Flexible Configural Learning of Non-Linear Discriminations and Detection of Stimulus Compounds

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Abstract

Previous work showed that prior experience with discriminations requiring configural solutions (e.g. biconditional discrimination) confers an advantage for the learning of new configural discriminations (e.g. negative patterning) in comparison to prior experience with elemental discriminations. This effect is well established but its mechanism is not well understood. In the studies described below we assessed whether the saliences of configural and element cues were affected by prior training. We observed positive transfer to a new configural discrimination after configural pre-training but we were unable to find evidence for changes in cue salience using a signal-detection task. Our results confirm previous work by demonstrating experience dependent flexibility in cue processing but they also suggest that this flexibility occurs at a point in the stimulus processing pipeline later than 1-2s after the presentation of stimulus inputs. (138 words)

Keywords: associative learning, configural, elemental, representation, signal-detection, bi-conditional discrimination, true discrimination

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Successful learning implies acquisition of specific responses to specific stimulus situations but may also involve acquisition of general strategies which can be deployed in new tasks. For example, better discrimination performance after an intra-dimensional, rather than after an extra-dimensional shift condition (e.g. Roberts, Robbins, & Everitt, 1988) suggests that something is learned about the stimulus dimensions and this generalises between tasks. Intra-dimensional shift superiority could involve enhanced attention to the relevant dimension, ignoring the irrelevant dimension, or a combination of both. In a similar vein Alvarado and Rudy (1992) found evidence for changes in configural information processing with transverse patterning problems in rats. In transverse patterning a set of simple simultaneous discriminations is learned. For example, whenever cues A and B are presented reinforcement is obtained for selection of A (A+/B- trials). Whenever cues B and C are presented reinforcement is contingent on selection of B (B+/C- trials). Finally, whenever cues C and A are presented, reinforcement is given for selection of C (C+/A- trials). Although these discriminations are individually simple, successful performance in transverse patterning cannot be explained by simple elemental models of associative learning such as the Rescorla-Wagner Model (RWM, Rescorla & Wagner, 1972). In such models the associative strengths of stimuli A, B, and C would be the same due to the fact that they each occur on reinforced and non-reinforced trials equally often. In contrast, to explain performance in transverse patterning, it seems necessary for subjects to process the stimulus configurations (e.g. Pearce, 1987, 1994; Rescorla, 1973; Wagner & Rescorla, 1972) that are present on each trial in order to select the appropriate response.

However, Alvarado and Rudy's contribution was not the demonstration that rats could solve transverse patterning problems *per se*. It was the demonstration that components of transverse patterning problems could be solved more readily after 'configural' than after 'elemental' pre-training and that the configural pre-training effect generalised to new problems involving new stimuli. Alvarado and Rudy likened their

effect to the intra-dimensional shift effect, suggesting that the pre-training encouraged learning about the 'configural dimension' (Alvarado & Rudy, 1992). This configural pre-training effect can be understood to operate as the result of increases in the salience of configural cues that can arise when two or more stimulus elements are presented together in compound. For example, the stimulus elements used by Alvarado and Rudy were black patterns (e.g. black circle (A), diagonal line (B), or horizontal stripes (C)) presented on white backgrounds. When patterns A and B were presented side-by-side as an AB compound the edges of the black patterns closest to the mid-line of the compound could have caused a new pattern to appear from the background, producing a figure-ground effect such as that seen in the well known Rubin's vase illusion (Rubin, 1915). In the associative learning literature, stimulus configuration effects are often conceptualised theoretically to operate along a continuum. At one extreme A and B do not interact. In the middle an AB compound could be represented as ABx, where A and B are still perceived but x is a unitary representation of their conjunction. At the other extreme A and B would be considered to be represented entirely by a configural element, X (see Wagner, 2003, for a detailed account of one approach).

As well as varying in salience, configural cues are understood to arise at different stages in the processing of stimulus information. Configural cue information can be identified with an early perceptual interaction process (as above) but configural cue information can also be a product of late integration of information. Evidence for this come from studies of configuration effects involving stimuli from different sensory modalities (Kehoe & Gormezano, 1980). Numerous studies have shown that configural cue information is extracted from compound stimuli with elements drawn from auditory and visual modalities (e.g. Delamater, Sosa, & Katz, 1999; Harris, Livesey, Gharaei, & Westbrook, 2008; Kehoe & Graham, 1988). All of these reports showed that animals (rats and rabbits) could learn negative patterning (NP) discriminations (Woodbury, 1943) in which elements were reinforced and compounds non-reinforced (i.e. A+, B+, AB- trials) where A was an auditory stimulus (e.g. tone) and B was a visual stimulus (e.g. flashing light). In studies of this type configuration information is produced by

integration of information at the level of a central representational unit and does not depend on early perceptual interactions. In fact, in humans, it has been further argued that configural learning effects are based upon 'rule-learning' (e.g. Lachnit, Lober, Reinhard, & Kinder, 2001), a process well beyond simple association formation and one which must be assumed to occur after perceptual processing has been completed.

