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RUNNING HEAD: Similarity and patterning discriminations

Stimulus similarity affects patterning discrimination learning

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**Abstract**

In four experiments, participants' performance on a variety of non-linear patterning discriminations was assessed using a predictive learning task and visual patterns. Between groups, the similarity of the stimuli that composed these visual patterns was manipulated. When the stimuli were of low similarity, participants' performance was consistent with the predictions of one version of Pearce's (1987, 1994, 2002) configural theory of learning (Kinder & Lachnit, 2003); they were better able to discriminate between different patterns when they shared few, rather than many, stimuli. This effect was not observed when the similarity of the stimuli was high. Under these conditions, the results were more consistent with predictions of elemental theories of learning (e.g., Rescorla & Wagner, 1972; Wagner, 2003). This is the first time that these different patterns of performance on complex patterning discriminations have been shown within a single stimulus modality in the same experiment. The overall pattern of results is difficult to reconcile with either elemental or configural models of associative learning.

Keywords: human, configural, elemental, similarity, discrimination

### **Stimulus similarity affects patterning discrimination learning**

Mathematical models of associative learning may be divided broadly into two classes based on the assumptions that they make about the way in which configurations of stimuli are represented. Some models take an elemental approach and assume that when multiple stimuli are presented in compound, each individual stimulus may enter into a separate association with the outcome (e.g., Rescorla & Wagner, 1972). The alternative, configural, approach (e.g., Pearce, 1987, 1994, 2002) supposes that a single, holistic representation of the stimulus compound may become associated with the outcome. These different classes of model make quite different predictions about the rate at which certain patterning discrimination tasks may be learned and examination of participants' performance on those tasks may provide insight into the nature of the representation of stimulus configurations.

In a negative patterning discrimination (A+ B+ ABo), each of two stimuli (A and B) are followed by an outcome (+) when presented alone, but are followed by no outcome (o) when presented in compound with each other. This is an example of a non-linear discrimination problem which cannot be solved if the strength of responding to the AB compound is determined purely by the strength of the association between each individual stimulus and the outcome. In order to allow elemental models of learning like the Rescorla-Wagner model to solve such discriminations, it has been suggested that when stimuli are presented in compound, a unique, configural cue is generated (Spence, 1952; Wagner & Rescorla, 1972; Brandon, Vogel & Wagner, 2000; Wagner, 2003). Hence, the discrimination may be recast as A+ B+ ABXo where X is the configural cue generated by the combination of stimuli A and B. An inhibitory association may then develop between the configural cue and the outcome. This inhibitory association can counteract the effects of the excitatory

associations between the individual stimuli and the outcome on compound trials. The Rescorla-Wagner model predicts that the asymptotic associative strength of A, B, and X will be equal to  $\lambda$ ,  $\lambda$ , and  $-2\lambda$ , respectively, meaning that the net associative strengths of the patterns A, B, will each be equal to  $\lambda$  and that of AB will be 0.

According to Pearce's (1994) Configural Theory, training on such a negative patterning discrimination will lead to the recruitment of three configural units representing the patterns A, B, and AB. When any one of these patterns is presented it will maximally activate the corresponding configural unit. Other configural units may also be partially activated and their activation will be a function of the similarity between the pattern that they represent and the pattern that has been presented. Hence, when stimulus A is presented, the configural unit A will be fully activated, configural unit AB will be partially activated, and configural unit B will be inactive. When A and B are presented in compound, configural unit AB will be fully activated and configural units A and B will each be partially activated. In this manner, the associative strength of one pattern will generalize to other, similar patterns. Based on the assumption that A and AB (and B and AB) have a similarity of .5, Pearce's configural theory predicts that the configural units A, B, and AB will have asymptotic associative strengths of  $2\lambda$ ,  $2\lambda$ , and  $-2\lambda$  when the net associative strengths of the three patterns will equal  $\lambda$ ,  $\lambda$ , and 0, respectively.

Because Configural Theory assumes that associative strength will generalise between patterns to the extent that they are similar, it predicts that the ease with which discrimination tasks are learned is affected by the similarity of the patterns that must be discriminated between. Empirical evidence supports this prediction. For example, Pearce and Redhead

(1993) trained pigeons on two negative patterning discrimination tasks. The first was of the standard form A+ B+ ABo. The second discrimination was of the form CD+ CE+ CDEo. In this task stimuli D and E were treated in the same manner as A and B were in the first task, but a common stimulus, C, was present on all trials. This had the effect of increasing the similarity between the patterns that were paired with food and the one that was not. Consistent with the predictions of Configural Theory, the A+ B+ ABo discrimination was learned more rapidly than was the CD+ CE+ CDEo discrimination.

The Rescorla-Wagner model does not predict the pattern of results observed by Pearce and Redhead (1993). Indeed, it predicts that the addition of a common element should facilitate the acquisition of a negative patterning discrimination. This is because on each of the trials on which food was presented, there are more stimuli to which associative strength can accrue in the CD+ CE+ CDEo discrimination than in the A+ B+ ABo discrimination. This should result in greater responding to compounds CD and CE than to stimuli A and B. A further consequence is that early in training the compound CDE should have much greater net associative strength than the compound AB. Hence, the difference between the expected outcome and the actual outcome (nothing) on those trials will cause the CDE configural cue to acquire inhibitory associative strength more rapidly than the AB configural cue. Bahçekapılı (1997; described in Myers, Vogel, Shin & Wagner, 2001) reported the result of a rabbit eye-blink conditioning experiment which were consistent with these predictions.

There are many other situations in which the Rescorla-Wagner model and Configural Theory make rather different predictions and where the predictions of each model are supported by experimental results (see Wagner, 2003; 2008). Typically, results that are

consistent with the Rescorla-Wagner model have involved compounds of stimuli drawn from different modalities (auditory, visual, tactile) and eye-blink conditioning in rabbits (e.g., Bahçekapılı, 1997; Brandon, Vogel & Wagner, 2000; Whitlow & Wagner, 1972; Myers, Vogel, Shin & Wagner, 2001). Results supporting Configural Theory, however, have typically involved compounds of stimuli within a single modality (visual) and pigeon autoshaping preparations (e.g., Pearce, Adam, Wilson & Darby, 1992; Pearce, Aydin & Redhead, 1997; Pearce, Esber, George & Haselgrove, 2008; Pearce & Redhead, 1993; Rescorla & Coldwell, 1995). These differences in experimental paradigm and the types of stimuli used have been identified as possible reasons for the different patterns of results obtained.

In experiments employing an eye-blink procedure in rabbits, the subjects are restrained and often have a potentiometer attached to their nictitating membrane. Pearce (2002) suggested these conditions may serve as highly salient background cues which are present throughout the conditioning session, whereas the incidental background cues present during pigeon autoshaping are likely to be much less salient. Importantly, the addition of a salient background cue can affect the predictions of Configural Theory. Indeed, in the case of the patterning discrimination discussed earlier, a salient background cue reverses the predictions that configural theory makes about the relative speed of learning A+ B+ ABo and CD+ CE+ CDEo patterning discriminations. The top row of Figure 1 shows predictions derived from simulations of Configural Theory without (left panel) and with (right panel) the inclusion of a salient background cue. Configural Theory makes these predictions because the reinforced stimuli A and B are relatively difficult to detect against the background of a salient context which is itself non-reinforced during the long inter-trial intervals. Patterns A[Context]

and B[Context] will each activate the [Context] configural unit to a much greater extent than will the patterns CD[Context] and CE[Context].

<Figure 1 about here>

An alternative explanation for the conflicting results of experiments involving rabbit eye-blink conditioning and pigeon autoshaping was advanced by Brandon and Wagner (1998; Wagner & Brandon, 2001). Their Replaced Elements Model (REM) is an extension of the Rescorla-Wagner model and assumes that individual stimuli are represented as collections of elements. When two or more stimuli are presented in compound, they will activate additional configurational elements in the manner described by Wagner and Rescorla (1972). Other elements of the stimuli are, however, inhibited when they are presented in compound. The representation of any stimulus is, therefore, composed of context-independent elements which are activated whenever the stimulus is present, and context-dependent elements whose activation is affected by the presence of other stimuli. Some context-dependent elements are activated only when the stimulus is presented in compound, and others are activated only when the stimulus is presented alone. Wagner (2003) suggested that one determinant of the extent to which the representations of any two stimuli interact in this manner is the modalities to which they belong. Stimuli within the same modality are assumed to interact to a greater degree than stimuli which belong to different modalities. This interaction is captured within the model by varying the relative proportions of context-independent and context-dependent elements. The parameter,  $r$ , sets the proportion of elements within a stimulus' representation which are replaced when it is presented in compound – that is, the proportion of context-dependent elements.

A series of simulations of REM reported by Wagner (2003) shows that many of the conflicting results from studies employing pigeon autoshaping and rabbit eye-blink conditioning may be explained by the fact that the former set of experiments tend to involve visual stimuli only whereas the latter experiments used stimuli drawn from different modalities. Nevertheless, REM is unable to reconcile the patterning data reported by Pearce and Redhead (1993) and Bahçekapılı (1997). No matter what value is given to the replacement parameter,  $r$ , REM always predicts that the CD+ CE+ CDEo discrimination is learned more rapidly than the A+ B+ ABo discrimination. The middle row of Figure 1 shows predictions derived from simulations of REM when the stimuli interact perceptually to a greater (left panel,  $r = .8$ ) or lesser extent (right panel,  $r = .2$ ).

Despite this failure of REM to predict an effect of stimulus modality on the rate of acquisition of patterning discriminations, Redhead and Curtis (2013) reported just such an effect in a predictive learning experiment in humans. All of their participants were trained concurrently on A+ B+ ABo and CD+ CE+ CDEo discriminations. For half of the participants all stimuli were visual – differently coloured dots on a computer screen. For the remaining participants, they were drawn from visual, auditory, and tactile modalities such that within a discrimination no two stimuli belonged to the same modality. Redhead and Curtis found that when the stimuli were all drawn from the same modality, the A+ B+ ABo discrimination was acquired more rapidly than the CD+ CE+ CDo discrimination. When the stimuli belonged to different modalities, the reverse was true. These results are difficult to explain in terms of either of the models described above. REM predicts no effect of stimulus modality on the relative rate of acquisition of these discriminations. For Configural Theory to explain the findings, one would have to suppose background cues were more salient for the group trained



with stimuli from different modalities. There is no clear *a priori* reason to believe that this should be the case, although Redhead (2007) did find that in a similar predictive learning task participants trained with stimuli from different modalities gave higher ratings to the context than those trained with stimuli from a single modality.

More recently, another explanation of the effects of stimulus modality on the acquisition of patterning discriminations has been advanced by Harris and colleagues (Harris & Livesey, 2010; Thorwart, Livesey & Harris, 2012). Their Attention-Modulated Associative Network (AMAN) is an elemental model of learning in which the activation of representational elements is subject to a normalization processes. Importantly for the current discussion, normalization between elements is affected by their similarity. Harris and Livesey suggested that stimuli from the same modality are more similar to each other than those from different modalities and that this difference in similarity causes the modality effect. Simulations of their model (Harris & Livesey, 2010; Redhead & Curtis, 2013) have confirmed that it makes the appropriate predictions – addition of a common element to a negative patterning discrimination retards acquisition when stimulus similarity is high (common modality) but facilitates acquisition when similarity is low (different modalities). The bottom row of Figure 1 shows predictions derived from simulations of AMAN when the stimulus similarity is high (left panel) or low (right panel).

Unfortunately, it is not always possible to say with confidence which of two patterning discriminations tasks described by Pearce and Redhead (1993; A+ B+ ABCo, CD+ CE+ CDEo) is acquired more rapidly if overall response rates, or ratings, differ between tasks. For example, participants might respond more vigorously to both sets of patterns in one discrimination

than to the corresponding patterns in the other discrimination. In this situation, the absolute difference in response rates between reinforced and non-reinforced patterns might be greater for one discrimination than the other, whereas the relative difference in response rates could show the opposite trend. Where there is no *a priori* reason to believe that either absolute or relative difference in response rate provides a superior measure of learning, such results are ambiguous. This problem may be overcome by having a single signal for the absence of the outcome but multiple signals for the presence of the outcome (or vice versa).

Redhead and Pearce (1995) trained pigeons on complex negative patterning tasks in which a compound of three stimuli presented together was followed by no outcome (ABCo) whereas each individual stimulus (A, B, and C) and the compounds of two stimuli (AB, AC, and BC) were separately paired with food (i.e., A+ B+ C+ AB+ AC+ BC+ ABCo). Configural Theory predicts that the discrimination between the single- and the three-stimulus patterns (A+ B+ C+ ABCo) will be acquired more rapidly than the discrimination between the two- and three-stimulus patterns (AB+ AC+ BC+ ABCo). The Rescorla-Wagner model predicts the opposite pattern of results. In pigeon autoshaping experiments using visual stimuli, Redhead and Pearce observed results consistent with the predictions of Configural Theory, but in an eye-blink conditioning experiment where the three stimuli were drawn from different modalities, Myers et al. (2001) found that rabbits responded in the manner predicted by the Rescorla-Wagner model.

Experiments employing complex negative patterning procedures in humans have not provided such clear results as those involving non-human animals. Kinder and Lachnit (2003) found no difference in responding to single- and two-stimulus patterns in three experiments

involving eyelid conditioning with visual stimuli. In causal learning experiments, also with visual stimuli, Lachnit et al. (2008) observed results broadly consistent with the Rescorla-Wagner model. Lachnit et al. (2013) replicated this finding, but found that participants' performance was sensitive to time pressure. When participants had a limited time in which to respond, their performance was consistent with the predictions of Configural Theory. Redhead (2007) directly addressed the effect of stimulus modality on acquisition of the complex negative patterning discrimination. Some participants were trained using only visual stimuli, whereas for other participants visual, auditory, and tactile stimuli were used. In both cases, the participants gave higher ratings to the single- than to the two-stimulus patterns, as predicted by Configural Theory.

