finally, predictor variables (SCR rate and HP change scores) and outcome variables (fear ratings) were standardized within participants for analysis.

2.7 Analysis

2.7.1 Overview

A model comparison approach was used to determine which of seven, *a priori*-defined distinct Bayesian Linear Regression models best captured the relationship between subjective fear and autonomic change measures (see Model Definition below for information about each of the seven models). To do this, we first fit each model to our data. We then compared models using a measure of information criteria which balances model complexity and accuracy. This approach allowed us to quantitatively compare how well models perform relative to one another. These direct comparisons enabled us to assess the predictive validity of theoretical assumptions regarding the generalizability of the autonomic correlates of fear, across situations and participants by embedding these assumptions into different models.

2.7.2 Model Definition

We defined 7 linear regression models each of which we used to predict participants trial by trial fear response separately using the SCR rate and HP data. Each model took the form:

$$Y = \beta * X + b \quad (1)$$

Where Y is each participant's fear rating on each trial and X is a measure of autonomic activity for the same trial (SCR rate or HP). Across the examined models the extent which the models' parameters were situation- and participant-general or specific were varied systematically. The simplest regression model defined, assumed there is the same relationship between autonomic activity and fear experience across participants and situations. This model takes the form of a linear regression that predicts fear scores based on each trial-specific measure of autonomic change. We refer to this model for the rest of the text as the **general model** (See Table 1 for model definition).

Next, we defined three situation-dependent models. The **situation model** assumes the relationship between physiological change and fear experience varies independently by the situation. The **situation participant model** assumes the relationship between physiology and fear experience varies by situation *and* participant, independently of one another (i.e., a distinct beta and intercept is estimated for each situation and for each participant). Finally, we estimated the **situation hierarchical model**. In this case, like the situation participant model, parameters are estimated for

each situation and each participant, but this model assumes that participant parameter estimates are constrained by the higher-level situation estimates across participants (i.e., an individual participant's beta estimate is jointly probable with the situation beta estimate across all participants and the observed relationships in that participants data).

Next we defined two additional models which assumed participant variation but not situational variation. The **participant model** which assumes the relationship between physiology and fear experience varies independently by participant (and not by the situation). Finally, we defined the **participant hierarchical model**, which estimates participant specific parameter estimates that are constrained by a higher-level group parameter estimate across all participants in the sample. The model instantiates this assumption by jointly estimating a group-level distribution of beta and intercept parameters with participant specific parameters as instances of the group distribution.

Finally, we included a **null model** that assumes there is no relationship between autonomic activity and fear experience, and here we simply model the distribution of fear ratings across all participants. In terms of equation (1) this model is equivalent to β being set to zero and only estimating the distribution of b . This null model enables us to examine the strength of evidence for the null hypothesis that there is no relationship between autonomic change and fear experience.

All models were defined in the probabilistic programming language pymc3, with weakly informative priors to reflect our knowledge that in a standardized regression the beta estimates will likely be between 1 and -1 (McElreath, 2020; Salvatier et al., 2016). The pymc3 model definitions were then used to estimate the posterior distributions for each parameter with 10,000-step Monte Carlo Markov Chains (MCMC). All models were fit separately to SCR and HP data.

2.7.3 Model Comparison

Bayesian model comparison was used to determine which model was most consistent with the data. Model performance was evaluated using a measure of information criteria that quantified model deviance (i.e., how far a model's predictions were from observed values), while adding a penalty for model complexity. Penalization for complexity is required to guard against overfitting since more complex models, those with more parameters, will almost always fit the data better. Our measure of information criterion was the Pareto Smoothed Importance Sampling- Leave One Out (PSIS-LOO) Analysis (Vehtari, Gelman, & Gabry 2016). PSIS-LOO re-estimates each model's parameters from the MCMC chain with one data point left out, and then uses these parameter estimates to predict the held out data point. In comparison to the more commonly used Bayesian Information Criteria or Akaike Information Criteria, PSIS-LOO more accurately represents a Bayesian model's performance for two reasons. First, PSIS-LOO takes the full posterior distribution for each parameter into account when

estimating model fit, as opposed to using a single point estimate. This enables the uncertainty in parameter estimates to affect a model's performance. Second, it does not assume normality, which allows non-normal posterior distributions to be accurately represented in a model's performance.

In a Bayesian framework, there is no significance testing but rather assessment of a graded strength of evidence. Consistent with this approach, we use two approaches to determine the relative differences in fit between the models examined. First, we examined the difference between the PSIS-LOO scores of each model (dPSIS-LOO) normalized by the standard error of the difference (dSE). dPSIS-LOO and dSE are calculated by subtracting the PSIS-LOO score from the model with the lowest (best) PSIS-LOO score from all other models' PSIS-LOO scores. The larger the differences in PSIS-LOO scores relative to the standard error of the differences, the more the performance of the models differ. For example, if the difference between PSIS-LOO scores for two models is within one or two standard errors of zero, this would suggest that the two models do not fit the data very differently. Alternatively, if the difference in the PSIS-LOO scores across models is several standard errors from zero, this would be strong evidence that the models fit the data differently.