The foregoing indicates that there is much to explore in Alvarado and Rudy's (1992) suggestion that configural pre-training can produce generalised changes in the processing of configural cues. Their work has implications for associative models (e.g. Pearce, 1994; Rescorla & Wagner, 1972) which do not include any mechanism for adjustment of configurality. In the current work we focus on an analysis of facilitative transfer effects that have been reported to occur in the learning of NP discriminations in humans (Mehta & Russell, 2009; Melchers, Lachnit, Ungor, & Shanks, 2005). Our experiments are based upon the following analysis of the role of configural cues in the solution of NP (and other) non-linear discriminations. This analysis has been central to the development of simple models of associative learning, such as the RWM[1], because without using configural cue information associative models are unable to provide solutions of non-linear discriminations; there is no linear weighting of the cue elements that can be used to derive the correct responses. To explain this, taking NP as an example, the discrimination involves A+, B+, and AB- trials. If we attach response weights of α and β to cues A and B then we require Inequalities 1, 2, and 3 to hold in order to generate equivalent responses when cues A and B are individually present (1), to generate lower responses on the AB trials than on the A trials (2), and to generate lower responses on the AB trials than on the B trials (3). Amongst these inequalities, 2 and 3 are inconsistent with inequality 1 (e.g. because inequality 2 implies $\beta < 0$, which

[1] Although the original description of the RWM (Rescorla & Wagner, 1972) did not consider configural cues, developments of the simple model with configural cue encoding have been widely discussed since (e.g. Wagner & Rescorla, 1972)

is inconsistent with 1).

$$\alpha = \beta > 0 \tag{1}$$

$$\alpha + \beta < \alpha \tag{2}$$

$$\alpha + \beta < \beta \tag{3}$$

$$\alpha + \beta + \chi < \alpha \tag{4}$$

$$\alpha + \beta + \chi < \beta \tag{5}$$

In contrast, if it is assumed that the AB compound is represented with a configural cue (e.g. ABx), then it is easy to understand how this discrimination could be solved. If we attach a weight of χ to the configural cue x then to get a lower response on the AB trials than on the A and the B trials we need inequalities 1, 4, and 5 to hold; 4 and 5 imply $\chi < -\beta$ and $\chi < -\alpha$ neither of which is inconsistent with inequality 1. Therefore a model which generates appropriate responses in the NP discrimination can be produced if configural cues are introduced.

Learning of a NP discrimination can be faster after configural discrimination pre-training than after elemental discrimination pre-training (Mehta & Russell, 2009; Melchers et al., 2005). In both studies the pre-training and the NP transfer test involved different cues, showing that pre-training had a general effect on configural cue processing but the precise mechanism by which this transfer effect operates remains to be elucidated. We argued above that configural pre-training effects could be mediated by changes in the salience of configural cues and in order to test this hypothesis we asked if participants receiving elemental and configural pre-training would perform differently when asked to identify rapidly presented stimulus compounds. We reasoned that salient configural cues would improve performance in such a task because they would reduce the similarity between test items. For example Pearce (Pearce, 1987, 1994) proposed a similarity measure for two compounds, $s = {}^{c^2}/_{xy}$, in which c is the number of elements common to the two compounds and x and y are the numbers of elements in each of the compounds. Taking this measure we compute the similarity between compounds AB and AC as 1/4 but if configural cues are introduced the

similarity between ABx and ACy is 1/9. Reduced similarity between two compounds would mean that they would be less likely to be confused with one another. In the current experiments we looked for evidence of changes in configural cue processing using a signal-detection task (SDT) after elemental and configural pre-training. Performance in such a task should be better with dissimilar stimuli than with similar stimuli. As outlined above, configural cue information can arise at different loci in the time-course of stimulus processing. Our signal-detection methodology was designed to examine changes in configural cue salience that occur early, within 1-2s, of stimulus presentation. We also looked for replication of the previously reported results in a NP transfer task, and sought validation of the SDT as a measure of stimulus similarity and as a measure of stimulus configuration using stimulus compounds previously shown to differ in the extent to which they form configurations.

Experiment 1

Previous work showed that bi-conditional discrimination (Saavadra, 1975) pre-training facilitated performance in a NP transfer task in human skin conductance conditioning and predictive learning (Mehta & Russell, 2009; Melchers et al., 2005). A bi-conditional discrimination (BCD) problem involves AB+, BC-, CD+, and AD- trials. This is a non-linear discrimination which cannot be solved using just the information provided by the compound cue elements – each element occurs equally often reinforced and non-reinforced so all will generate equivalent response tendencies. Instead, successful solution of this discrimination follows straightforwardly if cue-conjunctions are encoded as configural cues. We trained groups of participants with a BCD using a predictive learning task and asked them to perform a SDT. In the SDT the stimulus compounds used in the BCD were presented briefly as targets (<81ms) and then masked. Participants were then presented with a probe compound which either matched the target or did not, and required to respond 'yes' or 'no' to judge the probe and target match. We expected that configural cues would facilitate performance in such a task, and therefore reasoned that if configural cue salience was increased by the

BCD training then signal-detection performance would be better than for a group that did not receive such training (We leave until Experiment 2 examination of the possibility that transfer effects are the product of changes in processing of element cues, as suggested by the results of Mehta and Russell (2009)). Control participants learned a true discrimination (TD) consisting of AB+, BC+, CD-, and AD- trials. This discrimination does not require configural cue processing since it is, in effect, a B+, D- discrimination. In related experiments Mehta and Williams (2002) found that pre-training effects were dependent upon having learned the pre-training discrimination well. We therefore gave participants extensive experience with their discriminations and only analysed the data from those participants showing good terminal levels of discrimination performance. As well as looking for evidence of changes in configural cue processing using our SDT we used a NP transfer task which was completed after learning. We expected better performance in the NP test for participants who had learned a BCD than for those who had learned a TD.

Method

Procedures were approved by the University of Southampton Research Governance Office and the School of Psychology's Ethics Committee. The methodological details below summarise the main features, see also the online supplemental materials[2].

Apparatus. The experiment was run on personal computers. Sixteen [A...P] distinguishable but similar characters were selected from the runic font character set 'Hnias' (Törnqvist, 2004) to serve as conditioning stimuli (CSs).

Participants. Twelve participants were recruited. Their mean age was 20 years (range 19-22) and they included seven males.