Kinder and Lachnit (2003) suggested that their failure to detect any difference in responding to single- and two-stimulus patterns might have been due to how discriminable the stimuli were from each other. They proposed a modification to Configural Theory which introduced a discriminability parameter,  $d$ , the effect of which is to alter generalization between stimulus patterns. When this parameter is equal to 2, their modified Configural Theory is equivalent to that described by Pearce (1994). Values greater than 2 result in steeper gradients of generalization around patterns. The effect of this is to reduce the predicted difference in responding to single- and two-stimulus patterns when stimuli are more discriminable. Pearce et al. (2008) showed that manipulating this parameter could explain the effects of stimulus similarity on another type of complex patterning discrimination. These observations support the proposal that stimulus similarity might contribute towards the effect of stimulus modality on patterning discrimination learning.

The purpose of the experiments reported here was to directly assess whether, as suggested by Harris and Livesey (2010), differences in stimulus similarity can account for the modality effect that has been reported in the non-human animal literature and, with somewhat less reliability, in the human literature. In each experiment, all participants were trained on patterning discriminations involving only visual stimuli. The similarity of the stimuli used in these patterning discriminations was manipulated between groups of participants. Effects of stimulus similarity under these conditions would support the argument that modality effects reflect differences in similarity.

### **Experiment 1**

In Experiment 1, participants were trained on a relatively simple negative patterning discrimination described by Redhead and Pearce (1995). Presentations of one stimulus (A+) or of two other stimuli in compound (BC+) were followed by one outcome, whereas the compound of all three stimuli was not (ABCo). To ensure that participants attended to the stimuli rather than simply learning to respond on the basis of the number of stimuli present, they were concurrently trained on a positive patterning discrimination involving three other stimuli (Do EFo DEF+).

The predictions of Configural Theory, REM, and AMAN concerning the acquisition of an A+ BC+ ABCo discrimination are less ambiguous than for the Pearce and Redhead (1993) patterning discriminations. Configural Theory predicts that the A+ ABCo component of the discrimination will be acquired more rapidly than the BC+ ABCo component regardless of whether there is a salient background cue present or not. The difference in the rate of acquisition of the two components diminishes as the value of the discriminability parameter,

$d$ , increases. REM, conversely, predicts that the BC+ ABCo component will be acquired more rapidly than the A+ ABCo component. This is true regardless of the degree of perceptual interaction between the stimuli, although when  $r \leq .5$ , the opposite pattern is predicted in the very early stages of learning. Figure 2 shows the predictions concerning the acquisition of an A+ BC+ ABCo discrimination task derived from simulations of Configural Theory (top row) and REM (middle row) under these different conditions. Interestingly, the effect of stimulus similarity on predictions derived from simulations of AMAN are not what might be expected based on the discussion above. These predictions are shown in the bottom row of Figure 2. AMAN predicts that the A+ ABCo discrimination will be acquired more rapidly than the BC+ ABCo discrimination regardless of whether all the stimuli belong to the same modality (high similarity) or if they belong to three different modalities (low similarity), although this difference is predicted to be smaller when the stimuli are less similar.

In the simulations shown in Figure 2, acquisition of the negative (A+ BC+ ABCo) and positive (Do Efo DEF+) patterning discriminations is generally symmetrical. Positive patterning has often been found to proceed more rapidly than negative patterning (e.g., Rescorla, 1972), and different patterns of results have been observed in positive and negative versions of a complex patterning discrimination. For example, (Lachnit et al., 2008) found that participants learned to discriminate between two- and three-stimulus patterns more readily than between single- and three-stimulus patterns in a negative patterning discrimination, but the opposite was true for a positive patterning discrimination. In the experiments reported here, however, symmetrical learning was expected because participants were asked to make predictions regarding two equally likely, and equally salient, alternatives. Livesey, Thorwart and Harris (2011) have shown that under these conditions, positive and negative patterning

discriminations are learned at the same rate. See the appendix for more details of the simulations reported here.

<Figure 2 about here>

The design of Experiment 1 is shown in Table 1. Participants received concurrent training on A+ BC+ ABCo and Do EFo DEF+ discrimination tasks. For all participants, A, B, C, D, E, and F were simple shapes presented on a computer screen (see Figure 3). For Group High Similarity, the six stimuli were identical shapes differing only in their location on the screen. For Group Low Similarity, six different shapes served as the stimuli which were also presented in different screen locations. At the end of the presentation of some patterns (A+; BC+; DEF+) a tone was played over headphones. On each trial, participants were asked to estimate the probability that a tone would be played by making a rating between 1 (certain than there would be no tone) and 9 (certain there would be tone). Based on the assumption that manipulating stimulus similarity would have an effect similar to that which manipulating stimulus modality has previously been shown to have in a similar discrimination task (Redhead & Curtis, 2013), it was expected that participants in Group High Similarity would learn more rapidly about the single stimulus patterns (A+; Do) than about the two stimulus patterns (BC+; EFo). This tendency was expected to be reduced, or reversed, in Group Low Similarity.

<Table 1 about here>

## Method

**Participants.** Thirty-six students at the University of Hull (28 female) were given credit toward course requirements for their participation. They had a mean age of 20.2 years (range 18 – 30), and six were left handed. Each participant was randomly assigned to one of two groups so that there were eighteen participants in each group. One group received training with high similarity stimuli, and the other group received training with low similarity stimuli. Experimental protocols were approved by the ethical review committee of the Department of Psychology, University of Hull.

**Apparatus.** Personal computers running the Windows 7 operating system (Microsoft Corporation, Redmond, WA) and the E-Prime 1.2 software (Psychology Software Tools Inc., Sharpsburg, PA) controlled the presentation of stimuli on a 48-cm colour monitor (aspect ratio 5:4) and recorded responses on a standard 105-key keyboard. Participants were seated approximately 100 cm from the screen and wore stereo headphones (Sennheiser, Wedemark, Germany).

**Stimuli.** Six shapes were, when presented, each located at one of the points of an imaginary regular hexagram. The centre of each shape was 8.3 cm from the middle of the screen, and each shape measured 4 cm x 4 cm (w x h). Stimuli A, B, and C were located at the top, lower-right, and lower-left points of the hexagram, respectively, at the corners of an upright equilateral triangle; D, E, and F were located at the bottom, upper-left, and upper-right points of the hexagram, at the corners of an inverted equilateral triangle. The six shapes were: a black isosceles triangle; a black square; a black circle with three, equally-spaced, 0.6 cm horizontal white stripes; the same circle rotated through 90°; a red circle; and a blue circle. For participants in Group High Similarity, one of these six shapes served as all six stimuli which

therefore differed only in their location on the screen. Which shape was used was determined randomly for each participant in this group, but so that three participants were trained with each of the six shapes. For participants in Group Low Similarity, stimulus A was the black isosceles triangle, and D was the black square. B was the black circle with horizontal white stripes. E was the rotated circle. C was the red circle, and F was the blue circle. The rest of the screen was white during stimulus presentation and the inter-trial-interval (ITI). A 500-ms 880-Hz tone was presented, when appropriate, over the headphones.

<Figure 3 about here>

**Procedure.** Stimuli were presented on the computer screen for 3500ms with an ITI of 2000ms. A small black fixation cross measuring 1cm x 1cm was displayed in the centre of the screen for the last 500ms of the ITI. Where appropriate, the tone was played over headphones during the final 500ms of the stimulus presentation. The order of presentation of the stimuli across trials was pseudo-random, with the constraint that each of the patterns containing one or two stimuli (A, BC, D, and EF) were presented three times, and each of the patterns containing three stimuli (ABC and DEF) were presented six times in each block of 32 trials. There were 8 blocks of trials, making a total of 256 trials.

During the first 3000ms of each trial, participants were required to press one of nine numbered keys (1 – 9) along the top of the keyboard to indicate the extent to which they expected the tone to occur, using a scale of 1 = very unlikely to 9 = very likely. Any responses made after 3000ms were discarded. This amounted to less than 1.3% of all trials, with each participant, on average, failing to respond on 3.2 trials (range 0 – 15; SD = 3.8). Participants were instructed to respond as quickly as they could whilst still making an accurate judgment



of their expectancy of the tone. The tone was played on trials with patterns A, BC, and DEF, but not on trials with patterns ABC, D, or EF. Hence, participants received concurrent training on a negative patterning (A+ BC+ ABCo) and a positive patterning (Do EFo DEF+) task.

## Results and discussion

Mean expectancy ratings for the single-, two-, and three-stimulus patterns for participants in Group High Similarity and Group Low Similarity are shown for each block of training trials in the left and right panels of Figure 4, respectively. Over the course of training, participants in both groups learned which patterns signalled the tone and which patterns did not. By the end of training, all participants were responding differentially on tone and no-tone trials. Participants in Group Low Similarity made more extreme expectancy ratings for single stimulus patterns A+ and Do than for two-stimulus patterns BC+ and EFo. Participants in Group High Similarity showed no such difference and made very similar expectancy ratings for these two types of pattern.

<Figure 4 about here>

To allow meaningful comparison of ratings across the negative and positive patterning tasks, all ratings from the positive patterning task (i.e. those comprising one or more of shapes D, E, and F), were subtracted from 10. This calculation reversed the scale for these stimuli. Consequently, the correct derived expectancy rating for all single- and two-stimulus patterns was greater than 5 regardless of whether the pattern predicted the tone or not. To further simplify the analysis, ratings for the three-stimulus compounds ABCo and DEF+ were not included. We were primarily concerned with the participants' ability to discriminate between single- and three-stimulus patterns relative to their ability to discriminate between two- and

three-stimulus patterns. Because the three-stimulus pattern was the same in each case (e.g., A+ vs. ABCo, BC+ vs. ABCo), this higher-order difference is equivalent to the direct comparison between ratings for the single- and two-stimulus patterns.

A four-way mixed ANOVA of mean expectancy rating was conducted with group (High vs. Low Similarity) as a between-subjects factor, and pattern (single- vs. two-stimulus), trial block (1 to 8), and discrimination (negative vs. positive patterning) as within-subject factors. There was a significant effect of pattern,  $F(1, 34) = 11.40$ ,  $p = .002$ , mean square error (MSE) = 4.94,  $\eta_p^2 = .25$ , 90% CI[.06, .42], reflecting more extreme overall ratings for single- than for two-stimulus patterns. The Group X Pattern interaction was also significant  $F(1, 34) = 7.45$ ,  $p = .01$ , MSE = 4.94  $\eta_p^2 = .18$ , 90% CI[.02, .35], and simple effects analysis of this interaction revealed a significant effect of pattern for Group Low Similarity  $F(1, 34) = 18.64$ ,  $p < .0001$ , but not for Group High Similarity,  $F < 1$ . Participants were better able to discriminate between the single- and three-stimulus patterns than they could discriminate between the two- and three-stimulus patterns in Group Low Similarity. There was no statistical difference in their ability to discriminate between these different patterns in Group High Similarity.

No other interaction involving group was significant, largest  $F(7, 238) = 1.71$ ,  $p = .11$ , and there was no main effect of group,  $F < 1$ . There was a significant effect of trial block,  $F(7, 238) = 82.39$ ,  $p < .0001$ , MSE = 1.71,  $\eta_p^2 = .71$ , 90% CI[.65, .73], and of discrimination,  $F(1, 34) = 9.37$ ,  $p = .004$ , MSE = 1.26,  $\eta_p^2 = .22$ , 90% CI[.04, .39]. A significant interaction of discrimination with trial block,  $F(7, 238) = 2.23$ ,  $p = .03$ , MSE = 1.36,  $\eta_p^2 = .06$ , 90% CI[.00, .09], and a significant Pattern X Trial Block X Discrimination interaction,  $F(7, 238) = 2.20$ ,  $p < .05$ ,

MSE = 1.34,  $\eta_p^2 = .06$ , 90% CI[.00, .09], appear to be caused by ratings for Efo changing at a slower pace than those for BC+ in Group Low Similarity.

These results are the opposite to those expected based on previous experiments involving stimuli drawn from either a single modality or from multiple modalities and the suggestion that differences in stimulus similarity are responsible for the influence of modality. The results from Group Low Similarity are, however, consistent with the predictions of Configural Theory and AMAN. Although both Configural Theory and AMAN predict the same pattern of results for Group High Similarity, participants in this group learned the discrimination very quickly, as predicted by all three theories (see Figure 2). The analysis reported above found no main effect of group or a Group X Block interaction, but inspection of Figure 4 suggests that participants in Group High Similarity learned about the outcome on ABC and DEF trials much more rapidly than those in Group Low Similarity. To determine whether this was the case, a composite rating for patterns ABC and DEF was calculated in the same manner as for single- and two-stimulus patterns described above. A two-way ANOVA conducted on this composite rating with the factors of group and trial block revealed a significant Group x Block interaction,  $F(7, 238) = 4.03$ ,  $p < .001$ , MSE = .47,  $\eta_p^2 = .11$ , 90% CI[.03, .15], confirming that Group High Similarity learned more rapidly than Group Low Similarity. Because of this rapid learning, it is possible that the procedure employed in Experiment 1 lacked sensitivity to detect differences in learning rate predicted for Group High Similarity. To explore this possibility, participants in Experiment 2 were trained on a more complex version of the same patterning discrimination which they were expected to acquire more slowly, allowing greater opportunity to observe differences in learning rate.

## Experiment 2

In Experiment 2 participants were trained on a complex patterning discrimination described by Redhead and Pearce (1995) where any one of three stimuli, and any combination of two of those stimuli signalled the presentation of a tone but the combination of all three stimuli signalled no tone (see Table 1). That is, a discrimination of the form  $A+ B+ C+ AB+ AC+ BC+ ABCo$ . To prevent participants from using numerosity as a predictor of the tone, they were concurrently trained on a  $Do Eo Fo DEo DFo Efo DEF+$  discrimination.

