# How to Measure Fear Generalization? Reliability and Validity of Commonly Used Indices

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Transparency and Openness: All data and code for the simulation analysis are publicly and openly available at: https://osf.io/4zsju/?view_only=2027e007c2de43098dd6f57acb330ff8.

**Abstract**

The ability to adaptively transfer acquired fear to novel situations is fundamental for survival in ever-changing environments and may contribute to the emergence and persistence of anxiety disorders. Consequently, research has focused on the assessment of fear generalization profiles to predict individual differences in trait anxiousness. However, substantial heterogeneity in the measurement and operationalization of generalization hampers comparisons across studies and poses a risk to the replicability of findings. To address these issues, we reviewed the literature to identify commonly used methods for characterizing fear generalization profiles. We then conducted simulation analyses to examine correlations between indices and probe their robustness against measurement noise. Finally, we used two large empirical datasets (*N* = 1,175 and *N* = 256) to examine the reliability of these indices and their validity in predicting psychopathology. All identified indices were substantially correlated but highly sensitive to measurement noise, with only minimal differences between methods. Reliabilities were moderate for subjective ratings but poor for skin conductance responses. All indices of fear generalization were unrelated to individual levels of anxiousness. Overall, a more comprehensive discussion of conceptual and methodological issues is needed to better understand how fear generalization contributes to the etiology and maintenance of anxiety disorders.

**Introduction**

Fear and anxiety are emotional states that help individuals to adaptively cope with threat or adverse situations. However, when these emotions occur unselectively across a variety of situations, when they are exaggerated and difficult to manage, and when they result in widespread avoidance behavior, they become maladaptive and mark the transition to an anxiety disorder. In fact, anxiety disorders are among the most frequent mental disorders with a lifetime prevalence of up to 33.7% in Western countries (Bandelow & Michaelis, 2015; Kessler et al., 2005; Michael et al., 2007). In addition to negative consequences for affected individuals such as a reduced ability to work, difficulties in establishing and maintaining social relationships and the risk of suicide, anxiety disorders also generate substantial economic costs for the society (Kasper, 2006).

Given the huge importance of an early detection of the risk for anxiety disorders and the need to provide appropriate and effective therapies, research has focused on identifying psychological and neural mechanisms that contribute to the etiology and maintenance of the broad variety of anxiety disorders. Such research frequently relied on laboratory tasks to characterize aberrant learning of aversive associations (Pittig et al., 2018). Pavlovian fear conditioning is a prime example of such a research paradigm (Fullana et al., 2020). In this task, participants are typically confronted with one stimulus that is paired with an aversive experience (so-called unconditioned stimulus, US) and thereby becomes a conditioned stimulus (so-called CS+). In differential fear conditioning protocols, another stimulus is presented but never paired with the aversive US and thereby becomes a conditioned stimulus signaling safety (so-called CS−). This paradigm has been extensively used to experimentally model the acquisition of fear in healthy individuals (Hamm & Weike, 2005; Rescorla, 1967; Seligman, 1971). However, it was also shown that patients with anxiety disorders show aberrant fear conditioning reflected in an enhanced fear response to the CS− and therefore a decreased CS differentiation (for a meta-analysis, see Duits et al., 2015). According to this latter finding, both highly anxious yet healthy individuals (Sep et al., 2019) as well as patients with anxiety disorders (Lissek et al., 2014) seem to generalize fear to stimuli that were never associated with threat before.

The phenomenon of fear generalization was already described more than a century ago in the seminal study of “little Albert” (Watson & Rayner, 1920), who was initially conditioned to associate a white rat (CS+) with an aversive sound (US) and later showed fear responses to stimuli that had perceptual similarity to the CS+ (e.g., rabbit, fur coat, cotton wool). After this initial description, research on fear generalization was sparse for several decades. However, it has experienced enormous impetus after initial studies have observed differences in fear generalization between healthy individuals and patients with anxiety disorders (Dunsmoor & Paz, 2015; Dymond et al., 2015; Kopp et al., 2005; Lissek et al., 2014; Lissek et al., 2010). These studies frequently relied on a fear conditioning procedure as described above but included generalization stimuli (GS, e.g. circles of different sizes Lissek et al., 2010) that covered the similarity continuum between CS+ (e.g., large circle) and CS− (e.g., small circle). Several studies have shown that the gradient of fear responses (e.g., startle responses or risk ratings) is more linear for anxiety patients, whereas it shows a substantial curvature in healthy participants with only those GSs that are most similar to the CS+ eliciting increased fear responses (Lissek et al., 2014; Lissek et al., 2010).

Although recent meta-analyses confirmed significant relationships between the extent of fear generalization and anxious yet healthy personality traits (Sep et al., 2019) as well as pathological anxiety (Cooper et al., 2022; Fraunfelter et al., 2022), they also reported a significant heterogeneity across studies. This might result from a lack of a default or gold standard or consensus method to quantify the extent of fear generalization. In fact, numerous methods have been proposed in the literature, but their psychometrics, which are key for the prediction of anxiety symptoms (Hedge et al., 2018; Zorowitz & Niv, 2023), are largely unexplored. This is problematic since individualized treatments, which have been proposed as a viable alternative to manualized psychotherapy (Cohen et al., 2021; Lueken & Hahn, 2020), critically rely on the accurate measurement of potentially maladaptive processes. Moreover, imprecise measurements also hamper scientific progress and reduce the replicability of previous discoveries (Nebe et al., 2023).

The current article therefore aims to achieve the following goals: First, we review the literature to identify commonly used methods for characterizing fear generalization profiles. Second, we describe the psychometric properties of these indices, their robustness against measurement noise and their interrelations based on simulations. Finally, we use two large datasets (*N* = 1,175 and *N* = 256) including subjective ratings and electrodermal responses to estimate the test-retest reliability of these indices as well as their validity in predicting anxious personality traits.

## Literature review of methods for characterizing fear generalization profiles

In order to identify commonly used generalization indices, we conducted a systematic literature review based on the PRISMA guidelines (Moher et al., 2015; Radua, 2021). The search was carried out in Web of Science and in PsycInfo. Articles published between 1990 and (22nd June) 2023 as well as written in English were considered. Reviews, conference abstracts, books, and editorials were excluded. The terms for the search included: “fear generalization” OR “generalization gradient” OR “generalization processes” OR “memory generalization”.

The search returned 506 articles from the Web of Science and 667 articles from PsycInfo, with 500 being duplicates. Articles were then screened based on their abstract. In order to be considered into this systematic review, the studies had to meet the following criteria: 1) being a classical conditioning study; 2) not being a conference abstract; 3) not being a review, comment or meta-analysis; 4) not relying on appetitive classical conditioning with a rewarding US; 5) not using a context-dependent generalization design (i.e., conditioned defensive responses are generalized according to context rather than stimulus similarity); and 6) generalization of conditioned defensive responses was tested over multiple stimuli. The eligible articles were 308, which were read and evaluated in detail focusing on the above-mentioned inclusion criteria. After this careful evaluation, 82 records were considered for the systematic review and six articles were manually added (see Supplemental Figure 1).

**Table 1 -** *Overview of the Studies and their Quantification of the Strength of Fear Generalization*

| | |
|---|---|
| *Studies, which arithmetically calculated an index to quantify fear generalization* | |
| Linear Deviation Score (LDS) | Imholze et al. (2023), Kaczkurkin et al. (2017), Lange et al. (2019), Lange et al. (2017), Lissek et al. (2017), Reutter et al. (2023), Stegmann et al. (2019), Zhu et al. (2022) |
| Generalization Index (GI) | Herzog et al. (2021), Lenaert et al. (2016), Mertens et al. (2021), Reinhard et al. (2022) |
| *Studies, which modelled a generalization gradient* | |
| Gaussian (tuning) models | Dou et al. (2023), Grosso et al. (2018), Kampermann et al. (2019), Kausche et al. (2021), Kausche et al. (2021b), Kausche et al. (2021a), Onat et al. (2015), Porter et al. (2021), Resnik et al. (2015), Tuominen et al. (2019) Wang et al. (2022), Zaman et al. (2023), Zaman et al. (2019), Zaman et al. (2019), Zenses et al. (2021) |
| Quadratic-linear models | Cha et al. (2016), Cha et al. (2014), Cha et al. (2014), Dunning et al. (2015), El-Bar et al. (2017), Hammell et al. (2020), Laufer et al. (2016), Wickens et al. (1954), Zaman et al. (2023), Zaman et al. (2021) |
| *Studies, which examined the amount of generalization on the group level* | |
| ANOVA based - quadratic and linear trend | Ahmed et al. (2015), Dunning et al. (2015), Dunsmoor et al. (2017), Glenn et al. (2021), Glenn et al. (2012), Greenberg et al. (2010), Klein et al. (2023), Klein et al. (2020), Lange et al. (2019), Lange et al. (2019), Lee et al. (2018), Lissek et al. (2014), Lissek et al. (2010), Lissek et al. (2008), Manbeck et al. (2022), Michalska et al. (2016), Niederstrasser et al. (2017), Phillips (1958), Roesmann et al. (2022), Struyf et al. (2018), Vandael et al. (2023), Vandael et al. (2020), Van Meurs et al. (2014), Vervliet et al. (2006), Zoladz et al. (2022) |
| Quadratic and (difference of) Gaussian contrast comparisons | Antov et al. (2020), Friedl et al. (2021), McTeague et al. (2015), Plog et al. (2022), Stegmann et al. (2020) |
| Hierarchical models including quadratic terms | Ginat-Frohlich et al. (2019), Ginat-Frohlich et al. (2017), Keefe et al. (2022), Lommen et al. (2017), Meulders et al. (2017) |
| Various types of regression models | dos Santos et al. (2019), Fan et al. (2022), Michalska et al. (2016), Nelson et al. (2015), Resnik et al. (2015), Schroijen et al. (2015), Struyf et al. (2017), Zaman et al. (2016) |

The majority of studies applied three different procedures to describe the amount of fear generalization. 1) 12 studies relied on arithmetic solutions to calculate a generalization index, 2) 25 studies considered linear and quadratic trends resulting from ANOVA models, and 3) 23 studies modeled the generalization gradient (please note that the heterogeneity in modelling is very large, not only referring to the type of mathematical function but also regarding the data/responses considered in the model). Six additional studies added a discrimination task in order to determine the individual perceptual threshold in detecting visual differences between stimuli (see Supplemental Table 1).

To summarize, our review of the current literature shows great heterogeneity among fear generalization analyses and no gold standard for characterizing fear generalization profiles could be identified. Furthermore, many of the studies focused on group-level differences and thus only considered linear and quadratic trends within ANOVA models without acquiring indices of fear generalization on an individual level.

In the studies that examined individual differences in fear generalization, the most commonly used arithmetic index to describe the curvature of the generalization gradient is the Linear Deviation Score (LDS, Lissek et al., 2014), which can be calculated as

$$LDS = \frac{CS^{+} + CS^{-}}{2} - \frac{GS_1 + GS_2 + GS_3 + \cdots + GS_n}{n}$$

where $CS^{+}$ is the individual response to the CS+, $CS^{-}$ is the response to the CS− and $GS_n$ is the response to the $n^{th}$ level of the generalization stimuli. The LDS can be illustrated as a measure of how strongly the responses to the GSs deviate from a hypothetical straight line between CS− and CS+ responses. Values near zero indicate a linear gradient, whereas negative values indicate stronger generalization, respectively (for an illustration of LDS values for different generalization profiles, see Figure 1A). Please note that we changed the polarity of the LDS (i.e., higher values indicate stronger generalization) for the rest of the manuscript in order to achieve better comparability with other fear generalization indices. The range of the LDS is not restricted and varies depending on the range and the units of the measured variable.

A second frequently used method to describe the curvature of fear generalization gradients Is the generalization index (GI, Lenaert et al., 2016), which is calculated by dividing the sum of the responses to the GSs by the response to the CS+:

$$GI = \frac{GS_1 + GS_2 + GS_3 + \cdots + GS_n}{CS^{+}}$$

The GI can be considered as the combined response strength to the GS relative to the original fear stimulus (see Figure 1A). When interpreting the values of the GI, it is crucial to consider the number of generalization stimuli and the numerical range of the measured variable. Higher values indicate stronger fear generalization. In addition, it is important to note that (1) the GI does not include responses to the CS− and (2) the calculation of the GI will result in missing values if responses to the CS+ are zero.

Apart from indices that rely on an arithmetic combination of responses, several studies employed model fitting approaches that describe the individual fear generalization gradient by statistically fitting a pre-defined function and extracting its parameters. The choice of function can be based either on assumed theoretical considerations or subjective preferences. To find the best fit between the model function and the generalization gradient, usually methods like least squares are used that involve finding the values of the model parameters that minimize the sum of the squared differences between the predicted and the observed data. In addition, the residuals can then be used to calculate goodness of fit parameters (e.g., $R^2$), which provide an estimate of how well the model fits the individual generalization gradient.

The most frequently used function in the literature is the Gaussian function (Gaussian model fit, Gauss; e.g. Kausche, Zerbes, Kampermann, Büchel, et al., 2021; Onat & Buchel, 2015), which can be expressed as

$$y = a + b * \left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-n+2}{\sigma}\right)^2}\right)$$

with

$$y = \begin{pmatrix} CS^- \\ GS_1 \\ \dots \\ GS_n \\ CS^+ \\ GS_n \\ \dots \\ GS_1 \\ CS^- \end{pmatrix} and\ x = \begin{pmatrix} 1 \\ 2 \\ \dots \\ n+1 \\ n+2 \\ n+3 \\ \dots \\ 2n+2 \\ 2n+3 \end{pmatrix}$$

$CS^+$ is the individual response to the CS+, $CS^-$ is the response to the CS− and $GS_n$ is the response to the $n^{th}$ level of the generalization stimuli. The Gaussian function has three free parameters: the standard deviation of the normal distribution $\sigma_{Gauss}$, the scale factor $b_{Gauss}$, and the vertical translation factor $a_{Gauss}$. Assuming the other parameters remain constant, increases in $\sigma_{Gauss}$ widen the "bell"-shape of the Gaussian function, increases in $b_{Gauss}$ increase the maximum level at CS+, and increases in $a_{Gauss}$ increase the baseline of the Gaussian. Thus, $\sigma_{Gauss}$ is the best single parameter to describe the curvature of the generalization gradient, with higher values indicating more generalization. The Gaussian model is naturally suitable to describe fear generalization gradients where the CS+ lies in the center of the feature continuum but can also be used for gradients that extend from CS− to CS+. In such cases, the generalization gradient is conceptualized as the first half of a normal distribution. Consequently, individual data needs to be mirrored at the CS+ to obtain a full normal distribution before submitting them to the fitting algorithm (see Figure 1B).

As an alternative to the Gaussian function, the exponential function has been used to describe generalization gradients (exponential model fitting, exp; Resnik & Paz, 2015; Struyf et al., 2017):

$$y = a + n * e^{\lambda x}$$

with

$$y = \begin{pmatrix} CS^- \\ GS_1 \\ GS_2 \\ \dots \\ GS_n \\ CS^+ \end{pmatrix} \; and \; x = \begin{pmatrix} 1 \\ 2 \\ 3 \\ \dots \\ n+1 \\ n+2 \end{pmatrix}$$

As fitted parameters, the algorithm returns the growth factor $\lambda_{exp}$, the scale factor $n_{exp}$, and the vertical translation factor $a_{exp}$. Assuming the other factors remain constant, changes in $\lambda_{exp}$ and $n_{exp}$ affect the steepness, while $a_{exp}$ characterizes the horizontal asymptote of the exponential function. When both $\lambda_{exp}$ and $n_{exp}$ are positive, the exponential function is concave to the left, and the horizontal asymptote represents the minimum. Conversely, if both $\lambda_{exp}$ and $n_{exp}$ are negative, the function graph is concave to the right, and the horizontal asymptote represents the maximum of the exponential function. The exponential growth factor $\lambda_{exp}$ is primarily responsible for the curvature of the function and therefore most accurately describes the strength of generalization. Higher values indicate reduced generalization (see Figure 1C). Similar to the LDS, we changed the polarity of the $\lambda_{exp}$ (i.e., higher values indicate stronger generalization) for the rest of the manuscript in order to achieve better comparability with the other fear generalization indices.

Model fitting approaches also provide an opportunity to retrieve individual fear generalization parameters analogous to the linear and quadratic trends that are frequently reported for group-level analyses by fitting a polynomial function including a quadratic, linear, and constant term (quadratic polynomial, linquad, e.g. Cha, Tsafrir, et al., 2014; Dunning & Hajcak, 2015):

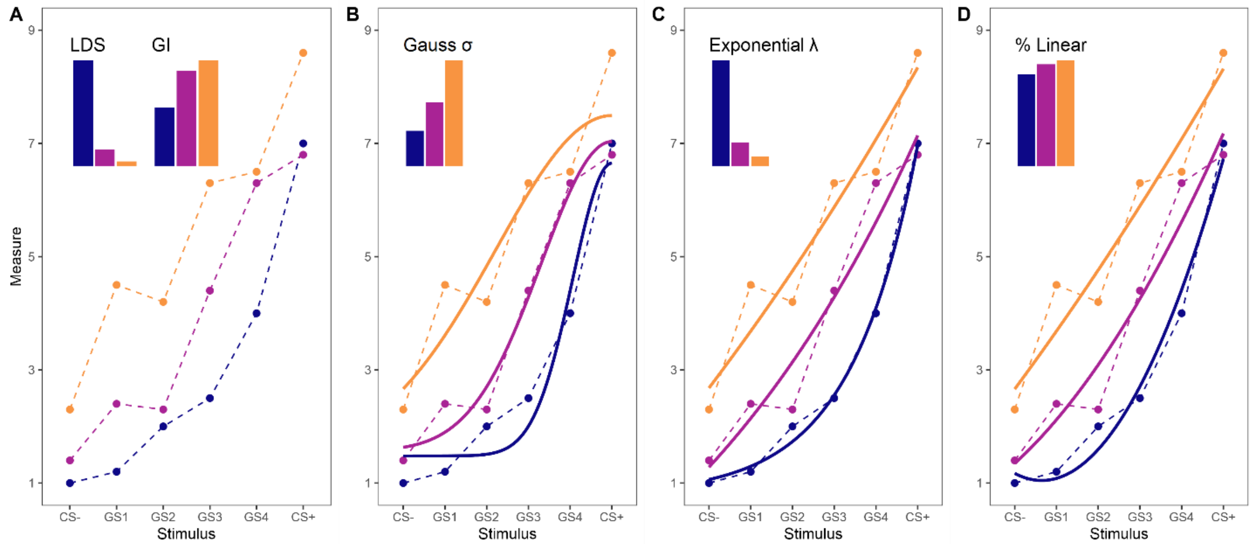
$$y = a + bx + cx^2$$

where

$$y = \begin{pmatrix} CS^- \\ GS_1 \\ GS_2 \\ \dots \\ GS_n \\ CS^+ \end{pmatrix} \; and \; x = \begin{pmatrix} 1 \\ 2 \\ 3 \\ \dots \\ n+1 \\ n+2 \end{pmatrix}$$

As fitted parameters, the algorithm returns the weight of the quadratic term c, the weight of the linear term b, and the intercept parameter $a_{linquad}$ (see Figure 1D). To combine the weights of the quadratic and linear terms into a single parameter, one can calculate the relative importance of the linear term ($\%_{linquad}$) over the quadratic term, which is expressed as the relative contribution of the linear term to the total explained variance (Feldman, 2005).

**Figure 1 -** *Comparison of Arithmetic Solutions (A) and Model Fitting Approaches (B to D) for Quantifying the Strength of Generalization in Three Schematic Participants.*

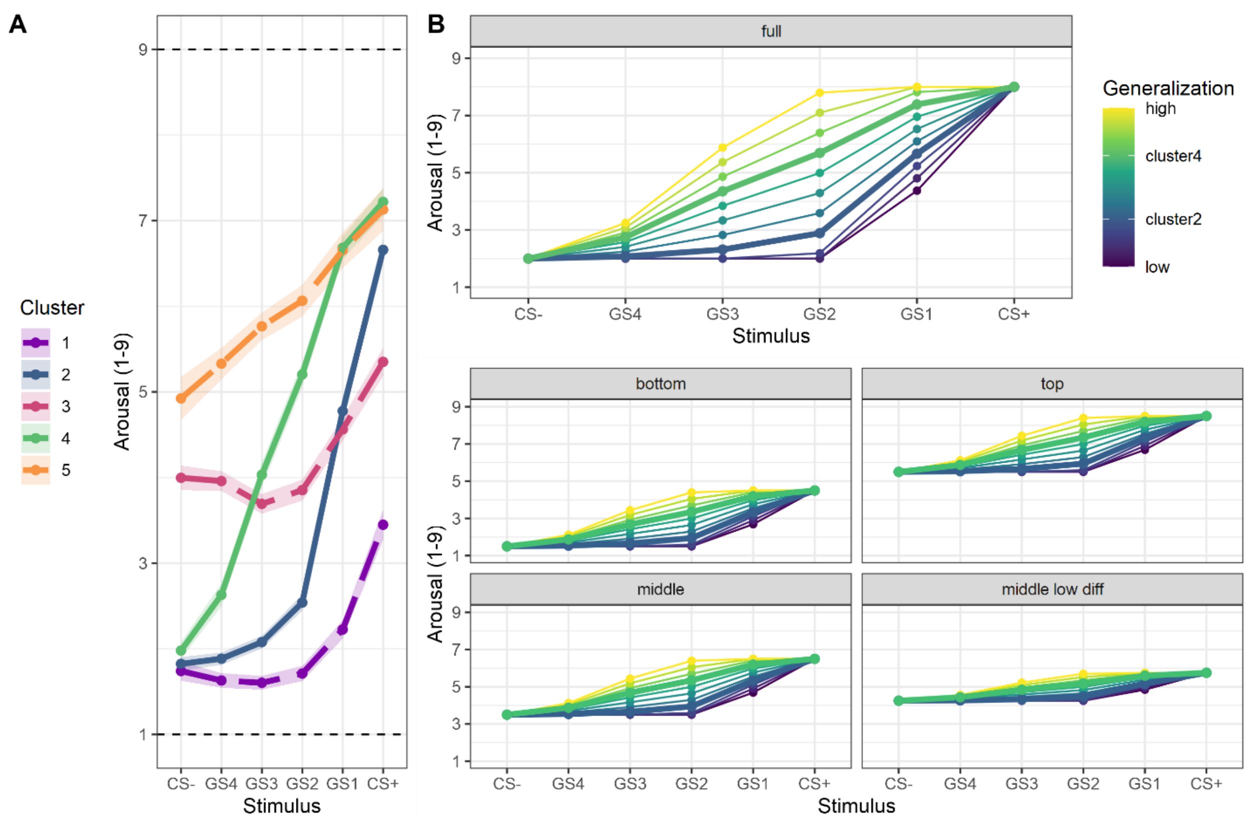



*Note.* Fear generalization data for three different participants are depicted as blue, purple, and orange dots connected by dashed lines. Solid curved lines illustrate the fitted models described by the respective parameter values. For LDS and $\lambda_{exp}$, high values indicate less fear generalization.

## Simulation analysis: Psychometric properties of fear generalization indices

We next conducted an empirically informed simulation analysis to better understand how measurement errors influence different indices of fear generalization. In order to simulate representative profiles of fear generalization gradients, we relied on a previous study by Stegmann et al. (2019) that identified five separate clusters of typical profiles in a large group of participants. These clusters resulted from an analysis of arousal ratings obtained for the CS+, CS−, and four GSs on a scale from 1 to 9. As can be seen in Figure 2A, clusters 2 and 4 show similarly high differentiation between CS+ and CS− but different levels of generalization. Clusters 1, 3, and 5, however, exhibit little differentiation and mostly differ according to their overall level of responses. Building upon these characteristics, we used the shapes of clusters 2 and 4, normalized their values from 0 to 1, and created a total of nine additional levels of generalization between as well as above and below both generalization profiles (3 interpolation steps and 3 equidistant extrapolations on either side). The resulting eleven fear generalization profiles were winsorized to assure that no GS has values more extreme than the CSs (Cecil et al., 1947). The final gradients then served as prototypes for five model cases that were tested in our simulation: The first case spanned almost the full rating scale, ranging from 2 to 8, thus showing high differentiation and an intermediate average level. We employed a bottom (1.5 to 4.5), middle (3.5 to 6.5), and top (5.5 to 8.5) case with intermediate differentiation but different proneness to floor and ceiling effects. Lastly, we included another middle cluster (4.25 to 5.75) similar to empirical cluster 3 but with even lower differentiation. The resulting model cases, each including eleven fear generalization profiles, thus exhibited different amounts of CS differentiation and general arousal level (see Figure 2B). Using the empirically informed cases described above as true scores, we conducted a simulation analysis. For each of the 55 gradients (5 model cases × 11 gradients per case; see Figure 2B), we calculated the LDS and GI. Furthermore, we extracted the curvature parameters $\sigma_{\text{Gauss}}$, from a Gaussian model fit and $\lambda_{\text{exp}}$, from an exponential model fit; as well as the relative importance of the linear over the quadratic component $\%_{\text{linquad}}$ from a quadratic polynomial model fit. All models were fitted to the data of individual cases using the Least-Squares approach in combination with the “Bound Optimization by Quadratic Approximation” (bobyqa) algorithm as implemented in the nloptr package (version 2.0.3) for R 4.1.2 (R Development Core Team, 2021). Across these 5 fear generalization indices, we first calculated their intercorrelations. Second, the range of values spanned across generalization gradients served as a measure of differentiation between generalization profiles. For comparison, we normalized the true score generalization indices across cases to the range from 0 to 1 by subtracting the minimum value and dividing the result by the range of values. Third, we added noise from a normal distribution (*M* = 0, *SD* see below) to every of the 6 ratings within each gradient. The amount of noise was informed by the average empirical standard deviation observed between arousal ratings of the same stimuli within the same subjects across the generalization phase (*SD* = 1.59) in the study by Stegmann et al. (2019). By doubling and halving this value, we created a total of three different noise levels ranging from low to medium to high. For each of these noise levels we simulated 50 pairs of noise-corrupted gradients (comparable to usual sample sizes in the field of fear generalization), for which we calculated the LDS and GI as well as extracted the curvature parameters $\sigma_{\text{Gauss}}$, $\lambda_{\text{exp}}$, and the relative importance of the linear over the quadratic component $\%_{\text{linquad}}$ as described above. To evaluate the robustness against noise, we then calculated the correlations between pairs of generalization profiles drawn from the same true scores at different levels of noise. Following this, we obtained the mean and standard deviation of differences between true scores and estimates of generalization indices, separated by levels of noise, to assess the presence of systematic bias. All code for the simulation analysis is publicly and openly available at: https://osf.io/4zsju/?view_only=2027e007c2de43098dd6f57acb330ff8.

**Figure 2 -** *Illustration of Representative Fear Generalization Gradients Spanning the Continuum between CS− and CS+.*




*Note.* Panel A shows the empirical basis taken from Stegmann et al. (2019) that was used for generating profiles illustrated in Panel B. Clusters 2 and 4 (solid lines) demonstrate high differentiation between the CS+ and CS−, with cluster 4 (green) showing an earlier and more steady increase in arousal from the CS− across GSs to the CS+, while cluster 2 (blue) is characterized by a slower and more sudden increase that is consistent with less fear generalization. Therefore, clusters 2 and 4 were used as a basis for response profiles with different amount of generalization (see bold lines in Panel B). Clusters 1, 3, and 5 (dashed lines in Panel A) on the other hand exhibit reduced differentiation between CS+ and CS− on different levels of general response strength and were thus used to inform the simulated profiles on a lower, middle, and high response level (Panel B). Finally, additional profiles with a substantially reduced amount of differentiation between CS+ and CS− were simulated.