Design and procedure. All participants attended for six sessions, each lasting approximately 30-35 minutes. On arrival for the first session participants were given a verbal description of the procedures and signed a consent form. Sessions took place on separate days except on the odd occasion when it was necessary to do two sessions in one day to expedite completion of the experiment. Sessions were completed in 21 days

[2]www.virtualpsyclab.net/data/online.pdf and www.virtualpsyclab.net/data/cfglrn.zip for data files.

on average and participants were debriefed on completion. During each of the first five sessions they twice performed a learning task followed by a SDT, with a short break after completion of the first SDT. Thus, all participants completed 10 runs of each task. During each run of the learning task participants experienced 80 trials. Each trial began with cue presentation (in Pavlovian terms the CSs) followed by a response window. During the response window participants could press a key to indicate that they expected the trial would end with a green flash outcome (in Pavlovian terms the US or unconditioned stimulus) on the computer screen. During each run of the SDT participants experienced 112 trials. Each trial began with a fixation cross and brief presentation of target cues (53ms or 80ms). The target cues were then masked before probe cues appeared. Participants were required to indicate whether or not there was a match between the target and probe cues by responding to the question 'Were these symbols both present?' (a 2-alternative-forced-choice (yes — or no)). Trials where the target and the probe matched were classed as hits or misses according to the participants' response. Trials where the target and probe mismatched were false alarms or correct rejections according to the participants' response. As well as having verbal introductory instructions participants were presented with more detailed onscreen instructions before performing each task. Participants were assigned alternately to either a true discrimination (TD) or a bi-conditional discrimination (BCD) group.

Figure 1a provides a timeline illustration for the learning task trials. The response window was active during the presence of the cue and a press of the space bar during the response window was counted as a prediction. Participants were instructed to make as many correct predictions as possible (i.e. a key press during a cue when the outcome was scheduled) whilst minimising incorrect predictions (i.e. a key press during a cue when the outcome was not scheduled). Key presses occurring outside the response window were coded as trials without a prediction. Participants were given continuous feedback, in the form of a message presented at the bottom of the screen, giving the total number of correct predictions. The correct response counter was set to zero for each run of the learning task.

Table 1 shows the training discriminations that were used in the learning task. Each participant learned two exemplars of either a TD or a BCD. Each discrimination involved four cue compounds, two of which were always followed by the green flash outcome, two of which were never followed by the green flash outcome. The first exemplar of each discrimination used cues A, B, C, and D; the second exemplar of each discrimination used cues E, F, G, and H. Trials were presented in eight blocks of sixteen trials. Each block contained two presentations of each exemplar. Eight stimuli were randomly selected without replacement, for each participant, from our Hnias set to fulfil the learning task cue functions A-H. The learning task for TD participants also contained some additional partially reinforced filler trials. The filler trials were two each of IJ+.75, JK+.25, KL+.25, and IL+.75 in each block. The number following the + sign indicates the probability with which the US occurred on those trials. The fillers were not analysed, they were included in an attempt to equate the TD and BCD conditions for task difficulty after unpublished preliminary experiments (e.g. see Experiment 0 in online supplement) showed that participants in the TD condition acquired their discriminations more rapidly than BCD participants. The right-left position of the symbols making up each compound was randomised at every trial and the order of trials was randomised within block.

Figure 1b provides a timeline illustration for the SDT trials. Signal detection trials were presented in two blocks of 56 trials with the order randomised within each block. Each block had either a short (67ms) or long (80ms) target duration and the ordering of short/long blocks were approximately counterbalanced by alternating SL or LS from participant to participant. The right-left position of the symbols making up each compound was randomised at every trial and all of the exemplars from the training discriminations appeared in the signal detection tasks equally often. A run of 14 trials at each target duration comprised a signal detection test for a cue. On seven of these trials the target and the probe matched and on seven trials the target and probe mismatched. Mismatching targets were selected without replacement from the list of seven possible mismatches (e.g. AB mismatches were BC, CD, AD, EF, FG, GH, EH)

for each of the seven mismatch trials.

On the sixth session participants completed the transfer task. The transfer task had the same format as the learning task; participants had to predict the occurrence of a green flash US on the basis of CSs in the form of Hnias symbols. The design of the transfer task is shown in Table 1. We were interested primarily in NP but because NP discriminations can be solved on the basis of cue cardinality (one cue reinforced, two cues non-reinforced), and thus not require configural processing, we were concerned that this could obscure any differences that may exist between groups on configural cue processing. To remove this possibility we included a concurrent positive patterning (PP) discrimination in the transfer test. In PP the elements are non-reinforced and the compound is reinforced (e.g. C-, D-, CD+). Our transfer test therefore had the form A+, B+, AB-, C-, D-, CD+ so could not be solved using the principle of cardinality, and therefore would require a configural solution. The trial types making up these two discriminations were each presented four times within each of three blocks making a total of 72 trials. On compound trials the right-left screen position of symbols was randomised and trial order was randomised within block. The CS symbols used in the transfer task differed from those that had been used previously. Symbols were randomly selected without replacement, for each participant, to serve the cue roles [M...P].