Figure 5 shows predictions derived from simulations of Configural Theory (top row), REM (middle row), and AMAN (bottom row). In the absence of a salient contextual cue, Configural Theory predicts that the  $A/B/C+ ABCo$  and  $D/E/Fo DEF+$  discriminations will be acquired more rapidly than the  $AB/AC/BC+ ABCo$  and  $DE/DF/Efo DEF+$  discriminations. The difference between these sets of discriminations is predicted to diminish, but not reverse, when the discriminability of the individual stimuli is high. With the addition of a salient contextual cue, Configural Theory makes the same general prediction, with the exception that the associative strength of the two-stimulus patterns AB, AC, and BC is predicted to be slightly higher than that of the individual stimuli A, B, and C, very early in training. AMAN predicts that the associative strength of the two-stimulus patterns will be higher than that of the individual stimuli which compose them for both the positive and negative patterning discrimination tasks. This effect is predicted to be greater for stimuli within the same modality. The simulations of REM predict the opposite effect to that which has been observed in non-human animals. When perceptual interaction between stimuli is high ( $r = .8$ ), the discrimination between two- and three-stimulus patterns is predicted to be acquired more

rapidly than that between single- and three-stimulus patterns. The opposite result is predicted when perceptual interaction between stimuli is low ( $r = .2$ ).

<Figure 5 about here>

## Method

**Participants.** Thirty six students at UNSW Australia (23 female) were given credit toward course requirements for their participation. They had a mean age of 19.3 years (range 17 – 39), and 3 were left handed. Each participant was randomly assigned to one of two groups so that there were eighteen participants in each group. The first group received training with low similarity stimuli, and the second group received training with high similarity stimuli. Experimental protocols were approved by the ethical review committee of the School of Psychology, UNSW Australia.

**Apparatus and stimuli.** Details of the apparatus and stimuli were the same as for Experiment 1.

**Procedure.** The procedure were the same as for Experiment 1 with the following exceptions. Within each block of 48 trials, each of the patterns A, B, C, AB, AC, BC, D, E, F, DE, DF, and EF was presented twice and patterns ABC and DEF were each presented 12 times. There were 8 blocks of trials, making a total of 384 trials. The tone was played on trials with patterns A, B, C, AB, AC, BC, and DEF but not on trials with patterns ABC, D, E, F, DE, DF, or EF. Hence, participants received concurrent training on a complex negative patterning (A+B+ C+ AB+ AC+ BC+ ABCo) and a complex positive patterning (Do Eo Fo DEo DFo Efo DEF+) task.

1.7% of responses were discarded because they were made more than 3000ms after the beginning of the trial. On average each participant failed to respond on 6.4 trials (range 0 – 31; SD = 8.4).

## Results and discussion

The left and right panels of Figure 6 show the mean expectancy ratings for the single-, two-, and three-stimulus patterns for participants in Group High Similarity and Group Low Similarity, respectively. Participants in the Group Low Similarity showed much the same pattern of responding as those in Experiment 1. They made more extreme expectancy rating for single-stimulus patterns than for two-stimulus patterns. Participants in Group High Similarity, however, showed the opposite pattern of results. They made more extreme ratings for two-stimulus patterns than for single-stimulus patterns.

<Figure 6 about here>

Data were transformed in the same manner as described for Experiment 1 to simplify analysis. A four-way ANOVA of mean expectancy rating was conducted with group (Low vs. High similarity), pattern (single- vs. two-stimulus), trial block (1 to 8), and discrimination (negative vs. positive patterning) as factors. There was no significant effect of pattern,  $F(1, 34) = .17, p = .68$ , or of group,  $F < 1$ , but there was a significant Pattern X Group interaction,  $F(1, 34) = 21.57, p < .0001, MSE = 2.17, \eta_p^2 = .39, 90\% CI[.17, .54]$ . Simple effects analysis revealed that participants in Group Low Similarity made significantly higher ratings for single-stimulus patterns than for two-stimulus patterns,  $F(1, 34) = 8.95, p = .005$ , and that participants in Group High Similarity made significantly higher ratings for two-stimulus patterns than for single-stimulus patterns,  $F(1, 34) = 12.77, p = .001$ . Hence, participants in

Group Low Similarity learned the discrimination between A/B/C+ and ABCo more rapidly than the discrimination between AB/AC/BC+ and ABCo. Participants in Group High Similarity learned the discrimination between AB/AC/BC+ and ABCo more rapidly than the discrimination between A/B/C+ and ABCo. The equivalent pattern of results was evident in the positive patterning discrimination.

There were significant effects of discrimination,  $F(1, 34) = 7.16, p = .01, MSE = 5.42, \eta_p^2 = .17, 90\% CI[.02, .35]$ , and of trial block,  $F(7, 238) = 73.41, p < .0001, MSE = 5.42, \eta_p^2 = .68, 90\% CI[.62, .72]$ , and a significant interaction between these factors,  $F(7, 238) = 2.32, p = .03, MSE = 1.88, \eta_p^2 = .06, 90\% CI[.00, .09]$ . This interaction reflects more extreme ratings for the negative patterning discrimination than for the positive patterning discrimination on the second trial block. No other interaction was significant, largest  $F(7, 238) = 1.66, p = .12$ .

The results from Group Low Similarity are very similar to those in the corresponding group in Experiment 1. Participants learned more rapidly about the outcomes associated with single stimuli than they did about the outcomes associated with two-stimulus patterns – results consistent with those that have previously been observed in pigeon autoshaping experiments by Redhead and Pearce (1995). Whereas no statistical difference was found between the rates of learning about single- and two-stimulus patterns for Group High Similarity in Experiment 1, here the corresponding group learned more rapidly about the outcomes associated with two-stimulus patterns than they did about the individual stimuli. This pattern of results is consistent with those obtained in a rabbit eye-blink experiment by Meyer et al (2001).

The overall pattern of results is not consistent with Configural Theory, which predicts no overall effect of stimulus similarity, or of AMAN, which fails to capture the performance of either group of participants. The results are, however, consistent with the predictions of REM if we assume that perceptual interaction between stimuli is correlated with their similarity, and that there was a substantial difference in perceptual interaction between the two groups. While these predictions might at first appear to be opposite to those expected based on the results of experiments involving non-human animals (e.g., Redhead & Pearce, 1995; Myers et al, 2001), this difference is a consequence of how the outcomes were represented in these simulations. The two outcomes in the current experiment (tone and no-tone) were equally salient and equally likely alternatives, and at the start of the experiment participants had no reason to associate either more strongly with any pattern. Hence, the outcomes were given values equally, and oppositely, different to the neutral baseline associative strength of each stimulus element ( $+\lambda$ ;  $-\lambda$ ).

### Experiment 3

In Experiment 3, participants were trained on a variant of the patterning discrimination task used in Experiment 1. This problem can be described as a parity problem since patterns containing an odd number of stimulus elements were associated with a different outcome to patterns containing an even number of stimuli. The design of the experiment is shown in Table 1. All participants were trained on a negative parity discrimination of the form  $A+ BCo ABC+$  and a positive parity problem of the form  $Do EF+ DEFo$ . The two discrimination problems were presented concurrently to prevent participants from being able to solve them based purely on the number of stimuli present on each trial.



Predictions concerning the acquisition of an A+ BCo ABC+ discrimination by Configural Theory, REM, and AMAN are shown in Figure 7. Like those for the complex patterning discrimination used in Experiment 2, the predictions derived from each model are different to each other but are largely unaffected by variations in stimulus modality or stimulus similarity except in the case of REM. Configural Theory (top row) predicts more extreme ratings for A and D than for ABC and DEF. AMAN (bottom row) makes similar predictions to Configural Theory. REM predicts that ratings of ABC and DEF will be more extreme than those of A and D when perceptual interaction is high ( $r \geq .5$ ) but that ratings of A and D will be more extreme than those of ABC and DEF when perceptual interaction is low ( $r = .2$ ).

<Figure 7 about here>

A discrimination of the form A+ BCo ABC+ has previously been used with human participants in skin conductance response (SCR) and eye-blink conditioning procedures by Thorwart and Lachnit (2007). Using coloured dot stimuli very similar to those employed by Redhead and Pearce (1995), their results were mixed, but provided some support for the predictions of Configural Theory. The first interval response of SCR conditioning was greater on A+ trials than on ABC+ trials. Based on the results from Experiments 1 and 2, this pattern of results was expected for participants in Group Low Similarity. For Group High Similarity, the difference in rating for single stimuli and the three-stimulus compound was expected to be reduced or reversed.

## Method

**Participants.** Thirty six students at the University of Hull (25 female) were given credit toward course requirements for their participation. They had a mean age of 20.3 years (range 19 –

35), and one was left handed. Each participant was randomly assigned to one of two groups so that there were eighteen participants in each group. The first group received training with low similarity stimuli, and the second group received training with high similarity stimuli. Experimental protocols were approved by the ethical review committee of the Department of Psychology, University of Hull.

**Apparatus and stimuli.** The apparatus and stimuli were the same as for Experiment 1.

**Procedure.** All details of the procedure were the same as for Experiment 1 with the following exceptions. Within each block of 24 trials, each of the patterns A, BC, ABC, D, EF, and DEF was presented four times. There were 8 blocks of trials, making a total of 192 trials. The tone was played on trials with patterns A, ABC, and EF, but not on trials with patterns BC, D, or DEF. Hence, participants received concurrent training on a negative parity (A+ BCo ABC+) and a positive parity (Do EF+ DEFo) task.

Responses from 1.2% of trials were discarded because they were made more than 3000ms after the beginning of the trial. On average each participant failed to respond on 2.2 trials (range 0 – 8; SD = 2.3).

## **Results and discussion**

Mean expectancy ratings for participants in Group High Similarity and Group Low Similarity are shown for each block of training trials in the left and right panels of Figure 8, respectively. Participants in Group Low Similarity made more extreme expectancy rating for single-stimulus patterns than for three-stimulus patterns. For participants in Group High Similarity, the rating given to the three-stimulus patterns were more extreme than those

given to the single-stimulus patterns, but the difference in these ratings was much smaller than for Group Low similarity.

<Figure 8 about here>

Data were transformed in the same manner as described for Experiment 1. The type of patterning discriminations used in this experiment was rather different to those used in the previous experiments. Here, we were interested in participants' ability to discriminate between single- and two-stimulus patterns and between three- and two-stimulus patterns. Hence, the most meaningful comparison was between ratings for single- and three-stimulus patterns. Only these data were analysed. A four-way ANOVA of mean expectancy rating was conducted with group (Low vs. High similarity), pattern (single- vs. three-stimulus), trial block (1 to 8), and discrimination (negative vs. positive patterning) as factors. There was a significant effect of trial block,  $F(7, 238) = 76.36$ ,  $p < .0001$ ,  $MSE = 1.44$ ,  $\eta_p^2 = .69$ , 90% CI[.63, .72]; participants' ratings became more extreme over the course of training. There were also significant effects of pattern,  $F(1, 34) = 5.99$ ,  $p = 0.02$ ,  $MSE = 3.00$ ,  $\eta_p^2 = .15$ , 90% CI[.01, .32], and discrimination,  $F(1, 34) = 9.25$ ,  $p = .005$ ,  $MSE = 1.50$ ,  $\eta_p^2 = .21$ , 90% CI[.04, .39], but not of group,  $F < 1$ . The Group X Pattern,  $F(1, 34) = 8.60$ ,  $p = .006$ ,  $MSE = 3.00$ ,  $\eta_p^2 = .20$ , 90% CI[.04, .38], and Group X Pattern X Trial Block,  $F(7, 238) = 7.80$ ,  $p < .0001$ ,  $MSE = .78$ ,  $\eta_p^2 = .19$ , 90% CI[.10, .24], interactions were significant. Simple effects analyses revealed that Group Low Similarity made significantly higher rating for the single-stimulus patterns than for the three-stimulus patterns,  $F(1, 34) = 14.47$ ,  $p < .001$ , and that rating for these patterns did not differ for Group High Similarity,  $F < 1$ . The difference in ratings for Group Low Similarity was large

on early trial blocks, but diminished as training progressed as ratings for both types of pattern approached ceiling.

Interactions of Pattern X Discrimination,  $F(1, 34) = 4.16, p < .05, \text{MSE} = 1.83, \eta_p^2 = .11, 90\% \text{ CI} [.00, .28]$ , Pattern X Trial Block,  $F(7, 238) = 3.35, p = .002, \text{MSE} = .78, \eta_p^2 = .09, 90\% \text{ CI} [.02, .13]$ , Discrimination X Trial Block,  $F(7, 238) = 5.73, p < .0001, \eta_p^2 = .14, 90\% \text{ CI} [.06, .19]$ , and Pattern X Discrimination X Trial Block,  $F(7, 238) = 4.22, p < .001, \text{MSE} = .77, \eta_p^2 = .11, 90\% \text{ CI} [.04, .15]$ , were also significant. Remaining interactions failed to reach significance, largest  $F(7, 238) = 1.11, p = .36$ .

The results of this experiment are consistent with those from Experiment 1. Participants in Group Low Similarity made more extreme ratings for the single stimuli (A+ and Do) than for the three-stimulus compounds (ABC+ and DEFo). There was no statistical difference in ratings for participants in Group High Similarity. The results from Group Low Similarity are consistent with all three models. Neither Configural Theory nor AMAN can explain the results from Group High Similarity. REM can explain the results from both groups, but only if we assume that there was relatively little perceptual interaction between stimuli in both cases. REM predicts that the A+ BCo and ABC+ BCo discriminations will be learned at approximately the same rate when  $r = .3$ , however to explain the performance of Group High Similarity in Experiment 2 we must assume that  $r \geq .5$  for the same stimuli.

Inspection of Figure 8 suggest that, like in Experiment 1, Group High Similarity learned the discrimination rapidly. It is possible that this rapid learning masked any differences in the rate of acquisition of the component discriminations for this group. Consequently, in Experiment 4, participants were trained on a more complex version of the same parity

discrimination which they were expected to acquire more slowly, allowing greater opportunity to observe differences in learning rate.