We also used models' Akaike weights to compare the strength of evidence for each model (Wagenmakers & Farrell, 2004). A common interpretation of the Akaike weight is "the probability that the model will make the best predictions on new data, conditional on the set of models considered" (Mcelreath, 2019). Since Akaike weights are probabilities that range between 0.00-1.00, the sum of all Akaike weights is equal to 1, and the higher an Akaike weight, the better the corresponding model performed relative to other models examined. For instance in the scenario where all models examined have similar Akaike weights, even if one model has a higher absolute weight, there would be little evidence that any one model makes better predictions than any other model. In contrast, if nearly all of the Akaike weight is on one model, this would be strong evidence that this model best fits the data compared to any other models considered. We used the above model comparison strategies to assess the strength of evidence for each model across each of the 7 models, this comparison was done separately for SCR and HP data.

Data and Code Availability.

Code for all analyses and visualization is available at the following github link: https://github.com/ABS-Lab/Fear_Physio. Aggregated physiological data is available at the same link. Raw physiological and behavioral data will be made available upon request.

Results

3.1 A Situation Hierarchical Model Best Explains the Relationship between SCR rate and Fear

To facilitate the interpretation of the trade-off between model complexity and model accuracy (i.e., variance explained or model deviance in terms of the log likelihood of the model), we first estimated the “null model” which modeled the mean and variance of the intercept (i.e., only two parameters) and assumed no relationship between autonomic changes (here, the SCR rate) and subjective fear ratings. Without taking into account model complexity, as expected, all models outperformed the null model as illustrated by the lower model deviance scores - or PSIS-LOO scores, when uncorrected for the number of parameters (Figure 1, open circles). Also as expected, model performance increased in accordance with an increase in the number of parameters; the model with the most complexity, the situation participant model, had the lowest model deviance score, followed by the situation hierarchical model and the participant model, in order of decreasing complexity (Figure 1, filled circles).

To balance model deviance against model accuracy and protect against overfitting, we calculated PSIS-LOO scores with adjustment for model complexity. Here, the situation hierarchical model clearly emerged as the winning model (Figure 1, open circles). This result suggests that it is optimal to model variation in the relationship between SCR rate and fear experience independently across situations, but with shared variance at the participant level. The runner up model - the situation model - also parameterized the variation in the relationship between SCR rate and fear experience by situation.

We more formally quantified the statistical evidence in support of the situation hierarchical model compared to each other model using the difference between PSIS-LOO score (dPSIS-LOO), the standard of this difference (dSE), and each model's Akaike weights. The dPSIS-LOO between the situation hierarchical model and the next-best performing model, the situation model, was nearly seven standard error units from zero (Table 2). This difference provides strong evidence in favor of the situation hierarchical model. While dPSIS-LOO scores involve pairwise comparisons of each model versus the best-fitting model, the Akaike weight assesses the probability that a given model is the best-fitting model across all models examined. The Akaike weight loaded nearly entirely on the situation hierarchical model (Akaike weight $>.999$) with all other models having negligible Akaike weights (Akaike weight $<.001$). Overall, the results for the relationship of SCR rates with fear experience are unambiguously consistent with the situation hierarchical model.

The success of the situation hierarchical model suggests that both situation and participant variation are important when modeling the relationship between SCR rate and fear experience ratings. To more precisely document the relevant features of the situation hierarchical model, we plotted the posterior beta estimates from the model for each participant in Figure 2 along with the posterior beta estimates from the next three best-fitting other models for comparison. The figure highlights three qualities of the situation hierarchical model. First, the posterior distributions clearly illustrate that the relationship between SCR rate and fear experience varies predominantly by situation. There is a stronger relationship between SCR rate and fear experience in the heights situation than in the other two situations (heights: 95% Highest Posterior Density (HPD) [0.35,0.47]; spiders: 95% HPD [.03,.15]; social: 95% HPD [-.03,.11]). As such, models that formalized situational variation outperformed those that did not (e.g., the participant model). Second, there is also a significant amount of participant variability. The situation hierarchical model explicitly models this variation and in doing so, outperforms the situation (only) model in which participant variance is assumed to be noise. Third, when the plots for the situation hierarchical and the situation participant models are compared, we see that both models similarly capture situation variance, however, there is considerably more variation in the (much more flexible) situation participant model. Yet, the model comparison analysis suggests that the gains of modeling participant variation hierarchically within a situation outweighs the increased flexibility of the situation participant model. Although interestingly this variation did not correlate with phobia scores (see Table S6-7). In summary, the model comparison and the posterior estimates of SCR rate betas indicate that the relationship between SCR rate and fear experience varies across situations and participants with participant variation structured at the group-level by situation.

3.2 A Situation Hierarchical Model Best Explains the Relationship between HP response and Fear

We again compared the same seven models as for SCR rate to assess the relationship between HP response and fear experience. Without accounting for model complexity, as expected, all models outperformed the null model (open circles, Figure 3) and, as expected, more complex models had lower deviance scores. Upon accounting for model complexity, the situation hierarchical model again had the best performance (open circles, Figure 3). The dPIS-LOO between the situation hierarchical model and the next-best performing model, the situation model, was more than 5 dSEs from zero. The Akaike weight across all models also loaded nearly completely (>.999) on the situation hierarchical model (Table 3). These results strongly suggest that the situation hierarchical model best explains the relationship between HP responses and fear experience.