Analyses

Data analysis was undertaken using R and associated packages (Deepayan, 2008; Lawrence, 2012; R Core Development Team, 2012). For brevity only a graphical analysis of the learning task is reported – the main results are clear-cut and statistical support is not required (but analyses are given in the online supplement). For the SDT d' and bias were calculated for each session and analysed as a function of two repeated-measures factors: session (5 levels) and target duration (2 levels; 53ms and 80ms), and one between-participants factor: group (2 levels; TD or BCD). The formulae given in Macmillan and Creelman (2005, see online supplement) were used to calculate d' and bias; bias here provides an estimate of the location of the decision criterion. As

with the learning task, transfer discrimination performance was analysed as the proportion of trials with an outcome prediction. These proportions were subject to ANOVA as a function of two repeated-measures factors: block (3 levels) and cue (2 levels; non-reinforced (CS-) and reinforced (CS+)) and one between-participants factor: group (2 levels; TD or BCD). Separate ANOVAs were carried out on the NP and PP problems. In cases of sphericity violation significant ANOVA results are reported with Greenhouse-Geisser adjusted degrees of freedom (Greenhouse & Geisser, 1959; Mauchley, 1940). Significant results from overall ANOVAs are given below where $\alpha < .05$ and are followed-up using simple interaction and simple main effect analyses (Howell, 2002) and t-tests as appropriate. Generalised eta squared effect sizes ($\hat{\eta}^2_G$ Bakeman, 2005) from ANOVAs are given. One BCD participant was excluded from analysis because they failed to learn their discrimination. Learning success was defined as being twice as likely to respond to a reinforced cue than to a non-reinforced cue during the final run of the learning task.

Results

Learning task. Figure 2 shows that both groups learned to respond appropriately to reinforced and non-reinforced cues over the series of runs but despite the inclusion of filler trials, the TD participants did perform better than the BCD participants during the early runs.

Signal detection. Figure 3 shows the d' and bias data. In the case of d' the TD participants generally had higher d' values than the BCD participants but the differences were not large. ANOVA only produced an effect of duration and an effect of session ($F(1, 9) = 11.6, p < .01, \hat{\eta}^2_G = .01$ and $F(2, 18) = 6.91, p < .01, \hat{\eta}^2_G = .18$ respectively). Participants had higher d' values for the 80ms targets than for the 53ms targets, and d' increased over sessions. In the case of bias, BCD participants tended to have slightly higher values than the TD participants but again these differences were not large with ANOVA only producing a session effect, $F(4, 36) = 2.77, p < .05, \hat{\eta}^2_G = .07$.

Transfer discrimination. Figure 4 shows transfer discrimination performance in the PP (left-hand side) and NP (right-hand side) tasks. Both discriminations were learned with a higher proportion of trials with responses for reinforced cues than for non-reinforced cues clearly present after the first block in both groups and for both discriminations. Performance was better for the BCD participants than for the TD participants and this difference was more marked for the NP discrimination. Analysis of the PP data produced a significant cue x block interaction, $F(1.2, 10.6) = 18.1, p < .01, \hat{\eta}^2_G = .26$. This was followed-up with simple main effect analyses for cue at each of the three blocks. There were highly significant cue effects in each block with the smallest F-value occurring in block 1, $F(1, 9) = 11.9, p < .01, \hat{\eta}^2_G = .46$. Analysis of the NP data produced a significant cue x block x group interaction, $F(2, 18) = 3.6, p < .05, \hat{\eta}^2_G = .06$, which was followed with simple interaction ANOVAs using cue and group as factors for each of the three blocks. There were highly significant cue effects in each block with the smallest F-value occurring in block 1, $F(1, 9) = 16.1, p < .01, \hat{\eta}^2_G = .41$. There was also a cue x group interaction in block 1 $F(1, 9) = 5.68, p < .05, \hat{\eta}^2_G = .2$. Responses to CS+ and CS- differed in block 1 for the BCD participants $F(1, 4) = 28.2, p < .01, \hat{\eta}^2_G = .64$ but not for the TD participants $F(1, 5) = 1.5, p = 0.28, \hat{\eta}^2_G = .13$.

Discussion

BCD and TD groups both learned their discriminations but we did not find any evidence of between group differences in our SDT, consistent with our preliminary unpublished data. On the assumption that increased configural cue salience would result in improvements in signal-detection performance this implies that learning different discriminations did not induce differences in configural cue salience that were detectable early in the stimulus processing chain, at least within 1-2s of stimulus presentation. However, the different discrimination training regimes were not without effect. BCD participants performed better in a NP transfer test than TD participants. This replicates the facilitative transfer effect on NP that was reported by Mehta and

Russell (2009) and Melchers et al. (2005). Since participants had longer (up to 4s) to respond in the transfer task this suggests that facilitative transfer depends on configuration effects that appear at later stages of stimulus processing. We report two further experiments which strengthen these conclusions. Experiments 2 and 3 refine and validate the SDT, verify that the filler trials used in the elemental pre-training did not contribute to group differences in the transfer task, and provide further replication of the results of Experiment 1.

Experiment 2

Experiment 1 assumed, but did not check, that the SDT was a valid measure of configural cue processing. In Experiment 2 we therefore repeated the procedures of Experiment 1 to replicate our results and added tests of our assumption that the SDT would be sensitive to configural cue salience. The tests of the SDT involved the use of a validation stimulus set based on parenthesis pairs placed in either configural (e.g. ((left, left) or in elemental (e.g. (⌒ left, up) arrangements (Pomerantz & Garner, 1973). Thus, target and probe stimuli were made-up of stimulus compounds in arrangements previously demonstrated to differ in terms of configurality.

As well as including signal-detection trials with validation stimuli we also modified the signal-detection trials with the training stimuli 1) to include tests (described below) to determine whether or not the different pre-training regimes might affect transfer performance via changes in element-detection and 2) to refine the compound-detection tests to distinguish two different trial types (compound-detection and compound-analysis, defined below) to examine the possibility that configural pre-training effects may only arise in a subset of the tests previously presented and analysed together. 1) Including the element-detection trials allowed an exploration of a suggestion from Mehta and Russell (2009) that pre-training effects might be mediated by changes in elemental processing. Using a control condition Mehta and Russell found that superior NP transfer performance of configural pre-training over elemental pre-training was due to poor performance of the elemental group, rather than due to

better performance of the configural group, relative to the control. As noted in the introduction to Experiment 1, this could occur if the salience of element cues was enhanced in the elemental group. If that was the case we might observe superior performance for the TD group over the BCD on element-detection trials.