#### **Experiment 4**

Participants in Experiment 4 were trained on two concurrent complex parity discriminations of the forms A+ B+ C+ ABo ACo BCo ABC+ and Do Eo Fo DE+ DF+ EF+ DEFo (see Table 1). One group of participants was trained using the high similarity stimuli used in Experiments 1 to 3, whereas a second group of participants was trained using the low similarity stimuli. This type of discrimination problem has previously been employed by Pearce et al (2008). In one experiment, they trained pigeon using stimuli comprising dots of different colours, and found that pigeons responded more rapidly in the presence of A, B, or C than in the presence of ABC, and much less rapidly in the presence of AB, AC, or BC. In a second experiment, they employed stimuli much like those used with the high similarity groups in the experiments reported here. The stimuli were simple white circles differentiated only by their position. In that experiment, the pigeons were unable to solve the discrimination. They responded most rapidly in the presence of A, B, or C, but less rapidly to the compound ABC than to the two-stimulus patterns AB, AC, and BC. A Simulation of Configural Theory reported by Pearce et al generated predictions that were consistent with this latter result. Pearce et al also found that when Kindle and Lachnit's (2003) discriminability parameter was increased from 2 to 3, Configural Theory predicted that the net associative strength of the two-stimulus patterns AB, AC, and BC would be lower than that of the individual stimuli or the compound ABC. Based on these results and simulations, we would predict that participants in Group High Similarity should behave much like the pigeons in

Pearce et al's second experiment and fail to solve the discrimination. Participants in Group Low Similarity, however, should learn the discrimination in much the same way as in Experiment 3, solving the A+ B+ C+ ABo ACo BCo discrimination more rapidly than the ABC+ ABo ACo BCo discrimination. These predictions are shown in the top row of Figure 9. Inclusion of a salient contextual cue is predicted to significantly retard learning, but does not affect the ordinal associative strength of single- and three-stimulus patterns.

<Figure 9 about here>

REM (Figure 9, middle row) predicts that the three-stimulus patterns will attract more extreme rating than the single-stimulus patterns regardless of the value of the replacement parameter,  $r$ . AMAN predicts the opposite pattern of results – generally more extreme rating for single- than for three-stimulus patterns, although rating for ABC+ are predicted to be higher than those for A+, B+, and C+ early in training. This early reversal is predicted to be more extreme and longer lasting when the stimuli are more similar to each other.

## Method

**Participants.** Thirty six students at UNSW Australia (20 female) were given credit toward course requirements for their participation. They had a mean age of 19.1 years (range 18 – 23), and 4 were left handed. Each participant was randomly assigned to one of two groups so that there were eighteen participants in each group. The first group received training with low similarity stimuli, and the second group received training with high similarity stimuli. Experimental protocols were approved by the ethical review committee of the School of Psychology, UNSW Australia.

**Apparatus and stimuli.** Details of the apparatus and stimuli were the same as for Experiment 1.

**Procedure.** The procedure were the same as for Experiment 1 with the following exceptions. Within each block of 42 trials, each of the patterns A, B, C, AB, AC, BC, ABC, D, E, F, DE, DF, EF, and DEF was presented three times. There were 8 blocks of trials, making a total of 336 trials. The tone was played on trials with patterns A, B, C, ABC, DE, DF, and EF but not on trials with patterns AB, AC, BC, D, E, F, or DEF. Hence, participants received concurrent training on a complex negative parity (A+B+ C+ ABo ACo BCo ABC+) and a complex positive patterning (Do Eo Fo DE+ DF+ EF+ DEFo) task.

Participants failed to respond within 3000ms of the beginning of 1.9% of trials. On average each participant failed to respond on 6.3 trials (range 0 – 22; SD = 6.0).

## Results and discussion

Expectancy ratings for the single-, two-, and three-stimulus patterns for participants in the Group High Similarity and Group Low Similarity are shown for each block of training trials in the left and right panels of Figure 10, respectively. Participants in Group Low similarity made more extreme expectancy rating for single-stimulus patterns than for three-stimulus patterns, although this pattern of responding was only evident for the positive parity discrimination. Rating of single- and three-stimulus patterns in the negative parity discrimination were equivalent for this group. For participants in Group High Similarity, the rating given to the three-stimulus patterns were more extreme than those given to the single-stimulus patterns, and the difference in these ratings was present in both the negative and positive parity discriminations.

<Figure 10 about here>

Data were transformed in the same manner as described for Experiment 3. A four-way ANOVA of mean expectancy rating was conducted with group (Low vs. High similarity), pattern (single- vs. three-stimulus), trial block (1 to 8), and discrimination (negative vs. positive patterning) as factors. There was no significant effect of either group,  $F(1, 34) = 2.88$ ,  $p = .10$ , or pattern,  $F(1, 24) = 1.19$ ,  $p = 0.29$ , but there was a significant Group x Pattern interaction,  $F(1, 34) = 27.44$ ,  $p < .0001$ ,  $MSE = 4.27$ ,  $\eta_p^2 = .45$ , 90% CI[.23, .59]. There was also a significant interaction of group and pattern with discrimination,  $F(1, 34) = 6.31$ ,  $p = .02$ ,  $MSE = 2.06$ ,  $\eta_p^2 = .16$ , 90% CI[.02, .33]. Simple effects analysis revealed that there was a significant effect of pattern in Group Low Similarity for the positive parity discrimination,  $F(1, 68) = 42.99$ ,  $p < .0001$ , but not for the negative parity discrimination,  $F < 1$ . There was a significant effect of pattern for Group High Similarity for both the positive,  $F(1, 68) = 8.62$ ,  $p = .005$ , and negative parity,  $F(1, 68) = 19.47$ ,  $p < .0001$ , discriminations.

There were also effects of discrimination,  $F(1, 34) = 28.0$ ,  $p < .0001$ ,  $MSE = 2.81$ ,  $\eta_p^2 = .45$ , 90% CI[.23, .59], and trial block,  $F(7, 238) = 140.37$ ,  $p < .0001$ ,  $MSE = 1.69$ ,  $\eta_p^2 = .81$ , 90% CI[.77, .83], and a significant Discrimination X Trial Block interaction,  $F(7, 238) = 3.75$ ,  $p = .001$ ,  $MSE = 1.19$ ,  $\eta_p^2 = .10$ , 90% CI[.03, .14]. The interactions of discrimination with pattern,  $F(1, 34) = 18.84$ ,  $p = .0001$ ,  $MSE = 2.06$ ,  $\eta_p^2 = .36$ , 90% CI[.14, .51], and trial block with pattern,  $F(7, 238) = 2.24$ ,  $p = .03$ ,  $MSE = 1.49$ ,  $\eta_p^2 = .06$ , 90% CI[.00, .09], were significant. There was no significant interaction of group with either discrimination,  $F(1, 34) = 1.1$ ,  $p = .30$ , or trial block,  $F(7, 238) = 1.51$ ,  $p = .16$ . The three-way interactions of Group X Pattern X Trial Block,  $F(7, 238) = 3.92$ ,  $p < .001$ ,  $MSE = 1.49$ ,  $\eta_p^2 = .10$ , 90% CI[.03, .14], and Pattern X Discrimination X Trial



Block,  $F(7, 238) = 2.79$ ,  $p < .01$ ,  $MSE = 1.18$ ,  $\eta_p^2 = .08$ , 90% CI[.01, .11], were significant. The remaining three-way interaction of Group X Discrimination X Trial Block,  $F(7, 238) = 1.36$ ,  $p = .22$ , and the four-way interaction,  $F < 1$ , were not significant.

The results are consistent with those from the previous three experiments. Participants trained with low similarity stimuli performed in a manner broadly consistent with Configural Theory when the discriminability parameter  $d > 2$ , and with AMAN; they made more extreme ratings when presented with individual stimuli than they did when presented with compounds containing three stimuli. Participants trained with the high similarity stimuli showed the opposite pattern of behaviour, which was consistent with the prediction of REM.

### General Discussion

In four experiments, the effects of stimulus similarity on the acquisition of complex patterning discrimination tasks was investigated. Previous research has found that when animals or humans are trained with stimuli drawn from a single stimulus modality, such patterning discriminations are often acquired in a manner consistent with the predictions of Configural Theory (e.g., Pearce & Redhead, 1995; Redhead, 2007; Redhead & Curtis, 2013). If, however, the stimuli are drawn from different modalities, the discriminations are sometimes acquired in a manner consistent with elemental models of learning such as the Rescorla-Wagner model or REM (e.g., Bahçekapılı, 1997; Redhead & Curtis, 2013). The primary purpose of the experiments reported here was to test the suggestion that the effects of stimuli modality might be explained in terms of variation in stimulus similarity (Harris & Livesey, 2010). It is difficult to derive absolute predictions concerning the acquisition of the discrimination tasks used in these experiments in the absence of an objective measure of

stimulus similarity. Nevertheless, we might assume that patterning discriminations involving highly similar stimuli should have a greater probability of being solved in a manner consistent with Configural Theory than those involving less similar stimuli. Conversely, patterning discriminations involving very dissimilar stimuli should have a greater probability of being solved in a manner consistent with the Rescorla-Wagner model than those involving more similar stimuli.

The results of the experiments did not support these predictions. In Experiment 1, participants were trained on a patterning discrimination of the form A+ BC+ ABCo. When the stimuli were drawn from different perceptual dimensions (colour, shape, and orientation), participants acquired the A+ ABCo discrimination more rapidly than the BC+ ABCo discrimination, consistent with the predictions of Configural Theory. When the stimuli were highly similar, differing only in location, there was no statistical difference in the rates of acquisition of the two discriminations. Experiment 3 employed a parity discrimination of the form A+ BCo ABC+ and yielded very similar results. Participants trained with the low similarity stimuli solved the A+ BCo discrimination more readily than they solved the ABC+ BCo discrimination, whereas participants trained with highly similar stimuli solved the two discriminations at the same rate.

In both of these experiments there was some indication that participants learned the discrimination tasks more rapidly when the stimuli were highly similar. In case this rapid learning masked any differences in the rate of learning different components of the patterning discrimination, Experiments 2 and 4 employed more complex versions of the tasks in an attempt to retard learning. In Experiment 2, participants were trained on the complex

patterning discrimination A+ B+ C+ AB+ AC+ BC+ ABCo. When participants were trained with the low similarity stimuli, results were again consistent with the predictions of Configural Theory; the A/B/C+ ABCo discrimination was learned more rapidly than the AB/AC/BC+ ABCo discrimination. Results consistent with the predictions of the Rescorla-Wagner model were found when the stimuli were highly similar; the AB/AC/BC+ ABCo discrimination was learned more rapidly than the A/B/C+ ABCo discrimination. In Experiment 4, a complex parity discrimination of the form A+ B+ C+ ABo ACo BCo ABC+ generated similar results. The ABC+ AB/AC/BCo discrimination was acquired more rapidly when the stimuli were very similar, and the A/B/C+ AB/AC/BCo discrimination was learned more rapidly when the stimuli were less similar.

Taken together the results of the four experiments are difficult to explain in terms of either Configural Theory, REM, or AMAN. The predictions of Configural Theory regarding the each experiment are largely unaffected either by the addition of a salient contextual stimulus or an increase in the discriminability of the stimuli operationalised as an increase in the value of the parameter  $d$ . The former manipulation tends to retard learning whereas the latter manipulation speeds it up, but the relative pattern of ratings remains the same. The exception is Experiment 4, where the discrimination is predicted to be insoluble when  $d = 2$ . The predictions of AMAN are more complicated, but again are unaffected by stimulus modality (or stimulus similarity) in the case of the patterning tasks used in these experiments. For Experiment 1 and 3, AMAN predicts that rating should be more extreme for individual stimuli than for compound stimuli. In Experiment 2, it predict that rating should be higher for compound stimuli than for individual stimuli for both the positive and negative patterning discriminations. In Experiment 4, it predicts same pattern as for Experiment 2 very early in

training but the same pattern as for Experiments 1 and 3 later on. No such switch-over was observed in any of the experiments, and the performance of Group Low Similarity and Group High Similarity differed in each experiment in contrast to these predictions. Simulations of REM suggest that its predictions are sensitive to changes in perceptual interaction between stimuli for the discriminations reported here. For Experiments 1 and 4 REM predicts more extreme rating to stimulus compounds than to the individual stimuli, and this difference is predicted to be smaller for smaller values of  $r$ . For Experiment 2 and 3, REM correctly predicts this same pattern when  $r$  is large, but the opposite pattern when  $r$  is small. Although these latter predictions are broadly consistent with the results of those Experiments, parameter values for the two sets of stimuli must differ between the two experiments in order to predict the correct results. In Experiment 3, REM makes the correct predictions when  $r > .5$  for the high similarity stimuli and  $r < .5$  for the low similarity stimuli. In Experiment 4, the corresponding values are  $r \approx .3$ , and  $r < .3$ .

While we have considered two elemental models of learning – REM and AMAN – in some detail, other models might also be able to account for modality effects in patterning discriminations. McLaren and Mackintosh (2000, 2002; McLaren, Kaye & Mackintosh, 1989) proposed a real-time elemental model of learning the predictions of which may be influenced by the amount of learning which occurs on each trial. McLaren and Mackintosh (2002) considered the simple case of an A+ AYo discrimination and the effect of adding a common element on each trial to generate an AX+ AXYo discrimination. They showed that when the amount learned on any trial is low, then their model makes the same predictions as the Rescorla-Wagner model; the addition of the common element facilitates acquisition. When, however, the amount learned on each trial is high, the model makes the same prediction as

Configural Theory; the addition of a common element retards learning. This effect of learning rate is a consequence of the model's real-time nature and its prediction of one-trial overshadowing. There is, however, little reason to suppose that McLaren and Mackintosh's provides an adequate explanation of the results reported here. Visual inspection of Figures 4, 6, 8, and 10 suggests that in each experiment participants in Group High Similarity learned more rapidly than those in Group Low Similarity, although this observation was not confirmed in any case by analysis of variance. Nevertheless, this apparent difference is in the direction opposite to that expected based on the predictions of McLaren and Mackintosh's model. In each experiment Group High Similarity acquired the discriminations in the manner predicted by the Rescorla-Wagner model whereas results from Group Low Similarity were more consistent with the predictions of Configural Theory.

