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Fear-Related Psychophysiological Patterns Are Situation and Individual Dependent: A Bayesian Model Comparison Approach

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Is there a universal mapping of physiology to emotion, or do these mappings vary substantially by person or situation? Psychologists, philosophers, and neuroscientists have debated this question for decades. Most previous studies have focused on differentiating emotions on the basis of accompanying autonomic responses using analytical approaches that often assume within-category homogeneity. In the present study, we took an alternative approach to this question. We determined the extent to which the relationship between subjective experience and autonomic reactivity generalizes across, or depends upon, the individual and situation for instances of a single emotion category, specifically, fear. Electrodermal activity and cardiac activity—two autonomic measures that are often assumed to show robust relationships with instances of fear—were recorded while participants reported fear experience in response to dozens of fear-evoking videos related to three distinct situations: spiders, heights, and social encounters. We formally translated assumptions from diverse theoretical models into a common framework for model comparison analyses. Results exceedingly favored a model that assumed situation-dependency in the relationship between fear experience and autonomic reactivity, with subject variance also significant but constrained by situation. Models that assumed generalization across situations and/or individuals performed much worse by comparison. These results call into question the assumption of generalizability of autonomic-subjective mappings across instances of fear, as required in translational research from nonhuman animals to humans, and advance a situated approach to understanding the autonomic correlates of fear experience.

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

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Since the very beginnings of psychological science, philosophers and physiologists debated whether certain categories of emotional experiences have particular autonomic activation patterns (Cannon, 1927; Dror, 2014; James, 1894). Over a century later, despite advances in experimental and analytical methods, the answer to this question remains contested (Mendes, 2016; Mobbs et al., 2019; Siegel et al., 2018; Taschereau-Dumouchel et al., 2022). Here, we approached this question from a slightly different perspective than has been explored in the past. Most research has focused primarily on emotion differentiation—i.e., whether autonomic responses for certain emotion categories have distinct profiles of autonomic reactivity (i.e., between-category variation; Ekman et al., 1983; Levenson, 1992, 2003; Siegel et al., 2018), typically by averaging responses within each category and examining differences between categories

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This study was not preregistered. Code for all analyses and visualization is available at the following github link: https://github.com/ABS-Lab/Fear_Physio. Aggregated autonomic data is available at the same link. Raw autonomic and behavioral data will be made available upon request.

A previous version of this paper was posted as a preprint here: https://psyarxiv.com/7uk4z/.

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(but see, Christie & Friedman, 2004; Kragel & LaBar, 2013). Alternatively, we focused on understanding the within-category variation in autonomic reactivity for a single emotion category: fear (for a discussion of within-category variation across emotion categories, see Siegel et al., 2018). Evidence of substantial within-category variation in fear may have broad implications for both emotion theory and translational research pertaining to fear and anxiety disorders.

According to classical or "strong views" of autonomic specificity (Lang, 2014; Levenson, 2014), certain emotion categories, like fear, have specific autonomic response profiles that are assumed to generalize across situations, individuals, and even species (for discussions, see Mendes, 2016; Siegel et al., 2018). This view follows from work on ecological threat and "basic emotions" models which propose that fear evolved as a natural kind or action program to drive specific survival-oriented behaviors in response to threat (Ekman et al., 1983; Fanselow & Pennington, 2018; Levenson, 2011; Mobbs et al., 2019). In some of these models, fearful feelings are also considered to be part of a common "fear response" that also drives autonomic activities and defensive behaviors (Calhoon & Tye, 2015; Fanselow & Pennington, 2018; Mobbs et al., 2020). This assumption is important to support the generalization of findings in nonhuman animals. If autonomic reactivity or other behavioral measures do not uniformly relate with subjective fear (as we have previously argued; Hoemann et al., 2020; Siegel et al., 2018), it calls into question whether findings on defensive behavior involving nonhuman animals generalize to human subjective experiences of fear, and how these nonhuman animal findings relate to the psychology of fear and anxiety disorders wherein subjective experience is a defining feature (Barrett et al., 2007; Bliss-Moreau, 2017; LeDoux & Pine, 2016).

Alternatively, constructionist models take a different approach to understanding fear. Rather than defining fear as an ingrained mechanism or particular behavior, constructionist models approach fear (and other emotions) as a "category construction problem" (Barrett, 2006, 2017; Quigley & Barrett, 2014). According to this view, for a given person the mental state category, "fear," is comprised of a set of instances with potentially variable features (e.g., an instance of fear involving heights, being chased by a predator, or of giving a public speech). Modeling fear requires sampling a variety of fearful instances from this distribution, determining whether certain features (e.g., autonomic responses, facial behaviors) are uniform or variable across them, and identifying factors that predict such variation (Azari et al., 2020; Doyle et al., 2022; Hoemann et al., 2020; Wang et al., 2022; Wilson-Mendenhall et al., 2011). Here, constructionist theory hypothesizes that fearful instances are unlikely to cluster around a single prototype; rather, they will form multiple clusters (Satpute & Lindquist, 2019). That is, the systematic or structured variance across instances of fear will be better approximated by a multimodal distribution. One factor that can organize such variation is the situation since instances from similar situations (e.g., instances of fear involving heights), are more likely to share similar sensory, cognitive, behavioral, or functional features. Another factor is the person, since each person's set of instances that comprise fear, may vary from another person's set. By this account, autonomic profiles associated with subjective fear may vary substantially across instances, but not randomly; rather, they will vary in a structured way depending on the situation and person. Correspondingly, the extent of generalizability of autonomic response patterns during fear instances is proposed to depend on the situation and/or person.

Currently, it remains unclear whether classical or constructionist models better account for the relationship between fear experience and autonomic reactivity. One reason is methodological. Most studies average data across instances (or trials) and participants. This approach assumes that each emotion category has a prototypic response profile consistent with the classical model, but it does not test the fundamental assumptions of the view (Azari et al., 2020; Lee et al., 2021). Even so, these studies do not appear to converge on a particular autonomic response profile for fear. A meta-analysis involving data from 111 studies found significant heterogeneity in effect sizes across nearly all autonomic correlates of instances of fear, and little evidence for a distinct pattern of autonomic correlates of fear compared to other emotions, even when using a multivariate approach (Siegel et al., 2018, see also Quigley & Barrett, 2014). A handful of empirical studies also support the constructionist account. For example, while not examining fear, one study found that different patterns of autonomic reactivity were observed for different varieties of disgust-eliciting stimuli (Shenhav & Mendes, 2014 see also Bernat et al., 2006). A few studies found divergent autonomic reactions across individuals in response to the same affective stimulus (e.g., threat of shock Hodes et al., 1985; Stemmler & Wacker, 2010; Van Diest et al., 2009). Further, a study that collected self-generated emotion terms concurrent with ambulatory physiology in daily life, also documented considerable variation across individuals and instances, even when the same emotion term was reported (Hoemann et al., 2020). Collectively, these findings suggest the possibility that autonomic responses during fear may depend on the stimuli or task paradigm and/or on the individual.