2) Studies noted in the introduction (Delamater et al., 1999; Harris et al., 2008; Kehoe & Graham, 1988) showed successful learning of non-linear discriminations using stimuli from different sensory modalities. These indicate that learners can extract configural information independently of any configural information that may exist within the earliest, single sensory modality, pathways. Of course, that does not mean that learners cannot use such information and it does not rule out such information as the locus of transfer effects. In Experiment 1 we randomised, but did not record, the left/right locations of the elements used in the targets and probes in the signal detection task. Consequently we could only expect better signal-detection performance for the BCD group over the TD group if the difference between groups was due to changes in the processing of configural information unrelated to the spatial relationship between the elements. To see this, suppose that configural information does depend on spatial positioning of the elements. We need to revisit the similarity relations between target and probe that we outlined in the introduction. Consider first the trials where the target and probe do not match. Here we expect the BCD group to do better than the TD group because the similarity between target and probe ABx, ACy is 1/9 (BCD group) whereas the similarity between AB, AC is 1/4 (TD group). The BCD group should be less likely to register false alarms than the TD group (better performance). The same similarity relations hold when we change the left/right position of the elements in either the target or probe (ABx, CAz (BCD) and AB, CA (TD)). Consider next the trials where the target and probe do match. Here, we expect the BCD group to do worse than the TD group. For the BCD group we have ABx, ABx (compound-detection trials with similarity = 1) and ABx, BAw (compound-analysis trials with similarity=4/9). For the TD group we have AB, AB and AB, BA trials with similarity between target and probe equal to 1 in both cases. The BCD group should be less likely to register hits than the

TD group on the compound-analysis trials (worse performance). Thus, if configural information does depend on the left/right positioning of the elements, then analysis of signal-detection trial performance can be improved by taking account of two trial types. Namely, those where the target and probe compounds contain elements that match on both identity and spatial location (compound-detection) and those where the target and probe compounds contain elements that match only on identity (compound-analysis).

Method

In addition to the main changes from Experiment 1 just outlined we reduced the number of learning task runs, used a modified masking procedure, and recruited a much larger sample of participants. Details of these changes are described below.

Participants. Thirty-nine participants were recruited. They included six males and their average age was 20 years (range 18-32). Four participants had some missing data due to technical error for one or more of the four main analyses carried out below. Each analysis used all participants with complete data for that analysis.

Apparatus. The mask used in the SDT was selected randomly on each trial from a selection of four different masks. The parentheses used for the construction of the signal-detection validation set were black against a white background. Beginning with a left parenthesis (L) three more were formed by successive 90° anti-clockwise rotations to give an upward parenthesis (U), a right parenthesis (R), and a downward parenthesis (D) were formed. Following Pomerantz and Garner (1973, p.565) two sets of four compound stimuli were constructed from these stimuli. Four (LL, RL, LR, and RR) were designated configural arrangements as they tend to be perceived and processed as wholistic compounds. Four (LU, RU, LD, and RD) were designated elemental arrangements as they tend to be perceived and processed piecewise. The masking stimulus used in the SDT with these validation stimuli was randomly selected for each trial from a selection of four.

Design and procedure. Sessions were completed in an average of 16 days. The key changes were 1) modification of the signal-detection masking procedure, 2) modification of the SDT for the training stimuli to include three trial types, 3) addition

of a SDT for a set of validation stimuli, and 4) changes in the structure of sessions to incorporate these changes.

1) Modification of the masking procedure. In Experiment 1 a single mask was used in the SDT. In this experiment we used a variable mask to reduce any mask habituation that might occur.

2) Signal detection trial types. Experiment 1 treated all signal-detection trials alike. For example if the target was AB with A on the left and B on the right then the correct response to our probe question 'Were these symbols both present?' is 'yes' for both probes AB and BA (respecting the right-left positioning) but only in the former case could the match be confirmed on the basis of perception-based configural cues formed by the juxtaposition of the two elements. In Experiment 2 we distinguished between these different trial types and thereby sought to rule out the possibility that a more focussed comparison of the TD and BCD groups, separately for compound-detection and compound-analysis trials, would reveal differences indicative of a configural pre-training effect.

A third type of signal-detection trial was added, element-detection trials, in which probes consisted of a single element accompanied by the question 'Was this symbol present?'. Each run of the SDT with the training stimuli now consisted of 208 trials divided into two blocks of 104 trials. In each block there were 56 compound trials and 48 element trials presented in a random order. The compound trials were arranged as previously described for Experiment 1 but half were compound-detection trials and half were compound-analysis trials. Within each block of element trials half were recognition tests for elements from reinforced compounds and half were for elements from non-reinforced compounds.

3) Signal detection task validation stimuli. Signal detection trials with stimuli from the validation stimulus set were presented in two blocks of 72 trials with the order randomised within block. In one block the target duration was short (93ms) and in the other it was long (107ms). Pilot experiments showed that longer target durations were needed for these stimuli than for the Hnias characters. Each block of 72 trials consisted

of 36 trials with elementally arranged target parentheses (from the set LU, RU, LD, and RD) and 36 trials with configurally arranged target parentheses (from the set LL, RL, LR, and RR). In each case there were 16 element-detection trials (single-item probe), and 20 compound trials (double-item probe). As with the signal detection task for training stimuli, compound trials were divided into compound-detection and compound-analysis trials, depending on left/right position changes.

