# **Computational Mechanisms of Aversive Generalisation in Anxiety**

### Luianta Verra (verra@mpib-berlin.mpg.de)

Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany

## Bernhard Spitzer (spitzer@mpib-berlin.mpg.de)

Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany

### Nicolas W. Schuck (nicolas.schuck@uni-hamburg.de)\*

Institute of Psychology, Universität Hamburg, Von-Melle-Park 5, 20146 Hamburg, Germany

### Ondrej Zika (zika@mpib-berlin.mpg.de)\*

Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany

### Abstract:

\*NWS and OZ contributed equally

Excessive generalisation of threat to similar stimuli is characteristic in anxiety. Such generalisation can arise from a failure to correctly identify the threatening stimulus or from the transfer of learned values to similar stimuli. Here we use computational modelling to characterise how perceptual and value-based mechanisms shape generalisation functions and how they relate to anxiety.

Participants (n=140) learned probabilistic stimulusoutcome associations that were then tested for generalisation on morphs of the original stimulus. Within each participant, we varied stimulus discriminability (high/low; perceptual manipulation) and the rate of reinforcement (25/50/75%; value manipulation). We found that participants generalized threat expectancy to new stimuli. Interestingly, participants generalized either by extrapolating linearly (linear function) or by using a similarity-based strategy (gaussian function). Both perceptual uncertainty and reinforcement rate impacted generalisation. Value generalisation was mediated by the generalisation strategy while perceptual uncertainty increased generalisation independently of it. Anxiety was associated with stronger generalisation for stimuli further from the original stimulus, especially when reinforcement rate was high.

This study characterises different mechanisms of aversive generalisation and contributes to our understanding of excessive generalisation in anxiety.

Keywords: fear generalisation; function learning; anxiety

# **Mechanisms of Fear Generalisation**

Generalisation of aversive associations to visually similar cues is adaptive for the detection and prevention of potential harm. However, excessive generalisation to safe stimuli increases the amount of perceived threat in one's environment and has been associated with anxiety disorders (Cooper et al., 2022).

Previous work has highlighted two possible mechanisms when generalizing along a dimension of perceptual similarity. Generalisation can result from the inability to discriminate a new stimulus from the threatening one or from the active transfer of learned values to similar stimuli (Norbury & Seymour, 2018; Yu et al., 2023). Recent work has further shown that people use different strategies to generalize value, generalizing either based on stimulus similarity (which results in a Gaussian-like function) or by extrapolating their expectations linearly (linear function; Wong & Lovibond, 2017).

To date, we don't know if anxiety affects perceptual or value-based processes and whether anxiety affects the generalisation strategy. Here we aim to characterise individual contributions of perceptual and value-based processes to generalisation and relate them to subclinical variations in anxiety.

# **Experimental Design**

Participants first learned to probabilistically associate a flower-like shape (conditioned stimulus, CS+) with an aversive scream (learning phase). Next, expectancy ratings (0-100%) for the CS+ and for 8 shapes varying in similarity to the CS+ were collected as a measure of generalisation (generalisation phase). We varied reinforcement rate during learning (25/50/75%; value manipulation) and discriminability of neighbouring shapes during generalisation (80/60%; perceptual manipulation; Fig.1). Participants completed the STICSA questionnaire (Ree et al., 2008) as a measure of trait anxiety.

Perceptual uncertainty			CS+		Reinforcement			Rate
~ r <del>×</del>	* *	*	*	-		٠	٠	25%
≥{+	★***	*	*	-	-	٠	۲	50%
- <del>`</del> *	* *	*	*	- <b>4</b>		٠	۲	75%
(								
( <del>/</del>	* *	*	*	-	-			25%
₽{ ★	★	*	*	- <b>4</b> K	-			50%
- L <del>×</del>	* *	*	*	-	-			75%
Generalisation stimuli				Gen	Generalisation stimuli			

Figure 1: Example stimulus set.