Despite these findings, the notion that fear has a prototypic autonomic response profile remains prevalent and suggests a second reason as to why this issue remains unresolved. Most contemporary theoretical models spanning from basic to constructionist approaches acknowledge at least some sources of variability across instances of fear (Azari et al., 2020; Cowen & Keltner, 2017; Ekman, 1993; Hoemann et al., 2020; Levenson, 2003). Consequently, it remains unclear as to whether the observed variation from prior studies reflects relatively minor fluctuations around a prototypic pattern that generalizes across at least most situations and individuals, or whether the variation is sufficient to abandon the idea of a "fear response profile" in favor of more contextualized, situation- and person-dependent models. These more fine-grained distinctions between theoretical models can be difficult to distinguish using traditional null-hypothesis testing statistical approaches.

In the present study, we address two key limitations of prior work that may help clarify this issue. The first limitation concerns study design. Most studies do not examine the *relationship* between subjective experience and autonomic reactivity at the level of each individual, and then test whether that relationship *generalizes* across contexts. Rather, they usually compare the means of two (or more) experimental conditions against one another. However, it is a statistical fallacy to assume that task conditions that evoke specific mean changes in subjective fear and skin conductance responses (SCR) imply the two are coupled to one another (see, "ecological fallacy"; Freedman, 2001). Indeed, some studies found that the relationship between autonomic activity and subjective experiences of amusement and sadness (Mauss et al., 2005) and valence (Brown et al.,

2020) varied considerably across individuals (see also Hoemann et al., 2020). We addressed this limitation using a novel study design wherein the relationship between subjective fear and autonomic activity was examined within each individual across trials, and sampled across three distinct situations: heights, spiders, and social threats. We selected stimuli from these situations for several reasons. First, they include a diversity of features, which makes them particularly useful for testing generalization. For example, while fear is often studied in contexts involving another agent (e.g., predator–prey contexts), fear of heights is both impactful and yet does not require another agent. Similarly, we reasoned that fear of social threats should rely on different features (e.g., more complex mentalizing about other people's thoughts and actions), relative to fear of a spider, or of heights. Second, all three situations are thought to induce fear in neurotypical individuals, not just in those with clinically diagnosed phobias (Siedlecka & Denson, 2019; Öhman & Mineka, 2001). Third, and a critical feature of our design, is that we could present several stimuli per situated context that spanned the range of normative fear experiences. For example, some heights content videos evoked higher levels of fear experiences (e.g., walking along the edge of a sheer cliff) whereas other heights content videos evoked little to no fear experience (e.g., walking down a set of stairs). With this parametric-like design, we can examine the relationship between instances of fear experience and autonomic reactivity measures, per person, per context.

To measure autonomic reactivity, we focused on a measure of electrodermal activity (i.e., SCR) and cardiac activity (i.e., interbeat interval duration; IBI). Both measures have been robustly but variably associated with instances of fear at a group level in prior studies (Siegel et al., 2018). They are also considered to be part of a presumed "fear response" as outlined in classical views (Fanselow & Pennington, 2018) and in translational research on aversive learning or "fear conditioning" paradigms (Lonsdorf et al., 2017). Consequently, it is of particular interest to test whether these measures generalize in predicting subjective fear across instances and individuals.

The second key limitation of prior work is that few studies formally compare theoretical models to one another. Most studies average data across trials and subjects and compare their findings against a null hypothesis. However, even if the null hypothesis is rejected, it remains possible that the data would be better fit by models that explicitly account for situation and person variance. The converse can also be true. Even if a study shows that autonomic reactivity during fear experience varies by the situation or person, it may still be more parsimonious to propose a "fear" response with more subtle variation across individuals rather than advancing more complex situation- and person-dependent models.

To address this limitation, we used a Bayesian model comparison approach, which enables us to draw specific inferences about the support for tested models than is possible with a simple null-hypothesis significance testing approach (Wagenmakers & Farrell, 2004). A more detailed description of these models is provided below and in Table 1. Each model was designed to capture relationships between fear experience with autonomic reactivity, but models differed in the extent to which they allowed these relationships to vary by situation and person. In the *general model*, the relationship between fear experience with autonomic reactivity is assumed to generalize across situations and individuals, consistent with the classical approach. Also consistent with the classical models is the *participant hierarchical model*, which proposes that this relationship does not depend on the situation and that there is a common component to this relationship shared across individuals to a degree, but that participant variation also matters (i.e., a common set of parameters constrain variation across individuals; this notion is theoretically consistent with ideas from Mauss et al., 2005). The *participant model* assumes this relationship would require distinct parameters for each participant, but that situation has no effect on the relationship and there is no common component (i.e., a purely idiographic model). Finally, there are two *situation* models that are more consistent with constructionist views. The *situation (only) model* proposes that the relationship between fear experience and autonomic reactivity depends on the situation, but not the participant. The *situation hierarchical model* proposes that this relationship depends on the situation and the participant, but that participant variance is constrained by the situation. Thus, the modeling approach in combination with the experimental design provides a formal means to determine which family of theoretical models, given specific computational implementations, fits the data best.

Method and Materials

Participants

Consenting adult participants ($N = 123$) were recruited from introductory psychology classes at Northeastern University (age $M = 20.68$; age range: 18–33 years; 70 women, 53 men, zero nonbinary) during 2019 and 2020. Participants were excluded based on self-identified history of mental illness, vision if not not corrected to normal, lack of English proficiency, and use of drugs that interfere with autonomic function. Upon further exclusions due to data loss, we had a sample of 95 participants with complete EDA data (age $M = 19.91$, range: 18–33; 55 women, 40 men, zero nonbinary), and 93 participants with complete electrocardiogram (ECG) data (age $M = 19.93$, range: 18–33, 54 women, 39 men, zero nonbinary). Data loss was primarily due to loss of Bluetooth connectivity during the experiment for the autonomic recording devices. Of the 95 EDA participants, participants self-identified as Asian (37%), American Indian (1%), Black (4%), Latino (3%), Multiracial (Asian and Black 1%, Asian and White 4%, Pacific Islander and White 1%), and White (48%). Of the 93 ECG participants, participants self-identified as Asian (37%), American Indian (1%), Black (3%), Latino (3%), Multiracial (Asian and Black 1%, Asian and White 5%), and White (49%). Typical sample sizes for studies examining the psychophysiology of fear, as reviewed in Siegel et al. (2018), included, on average, approximately 40 participants with 25th quartile of 24 and 75th quartile of 48 participants. Furthermore, data quality checks routinely lead to exclusions of approximately 25% of samples (see for a recent example Wormwood et al., 2019). We originally aimed to recruit 133 participants (anticipating exclusion of approximately 33 participants). The COVID-19 pandemic interrupted our data collection, so we stopped recruitment at 123 participants. Participants received course credit for participating in the study. Study procedures were approved by the Northeastern University Institutional Review Board (NU IRB 8-02-20).