Some consideration must be given to the choice of stimuli in the current experiments. It is possible that the low similarity stimuli, all drawn from the same modality, were insufficiently dissimilar to have the same effect on learning as stimuli drawn from different modalities. Indeed, these stimuli were almost the same as those employed by Pearce and George (2002) in a pigeon autoshaping experiment with the exception that those involved in the positive and negative patterning discriminations were displayed in different locations on the screen. Pearce and George argued that stimuli from different perceptual dimensions, even within a single modality, should be less likely to perceptually interact with each other than the colour dots used by Redhead and Pearce (1995). Nevertheless, they found the same pattern of results as Redhead and Pearce. Pigeons trained on a complex negative patterning discrimination of the form A+ B+ C+ AB+ AC+ BC+ ABCo responded more rapidly in the presence of the individual stimuli than in the presence of the two-stimulus patterns. The

behaviour of participants in Group Low Similarity in Experiment 2 was consistent with that of the pigeons; they made more extreme rating for the individual stimuli. This does not, however, undermine the rationale for these experiments. If modality effects in patterning discriminations are a consequence of differences in stimulus similarity, increasing similarity should have resulted in more evidence of configural processing and a greater advantage for the individual stimuli, rather than abolishing or reversing it. This prediction does not depend upon absolute positions of the stimulus sets on the similarity continuum, but rather their relative positions.

Similarly, the high similarity stimuli used here are much like those that Pearce et al (2008) employed to train pigeons on a complex parity discrimination of the form  $A+ B+ C+ ABo ACo BCo ABC+$ , in that they were differentiated only by screen location. Consistent with the predictions of Configural Theory, Pearce et al found that pigeons could not solve the discrimination; they responded less rapidly to the reinforced three-stimulus compound than to the non-reinforced two-stimulus compounds. When trained with less similar stimuli – dots of different colours – pigeons could solve the discrimination. Pearce et al suggested that stimulus similarity might affect the shape of gradients of generalization between stimulus patterns (c.f. Kinder & Lachnit, 2003). Participants in Group Low Similarity in Experiment 4 acquired the discrimination in much the same way as the pigeons that Pearce et al trained with coloured dots. They made more extreme ratings for single stimuli than for the three-stimulus compounds. Group High Similarity also solved the discrimination, but showed the opposite patterning; they made more extreme ratings for the three-stimulus compounds. Not only is this not consistent with Pearce et al's results, there is no value of Kinder and Lachnit's discriminability parameter which will allow Configural Theory to predict these results.

A number of authors have suggested that the reason why some experiments provide support for elemental processing of stimuli, while others support configural processing, is that the two approaches are not mutually exclusive, but may be used with some flexibility (e.g., Melchers, Shanks, & Lachnit, 2008; Thorwart & Lachnit, 2010; Lachnit et al., 2013). That is, under some conditions, humans and animals might process stimuli elementally, whereas under other conditions they might process them configurally. If this is the case, then a model of learning based on one representational scheme or the other is unlikely to be able to predict behaviour in each situation. Melchers et al reviewed the evidence for flexible stimulus processing and identified five factors which influence whether stimuli are processed elementally or configurally: task demands, prior experience, experimental instructions, stimulus properties, and stimuli organisation. In the experiments reported here, the task demands and participant instructions did not differ between conditions, and since participants were randomly assigned to one condition or the other there is no reason to suppose that their prior experience differed systematically. Stimulus properties did differ between conditions, and these in turn may have affected apparent stimulus organisation.

One stimulus property which has already been discussed at length is modality. The purpose of the experiments was to determine whether modality effects might be explained in terms of differences in stimulus similarity. Hence, all of the stimuli employed were visual but differed in similarity. There are, however, explanations for the modality effect other than similarity. One is that stimuli from within the same modality might be more likely to perceptually interact with each other than those from different dimensions (e.g., Wagner, 2003). The low similarity stimuli were chosen from different perceptual dimensions specifically to avoid such interactions (see Pearce & George, 2002). The high similarity stimuli

were identical, save for location, and might therefore also be expected to interact little with each other. It is possible that greater perceptual interaction between the low similarity stimuli may explain the results of all four experiments, but there is no strong case for believing this to be true. A related explanation is that stimuli might mask the perception of each other (Myers et al, 2001). Masking should be greater when stimuli are competing for the same perceptual resources, within a modality, or perhaps within a stimulus dimension. It is difficult to derive clear predictions of how masking might differentially affect the low and high similarity stimuli. Given an assumption that people have a limited capacity to process visual information, it is possible that the more information dense low similarity stimuli would mask each other to a greater extent, biasing people towards configural processing. Equally, if some aspects of stimulus processing occur in parallel, one could argue that the high similarity stimuli will compete more effectively for the same processing resources than compounds of more diverse stimuli which might be processed through more distributed channels. In that case, the opposite prediction would be made.

A third factor that might influence the processing of different stimuli within a single modality is whether they differ on integral or separable dimensions (Garner, 1974). In summation experiments, Lachnit (1988) found results consistent with elemental processing when stimuli differed on separable dimensions (line drawings which differed in size and orientation), and configural processing when they differed along integral dimensions (chroma and value of colour patches). Again, this factor is unlikely to provide an adequate explanation of the current results since the low similarity stimuli which differed along four separable dimensions (shape, colour, orientation, and location) yield results consistent with configural models of learning, whereas the high similarity stimuli which differed along a single dimension



(location) were learned about in a manner more consistent with elemental models of learning.

The final factor that might be relevant to the stimuli employed here is their organization. Glautier (2002; see also Livesey & Boakes, 2004) found evidence that stimuli presented close together were processed configurally, whereas those presented more distant to each other were processed elementally. In the current experiments, the stimuli were arranged in triangular formations. Since the high similarity stimuli differed only in their location it is possible that their spatial organisation was more salient than for the low similarity stimuli where location may have been overshadowed to some degree by the other differences between the stimuli. In that case, however, the low similarity stimuli would have been less likely to be processed configurally than the high similarity stimuli which was not what was observed.

Taken together, the results of the experiments presented here present a challenge for current models of associative learning and for the explanations of modality effects in patterning discriminations that they provide. One explanation for the results is that people may flexibly process stimuli in either a configural or elemental manner, and that the manipulation of stimulus similarity biased the participants in one direction or the other. It is, however, difficult to identify exactly why that might be the case given the stimuli used here. Nevertheless, the current experiments do provide reliable evidence that a within-modality manipulation of stimulus similarity affects the acquisition of patterning discrimination tasks.

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### **Appendix – details of simulations**

For all simulations reported here, training was divided in a number of cycles. Each cycle consisted of the presentation of each training pattern, weighted in the same manner as in the corresponding experiment. Hence, for simulations of Experiment 1, each cycle consisted on one presentation of each of the patterns A+, BC+, Do, and Efo, and two presentations of ABCo and of DEF+. For simulations of Experiment 2, each cycle consisted of one presentation of each individual stimuli (A+, B+, C+, Do, Eo, and Fo) and of each of the two-stimulus compounds (AB+, AC+, BC+, DEo, DFo, and Efo) and six presentations of each three-stimulus compound (ABCo and DEF+). For simulations of Experiments 3 and 4, each pattern was presented once in each cycle. Because REM and AMAN tend to solve the discrimination problems less rapidly than Configural Theory with the chosen parameter values, simulations of these models are blocked over multiple cycles of training.

#### **Configural Theory**

Simulations of Configural Theory were based on the descriptions of the network model and the equations presented by Pearce (1994). The simulations, and those of REM, were run using MATLAB (MathWorks Inc., Natick, MA) programmes written by the author and available for download from the 'learnSim' repository on GitHub (GitHub Inc., San Francisco, CA) at <https://github.com/DavidNGeorge/learnSim>.

Presentation of a pattern of stimuli resulted in activity in an input network. This network consisted of an input layer where each unit responded to the presence of a particular stimulus element and was connected to a corresponding unit in an output layer. The activation value,  $P$ , of a given input unit was determined by the intensity of the stimulus



element which activated it. In the simulations reported in this article, the intensity of all stimulus elements was 1 except for the salient contextual cue which had an intensity of 2. Activity in output unit  $k$ ,  $o_k$ , was scaled by the number of stimulus elements present,  $n$ , and their intensities according to Equation A1 where  $P_k$  was the activity level (intensity) of input unit  $k$ .

$$o_k = \frac{P_k}{\sqrt{\sum_{i=1}^n P_i^2}} \quad (\text{A1})$$

When a pattern was presented for the first time, a configural unit,  $j$ , was recruited and the strength of the connection,  $w_{i,j}$ , between an individual output unit and this configural unit was set to equal the activation level of the output unit ( $o_i$ ). Subsequently, following presentation of any stimulus pattern, the activation of a given configural unit  $j$ ,  $a_j$ , was given by Equation A2 where  $n$  was the number of output units in the network. Here,  $d$  is a discriminability parameter which was fixed at 2 by Pearce (1994), but which Kinder and Lachnit (2003; see also Pearce et al, 2008) suggested might vary dependent on stimulus properties.

$$a_j = \left( \sum_{i=1}^n w_{i,j} \times o_i \right)^d = \left( \sum_{i=1}^n o_i^2 \right)^d \quad (\text{A2})$$

Configural units could enter into an association with a US unit and this association could have either a positive (excitatory), negative (inhibitory), or zero value. The net associative strength of a pattern was the sum of the activations of configural units weighted by the strength of their association with the US unit. Hence, Equation A3 gives the net associative strength,  $V_j$ , of Pattern  $j$  where  $a_i$  is the activation level of configural unit  $i$ ,  $E_i$  is the

strength of the association between configural unit  $i$  and the US, and  $n$  is the number of configural units in the network.

$$V_j = \sum_{i=1}^n a_i \times E_i \quad (\text{A3})$$

Following a conditioning trial, only the strength of the association between the configural unit for the pattern presented and the US unit was changed according to Equation A4.  $\alpha$  was a learning rate parameter associated with the configural unit and had a value of 1 in all cases for the simulations reported here.  $\beta$  was a learning rate parameter associated with the US and had a value of .05 for all simulations reported here.  $\lambda$  was the magnitude of the US and was 1 when the outcome was delivered. When no outcome was delivered,  $\lambda = 0$  for the simulations reported in Figure 1, and  $\lambda = -1$  for all other simulations.

$$\Delta E = \alpha \times \beta \times (\lambda - E) \quad (\text{A4})$$

### Replaced Elements Model

Simulations of REM were based on the description of the model given in Wagner and Brandon (2001) and Wagner (2003) using a MATLAB programme that can be found in the ‘learnSim’ repository on GitHub. The model is based on the assumption that a stimulus is represented by a large but finite collection of micro features or elements. Some of those elements are context independent and will be activated whenever the stimulus is presented, whereas the activation of others is dependent upon the context in which the stimulus is presented. Different stimuli will interact with each other to a greater or lesser extent which determines the relative proportions of context dependent and independent elements. For example, context independent elements within the representation of Stimulus A,  $A_i$ , will be

active whenever A is presented. Other elements might be active only when A is presented in compound with Stimulus B,  $A_b$ , while a third population of elements might be active only when A is presented in the absence of B,  $A_{\sim b}$ . It is assumed that the total number of elements activated by A is the same whether it is presented alone or in compound with another stimulus, and so changes in the context will result in the replacement of activity within some elements with activity within others. The parameter  $r$  determines the degree of replacement, such that the relative size of the three populations of elements described above will be  $(1 - r)$ ,  $r$ , and  $r$ , respectively. When A might also be presented in compound with Stimulus C, this will result in replacement in a manner that is statistically independent of replacement by Stimulus B. Hence, as shown in Table A1, in this situation we can identify nine separate populations of elements within the representation of A:  $A_i$ ,  $A_b$ ,  $A_{\sim b}$ ,  $A_c$ ,  $A_{\sim c}$ ,  $A_{b\sim c}$ ,  $A_{c\sim b}$ ,  $A_{bc}$ ,  $A_{\sim bc}$ .

<Table A1 about here>

For the sake of computational simplicity and precision, individual stimulus elements were not represented within the simulation programme. Instead, each population of elements was represented by a single node and changes in associative strength were scaled to mimic differences in population size. For a given simulation, the same value of the  $r$  parameter was used to determine the interaction between all stimuli. This was either .8 to simulate the effects of training with stimuli belonging to the same modality, .2 to simulate training with stimuli from different modalities, or an intermediate value of .5. Following a conditioning trial, the associative strength of each active node was updated according to Equation A5 where  $\Delta V_i$  was the change in the associative strength of node  $i$ ,  $\alpha_i$  was the salience of that node,  $\beta$  was a learning rate parameter associated with the US,  $c_i$  was the

scaling factor used to mimic population size,  $\lambda$  was the magnitude of the outcome, and  $\Sigma V$  was the summed associative strength of all active nodes. Table A2 shows the activation level of each population within the representation of stimulus A following presentation of various patterns containing that stimulus. These values were used for the scaling factor,  $c$ . For all simulations reported here, the salience,  $\alpha$ , of all nodes was .05 and the rate parameter  $\beta$  was also .05.  $\lambda$  was 1 for trials on which the outcome was delivered. When no outcome was delivered,  $\lambda = 0$  for the simulations reported in Figure 1, and  $\lambda = -1$  for all other simulations.

$$\Delta V_i = \alpha_i \times \beta \times c_i \times (\lambda - \sum V) \quad (\text{A5})$$

<Table A2 about here>

### **Attention Modulated Associative Network**

Simulations of AMAN were conducted using the MATLAB programme described by Thorwart, Livesey and Harris (2012). The programme is available for download from the websites <http://sydney.edu.au/science/psychology/staff/justinh/downloads/> and <https://www.uni-marburg.de/fb04/team-lachnit/mitarbeiter/thorwart/simulators/AMAN/>. Because connectivity between E elements is probabilistic, individual simulations of the network can generate slightly different results. Hence, each of the predictions of AMAN presented in this article was the averaged result of ten individual simulations. All parameter values were the same as those used by Harris and Livesey (2010). In the following description, variable names used in the parameter definition file are shown in square brackets and are listed in the order in which they appear in that file. Other values were defined in the stimuli and trial definition files.