Consistent with our SCR rate findings, the success of the situation hierarchical model suggests that both situation and participant variation are also important when modeling the relationship between HP responses and fear experience ratings. We again plotted the posterior beta estimates from the model for each participant along with the posterior beta estimates from the three next-best other models for comparison (Figure 4). The posteriors of the situation hierarchical model for the HP model in Figure 4 shows the same 3 trends as the posteriors for the SCR rate model (Figure 2). First, the posterior distributions clearly illustrate that the relationship between SCR rate and fear experience varies by situation. There is a stronger relationship between HP responses and fear experience in the heights situation than in the other two situations (heights: 95% HPD [0.14,0.27], spiders 95% HPD [-0.07, 0.05], social: 95% HPD [0.05, 0.17]). Second, there is also a significant amount of participant variability. Third, the situation hierarchical and the situation participant models capture situation variance, however, there is considerably more variation in the situation participant model. Yet, the model comparison analysis suggested that the gains of modeling participant variation hierarchically within a situation outweighed the increased flexibility of the situation participant model. Although interestingly this variation did not correlate with phobia scores (see Table S6-7). In summary, the model comparison and the posterior estimates of HP betas indicate that the relationship between HP responses and fear experience varies across situations and participants with participant variation structured at the group-level by situation.

3.3 Addressing the General Model

A model comparison approach makes it possible to formally adjudicate between multiple models that outperformed the null model. In contrast, prior research using more traditional statistical methods only provides evidence that the null model is unlikely and subsequently assumed a general model. Notably, the general model, which collapses across variation by situation, also clearly outperformed the null model. When using model comparison to compare only these two models against each other for SCR rate, the general model's dPSIS-LOO compared to the null model was 81.19, which was approximately 6 dSE from zero, and the general model had nearly all of the Akaike weight (>.999). In the general model, group-level parameters showed that fear experience was reliably associated with increased SCR rate (95% HPD [0.09,0.16]). For HP responses, the general model outperformed the null model, albeit more weakly. The dPSIS-LOO between the two models was 9.70, only about 1.5 dSEs from zero, and the general model still had nearly all of the Akaike weight (>.999). The beta for the general model still suggested that fear experience was reliably associated with increasing HP responses (HPD [.05,.13]). Intriguingly, if we were only able to compare the general and

null models against each other using the null hypothesis testing statistical approach, we might mistakenly conclude that SCR rate and HP responses both positively predicted fear experience across our three contexts. Yet, our other models showed that the relationship between SCR rate and HP responses is context-dependent. Specifically, in the hierarchical model at the group level only electrodermal activity (i.e., SCR rates) predicted subjective fear in the spiders situation, only heart period response predicted subjective fear in the social situation, and both autonomic measures predicted subjective fear for the heights situation (See figure 5). Additionally our model comparison analyses showed that the predictive validity of the general model paled in comparison to the situation hierarchical model.

Discussion

In this study, we examined the uniformity and generalizability of the relationship between measures of change in SCR rate and heart period and subjective fear experiences. Our study was motivated by comparing two overarching theoretical assumptions. A prevailing (or classical) view is that fear consists of a central state that underlies a reliable set of autonomic responses which generalize across situations, people, and even species. It is under these assumptions of uniformity and generalizability that findings from studies examining defensive behavior in non-human animals (e.g., “fear conditioning” studies) would be directly informative for understanding fear experience of people in everyday life (Fanselow & Pennington, 2018; Hermans et al., 2006). Alternatively, other theoretical models, particularly from constructionist theoretical accounts, predict heterogeneity in the relationship between autonomic responses and subjective fear experience and their dependence on the situation and/or the person (Bliss-Moreau, 2017; Quigley & Barrett, 2014; Satpute & Lindquist, 2019). These theoretical approaches suggest that whether changes in autonomic activity can serve as a proxy for subjective experiences of fear will depend on the context and individual. It has remained unclear from prior work whether variability in the relationship between autonomic activity and subjective fear experience reflects residual error around a core theme (Fanselow & Pennington, 2018; Stemmler, 2004) or is reliably structured as heterogeneous patterns (Azari et al., 2020; Siegel et al., 2018).

The present study takes three critical steps to help address this gap. First, we examined measures of autonomic activity during fear inductions and the co-occurring subjective fear experiences correlate with one another at the level of individual participants (Beckers et al., 2013; Boddez et al., 2013; Shenhav & Mendes, 2014; Taschereau-Dumouchel et al., 2020). This analysis provides a straightforward test of convergence and divergence of measures that goes beyond that demonstrated by most

prior studies, which only examined whether a sample shows increased heart rate or skin conductance responses, and increased subjective fear, on average, but without directly analyzing these relationships at the participant- and situation-level (See Table S8 for a similar analysis of our data). Second, building on prior literature showing changes in autonomic responses across different affective contexts (Bradley et al., 2001; Shenhav & Mendes, 2014; Stemmler et al., 2001), we examined these correlations across three distinct fear-evocative situations (spiders, heights, and social situations), each with situation-specific baselines, and all in the same sample of participants. These design characteristics enabled us to test for generalization or dependency of correlations across situations, while at the same time mitigating alternative explanations due to methodological confounds, or due to sample differences by examining relationships within the same sample rather than comparing different samples. Third, we used a data-driven, Bayesian model comparison approach for statistical analysis (Vehtari et al., 2017; Wagenmakers & Farrell, 2004). This analytical approach quantifies the statistical evidence for each model, and thus provides a formal quantitative method for adjudicating among alternative theoretical accounts.