Stimuli

This study required developing a novel video stimulus set in which subjective fear would likely vary from low to high levels

Table 1
Model Definitions

Model name	Definition	Variation across situation	Variation across participants
Null model	$y \sim N(\mu, \boldsymbol{\sigma})$ $\mu \sim N(0, 1)$ $\boldsymbol{\sigma} \sim \textit{Half Cauchy}(5)$	No, models the distribution of fear scores across all situations	No, models the distribution of fear scores across all participants
General model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta \times X + b$ $\beta \sim N(0, 1)$ $b \sim N(0, 1)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauchy}(5)$	No, assumes there is the same relationship between autonomic reactivity and fear across all situations	No, assumes all subjects have the same relationship between autonomic reactivity and fear
Situation model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta\_s \times X + b\_s$ $\beta\_s \sim N(0, 1)$ $b\_s \sim N(0, 1)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauchy}(5)$	Yes, assumes relationships of autonomic reactivity and fear vary independently across situations	No, assumes all subjects have the same relationship between autonomic reactivity and fear
Participant model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta\_p \times X + b\_p$ $\beta\_p \sim N(0, 1)$ $b\_p \sim N(0, 1)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauchy}\ (5)$	No, assumes there is the same relationship between autonomic reactivity and fear across all situations	Yes, assumes relationships of autonomic reactivity and fear vary independently across participants
Situation participant model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta\_p, s \times X + b\_p, s$ $\beta\_p, s \sim N(0, 1)$ $b\_p, s \sim N(0, 1)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauchy}(5)$	Yes, assumes relationships of autonomic reactivity and fear vary independently across situations	Yes, assumes relationships of autonomic reactivity and fear vary independently across participants
Subject hierarchical model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta\_p \times X + b\_p$ $\beta\_p \sim N(\boldsymbol{\mu}\_\beta, \boldsymbol{\sigma}\_\beta)$ $b\_p \sim N(\boldsymbol{\mu}\_b, \boldsymbol{\sigma}\_b)$ $\boldsymbol{\mu}\_\beta \sim N(0, 1)$ $\boldsymbol{\sigma}\_\beta \sim \textit{Half Cauchy}(5)$ $\boldsymbol{\mu}\_b \sim N(0, 1)$ $\boldsymbol{\sigma}\_b \sim \textit{Half Cauchy}(5)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauhy}(5)$	No, assumes there is the same relationship between autonomic reactivity and fear across all situations	Yes, assumes relationships of autonomic reactivity and fear vary across participants, but that at a group level all estimates come from the same joint distribution.
Situation hierarchical model	$y \sim N(\mu, \boldsymbol{\sigma}\_l)$ $\mu = \beta\_p, s \times X + b\_p, s$ $\beta\_p, s \sim N(\boldsymbol{\mu}\_\beta, s, \boldsymbol{\sigma}\_\beta, s)$ $b\_p, s \sim N(\boldsymbol{\mu}\_b, s, \boldsymbol{\sigma}\_b, s)$ $\boldsymbol{\mu}\_\beta, s \sim N(0, 1)$ $\boldsymbol{\sigma}\_\beta, s \sim \textit{Half Cauchy}(5)$ $\boldsymbol{\mu}\_b, s \sim N\ (0, 1)$ $\boldsymbol{\sigma}\_b, s \sim \textit{Half Cauchy}(5)$ $\boldsymbol{\sigma}\_l \sim \textit{Half Cauchy}(5)$	Yes, assumes relationships of autonomic reactivity and fear vary independently across situations	Yes, assumes relationships of autonomic reactivity and fear vary across participants, but that at a group level all estimates come from the same joint distribution.

Note. 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 was compared. Notice, the Subject Hierarchical model defines a group-level distribution of parameters ($\boldsymbol{\mu}\_\beta$, $\boldsymbol{\sigma}\_\beta$) that define the priors for individual subject parameter estimates ($\beta\_subj \sim \text{Normal}(\boldsymbol{\mu}\_\beta, \boldsymbol{\sigma}\_\beta)$). 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.

for each person and situation. We used 36, 20-s-long videos evenly divided between content related to heights, social, and spider situations. Videos were shot from an immersive first-person perspective and depicted real or naturalistic footage, and were extensively normed online ($N > 100$ per video; results from norming analysis and video descriptions are available at https://github.com/ABS-Lab/AffectiveVideosRatings). For example, in a normative high-fear experience heights video, "you" (i.e., 1st person footage) are looking out while walking along the edge of a cliff, whereas in a normative low-fear experience heights video, "you" are looking at and walking down a set of stairs. In a normative high-fear experience social video, "you" are interrogated by three police officers, whereas in a normative low-fear experience social video, "you" are walking down a city street with several other pedestrians. In a normative high-fear experience spider video, "you" watch a large, scary-looking spider crawling along the wall indoors whereas in a normative low-fear experience spider video, "you" watch a small spider (but not necessarily small in terms of visual field) crawl along a web outside in the woods. We note that these are just some example clips and that the clips themselves varied considerably within each category (heights, social, and spiders). Further, normative ratings were only used for stimulus selection, all analyses reported in this manuscript used participants' own fear experience ratings.

Task

To acclimate to the task, participants were provided with three practice trials, one from each category (heights, social, and spiders) using a separate set of videos. Practice trials used videos with an average normative fear experience rating across the videos in the stimulus set. The experimental video trials were organized into three, 12-trial blocks. Each block consisted of four videos from each content category presented in pseudorandom order. A 1-min break was provided after each block of videos. In each trial, participants were first shown a video category cue (the word "spiders," "heights," or "social") for 4 s followed by an interstimulus interval of a fixation cross and then an approximately 20-s video from the corresponding category. The cue was provided to reduce any extraneous effects due to semantic and perceptual updating that otherwise typically occur at the onset of any stimulus and to address other research questions regarding expected fear experience (not reported here). After the fixation cross, participants indicated their expected fear experience and current anxiety experience on a sliding scale anchored from "low" to "high." Due to a coding error, the duration of the fixation cross was jittered ($M = 3.75$ s) prior to most videos but was fixed at 8 s before height videos. This coding error precludes the ability to examine effects related to expected fear experience 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 Tables S1–S4 in the online supplemental materials). The video was then shown. Prior to beginning the experimental tasks participants were instructed to immerse themselves in the situation depicted in the video as much as possible during the video watching period. Immediately after each video, participants rated the fear, anxiety, arousal, and valence they felt in response to 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 8 s to allow any SCRs during the trial to resolve. Continuous self-report ratings were recorded on a decimal scale [0.00, 1.00].

Physiological Recordings

Electrodermal activity (EDA), ECG, and 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 ConsensysPro 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″ × 1″ EDA electrodes containing isotonic paste (Mindware Technologies, Westerville, Ohio, United States). To collect the ECG, we used pregelled-Ag/AgCl sensors (Biopac Systems Inc. Goleta, California, United States) 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.

Procedure

After 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 autonomic signals were recorded during a 5-min 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.

Data Preprocessing and Dependent Measure Extraction

ECG and EDA data were preprocessed using custom Matlab scripts. EDA data was filtered with a 1 Hz low-pass filter. Additional segments of noise in the data were removed using the EDAQA toolbox (Kleckner et al., 2018), which recommends defining noise as any signal change faster than 10 μS/s, tonic signal <0.05 μS, or signal greater than 60 μS. As an initial step to identify SCRs, peaks were identified on the cleaned EDA data using using the *findpeaks* algorithm (Matlab), with a minimum amplitude threshold for peak identification at 0.01 μS (i.e., an SCR was defined only when there was a minimum 0.01 μS difference from SCR onset to SCR peak). Trained research assistants manually inspected and corrected the data for any misidentified peaks. After this initial detection step, we used an adaptive thresholding technique 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). 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 results. We extracted the rate of SCRs during the video-watching period, such that all SCR peaks occurring in the 20-s video-watching period were counted as an SCR response for that trial. 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, R-spikes in the ECG waveform were identified using the *findpeaks* (Matlab). Trained research assistants then inspected and manually corrected the detection of R waves in the ECG. For analysis, IBI was calculated (instead of heart rate) because it scales more linearly with changes in autonomic reactivity across different basal IBIs (Berntson et al., 1993). For each epoch of interest, the mean IBI between successive R waves within the epoch was calculated. The IBI, SCR, and subjective fear rating data were z-scored prior to statistical modeling.