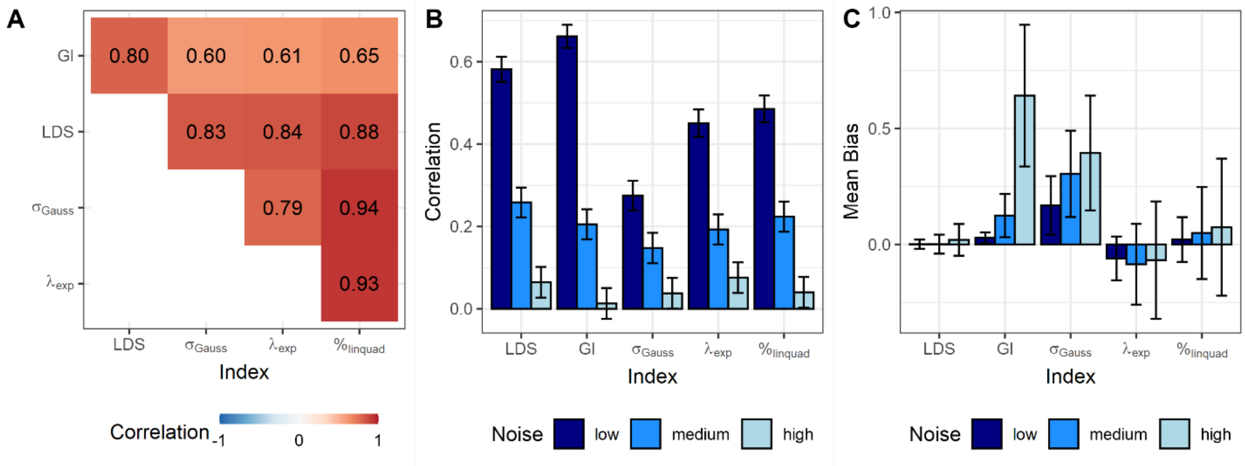
**Correlations between fear generalization indices**

The correlations between the different generalization indices ranged from $r$ = .60 to $r$ = .94, indicating a relatively strong similarity between the indices (see Figure 3A). At the same time, the strength of correlations suggests that the indices are not identical and should therefore not be used interchangeably. On average, the relative importance of the linear over the quadratic component $\%_{linquad}$ from a quadratic polynomial model fit showed the strongest mutual correlations with the other fear generalization indices ($r_{avg}$ = .85), closely followed by the LDS ($r_{avg}$ = .84), $\lambda_{exp}$ ($r_{avg}$ = .79), and $\sigma_{Gauss}$ ($r_{avg}$ = .79). Only the GI showed substantially smaller correlations with the other indices ($r_{avg}$ = .67). It is important to note that these correlations were based on true scores and can thus be interpreted as an upper limit for their similarity in noiseless measurements.

**Differentiation**

Both LDS and GI are sensitive to restrictions of the response scale and show less differentiation between generalization profiles with increasing scale restriction (LDS: 100%, 50%, and 25%; GI: 76%, 47%, and 26% differentiation for full, middle, and low diff cases respectively; cf. Supplemental Table 2). Thus, LDS and GI interpret the profiles of the “full” model case as more diverse than other cases even though the latter are just scaled variants of the former. The model-fitted indices, however, show no such dependency on the variance of response values (differentiation ≥ 98%). Additionally, the GI also factors in the absolute level of the CS+, rendering profiles as less diverse that are shifted upwards (bottom: 67%, middle: 47%, top: 36% differentiation). Importantly, the superior differentiation of Gaussian, exponential, and quadratic fits is merely theoretical. As soon as noise is included and true scores are not accessed directly, differentiation across generalization levels decreases and differentiation graphs become similarly less steep as for the LDS or GI (Figure 4).

**Figure 3** - *Summary of the Psychometric Properties of Fear Generalization Indices*




*Note.* Panel A: Correlations between the individual fear generalization indices across the 55 different true-score generalization gradients (without noise). Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability. Panel B: Correlations between pairs of generalization profiles drawn from the same true scores at different levels of noise (medium levels reflect the empirical variability found between repeated measures in the large sample of Stegmann et al., 2019). The amount of noise greatly influences the strength of correlations but differences between generalization indices also emerge. Values can be interpreted as reliability estimates. Error bars indicate 95% confidence intervals of correlation parameter estimates. Panel C: Mean and standard deviation of differences between true scores and estimates of generalization indices, separated by levels of noise.

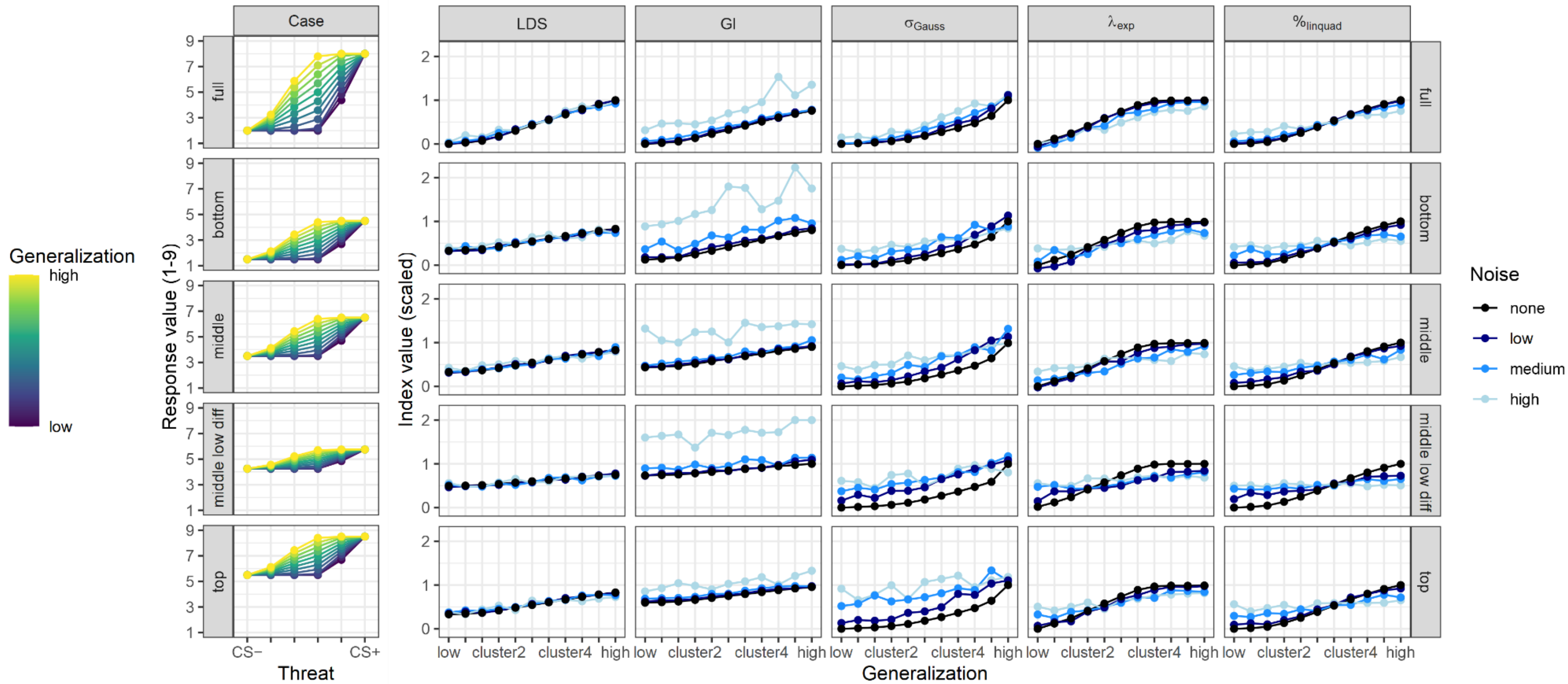
### Robustness against noise

Correlations between pairs of generalization profiles drawn from the same true scores at different levels of noise indicate that the LDS shows the greatest robustness against different levels of noise. Only the GI shows a higher correlation at low noise, but robustness quickly decreases at medium noise and is worst of all indices for high noise. Exponential and quadratic fits show an overall similar pattern of susceptibility to noise while Gaussian fits performed at the lowest two ranks across all noise levels. The results are summarized in Figure 3B.

**Bias**

As evident from Figure 3C, the LDS exhibits overall low bias even at high levels of noise. The GI achieves low bias for low noise but estimates skyrocket for high noise. Gaussian fits exhibit bias of overestimation already at low levels of noise. Exponential and quadratic polynomial fits have no overall bias across different generalization profiles and model cases but show systematic deviations from the true scores for certain combinations of variables (cf. Figure 4): Quadratic polynomial fits suffer from a tendency towards a medium generalization estimate across all model cases. Exponential fits show a similar tendency, but their bias is shifted into the direction of cluster 2 (low generalization), providing a bigger problem for underestimation.

**Figure 4** - *Differentiation Graphs of Various Generalization Indices Separated by Model Case and Noise Level*




Note. Generalization indices are depicted in columns for each model case (rows, depicted in first column) and noise level (colors). True scores without noise are depicted in black. Conformity between black and other lines indicates low bias. Higher average slopes reflect better differentiation between different generalization profiles within the same case. Susceptibility to noise is reflected by systematic deviation of the blue lines from the black line and unsystematic variance within blue differentiation graphs across the 50 pairs drawn from the same true scores. The latter is depicted in Supplemental Figure 2.

**Empirical analysis: Reliability and validity of fear generalization indices**

As a final step, we used the previously identified and characterized fear generalization indices to examine their reliability and validity in two large samples of healthy participants. The first sample (cf. Stegmann et al., 2019) consisted of 1,175 healthy participants, who underwent a fear acquisition and generalization experiment (Schiele et al., 2016). The second sample (n = 256) underwent the same fear generalization paradigm, except that a discrimination training took place between the first and second block of the generalization phase (Herzog et al., 2021). Inclusion criteria and descriptive statistics of both samples are reported in the Supplementary Material. Subjective ratings as well as skin conductance responses were available in each sample and were used to calculate the extent of fear generalization on the level of individual subjects. Further information about the fear acquisition and generalization task, as well as the data processing can be found in the Supplementary Material. As for the simulation analysis, we obtained the different indices of fear generalization for each participant and dependent measure, including the LDS, GI, $\sigma_{\text{Gauss}}$, $\lambda_{\text{exp}}$, and the relative importance of the linear over the quadratic component $\%_{\text{linquad}}$. In addition, we obtained basic indices of threat responsiveness for each participant, since they have been related to individual trait anxiety in previous analyses (Stegmann et al., 2019). These include the mean response levels (mean level), calculated as the average of responses to all six conditioned and generalization stimuli, the difference between CS+ and CS- responses (CS differentiation), and we also extracted the scale parameter $b_{\text{Gauss}}$, and vertical translation parameter $a_{\text{Gauss}}$ from a Gaussian model fit; the scale parameter $n_{\text{exp}}$, and vertical translation parameter $a_{\text{exp}}$ from an exponential model fit; as well as the intercept parameter $c_{\text{linquad}}$ from a quadratic polynomial model fit. Descriptive statistics of the fear generalization indices and model parameters for arousal ratings and skin conductance responses can be found in Supplemental Table 4.

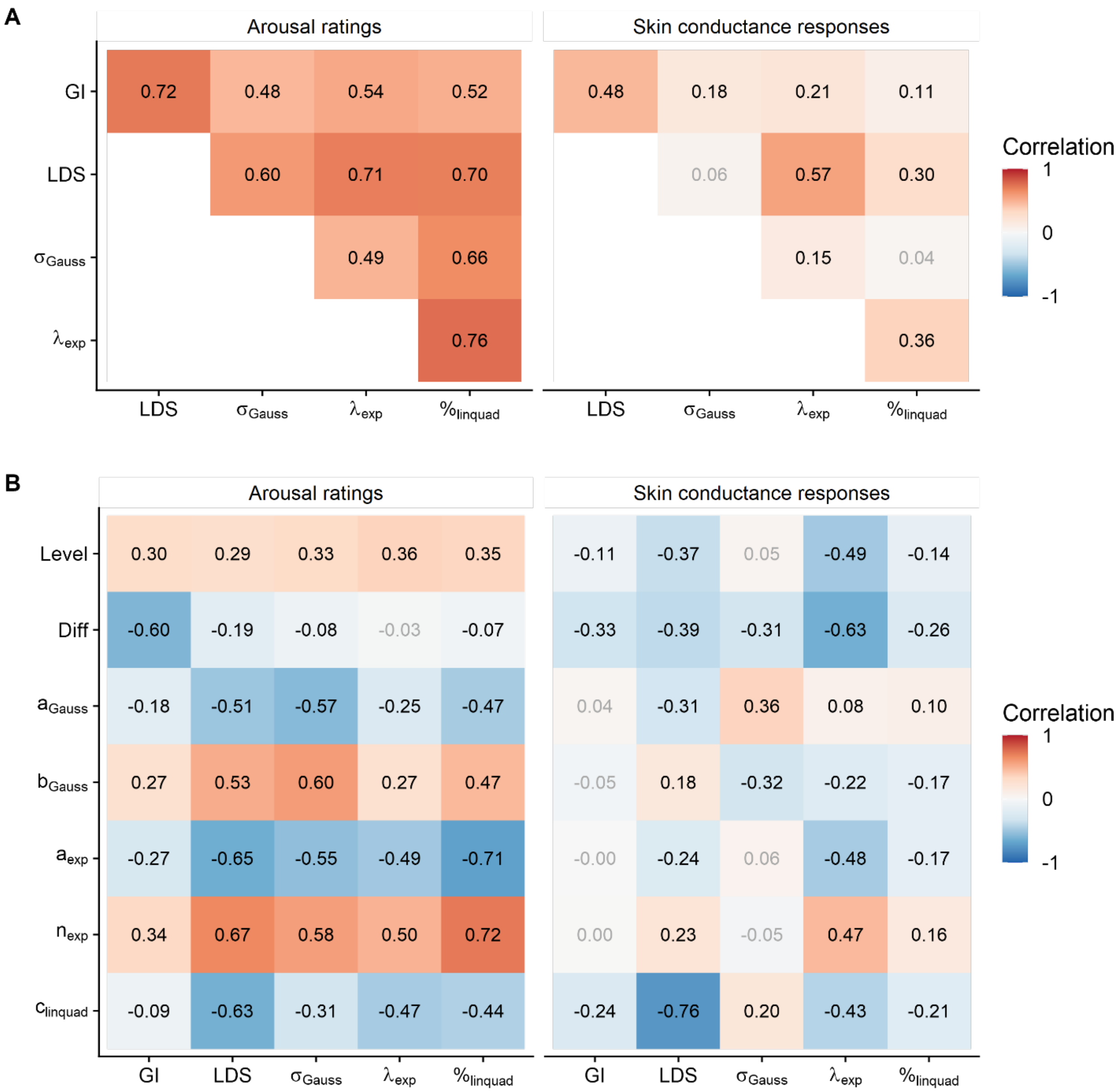
Based on the derived indices of fear generalization, we conducted the following analyses: First, in order to examine to what degree individual measures capture the same construct, we calculated bivariate linear correlations between indices using Pearson’s correlation coefficients (r). Second, to assess short-term test-retest reliability, we calculated correlations between the first and second half of the generalization phase. Test-retest reliabilities were only calculated for the first sample, as the second test block could not be analyzed in the second sample due to the discrimination training that was conducted before. Third, as a validity estimate, we determined associations of the different indices with individual levels of anxiety using correlations between fear generalization indices for the whole generalization phase (data were first averaged between blocks in the first sample and then submitted to the calculations and model fitting procedures) and questionnaire scores as a measure of anxiety psychopathology.

All statistical analyses were conducted with R 4.1.2 (R Development Core Team, 2021). The alpha level was set to .05. All analyses were carried out separately for arousal, valence, and US expectancy ratings, as well for skin conductance responses (SCR). Due to their similarity with arousal ratings, results for valence and US expectancy are reported in the supplemental material.

**Correlations of fear generalization indices**

The magnitude of intercorrelations between indices of fear generalization was generally higher for arousal, unpleasantness, and US expectancy ratings than for SCR amplitudes. Alike for the simulation analyses, the pattern of correlations indicates that the different indices tap into the same construct but are not identical and should therefore not be used interchangeably (see Figure 5A and Supplemental Figure 3A). An additional correlational analysis between generalization measures and basic indices of threat responsiveness (see Figure 5B and Supplemental Figure 3B) revealed generally moderate associations, suggesting that none of the curvature parameters can be adequately explained by mean response levels or CS differentiation. Furthermore, we found a general tendency that fear generalization indices were negatively associated with their respective vertical translation and intercept parameters ($a_{\text{Gauss}}$, $a_{\text{exp}}$, and $c_{\text{linquad}}$) and positively associated with their respective scaling parameter ($b_{\text{Gauss}}$, and $n_{\text{exp}}$). These results were less consistent for SCR amplitudes and highly stable across both samples (see Supplemental Figure 6 and Supplemental Figure 7)

**Figure 5 -** *Correlations Between Different Indices of Fear Generalization and Their Correlation with Basic Indices of Threat Responsiveness.*

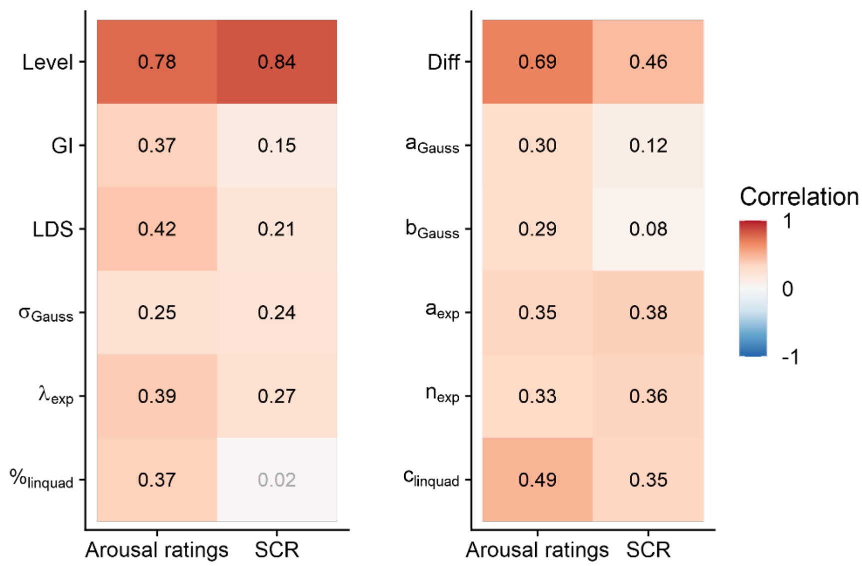



*Note.* Correlations between different indices of fear generalization are depicted in Panel A. Their correlations with basic indices of threat responsiveness are depicted in Panel B. LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS differentiation. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Test-retest reliability**

The correlations between the first and the second half of the fear generalization phase were generally higher for arousal, unpleasantness and US expectancy ratings than for skin conductance responses (see Figure 6 and Supplemental Figure 4), with highest reliabilities for mean response levels (arousal: $r = .78$, SCR: $r = .84$) and CS differentiation (arousal ratings: $r = .69$, SCR amplitudes: $r = .46$), while reliability scores for the different indices of fear generalization were substantially lower (arousal ratings: ranging from $r = .25$ to $r = .49$, SCR amplitudes: ranging from $r = .02$ to $r = .38$). Importantly, there were no systematic differences between the different indices of gradient curvature.

**Figure 6 -** *Correlations Between Various Parameters of the First and Second Half of the Fear Generalization Phase*

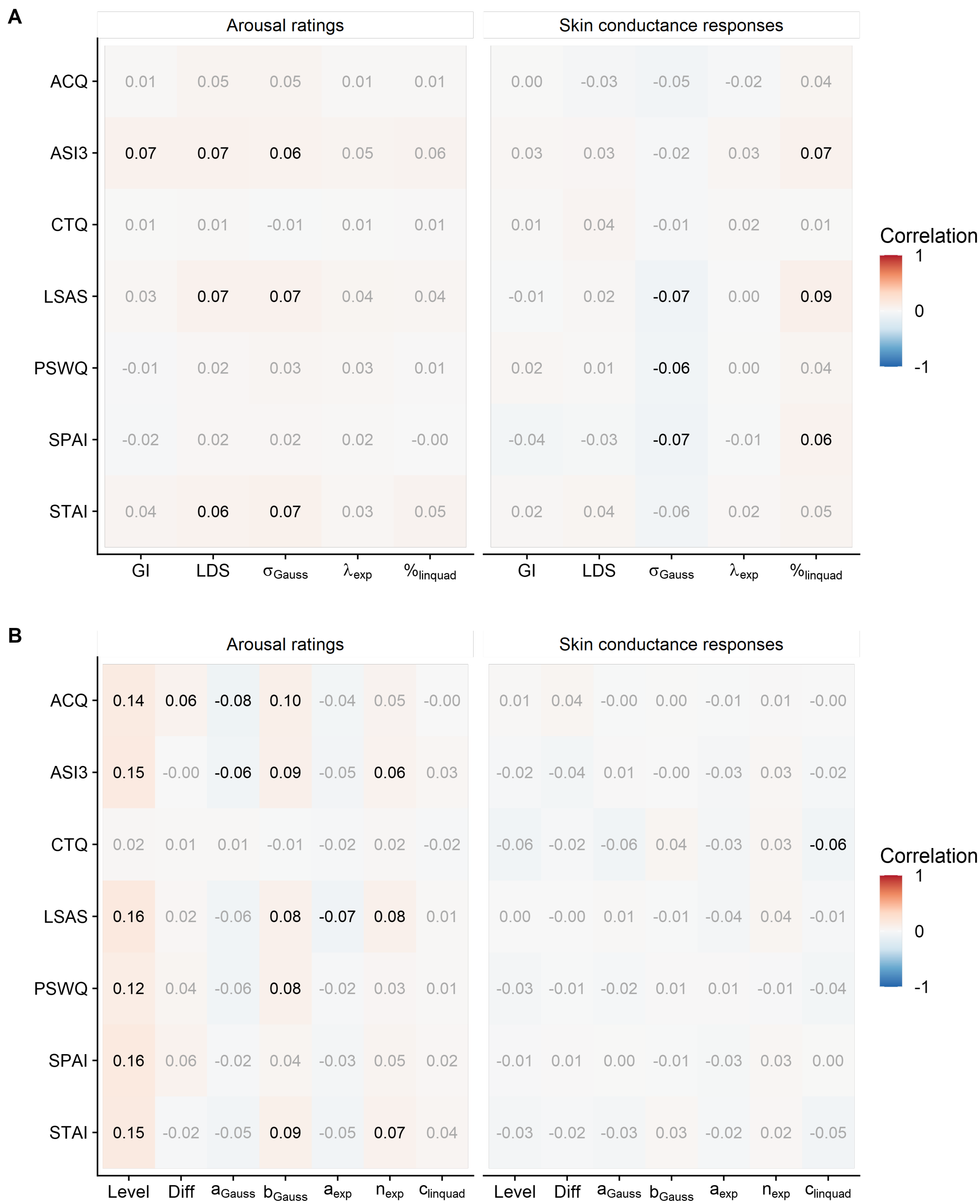



*Note.* LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS differentiation. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Validity**

Since overgeneralization of learned fear is frequently discussed as a key mechanism contributing to the etiology and maintenance of anxiety disorders, we next compared the different indices of fear generalization in terms of their performance in predicting individual levels of anxiety psychopathology as measured by questionnaires. In the first sample, the correlations were generally weak, and we were unable to identify any systematic relationship between any of the questionnaire measures and the indices of fear generalization. This lack of correlation was evident across arousal, unpleasantness, US expectancy ratings, and skin conductance responses (see Figure 7A and Supplemental Figure 5A). In the second sample, we could replicate these results. There were no systematic associations between any of the questionnaire measures and fear generalization indices, although we found slightly stronger associations for arousal ratings (see Supplemental Figure 8). Analyses of the basic indices of threat responsiveness revealed only slightly higher correlations (see Figure 7B and Supplemental Figure 5B). In particular, for arousal ratings, we identified systematic associations between mean response levels and measures of trait anxiousness in both samples (see Supplemental Figure 9). No such associations could be obtained for skin conductance responses.

**Figure 7 -** *Correlations Between Trait Measures of Anxiety Psychopathology and Indices of Fear Generalization and Basic Indices of Threat Responsiveness*




*Note.* Correlations of indices of fear generalization (Panel A) as well as basic indices of threat responsiveness (Panel B) with various measures of trait anxiousness. STAI-T = State-Trait Anxiety Inventory – Trait, ASI-3 = Anxiety Sensitivity Index 3, ACQ = Agoraphobic Cognition Questionnaire, SPAI = Social Phobia Anxiety Index, LSAS = Liebowitz Social Anxiety Scale, CTQ = Childhood Trauma Questionnaire, LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS differentiation. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

## Discussion

The aims of the current article were threefold: First, we reviewed the literature to identify commonly used methods for characterizing fear generalization profiles. Second, we described the psychometric properties of these indices, their robustness against measurement noise, and their interrelations based on simulations. Third, we used two large datasets (*N* = 1,175 and *N* = 256) to examine test-retest reliability and validity of these different approaches that aim to quantify the extent of fear generalization on the individual level.

The literature review revealed large heterogeneity in the quantification of individual fear generalization profiles across studies. Most studies concentrated on group-level effects and did not report any measures of individual fear generalization profiles (e.g., Greenberg et al., 2013; Lissek et al., 2010; Vervliet et al., 2006). In the studies that examined individual differences, several indices were used, but heterogeneity exists regarding how these indices were calculated. The most frequently used measures include the linear deviation score (LDS; e.g., Lange et al., 2017; Lissek et al., 2014), the generalization index (GI; e.g., Lenaert et al., 2016), and curvature parameters obtained from model fitting approaches based on Gaussian functions (e.g., Onat & Buchel, 2015; Tuominen et al., 2019), exponential functions (Resnik & Paz, 2015; Struyf et al., 2017), or quadratic polynomials (e.g., Cha, Tsafrir, et al., 2014; Dunning & Hajcak, 2015). All these indices are based on theoretical considerations or were defined on the basis of empirically observed fear generalization profiles. While the Gaussian function is well-suited for bidirectional generalization paradigms (i.e., the CS+ is at the center of the generalization gradient), the other indices can be easily adjusted for this purpose. None of the indices provides a normalized outcome, as their ranges depend on the measured variable (and in the case of the GI, on the number of GSs), which makes it difficult to compare results between studies.