The top two performing models strongly indicate that the relationship between both electrodermal activity and subjective fear, and between heart period and subjective fear, depends on the situation. Only electrodermal activity (i.e., SCR rates) predicted subjective fear in the spider situation, only heart period response predicted subjective fear in the social situation, and both autonomic measures predicted subjective fear for the heights situation (See figure 5). We speculate on the nature of these specific differences below, however, here we note these findings are sufficient to reject assumptions of uniformity and generalizability. In contrast, these findings are consistent with constructionist models of emotion that hypothesize heterogeneity in the relationship between autonomic measures and subjective measures during fear experiences (Barrett, 2017; Hoemann et al., 2020; Quigley & Barrett, 2014; Satpute & Lindquist, 2019; Siegel et al., 2018). These findings also unequivocally lead to the conclusion that autonomic measures cannot be used as a proxy for subjective fear, at least not unconditionally; rather, the generalization of results from a given experiment on fear should be conditioned on the situation and/or the experimental paradigm.

The main difference between the top two models concerns how they treat participant variance (Figure 2, see Stemmler & Wacker, 2010 for a discussion of participant variance across different tasks). The top-performing situation hierarchical model assumes that participant variance is statistically meaningful but constrained by situation-level parameters. This model by far outperformed the runner-up situation model, which assumes that participant variance does not matter. Notably, it also outperformed several other models that parameterized participant-level variation, but did so independently of the situation. Taken together, these findings suggest that

variability in the relationship between autonomic responses and subjective fear across participants is neither negligible, nor is it wholly dependent on the person; rather, it is constrained by the situation.

It is worth keeping in mind both the strengths and limitations of our study with regard to the autonomic measures we used and our focussed examination of fear experience. First, we only examined a specific measure of electrodermal activity, the rate of SCRs/second and heart period. A number of autonomic response measures have been shown to be altered during fear experience (including respiration rate, heart rate and SCR amplitude; Table 9, (Siegel et al., 2018), however, there was significant heterogeneity in the effect sizes across previous studies, suggesting unexamined variance, which given the current results, may have stemmed from both situation-level and participant-level variance. Consistent with this prior work, our findings also suggest that neither SCR rate nor heart period have a uniform and generalizable association with fear experience; rather the relationship between autonomic responses and fear experience appears to strongly depend on the situation and person. Second, we did not examine how SCR rate and heart period change during inductions of other emotional experiences. While this may seem to be a limitation, our goal was not to test for autonomic response specificity during fear versus other emotion experiences, but rather to test models that assume uniformity and generalizability against those that assume dependency on situation and participant for fear experience in particular - given the large volume of work that relies on the uniformity and generalizability assumptions. Thus, we designed our study to examine fear experience in three distinct situations and in a large sample to test these assumptions.

The results of the present study raise the question of why uniformity has been, and often continues to be, the prevailing assumption (Yarkoni, 2020). Uniformity is predicted by theoretical models that assume there is a reliable and specific autonomic biomarker for fear that generalizes across situations and individuals or even species (Delgado et al., 2006; Fanselow & Pennington, 2018; Stemmler, 2004). It is implied in studies that model fear in only a single situation (e.g., fear of shock), analyze data by only performing statistical tests against a null model of no relationship, and do not contextualize conclusions with respect to the specific experimental situation or induction, suggesting that their results lead to generalizable conclusions about the nature of fear more broadly. We formally instantiated these assumptions in the general model. The general model outperformed a null model of no relationship, however, it was also outmatched by several models that assumed heterogeneity in the relationship, and specifically suggested the existence of structured heterogeneity as a function of situation and participant. This pattern of findings illustrates how the general model may appear to be supported by dozens of prior studies and yet not be the model that is best supported by the data.

Importantly, our findings do not suggest that it is impossible to find generalizability across studies, or potentially even across species. Rather, on the basis of these results, we suggest that robust generalization is possible when conditioned on situational and subject variables (Jolly & Chang, 2019; Satpute & Lindquist, 2019). Our results showed that subjective fear correlated with electrodermal responses during fear involving heights and spiders content, and with heart period decreases during fear involving heights and social situations. These findings indicate that relationships are situation-dependent, but *not* necessarily situation-specific. Research may advance by characterizing each instance of fear in terms of its features, and eventually we may be able to generalize across situations on the basis of shared features. For example, fear experience in a predator-prey situation likely involves multiple features, including mentalizing about the predicted actions of the predator, computing (or gauging) likelihoods of engaging in certain defensive actions (e.g., fleeing, freezing, fighting), and gauging the probability of physical harm. In comparison, fear of heights does not involve a predator, but may still share certain features with predator-prey situations (e.g., probability of physical harm). Fear pertaining to spiders or social encounters, also clearly vary in terms of shared and distinct relevant features. Characterizing situations as similar or distinct to one another in terms of latent features (Rauthmann et al., 2014; Reis, 2008; Tamir & Thornton, 2018) eventually could be used to identify features of situations and subjects that impact the relationship between autonomic activity and subjective fear to ultimately enable better generalization across diverse instances of fear.