4) Sessions structure. Each participant now attended five two-part sessions. The first part of session one contained the first run of the SDT with the validation stimuli. The second part of session one contained the first run of the learning task followed by the first run of the SDT with training stimuli. Sessions 2-4 all had the same structure. Part one contained a single run of the learning task. Part two contained a run of the learning task followed by a run of the SDT with the training stimuli. Part one of session five contained the transfer task. Part two of session five contained the second run of the SDT with the validation stimuli.

Analyses

As previously, signal-detection analysis was performed on the data obtained from tests using the training stimuli but in this experiment the factor 'session' used four levels and there was an additional repeated-measures factor, test-type (3 levels; element-detection, compound-detection, and compound-analysis). A new signal-detection analysis was performed on the data obtained from tests using the validation stimuli. Signal detection analysis for the validation stimuli used four repeated-measures factors: session (2 levels; session 1 and session 5), target duration (2 levels, 93ms and 107ms), stimulus arrangement (2 levels; elemental and configural), and test-type (3 levels; element-detection, compound-detection, and compound-analysis) and one between-participants factor: group (2 levels; TD or BCD). When calculating d' and bias for the compound-detection and analysis trials the same mismatching trial data were used in both cases. Thirty-seven participants had complete datasets for the learning task (19 BCD and 18 TD). Of these nine BCD and four TD participants were

excluded from analyses due to failure to acquire the learning task discrimination. Data from the 14 remaining TD participants and the 10 remaining BCD participants are presented below for analyses of the learning task, the SDT using the validation stimuli, and the transfer task. One of these 14 TD participants had missing data for the SDT using the training stimuli giving n=13 (TD) and n=10 (BCD) for that analysis.

Results

Learning task. Figure 2 shows that once again participants learned to respond appropriately in both the BCD and the TD tasks.

Signal detection training stimuli. Figures 5 and 6 show d' and bias values. In contrast to Experiment 1 there is some evidence that d' values are higher for the BCD participants than for the TD participants, especially for the long duration targets. Between group differences on bias are less evident. However, the group differences on d' were not significant, the four-way ANOVA on the d' data only produced effects of session, target duration, and test-type ($F(1.8, 36.9) = 9.49, p < .001, \hat{\eta}^2_G = .03$; $F(1, 21) = 17.8, p < .001, \hat{\eta}^2_G = .01$; and $F(2, 42) = 8.13, p < .01, \hat{\eta}^2_G = .01$, respectively). The d' values increased across sessions 1-4 with means of 1.46, 1.6, 1.8, and 2.02. For target duration d' values were higher for the 80ms than for the 53ms presentations with means of 1.86 and 1.58 respectively. For test-type mean d' values for element-detection, compound-analysis, and compound-detection trials are shown in Table 3. Pairwise t-tests showed no difference between for element-detection and compound-analysis but that d' for compound-detection was significantly higher than for the other two test types. The smallest significant t-value occurred in the comparison of compound-analysis and compound-detection tests, $t(22) = 2.8, p < .05$.

ANOVA on the bias data produced only an effect of test type, $F(2, 42) = 3.6, p < .05, \hat{\eta}^2_G = .02$. The mean bias values for element-detection, compound-analysis, and compound-detection are shown in Table 3. Pairwise t-tests showed that the means did not differ for element-detection and compound-detection but that bias for compound-analysis was significantly higher than for the other two test

types; participants were less likely to report that the probe matched the target in the compound-analysis condition than in the other conditions. The smallest significant t-value occurred in the comparison of compound-analysis and element-detection tests, $t(22) = 2.25, p < .05$.

Transfer discrimination. Figure 7 shows PP and NP transfer task discrimination performance. Both discriminations were learned by both groups but, as in Experiment 1, the performance of the BCD group was better than that of the TD group, especially in the NP condition. Analysis of the PP data produced a significant block x cue interaction, $F(2, 44) = 26.8, p < .001, \hat{\eta}^2_G = .18$. Simple main effect analyses for cue at each block showed significant effects in each case with the smallest F-value occurring in block 1, $F(1, 22) = 61.6, p < .001, \hat{\eta}^2_G = .55$. Analysis of the NP data also produced a block x cue interaction, $F(2, 44) = 27.5, p < .001, \hat{\eta}^2_G = .23$ and simple main effect ANOVAs produced highly significant cue effects in each block with the smallest F-value in block 1, $F(1, 22) = 10.9, p < .01, \hat{\eta}^2_G = .19$. Importantly though, analysis of the NP data produced a significant cue x group interaction, $F(1, 22) = 6.69, p < .05, \hat{\eta}^2_G = .09$. The mean proportions of trials with responses for CS- and CS+ in the BCD group were 0.26, and 0.91, respectively. The mean proportions of trials with responses for CS- and CS+ in the TD group were 0.48, and 0.86, respectively. Simple main effect analyses showed that the cue effect was significant in both groups ($F(1, 9) = 135, p < .001, \hat{\eta}^2_G = .75$ and $F(1, 13) = 24.9, p < .001, \hat{\eta}^2_G = .43$, for BCD and TD respectively) and that the group effect was significant for CS- but not for CS+ ($F(1, 43) = 10.4, p < .01, \hat{\eta}^2_G = .13$ and $F(1, 43) = 0.51, p = 0.48, \hat{\eta}^2_G = .05$ respectively).