To gain more insight into the psychometric properties of the different indices, we conducted a simulation analysis to systematically examine the interrelation of indices and their robustness against different levels of measurement noise. To this end, we created five model cases, paralleling generalization gradients that are frequently observed in empirical studies. For each case, we created eleven gradients that differed only in the amount of fear generalization, resulting in 55 true score gradients in total. Comparing the individual fear generalization indices across these simulated gradients revealed generally strong correlations up to $r = .94$, suggesting that all indices tap into the same construct. Crucially, these scores can be interpreted as a theoretical upper limit for their similarity, and we assume reduced correlations for empirical, noisy measurements. In line with this notion, correlations among generalization indices in real-life fear generalization data revealed generally moderate to high correlations ($.46 < r < .78$) for arousal ratings but substantially lower effect sizes for SCR amplitudes ($.04 < r < .57$). These findings have several important implications. While each of these indices can in principle be used to describe the curvature of individual generalization gradients, they are not equivalent and thus should not be used interchangeably. Based on the intercorrelations alone, we were not able to identify an index that performed systematically worse or better than the other indices, suggesting that other factors should be considered when choosing a suitable generalization index.

One of these factors is the robustness of the individual fear generalization indices against different levels of unsystematic noise, which can be particularly important for clinical studies. To examine this issue, we simulated three levels of noise, ranging from low to medium to high. Average correlations between indices derived from these noisy data demonstrated unexpectedly low robustness against medium levels of measurement noise for all generalization indices ($.15 < r < .26$), which were even lower for high noise levels ($.01 < r < .06$). Correlations for low noise levels were substantially higher, ranging between $r = .27$ for $\sigma_{Gauss}$ and $r = .70$ for the GI. These findings are supported by the analyses of the empirical data sets. In fact, test-retest reliabilities for arousal ratings were moderate ($.25 < r < .42$), while when we considered a noisier variable such as SCR amplitudes (Constantinou et al., 2021; Zeidan et al., 2012) they were drastically reduced ($.02 < r < .27$). This suggests that these generalization indices are not reliable under conditions of high measurement noise, which is in line with previous findings of modest reliabilities in fear generalization paradigms for specific types of measures (Cooper et al., 2023; Torrents-Rodas et al., 2014). Consequently, it is strongly advised to monitor and eliminate any potential sources of measurement noise in fear generalization paradigms. This may be achieved by repeatedly prompting responses of individuals across the generalization phase (Reutter & Gamer, 2023) instead of only acquiring them once at the end of it (but see Atlas et al., 2022 for a demonstration of how repeated prompts my alter physiological measurements). This has the additional benefit that standard errors can be obtained for individual participants ("subject-level precision"; Nebe et al., 2023) as an index of data quality. For physiological measurements like SCRs, for which reducing noise seems even more relevant, there are several ways during data collection and analysis to optimize the precision of acquired data (for an overview, see Nebe et al., 2023).

While the previously discussed issues apply to all generalization indices, our simulation analysis also revealed important differences between them. The LDS was most robust against different levels of noise and showed minimum bias. Nevertheless, the LDS was characterized by reduced differentiation between generalization profiles if the range of responses was restricted, which could result in a reduced between-subject variance that has important implications for investigating reliability and interindividual differences (Nebe et al., 2023). In contrast, modelling fitting indices were not dependent on the range of response values. However, $\sigma_{\text{Gauss}}$ overestimated the amount of generalization, especially in the context of high measurement noise. The exponential and quadratic fits showed some robustness for highly noisy data but also demonstrated stronger bias than the LDS. Compared to the other indices, only the GI was characterized by a combination of several negative features. The GI was the most sensitive to varying levels of noise and showed an overestimation of generalization under conditions of high levels of measurement noise. Similar to the LDS, the GI was dependent on the variance of response values and did not fully differentiate between generalization profiles if the response range was restricted. These problematic issues can be attributed to two factors. Firstly, the GI is the only index that does not incorporate responses to the CS−. Secondly, the GI emphasizes the response to the CS+ as it is the only variable in the denominator, making it particularly susceptible to measurement noise.

Previous studies noted that threat responsiveness in fear generalization paradigms should not only be characterized by indices that focus on the curvature of generalization gradients but should also take into account the general response strength across all stimuli as well as the differentiation between CS+ and CS− (Imholze et al., 2023; Stegmann et al., 2019). While these additional measures are complementary to the LDS and GI, model fitting approaches capture these characteristics with their remaining free parameters, e.g., the vertical translation and scaling factors of the Gaussian and exponential functions or the intercept parameter of the quadratic polynomial. While these parameters cannot be considered as direct equivalents of the mean response level or the CS differentiation, they correlate significantly with them. For ratings, generalization indices were positively associated with mean response levels, reflecting that stronger fear generalization naturally leads to increased mean response levels. Only the GI showed a strong dependency on CS differentiation, which can again be attributed to the fact that the GI is the only parameter that neglects responses to the CS−. For the model fitting parameters, there was a general tendency that the extent of fear generalization is negatively correlated to vertical translation and intercept parameters, implicating that higher offsets are associated with less linear generalization gradients. At the same time the extent of fear generalization was positively correlated to the scaling factors of the Gaussian and exponential function, indicating that both types of parameters are related to the steepness of the generalization gradient. For skin conductance responses, results were much less coherent. We observed a general tendency for stronger fear generalization to be associated with lower mean response levels as well as with lower CS differentiation. We think that this can be partly explained by floor-effects since mean SCR amplitudes were generally low and non-zero responses were predominantly found for the CS+ compared to the CS− and GS. Thus, the interindividual variability in mean response levels and CS differentiation might be particularly driven by CS+ responses, which results in steeper generalization gradients and thus weaker fear generalization.

Given the observed differences between fear generalization indices, it was a plausible assumption that these differences also play a role in how well the generalization indices perform in capturing individual levels of anxiety psychopathology. In a recent study, the subgroup of participants that demonstrated the most extreme fear generalization gradients (i.e., highest LDS scores) also showed higher levels of trait anxiety, although the effect sizes were rather small (Stegmann et al., 2019). In the current study, we reanalyzed these data by focusing on individual generalization profiles instead of group effects. Correlational analyses revealed no systematically significant associations between the different generalization indices and trait measures of anxiety as assessed by questionnaires. In addition, no differences were found among the indices, indicating that they all performed relatively poorly. To substantiate these findings, all analyses were repeated in an independent sample. Even though individual correlations were slightly stronger, the overall pattern of results remained similar and showed no systematic correlations between measures of fear generalization and questionnaire data (see Supplemental Figure 5). In general, basic measures of threat responsiveness such as CS differentiation, vertical translation, or scaling factors did not perform any better in predicting individual levels of anxiousness, except for mean response levels, which showed small but consistent correlations for all subjective measures in both samples. These findings are in line with previous observations that the mean response levels appear to be a better predictor of individual levels of trait anxiety than the curvature of the fear generalization gradient per se (Stegmann et al., 2019). An explanation for these relatively weak correlations can be derived from our findings of the simulation and empirical analyses, demonstrating low reliabilities for all fear generalization indices. From a theoretical perspective, these reliabilities provide the upper limit for correlations with measures of individual levels of anxiousness. This also explains the relatively consistent correlations between questionnaires measures and mean response levels, since they were most robust in terms of test-retest reliability.

Collectively, these findings raise the question of how the phenomenon of fear generalization can be adequately conceptualized and quantified. Fear generalization is typically defined as the extent to which the conditioned fear response is elicited by other, similar stimuli that have not predicted the US before (Dunsmoor & Murphy, 2015; Dunsmoor & Paz, 2015). For quantification, researchers predominantly relied on indices that describe the curvature (or deviation from linearity) of the fear generalization gradient. As shown above, however, it is difficult to condense this phenomenon to a single parameter. Considering only curvature parameters, for example, it is possible to imagine two parallel generalization gradients that are characterized by the same steepness, while one gradient constantly surpasses the other (see the comparisons between the top and bottom model case in Figure 4). Since the upper gradient shows relatively higher responses to the CS+ as well as to the GS, one could argue that this participant showed both stronger fear responses and stronger fear generalization. Such variability would only be captured by mean response levels. One could also argue that both gradients share a similar extent of fear generalization, while the upper gradient is characterized by a generally higher sensitivity to threat, which may theoretically be independent of fear generalization or learning processes. However, since fear generalization indices are empirically not independent of basic parameters like mean response levels and CS differentiation, this narrow conceptualization of fear generalization might not be useful for future research on these processes. Therefore, we propose that threat responsiveness should be characterized more comprehensively by quantifying fear generalization gradients along with mean response levels and the differentiation between CS+ and CS−. Alternatively, model fitting approaches overcome this problem by using a set of free parameters. It is important to mention, however, that it is not always straightforward to interpret these parameters as their impact on the generalization gradient depends on the values of the other parameters. For example, in exponential models, the properties of the generalization gradient depend on the signs of both $\lambda$ and n. Specifically, when $\lambda$ and n are both positive, the minimum of the generalization gradient converges to the level defined by the vertical translation parameter. Conversely, if both $\lambda$ and n are negative, the vertical translation parameter represents the maximum of the generalization gradient. Similarly, in Gaussian models, the CS differentiation is integrated in the combination of all three parameters and cannot be read from a single parameter. Therefore, caution is warranted when interpreting single parameters from model fitting approaches as purely reflecting the degree of fear generalization. Instead, it might be preferable to examine the full set of parameters in future studies. Moreover, it seems promising to estimate parameter values based on hierarchical modeling that has been shown to improve test-retest reliabilities due to a regularization of individual measures (Waltmann et al., 2022; Zech et al., 2022).

Although the current study provides a comprehensive overview and assessment of fear generalization measures, some limitations should be mentioned: First, our analyses relied on one standard preprocessing pipeline of all empirical data. Our simulation, however, suggests that some indices of fear generalization are highly sensitive to transformations of the response variables. For example, the GI shows less differentiation between generalization profiles with increasing scale restriction and might therefore be better suited for normalized compared to untransformed SCR amplitudes. The multitude of possible transformations, however, would quickly lead to an explosion of combinations to be analyzed. In the field of fear conditioning, these problems have begun to be addressed with the help of so-called multiverse or specification curve analyses (Kuhn et al., 2022; Lewis et al., 2023; Lonsdorf et al., 2022; Sjouwerman et al., 2022), that consider all equally plausible combinations of preprocessing and analysis approaches, providing a comprehensive comparison of the different (sets of) methodologies (Steegen et al., 2016). Similarly, applying a multiverse approach to fear generalization could be beneficial for further elucidating the impact of heterogeneity within the preprocessing and/or analysis approaches on the robustness and reliability of individual fear generalization parameters. Second, the current analyses relied on relatively homogeneous samples of young, healthy participants although higher variability as evident in more heterogeneous samples, might be beneficial for increasing reliability estimates. However, it is important to note that even in the current samples, we observed a substantial variability in questionnaire scores and fear generalization measures. Complying with the conceptualization of psychopathology as a continuum rather than a binary assignment to clinical or healthy groups (Cuthbert, 2014), the current study aimed at identifying to what degree individual differences in fear generalization are related to anxious personality traits. Since we largely failed to observe such a relationship, which was documented before (Sep et al., 2019), it seems relevant to replicate the current findings in patient groups.

To conclude, we identified substantial heterogeneity in the literature with respect to how fear generalization profiles are characterized on the individual level. We were, however, able to identify commonly used indices including the LDS, GI, and parameters extracted from model fitting approaches. Exploring their robustness against measurement noise, their test-retest reliability, and their validity in predicting anxiety psychopathology, we demonstrated a large conceptual overlap among indices but also a substantial sensitivity to measurement noise. None of the indices performed well in predicting individual anxiety levels as assessed by questionnaires. However, mean response levels, as a more general index of threat responsiveness, were more robustly associated with these questionnaire data. Taken together, the current results highlight the need for more systematic research on methodological aspects to better understand heterogeneity in the literature and to allow for informed decisions about how fear generalization could be reliably estimated from subjective and physiological data. In this vein, we propose to consider basic aspects of threat responsiveness alongside fear generalization indices to characterize individual differences in threat processing more comprehensively and thereby improve future research on risk factors for the etiology and maintenance of anxiety disorders.

**References**

Ahmed, O., & Lovibond, P. F. (2015). The Impact of Instructions on Generalization of Conditioned Fear in Humans. *Behavior Therapy*, *46*(5), 597-603. https://doi.org/https://doi.org/10.1016/j.beth.2014.12.007

Antov, M. I., Plog, E., Bierwirth, P., Keil, A., & Stockhorst, U. (2020). Visuocortical tuning to a threat-related feature persists after extinction and consolidation of conditioned fear. *Scientific Reports*, *10*(1), 3926. https://doi.org/10.1038/s41598-020-60597-z

Atlas, L. Y., Sandman, C. F., & Phelps, E. A. (2022). Rating expectations can slow aversive reversal learning [https://doi.org/10.1111/psyp.13979]. *Psychophysiology*, *59*(3), e13979. https://doi.org/https://doi.org/10.1111/psyp.13979

Bandelow, B., & Michaelis, S. (2015). Epidemiology of anxiety disorders in the 21st century. *Dialogues in Clinical Neuroscience*, *17*(3), 327-335. https://doi.org/10.31887/DCNS.2015.17.3/bbandelow

Beidel, D. C., Turner, S. M., Stanley, M. A., & Dancu, C. V. (1989). The social phobia and anxiety inventory: Concurrent and external validity. *Behavior Therapy*, *20*(3), 417-427. https://doi.org/https://doi.org/10.1016/S0005-7894(89)80060-7

Bernstein, D. P., Stein, J. A., Newcomb, M. D., Walker, E., Pogge, D., Ahluvalia, T., Stokes, J., Handelsman, L., Medrano, M., Desmond, D., & Zule, W. (2003). Development and validation of a brief screening version of the Childhood Trauma Questionnaire. *Child Abuse Negl*, *27*(2), 169-190. https://doi.org/https://doi.org/10.1016/S0145-2134(02)00541-0

Boucsein, W., Fowles, D. C., Grimnes, S., Ben-Shakhar, G., roth, W. T., Dawson, M. E., Filion, D. L., & Society for Psychophysiological Research Ad Hoc Committee on Electrodermal, M. (2012). Publication recommendations for electrodermal measurements. *Psychophysiology*, *49*(8), 1017-1034. https://doi.org/10.1111/j.1469-8986.2012.01384.x

Cecil, H., Jr., Frederick, M., John, W. T., & Charles, P. W. (1947). Low Moments for Small Samples: A Comparative Study of Order Statistics. *The Annals of Mathematical Statistics*, *18*(3), 413-426. https://doi.org/10.1214/aoms/1177730388

Cha, J., Daniel, D., Sanja, N., Jaime, I., Tsafrir, G., Greg, H., & Lilianne Rivka, M.-P. (2016). Clinically Anxious Individuals Show Disrupted Feedback between Inferior Frontal Gyrus and Prefrontal-Limbic Control Circuit. *The Journal of Neuroscience*, *36*(17), 4708. https://doi.org/10.1523/JNEUROSCI.1092-15.2016

Cha, J., Joshua, M. C., Daniel, J. D., Tsafrir, G., Greg, H. P., & Lilianne, R. M.-P. (2014). Hyper-Reactive Human Ventral Tegmental Area and Aberrant Mesocorticolimbic Connectivity in Overgeneralization of Fear in Generalized Anxiety Disorder. *The Journal of Neuroscience*, *34*(17), 5855. https://doi.org/10.1523/JNEUROSCI.4868-13.2014

Cha, J., Tsafrir, G., Joshua, M. C., Daniel, J. D., Greg, H., & Lilianne, R. M.-P. (2014). Circuit-Wide Structural and Functional Measures Predict Ventromedial Prefrontal Cortex Fear Generalization: Implications for Generalized Anxiety Disorder. *The Journal of Neuroscience*, *34*(11), 4043. https://doi.org/10.1523/JNEUROSCI.3372-13.2014

Chambless, D. L., Caputo, G. C., Bright, P., & Gallagher, R. (1984). Assessment of fear of fear in agoraphobics: the body sensations questionnaire and the agoraphobic cognitions questionnaire. *J Consult Clin Psychol*, *52*(6), 1090-1097. https://doi.org/10.1037/0022-006X.52.6.1090

Cohen, Z. D., Delgadillo, J., & DeRubeis, R. J. (2021). Personalized treatment approaches. In *Bergin and Garfield's handbook of psychotherapy and behavior change: 50th anniversary edition, 7th ed.* (pp. 673-703). John Wiley & Sons, Inc.

Constantinou, E., Purves, K. L., McGregor, T., Lester, K. J., Barry, T. J., Treanor, M., Craske, M. G., & Eley, T. C. (2021). Measuring fear: Association among different measures of fear learning. *Journal of*

*Behavior Therapy and Experimental Psychiatry*, *70*, 101618. https://doi.org/https://doi.org/10.1016/j.jbtep.2020.101618

Cooper, S. E., Dunsmoor, J. E., Koval, K. A., Pino, E. R., & Steinman, S. A. (2023). Test–retest reliability of human threat conditioning and generalization across a 1-to-2-week interval. *Psychophysiology*, *60*(6), e14242. https://doi.org/https://doi.org/10.1111/psyp.14242

Cooper, S. E., van Dis, E. A. M., Hagenaars, M. A., Krypotos, A.-M., Nemeroff, C. B., Lissek, S., Engelhard, I. M., & Dunsmoor, J. E. (2022). A meta-analysis of conditioned fear generalization in anxiety-related disorders. *Neuropsychopharmacology*. https://doi.org/10.1038/s41386-022-01332-2

Cuthbert, B. N. (2014). The RDoC framework: facilitating transition from ICD/DSM to dimensional approaches that integrate neuroscience and psychopathology [https://doi.org/10.1002/wps.20087]. *World Psychiatry*, *13*(1), 28-35. https://doi.org/https://doi.org/10.1002/wps.20087

Dos Santos Corrêa, M., Vaz, B. D. S., Grisanti, G. D. V., de Paiva, J. P. Q., Tiba, P. A., & Fornari, R. V. (2019). Relationship between footshock intensity, post-training corticosterone release and contextual fear memory specificity over time. *Psychoneuroendocrinology*, *110*, 104447. https://doi.org/10.1016/j.psyneuen.2019.104447

Dou, H., Lei, Y., Pan, Y., Li, H., & Astikainen, P. (2023). Impact of observational and direct learning on fear conditioning and generalization in humans. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *121*, 110650. https://doi.org/https://doi.org/10.1016/j.pnpbp.2022.110650

Dou, H., Zou, L., Becker, B., & Lei, Y. (2021). Intranasal oxytocin decreases fear generalization in males, but does not modulate discrimination threshold. *Psychopharmacology (Berl)*, *238*(3), 677-689. https://doi.org/10.1007/s00213-020-05720-8

Duits, P., Cath, D. C., Lissek, S., Hox, J. J., Hamm, A. O., Engelhard, I. M., van den Hout, M. A., & Baas, J. M. (2015). Updated meta-analysis of classical fear conditioning in the anxiety disorders. *Depress Anxiety*, *32*(4), 239-253. https://doi.org/10.1002/da.22353

Dunning, J. P., & Hajcak, G. (2015). Gradients of Fear Potentiated Startle During Generalization, Extinction, and Extinction Recall--and Their Relations With Worry. *Behavior Therapy*, *46*(5), 640-651. https://doi.org/10.1016/j.beth.2015.06.005

Dunsmoor, J. E., Kroes, M. C. W., Braren, S. H., & Phelps, E. A. (2017). Threat intensity widens fear generalization gradients. *Behavioral neuroscience*, *131*(2), 168-175. https://doi.org/10.1037/bne0000186

Dunsmoor, J. E., & Murphy, G. L. (2015). Categories, concepts, and conditioning: how humans generalize fear. *Trends in Cognitive Sciences*, *19*(2), 73-77. https://doi.org/https://doi.org/10.1016/j.tics.2014.12.003

Dunsmoor, J. E., & Paz, R. (2015). Fear Generalization and Anxiety: Behavioral and Neural Mechanisms. *Biol Psychiatry*, *78*(5), 336-343. https://doi.org/10.1016/j.biopsych.2015.04.010

Dymond, S., Dunsmoor, J. E., Vervliet, B., Roche, B., & Hermans, D. (2015). Fear Generalization in Humans: Systematic Review and Implications for Anxiety Disorder Research. *Behavior Therapy*, *46*(5), 561-582. https://doi.org/10.1016/j.beth.2014.10.001

Ehlers, A., Margraf, J., & Chambless, D. (2001). *Fragebogen zu körperbezogenen Ängsten, Kognitionen und Vermeidung: AKV*. Beltz-Test.

El-Bar, N., Laufer, O., Yoran-Hegesh, R., & Paz, R. (2017). Over-generalization in youth with anxiety disorders. *Social Neuroscience*, *12*(1), 76-85. https://doi.org/10.1080/17470919.2016.1167123

Fan, M., Zhang, D., Zhao, S., Xie, Q., Chen, W., Jie, J., Wang, Y., & Zheng, X. (2022). Stimulus diversity increases category-based fear generalization and the effect of intolerance of uncertainty.

*Behaviour Research and Therapy*, *159*, 104201. https://doi.org/https://doi.org/10.1016/j.brat.2022.104201

Feldman, B. E. (2005). Relative importance and value. *Available at SSRN 2255827*.

Fraunfelter, L., Gerdes, A. B. M., & Alpers, G. W. (2022). Fear one, fear them all: A systematic review and meta-analysis of fear generalization in pathological anxiety. *Neuroscience & Biobehavioral Reviews*, *139*, 104707. https://doi.org/https://doi.org/10.1016/j.neubiorev.2022.104707

Friedl, M. W., & Keil, A. (2021). Aversive Conditioning of Spatial Position Sharpens Neural Population-Level Tuning in Visual Cortex and Selectively Alters Alpha-Band Activity. *The Journal of Neuroscience*, *41*(26), 5723. https://doi.org/10.1523/JNEUROSCI.2889-20.2021

Fullana, M. A., Dunsmoor, J. E., Schruers, K. R. J., Savage, H. S., Bach, D. R., & Harrison, B. J. (2020). Human fear conditioning: From neuroscience to the clinic. *Behaviour Research and Therapy*, *124*, 103528. https://doi.org/https://doi.org/10.1016/j.brat.2019.103528

Ginat-Frolich, R., Gendler, T., Marzan, D., Tsuk, Y., & Shechner, T. (2019). Reducing fear overgeneralization in children using a novel perceptual discrimination task. *Behaviour Research and Therapy*, *116*, 131-139. https://doi.org/https://doi.org/10.1016/j.brat.2019.03.008

Ginat-Frolich, R., Klein, Z., Katz, O., & Shechner, T. (2017). A novel perceptual discrimination training task: Reducing fear overgeneralization in the context of fear learning. *Behaviour Research and Therapy*, *93*, 29-37. https://doi.org/https://doi.org/10.1016/j.brat.2017.03.010

Glenn, C. R., Klein, D. N., Lissek, S., Britton, J. C., Pine, D. S., & Hajcak, G. (2012). The development of fear learning and generalization in 8–13 year-olds [https://doi.org/10.1002/dev.20616]. *Dev Psychobiol*, *54*(7), 675-684. https://doi.org/https://doi.org/10.1002/dev.20616

Glenn, D. E., Feldman, J. S., Ivie, E. J., Shechner, T., Leibenluft, E., Pine, D. S., Peters, M. A. K., & Michalska, K. J. (2021). Social relevance modulates multivariate neural representations of threat generalization in children and adults [https://doi.org/10.1002/dev.22185]. *Dev Psychobiol*, *63*(7), e22185. https://doi.org/https://doi.org/10.1002/dev.22185

Greenberg, T., Carlson, J. M., Cha, J., Hajcak, G., & Mujica-Parodi, L. R. (2013). Neural reactivity tracks fear generalization gradients. *Biol Psychol*, *92*(1), 2-8. https://doi.org/10.1016/j.biopsycho.2011.12.007

Grosso, A., Santoni, G., Manassero, E., Renna, A., & Sacchetti, B. (2018). A neuronal basis for fear discrimination in the lateral amygdala. *Nature Communications*, *9*(1), 1214. https://doi.org/10.1038/s41467-018-03682-2

Hamm, A. O., & Weike, A. I. (2005). The neuropsychology of fear learning and fear regulation. *International Journal of Psychophysiology*, *57*(1), 5-14. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2005.01.006

Hammell, A. E., Helwig, N. E., Kaczkurkin, A. N., Sponheim, S. R., & Lissek, S. (2020). The temporal course of over-generalized conditioned threat expectancies in posttraumatic stress disorder. *Behaviour Research and Therapy*, *124*, 103513. https://doi.org/https://doi.org/10.1016/j.brat.2019.103513

Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behav Res Methods*, *50*(3), 1166-1186. https://doi.org/10.3758/s13428-017-0935-1

Herzog, K., Andreatta, M., Schneider, K., Schiele, M. A., Domschke, K., Romanos, M., Deckert, J., & Pauli, P. (2021). Reducing Generalization of Conditioned Fear: Beneficial Impact of Fear Relevance and Feedback in Discrimination Training [Original Research]. *Front Psychol*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.665711

Holt, D. J., Boeke, E. A., Wolthusen, R. P. F., Nasr, S., Milad, M. R., & Tootell, R. B. H. (2014). A parametric study of fear generalization to faces and non-face objects: relationship to discrimination thresholds [Original Research]. *Front Hum Neurosci*, *8*. https://www.frontiersin.org/articles/10.3389/fnhum.2014.00624

Imholze, C., Hutterer, K., Gall, D., Dannlowski, U., Domschke, K., Leehr, E. J., Lonsdorf, T. B., Lueken, U., Reif, A., Rosenkranz, K., Schiele, M. A., Zwanzger, P., Pauli, P., & Gamer, M. (2023). Prediction of Changes in Negative Affect During the COVID-19 Pandemic by Experimental Fear Conditioning and Generalization Measures. *Zeitschrift für Psychologie*, *231*(2), 137-148. https://doi.org/10.1027/2151-2604/a000523

Kaczkurkin, A. N., Burton, P. C., Chazin, S. M., Manbeck, A. B., Espensen-Sturges, T., Cooper, S. E., Sponheim, S. R., & Lissek, S. (2017). Neural Substrates of Overgeneralized Conditioned Fear in PTSD. *Am J Psychiatry*, *174*(2), 125-134. https://doi.org/10.1176/appi.ajp.2016.15121549

Kampermann, L., Wilming, N., Alink, A., Büchel, C., & Onat, S. (2019). Fixation-pattern similarity analysis reveals adaptive changes in face-viewing strategies following aversive learning. *eLife*, *8*, e44111. https://doi.org/10.7554/eLife.44111

Kasper, S. (2006). Anxiety disorders: under-diagnosed and insufficiently treated. *International Journal of Psychiatry in Clinical Practice*, *10*(sup1), 3-9. https://doi.org/10.1080/13651500600552297

Kass, M. D., & McGann, J. P. (2017). Persistent, generalized hypersensitivity of olfactory bulb interneurons after olfactory fear generalization. *Neurobiology of Learning and Memory*, *146*, 47-57. https://doi.org/https://doi.org/10.1016/j.nlm.2017.11.004

Kausche, F. M., Zerbes, G., Kampermann, L., Büchel, C., & Schwabe, L. (2021). Neural signature of delayed fear generalization under stress [https://doi.org/10.1111/psyp.13917]. *Psychophysiology*, *58*(11), e13917. https://doi.org/https://doi.org/10.1111/psyp.13917