Over a century ago, William James argued that while visceral states underlie fear (and other emotions), different varieties of fears will involve different visceral states (James, 1894). Our results are consistent with James' views. Even though increases in the rate of skin conductance responses and decreases in heart period (i.e., increases in heart rate) are among the most reliable autonomic changes that occur in studies examining fear experience, their associations with subjective fear were also found to be situation-dependent. Our findings are inconsistent with the notion that electrodermal activity and heart period can serve as proxies for subjective fear that generalizes across situations, or persons. These data suggest that to understand the relationships between autonomic responses and subjective fear will require identifying features that enable conditional generalization of relationships across distinct situations and across individuals.

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Author Contributions

K.M. and A.S. conceptualized the experiment and wrote the initial and final manuscript. K.M. designed experiments and analyzed data. I.K. and K.Q. gave feedback on initial experiment design, analyses, and comments on manuscript drafts.

Competing Interests

The authors declare no competing interests.

Works Cited

Azari, B., Westlin, C., Satpute, A. B., Hutchinson, J. B., Kragel, P. A., Hoemann, K., Khan, Z., Wormwood, J. B., Quigley, K. S., Erdogmus, D., Dy, J., Brooks, D. H., & Barrett, L. F. (2020). Comparing supervised and unsupervised approaches to emotion categorization in the human brain, body, and subjective experience. *Scientific Reports*, 10(1), 20284. <https://doi.org/10.1038/s41598-020-77117-8>

- Barrett, L. F. (2014). The Conceptual Act Theory: A Précis. *Emotion Review*, 6(4), 292–297.
<https://doi.org/10.1177/1754073914534479>
- Barrett, L. F. (2017). The theory of constructed emotion: An active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, 12(1), 1–23. <https://doi.org/10.1093/scan/nsw154>
- Beckers, T., Krypotos, A.-M., Boddez, Y., Effting, M., & Kindt, M. (2013). What's wrong with fear conditioning? *Biological Psychology*, 92(1), 90–96.
<https://doi.org/10.1016/j.biopsycho.2011.12.015>
- Berntson, G. G., Cacioppo, J. T., & Quigley, K. S. (1993). Cardiac psychophysiology and autonomic space in humans: Empirical perspectives and conceptual implications. *Psychological Bulletin*, 114(2), 296–322. <https://doi.org/10.1037/0033-2909.114.2.296>
- Bliss-Moreau, E. (2017). Constructing nonhuman animal emotion. *Current Opinion in Psychology*, 17, 184–188. <https://doi.org/10.1016/j.copsyc.2017.07.011>
- Boddez, Y., Baeyens, F., Luyten, L., Vansteenwegen, D., Hermans, D., & Beckers, T. (2013). Rating data are underrated: Validity of US expectancy in human fear conditioning. *Journal of Behavior Therapy and Experimental Psychiatry*, 44(2), 201–206.
<https://doi.org/10.1016/j.jbtep.2012.08.003>
- Bradley, M. M., Codispoti, M., Cuthbert, B. N., & Lang, P. J. (2001). Emotion and motivation I: Defensive and appetitive reactions in picture processing. *Emotion*, 1(3), 276–298.
<https://doi.org/10.1037/1528-3542.1.3.276>
- Davis, M. (1992). The role of the amygdala in fear and anxiety. *Annual Review of Neuroscience*, 15, 353–375. <https://doi.org/10.1146/annurev.ne.15.030192.002033>
- Delgado, M. R., Olsson, A., & Phelps, E. A. (2006). Extending animal models of fear conditioning to humans. *Biological Psychology*, 73(1), 39–48.

<https://doi.org/10.1016/j.biopsycho.2006.01.006>

Fanselow, M. S., & Pennington, Z. T. (2018). A return to the psychiatric dark ages with a two-system framework for fear. *Behaviour Research and Therapy*, 100, 24–29.

<https://doi.org/10.1016/j.brat.2017.10.012>

Hermans, D., Craske, M. G., Mineka, S., & Lovibond, P. F. (2006). Extinction in Human Fear Conditioning. *Biological Psychiatry*, 60(4), 361–368.

<https://doi.org/10.1016/j.biopsych.2005.10.006>

Hodes, R. L., Cook, E. W., & Lang, P. J. (1985). Individual Differences in Autonomic Response: Conditioned Association or Conditioned Fear? *Psychophysiology*, 22(5), 545–560.

<https://doi.org/10.1111/j.1469-8986.1985.tb01649.x>

Hoemann, K., Khan, Z., Feldman, M. J., Nielson, C., Devlin, M., Dy, J., Barrett, L. F., Wormwood, J. B., & Quigley, K. S. (2020). Context-aware experience sampling reveals the scale of variation in affective experience. *Scientific Reports*, 10(1), 12459.