Each trial was simulated over 150 time steps [num\_TicksPerTrial = 150]. CSs were presented between time steps 20 and 50. The US was, where appropriate, presented between time steps 51 and 60. Activation of the US was recorded between time steps 40 and 50. Each stimulus was represented by 20 elements [num\_elements = 20], and the probability that any two E units were connected was .5 [connect\_p = .5].

Activation of stimulus elements by sensory input was varied uniformly from a minimum value of .05 to a maximum value of 1 for CSs and a minimum value of .1 and a maximum value of 2 for the US [S\_distribution = 1]. The exponent used in the response potential function was 2 for E and I units and 5 for A units [Power\_E = 2; Power\_I = 2; Power\_A = 5]. The value of the constant used in this function was .04 [D = .04]. The rate parameter for increases in activation was .5 for all units [Growth\_E = .5; Growth\_I = .5; Growth\_A = .5] and for decreases in activation was .2 for all units [Decay\_E = .2; Decay\_I = .2; Decay\_A = .2].

The normalization of I units was not affected by E units of elements belonging to different stimuli [norm\_across\_all = 0], but was influenced by E units of elements belonging to the same modality with a weighting of 1/40 [norm\_within\_modality = .5], and E units of elements belonging to the same stimulus with a weighting of 1/20 [norm\_within\_stim = 1]. The connection weight from A to I units was 4 [Weight\_IA = 4], and between A units was .04 [Weight\_AA = .04].

The rate parameters  $\beta_E$  and  $\beta_I$  were equal to .02 and .1, respectively, when activation of E and I elements was increasing and to 0 when they were decaying [Beta\_E\_pos = .02; Beta\_E\_neg = 0; Beta\_I\_pos = .1; Beta\_I\_neg = 0]. The rate parameter for changes in the

connection weight function was .05 [ $k_V = .05$ ] and for changes in associability was .33 [ $k_{\text{Alpha}} = .33$ ].

For simulations of Experiments 1-4, the network was pre-trained to ensure that presentation of each pattern resulted in moderate, and approximately equal, activation of E units. Pre-training consisted of 1000 cycles of training in which each pattern was partially reinforced. That is, each pattern was presented twice in each cycle; once paired with the US, and once in the absence of the US.

**Author Note**

This research is based on ideas developed when the author was a visiting fellow at the School of Psychology, UNSW Australia. He is grateful to UNSW Australia for the generous provision of facilities during this period for technical support during the collection of data for Experiments 2 and 4.

### Tables

*Table 1.* The design of Experiments 1-4. A, B, C, D, E, and F were six different stimuli. + denotes that a pattern was followed by the presentation of a tone, o denotes that it was not. Participants were concurrently trained on negative and positive discrimination tasks.

	<i>Negative</i>	<i>Positive</i>
Experiment 1	A+ BC+ ABCo	Do EFo DEF+
Experiment 2	A+ B+ C+ AB+ AC+ BC+ ABCo	Do Eo Fo DEo DFo EFo DEF+
Experiment 3	A+ ABC+ BCo	Do DEFo EF+
Experiment 4	A+ B+ C+ ABC+ ABo ACo BCo	Do Eo Fo DEFo DE+ DF+ EF+



*Table A1.* Populations of elements within the representation of Stimulus A which might be presented alone or in compound with two other stimuli, B and C. With respect to each stimulus, the population of elements might be active only in its presence, only in its absence, or might be independent of it.

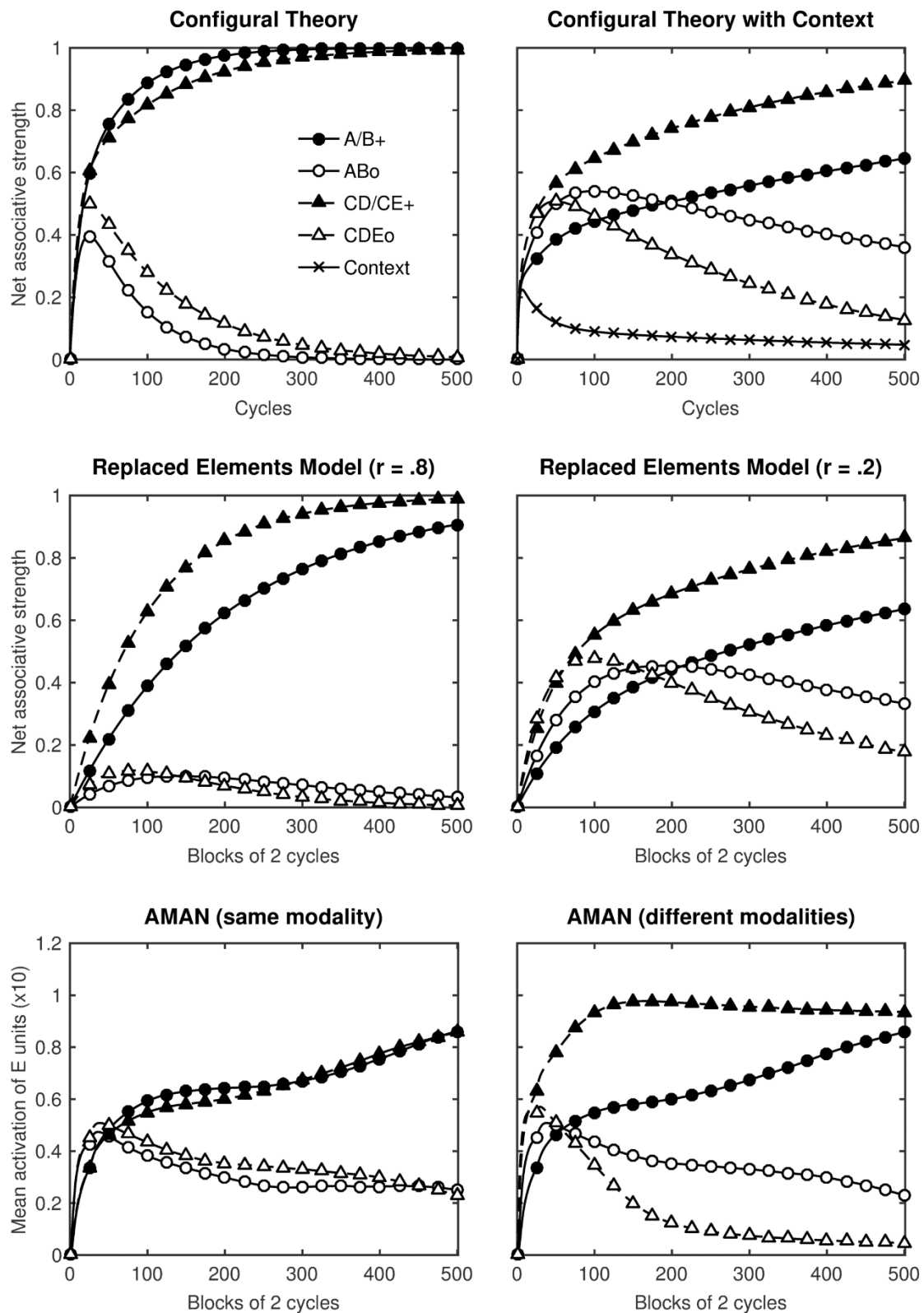
		Dependence on Stimulus B		
		Independent	Presence	Absence
Dependence on Stimulus C	Independent	$A_i$	$A_b$	$A_{\sim b}$
	Presence	$A_c$	$A_{bc}$	$A_{c\sim b}$
	Absence	$A_{\sim c}$	$A_{b\sim c}$	$A_{\sim bc}$

*Table A2.* Activation in nodes contributing to the representation of Stimulus A in simulations of REM when A is presented alone or in combination with B, C, or B and C.

	A	AB	AC	ABC
$A_i$	$(1-r)^2$	$(1-r)^2$	$(1-r)^2$	$(1-r)^2$
$A_b$	-	$r(1-r)$	-	$r(1-r)$
$A_{\sim b}$	$r(1-r)$	-	$r(1-r)$	-
$A_c$	-	-	$r(1-r)$	$r(1-r)$
$A_{\sim c}$	$r(1-r)$	$r(1-r)$	-	-
$A_{b\sim c}$	-	$r^2$	-	-
$A_{c\sim b}$	-	-	$r^2$	-
$A_{bc}$	-	-	-	$r^2$
$A_{\sim bc}$	$r^2$	-	-	-

Figures

Figure 1



*Figure 1.* Predictions concerning the course of acquisition of A+ B+ ABo and CD+ CE+ CDEo patterning discriminations derived from simulations of three different models. Top row: Pearce's (1994) Configural Theory either without (left panel) or with (right panel) the inclusion of a salient contextual cue. Middle row: Wagner's (2003) Replaced Elements Model (REM) with either a high (left panel) or a low (right panel) value of the replacement parameter,  $r$ . Bottom row: Harris and Livesey's (2010) attention-modulated associative network (AMAN) where the three stimuli are drawn from the same modality (left panel), or to three different modalities (right panel). The simulations presented in the left column are consistent with the conditions assumed to exist in pigeon autoshaping experiments involving stimuli drawn from a single modality whereas the simulations presented in the right column are consistent with the conditions assumed to exist in rabbit eye-blink experiments involving stimuli drawn from three different modalities.

Figure 2

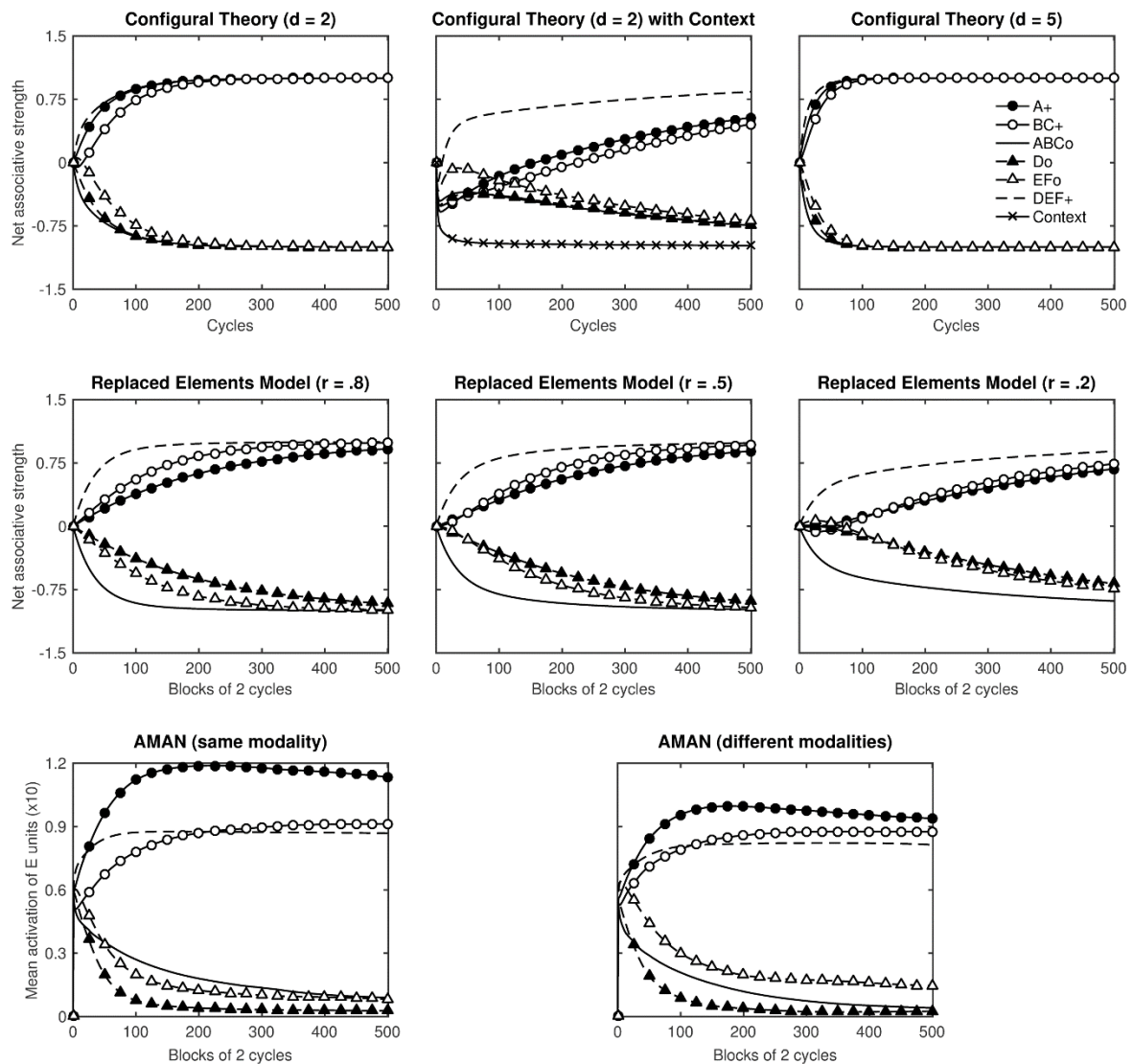
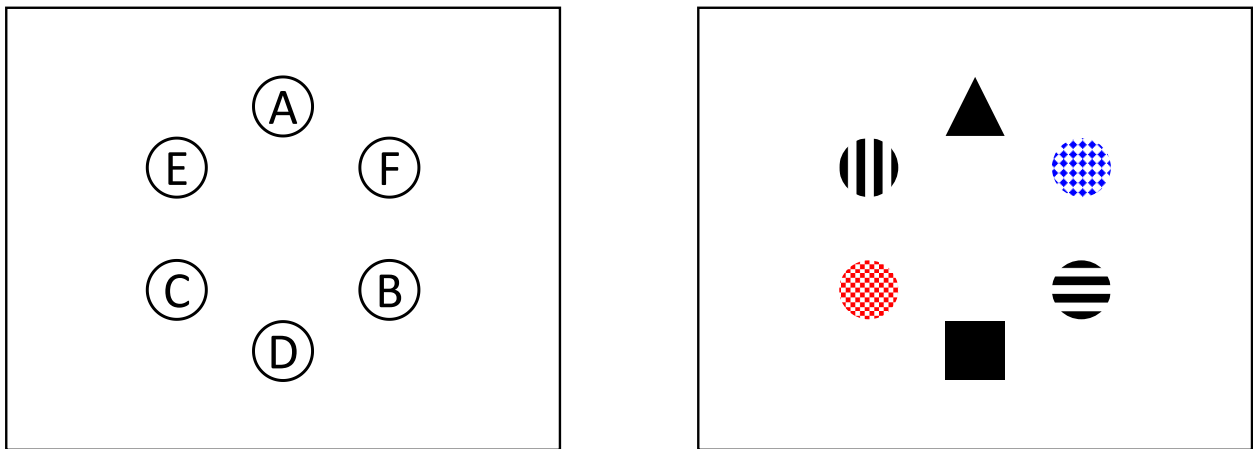