Fear, Anxiety, and Valence

While the goal of our analysis concerns subjective experiences of fear, we also measured self-reported anxiety and valence. Of note, while ecological models often define fear and anxiety in terms of distinct stages of a predator–prey interaction, there is far less evidence that these constructs are necessarily distinguishable at a subjective level. Indeed, recent theory as well as behavioral and neuroscience findings suggests that fear and anxiety are not necessarily distinct constructs (Cowen & Keltner, 2017; Daniel-Watanabe & Fletcher, 2022; Hoemann et al., 2017; LeDoux & Pine, 2016; Shackman & Fox, 2021). Here, to assess the relationship among self-reported fear, anxiety, and valence, we conducted preliminary analyses in which we calculated correlations among these measures for each participant across trials. As expected, on average across individuals, fear experience correlated highly with anxiety experience—mean Pearson's $r(93) = 0.87$—and with negative affect—mean Pearson's $r(93) = 0.67$. Because our interest is in studying the variation in autonomic correlates of fear experience, our subsequent analyses focus on reported fear experience as the construct of interest.

Analysis

We defined seven linear regression models each of which we used to predict participants' trial-by-trial fear responses separately for the SCR rate and IBI change data (Table 1). Each model took the form:

$$Y = \beta \times X + b, \tag{1}$$

where Y is a vector of each participant's fear rating on each trial and X is a measure of autonomic reactivity for the same trial (SCR rate or IBI). In the *general model*, we assumed that the relationship between autonomic reactivity and fear experience generalized across participants and situations. This model takes the form of a linear regression that predicts fear ratings from autonomic changes on a trial-by-trial basis.

We then defined three situation-dependent models. The *situation model* assumes the relationship between autonomic change and fear experience varies independently by the situation. The *situation participant model* assumes the relationship between physiology and fear experience varies independently by situation *and* participant (i.e., a distinct beta and intercept are estimated for each situation and for each participant). Finally, we estimated the *situation hierarchical model*. 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 participant's data). Notably, this assumption of nested participant variance greatly limits the amount of variance across participant-specific parameter estimates compared with the situation participant model.

Two additional models were tested that assumed participant variation, but not situation variation. The *participant model* assumed the relationship between autonomic change and fear experience varies independently by participant. The *participant hierarchical model* 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 reactivity 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 changes and fear experience.

A model comparison approach was used to determine which of seven, a priori defined linear regression models best captured the relationship between fear experience and autonomic change measures (see Table 1 for model definition and explanation). Each model was fit to the data with a10,000 step Monte Carlo Markov Chain. Models were compared using a measure of information criteria that balances model complexity and accuracy to score each model's performance, specifically, Pareto Smoothed Importance Sampling Leave One Out (PSIS-LOO, Vehtari et al., 2017). We then calculated the difference between models PSIS-LOO scores (dPSIS-LOOs) and the standard error of these differences (dSE). Finally, we used Akaike Weights to compare models all models to each other (Wagenmakers & Farrell, 2004); while dPSIS-LOO scores involve pairwise comparisons of each model versus the best-fitting model, the Akaike weight is a way to quantify the probability that a given model is the best-fitting model across all models examined (McElreath, 2020). These comparisons enabled us to assess the predictive validity of theoretical assumptions regarding the generalizability of the autonomic correlates of fear experience, across situations and participants by comparing the performance of models embedded with different theoritical assumptions. All analyses were performed separately for SCR rate and IBI data. Code for all analyses and visualization is available at the following github link: https://github.com/ABS-Lab/Fear_Physio and aggregated autonomic data is available at the same link (McVeigh, 2022). Raw autonomic and behavioral data will be made available upon request.