Signal detection configurality validation. Figure 8 shows d' and bias values for the SDT of sessions 1 and 5 using stimuli from the validation set. There were higher d' values for the configural arrangement and d' was higher for trials of the element and compound-detection test-types than for the compound-analysis test-type. ANOVA produced a significant main effect of test-type, $F(2, 44) = 23.3, p < .001, \hat{\eta}^2_G = .05$ but this was subject to a 4-way interaction involving session, target duration, and group $F(2, 44) = 3.84, p < .05, \hat{\eta}^2_G < .01$. This interaction was followed-up with simple

interaction ANOVAs carried out separately at each level of session, target duration, and group. No further significant simple interactions were found and the effect of type was significant in all simple interaction analyses (smallest F-value $F(1.5, 19.9) = 8.75, p < .01, \hat{\eta}^2_G = .03$). In each simple interaction analysis the pattern of means across the three levels of type was consistent with the overall mean d' values for the trials involving element-detection, compound-analysis, and compound-detection; d' was lowest in the compound-analysis trials (see Table 4). Following-up the overall main effect pairwise t-tests showed that the means did not differ for element and compound-detection but that d' for compound-analysis was significantly lower than for the other two test-types. The smallest significant t-value occurred in the comparison of compound-analysis and compound-detection trials, $t(23) = 5.16, p < .001$. The omnibus ANOVA also produced a main effect of arrangement, $F(1, 22) = 33.2, p < .001, \hat{\eta}^2_G = .08$; d' was higher for configural than for elemental arrangements (see right-hand column of Table 4).

The mean bias value was 0.1 indicating a high threshold for responding – a tendency to report mismatch. However, whilst the configural arrangement produced higher bias values than the elemental arrangement for the compound-analysis and compound-detection test-types, there were lower bias values (a lower response threshold) in the configural than in the elemental condition for the element-detection trial-types. The omnibus ANOVA for bias produced a significant arrangement x test-type interaction $F(2, 44) = 22.8, p < .001, \hat{\eta}^2_G = .08$ which was followed-up by simple main effect ANOVAs for each of the element-detection, compound-analysis, and compound-detection test-types. Each of these produced significant simple main effects of arrangement with the smallest F-value occurring for the element-detection tests $F(1, 22) = 6.85, p < .05, \hat{\eta}^2_G = .04$. The effect of arrangement was much larger for the compound-analysis and compound-detection test-types with the smallest F-value occurring for the compound-detection tests $F(1, 22) = 20.4, p < .001, \hat{\eta}^2_G = .12$ and the direction of the effect on the compound-analysis and compound-detection tests was opposite to that obtained on the element-detection tests. The mean bias values for the

arrangement x test-type interaction are shown in the body of Table 4 alongside d' values.

Discussion

Despite refinements our SDT still did not detect group differences with the training stimuli. As well as separating compound-analysis and compound-detection trials we included element-detection trials. The element-detection trials were used to check whether the configural pre-training effect might be mediated by changes in elemental processing. Mehta and Russell found that elemental training worsened performance on a configural task relative to a control group (Mehta & Russell, 2009). This suggests that elemental pre-training could increase the distinctiveness of individual stimulus elements instead of (or as well as) configural pre-training increasing the salience of configural cues. Our SDT did not support either of these hypotheses but we still observed the pre-training effect in the transfer task. Importantly though, Experiment 2 provided a validation test of our SDT. The SDT was indeed easier (higher d' values) using stimuli placed in configural rather than in elemental arrangements. This confirms our earlier theoretical analysis in which we argued that compounds made-up of strongly configural elements would be more dissimilar, and hence less easily confused, than compounds made-up of weakly configural elements. However, a note of caution about the validation is appropriate. The stimuli used in the validation were not representative of those used in the main experimental tasks. In Experiment 3 we therefore sought further validation using stimuli drawn from the same set as those used for the main tasks.

Experiment 3

Two major changes were made between Experiment 2 and the current experiment. The first was removal of filler trials from the TD training. The second was a change in the signal-detection validation procedure by using stimuli drawn from the same stimulus set as the training stimuli. In Experiments 1 and 2 participants were trained with either an elemental (TD) or a configural discrimination (BCD) before completing a transfer test. In the transfer test BCD participants learned a new configural discrimination,

negative patterning, more readily than TD participants. We attribute this performance advantage to the fact that BCD participants had experience of a configural problem during the training stage but their training differed from that experienced by TD participants in another aspect. Recall that Experiments 1 and 2 included partially reinforced filler trials in the training for TD participants. This was justified on the basis of unpublished data which showed that the TD participants learned the training discrimination more quickly than the BCD participants and we used the filler trials to try to equate the training tasks for difficulty (see Experiment 1, Design and procedure). Unfortunately, including the filler trials did not achieve this aim, TD participants still learned the training discriminations more quickly than BCD participants. Of course this means that the presence of filler trials was confounded with configurality during training and thus complicates the interpretation of the transfer test results. In the current experiment we sought to eliminate this confound by dropping the filler trials from the TD condition. In all other respects the learning task, SDT with the training stimuli, and the transfer test was the same as Experiment 2.

The second major change from Experiment 2 was in the signal-detection validation procedure. In Experiment 2 validation focussed on comparison of signal-detection performance using stimuli with previously established differences in configurality. In this experiment we used a signal-detection validation procedure that focussed upon target-probe similarity and which used stimuli drawn from the same set as those used in the main experimental task. According to the model of configurality described in the introduction, stimulus configuration involves increased salience of elements which represent stimulus conjunctions. A corollary is that similarity between two stimulus compounds will be reduced if configural cues are made more salient and this occurs because the overall proportion of common elements goes down. Thus, further validation of the signal-detection procedure was obtained by looking at whether or not performance was influenced by the number of elements common to target and probe stimuli.

Method

Differences from Experiment 2 are detailed below.

Participants. Forty-eight participants were recruited. They included 10 males and their average age was 23 years (range 18-50). Three participants had some missing data due to technical error for one or more of the analyses to be reported below. Each analysis used all available data.

Apparatus. Four symbols were selected from our set of 16 Hnias characters to fulfil stimulus roles I, J, K, and L in the signal-detection validation procedure (the remaining 12 were used for the training and transfer set).