Kausche, F. M., Zerbes, G., Kampermann, L., Müller, J. C., Wiedemann, K., Büchel, C., & Schwabe, L. (2021a). Acute stress leaves fear generalization in healthy individuals intact. *Cognitive, Affective, & Behavioral Neuroscience*, *21*(2), 372-389. https://doi.org/10.3758/s13415-021-00874-0

Kausche, F. M., Zerbes, G., Kampermann, L., Müller, J. C., Wiedemann, K., Büchel, C., & Schwabe, L. (2021b). Noradrenergic stimulation increases fear memory expression. *European Neuropsychopharmacology*, *43*, 71-81. https://doi.org/https://doi.org/10.1016/j.euroneuro.2020.11.015

Keefe, J. R., Suarez-Jimenez, B., Zhu, X., Lazarov, A., Durosky, A., Such, S., Marohasy, C., Lissek, S., & Neria, Y. (2022). Elucidating behavioral and functional connectivity markers of aberrant threat discrimination in PTSD. *Depression and Anxiety*, *39*(12), 891-901. https://doi.org/https://doi.org/10.1002/da.23295

Kemper, C. J., Ziegler, M., & Taylor, S. (2009). Überprüfung der psychometrischen Qualität der deutschen Version des Angstsensitivitätsindex-3. *Diagnostica*, *55*(4), 223-233. http://econtent.hogrefe.com/doi/pdf/10.1026/0012-1924.55.4.223

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E. E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Arch Gen Psychiatry*, *62*(6), 593-602. https://doi.org/10.1001/archpsyc.62.6.593

Klein, Z., Shner-Livne, G., Danon-Kraun, S., Ginat-Frolich, R., Pine, D. S., & Shechner, T. (2023). Enhanced late positive potential to conditioned threat cue during delayed extinction in anxious youth [https://doi.org/10.1111/jcpp.13814]. *Journal of Child Psychology and Psychiatry*, *n/a*(n/a). https://doi.org/https://doi.org/10.1111/jcpp.13814

Klein, Z., Shner, G., Ginat-Frolich, R., Vervliet, B., & Shechner, T. (2020). The effects of age and trait anxiety on avoidance learning and its generalization. *Behaviour Research and Therapy*, *129*, 103611. https://doi.org/https://doi.org/10.1016/j.brat.2020.103611

Kopp, B., Schlimm, M., & Hermann, C. (2005). Memory–emotional interactions as revealed by fear generalization in animal-fearful individuals. *Journal of Behavior Therapy and Experimental Psychiatry*, *36*(2), 145-166. https://doi.org/https://doi.org/10.1016/j.jbtep.2004.08.007

Kuhn, M., Gerlicher, A. M. V., & Lonsdorf, T. B. (2022). Navigating the manyverse of skin conductance response quantification approaches – A direct comparison of trough-to-peak, baseline correction, and model-based approaches in Ledalab and PsPM. *Psychophysiology*, *59*(9), e14058. https://doi.org/https://doi.org/10.1111/psyp.14058

Lange, I., Goossens, L., Bakker, J., Michielse, S., Marcelis, M., Wichers, M., van Os, J., van Amelsvoort, T., & Schruers, K. (2019). Functional neuroimaging of associative learning and generalization in specific phobia. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *89*, 275-285. https://doi.org/https://doi.org/10.1016/j.pnpbp.2018.09.008

Lange, I., Goossens, L., Bakker, J., Michielse, S., van Winkel, R., Lissek, S., Leibold, N., Marcelis, M., Wichers, M., van Os, J., van Amelsvoort, T., & Schruers, K. (2019). Neurobehavioural mechanisms of threat generalization moderate the link between childhood maltreatment and psychopathology in emerging adulthood. *J Psychiatry Neurosci*, *44*(3), 185-194. https://doi.org/10.1503/jpn.180053

Lange, I., Goossens, L., Michielse, S., Bakker, J., Lissek, S., Papalini, S., Verhagen, S., Leibold, N., Marcelis, M., Wichers, M., Lieverse, R., van Os, J., van Amelsvoort, T., & Schruers, K. (2017). Behavioral pattern separation and its link to the neural mechanisms of fear generalization. *Social Cognitive and Affective Neuroscience*, *12*(11), 1720-1729. https://doi.org/10.1093/scan/nsx104

Lau, J. Y., Lissek, S., Nelson, E. E., Lee, Y., Roberson-Nay, R., Poeth, K., Jenness, J., Ernst, M., Grillon, C., & Pine, D. S. (2008). Fear conditioning in adolescents with anxiety disorders: results from a novel experimental paradigm. *J Am Acad Child Adolesc Psychiatry*, *47*(1), 94-102. https://doi.org/10.1097/chi.0b01e31815a5f01

Laufer, O., Israeli, D., & Paz, R. (2016). Behavioral and Neural Mechanisms of Overgeneralization in Anxiety. *Current Biology*, *26*(6), 713-722. https://doi.org/https://doi.org/10.1016/j.cub.2016.01.023

Laux, L., & Spielberger, C. D. (1981). *Das State-Trait-Angstinventar: STAI*. Beltz Weinheim.

Lee, J. C., Hayes, B. K., & Lovibond, P. F. (2018). Peak shift and rules in human generalization. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(12), 1955-1970. https://doi.org/10.1037/xlm0000558

Lenaert, B., van de Ven, V., Kaas, A. L., & Vlaeyen, J. W. S. (2016). Generalization on the Basis of Prior Experience Is Predicted by Individual Differences in Working Memory. *Behavior Therapy*, *47*(1), 130-140. https://doi.org/https://doi.org/10.1016/j.beth.2015.10.001

Levine, S. M., Kumpf, M., Rupprecht, R., & Schwarzbach, J. V. (2021). Supracategorical fear information revealed by aversively conditioning multiple categories. *Cognitive Neuroscience*, *12*(1), 28-39. https://doi.org/10.1080/17588928.2020.1839039

Lewis, M. W., Bradford, D. E., Pace‐Schott, E. F., Rauch, S. L., & Rosso, I. M. (2023). Multiverse analyses of fear acquisition and extinction retention in posttraumatic stress disorder. *Psychophysiology*, e14265.

Liebowitz, M. R. (1987). Social phobia. *Modern Problems of Pharmacopsychiatry*.

Lissek, S., Kaczkurkin, A. N., Rabin, S., Geraci, M., Pine, D. S., & Grillon, C. (2014). Generalized anxiety disorder is associated with overgeneralization of classically conditioned fear. *Biol Psychiatry*, *75*(11), 909-915. https://doi.org/10.1016/j.biopsych.2013.07.025

Lissek, S., Levenson, J., Biggs, A. L., Johnson, L. L., Ameli, R., Pine, D. S., & Grillon, C. (2008). Elevated fear conditioning to socially relevant unconditioned stimuli in social anxiety disorder. *Am J Psychiatry*, *165*(1), 124-132. https://doi.org/10.1176/appi.ajp.2007.06091513

Lissek, S., Rabin, S., Heller, R. E., Lukenbaugh, D., Geraci, M., Pine, D. S., & Grillon, C. (2010). Overgeneralization of conditioned fear as a pathogenic marker of panic disorder. *Am J Psychiatry*, *167*(1), 47-55. https://doi.org/10.1176/appi.ajp.2009.09030410

Liu, S. S. (1971). Differential conditioning and stimulus generalization of the rabbit's nictitating membrane response. *Journal of Comparative and Physiological Psychology*, *77*(1), 136-142. https://doi.org/10.1037/h0031587

Lommen, M. J. J., Duta, M., Vanbrabant, K., de Jong, R., Juechems, K., & Ehlers, A. (2017). Training discrimination diminishes maladaptive avoidance of innocuous stimuli in a fear conditioning paradigm. *PLoS ONE*, *12*(10), e0184485. https://doi.org/10.1371/journal.pone.0184485

Lonsdorf, T. B., Gerlicher, A., Klingelhöfer-Jens, M., & Krypotos, A.-M. (2022). Multiverse analyses in fear conditioning research. *Behaviour Research and Therapy*, *153*, 104072. https://doi.org/https://doi.org/10.1016/j.brat.2022.104072

Lueken, U., & Hahn, T. (2020). Chapter 17 - Personalized mental health: Artificial intelligence technologies for treatment response prediction in anxiety disorders. In B. T. Baune (Ed.), *Personalized Psychiatry* (pp. 201-213). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-813176-3.00017-1

Manbeck, A. B., Cooper, S. E., & Lissek, S. (2022). Reversing threat contingencies enhances generalization of conditioned fear. *Learning and Motivation*, *80*, 101843. https://doi.org/https://doi.org/10.1016/j.lmot.2022.101843

McTeague, L. M., Gruss, L. F., & Keil, A. (2015). Aversive learning shapes neuronal orientation tuning in human visual cortex [Article]. *Nat Commun*, *6*, 7823. https://doi.org/10.1038/ncomms8823

Mertens, G., Bouwman, V., & Engelhard, I. M. (2021). Conceptual fear generalization gradients and their relationship with anxious traits: Results from a Registered Report. *International Journal of Psychophysiology*, *170*, 43-50. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2021.09.007

Meulders, A., Meulders, M., Stouten, I., De Bie, J., & Vlaeyen, J. W. S. (2017). Extinction of Fear Generalization: A Comparison Between Fibromyalgia Patients and Healthy Control Participants. *The Journal of Pain*, *18*(1), 79-95. https://doi.org/https://doi.org/10.1016/j.jpain.2016.10.004

Miasnikov, A. A., Chen, J. C., & Weinberger, N. M. (2009). Behavioral memory induced by stimulation of the nucleus basalis: Effects of contingency reversal. *Neurobiology of Learning and Memory*, *91*(3), 298-309. https://doi.org/https://doi.org/10.1016/j.nlm.2008.12.010

Michael, T., Zetsche, U., & Margraf, J. (2007). Epidemiology of anxiety disorders. *Psychiatry*, *6*(4), 136-142. https://doi.org/https://doi.org/10.1016/j.mppsy.2007.01.007

Michalska, K. J., Shechner, T., Hong, M., Britton, J. C., Leibenluft, E., Pine, D. S., & Fox, N. A. (2016). A developmental analysis of threat/safety learning and extinction recall during middle childhood. *Journal of Experimental Child Psychology*, *146*, 95-105. https://doi.org/https://doi.org/10.1016/j.jecp.2016.01.008

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L. A., & Group, P.-P. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, *4*(1), 1. https://doi.org/10.1186/2046-4053-4-1

Nebe, S., Reutter, M., Baker, D., Bölte, J., Domes, G., Gamer, M., Gärtner, A., Gießing, C., née Mann, C. G., & Hilger, K. (2023). Enhancing Precision in Human Neuroscience.

Nelson, B. D., Weinberg, A., Pawluk, J., Gawlowska, M., & Proudfit, G. H. (2015). An Event-Related Potential Investigation of Fear Generalization and Intolerance of Uncertainty. *Behavior Therapy*, *46*(5), 661-670. https://doi.org/10.1016/j.beth.2014.09.010

Niederstrasser, N. G., Meulders, A., Meulders, M., Struyf, D., & Vlaeyen, J. W. (2017). Executive functions deficits impair extinction of generalization of fear of movement-related pain [https://doi.org/10.1002/ejp.991]. *European Journal of Pain*, *21*(5), 886-899. https://doi.org/https://doi.org/10.1002/ejp.991

Onat, S., & Buchel, C. (2015). The neuronal basis of fear generalization in humans. *Nat Neurosci*, *18*(12), 1811-1818. https://doi.org/10.1038/nn.4166

Phillips, L. W. (1958). Mediated verbal similarity as a determinant of the generalization of a conditioned GSR. *Journal of Experimental Psychology*, *55*(1), 56-62. https://doi.org/10.1037/h0047453

Pittig, A., Treanor, M., LeBeau, R. T., & Craske, M. G. (2018). The role of associative fear and avoidance learning in anxiety disorders: Gaps and directions for future research. *Neuroscience & Biobehavioral Reviews*, *88*, 117-140. https://doi.org/https://doi.org/10.1016/j.neubiorev.2018.03.015

Plog, E., Antov, M. I., Bierwirth, P., Keil, A., & Stockhorst, U. (2022). Phase-Synchronized Stimulus Presentation Augments Contingency Knowledge and Affective Evaluation in a Fear-Conditioning Task. *eneuro*, *9*(1), ENEURO.0538-0520.2021. https://doi.org/10.1523/ENEURO.0538-20.2021

Porter, D. B., Qu, L. P., Kahnt, T., & Gottfried, J. A. (2021). Aversive outcomes impact human olfactory discrimination learning and generalization. *Behavioral neuroscience*, *135*(5), 642-653. https://doi.org/10.1037/bne0000476

R Development Core Team. (2021). *R: A language and environment for statistical computing*. In R Foundation for Statistical Computing.

Radua, J. (2021). PRISMA 2020 – An updated checklist for systematic reviews and meta-analyses. *Neuroscience & Biobehavioral Reviews*, *124*, 324-325. https://doi.org/https://doi.org/10.1016/j.neubiorev.2021.02.016

Reinhard, J., Slyschak, A., Schiele, M. A., Andreatta, M., Kneer, K., Reif, A., Domschke, K., Gamer, M., Pauli, P., Deckert, J., & Romanos, M. (2022). Fear conditioning and stimulus generalization in association with age in children and adolescents. *European Child & Adolescent Psychiatry*, *31*(10), 1581-1590. https://doi.org/10.1007/s00787-021-01797-4

Rescorla, R. A. (1967). Pavlovian conditioning and its proper control procedures. *Psychol Rev*, *74*(1), 71-80. https://doi.org/10.1037/h0024109

Resnik, J., & Paz, R. (2015). Fear generalization in the primate amygdala. *Nature Neuroscience*, *18*(2), 188-190. https://doi.org/10.1038/nn.3900

Reutter, M., & Gamer, M. (2023). Individual patterns of visual exploration predict the extent of fear generalization in humans. *Emotion*, *23*(5), 1267-1280. https://doi.org/10.1037/emo0001134

Roesmann, K., Wessing, I., Kraß, S., Leehr, E. J., Klucken, T., Straube, T., & Junghöfer, M. (2022). Developmental aspects of fear generalization – A MEG study on neurocognitive correlates in adolescents versus adults. *Developmental Cognitive Neuroscience*, *58*, 101169. https://doi.org/https://doi.org/10.1016/j.dcn.2022.101169

Scarlata, M. J., Lee, S. H., Lee, D., Kandigian, S. E., Hiller, A. J., Dishart, J. G., Mintz, G. E., Wang, Z., Coste, G. I., Mousley, A. L., Soler, I., Lawson, K., Ng, A. J., Bezek, J. L., & Bergstrom, H. C. (2019). Chemogenetic stimulation of the infralimbic cortex reverses alcohol-induced fear memory overgeneralization. *Scientific Reports*, *9*(1), 6730. https://doi.org/10.1038/s41598-019-43159-w

Schiele, M. A., Reinhard, J., Reif, A., Domschke, K., Romanos, M., Deckert, J., & Pauli, P. (2016). Developmental aspects of fear: Comparing the acquisition and generalization of conditioned fear in children and adults. *Dev Psychobiol*, *58*(4), 471-481. https://doi.org/10.1002/dev.21393

Schroijen, M., Pappens, M., Schruers, K., Van den Bergh, O., Vervliet, B., & Van Diest, I. (2015). Generalization of Fear to Respiratory Sensations. *Behavior Therapy*, *46*(5), 611-626. https://doi.org/10.1016/j.beth.2015.05.004

Seligman, M. E. (1971). Phobias and preparedness. *Behavior Therapy*, *2*(3), 307-320. https://doi.org/10.1016/S0005-7894(71)80064-3

Sep, M. S. C., Steenmeijer, A., & Kennis, M. (2019). The relation between anxious personality traits and fear generalization in healthy subjects: A systematic review and meta-analysis. *Neuroscience & Biobehavioral Reviews*, *107*, 320-328. https://doi.org/https://doi.org/10.1016/j.neubiorev.2019.09.029

Shalev, L., Paz, R., & Avidan, G. (2018). Visual Aversive Learning Compromises Sensory Discrimination. *Journal of Neuroscience*, *38*(11), 2766-2779. https://doi.org/10.1523/jneurosci.0889-17.2017

Sjouwerman, R., Illius, S., Kuhn, M., & Lonsdorf, T. B. (2022). A data multiverse analysis investigating non-model based SCR quantification approaches [https://doi.org/10.1111/psyp.14130]. *Psychophysiology*, *59*(12), e14130. https://doi.org/https://doi.org/10.1111/psyp.14130

Stangier, U., & Heidenreich, T. (2004). Die Liebowitz Soziale Angst-Skala (LSAS)[Liebowitz Social Anxiety Scale]. Collegium Internationale Psychiatriae Scalarum (Ed.), Internationale Skalen für Psychiatrie [International Psychiatry Scales]. In: Weinheim: Beltz. German.

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing Transparency Through a Multiverse Analysis. *Perspectives on Psychological Science*, *11*(5), 702-712. https://doi.org/10.1177/1745691616658637

Stegmann, Y., Ahrens, L. M., Pauli, P., Keil, A., & Wieser, M. J. (2020). Social aversive generalization learning sharpens the tuning of visuocortical neurons to facial identity cues. *eLife*, *9*, e55204. https://doi.org/10.7554/eLife.55204

Stegmann, Y., Schiele, M. A., Schümann, D., Lonsdorf, T. B., Zwanzger, P., Romanos, M., Reif, A., Domschke, K., Deckert, J., Gamer, M., & Pauli, P. (2019). Individual differences in human fear generalization—pattern identification and implications for anxiety disorders. *Translational Psychiatry*, *9*(1), 307. https://doi.org/10.1038/s41398-019-0646-8

Struyf, D., Hermans, D., & Vervliet, B. (2018). Maximizing the generalization of fear extinction: Exposures to a peak generalization stimulus. *Behaviour Research and Therapy*, *111*, 1-8. https://doi.org/https://doi.org/10.1016/j.brat.2018.09.005

Struyf, D., Zaman, J., Hermans, D., & Vervliet, B. (2017). Gradients of fear: How perception influences fear generalization. *Behaviour Research and Therapy*, *93*, 116-122. https://doi.org/https://doi.org/10.1016/j.brat.2017.04.001

Taylor, S., Zvolensky, M. J., Cox, B. J., Deacon, B., Heimberg, R. G., Ledley, D. R., Abramowitz, J. S., Holaway, R. M., Sandin, B., Stewart, S. H., Coles, M., Eng, W., Daly, E. S., Arrindell, W. A., Bouvard, M., & Cardenas, S. J. (2007). Robust dimensions of anxiety sensitivity: development and initial validation of the Anxiety Sensitivity Index-3. *Psychol Assess*, *19*(2), 176-188. https://doi.org/10.1037/1040-3590.19.2.176

Torrents-Rodas, D., Fullana, M. A., Bonillo, A., Andión, O., Molinuevo, B., Caseras, X., & Torrubia, R. (2014). Testing the temporal stability of individual differences in the acquisition and generalization of fear [https://doi.org/10.1111/psyp.12213]. *Psychophysiology*, *51*(7), 697-705. https://doi.org/https://doi.org/10.1111/psyp.12213

Tuominen, L., Boeke, E., DeCross, S., Wolthusen, R. P. F., Nasr, S., Milad, M., Vangel, M., Tootell, R., & Holt, D. (2019). The relationship of perceptual discrimination to neural mechanisms of fear generalization. *Neuroimage*, *188*, 445-455. https://doi.org/https://doi.org/10.1016/j.neuroimage.2018.12.034

Tuominen, L., DeCross, S. N., Boeke, E., Cassidy, C. M., Freudenreich, O., Shinn, A. K., Tootell, R. B. H., & Holt, D. J. (2021). Neural Abnormalities in Fear Generalization in Schizophrenia and Associations With Negative Symptoms. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *6*(12), 1165-1175. https://doi.org/https://doi.org/10.1016/j.bpsc.2021.01.006

van Meurs, B., Wiggert, N., Wicker, I., & Lissek, S. (2014). Maladaptive behavioral consequences of conditioned fear-generalization: A pronounced, yet sparsely studied, feature of anxiety pathology. *Behaviour Research and Therapy*, *57*, 29-37. https://doi.org/https://doi.org/10.1016/j.brat.2014.03.009

Vandael, K., Meulders, A., Peters, M., & Vervliet, B. (2023). The effect of experimentally induced positive affect on the generalization of pain-related avoidance and relief. *Behaviour Research and Therapy*, *165*, 104324. https://doi.org/https://doi.org/10.1016/j.brat.2023.104324

Vandael, K., Meulders, M., Vanden Boer, C., & Meulders, A. (2020). The relationship between fear generalization and pain modulation: an investigation in healthy participants. *20*(1), 151-165. https://doi.org/doi:10.1515/sjpain-2019-0065 (Scandinavian Journal of Pain)

Vervliet, B., Vansteenwegen, D., & Eelen, P. (2006). Generalization Gradients for Acquisition and Extinction in Human Contingency Learning. *Experimental Psychology*, *53*(2), 132-142. https://doi.org/10.1027/1618-3169.53.2.132

Waltmann, M., Schlagenhauf, F., & Deserno, L. (2022). Sufficient reliability of the behavioral and computational readouts of a probabilistic reversal learning task. *Behav Res Methods*, *54*(6), 2993-3014. https://doi.org/10.3758/s13428-021-01739-7

Wang, J., Sun, X., Becker, B., & Lei, Y. (2022). Common and separable behavioral and neural mechanisms underlie the generalization of fear and disgust. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *116*, 110519. https://doi.org/https://doi.org/10.1016/j.pnpbp.2022.110519

Watson, J. B., & Rayner, R. (1920). Conditioned emotional reactions. *Journal of Experimental Psychology*, *3*(1), 1-14. https://doi.org/10.1037/h0069608

Wickens, D. D., Schroder, H. M., & Snide, J. D. (1954). Primary stimulus generalization of the GSR under two conditions. *Journal of Experimental Psychology*, *47*(1), 52-56. https://doi.org/10.1037/h0053617

Wingenfeld, K., Spitzer, C., Mensebach, C., Grabe, H. J., Hill, A., Gast, U., Schlosser, N., Hopp, H., Beblo, T., & Driessen, M. (2010). [The German version of the Childhood Trauma Questionnaire (CTQ): preliminary psychometric properties] [The German Version of the Childhood Trauma Questionnaire (CTQ):Preliminary Psychometric Properties]. *Psychother Psychosom Med Psychol*, *60*(11), 442-450. https://doi.org/10.1055/s-0030-1247564 (Die deutsche Version des Childhood Trauma Questionnaire (CTQ): Erste Befunde zu den psychometrischen Kennwerten.)

You, Y., Novak, L. R., Clancy, K. J., & Li, W. (2022). Pattern differentiation and tuning shift in human sensory cortex underlie long-term threat memory. *Current Biology*, *32*(9), 2067-2075.e2064. https://doi.org/https://doi.org/10.1016/j.cub.2022.02.076

Zaman, J., Ceulemans, E., Hermans, D., & Beckers, T. (2019). Direct and indirect effects of perception on generalization gradients. *Behaviour Research and Therapy*, *114*, 44-50. https://doi.org/https://doi.org/10.1016/j.brat.2019.01.006

Zaman, J., Struyf, D., Ceulemans, E., Beckers, T., & Vervliet, B. (2019). Probing the role of perception in fear generalization. *Scientific Reports*, *9*(1), 10026. https://doi.org/10.1038/s41598-019-46176-x

Zaman, J., Struyf, D., Ceulemans, E., Vervliet, B., & Beckers, T. (2021). Perceptual errors are related to shifts in generalization of conditioned responding. *Psychological Research*, *85*(4), 1801-1813. https://doi.org/10.1007/s00426-020-01345-w

Zaman, J., Weltens, N., Ly, H. G., Struyf, D., Vlaeyen, J. W. S., Van den Bergh, O., Wiech, K., Van Oudenhove, L., & Van Diest, I. (2016). Influence of Interoceptive Fear Learning on Visceral Perception. *Psychosomatic Medicine*, *78*(2).

https://journals.lww.com/psychosomaticmedicine/Fulltext/2016/02000/Influence_of_Interoceptive_Fear_Learning_on.14.aspx

Zaman, J., Yu, K., & Lee, J. C. (2023). Individual differences in stimulus identification, rule induction, and generalization of learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *49*(6), 1004-1017. https://doi.org/10.1037/xlm0001153

Zaman, J., Yu, K., & Verheyen, S. (2023). The idiosyncratic nature of how individuals perceive, represent, and remember their surroundings and its impact on learning-based generalization. *Journal of Experimental Psychology: General*, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/xge0001403

Zech, H., Waltmann, M., Lee, Y., Reichert, M., Bedder, R. L., Rutledge, R. B., Deeken, F., Wenzel, J., Wedemeyer, F., Aguilera, A., Aslan, A., Bach, P., Bahr, N. S., Ebrahimi, C., Fischbach, P. C., Ganz, M., Garbusow, M., Großkopf, C. M., Heigert, M., . . . the, R.-C. (2022). Measuring self-regulation in everyday life: Reliability and validity of smartphone-based experiments in alcohol use disorder. *Behav Res Methods*. https://doi.org/10.3758/s13428-022-02019-8

Zeidan, M. A., Lebron-Milad, K., Thompson-Hollands, J., Im, J. J. Y., Dougherty, D. D., Holt, D. J., Orr, S. P., & Milad, M. R. (2012). Test–Retest Reliability during Fear Acquisition and Fear Extinction in Humans [https://doi.org/10.1111/j.1755-5949.2011.00238.x]. *CNS Neuroscience & Therapeutics*, *18*(4), 313-317. https://doi.org/https://doi.org/10.1111/j.1755-5949.2011.00238.x

Zenses, A.-K., Lee, J. C., Plaisance, V., & Zaman, J. (2021). Differences in perceptual memory determine generalization patterns. *Behaviour Research and Therapy*, *136*, 103777. https://doi.org/https://doi.org/10.1016/j.brat.2020.103777

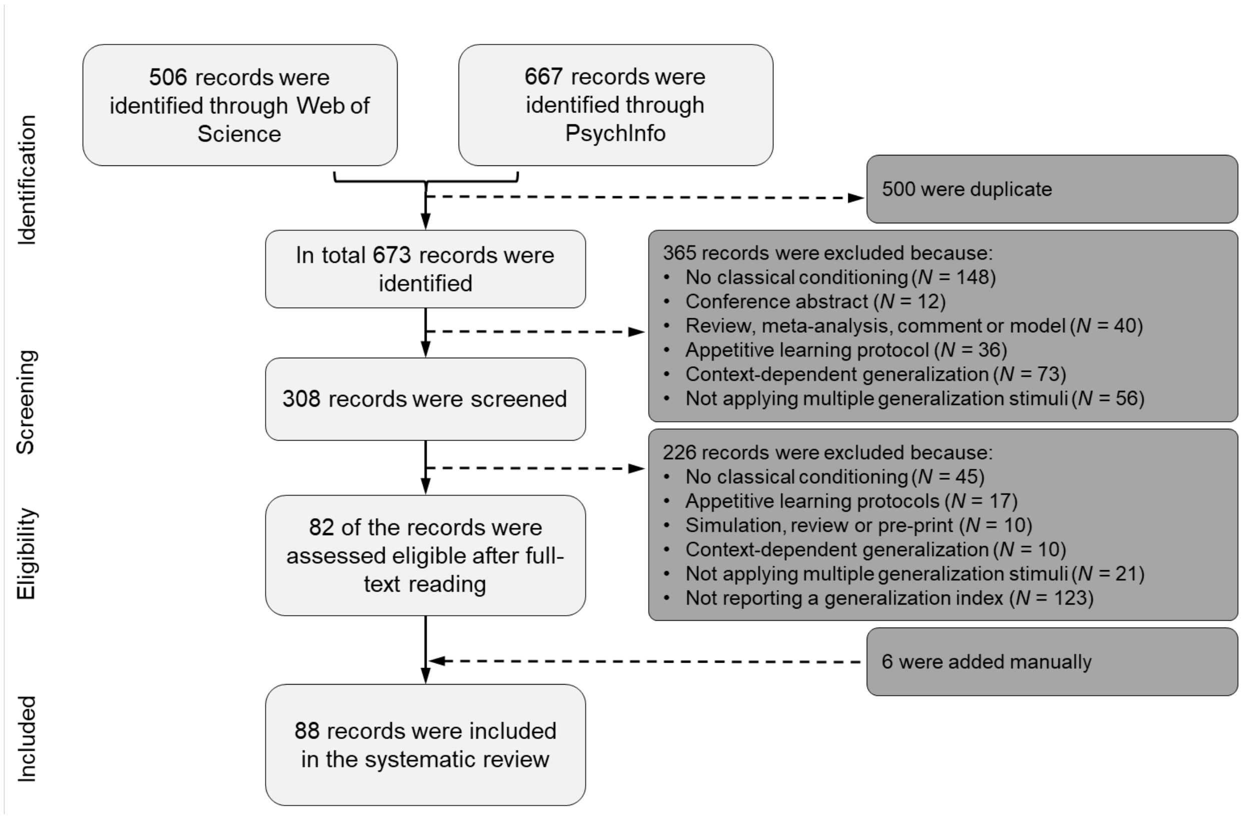
Zhu, X., Suarez-Jimenez, B., Lazarov, A., Such, S., Marohasy, C., Small, S. S., Wager, T. D., Lindquist, M. A., Lissek, S., & Neria, Y. (2022). Sequential fear generalization and network connectivity in trauma exposed humans with and without psychopathology. *Communications Biology*, *5*(1), 1275. https://doi.org/10.1038/s42003-022-04228-5

Zoladz, P., Reneau, K., Weiser, J., Cordes, C., Virden, E., Helwig, S., Thebeault, C., Pfister, C., Getnet, B., Boaz, K., Niese, T., Stanek, M., Long, K., Parker, S., Rorabaugh, B., & Norrholm, S. (2022). Childhood Maltreatment in Females Is Associated with Enhanced Fear Acquisition and an Overgeneralization of Fear. *Brain Sciences*, *12*(11).