Results

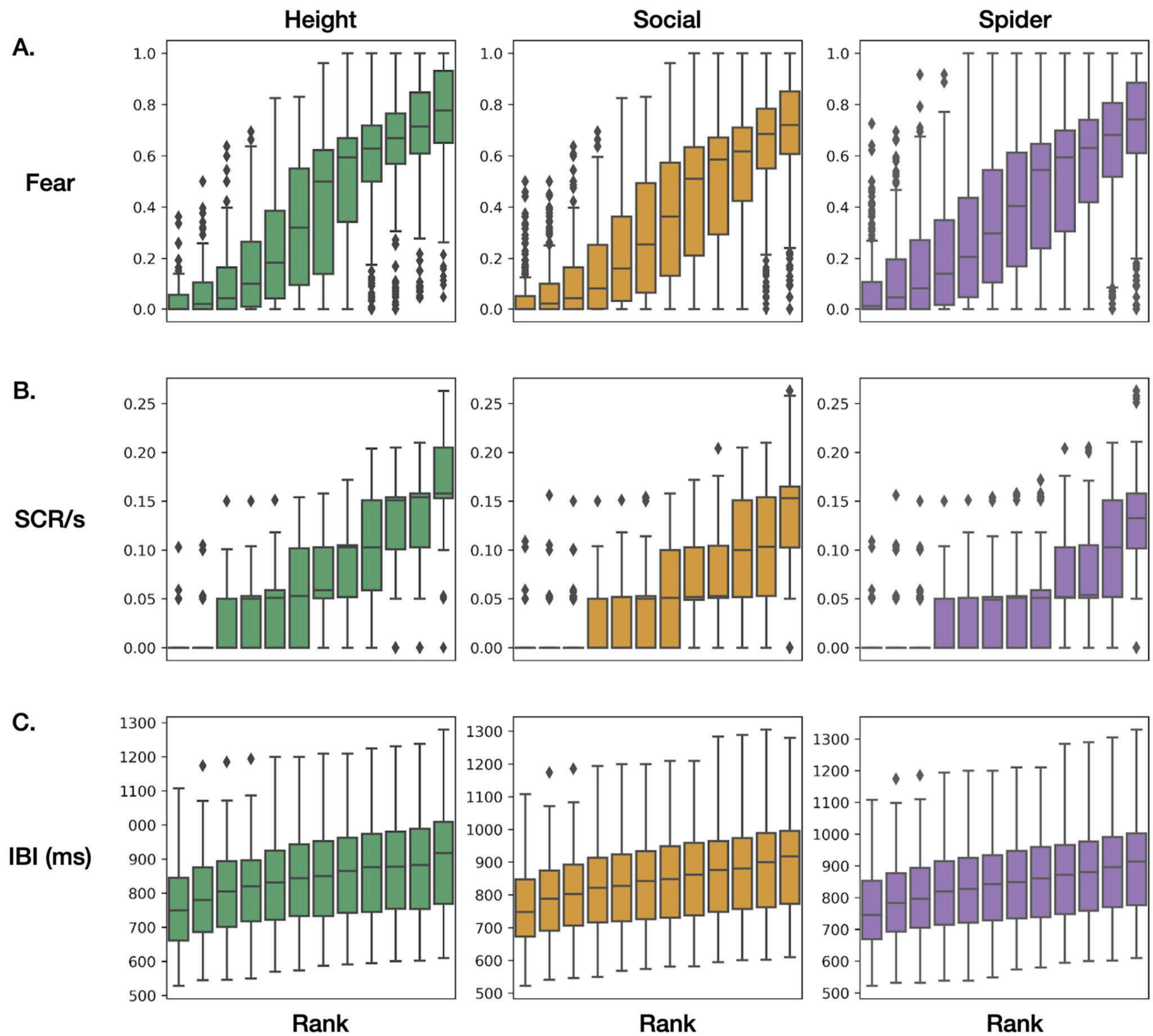
Manipulation Check

The aim of our experimental design was to introduce a high degree of variation in subjective fear across trials for each situation and participant. As shown in Figure 1A (additional descriptive statistics are presented in Table S1 in the online supplemental materials), on average participants showed a wide range of self-reported fear experience within each situation. Similar plots for SCR rate and mean IBIs (Figure 1B and C) showed considerable variation in autonomic reactivity for each situation. Hence, we proceeded with examining how the relationship between subjective fear and autonomic reactivity was structured in accordance with the models outlined in Table 1.

A Situation Hierarchical Model Best Explains the Relationship Between SCR Rate and Fear Experience

Model comparison analyses were performed to identify which model best explained the relationship between subjective fear and SCR rate. As shown in Figure 2, the situation hierarchical model clearly emerged as the best-performing model. This result

Figure 1
Parametric Modulation of Fear Experience Within Each Situation



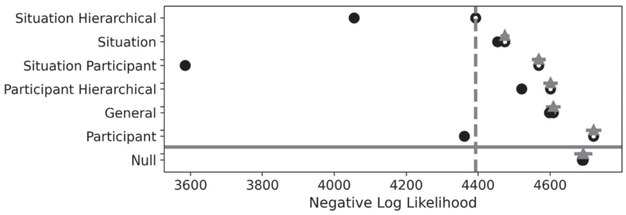
Note. The above plots show the mean and variations of rank order distribution of fear ratings, SCR rate, and Mean IBI across participants. Note, that the *x*-axis is ordered idiographically, that is, by each participant's recorded observation. Overall, the plots illustrate as intended that participants on average showed considerable within-condition variation in fear experience, and autonomic reactivity supporting a parametric analysis approach. SCR = skin conductance responses; IBI = interbeat interval. See the online article for the color version of this figure.

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 superior performance of the situation hierarchical model was reflected by the lowest PSIS-LOO score. The large difference between the situation hierarchical and the next best-performing model's PSIS-LOO score (dPSIS-LOO), nearly seven standard error units from zero (Table 2), provides strong statistical evidence for the model's superiority. The superiority of the situation hierarchical model was also reflected in the Akaike weight. The Akaike weight loaded nearly entirely on the situation hierarchical model (Akaike weight > 0.999) with all other models having negligible Akaike weights (Akaike weight < 0.001). Overall, the results for the relationship of SCR rates with fear experience are unambiguously most consistent with the situation hierarchical model of the models we specified.

To illustrate the relationships between fear experience and SCR rate, we plotted the posterior beta estimates in Figure 3 along with the posterior beta estimates from the next three best-fitting other models for comparison. The figure highlights three qualities of our

Figure 2

Measures of Information Criteria for Models Predicting Fear Experience From SCR Rate



Note. 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). SCR = skin conductance responses; PSIS-LOO = Pareto smoothed importance sampling leave one out; dSE = standard error of the differences.

results favoring the situation hierarchical model. First, the posterior distributions clearly illustrate that the relationship between SCR rate and fear experience varies by situation. This variation is seen in the 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: [0.03, 0.15]; social: [−0.03, 0.11] (Figure 3). The importance of the situation is also reflected in that models that formalized variation by situation outperformed those that did not (e.g., the participant model). Second, figure 3 highlights there is a significant amount of participant variability in the situation hierarchical model. The runner-up model—the situation model—also parameterized the variation in the relationship between SCR rate and fear experience by situation but ignored participant variance. 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 capture situation variance, however, there is considerably more variation in the (much more flexible) situation participant model. The model comparison analysis suggests that the benefits of modeling participant variation hierarchically within a situation outweigh the increased flexibility of the situation participant model. 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 (see Figure 6 left panel).

A Situation Hierarchical Model Best Explains the Relationship Between IBI and Fear Experience

Consistent with our SCR rate findings, the situation hierarchical model also performed the best when fit to the IBI data (see Figure 4). Also similar to the SCR results, the situation (only) model was the next best-performing model. The situation hierarchical model's superiority was again reflected in the dPSIS-LOO, which was over five dSEs from the next best-performing model, with nearly all the Akaike weight (>0.999) loading on it (see Table 3). These results suggest that situation and participant variation are also important when modeling the relationship between IBI 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 5). The posteriors of the situation hierarchical model for the IBI model in Figure 4 show the same trends in the posteriors as for the SCR rate model (Figure 3). The posterior distributions clearly illustrate that the relationship between IBI rate and fear experience varies by situation. Interestingly, in the heights situation, there was again the strongest relationship between IBI responses and fear experience—heights: 95% HPD [0.14, 0.27]. In contrast to SCR results, the weakest relationship was between IBI and fear experience in the spiders' situation (95% HPD [−0.07, 0.05]) while a modest relationship was observed in the social situation ([0.05, 0.17]; Figure 5).

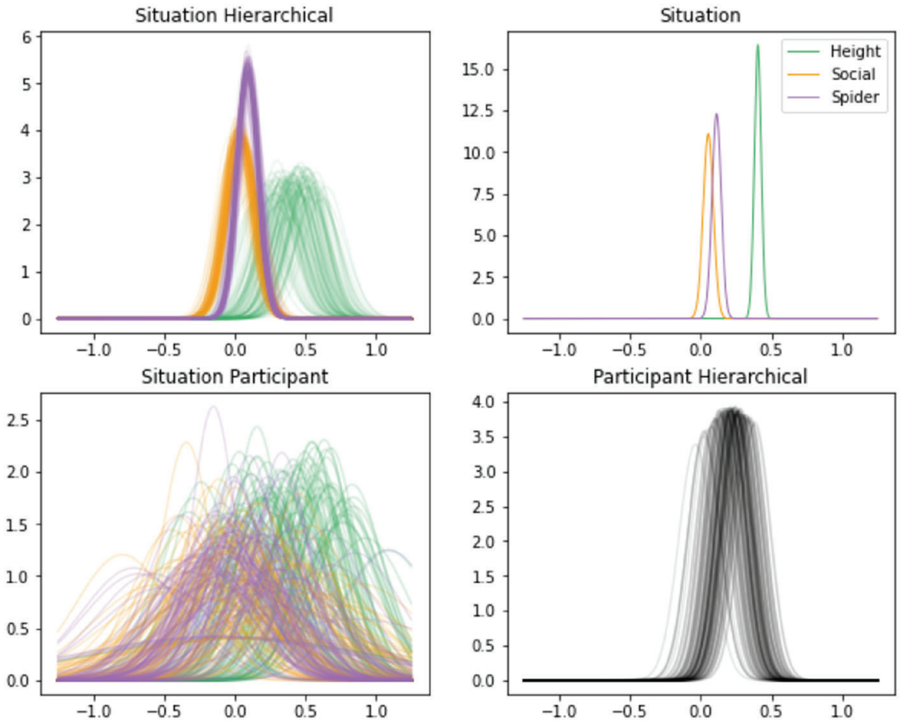
Table 2

SCR Model Comparison Statistics

Model	PSIS-LOO	pPSIS-LOO	dPSIS-LOO	dSE	Akaike weight
Situation hierarchical	4,509.92	175.14	0.00	0.00	1.00
Situation	4,591.47	10.01	81.55	12.57	0.00
Situation participant	4,689.04	496.29	179.12	18.90	0.00
Subject hierarchical	4,713.31	42.89	203.39	19.87	0.00
General	4,724.21	5.23	214.29	20.17	0.00
Participant	4,832.16	179.31	322.24	21.23	0.00
Null	4,805.41	1.28	295.48	24.52	0.00