Figure 2. Predictions concerning the course of acquisition of A+ BC+ ABCo and Do EFo DEF+ patterning discriminations derived from simulations of three different models. Top row: Pearce’s (1994) Configural Theory either without (left panel,  $d = 2$ ; right panel,  $d = 5$ ) or with (middle panel,  $d = 2$ ) the inclusion of a salient contextual cue. Middle row: Wagner’s (2003) Replaced Elements Model (REM) with either a high (left panel), intermediate (middle panel) or a low (right panel) value of the replacement parameter,  $r$ . Bottom row: Harris and Livesey’s

(2010) attention-modulated associative network (AMAN) where the three stimuli are drawn from the same modality (left panel), or to three different modalities (right panel).

Figure 3



*Figure 3.* The arrangement of stimuli in Experiments 1-4. The left panel shows the locations in which the six stimuli, A, B, C, D, E, and F, were presented. The right panel shows the six shapes that served as stimuli. Stimulus C was a solid red circle (shown here in a square checkerboard pattern). Stimulus F was a solid blue circle (shown here in a diamond checkerboard pattern).

Figure 4

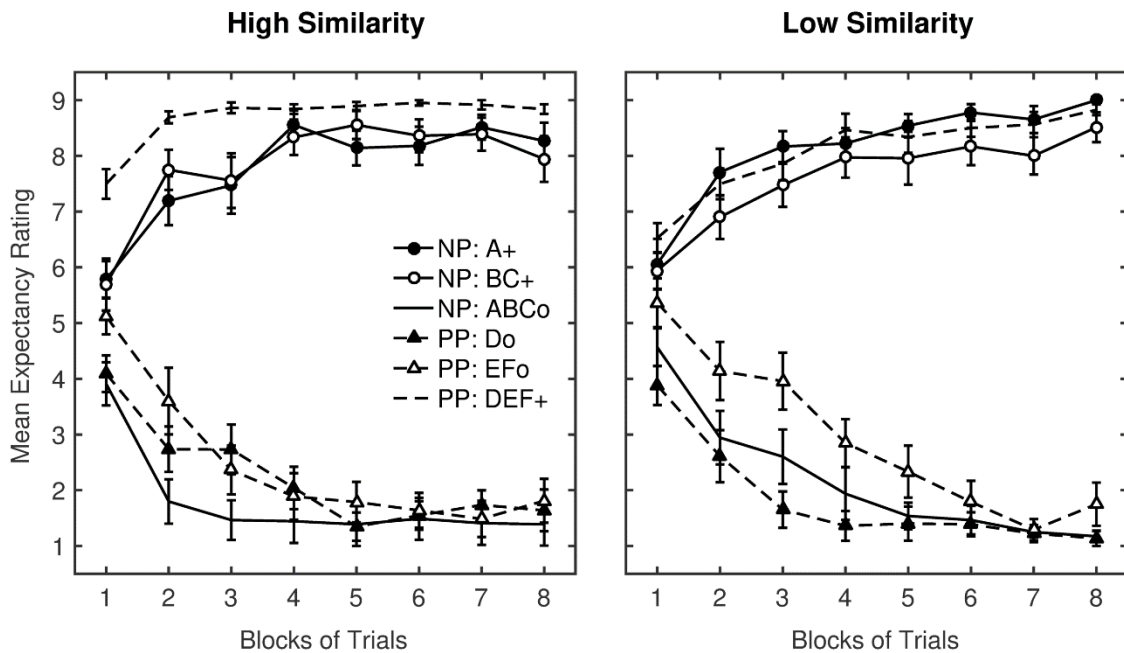


Figure 4. The course of acquisition of concurrent negative (A+ BC+ ABCo) and positive (Do Efo DEF+) patterning discriminations by participants in Experiment 1. Participants trained with low similarity stimuli (right panel) made more extreme ratings for single stimulus patterns (A+; Do) than for the corresponding two stimulus patterns (BC+; Efo). No such difference was seen in the ratings of participants trained with high similarity stimuli (left panel). Error bars show 1 standard error of the mean (SEM).



Figure 5

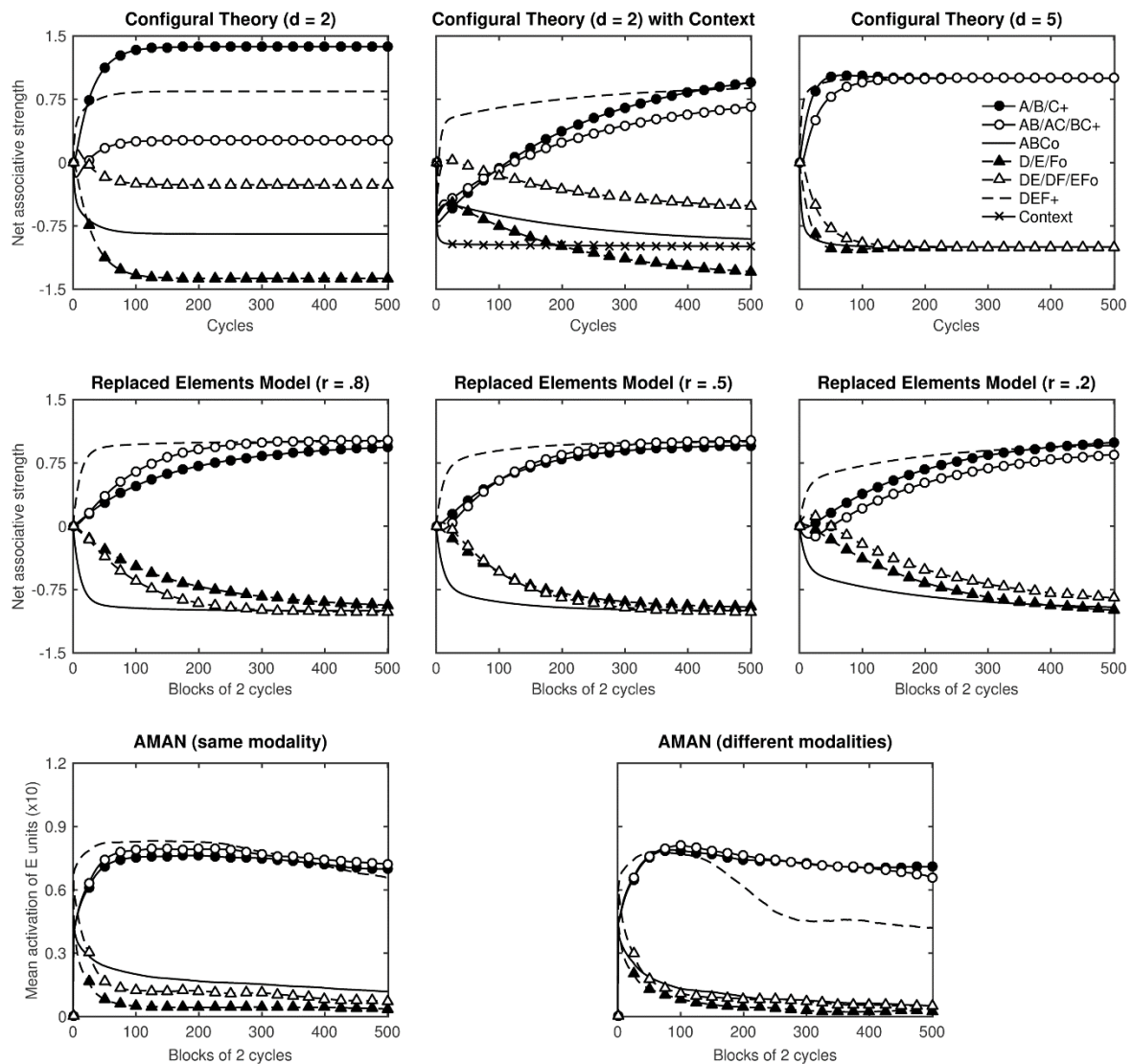


Figure 5. Predictions concerning the course of acquisition of A+ B+ C+ AB+ AC+ BC+ ABCo and Do Eo Fo D Eo D Eo Eo DEF+ patterning discriminations derived from simulations of three different models. Top row: Pearce’s (1994) Configural Theory either without (left panel,  $d = 2$ ; right panel,  $d = 5$ ) or with (middle panel,  $d = 2$ ) the inclusion of a salient contextual cue. Middle row: Wagner’s (2003) Replaced Elements Model (REM) with either a high (left panel), intermediate (middle panel) or a low (right panel) value of the replacement parameter,  $r$ .

Bottom row: Harris and Livesey's (2010) attention-modulated associative network (AMAN) where the three stimuli are drawn from the same modality (left panel), or to three different modalities (right panel).

Figure 6

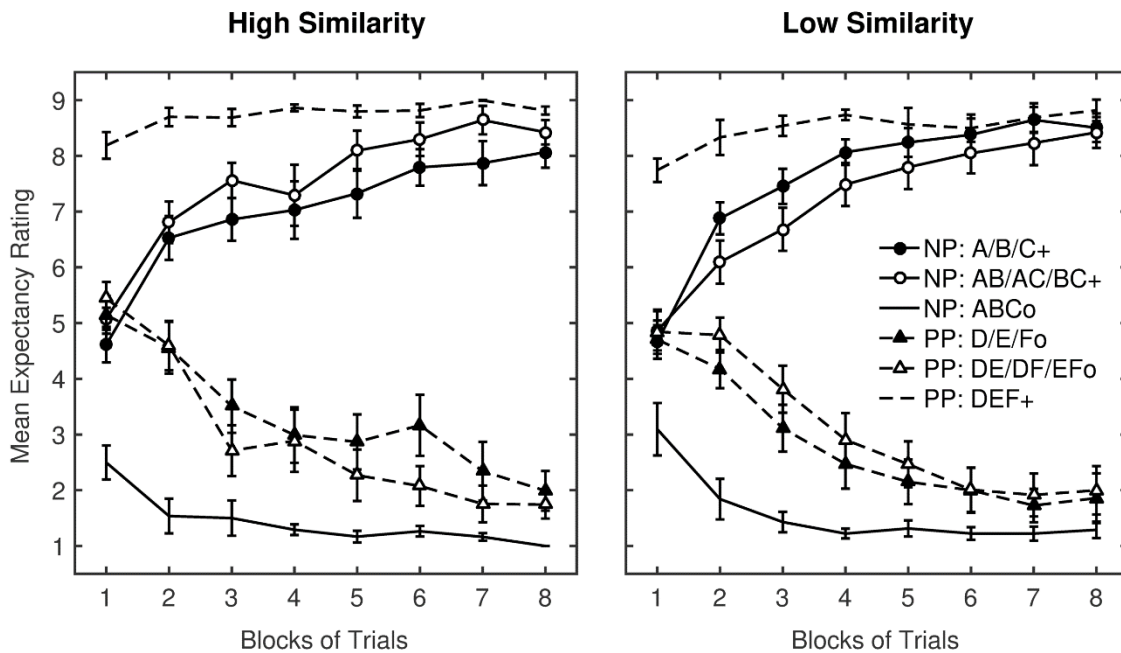


Figure 6. The course of acquisition of concurrent negative (A/B/C+ AB/AC/BC+ ABCo) and positive (D/E/Fo DE/DF/EFo DEF+) complex patterning discriminations by participants in Experiment 2. Participants trained with high similarity stimuli (left panel) made more extreme ratings for two stimulus patterns (AB/AC/BC+; DE/DF/EFo) than for the corresponding single stimulus patterns (A/B/C+; D/E/Fo). The opposite pattern was observed in the ratings of participants trained with low similarity stimuli (right panel). Error bars show 1 SEM.