Zorowitz, S., & Niv, Y. (2023). Improving the Reliability of Cognitive Task Measures: A Narrative Review. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *8*(8), 789-797. https://doi.org/https://doi.org/10.1016/j.bpsc.2023.02.004

## Supplemental Material

**Supplemental Figure 1.** *PRISMA Flowchart of Study Selection and Inclusion*



**Supplemental Table 1.** *Overview of the Studies for the Different Experimental Settings*

| *Reference* | *Sample type* | *Learning* | *n. GSs* | *Type of US* | *Type of CS/GS* | *US-contingency* |
|---|---|---|---|---|---|---|
| ***Studies including an arithmetic index to quantify fear generalization: LDS*** | | | | | | |
| Imholze et al. (2023) | Humans (*N* = 441) | Differential cue | 4 | Desperate female scream | Faces | Acq.: 83%<br>Test: 50% |
| Kackurkin et al. (2017) | Humans (*N* = 71) | Differential cue | 3 | Electric stimulation | Geometrical shapes | Acq: 80%<br>Test: 50% |
| Lange et al. (2019) | Youth (*N* = 113) | Differential cue | 5 | Electric stimulation | Geometrical shapes | Acq.: 50%<br>Test: n.a. |
| Lange et al. (2017) | Humans (*N* = 46) | Differential cue | 5 | Electric stimulation | Geometrical shapes | Acq.: 66%<br>Test: 50% |
| Lissek et al. (2017) | Humans (*N* = 48) | Differential cue | 8 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 50% |
| Reuter & Gamer (2023) | Humans (*N* = 44) | Differential cue | 4 | Electric stimulation | Faces | Acq.: 75%<br>Test: 50% |
| Stegmann et al. (2019) | Humans (*N* = 1175) | Differential cue | 4 | Desperate female scream | Faces | Acq.: 83.3%<br>Test: 50% |
| Zhu et al. (2022) | Humans (*N* = 114) | Differential cue | 3 | Electric stimulation | Geometrical shapes | Acq.: 80%<br>Test: 33% |
| ***Studies including an arithmetic index to quantify fear generalization: GI*** | | | | | | |
| Herzog et al. (2021) | Humans (*N* = 80) | Differential cue | 4 | Desperate female scream | Faces | Acq.: 83%<br>Test: 50% |
| Lenaert et al. (2016) | Humans (*N* = 25) | Differential cue | 6 | Symbol of electricity | Faces | Acq: 75%<br>Test: 50% |
| Mertens et al. (2021) | Humans (*N* = 120) | Differential cue | 3 | Electric stimulation | Words | Acq.: 75%<br>Test: 50% |
| Reinhard et al. (2022) | Children (*N* = 188) | Differential cue | 4 | Desperate female scream | Faces | Acq: 82%<br>Test: 50% |

| | | | | | | |
|---|---|---|---|---|---|---|
| ***Studies modelling a generalization gradient: Gaussian (tuning) models*** | | | | | | |
| Dou et al. (2023) | Humans (*N* = 58) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 10% |
| Grosso et al. (2018) | Rats (*N* = n.a.) | Single cue | 3 | Electric stimulation | Sounds | Acq.: 100%<br>Test: n.a. |
| Kampermann et al. (2019) | Humans (*N* = 74) | Differential cue | 6 | Electric stimulation | Faces | Acq: 30%<br>Test: n.a. |
| Kausche et al. (2021) | Humans (*N* = 64) | Differential cue | 6 | Electric stimulation | Faces | Acq.: 30%<br>Test: 30% |
| Kausche et al. (2021b) | Humans (*N* = 109) | Differential cue | 6 | Electric stimulation | Faces | Acq.: 23%<br>Test: 23% |
| Kausche et al. (2021a) | Humans (*N* = 136) | Differential cue | 6 | Electric stimulation | Faces | Acq.: 23%<br>Test: 23% |
| Onat & Büchel (2015) | Humans (*N* = 29) | Differential cue | 6 | Electric stimulation | Faces | Acq.: 30%<br>Test: 30% |
| Porter et al. (2021) | Humans (*N* = 30) | Differential cue | 11 | Electric stimulation | Odors | Acq: 75%<br>Test: 0% |
| Resnik & Paz (2015) | Monkey (*N* = 2) | Single cue | 7 | Odor | Sounds | Acq.: n.a.<br>Test: n.a. |
| Tuominen et al. (2019) | Humans (*N* = 38) | Differential cue | 5 | Electric stimulation | Faces | Acq.: 62.5%<br>Test: 100% |
| Wang et al. (2022) | Humans (*N* = 62) | Differential cue | 8 | Aversive pictures | Geometrical shapes | Acq: 75%<br>Test: 50% |
| Zaman et al. (2023) | Humans (*N* = n.a.) | Differential cue | 9 | Electric stimulation | Colors | Acq.: 75%<br>Test: n.a. |
| Zaman et al. (2019) | Humans (*N* = 133) | Single cue | 7 | Aversive pictures | Geometrical shapes | Acq.: 80%<br>Test: n.a. |
| Zaman et al. (2019) | Humans (*N* = 43) | Single cue | 7 | Electric stimulation | Geometrical shapes | Acq.: 50%<br>Test: n.a. |
| Zenses et al. (2021) | Humans (*N* = 40) | Single cue | 7 | Electric stimulation | Geometrical shapes | Acq.: 80%<br>Test: 80% |

***Studies modelling a generalization gradient: Quadratic-linear models***

| | | | | | | |
|---|---|---|---|---|---|---|
| Cha et al. (2016) | Humans (*N* = 51) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq: 100%<br>Test: 50% |
| Cha et al. (2014) | Humans (*N* = 54) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq.: 100%<br>Test: 50% |
| Cha et al. (2014) | Humans (*N* = 54) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq.: 100%<br>Test: 50% |
| Dunning et al. (2015) | Humans (*N* = 115) | Single cue | 6 | Electric stimulation | Geometrical shapes | Acq.: n.a.<br>Test: 80% |
| El-Bar et al. (2017) | Youth (*N* = 40) | Differential cue | 12 | Loss of points | Sounds | Acq: 100%<br>Test: 0% |
| Hammell et al. (2020) | Humans (*N* = 52) | Differential cue | 3 | Electric stimulation | Geometrical shapes | Acq: 80%<br>Test: 33% |
| Laufer et al. (2016) | Humans (*N* = 44) | Differential cue | 12 | Loss of money | Sounds | Acq: 100%<br>Test: 0% |
| Wickens et al. (1954) | Humans (*N* = 144) | Single cue | 2 | Electric stimulation | Sounds | Acq: 100%<br>Test: 0% |
| Zaman et al. (2023) | Humans (*N* = 105) | Differential cue | 12 | Symbol of electricity | Color | Acq: 75%<br>Test: 75% |
| Zaman et al. (2021) | Humans (*N* = 200) | Differential cue | 10 | Aversive pictures | Geometrical shapes | Acq: 87.5%<br>Test: n.a. |

***Studies examining the amount of generalization on the group level: ANOVA-based linear and quadratic trends***

| | | | | | | |
|---|---|---|---|---|---|---|
| Ahmed et al. (2015) | Humans (*N* = 59) | Differential cue | 2 | Electric stimulation | Geometrical shapes | Acq: 100%<br>Test: n.a. |
| Dunsmoor et al. (2017) | Humans (*N* = 42) | Differential cue | 6 | Electric stimulation | Sounds | Acq: 40%<br>Test: 42% |
| Glenn et al. (2021) | S1: Youth (*N* = 16)<br>S2: Youth (*N* = 20) | Differential cue | 4 | Desperate female scream | Faces and bells | Acq.: 80%<br>Test: 80% |
| Glenn et al. (2012) | Children (*N* = 40) | Differential cue | 1 | Desperate female scream | Faces | Acq: 75%<br>Test: 75% |

| | | | | | | |
|---|---|---|---|---|---|---|
| Greenberg et al. (2010) | S1: Humans (*N* = 32)<br>S2: Humans (*N* = 25) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq: instructed<br>Test: 50% |
| Klein et al. (2023) | Humans (*N* = 61) | Differential cue | 5 | Alarm sounds | Colored cartoons | Acq: 80%<br>Test: n.a. |
| Klein et al. (2020) | Youth (*N* = 74) | Differential cue | 9 | Alarm sound | Colored cartoons | Acq: 100%<br>Test: 0% |
| Lange et al. (2019) | Humans (*N* = 94) | Single cue | 5 | Electric stimulation | Geometrical shapes | Acq: 66%<br>Test: 50% |
| Lee et al. (2018) | Humans (*N* = 71) | Single vs. Differential cue | 10 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 75% |
| Lissek et al. (2010) | Humans (*N* = 38) | Differential cue | 8 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 50% |
| Lissek et al. (2008) | Humans (*N* = 20) | Differential cue | 8 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 50% |
| Manbeck et al. (2022) | Humans (*N* = 71) | Differential cue | 3 | Electric stimulation | Geometrical shapes | Acq: 50%<br>Test: 75% |
| Michalska et al. (2016) | Children (*N* = 48) | Differential cue | 9 | Sound | Colored cartoons | Acq: 80%<br>Test: 0% |
| Niederstrasser et al. (2017) | Humans (*N* = 48) | Differential cue | 5 | Electric stimulation | Movements of the harm | Acq: 75%<br>Test: 50% |
| Philips et al. (1958) | Humans (*N* = 21) | Single cue | 4 | Sound | Colored words | Acq: 100%<br>Test: 0% |
| Roesmann et al. (2022) | Humans (*N* = 90) | Differential cue | 7 | Phobic pictures | Gabors | Acq: 33%<br>Test: 33% |
| Struyf et al. (2018) | Humans (*N* = 84) | Differential cue | 2 | Electric stimulation | Faces | Acq: 75%<br>Test: 0% |
| Vandael et al. (2023) | Humans (*N* = 50) | Differential cue | 5 | Electric stimulation | Colored lights | Acq: 100%<br>Test: n.a. |
| Vandael et al. (2020) | Humans (*N* = 50) | Differential cue | 5 | Electric stimulation | Movement trajectory | Acq: 75%<br>Test: 50% |
| Van Meurs et al. (2014) | Humans (*N* = 50) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq: 50% |

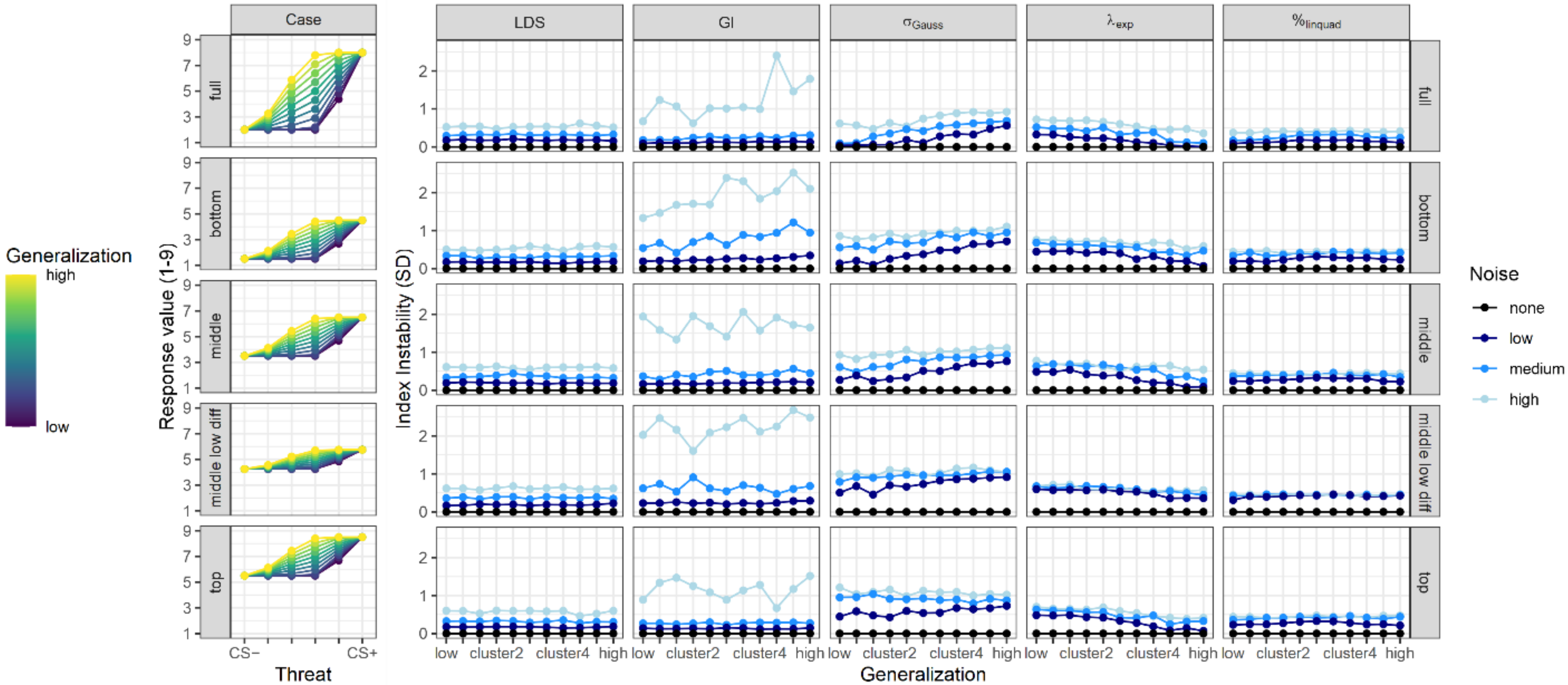
| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | Test: 50% |
| Vervliet et al. (2006) | S1: Humans (*N* = 58)<br>S2: Humans (*N* = 46) | Differential cue | 6 | Aversive pictures | Geometrical shapes | Acq: 100%<br>Test: 0% |
| Zoladz et al. (2022) | Humans (*N* = 291) | Differential cue | 7 | Air-blast | Geometrical shapes | Acq: 100%<br>Test: 0% |
| ***Studies examining the amount of generalization on the group level: Quadratic and (difference of) Gaussian contrast comparisons*** | | | | | | |
| Antov et al. (2020) | Humans (*N* = 19) | Differential cue | 6 | White noise | Gabor | Acq.: 100%<br>Test: 0% |
| Friedl et al. (2021) | Humans (*N* = 51) | Differential cue | 4 | Noxious noise | Gabors | Acq: 100%<br>Test: n.a. |
| McTeague et al. (2015) | Humans (*N* = 15) | Differential cue | 6 | White noise | Gabor | Acq.: 100%<br>Test: 0% |
| Plog et al. (2022) | Humans (*N* = 40) | Differential cue | 4 | Sound | Gabors | Acq: 66%<br>Test: n.a. |
| Stegmann et al. (2020) | Humans (*N* = 67) | Differential cue | 4 | Desperate female scream | Faces | Acq.: 80%<br>Test: 40% |
| ***Studies examining the amount of generalization on the group level: Hierarchical models including quadratic terms*** | | | | | | |
| Ginat-Frohlich et al. (2019) | Children (*N* = 46) | Differential cue | 11 | White noise | Colored cartoons | Acq.: 80%<br>Test: n.a. |
| Ginat-Frohlich et al. (2017) | Children (*N* = 70) | Differential cue | 9 | White noise | Colored cartoons | Acq.: 80%<br>Test: 0.1% |
| Keefe et al. (2022) | Humans (*N* = 108) | Differential cue | 3 | Electric stimulation | Geometrical shapes | Acq: 100%<br>Test: n.a. |
| Lommen et al. (2017) | Humans (*N* = 78) | Differential cue | 6 | Electric stimulation | Geometrical shapes | Acq: 100%<br>Test: 100% |
| Meulders et al. (2017) | Humans (*N* = 60) | Differential cue | 5 | Electric stimulation | Movement of the harm | Acq.: 75%<br>Test: 75% |
| ***Studies examining the amount of generalization on the group level: Various types of regression models*** | | | | | | |
| Dos Santos et al. (2019) | Rats (*N* = 232) | Single context | 1 | Electric stimulation | Cage | Acq.: 100% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | Test: n..a. |
| Fan et al. (2022) | Humans (*N* = 88) | Differential cue | 4 | Electric stimulation | Animal pictures | Acq: 100%<br>Test: 0% |
| Michalska et al. (2016) | Children (*N* = 48) | Differential cue | 9 | White noise | Colored cartoons | Acq: 80%<br>Test: 0% |
| Nelson et al. (2015) | Humans (*N* = 48) | Single cue | 3 | Electric stimulation | Geometrical shapes | Acq.: 100%<br>Test: 100% |
| Schroijen et al. (2015) | Humans (*N* = 43) | Differential cue | 4 | Breathing occlusion | Breathing pressure | Acq: 88%<br>Test: 100% |
| Struyf et al. (2017) | Humans (*N* = 168) | Differential cue | 8 | Aversive pictures | Geometrical shapes | Acq: 100%<br>Test: n.a. |
| Zaman et al. (2016) | Human (*N* = 60) | Single cue | 3 | Electric stimulation | Interoceptive sensation | Acq.: 75%<br>Test: n.a. |
| ***Studies reporting an index to quantify fear generalization, but without considering the generalization stimuli*** | | | | | | |
| Kass et al. (2017) | Mice (*N* = 66) | Single cue | 4 | Electric stimulation | Odors | Acq.: 100%<br>Test: 0% |
| Kopp et al. (2005) | Humans (*N* = 48) | Differential cue | 9 | Electric stimulation | Phobic animals | Acq.: 80%<br>Test: 0% |
| Liu et al. (1971) | Rabbits (*N* = 40) | Both differential and single cue | 4 | Electric stimulation | Sounds | Acq: 50%-100%<br>Test: n.a. |
| Miasknikov et al. (2009) | Children (*N* = 59) | Differential cue | 9 | Sound | Colored cartoons | Acq: 80%<br>Test: n.a. |
| Scarlata et al. (2019) | S1: Mice (*N* = 27)<br>S2: Mice (*N* = 12) | Single cue | 1 | Electric stimulation | Sounds | Acq: 100%<br>Test: 0% |
| Torrents-Rodas et al. (2014) | Humans (*N* = 71) | Differential cue | 8 | Electric stimulation | Geometrical shapes | Acq: 75%<br>Test: 50% |
| You et al. (2022) | Humans (*N* = 29) | Differential cue | 30 | Picture + audio of vomiting | Odors | Acq: 100%<br>Test: 71.4% |

***Studies reporting a discrimination index before learning: just noticeable difference (JND)***

| | | | | | | |
|---|---|---|---|---|---|---|
| Dou et al. (2021) | Humans (*N* = 63) | Differential cue | 4 | Electric stimulation | Faces | Acq.: 75%<br>Test: 50% |
| El-Bar et al. (2017) | Youth (*N* = 40) | Differential cue | 12 | Loss of points | Sounds | Acq: 100%<br>Test: 0% |
| Holt et al. (2014) | Humans (*N* = 47) | Differential cue | 5 | Electric stimulation | Faces | Acq.: 63%<br>Test: 100% |
| Levine et al. (2021) | Humans (*N* = 21) | Differential cue | 30 | Electric stimulation | Animals, Tools, Fruits/Vegetables | Acq.: 50%<br>Test: n.a. |
| Shalev et al. (2018) | Humans (*N* = 315) | Differential cue | 1 | Aversive pictures | Gabor patchs + sounds | Acq: 100%<br>Test: n.a. |
| Tuominen et al. (2021) | Humans (*N* = 37) | Differential cue | 5 | Electric stimulation | Faces | Acq.: 62.5%<br>Test: 100% |

**Supplemental Figure 2.** *Unsystematic Variance between Pairs of Gradients drawn from the Same True Scores for Various Generalization Indices Separated by Model Case and Noise Level*




*Note.* LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term. Please note, that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Supplemental Table 2.** *Normalized Range Covered by Each Generalization Index per Model Case*

| Case | LDS | GI | $\sigma_{Gauss}$ | $\lambda_{exp}$ | $\%_{linquad}$ |
|---|---|---|---|---|---|
| full | 1 | 0.76 | 1 | 1 | 1 |
| bottom | 0.50 | 0.67 | 1 | 0.99 | 1 |
| middle | 0.50 | 0.47 | 0.99 | 0.99 | 1 |
| middle low diff | 0.25 | 0.26 | 1 | 0.98 | 1 |
| top | 0.50 | 0.36 | 1 | 0.99 | 1 |

*Note*. LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term.

## Empirical analysis: Reliability and validity of fear generalization indices

### Methods

*Samples*

The first sample consisted of 1,175 healthy participants, who completed a differential fear acquisition phase followed by a generalization test (Stegmann et al., 2019). Exclusion criteria included left-handedness, non-Caucasian descent, intake of psychoactive medication, excessive consumption of alcohol, nicotine, and caffeine, consumption of illegal drugs, severe medical diseases, current and/or lifetime diagnosis of mental disorders, or being pregnant. The second sample (n = 256) was recruited using similar criteria and underwent the same fear generalization paradigm, except that a discrimination training took place between the first and second block of the generalization phase (Herzog et al., 2021). For that reason, only the data of the first block from the second sample was used for the analyses. Descriptive statistics of both samples are reported in Suppl. Table 3.

All participants were screened for dimensional anxiety using the German trait version of the State-Trait Anxiety Inventory (Laux & Spielberger, 1981), the Anxiety Sensitivity Index 3 (Kemper et al., 2009; Taylor et al., 2007), the Agoraphobic Cognitions Questionnaire (Chambless et al., 1984; Ehlers et al., 2001), the Liebowitz Social Anxiety Scale (Liebowitz, 1987; Stangier & Heidenreich, 2004), and the Social Phobia and Anxiety Inventory (Beidel et al., 1989). The Childhood Trauma (Bernstein et al., 2003; Wingenfeld et al., 2010) was used for a retrospective assessment of childhood maltreatment. We calculated sum scores for all measures of trait anxiousness. All volunteers gave written informed consent and were paid 50 Euros. All procedures complied with the Declaration of Helsinki (Version 2008) and the studies were approved by the ethics committees of the involved Universities.

**Supplemental Table 3.** *Summary of the Sample Characteristics*

| | Sample 1 (n = 1,175) | | | | Sample 2 (n = 256) | | | |
|---|---|---|---|---|---|---|---|---|
| | *M* | *SD* | *Min* | *Max* | *M* | *SD* | *Min* | *Max* |
| Age (years) | 25.7 | 5.9 | 18.0 | 50.0 | 24.0 | 5.2 | 18.0 | 50.0 |
| STAI-T | 34.6 | 8.2 | 20.0 | 67.0 | 35.7 | 8.6 | 20.0 | 59.0 |
| ASI-3 | 12.1 | 8.3 | 0.0 | 48.0 | 15.1 | 9.5 | 0.0 | 48.0 |
| ACQ | 1.3 | 0.2 | 1.0 | 2.7 | 1.4 | 0.3 | 1.0 | 2.4 |
| PSWQ | 40.4 | 9.8 | 17.0 | 73.0 | 42.2 | 10.7 | 21.0 | 75.0 |
| SPAI | 33.2 | 17.0 | 0.0 | 103.7 | 36.1 | 18.0 | 2.7 | 118.0 |
| LSAS | 21.4 | 15.3 | 0.0 | 90.0 | 25.5 | 16.4 | 0.0 | 98.0 |
| CTQ | 32.1 | 8.1 | 25.0 | 97.0 | 32.9 | 10.1 | 25.0 | 87.0 |

*Note. M* = mean, *SD* = standard deviation, *Min* = Minimum, *Max* = Maximum, STAI-T = State-Trait Anxiety Inventory – Trait, ASI-3 = Anxiety Sensitivity Index 3, ACQ = Agoraphobic Cognition Questionnaire, SPAI = Social Phobia Anxiety Index, LSAS = Liebowitz Social Anxiety Scale, CTQ = Childhood Trauma Questionnaire.

*Fear acquisition and generalization tasks*

Participants completed a differential fear conditioning and generalization paradigm adapted from Lau et al. (2008), in which two female faces with neutral expression served as CS. The paradigm consisted of three phases: During pre-acquisition each of the two faces was singularly presented four times each for a duration of 6 s each (8 trials). In the acquisition phase, both faces were presented 12 times each (24 trials). Ten presentations of one face (CS+) were followed by the US, consisting of a fearful facial expression of the same person with a simultaneous presentation of a 95 dB loud female scream for a duration of 1.5 s. Participants were not instructed about the CS-US contingencies and the assignment of faces to CS+ and CS− was counter-balanced across participants. During the generalization test, four generalization stimuli (GS) were presented in addition to the CSs. Generalization stimuli were morphs of the original CS faces in 20% steps. Each stimulus was presented 12 times (72 trials). Half of CS+ presentations were paired with the US to prevent extinction. After the first half and at the end of the acquisition as well as of the generalization phase, participants were asked to rate the faces regarding valence, arousal (both 9-point Likert-scales; from 1 = very unpleasant/ very calm to 9 = very pleasant/ very arousing) and US-contingency (11-point Likert-scale; from 0 to 100% in 10% increments). Please note that valence ratings were inverted for subsequent analyses to increase comparability. Skin conductance was continuously recorded throughout the whole experimental paradigm.