Note. 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 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. PSIS-LOO = Pareto smoothed importance sampling leave one out; dSE = standard error of the differences; SCR = skin conductance responses.

Figure 3
Beta Estimates Visualized for Four Different Models



Note. 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 model. The graphs for situation hierarchical and situation models (top row) clearly show that the betas vary by situation (social—left-most distribution(s); spider—middle distribution(s); height—right-most distribution(s)). 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, for the height 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. SCR = skin conductance responses. See the online article for the color version of this figure.

In summary, the model comparison and the posterior estimates of IBI change betas indicate that the relationship between IBI responses and fear experience varies across situations and participants with participant variation structured at the group-level by situation (see Figure 6, right panel).

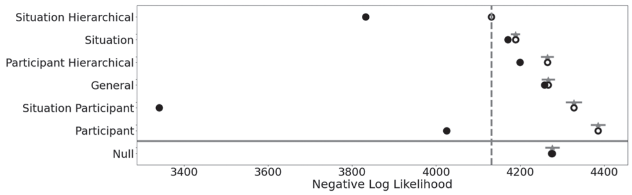
Addressing the General Model

It is illustrative to also test how the general model, which assumes a singular relationship between autonomic reactivity and fear experience, performs relative to the null model, as most studies examining autonomic reactivity during fear experience draw on the same underlying assumptions. For SCR rate, the difference between the null and general model's PSIS-LOO was approximately six dSE from zero, and the general model had nearly all of the Akaike weight (>0.999) when restricting the analysis to only these two models. For IBI responses, the general model outperformed the null model, albeit more weakly. The dPSIS-LOO between the two models was only about 1.5 dSEs from zero, but the general model still had nearly all of the Akaike weight (>0.999), again when restricting the model comparison space. These findings may help account for how studies focusing on hypothesis confirmation may support the general model in comparison to a null model even though the predictive validity of the general model paled in comparison to the situation hierarchical model.

Discussion

A critical question of both fundamental and translational interest in affective science concerns how robustly certain autonomic measures relate with fear experience. Here, we approached this question as a "category construction problem" wherein fear is treated as a population of instances that may vary in their particular features. An important goal for emotion research then is to characterize

Figure 4
Interbeat Interval PSIS-LOO Model Performances Depiction



Note. Measures of information criteria for models predicting fear experience from IBI 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). PSIS-LOO = Pareto smoothed importance sampling leave one out; IBI = interbeat interval; dSE = standard error of the differences.

how instances of fear are distributed within this population category. Is there a unimodal prototype wherein most instances cluster around a so-called unitary "fear response" (i.e., a one-to-one relationship between autonomic change and fear experience), or are there multiple distinct autonomic profiles that relate with subjective fear (i.e., a many-to-one relationship or degeneracy; Barrett & Satpute, 2019).

Our study addressed this issue by using a synergistic combination of three methods. First, we modeled the relationship between autonomic reactivity and fear experience at the level of individual participants (Hodes et al., 1985; Taschereau-Dumouchel et al., 2020). This approach avoids drawing an ecological fallacy (Freedman, 2001) in contrast to prior studies that typically only examined mean effects by averaging across individuals. Second, we examined these relationships across three distinct fear-evoking situations (spiders, heights, and social situations), wherein fear experience varied from low to high levels across stimuli within each content condition, and all in the same sample of participants. These design characteristics enabled us to test for generalization or dependency of the relationship between autonomic reactivity and fear experience across situations, while at the same time mitigating alternative explanations due to certain content confounds (e.g., as may occur when comparing spider stimuli to nonspider stimuli) or sample differences (e.g., as may occur when comparing phobic to nonphobic participants). Third, we used a model comparison approach for statistical analysis (McElreath, 2020; 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 multiple theoretical accounts.

The model comparison analyses strongly support the notion that the relationship between autonomic reactivity and fear experience is reliably structured as heterogeneous sets of situation- and participant-dependent patterns (Hoemann et al., 2020; Jolly & Chang, 2019; Quigley & Barrett, 2014). The top two performing models indicate that the relationship between autonomic responses and fear experience varies across situations. The main difference between these two models is the treatment of participant variance (Figures 2 and 4; see Stemmler & Wacker, 2010 for another discussion of participant variance). The top-performing situation hierarchical model suggests participant variance is also statistically meaningful but constrained by group-level situation parameters. This model far outperformed the runner-up situation (only) model, in which participant variance is not explicitly modeled. Perhaps more critically, these models vastly outperformed the general model wherein situation and participant variance are assumed to reflect minor variations around a core theme.

These findings are consistent with the constructionist hypothesis that the relationship between fear and autonomic activity depends on the person and situation.The results are inconsistent with the notion of a single, prototypical "fear response." Mechanistically speaking, constructionist theory proposes that structured variation emerges because collections of prior instances that share similar features and serve as predictions that guide how future instances are processed (e.g., in a predictive processing architecture; see Barrett, 2017; Lee et al., 2021). That is, specific signals (e.g., cardiac or SCR) do not themselves inherently mean "fear." Rather, they become meaningful through integration of the current context with prior information (Barrett, 2022). Insofar as these instances will vary idiosyncratically from person-to-person, in part depending on one's cultural upbringing (Lindquist et al., 2022) and specific personal history (e.g., exposure to potentially traumatic events), the representational space for fear is expected to be multimodal and heterogeneous (Satpute & Lindquist, 2019).