<https://doi.org/10.1038/s41598-020-69180-y>

James, W. (1894). Discussion: The physical basis of emotion. *Psychological Review*, 1(5), 516–529. <https://doi.org/10.1037/h0065078>

Jolly, E., & Chang, L. J. (2019). The Flatland Fallacy: Moving Beyond Low-Dimensional Thinking. *Topics in Cognitive Science*, 11(2), 433–454.

<https://doi.org/10.1111/tops.12404>

Kleckner, I. R., Jones, R. M., Wilder-Smith, O., Wormwood, J. B., Akcakaya, M., Quigley, K. S., Lord, C., & Goodwin, M. S. (2018). Simple, Transparent, and Flexible Automated Quality Assessment Procedures for Ambulatory Electrodermal Activity Data. *IEEE Transactions on Biomedical Engineering*, 65(7), 1460–1467.

<https://doi.org/10.1109/TBME.2017.2758643>

- Kleckner, I., Wormwood, J. B., Jones, R. M., Erika Siegel, P., Culakova, E., Heathers, J., Barrett, L. F., Lord, C., Quigley, K., & Goodwin, M. (2021). *Adaptive thresholding increases ability to detect changes in rate of skin conductance responses to psychologically arousing stimuli*. PsyArXiv. <https://doi.org/10.31234/osf.io/b4agz>
- LeDoux, J. E. (2014). Coming to terms with fear. *Proceedings of the National Academy of Sciences*, 111(8), 2871–2878. <https://doi.org/10.1073/pnas.1400335111>
- McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and STAN*. CRC Press.
- Mobbs, D., Adolphs, R., Fanelow, M. S., Barrett, L. F., LeDoux, J. E., Ressler, K., & Tye, K. M. (2019). Viewpoints: Approaches to defining and investigating fear. *Nature Neuroscience*, 22(8), 1205–1216. <https://doi.org/10.1038/s41593-019-0456-6>
- Öhman, A., & Mineka, S. (2001). Fears, phobias, and preparedness: Toward an evolved module of fear and fear learning. *Psychological Review*, 108(3), 483–522. <https://doi.org/10.1037/0033-295X.108.3.483>
- Quigley, K. S., & Barrett, L. F. (2014). Is there consistency and specificity of autonomic changes during emotional episodes? Guidance from the Conceptual Act Theory and psychophysiology. *Biological Psychology*, 98, 82–94. <https://doi.org/10.1016/j.biopsycho.2013.12.013>
- Rauthmann, J. F., Gallardo-Pujol, D., Guillaume, E. M., Todd, E., Nave, C. S., Sherman, R. A., Ziegler, M., Jones, A. B., & Funder, D. C. (2014). The Situational Eight DIAMONDS: A Taxonomy of Major Dimensions of Situation Characteristics. *Journal of Personality and Social Psychology*. <https://doi.org/10.1037/a0037250>
- Reis, H. T. (2008). Reinvigorating the Concept of Situation in Social Psychology. *Personality and Social Psychology Review*, 12(4), 311–329. <https://doi.org/10.1177/1088868308321721>

- Salvatier, J., Wiecki, T. V., & Fonnesbeck, C. (2016). Probabilistic programming in Python using PyMC3. *PeerJ Computer Science*, 2, e55. <https://doi.org/10.7717/peerj-cs.55>
- Satpute, A. B., & Lindquist, K. A. (2019). The Default Mode Network's Role in Discrete Emotion. *Trends in Cognitive Sciences*, 23(10), 851–864.
<https://doi.org/10.1016/j.tics.2019.07.003>
- Scarantino, A. (2018). Are LeDoux's survival circuits basic emotions under a different name? *Current Opinion in Behavioral Sciences*, 24, 75–82.
<https://doi.org/10.1016/j.cobeha.2018.06.001>
- Shenhav, A., & Mendes, W. B. (2014). Aiming for the stomach and hitting the heart: Dissociable triggers and sources for disgust reactions. *Emotion (Washington, D.C.)*, 14(2), 301–309.
<https://doi.org/10.1037/a0034644>
- Siegel, E. H., Sands, M. K., Van den Noortgate, W., Condon, P., Chang, Y., Dy, J., Quigley, K. S., & Barrett, L. F. (2018). Emotion fingerprints or emotion populations? A meta-analytic investigation of autonomic features of emotion categories. *Psychological Bulletin*, 144(4), 343–393. <https://doi.org/10.1037/bul0000128>
- Stemmler, G. (2004). Physiological processes during emotion. In *The regulation of emotion* (pp. 33–70). Lawrence Erlbaum Associates Publishers.
- Stemmler, G., Heldmann, M., & Pauls, C. A. (2001). *Constraints for emotion specificity in fear and anger: The context counts*. 17.
- Stemmler, G., & Wacker, J. (2010). Personality, emotion, and individual differences in physiological responses. *Biological Psychology*, 84(3), 541–551.
<https://doi.org/10.1016/j.biopsycho.2009.09.012>
- Tamir, D. I., & Thornton, M. A. (2018). Modeling the Predictive Social Mind. *Trends in Cognitive Sciences*, 22(3), 201–212. <https://doi.org/10.1016/j.tics.2017.12.005>

Taschereau-Dumouchel, V., Kawato, M., & Lau, H. (2020). Multivoxel pattern analysis reveals dissociations between subjective fear and its physiological correlates. *Molecular Psychiatry*, 25(10), 2342–2354. <https://doi.org/10.1038/s41380-019-0520-3>

Van Diest, I., Bradley, M. M., Guerra, P., Van den Bergh, O., & Lang, P. J. (2009).