*Physiological data processing*

Skin conductance was measured at the thenar and hypothenar eminences of the participant's left hand with Ag/AgCl electrodes, using a constant-voltage system (0.5 V). Signals were amplified and recorded using a V-Amp-16 and Vision Recorder software (Brainproducts, Gilching, Germany) at a sampling rate of 1,000 Hz. Offline data processing within the Vision Analyzer 2 software included filtering with a high cutoff filter of 1 Hz and a notch filter of 50 Hz. Skin conductance responses to CS+, CS- and the GS were analyzed by quantifying SCR amplitudes as the base-to-peak difference in µS between response onset (900–4,000 ms after stimulus onset) and peak (2,000–6,000 ms after stimulus onset; Boucsein et al., 2012). A minimum response criterion of 0.02 µS was applied, with lower responses scored as 0. To compensate for the skewed distribution of SCR amplitudes, we employed a square-root transformation.

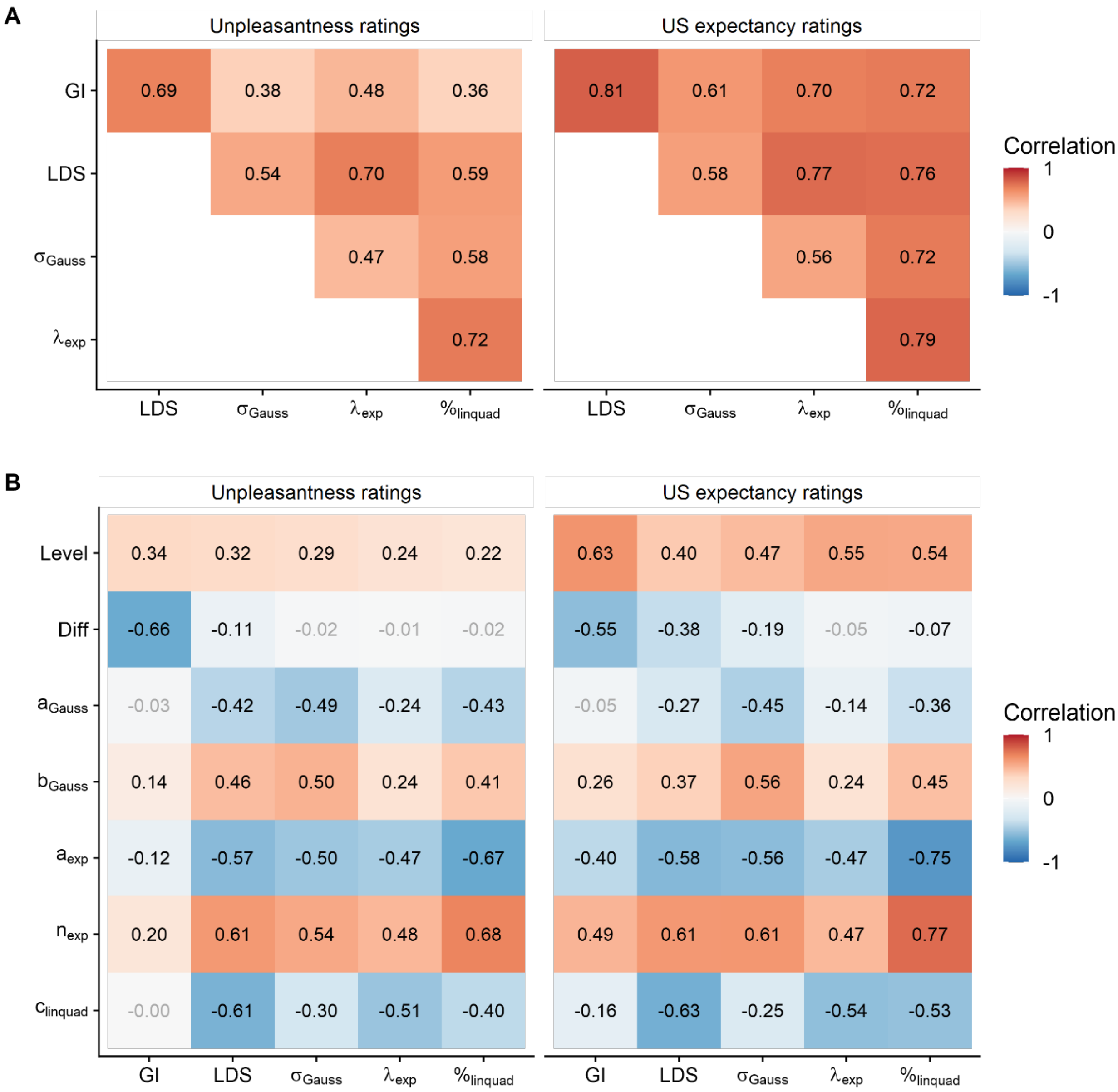
**Supplemental Table 4.** *Summary of Generalization Indices and Model Parameters of Study 1 (n = 1175) and Study 2 (n = 256)*

| Study 1 | Arousal ratings | | | | | Skin conductance responses | | | | | Unpleasantness ratings | | | | | US expectancy ratings | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs |
| Level | 3.78 | 1.27 | 1.00 | 7.83 | 0 | 0.10 | 0.09 | 0.00 | 0.67 | 0 | 4.49 | 1.05 | 1.17 | 8.08 | 0 | 3.94 | 1.51 | 1.00 | 9.58 | 0 |
| Diff | 3.27 | 2.30 | -5.00 | 8.00 | 0 | 0.05 | 0.11 | -0.30 | 1.05 | 0 | 2.76 | 2.41 | -5.00 | 8.00 | 0 | 6.00 | 2.60 | -5.00 | 10.00 | 0 |
| LDS | 0.70 | 1.09 | -4.25 | 5.62 | 0 | 0.01 | 0.05 | -0.17 | 0.32 | 0 | 0.75 | 1.07 | -3.12 | 5.00 | 0 | 1.77 | 1.38 | -2.75 | 7.25 | 0 |
| GI | 2.57 | 1.15 | 0.56 | 15.00 | 0 | 4.60 | 5.55 | 0.00 | 92.00 | 126 | 2.81 | 1.03 | 0.44 | 11.20 | 0 | 1.71 | 0.87 | 0.36 | 7.00 | 0 |
| Gaussian model fit: | | | | | | | | | | | | | | | | | | | | |
| $\sigma$ | 2.22 | 2.81 | 0.20 | 14.30 | 0 | 4.71 | 2.58 | 0.20 | 14.40 | 0 | 2.18 | 2.85 | 0.20 | 13.60 | 0 | 1.32 | 1.61 | 0.19 | 13.20 | 0 |
| $b$ | 54.80 | 170.00 | -1000 | 1000 | 0 | -0.21 | 3.81 | -43.5 | 20.30 | 0 | 45.1 | 153.00 | -1000 | 1000 | 0 | 30.10 | 106.00 | -1000 | 1000 | 0 |
| $\alpha$ | 0.69 | 6.41 | -35.20 | 32.40 | 0 | 0.09 | 0.19 | -0.71 | 1.77 | 0 | 1.87 | 6.07 | -35.00 | 32.90 | 0 | 1.41 | 4.36 | -40.30 | 37.50 | 0 |
| $R^2$ | 0.83 | 0.18 | 0.00 | 1.00 | 18 | 0.27 | 0.27 | 0.00 | 1.00 | 42 | 0.75 | 0.29 | 0.00 | 1.00 | 30 | 0.92 | 0.14 | 0.00 | 1.00 | 13 |
| Exponential model fit: | | | | | | | | | | | | | | | | | | | | |
| $\lambda$ | 0.56 | 0.57 | 0.00 | 2.00 | 0 | 0.11 | 0.23 | 0.00 | 1.14 | 0 | 0.58 | 0.59 | 0.00 | 1.94 | 0 | 0.82 | 0.62 | 0 | 2 | 0 |
| b | 6.51 | 11.80 | 0.00 | 62.40 | 0 | 1.45 | 1.41 | 0.00 | 3.36 | 0 | 5.42 | 10.30 | 0.00 | 55.60 | 0 | 3.80 | 9.62 | 0 | 67.50 | 0 |
| a | -4.36 | 12.20 | -59.20 | 6.85 | 0 | -1.37 | 1.43 | -3.21 | 0.41 | 0 | -2.31 | 10.80 | -55.10 | 7.34 | 0 | -2.24 | 9.84 | -65.80 | 9.58 | 0 |
| $R^2$ | 0.80 | 0.22 | 0.00 | 1.00 | 101 | 0.35 | 0.30 | 0.00 | 0.99 | 357 | 0.77 | 0.24 | 0.00 | 1.00 | 144 | 0.90 | 0.14 | 0.01 | 1.00 | 25 |
| Quadratic polynomial model fit: | | | | | | | | | | | | | | | | | | | | |
| c | 0.15 | 0.22 | -0.76 | 1.10 | 0 | 0.00 | 0.01 | -0.03 | 0.06 | 0 | 0.16 | 0.21 | -0.62 | 0.99 | 0 | 0.36 | 0.26 | -0.54 | 1.43 | 0 |
| b | -0.40 | 1.56 | -7.72 | 5.87 | 0 | -0.01 | 0.06 | -0.38 | 0.24 | 0 | -0.56 | 1.55 | -6.97 | 5.26 | 0 | -1.41 | 1.81 | -10.00 | 5.64 | 0 |
| a | 2.90 | 2.35 | -3.95 | 14.80 | 0 | 0.09 | 0.12 | -0.20 | 0.79 | 0 | 4.06 | 2.51 | -3.45 | 14.40 | 0 | 3.34 | 2.44 | -3.60 | 18.60 | 0 |
| $\%_{linquad}$ | 0.47 | 0.06 | 0.40 | 0.60 | 18 | 0.51 | 0.07 | 0.40 | 0.60 | 20 | 0.47 | 0.06 | 0.40 | 0.60 | 29 | 0.45 | 0.05 | 0.40 | 0.60 | 13 |
| $R^2$ | 0.83 | 0.18 | 0.01 | 1.00 | 18 | 0.45 | 0.28 | 0.00 | 1.00 | 20 | 0.81 | 0.20 | 0.01 | 1.00 | 29 | 0.88 | 0.11 | 0.14 | 1.00 | 13 |

| Study 2 | Arousal ratings | | | | | Skin conductance responses | | | | | Unpleasantness ratings | | | | | US expectancy ratings | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs | Mean | S.D. | Min | Max | NAs |
| Level | 4.33 | 1.49 | 1.00 | 8.25 | 0 | 0.19 | 0.18 | 0.00 | 0.97 | 0 | 4.49 | 1.05 | 1.17 | 8.08 | 0 | 3.48 | 1.48 | 1.00 | 8.5 | 0 |
| Diff | 3.93 | 2.12 | -1.50 | 8.00 | 0 | 0.07 | 0.33 | -1.45 | 1.14 | 0 | 3.30 | 2.52 | -7.50 | 8.00 | 0 | 5.80 | 2.61 | -4.50 | 10.00 | 0 |
| LDS | 0.62 | 1.11 | -3.62 | 4.12 | 0 | 0.01 | 0.18 | -0.49 | 0.72 | 0 | 0.37 | 1.12 | -3.00 | 3.88 | 0 | 1.59 | 1.57 | -5 | 5 | 0 |
| GI | 2.51 | 0.90 | 0.56 | 5.17 | 0 | 4.94 | 6.49 | 0.00 | 51.6 | 85 | 3.10 | 2.21 | 0.50 | 28.00 | 0 | 1.80 | 1.56 | 0.36 | 12.60 | 0 |
| Gaussian model fit: | | | | | | | | | | | | | | | | | | | | |
| $\sigma$ | 2.38 | 2.58 | 0.20 | 10.80 | 0 | 4.43 | 3.21 | 0.20 | 12.30 | 0 | 3.22 | 3.37 | 0.20 | 12.00 | 0 | 1.19 | 1.29 | 0.20 | 10.40 | 0 |
| $b$ | 71.20 | 160.00 | -90.50 | 1000 | 0 | -5.01 | 46.00 | -390 | 105 | 0 | 98.60 | 207.0 | -372.0 | 1000 | 0 | 29.70 | 96.20 | -7.02 | 1000 | 0 |
| $a$ | 0.25 | 6.57 | -37.30 | 8.76 | 0 | 0.32 | 1.57 | -3.39 | 13.40 | 0 | -0.16 | 8.20 | -38.30 | 14.90 | 0 | 1.03 | 3.60 | -32.80 | 7.87 | 0 |
| $R^2$ | 0.88 | 0.18 | 0.06 | 1.00 | 7 | 0.26 | 0.27 | 0.00 | 1.00 | 16 | 0.78 | 0.27 | 0.00 | 1.00 | 5 | 0.92 | 0.15 | 0.00 | 1.00 | 1 |
| Exponential model fit: | | | | | | | | | | | | | | | | | | | | |
| $\lambda$ | 0.51 | 0.57 | 0.00 | 1.86 | 0 | 0.13 | 0.29 | 0.00 | 1.23 | 0 | 0.45 | 0.56 | 0.00 | 1.87 | 0 | 0.82 | 0.65 | 0.00 | 1.91 | 0 |
| b | 9.23 | 13.60 | 0.00 | 63.30 | 0 | 1.76 | 1.53 | 0.00 | 10.30 | 0 | 9.52 | 13.60 | 0.00 | 68.20 | 0 | 4.56 | 10.50 | 0.00 | 63.20 | 0 |
| a | -6.91 | 14.00 | -63.00 | 7.53 | 0 | -1.63 | 1.56 | -10.40 | 0.64 | 0 | -6.44 | 14.20 | -66.60 | 6.99 | 0 | -3.46 | 10.60 | -62.40 | 6.29 | 0 |
| $R^2$ | 0.85 | 0.19 | 0.09 | 1.00 | 10 | 0.28 | 0.27 | 0.00 | 0.95 | 96 | 0.78 | 0.25 | 0.00 | 1.00 | 21 | 0.88 | 0.17 | 0.05 | 1.00 | 4 |
| Quadratic polynomial model fit: | | | | | | | | | | | | | | | | | | | | |
| c | 0.13 | 0.22 | -0.74 | 0.78 | 0 | 0.00 | 0.03 | -0.14 | 0.13 | 0 | 0.07 | 0.22 | -0.61 | 0.75 | 0 | 0.34 | 0.29 | -1.03 | 0.89 | 0 |
| b | -0.12 | 1.59 | -5.54 | 6.29 | 0 | 0.01 | 0.25 | -1.10 | 0.94 | 0 | 0.14 | 1.57 | -5.72 | 5.64 | 0 | -1.26 | 1.92 | -5.59 | 7.56 | 0 |
| a | 2.80 | 2.43 | -4.85 | 13.80 | 0 | 0.15 | 0.42 | -0.84 | 2.17 | 0 | 3.23 | 2.45 | -4.10 | 14.40 | 0 | 2.71 | 2.19 | -5.55 | 11.20 | 0 |
| $\%_{linquad}$ | 0.48 | 0.06 | 0.40 | 0.60 | 6 | 0.50 | 0.07 | 0.40 | 0.60 | 16 | 0.49 | 0.06 | 0.40 | 0.60 | 5 | 0.45 | 0.05 | 0.40 | 0.60 | 1 |
| $R^2$ | 0.86 | 0.17 | 0.03 | 1.00 | 6 | 0.38 | 0.25 | 0.00 | 0.97 | 16 | 0.82 | 0.19 | 0.09 | 1.00 | 5 | 0.85 | 0.13 | 0.12 | 1.00 | 1 |

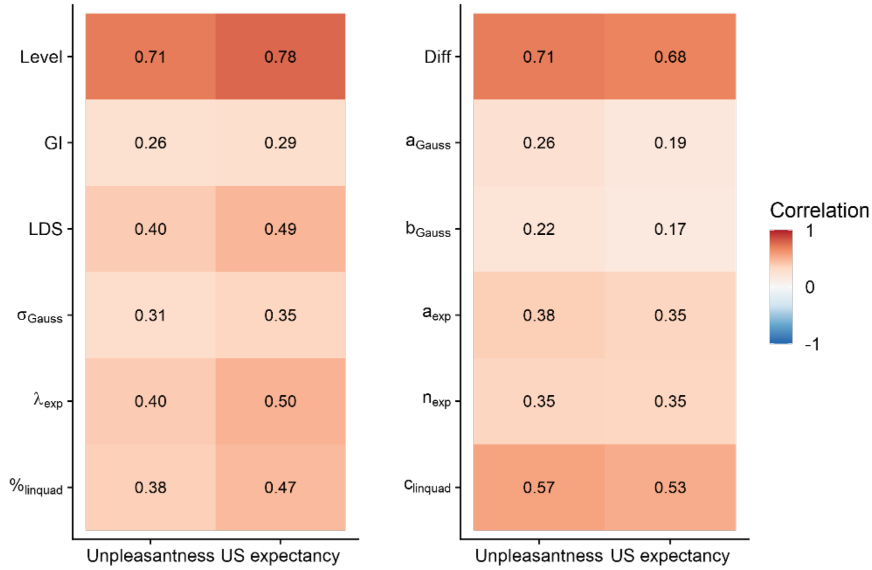
*Note*. S.D. = standard deviation, Min = minimum, Max = maximum, NAs = number of missing values, LDS = linear deviation score, GI = generalization index, $R^2$ = explained variance of the individual generalization gradients. Note that missing values in $R^2$ are due to either the observed or the estimated data being on a flat line resulting in zero variance, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term.

**Supplemental Figure 3.** *Correlations Between Different Indices of Fear Generalization (Panel A) and their Correlations with Basic Indices of Threat Responsiveness (Panel B) for Unpleasantness and US Expectancy Ratings.*



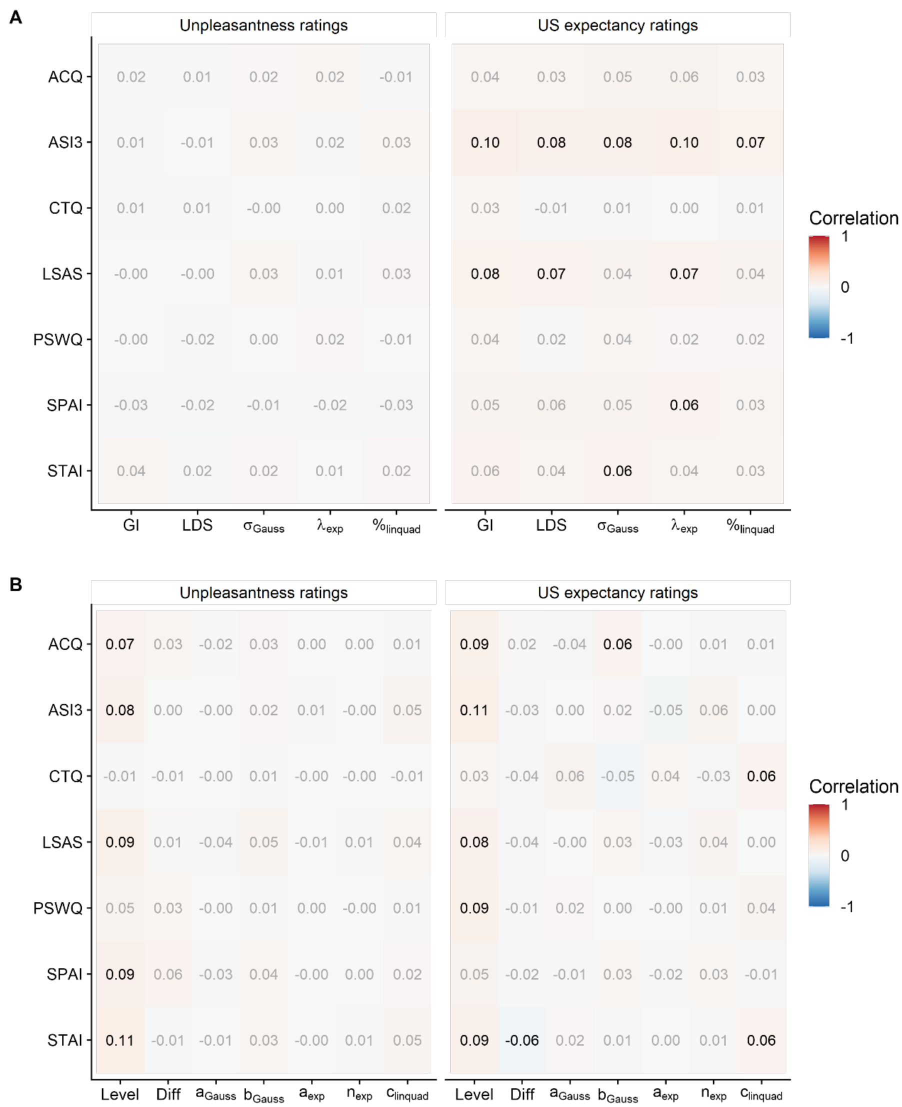

*Note.* LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS differentiation. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Supplemental Figure 4.** *Correlations Between Various Parameters of the First and Second Half of the Fear Generalization Phase for Unpleasantness and US Expectancy Ratings*



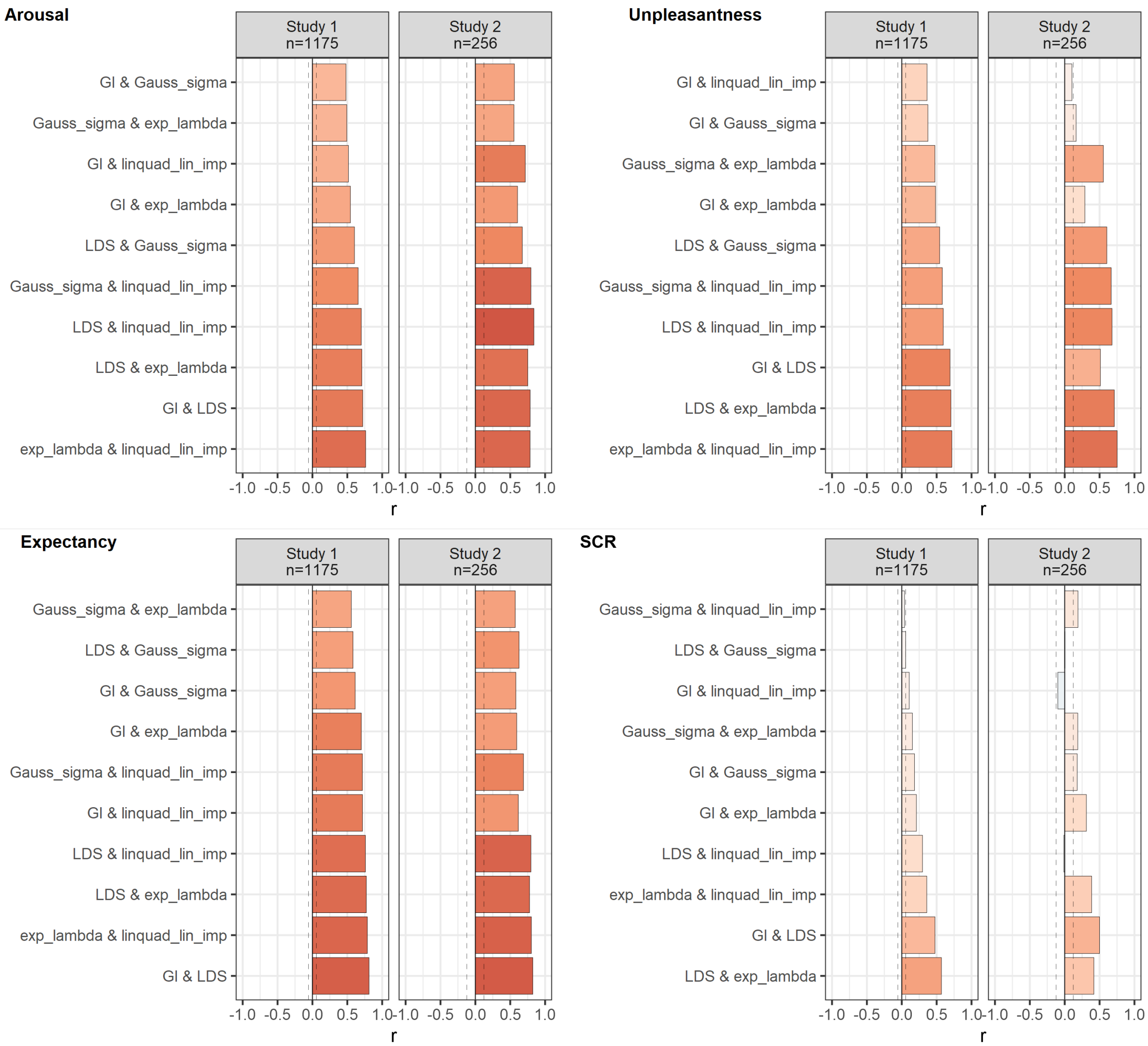

*Note.* LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS difference. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Supplemental Figure 5.** *Correlations Between Trait Measures of Anxiety Psychopathology and Indices of Fear Generalization (Panel A) as well as Basic Indices of Fear Responsiveness (Panel B) for Unpleasantness and US Expectancy Ratings*



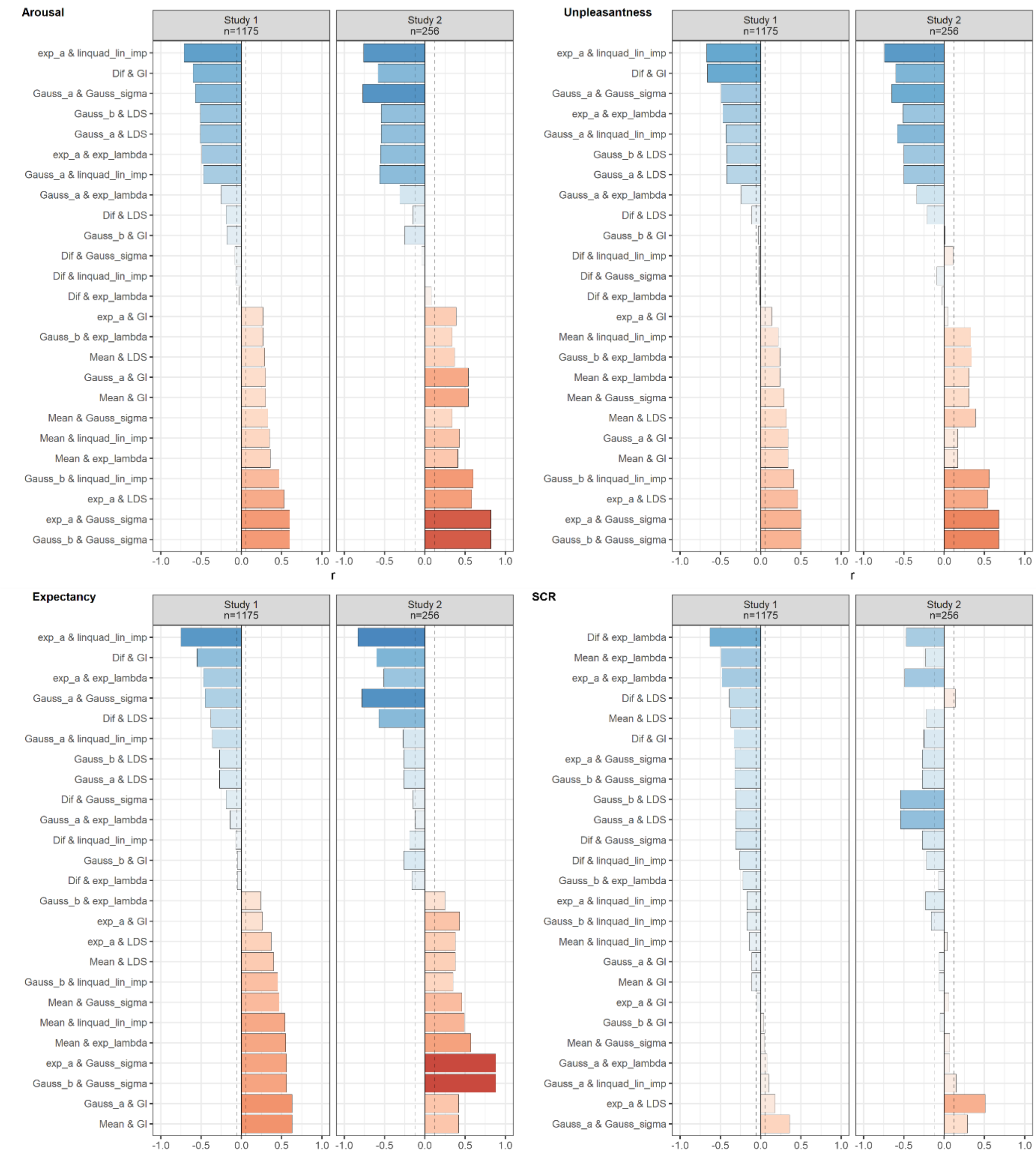

*Note*. STAI-T = State-Trait Anxiety Inventory – Trait, ASI-3 = Anxiety Sensitivity Index 3, ACQ = Agoraphobic Cognition Questionnaire, SPAI = Social Phobia Anxiety Index, LSAS = Liebowitz Social Anxiety Scale, CTQ = Childhood Trauma Questionnaire, LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, % = relative importance of the linear compared to the quadratic term, Level = mean response level, Diff = CS differentiation. Statistically significant correlations are printed in black. Please note that the LDS and the $\lambda_{exp}$ are inverted for better comparability.