Figure 2: Expectancy ratings a) for CS+ after learning b) during generalisation for all shapes, grouped by participant and strategy c) slopes for perceptual uncertainty conditions by strategy d) distance-based generalisation gradients grouped by reinforcement rate and strategy e) example generalisation functions G for varying parameter  $\lambda$ .

### **Behavioural Results**

Expectancy ratings after learning show that participants learned outcome probabilities for different conditions (Fig. 2a). Participants generalized threat expectancy along the continuum of perceptually similar shapes following a linear (n=61) or gaussian (n=64) strategy (Fig. 2b, n=15 no clear strategy).

We analysed ratings as a function of distance from the CS+. To jointly look at gaussian and linear gradients we transformed linear ratings for stimuli on the left of the CS+ by subtracting them from the mean CS+ of the respective reinforcement rate condition. A GLM revealed that ratings decreased with increasing distance from the CS+. This decrease was stronger in low uncertainty compared to high uncertainty conditions (Fig. 2c) which indicates a tendency for wider generalisation when discriminability is low. The effect of perceptual uncertainty was stronger in linear compared to gaussian gradients (gaussian low-high - linear lowhigh: 0.08, Cl95=[0.04, 0.11]). Higher reinforcement rate was associated with higher ratings for the CS+ and with steeper slopes in gaussian but not in linear gradients (Fig. 2d; gaussian 50-75%: 0.11 Cl95= [0.09, 0.15], 25-50%: 0.13 Cl95= [0.1,0.16]). This indicates that higher outcome probability shifted the peak of gaussian gradients and the overall gradient in linear generalizers.

We found no anxiety related learning differences after threat conditioning. Anxiety was however associated with stronger generalisation across strategies, especially for high reinforcement rates (75-50%: 0.05 Cl95=[0.03,0.08], 75-25%: 0.03 Cl95=[0.001, 0.06]).

### **Modelling Framework**

We model value generalisation strength  $\lambda$  across strategies while accounting for perceptual confusability

 $\rho$ . In our model, the value for the CS+ ( $V_{CS+}$ ) generalizes to neighbouring stimuli following a generalisation function  $G_{\Omega}$ :  $V_{CS+} * G_{\Omega}$ , where  $G_{\Omega}$  governs the shape of generalisation and takes a sigmoid or gaussian shape depending on the strategy parameter  $\Omega$ . If  $\Omega = 1$ :  $G_{gauss} = 2/(1 + e^{\frac{d_{abs}}{\lambda}})$ , if  $\Omega = 0$ :  $G_{linear} = 2/(1 + e^{\frac{d_{eu}}{\lambda}})$ , where  $d_{abs}$  and  $d_{eu}$  indicate absolute or Euclidean distance from the CS+. In both cases  $\lambda$  determines generalisation width (Fig 2e).

To model perceptual uncertainty on each trial *t*, the current stimulus  $S_{C,t}$  can be mistaken for a neighbouring stimulus  $S_{perc,t}$  with probability *P*. *P* for  $S_{C,t}$  depends on the perceptual uncertainty level  $\rho$ :  $P(s_{C,t}) = 1 - \rho$  and for all other stimuli on  $\rho$  and distance from the shown stimulus  $P(s_d) = \rho^{d_{abs}}$ . The expectancy rating  $y_t$  on each trial results from the value of  $S_{perc,t}$ .

We performed parameter and model recovery for a set of full and lesioned models. We found that the model accounting for value generalisation only fit our data best, even in participants with gaussian generalisation gradients. Further analyses will focus on relating modelling results to anxiety.

### Conclusion

Our data provides evidence for threat generalisation along a dimension of perceptual similarity. We show that perceptual uncertainty increases generalisation to similar stimuli and that value impacts generalisation differently depending on the latent structure that participants infer. We find that trait anxiety is associated with stronger generalisation and that this relates to value processing rather than perceptual mechanisms.

Our results contribute to a mechanistic understanding of aversive generalisation and attempt to model generalisation across strategies to provide a unifying measure for generalisation tendency.

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