Fear-conditioned respiration and its association to cardiac reactivity. *Biological Psychology*, 80(2), 212–217. <https://doi.org/10.1016/j.biopsycho.2008.09.006>

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, 27(5), 1413–1432. <https://doi.org/10.1007/s11222-016-9696-4>

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights.

Psychonomic Bulletin & Review, 11, 192–196.

Yarkoni, T. (2020). The generalizability crisis. *Behavioral and Brain Sciences*, 1–37.

<https://doi.org/10.1017/S0140525X20001685>

Model Name	Definition	Variation Across Situation	Variation Across Participants
Null Model	$y \sim N(\mu, \sigma)$ $\mu \sim N(0, 1)$ $\sigma \sim \text{Half Cauchy}(0, 5)$	No, models the distribution of fear scores across all situations	No models the distribution of fear scores across all participants
General Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta * X + b$ $\beta \sim N(0, 1)$ $b \sim N(0, 1)$ $\sigma_l \sim \text{Half Cauchy}(5)$	No, assumes there is the same relationship between autonomic activity and fear across all situations	No, assumes all subjects have the same relationship between autonomic activity and fear
Situation Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta_s * X + b_s$ $\beta_s \sim N(0, 1)$ $b_s \sim N(0, 1)$ $\sigma_l \sim \text{Half Cauchy}(5)$	Yes, assumes relationships of autonomic activity and fear vary independently across situations	No, assumes all subjects have the same relationship between autonomic activity and fear

Participant Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta_p * X + b_p$ $\beta_p \sim N(0, 1)$ $b_p \sim N(0, 1)$ $\sigma_l \sim \text{Half Cauchy}(5)$	No, assumes there is the same relationship between autonomic activity and fear across all situations	Yes, assumes relationships of autonomic activity and fear vary independently across participants
Situation Participant Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta_{p,s} * X + b_{p,s}$ $\beta_{p,s} \sim N(0, 1)$ $b_{p,s} \sim N(0, 1)$ $\sigma_l \sim \text{Half Cauchy}(5)$	Yes, assumes relationships of autonomic activity and fear vary independently across situations	Yes, assumes relationships of autonomic activity and fear vary independently across participants
Subject Hierarchical Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta_p * X + b_p$ $\beta_p \sim \text{Normal}(\mu_\beta, \sigma_\beta)$ $b_p \sim \text{Normal}(\mu_b, \sigma_b)$ $\mu_\beta \sim N(0, 1)$ $\sigma_\beta \sim \text{Half Cauchy}(5)$ $\mu_b \sim N(0, 1)$ $\sigma_b \sim \text{Half Cauchy}(5)$ $\sigma_l \sim \text{Half Cauchy}(5)$	No, assumes there is the same relationship between autonomic activity and fear across all situations	Yes, assumes relationships of autonomic activity and fear vary across participants, but that at a group level all estimates come from the same joint distribution.
Situation Hierarchical Model	$y_i \sim N(\mu, \sigma_{like})$ $\mu = \beta_{p,s} * X + b_{p,s}$ $\beta_{p,s} \sim N(\mu_{\beta,s}, \sigma_{\beta,s})$ $b_{p,s} \sim N(\mu_{b,s}, \sigma_{b,s})$ $\mu_{\beta,s} \sim N(0, 1)$ $\sigma_{\beta,s} \sim \text{Half Cauchy}(5)$ $\mu_{b,s} \sim N(0, 1)$ $\sigma_{b,s} \sim \text{Half Cauchy}(5)$ $\sigma_l \sim \text{Half Cauchy}(5)$	Yes, assumes relationships of autonomic activity and fear vary independently across situations	Yes, assumes relationships of autonomic activity and fear vary across participants, but that at a group level all estimates come from the same joint distribution.

Table 1. Model definitions. This table describes for each model examined, the model definition and assumptions encapsulated in that definition. The first column is the name by which the model is referred to throughout the text. The second column shows the model definition, and the choice of prior distributions for each model that were compared. Notice, the Subject Hierarchical model defines a group-level distribution of parameters (μ_β, σ_β) that define the priors for individual subject parameter estimates ($\beta_{\text{subj}} \sim \text{Normal}(\mu_\beta, \sigma_\beta)$). The same is true for the situation hierarchical model, except different group-level distributions are defined for each situation. The third column outlines the assumptions made by each model about variability in the relationship between autonomic responses and fear experience across situations. The fourth column outlines the assumptions made by each model about the variability in the relationship between autonomic responses and fear experience across participants. Sit = Situation, p=participant.