**Supplemental Figure 6.** *Comparison of Correlations Among Gradient Curvature Parameters Between the First Sample and the Second Sample*



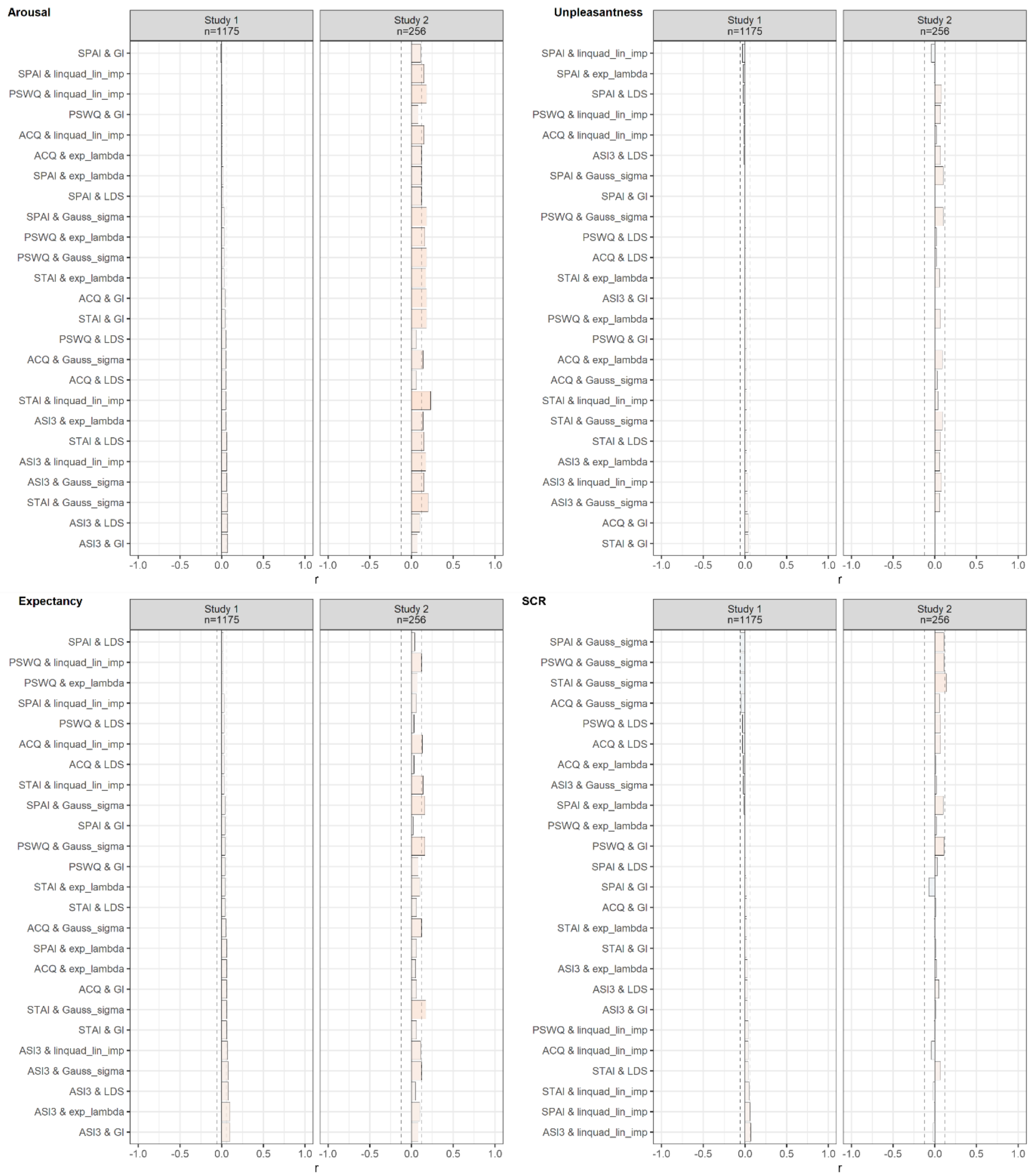

*Note*. LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, lin_imp = relative importance of the quadratic compared to the linear term. Dashed lines indicate statistical significance at $p < .05$.

**Supplemental Figure 7.** *Comparison of Correlations Among Gradient Curvature Parameters and Basic Parameters of Fear Generalization Between the First Sample and the Second Sample*



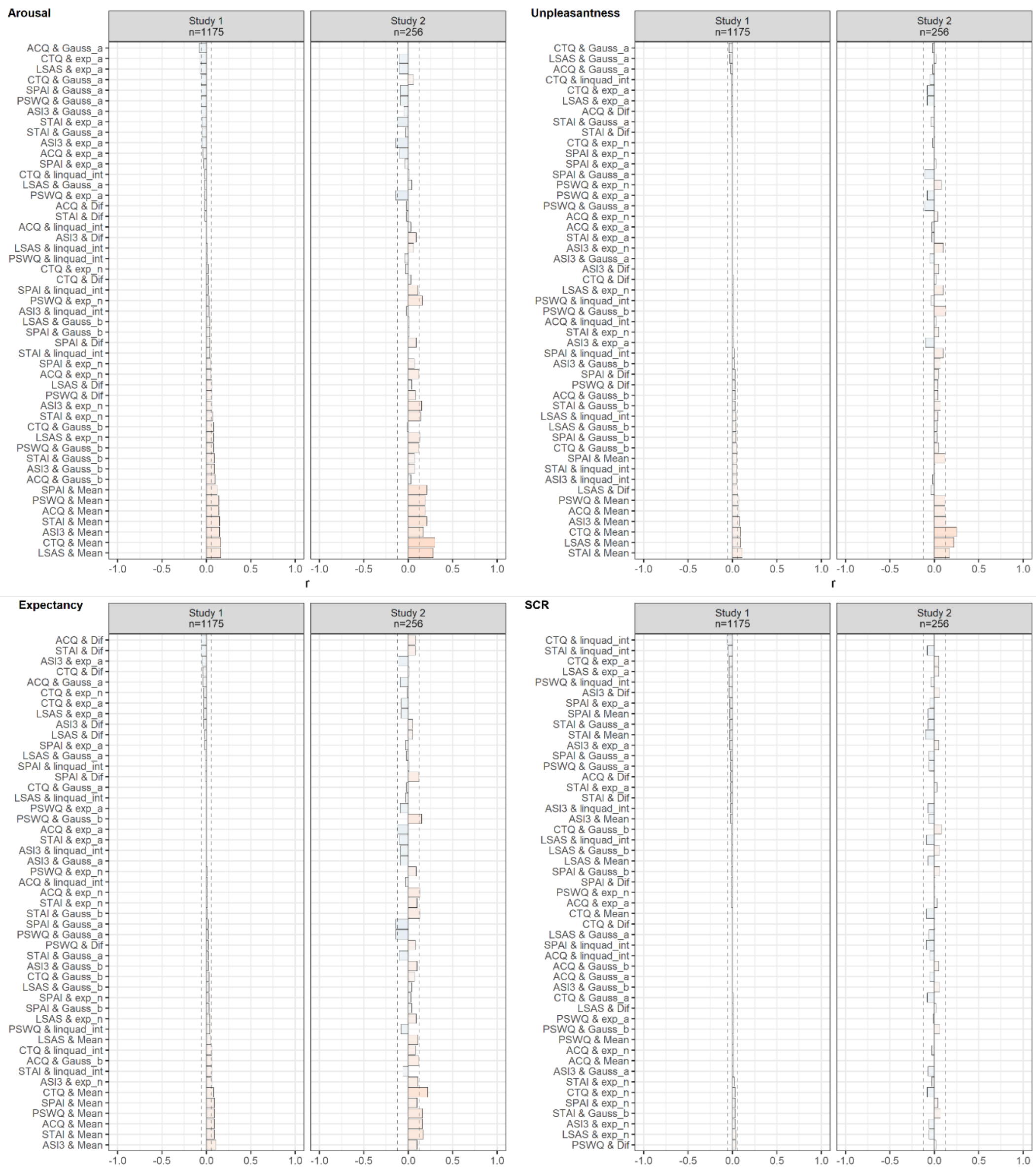

*Note.* LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, lin_imp = relative importance of the quadratic compared to the linear term, Mean = mean response level, Dif = CS difference. Dashed lines indicate statistical significance at $p < .05$.

**Supplemental Figure 8.** *Comparison of Correlations Among Gradient Curvature Parameters and Trait Measures of Anxiety Psychopathology Between the First Sample and the Second Sample.*




*Note*. LDS = linear deviation score, GI = generalization index, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, lin_imp = relative importance of the quadratic compared to the linear term, STAI-T = State-Trait Anxiety Inventory – Trait, ASI-3 = Anxiety Sensitivity Index 3, ACQ = Agoraphobic Cognition Questionnaire, SPAI = Social Phobia Anxiety Index, LSAS = Liebowitz Social Anxiety Scale, CTQ = Childhood Trauma Questionnaire. Dashed lines indicate statistical significance at $p < .05$.

**Supplemental Figure 9.** *Comparison of Correlations Among Basic Parameters and Trait Measures of Anxiety Psychopathology Between the First Sample and the Second Sample*




*Note.* Mean = mean response level, Dif = CS difference, Gauss = Gaussian model fit, exp = exponential model fit, linquad = quadratic polynomial model fit, STAI-T = State-Trait Anxiety Inventory – Trait, ASI-3 = Anxiety Sensitivity Index 3, ACQ = Agoraphobic Cognition Questionnaire, SPAI = Social Phobia Anxiety Index, LSAS = Liebowitz Social Anxiety Scale, CTQ = Childhood Trauma Questionnaire. Dashed lines indicate statistical significance at $p < .05$.

**Supplemental References**

Ahmed, O., & Lovibond, P. F. (2015). The Impact of Instructions on Generalization of Conditioned Fear in Humans. *Behavior Therapy*, *46*(5), 597-603. https://doi.org/https://doi.org/10.1016/j.beth.2014.12.007

Antov, M. I., Plog, E., Bierwirth, P., Keil, A., & Stockhorst, U. (2020). Visuocortical tuning to a threat-related feature persists after extinction and consolidation of conditioned fear. *Scientific Reports*, *10*(1), 3926. https://doi.org/10.1038/s41598-020-60597-z

Atlas, L. Y., Sandman, C. F., & Phelps, E. A. (2022). Rating expectations can slow aversive reversal learning [https://doi.org/10.1111/psyp.13979]. *Psychophysiology*, *59*(3), e13979. https://doi.org/https://doi.org/10.1111/psyp.13979

Bandelow, B., & Michaelis, S. (2015). Epidemiology of anxiety disorders in the 21st century. *Dialogues in Clinical Neuroscience*, *17*(3), 327-335. https://doi.org/10.31887/DCNS.2015.17.3/bbandelow

Beidel, D. C., Turner, S. M., Stanley, M. A., & Dancu, C. V. (1989). The social phobia and anxiety inventory: Concurrent and external validity. *Behavior Therapy*, *20*(3), 417-427. https://doi.org/https://doi.org/10.1016/S0005-7894(89)80060-7

Bernstein, D. P., Stein, J. A., Newcomb, M. D., Walker, E., Pogge, D., Ahluvalia, T., Stokes, J., Handelsman, L., Medrano, M., Desmond, D., & Zule, W. (2003). Development and validation of a brief screening version of the Childhood Trauma Questionnaire. *Child Abuse Negl*, *27*(2), 169-190. https://doi.org/https://doi.org/10.1016/S0145-2134(02)00541-0

Boucsein, W., Fowles, D. C., Grimnes, S., Ben-Shakhar, G., roth, W. T., Dawson, M. E., Filion, D. L., & Society for Psychophysiological Research Ad Hoc Committee on Electrodermal, M. (2012). Publication recommendations for electrodermal measurements. *Psychophysiology*, *49*(8), 1017-1034. https://doi.org/10.1111/j.1469-8986.2012.01384.x

Cecil, H., Jr., Frederick, M., John, W. T., & Charles, P. W. (1947). Low Moments for Small Samples: A Comparative Study of Order Statistics. *The Annals of Mathematical Statistics*, *18*(3), 413-426. https://doi.org/10.1214/aoms/1177730388

Cha, J., Daniel, D., Sanja, N., Jaime, I., Tsafrir, G., Greg, H., & Lilianne Rivka, M.-P. (2016). Clinically Anxious Individuals Show Disrupted Feedback between Inferior Frontal Gyrus and Prefrontal-Limbic Control Circuit. *The Journal of Neuroscience*, *36*(17), 4708. https://doi.org/10.1523/JNEUROSCI.1092-15.2016

Cha, J., Joshua, M. C., Daniel, J. D., Tsafrir, G., Greg, H. P., & Lilianne, R. M.-P. (2014). Hyper-Reactive Human Ventral Tegmental Area and Aberrant Mesocorticolimbic Connectivity in Overgeneralization of Fear in Generalized Anxiety Disorder. *The Journal of Neuroscience*, *34*(17), 5855. https://doi.org/10.1523/JNEUROSCI.4868-13.2014

Cha, J., Tsafrir, G., Joshua, M. C., Daniel, J. D., Greg, H., & Lilianne, R. M.-P. (2014). Circuit-Wide Structural and Functional Measures Predict Ventromedial Prefrontal Cortex Fear Generalization: Implications for Generalized Anxiety Disorder. *The Journal of Neuroscience*, *34*(11), 4043. https://doi.org/10.1523/JNEUROSCI.3372-13.2014

Chambless, D. L., Caputo, G. C., Bright, P., & Gallagher, R. (1984). Assessment of fear of fear in agoraphobics: the body sensations questionnaire and the agoraphobic cognitions questionnaire. *J Consult Clin Psychol*, *52*(6), 1090-1097. https://doi.org/10.1037/0022-006X.52.6.1090

Cohen, Z. D., Delgadillo, J., & DeRubeis, R. J. (2021). Personalized treatment approaches. In *Bergin and Garfield's handbook of psychotherapy and behavior change: 50th anniversary edition, 7th ed.* (pp. 673-703). John Wiley & Sons, Inc.

Constantinou, E., Purves, K. L., McGregor, T., Lester, K. J., Barry, T. J., Treanor, M., Craske, M. G., & Eley, T. C. (2021). Measuring fear: Association among different measures of fear learning. *Journal of*

*Behavior Therapy and Experimental Psychiatry*, *70*, 101618. https://doi.org/https://doi.org/10.1016/j.jbtep.2020.101618

Cooper, S. E., Dunsmoor, J. E., Koval, K. A., Pino, E. R., & Steinman, S. A. (2023). Test–retest reliability of human threat conditioning and generalization across a 1-to-2-week interval. *Psychophysiology*, *60*(6), e14242. https://doi.org/https://doi.org/10.1111/psyp.14242

Cooper, S. E., van Dis, E. A. M., Hagenaars, M. A., Krypotos, A.-M., Nemeroff, C. B., Lissek, S., Engelhard, I. M., & Dunsmoor, J. E. (2022). A meta-analysis of conditioned fear generalization in anxiety-related disorders. *Neuropsychopharmacology*. https://doi.org/10.1038/s41386-022-01332-2

Cuthbert, B. N. (2014). The RDoC framework: facilitating transition from ICD/DSM to dimensional approaches that integrate neuroscience and psychopathology [https://doi.org/10.1002/wps.20087]. *World Psychiatry*, *13*(1), 28-35. https://doi.org/https://doi.org/10.1002/wps.20087

Dos Santos Corrêa, M., Vaz, B. D. S., Grisanti, G. D. V., de Paiva, J. P. Q., Tiba, P. A., & Fornari, R. V. (2019). Relationship between footshock intensity, post-training corticosterone release and contextual fear memory specificity over time. *Psychoneuroendocrinology*, *110*, 104447. https://doi.org/10.1016/j.psyneuen.2019.104447

Dou, H., Lei, Y., Pan, Y., Li, H., & Astikainen, P. (2023). Impact of observational and direct learning on fear conditioning and generalization in humans. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *121*, 110650. https://doi.org/https://doi.org/10.1016/j.pnpbp.2022.110650

Dou, H., Zou, L., Becker, B., & Lei, Y. (2021). Intranasal oxytocin decreases fear generalization in males, but does not modulate discrimination threshold. *Psychopharmacology (Berl)*, *238*(3), 677-689. https://doi.org/10.1007/s00213-020-05720-8

Duits, P., Cath, D. C., Lissek, S., Hox, J. J., Hamm, A. O., Engelhard, I. M., van den Hout, M. A., & Baas, J. M. (2015). Updated meta-analysis of classical fear conditioning in the anxiety disorders. *Depress Anxiety*, *32*(4), 239-253. https://doi.org/10.1002/da.22353

Dunning, J. P., & Hajcak, G. (2015). Gradients of Fear Potentiated Startle During Generalization, Extinction, and Extinction Recall--and Their Relations With Worry. *Behavior Therapy*, *46*(5), 640-651. https://doi.org/10.1016/j.beth.2015.06.005

Dunsmoor, J. E., Kroes, M. C. W., Braren, S. H., & Phelps, E. A. (2017). Threat intensity widens fear generalization gradients. *Behavioral neuroscience*, *131*(2), 168-175. https://doi.org/10.1037/bne0000186

Dunsmoor, J. E., & Murphy, G. L. (2015). Categories, concepts, and conditioning: how humans generalize fear. *Trends in Cognitive Sciences*, *19*(2), 73-77. https://doi.org/https://doi.org/10.1016/j.tics.2014.12.003

Dunsmoor, J. E., & Paz, R. (2015). Fear Generalization and Anxiety: Behavioral and Neural Mechanisms. *Biol Psychiatry*, *78*(5), 336-343. https://doi.org/10.1016/j.biopsych.2015.04.010

Dymond, S., Dunsmoor, J. E., Vervliet, B., Roche, B., & Hermans, D. (2015). Fear Generalization in Humans: Systematic Review and Implications for Anxiety Disorder Research. *Behavior Therapy*, *46*(5), 561-582. https://doi.org/10.1016/j.beth.2014.10.001

Ehlers, A., Margraf, J., & Chambless, D. (2001). *Fragebogen zu körperbezogenen Ängsten, Kognitionen und Vermeidung: AKV*. Beltz-Test.

El-Bar, N., Laufer, O., Yoran-Hegesh, R., & Paz, R. (2017). Over-generalization in youth with anxiety disorders. *Social Neuroscience*, *12*(1), 76-85. https://doi.org/10.1080/17470919.2016.1167123

Fan, M., Zhang, D., Zhao, S., Xie, Q., Chen, W., Jie, J., Wang, Y., & Zheng, X. (2022). Stimulus diversity increases category-based fear generalization and the effect of intolerance of uncertainty.

*Behaviour Research and Therapy*, *159*, 104201. https://doi.org/https://doi.org/10.1016/j.brat.2022.104201

Feldman, B. E. (2005). Relative importance and value. *Available at SSRN 2255827*.

Fraunfelter, L., Gerdes, A. B. M., & Alpers, G. W. (2022). Fear one, fear them all: A systematic review and meta-analysis of fear generalization in pathological anxiety. *Neuroscience & Biobehavioral Reviews*, *139*, 104707. https://doi.org/https://doi.org/10.1016/j.neubiorev.2022.104707

Friedl, M. W., & Keil, A. (2021). Aversive Conditioning of Spatial Position Sharpens Neural Population-Level Tuning in Visual Cortex and Selectively Alters Alpha-Band Activity. *The Journal of Neuroscience*, *41*(26), 5723. https://doi.org/10.1523/JNEUROSCI.2889-20.2021

Fullana, M. A., Dunsmoor, J. E., Schruers, K. R. J., Savage, H. S., Bach, D. R., & Harrison, B. J. (2020). Human fear conditioning: From neuroscience to the clinic. *Behaviour Research and Therapy*, *124*, 103528. https://doi.org/https://doi.org/10.1016/j.brat.2019.103528

Ginat-Frolich, R., Gendler, T., Marzan, D., Tsuk, Y., & Shechner, T. (2019). Reducing fear overgeneralization in children using a novel perceptual discrimination task. *Behaviour Research and Therapy*, *116*, 131-139. https://doi.org/https://doi.org/10.1016/j.brat.2019.03.008

Ginat-Frolich, R., Klein, Z., Katz, O., & Shechner, T. (2017). A novel perceptual discrimination training task: Reducing fear overgeneralization in the context of fear learning. *Behaviour Research and Therapy*, *93*, 29-37. https://doi.org/https://doi.org/10.1016/j.brat.2017.03.010

Glenn, C. R., Klein, D. N., Lissek, S., Britton, J. C., Pine, D. S., & Hajcak, G. (2012). The development of fear learning and generalization in 8–13 year-olds [https://doi.org/10.1002/dev.20616]. *Dev Psychobiol*, *54*(7), 675-684. https://doi.org/https://doi.org/10.1002/dev.20616

Glenn, D. E., Feldman, J. S., Ivie, E. J., Shechner, T., Leibenluft, E., Pine, D. S., Peters, M. A. K., & Michalska, K. J. (2021). Social relevance modulates multivariate neural representations of threat generalization in children and adults [https://doi.org/10.1002/dev.22185]. *Dev Psychobiol*, *63*(7), e22185. https://doi.org/https://doi.org/10.1002/dev.22185

Greenberg, T., Carlson, J. M., Cha, J., Hajcak, G., & Mujica-Parodi, L. R. (2013). Neural reactivity tracks fear generalization gradients. *Biol Psychol*, *92*(1), 2-8. https://doi.org/10.1016/j.biopsycho.2011.12.007

Grosso, A., Santoni, G., Manassero, E., Renna, A., & Sacchetti, B. (2018). A neuronal basis for fear discrimination in the lateral amygdala. *Nature Communications*, *9*(1), 1214. https://doi.org/10.1038/s41467-018-03682-2

Hamm, A. O., & Weike, A. I. (2005). The neuropsychology of fear learning and fear regulation. *International Journal of Psychophysiology*, *57*(1), 5-14. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2005.01.006

Hammell, A. E., Helwig, N. E., Kaczkurkin, A. N., Sponheim, S. R., & Lissek, S. (2020). The temporal course of over-generalized conditioned threat expectancies in posttraumatic stress disorder. *Behaviour Research and Therapy*, *124*, 103513. https://doi.org/https://doi.org/10.1016/j.brat.2019.103513

Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behav Res Methods*, *50*(3), 1166-1186. https://doi.org/10.3758/s13428-017-0935-1

Herzog, K., Andreatta, M., Schneider, K., Schiele, M. A., Domschke, K., Romanos, M., Deckert, J., & Pauli, P. (2021). Reducing Generalization of Conditioned Fear: Beneficial Impact of Fear Relevance and Feedback in Discrimination Training [Original Research]. *Front Psychol*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.665711

Holt, D. J., Boeke, E. A., Wolthusen, R. P. F., Nasr, S., Milad, M. R., & Tootell, R. B. H. (2014). A parametric study of fear generalization to faces and non-face objects: relationship to discrimination thresholds [Original Research]. *Front Hum Neurosci*, *8*. https://www.frontiersin.org/articles/10.3389/fnhum.2014.00624

Imholze, C., Hutterer, K., Gall, D., Dannlowski, U., Domschke, K., Leehr, E. J., Lonsdorf, T. B., Lueken, U., Reif, A., Rosenkranz, K., Schiele, M. A., Zwanzger, P., Pauli, P., & Gamer, M. (2023). Prediction of Changes in Negative Affect During the COVID-19 Pandemic by Experimental Fear Conditioning and Generalization Measures. *Zeitschrift für Psychologie*, *231*(2), 137-148. https://doi.org/10.1027/2151-2604/a000523

Kaczkurkin, A. N., Burton, P. C., Chazin, S. M., Manbeck, A. B., Espensen-Sturges, T., Cooper, S. E., Sponheim, S. R., & Lissek, S. (2017). Neural Substrates of Overgeneralized Conditioned Fear in PTSD. *Am J Psychiatry*, *174*(2), 125-134. https://doi.org/10.1176/appi.ajp.2016.15121549

Kampermann, L., Wilming, N., Alink, A., Büchel, C., & Onat, S. (2019). Fixation-pattern similarity analysis reveals adaptive changes in face-viewing strategies following aversive learning. *eLife*, *8*, e44111. https://doi.org/10.7554/eLife.44111

Kasper, S. (2006). Anxiety disorders: under-diagnosed and insufficiently treated. *International Journal of Psychiatry in Clinical Practice*, *10*(sup1), 3-9. https://doi.org/10.1080/13651500600552297

Kass, M. D., & McGann, J. P. (2017). Persistent, generalized hypersensitivity of olfactory bulb interneurons after olfactory fear generalization. *Neurobiology of Learning and Memory*, *146*, 47-57. https://doi.org/https://doi.org/10.1016/j.nlm.2017.11.004