As an important clarification, we distinguish the constructionist approach from a "typological" view wherein instances of fear are organized around potentially innate types (e.g., a social type, a heights type; or perhaps types corresponding to stages in a predatory

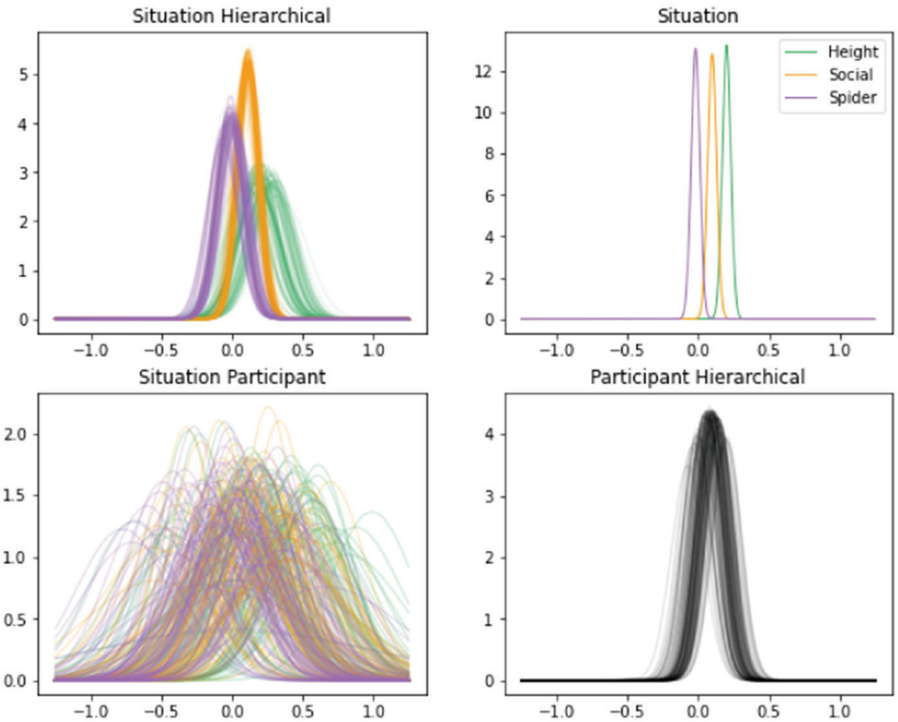
Table 3
IBI Model Comparison Statistics

Model	PSIS-LOO	pPSIS-LOO	dPSIS-LOO	dSE	Akaike weight
Situation hierarchical	4,130.91	151.27	0.00	0.00	1.00
Situation	4,188.33	8.62	57.42	10.74	0.00
Subject hierarchical	4,264.35	33.26	133.44	15.50	0.00
General	4,267.17	4.54	136.26	15.79	0.00
Situation participant	4,324.31	490.38	193.40	18.97	0.00
Participant	4,384.42	179.38	253.51	17.54	0.00
Null	4,276.74	1.23	145.83	16.75	0.00

Note. Consistent with the SCR rate results, the IBI model comparison statistics show strong evidence that the situation hierarchical model outperformed the other models examined (see Table 2 for descriptions). SCR = skin conductance responses; IBI = interbeat interval; PSIS-LOO = Pareto smoothed importance sampling leave one out; dSE = standard error of the differences.

Figure 5

Interbeat Interval Beta Estimates for Four Different Models



Note. Beta distributions for several models relating IBI responses and fear experience. Plotted above are the beta distributions relating IBI and fear experience for the situation hierarchical, situation, situation participant, and participant hierarchical models. The graphs for situation hierarchical and situation models (top row) clearly show that the betas vary by situation (spider—left-most distribution(s); social—middle distribution(s); height—right-most distribution(s)). 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. IBI = interbeat interval. See the online article for the color version of this figure.

imminence framework, e.g., Gray & McNaughton, 2000; also see Mobbs, 2018). While constructionist theories explicitly hypothesize heterogeneity in the behavioral, neural, and autonomic correlates of fear and other emotion categories (Barrett, 2017 ; Quigley & Barrett, 2014; Satpute & Lindquist, 2019), nonconstructionist theoretical frameworks that accommodate a many-to-one relationship between autonomic activity and fear (and that can be explained in part by the situation and the person) may also account for these findings (e.g., as in certain functionalist accounts of emotion; Adolphs, 2017; Adolphs & Andler, 2018).

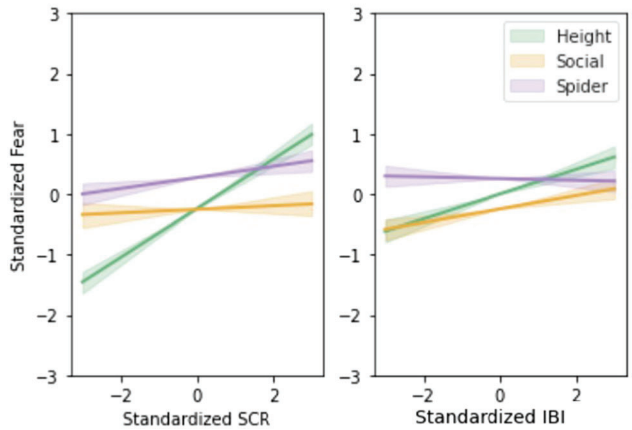
The theoretical distinction between constructionist and typological models is relevant when interpreting some of the more specific findings. Our results showed that fear experience positively correlated with SCR rates during instances of fear involving heights and spiders content, and with IBI increases (i.e., cardiac deceleration) during instances of fear involving heights and social situations. From a typological perspective, these relationships might be expected to generalize to ambulatory situations of the same type (e.g., when rock climbing, encountering a predator, or being accosted by someone). But from a constructionist account, this is not necessarily expected to be the case; an ambulatory context would likely involve different physical and autonomic features, which in turn may involve a different pool of prior instances from which a person is drawing when categorizing their experience. From the constructionist perspective, the conclusion that is expected to generalize is that variation is significantly structured by situation and individual.

Given the scope of our research question, we derived our hypotheses and computational models at a relatively broad or abstract level, and we did not make specific predictions about how autonomic activity might relate with fear in specific situations. Still, our more specific results may be informative. They suggest, at least, that relationships between fear and autonomic measures are situation-dependent, but *not* necessarily situation-specific. Correspondingly, future work may be advanced by organizing instances based on their similarities to one another, which may in some cases cut across the categories we defined here when modeled in a latent space (Rauthmann et al., 2014; Reis, 2008; Tamir & Thornton, 2018).

Our findings question the extent to which certain autonomic measures can be used as generalizable markers of fear experience. Even though on average participants showed considerable variation in subjective fear and autonomic measures (Figure 1), the relationship between these measures varied profoundly by situation and person. Consequently, changes in IBI activity and SCR rates, even in response

Figure 6

Plotted Regression Lines From the Situation Hierarchical Models



Note. Regressions from the group level parameters of the situation hierarchical 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. On the left side of the graph the spider situation regression line starts on y-axis at approximately 0, the social situation line starts on y axis between the other two situations, and the height situation line starts at the lowest value (approximately −1.5). The right graph represents the relationship between IBI and fear. On the left side of the right graph the spider line starts at the highest value, followed by the social line, with the height line starting at the lowest value. The importance of modeling situations is evident in the variation of the slopes across situations. SCR = skin conductance responses; IBI = interbeat interval. See the online article for the color version of this figure.

to normatively fear-evoking stimuli, cannot be assumed to generalize across all fear experiences. Our findings also suggest that it may be possible to find some generalizability across studies, or potentially even across species. But, our results suggest that generalization is likely to be conditioned on situational and subject variables (Barrett, 2022; Jolly & Chang, 2019; Satpute & Lindquist, 2019).

Modeling Strategies to Evaluate Nonlinearities in the Mind–Brain–Behavior Relationship

Our approach may be useful for investigating context-dependency in autonomic or other biological signals related to psychological phenomena more broadly. Our modeling framework can flexibly accommodate a set of contextual factors such as time of day, sleep quality, bodily posture, exercise, nutrition, and so on—any of which can be evaluated by modeling a conditional dependency between a predictor variable and the mental state or behavior of interest. Rather than searching for general biomarkers of certain psychological states, our findings suggest it may be more productive to establish the boundary conditions (situations, individuals, etc.) under which biological variables provide reliable information. Such conditions may introduce nonlinearities into the relationship between psychological and biological or behavioral variables that are often overlooked using conventional analytical approaches (cf., Azari et al., 2020; Khan et al., 2022).