<u>Model</u>	<u>PSIS-LOO</u>	<u>pPSIS-LOO</u>	<u>dPSIS-LOO</u>	<u>dSE</u>	<u>Akaike Weight</u>
Situation Hierarchical	4509.92	175.14	0.00	0.00	1.00
Situation	4591.47	10.01	81.55	12.57	0.00
Situation Participant	4689.04	496.29	179.12	18.90	0.00
Subject Hierarchical	4713.31	42.89	203.39	19.87	0.00
General	4724.21	5.23	214.29	20.17	0.00
Participant	4832.16	179.31	322.24	21.23	0.00
Null	4805.41	1.28	295.48	24.52	0.00

Table 2. SCR Model Comparison Statistics. Above are the metrics we calculated for our measure of information criterion and used to compare different models' performance. The first column shows the Leave One Out Deviance Score for each model (PSIS-LOO), the second column shows the number of effective of parameters for each model (pPSIS-LOO), the third column (dPSIS-LOO) shows the difference between each model's PSIS-LOO score, and the model with the lowest PSIS-LOO score, the fourth column (dSE) shows the standard error of the differences between each model, and the fifth column shows the Akaike weight for each model. As can be seen above by PSIS-LOOKing at the dPSIS-LOO, dSE, and Akaike weights, there is strong evidence that the situation hierarchical model performed better than the other models examined.

<u>Model</u>	<u>PSIS-LOO</u>	<u>pPSIS-LOO</u>	<u>dPSIS-LOO</u>	<u>dSE</u>	<u>Akaike Weight</u>
Situation Hierarchical	4130.91	151.27	0.00	0.00	1.00
Situation	4188.33	8.62	57.42	10.74	0.00
Subject Hierarchical	4264.35	33.26	133.44	15.50	0.00
General	4267.17	4.54	136.26	15.79	0.00
Situation Participant	4324.31	490.38	193.40	18.97	0.00
Participant	4384.42	179.38	253.51	17.54	0.00
Null	4276.74	1.23	145.83	16.75	0.00

Table 3. HP Model Comparison Statistics. (see Table 2 for descriptions). Consistent with the SCR rate results, the HP model comparison statistics show strong evidence that the situation hierarchical model outperformed the other models examined.

Figure 1. Measures of information criteria for models predicting subjective fear from SCR rate. Open circles depict a model's PSIS-LOO score after adjustment for the number of parameters in the model (also referred to as out of sample deviance). As indicated by the lowest PSIS-LOO score (open circles), the situation hierarchical model best fits the data (i.e., open circle at dashed vertical gray line). This model outperformed other models by several standard error units of the differences (dSE, as indicated by the gray triangles with a horizontal gray bar). Filled in circles denote PSIS-LOO scores before adjusting for the number of parameters in the model (also referred to as model deviance).

Figure 2. Beta distributions for several models relating SCR rate and Fear Experience. Plotted above are the beta distributions relating SCR rate and Fear experience for the Situation Hierarchical, Situation, Situation Participant, and Participant Hierarchical models. Individual participant beta estimates are plotted for the Situation Hierarchical, Situation Participant, and Participant Hierarchical, whereas there are only group-level estimates for the situation hierarchical model. The graphs for Situation Hierarchical and Situation models' (top row) clearly show that the betas vary by situation (Height - green, Social - orange, Spider - purple). Also clearly shown is that when models allow for it, betas vary across participants. This variation in participant betas is clearly seen in the situation participant model. For instance the heights (green) beta distributions for each participant (each curve) the vast majority have means well above zero but several have means well below zero. The tradeoff between modeling variation and statistical power is also evident in this figure, as shown by the wider variance in the situation participant beta estimates. The model comparison results suggest that the Situation Hierarchical model best balances the tradeoff of modeling situation and participant variation with optimizing statistical power.

Figure 3. Measures of information criteria for models predicting subjective fear from HP responses. Open circles depict a model's PSIS-LOO score after adjustment for the number of parameters in the model (also referred to as out of sample deviance). As indicated by the lowest PSIS-LOO score (open circles), the situation hierarchical model best fits the data (i.e., open circle at dashed vertical gray line). This model outperformed other models by several standard error units of the differences (dSE, as indicated by the gray triangles with a horizontal gray bar). Filled in circles denote PSIS-LOO scores before adjusting for the number of parameters in the model (also referred to as model deviance).

Fig 4. Beta distributions for several models relating HP responses and Fear Experience. Plotted above are the beta distributions relating HP and Fear experience for the Situation Hierarchical, Situation, Situation Participant, and Participant Hierarchical models. Individual participant beta estimates are plotted for the Situation Hierarchical, Situation Participant, and Participant Hierarchical, whereas there are only group-level estimates for the situation hierarchical model.

Figure 5. Regressions from the level group parameters of the hierarchical situation model. Bold lines represent the regression plotted from the mean beta and intercept for each situation. The shaded area around each line is the standard error of the mean of the beta estimates for the corresponding situation. Regressions plotted on the left represent the relationship between SCR and Fear, while the right represents HP and Fear. The importance of modeling situations is evident in the variation of the slopes across situations.