Kausche, F. M., Zerbes, G., Kampermann, L., Büchel, C., & Schwabe, L. (2021). Neural signature of delayed fear generalization under stress [https://doi.org/10.1111/psyp.13917]. *Psychophysiology*, *58*(11), e13917. https://doi.org/https://doi.org/10.1111/psyp.13917

Kausche, F. M., Zerbes, G., Kampermann, L., Müller, J. C., Wiedemann, K., Büchel, C., & Schwabe, L. (2021a). Acute stress leaves fear generalization in healthy individuals intact. *Cognitive, Affective, & Behavioral Neuroscience*, *21*(2), 372-389. https://doi.org/10.3758/s13415-021-00874-0

Kausche, F. M., Zerbes, G., Kampermann, L., Müller, J. C., Wiedemann, K., Büchel, C., & Schwabe, L. (2021b). Noradrenergic stimulation increases fear memory expression. *European Neuropsychopharmacology*, *43*, 71-81. https://doi.org/https://doi.org/10.1016/j.euroneuro.2020.11.015

Keefe, J. R., Suarez-Jimenez, B., Zhu, X., Lazarov, A., Durosky, A., Such, S., Marohasy, C., Lissek, S., & Neria, Y. (2022). Elucidating behavioral and functional connectivity markers of aberrant threat discrimination in PTSD. *Depression and Anxiety*, *39*(12), 891-901. https://doi.org/https://doi.org/10.1002/da.23295

Kemper, C. J., Ziegler, M., & Taylor, S. (2009). Überprüfung der psychometrischen Qualität der deutschen Version des Angstsensitivitätsindex-3. *Diagnostica*, *55*(4), 223-233. http://econtent.hogrefe.com/doi/pdf/10.1026/0012-1924.55.4.223

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E. E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Arch Gen Psychiatry*, *62*(6), 593-602. https://doi.org/10.1001/archpsyc.62.6.593

Klein, Z., Shner-Livne, G., Danon-Kraun, S., Ginat-Frolich, R., Pine, D. S., & Shechner, T. (2023). Enhanced late positive potential to conditioned threat cue during delayed extinction in anxious youth [https://doi.org/10.1111/jcpp.13814]. *Journal of Child Psychology and Psychiatry*, *n/a*(n/a). https://doi.org/https://doi.org/10.1111/jcpp.13814

Klein, Z., Shner, G., Ginat-Frolich, R., Vervliet, B., & Shechner, T. (2020). The effects of age and trait anxiety on avoidance learning and its generalization. *Behaviour Research and Therapy*, *129*, 103611. https://doi.org/https://doi.org/10.1016/j.brat.2020.103611

Kopp, B., Schlimm, M., & Hermann, C. (2005). Memory–emotional interactions as revealed by fear generalization in animal-fearful individuals. *Journal of Behavior Therapy and Experimental Psychiatry*, *36*(2), 145-166. https://doi.org/https://doi.org/10.1016/j.jbtep.2004.08.007

Kuhn, M., Gerlicher, A. M. V., & Lonsdorf, T. B. (2022). Navigating the manyverse of skin conductance response quantification approaches – A direct comparison of trough-to-peak, baseline correction, and model-based approaches in Ledalab and PsPM. *Psychophysiology*, *59*(9), e14058. https://doi.org/https://doi.org/10.1111/psyp.14058

Lange, I., Goossens, L., Bakker, J., Michielse, S., Marcelis, M., Wichers, M., van Os, J., van Amelsvoort, T., & Schruers, K. (2019). Functional neuroimaging of associative learning and generalization in specific phobia. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *89*, 275-285. https://doi.org/https://doi.org/10.1016/j.pnpbp.2018.09.008

Lange, I., Goossens, L., Bakker, J., Michielse, S., van Winkel, R., Lissek, S., Leibold, N., Marcelis, M., Wichers, M., van Os, J., van Amelsvoort, T., & Schruers, K. (2019). Neurobehavioural mechanisms of threat generalization moderate the link between childhood maltreatment and psychopathology in emerging adulthood. *J Psychiatry Neurosci*, *44*(3), 185-194. https://doi.org/10.1503/jpn.180053

Lange, I., Goossens, L., Michielse, S., Bakker, J., Lissek, S., Papalini, S., Verhagen, S., Leibold, N., Marcelis, M., Wichers, M., Lieverse, R., van Os, J., van Amelsvoort, T., & Schruers, K. (2017). Behavioral pattern separation and its link to the neural mechanisms of fear generalization. *Social Cognitive and Affective Neuroscience*, *12*(11), 1720-1729. https://doi.org/10.1093/scan/nsx104

Lau, J. Y., Lissek, S., Nelson, E. E., Lee, Y., Roberson-Nay, R., Poeth, K., Jenness, J., Ernst, M., Grillon, C., & Pine, D. S. (2008). Fear conditioning in adolescents with anxiety disorders: results from a novel experimental paradigm. *J Am Acad Child Adolesc Psychiatry*, *47*(1), 94-102. https://doi.org/10.1097/chi.0b01e31815a5f01

Laufer, O., Israeli, D., & Paz, R. (2016). Behavioral and Neural Mechanisms of Overgeneralization in Anxiety. *Current Biology*, *26*(6), 713-722. https://doi.org/https://doi.org/10.1016/j.cub.2016.01.023

Laux, L., & Spielberger, C. D. (1981). *Das State-Trait-Angstinventar: STAI*. Beltz Weinheim.

Lee, J. C., Hayes, B. K., & Lovibond, P. F. (2018). Peak shift and rules in human generalization. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(12), 1955-1970. https://doi.org/10.1037/xlm0000558

Lenaert, B., van de Ven, V., Kaas, A. L., & Vlaeyen, J. W. S. (2016). Generalization on the Basis of Prior Experience Is Predicted by Individual Differences in Working Memory. *Behavior Therapy*, *47*(1), 130-140. https://doi.org/https://doi.org/10.1016/j.beth.2015.10.001

Levine, S. M., Kumpf, M., Rupprecht, R., & Schwarzbach, J. V. (2021). Supracategorical fear information revealed by aversively conditioning multiple categories. *Cognitive Neuroscience*, *12*(1), 28-39. https://doi.org/10.1080/17588928.2020.1839039

Lewis, M. W., Bradford, D. E., Pace-Schott, E. F., Rauch, S. L., & Rosso, I. M. (2023). Multiverse analyses of fear acquisition and extinction retention in posttraumatic stress disorder. *Psychophysiology*, e14265.

Liebowitz, M. R. (1987). Social phobia. *Modern Problems of Pharmacopsychiatry*.

Lissek, S., Kaczkurkin, A. N., Rabin, S., Geraci, M., Pine, D. S., & Grillon, C. (2014). Generalized anxiety disorder is associated with overgeneralization of classically conditioned fear. *Biol Psychiatry*, *75*(11), 909-915. https://doi.org/10.1016/j.biopsych.2013.07.025

Lissek, S., Levenson, J., Biggs, A. L., Johnson, L. L., Ameli, R., Pine, D. S., & Grillon, C. (2008). Elevated fear conditioning to socially relevant unconditioned stimuli in social anxiety disorder. *Am J Psychiatry*, *165*(1), 124-132. https://doi.org/10.1176/appi.ajp.2007.06091513

Lissek, S., Rabin, S., Heller, R. E., Lukenbaugh, D., Geraci, M., Pine, D. S., & Grillon, C. (2010). Overgeneralization of conditioned fear as a pathogenic marker of panic disorder. *Am J Psychiatry*, *167*(1), 47-55. https://doi.org/10.1176/appi.ajp.2009.09030410

Liu, S. S. (1971). Differential conditioning and stimulus generalization of the rabbit's nictitating membrane response. *Journal of Comparative and Physiological Psychology*, *77*(1), 136-142. https://doi.org/10.1037/h0031587

Lommen, M. J. J., Duta, M., Vanbrabant, K., de Jong, R., Juechems, K., & Ehlers, A. (2017). Training discrimination diminishes maladaptive avoidance of innocuous stimuli in a fear conditioning paradigm. *PLoS ONE*, *12*(10), e0184485. https://doi.org/10.1371/journal.pone.0184485

Lonsdorf, T. B., Gerlicher, A., Klingelhöfer-Jens, M., & Krypotos, A.-M. (2022). Multiverse analyses in fear conditioning research. *Behaviour Research and Therapy*, *153*, 104072. https://doi.org/https://doi.org/10.1016/j.brat.2022.104072

Lueken, U., & Hahn, T. (2020). Chapter 17 - Personalized mental health: Artificial intelligence technologies for treatment response prediction in anxiety disorders. In B. T. Baune (Ed.), *Personalized Psychiatry* (pp. 201-213). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-813176-3.00017-1

Manbeck, A. B., Cooper, S. E., & Lissek, S. (2022). Reversing threat contingencies enhances generalization of conditioned fear. *Learning and Motivation*, *80*, 101843. https://doi.org/https://doi.org/10.1016/j.lmot.2022.101843

McTeague, L. M., Gruss, L. F., & Keil, A. (2015). Aversive learning shapes neuronal orientation tuning in human visual cortex [Article]. *Nat Commun*, *6*, 7823. https://doi.org/10.1038/ncomms8823

Mertens, G., Bouwman, V., & Engelhard, I. M. (2021). Conceptual fear generalization gradients and their relationship with anxious traits: Results from a Registered Report. *International Journal of Psychophysiology*, *170*, 43-50. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2021.09.007

Meulders, A., Meulders, M., Stouten, I., De Bie, J., & Vlaeyen, J. W. S. (2017). Extinction of Fear Generalization: A Comparison Between Fibromyalgia Patients and Healthy Control Participants. *The Journal of Pain*, *18*(1), 79-95. https://doi.org/https://doi.org/10.1016/j.jpain.2016.10.004

Miasnikov, A. A., Chen, J. C., & Weinberger, N. M. (2009). Behavioral memory induced by stimulation of the nucleus basalis: Effects of contingency reversal. *Neurobiology of Learning and Memory*, *91*(3), 298-309. https://doi.org/https://doi.org/10.1016/j.nlm.2008.12.010

Michael, T., Zetsche, U., & Margraf, J. (2007). Epidemiology of anxiety disorders. *Psychiatry*, *6*(4), 136-142. https://doi.org/https://doi.org/10.1016/j.mppsy.2007.01.007

Michalska, K. J., Shechner, T., Hong, M., Britton, J. C., Leibenluft, E., Pine, D. S., & Fox, N. A. (2016). A developmental analysis of threat/safety learning and extinction recall during middle childhood. *Journal of Experimental Child Psychology*, *146*, 95-105. https://doi.org/https://doi.org/10.1016/j.jecp.2016.01.008

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L. A., & Group, P.-P. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, *4*(1), 1. https://doi.org/10.1186/2046-4053-4-1

Nebe, S., Reutter, M., Baker, D., Bölte, J., Domes, G., Gamer, M., Gärtner, A., Gießing, C., née Mann, C. G., & Hilger, K. (2023). Enhancing Precision in Human Neuroscience.

Nelson, B. D., Weinberg, A., Pawluk, J., Gawlowska, M., & Proudfit, G. H. (2015). An Event-Related Potential Investigation of Fear Generalization and Intolerance of Uncertainty. *Behavior Therapy*, *46*(5), 661-670. https://doi.org/10.1016/j.beth.2014.09.010

Niederstrasser, N. G., Meulders, A., Meulders, M., Struyf, D., & Vlaeyen, J. W. (2017). Executive functions deficits impair extinction of generalization of fear of movement-related pain [https://doi.org/10.1002/ejp.991]. *European Journal of Pain*, *21*(5), 886-899. https://doi.org/https://doi.org/10.1002/ejp.991

Onat, S., & Buchel, C. (2015). The neuronal basis of fear generalization in humans. *Nat Neurosci*, *18*(12), 1811-1818. https://doi.org/10.1038/nn.4166

Phillips, L. W. (1958). Mediated verbal similarity as a determinant of the generalization of a conditioned GSR. *Journal of Experimental Psychology*, *55*(1), 56-62. https://doi.org/10.1037/h0047453

Pittig, A., Treanor, M., LeBeau, R. T., & Craske, M. G. (2018). The role of associative fear and avoidance learning in anxiety disorders: Gaps and directions for future research. *Neuroscience & Biobehavioral Reviews*, *88*, 117-140. https://doi.org/https://doi.org/10.1016/j.neubiorev.2018.03.015

Plog, E., Antov, M. I., Bierwirth, P., Keil, A., & Stockhorst, U. (2022). Phase-Synchronized Stimulus Presentation Augments Contingency Knowledge and Affective Evaluation in a Fear-Conditioning Task. *eneuro*, *9*(1), ENEURO.0538-0520.2021. https://doi.org/10.1523/ENEURO.0538-20.2021

Porter, D. B., Qu, L. P., Kahnt, T., & Gottfried, J. A. (2021). Aversive outcomes impact human olfactory discrimination learning and generalization. *Behavioral neuroscience*, *135*(5), 642-653. https://doi.org/10.1037/bne0000476

R Development Core Team. (2021). *R: A language and environment for statistical computing*. In R Foundation for Statistical Computing.

Radua, J. (2021). PRISMA 2020 – An updated checklist for systematic reviews and meta-analyses. *Neuroscience & Biobehavioral Reviews*, *124*, 324-325. https://doi.org/https://doi.org/10.1016/j.neubiorev.2021.02.016

Reinhard, J., Slyschak, A., Schiele, M. A., Andreatta, M., Kneer, K., Reif, A., Domschke, K., Gamer, M., Pauli, P., Deckert, J., & Romanos, M. (2022). Fear conditioning and stimulus generalization in association with age in children and adolescents. *European Child & Adolescent Psychiatry*, *31*(10), 1581-1590. https://doi.org/10.1007/s00787-021-01797-4

Rescorla, R. A. (1967). Pavlovian conditioning and its proper control procedures. *Psychol Rev*, *74*(1), 71-80. https://doi.org/10.1037/h0024109

Resnik, J., & Paz, R. (2015). Fear generalization in the primate amygdala. *Nature Neuroscience*, *18*(2), 188-190. https://doi.org/10.1038/nn.3900

Reutter, M., & Gamer, M. (2023). Individual patterns of visual exploration predict the extent of fear generalization in humans. *Emotion*, *23*(5), 1267-1280. https://doi.org/10.1037/emo0001134

Roesmann, K., Wessing, I., Kraß, S., Leehr, E. J., Klucken, T., Straube, T., & Junghöfer, M. (2022). Developmental aspects of fear generalization – A MEG study on neurocognitive correlates in adolescents versus adults. *Developmental Cognitive Neuroscience*, *58*, 101169. https://doi.org/https://doi.org/10.1016/j.dcn.2022.101169

Scarlata, M. J., Lee, S. H., Lee, D., Kandigian, S. E., Hiller, A. J., Dishart, J. G., Mintz, G. E., Wang, Z., Coste, G. I., Mousley, A. L., Soler, I., Lawson, K., Ng, A. J., Bezek, J. L., & Bergstrom, H. C. (2019). Chemogenetic stimulation of the infralimbic cortex reverses alcohol-induced fear memory overgeneralization. *Scientific Reports*, *9*(1), 6730. https://doi.org/10.1038/s41598-019-43159-w

Schiele, M. A., Reinhard, J., Reif, A., Domschke, K., Romanos, M., Deckert, J., & Pauli, P. (2016). Developmental aspects of fear: Comparing the acquisition and generalization of conditioned fear in children and adults. *Dev Psychobiol*, *58*(4), 471-481. https://doi.org/10.1002/dev.21393

Schroijen, M., Pappens, M., Schruers, K., Van den Bergh, O., Vervliet, B., & Van Diest, I. (2015). Generalization of Fear to Respiratory Sensations. *Behavior Therapy*, *46*(5), 611-626. https://doi.org/10.1016/j.beth.2015.05.004

Seligman, M. E. (1971). Phobias and preparedness. *Behavior Therapy*, *2*(3), 307-320. https://doi.org/10.1016/S0005-7894(71)80064-3

Sep, M. S. C., Steenmeijer, A., & Kennis, M. (2019). The relation between anxious personality traits and fear generalization in healthy subjects: A systematic review and meta-analysis. *Neuroscience & Biobehavioral Reviews*, *107*, 320-328. https://doi.org/https://doi.org/10.1016/j.neubiorev.2019.09.029

Shalev, L., Paz, R., & Avidan, G. (2018). Visual Aversive Learning Compromises Sensory Discrimination. *Journal of Neuroscience*, *38*(11), 2766-2779. https://doi.org/10.1523/jneurosci.0889-17.2017

Sjouwerman, R., Illius, S., Kuhn, M., & Lonsdorf, T. B. (2022). A data multiverse analysis investigating non-model based SCR quantification approaches [https://doi.org/10.1111/psyp.14130]. *Psychophysiology*, *59*(12), e14130. https://doi.org/https://doi.org/10.1111/psyp.14130

Stangier, U., & Heidenreich, T. (2004). Die Liebowitz Soziale Angst-Skala (LSAS)[Liebowitz Social Anxiety Scale]. Collegium Internationale Psychiatriae Scalarum (Ed.), Internationale Skalen für Psychiatrie [International Psychiatry Scales]. In: Weinheim: Beltz. German.

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing Transparency Through a Multiverse Analysis. *Perspectives on Psychological Science*, *11*(5), 702-712. https://doi.org/10.1177/1745691616658637

Stegmann, Y., Ahrens, L. M., Pauli, P., Keil, A., & Wieser, M. J. (2020). Social aversive generalization learning sharpens the tuning of visuocortical neurons to facial identity cues. *eLife*, *9*, e55204. https://doi.org/10.7554/eLife.55204

Stegmann, Y., Schiele, M. A., Schümann, D., Lonsdorf, T. B., Zwanzger, P., Romanos, M., Reif, A., Domschke, K., Deckert, J., Gamer, M., & Pauli, P. (2019). Individual differences in human fear generalization—pattern identification and implications for anxiety disorders. *Translational Psychiatry*, *9*(1), 307. https://doi.org/10.1038/s41398-019-0646-8

Struyf, D., Hermans, D., & Vervliet, B. (2018). Maximizing the generalization of fear extinction: Exposures to a peak generalization stimulus. *Behaviour Research and Therapy*, *111*, 1-8. https://doi.org/https://doi.org/10.1016/j.brat.2018.09.005

Struyf, D., Zaman, J., Hermans, D., & Vervliet, B. (2017). Gradients of fear: How perception influences fear generalization. *Behaviour Research and Therapy*, *93*, 116-122. https://doi.org/https://doi.org/10.1016/j.brat.2017.04.001

Taylor, S., Zvolensky, M. J., Cox, B. J., Deacon, B., Heimberg, R. G., Ledley, D. R., Abramowitz, J. S., Holaway, R. M., Sandin, B., Stewart, S. H., Coles, M., Eng, W., Daly, E. S., Arrindell, W. A., Bouvard, M., & Cardenas, S. J. (2007). Robust dimensions of anxiety sensitivity: development and initial validation of the Anxiety Sensitivity Index-3. *Psychol Assess*, *19*(2), 176-188. https://doi.org/10.1037/1040-3590.19.2.176

Torrents-Rodas, D., Fullana, M. A., Bonillo, A., Andión, O., Molinuevo, B., Caseras, X., & Torrubia, R. (2014). Testing the temporal stability of individual differences in the acquisition and generalization of fear [https://doi.org/10.1111/psyp.12213]. *Psychophysiology*, *51*(7), 697-705. https://doi.org/https://doi.org/10.1111/psyp.12213

Tuominen, L., Boeke, E., DeCross, S., Wolthusen, R. P. F., Nasr, S., Milad, M., Vangel, M., Tootell, R., & Holt, D. (2019). The relationship of perceptual discrimination to neural mechanisms of fear generalization. *Neuroimage*, *188*, 445-455. https://doi.org/https://doi.org/10.1016/j.neuroimage.2018.12.034

Tuominen, L., DeCross, S. N., Boeke, E., Cassidy, C. M., Freudenreich, O., Shinn, A. K., Tootell, R. B. H., & Holt, D. J. (2021). Neural Abnormalities in Fear Generalization in Schizophrenia and Associations With Negative Symptoms. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *6*(12), 1165-1175. https://doi.org/https://doi.org/10.1016/j.bpsc.2021.01.006

van Meurs, B., Wiggert, N., Wicker, I., & Lissek, S. (2014). Maladaptive behavioral consequences of conditioned fear-generalization: A pronounced, yet sparsely studied, feature of anxiety pathology. *Behaviour Research and Therapy*, *57*, 29-37. https://doi.org/https://doi.org/10.1016/j.brat.2014.03.009

Vandael, K., Meulders, A., Peters, M., & Vervliet, B. (2023). The effect of experimentally induced positive affect on the generalization of pain-related avoidance and relief. *Behaviour Research and Therapy*, *165*, 104324. https://doi.org/https://doi.org/10.1016/j.brat.2023.104324

Vandael, K., Meulders, M., Vanden Boer, C., & Meulders, A. (2020). The relationship between fear generalization and pain modulation: an investigation in healthy participants. *20*(1), 151-165. https://doi.org/doi:10.1515/sjpain-2019-0065 (Scandinavian Journal of Pain)

Vervliet, B., Vansteenwegen, D., & Eelen, P. (2006). Generalization Gradients for Acquisition and Extinction in Human Contingency Learning. *Experimental Psychology*, *53*(2), 132-142. https://doi.org/10.1027/1618-3169.53.2.132

Waltmann, M., Schlagenhauf, F., & Deserno, L. (2022). Sufficient reliability of the behavioral and computational readouts of a probabilistic reversal learning task. *Behav Res Methods*, *54*(6), 2993-3014. https://doi.org/10.3758/s13428-021-01739-7

Wang, J., Sun, X., Becker, B., & Lei, Y. (2022). Common and separable behavioral and neural mechanisms underlie the generalization of fear and disgust. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *116*, 110519. https://doi.org/https://doi.org/10.1016/j.pnpbp.2022.110519

Watson, J. B., & Rayner, R. (1920). Conditioned emotional reactions. *Journal of Experimental Psychology*, *3*(1), 1-14. https://doi.org/10.1037/h0069608

Wickens, D. D., Schroder, H. M., & Snide, J. D. (1954). Primary stimulus generalization of the GSR under two conditions. *Journal of Experimental Psychology*, *47*(1), 52-56. https://doi.org/10.1037/h0053617

Wingenfeld, K., Spitzer, C., Mensebach, C., Grabe, H. J., Hill, A., Gast, U., Schlosser, N., Hopp, H., Beblo, T., & Driessen, M. (2010). [The German version of the Childhood Trauma Questionnaire (CTQ): preliminary psychometric properties] [The German Version of the Childhood Trauma Questionnaire (CTQ):Preliminary Psychometric Properties]. *Psychother Psychosom Med Psychol*, *60*(11), 442-450. https://doi.org/10.1055/s-0030-1247564 (Die deutsche Version des Childhood Trauma Questionnaire (CTQ): Erste Befunde zu den psychometrischen Kennwerten.)

You, Y., Novak, L. R., Clancy, K. J., & Li, W. (2022). Pattern differentiation and tuning shift in human sensory cortex underlie long-term threat memory. *Current Biology*, *32*(9), 2067-2075.e2064. https://doi.org/https://doi.org/10.1016/j.cub.2022.02.076

Zaman, J., Ceulemans, E., Hermans, D., & Beckers, T. (2019). Direct and indirect effects of perception on generalization gradients. *Behaviour Research and Therapy*, *114*, 44-50. https://doi.org/https://doi.org/10.1016/j.brat.2019.01.006

Zaman, J., Struyf, D., Ceulemans, E., Beckers, T., & Vervliet, B. (2019). Probing the role of perception in fear generalization. *Scientific Reports*, *9*(1), 10026. https://doi.org/10.1038/s41598-019-46176-x

Zaman, J., Struyf, D., Ceulemans, E., Vervliet, B., & Beckers, T. (2021). Perceptual errors are related to shifts in generalization of conditioned responding. *Psychological Research*, *85*(4), 1801-1813. https://doi.org/10.1007/s00426-020-01345-w

Zaman, J., Weltens, N., Ly, H. G., Struyf, D., Vlaeyen, J. W. S., Van den Bergh, O., Wiech, K., Van Oudenhove, L., & Van Diest, I. (2016). Influence of Interoceptive Fear Learning on Visceral Perception. *Psychosomatic Medicine*, *78*(2).

https://journals.lww.com/psychosomaticmedicine/Fulltext/2016/02000/Influence_of_Interoceptive_Fear_Learning_on.14.aspx

Zaman, J., Yu, K., & Lee, J. C. (2023). Individual differences in stimulus identification, rule induction, and generalization of learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *49*(6), 1004-1017. https://doi.org/10.1037/xlm0001153

Zaman, J., Yu, K., & Verheyen, S. (2023). The idiosyncratic nature of how individuals perceive, represent, and remember their surroundings and its impact on learning-based generalization. *Journal of Experimental Psychology: General*, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/xge0001403

Zech, H., Waltmann, M., Lee, Y., Reichert, M., Bedder, R. L., Rutledge, R. B., Deeken, F., Wenzel, J., Wedemeyer, F., Aguilera, A., Aslan, A., Bach, P., Bahr, N. S., Ebrahimi, C., Fischbach, P. C., Ganz, M., Garbusow, M., Großkopf, C. M., Heigert, M., . . . the, R.-C. (2022). Measuring self-regulation in everyday life: Reliability and validity of smartphone-based experiments in alcohol use disorder. *Behav Res Methods*. https://doi.org/10.3758/s13428-022-02019-8

Zeidan, M. A., Lebron-Milad, K., Thompson-Hollands, J., Im, J. J. Y., Dougherty, D. D., Holt, D. J., Orr, S. P., & Milad, M. R. (2012). Test–Retest Reliability during Fear Acquisition and Fear Extinction in Humans [https://doi.org/10.1111/j.1755-5949.2011.00238.x]. *CNS Neuroscience & Therapeutics*, *18*(4), 313-317. https://doi.org/https://doi.org/10.1111/j.1755-5949.2011.00238.x

Zenses, A.-K., Lee, J. C., Plaisance, V., & Zaman, J. (2021). Differences in perceptual memory determine generalization patterns. *Behaviour Research and Therapy*, *136*, 103777. https://doi.org/https://doi.org/10.1016/j.brat.2020.103777

Zhu, X., Suarez-Jimenez, B., Lazarov, A., Such, S., Marohasy, C., Small, S. S., Wager, T. D., Lindquist, M. A., Lissek, S., & Neria, Y. (2022). Sequential fear generalization and network connectivity in trauma exposed humans with and without psychopathology. *Communications Biology*, *5*(1), 1275. https://doi.org/10.1038/s42003-022-04228-5

Zoladz, P., Reneau, K., Weiser, J., Cordes, C., Virden, E., Helwig, S., Thebeault, C., Pfister, C., Getnet, B., Boaz, K., Niese, T., Stanek, M., Long, K., Parker, S., Rorabaugh, B., & Norrholm, S. (2022). Childhood Maltreatment in Females Is Associated with Enhanced Fear Acquisition and an Overgeneralization of Fear. *Brain Sciences*, *12*(11).

Zorowitz, S., & Niv, Y. (2023). Improving the Reliability of Cognitive Task Measures: A Narrative Review. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *8*(8), 789-797. https://doi.org/https://doi.org/10.1016/j.bpsc.2023.02.004