We address nonlinearities by modeling conditional dependencies—that is, by estimating separate regression models depending on the situations and individuals. The advantage of our approach is its interpretability—the nature of conditional dependencies is stipulated a priori based on modeling assumptions (as specified in Table 1). Alternatively, another approach may be to use a more data-driven method to identify nonlinearities in the data (e.g., a decision tree or neural network), and then investigate whether and which variables may explain the mappings (e.g., Meuleman & Scherer, 2013). A data-driven approach may lead to discoveries of nonlinearities in the data that are outside those that are expected by researchers. However, the solutions can be more difficult to interpret. Our approach is particularly useful when many theoretically relevant contextual variables have been measured and can be included in the model.

Constraints on Generality

It bears discussing the generality of our findings of situation and individual variation in the autonomic correlates of fear experience given our experimental design. Here we describe four main constraints on the generality of our findings including the specific task paradigm, autonomic measures, subject population, and other (potentially) experienced emotions.

Task Paradigm

The use of a passive viewing paradigm here has certain advantages. The experimental design may favor uniformity (i.e., less variation) since, in many respects, the situations were quite similar (i.e., visual induction of an instance of fear while participants remained still). This makes our findings regarding heterogeneity all the more compelling. Passive viewing is also the dominant paradigm in the psychophysiology of emotion (Siegel et al., 2018). Thus, our work speaks directly to this large literature upon which much theory and research has been developed. Further, neuroimaging studies of fear and emotion categories more generally (Taschereau-Dumouchel et al., 2020; Wager et al., 2015) also rely heavily on both passive viewing paradigms and on the assumptions of the general model (Zhou et al., 2021). Here, our results coincide with a small but growing body of evidence suggesting that the neural representations of emotion may also depend on the situation (Caseras et al., 2010; Doyle et al., 2022; Michałowski et al., 2017; Wang et al., 2022; Wilson-Mendenhall et al., 2011). Finally, the use of passive viewing of video clips has been described as providing a useful balance between experimental control and ecological validity (Coan & Allen, 2007; Hagenaars et al., 2014).

Passive viewing paradigms also have limitations. In particular, autonomic responses often support overt behaviors that may occur during instances of fear, while passive viewing paradigms typically involve little overt behavior (Davis, 1992; Levenson et al., 1990; Quigley & Barrett, 2014; Roelofs, 2017; Siegel et al., 2018). Several laboratory studies also suggest that larger effects on physiology are observed when a task is performed "in real life" as compared to performing the same task in virtual reality (Marín-Morales et al., 2021), imagining performing the same task (Stemmler et al., 2001), or passively viewing affective stimuli (Dickerson & Kemeny, 2004). Thus, given the theoretical and empirical importance, it would also be of interest to examine the relationship between autonomic reactivity and subjective fear in more physically active contexts, such as in ambulatory studies (Hoemann et al., 2020). To this end, several recent studies have examined subjective responses and autonomic reactivity while participants walked through a haunted house, and found that subjective fear correlated with SCR frequency (Tashjian et al., 2022) and heart rate (Stasiak et al., 2023), in line with previous meta-analytic findings (Siegel et al., 2018).

Future research that examines how physically active situations shape autonomic correlates will be an important path forward for both laboratory and ambulatory studies. Here, our expectation is that such studies would support the broader constructionist hypothesis that the relationship between fear experience and autonomic activity will depend on the situation and person. However, in our view, the specific relationships we observed (e.g., cardiac deceleration when experiencing fear while watching videos involving heights or social encounters) would depend on whether and which potential actions come to mind, which may differ between passive viewing and ambulatory contexts.

Autonomic Measures

Here we focused only on SCR rates and IBI as our autonomic measures. We selected these measures in part because, on average across studies, they are two of the most commonly studied autonomic measures associated with fear (Siegel et al., 2018). As such, it makes sense to start with these variables to see if there is any evidence that certain autonomic measures contribute to a so-called "fear response" that generalizes across situations and individuals. Given that we found variation in SCR rates and changes in IBI, we think it is likely that other measures of autonomic activity will also show variation in their relationship with fear experience across individuals and situations, in part because many of these measures also show significant variation in effect sizes across studies (Siegel et al., 2018). Thus, examining whether situations and individuals structure the relationship between autonomic measures not measured here and fear experience will be an important area for future research.

Subject Population

Another issue to consider is whether our college student sample can generalize to a broader population. If anything, the constructionist hypothesis that autonomic reactions during fear experience will vary across situations and individuals seems even more likely with a more diverse sample. Although the exact findings we observed (i.e., in Figures 3 and 5) may differ across samples, the most relevant question here is not about the exact nature of the relationships between autonomic reactivity and fear experience, but about the degree of variation and whether that variation is structured by situation and/or individual, which it was, even in this relatively more homogeneous sample.

Critically, we selected our stimuli in order to introduce variation in subjective fear in neurotypical participants on average rather than only in phobic participants (e.g., see Figure 1). Even so, it is possible that trait measures of anxiety or phobia may explain observed individual differences in our model parameters. The best-performing model—the situation hierarchical model—suggested that participant variation is statistically reliable but constrained by the situation. In a set of exploratory analyses, this variance was not found to be associated with observed trait measures that we measured here (i.e., trait anxiety using anxiety sensitivity index, and trait measures of acrophobia, agoraphobia, and arachnophobia; see the online supplemental materials). Specifically, the slope of the relationship between autonomic reactivity and subjective fear (obtained per person and per situation) was not associated with phobia scores for each situation, trait anxiety, or demographic variables (Tables S7, S9–S12 in the online supplemental materials). Further, autonomic reactivity averaged across trials per person, by situation, also was not associated with corresponding phobia scores (Table S8 in the online supplemental materials). Other variables that may relate to variation in this measure (e.g., individual differences in interoceptive awareness (Barrett et al., 2004; Bechara & Naqvi, 2004; Pollatos et al., 2005) should be examined in future work.

Other Emotions

The current study focused only on the autonomic correlates of fear experience. In contrast, many previous studies examined the specificity of autonomic measures during instances of fear in comparison to instances of other emotion categories, wherein it may be more informative to examine a broader constellation of autonomic measures (Christie & Friedman, 2004; Kragel & LaBar, 2013; Siegel et al., 2018). At the same time, our focus on a single emotion category may be relevant to the study of autonomic responses during emotions in general. Fear holds a special place in emotion science due to its importance in emotion theory and translational work in mood and anxiety disorders. Thus, we believe it to be a useful test case that demonstrates more general principles. Based on our findings, previous literature (Hoemann et al., 2020; Shenhav & Mendes, 2014), and constructionist theory (Hoemann et al., 2020; Quigley & Barrett, 2014; Siegel et al., 2018), we expect that the relationship between subjective experience and autonomic responses for other emotion categories may also depend on the situation and person. Future studies may adopt our experimental and analytical approach to test this question for a variety of different emotion categories.

Summary and Conclusion

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

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