Figure 7

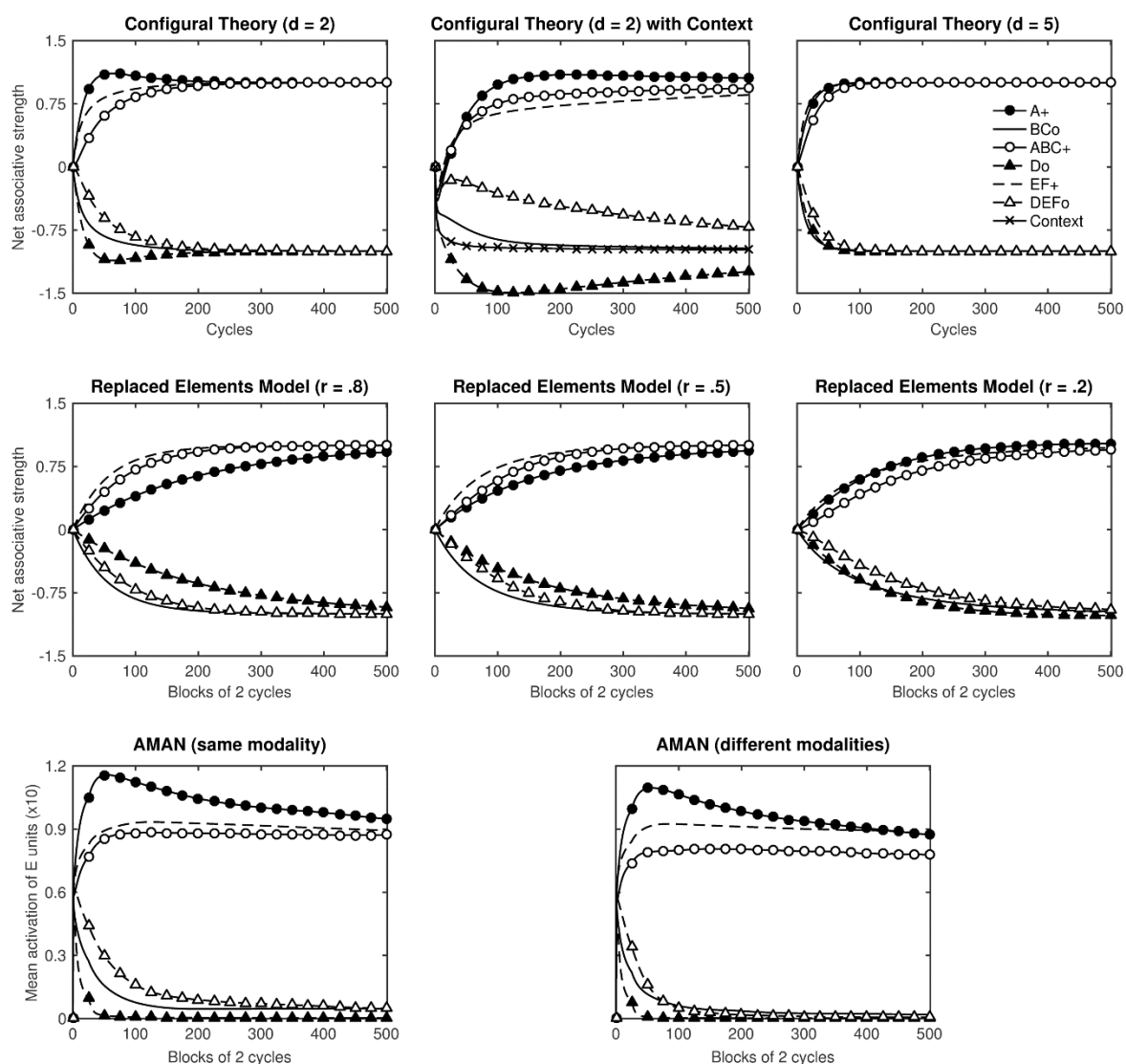


Figure 7. Predictions concerning the course of acquisition of A+ BCo ABC+ and Do EF+ DEFo 'parity' discriminations derived from simulations of three different models. Top row: Pearce's (1994) Configural Theory either without (left panel,  $d = 2$ ; right panel,  $d = 5$ ) or with (middle panel,  $d = 2$ ) the inclusion of a salient contextual cue. Middle row: Wagner's (2003) Replaced Elements Model (REM) with either a high (left panel), intermediate (middle panel) or a low (right panel) value of the replacement parameter,  $r$ . Bottom row: Harris and Livesey's (2010)

attention-modulated associative network (AMAN) where the three stimuli are drawn from the same modality (left panel), or to three different modalities (right panel).

Figure 8

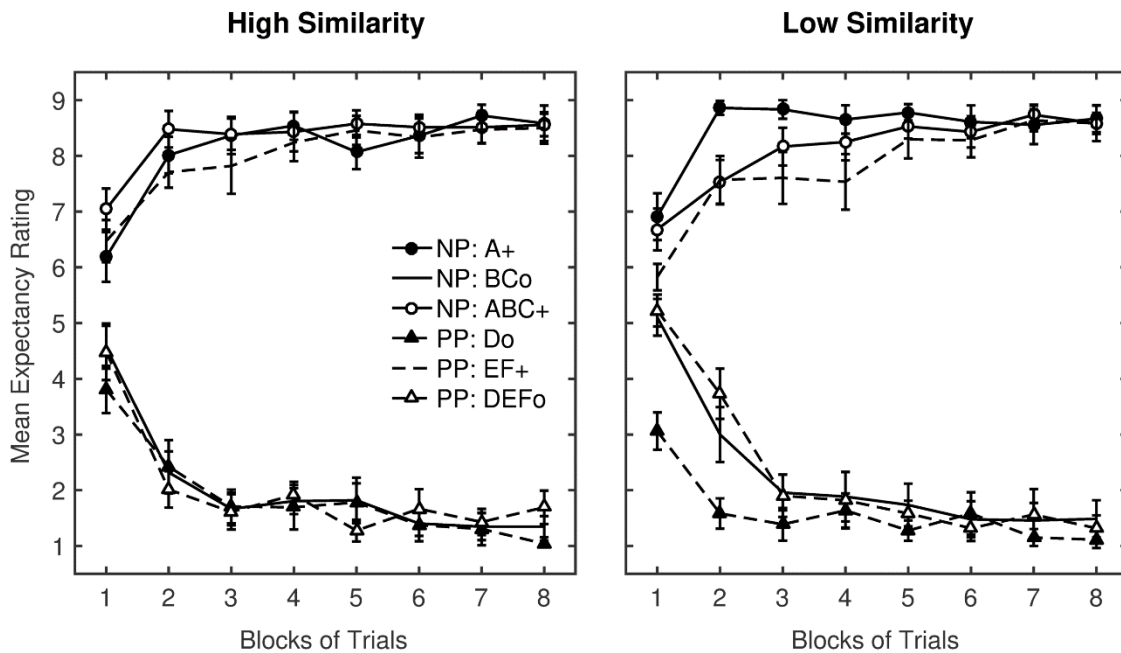


Figure 8. The course of acquisition of concurrent negative (A+ BCo ABC+) and positive (Do EF+ DEFo) ‘parity’ discriminations by participants in Experiment 3. Participants trained with low similarity stimuli (right panel) made more extreme ratings for single stimulus patterns (A+; Do) than for the corresponding three stimulus patterns (ABC+; DEFo). No such difference was seen in the ratings of participants trained with high similarity stimuli (left panel). Error bars show 1 SEM.

Figure 9

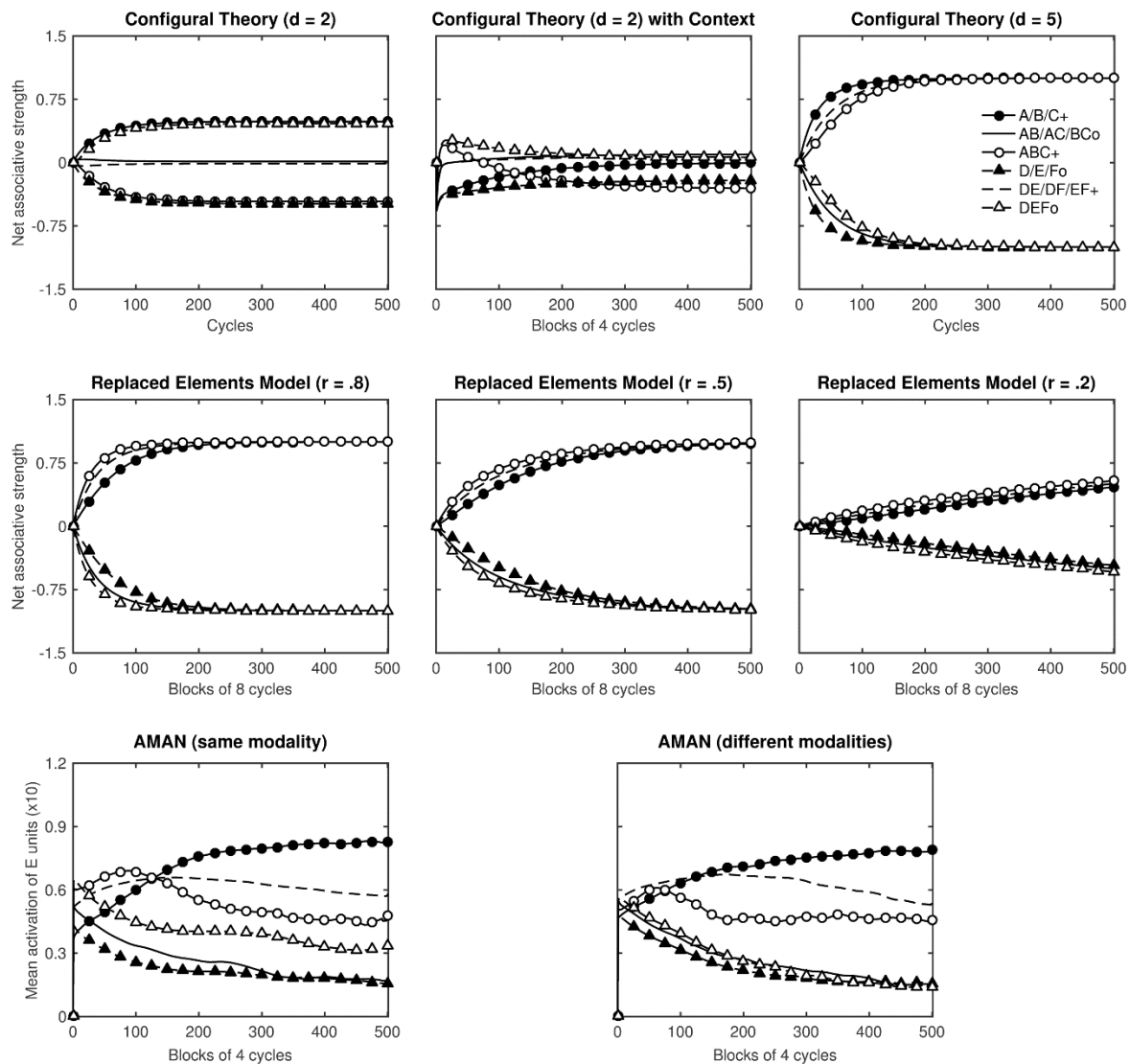


Figure 9. Predictions concerning the course of acquisition of A+ B+ C+ ABo ACo BCo ABC+ and Do Eo Fo DE+ DF+ EF+ DEFo 'parity' discriminations derived from simulations of three different models. Top row: Pearce's (1994) Configural Theory either without (left panel,  $d = 2$ ; right panel,  $d = 5$ ) or with (middle panel,  $d = 2$ ) the inclusion of a salient contextual cue. Middle row: Wagner's (2003) Replaced Elements Model (REM) with either a high (left panel), intermediate (middle panel) or a low (right panel) value of the replacement parameter,  $r$ .

Bottom row: Harris and Livesey's (2010) attention-modulated associative network (AMAN) where the three stimuli are drawn from the same modality (left panel), or to three different modalities (right panel).



Figure 10

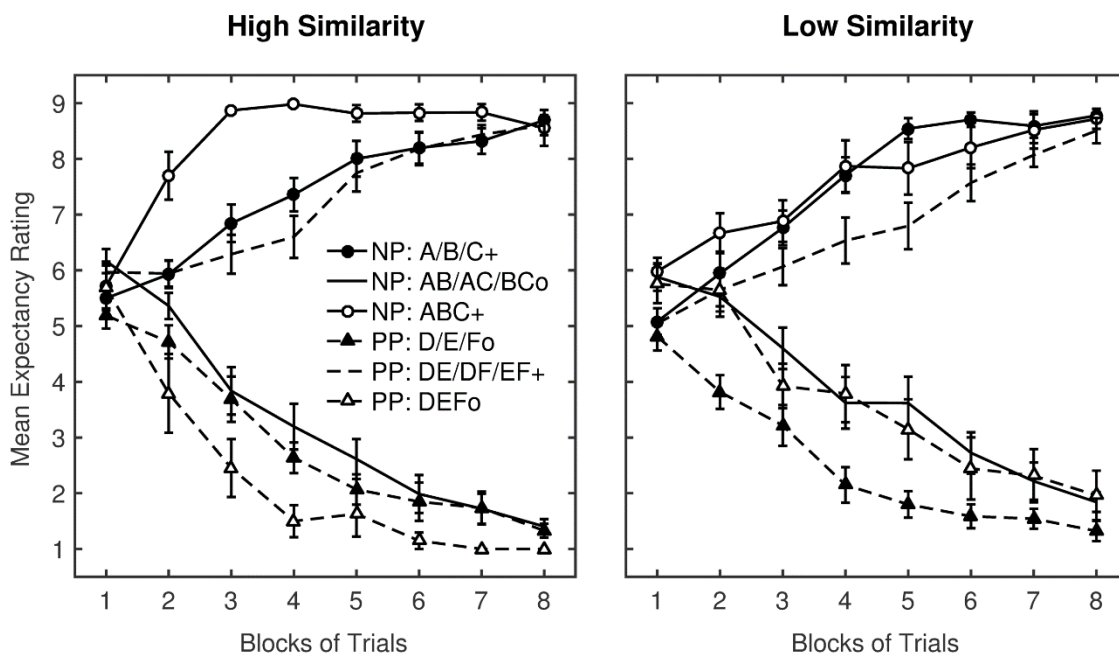


Figure 10. The course of acquisition of concurrent negative (A/B/C+ AB/AC/BCo ABC+) and positive (D/E/Fo DE/DF/EF+ DEFo) complex ‘parity’ discriminations by participants in Experiment 4. Participants trained with high similarity stimuli (left panel) made more extreme ratings for three stimulus patterns (ABC+; DEFo) than for the corresponding single stimulus patterns (A/B/C+; D/E/Fo). The opposite pattern was observed in the ratings of participants trained with low similarity stimuli (right panel). Error bars show 1 SEM.