Design and procedure. Sessions were completed in an average of 13 days. The signal-detection validation task was run in the first part of session one and the second part of session five. A single run of the task comprised 144 trials split into two blocks. One block had target duration 53ms (fast), the other had target duration 80ms (slow). Participants were allocated in order of recruitment to one of two order conditions - either fast block first in session one or fast block first in session five - so that the number in each order condition was approximately equal. There are six pairwise combinations that can be drawn from the four stimuli making up the validation set (IJ, IK, IL, JK, JL, and LK). In one block of the validation task three of these compounds appeared 24 times as probe and the corresponding target matched the probe on eight trials (high similarity condition), shared one common element on eight trials (medium similarity condition), or had no common elements on eight trials (low similarity condition). Within each set of eight trials four were compound-detection and four were compound-analysis trials. For the high and medium similarity condition the left/right position of the common elements in target and probe matched in the compound-detection trials and mismatched in the compound-analysis trials. For the low similarity condition the left/right position of the elements making-up the target was balanced across the compound-detection and analysis conditions. Table 2 illustrates the arrangements for one of the probe compounds, the others were treated alike. Compounds IJ, IK, and KL were used as probes in the slow blocks; JK, JL, and IL were

used in the fast blocks. Trial order was randomised independently for each block. The trials all had compound probes so the probe question was 'Were these symbols both present?' therefore in the high similarity condition a response of 'yes' was a hit and a 'no' was a miss. In the medium and low similarity condition 'yes' and 'no' responses were false alarms and correct rejections respectively.

Analysis

Forty-six participants had complete datasets for the learning task (24 BCD and 22 TD). Of these seven BCD and four TD participants were excluded from analyses due to failure to acquire the learning task discrimination. Data from the 18 remaining TD participants and the 17 remaining BCD participants are presented below for analyses of the learning task, the SDT for the validation stimuli, and the transfer task. One of the 18 TD participants had missing data for the SDT using the training stimuli giving n=17 (TD) and n=17 (BCD) for that analysis. Analysis of the signal-detection validation data was carried out separately for the high and medium/low similarity conditions. In both cases the proportion correct was analysed but, as mentioned above, this was two different dependent variables – proportion of hits $h/(h+m)$ and proportion of correct rejections $c/(c+f)$ for the two analyses[3]. For the high similarity condition (two elements common to target and probe) there were three repeated-measures factors: session (2 levels; session 1 and session 5), target duration (2 levels; 53ms and 80ms), and test-type (2 levels; compound-detection and compound-analysis) and one between-participants factor: group (2 levels; TD or BCD). For the medium/low similarity condition there was an additional repeated-measures factor: similarity (2 levels; medium (one element common to target and probe) and low (no elements common to target and probe)).

Results

Learning task. Figure 2 shows that participants learned to respond appropriately in both the BCD and TD tasks.

[3]h=hits, m=misses, c=correct rejections, and f=false alarms

Signal detection training stimuli. Figures 9 and 10 show d' and bias values. In contrast to Experiment 2 visual inspection did not suggest any overall group differences on d' (but note that analysis of Experiment 2 did not yield significant group effects). However, a four-way ANOVA on d' did produce significant session, target duration, and test-type effects as in Experiment 2 and, in addition, there was a significant group by test-type interaction ($F(1.5, 48.1) = 6.47, p < .01, \hat{\eta}^2_G = .04$; $F(1, 32) = 48.6, p < .001, \hat{\eta}^2_G = .02$; $F(2, 64) = 28.7, p < .001, \hat{\eta}^2_G = .03$; and $F(2, 64) = 4.59, p < .05, \hat{\eta}^2_G = .01$, respectively). The d' values increased across sessions 1-4 with means of 1.96, 1.94, 2.33, and 2.41. For target duration d' values were higher for the 80ms presentations than for the 53ms presentations with means of 2.29 and 2.03 respectively. The group by test-type interaction was followed-up by simple main effect analyses of test-type within each group and simple main effect analysis of the groups at each test-type. The effect of test-type was significant in both groups but larger in the case of the TD group than in the BCD group ($F(2, 32) = 25.3, p < .001, \hat{\eta}^2_G = .04$ and $F(2, 32) = 9.95, p < .001, \hat{\eta}^2_G = .04$, respectively). For test-type the mean d' values for element-detection, compound-analysis, and compound-detection trials are shown for each group in Table 3. For group TD pairwise t-tests showed that the means did not differ for element-detection and compound-analysis but that d' for compound-detection was significantly higher than for the other two test types. The smallest significant t-value occurred in the comparison of compound-analysis and compound-detection tests, $t(33) = 4.21, p < .001$. For group BCD pairwise t-tests showed that the means did not differ for compound-detection and compound-analysis trials but that d' for element-detection was significantly lower than for the other two test types. The smallest significant t-value occurred in the comparison of compound-analysis and element-detection tests, $t(33) = 2.23, p < .05$. The simple effect of group only approached significance in the compound-analysis tests $F(1, 37) = 3.69, p = 0.06, \hat{\eta}^2_G = .06$ (Fs(1,37)<1 otherwise).

ANOVA on the bias data produced an effect of session, target duration, and a three-way interaction between group, target duration, and test-type

($F(1.8, 58.2) = 4.06, p < .05, \hat{\eta}^2_G = .01$, $F(1, 32) = 14.3, p < .001, \hat{\eta}^2_G = .01$, and $F(1.7, 53.9) = 5.06, p < .05, \hat{\eta}^2_G < .01$, respectively). The mean bias values decreased across sessions 1-4 with means of 0.21, 0.09, 0.12, and 0.1, respectively. The bias values were smaller on the 80ms presentations than for the 53ms presentations with means of 0.1 and 0.16 respectively. For the three-way interaction simple interaction analysis at each duration did not reveal group by test-type interactions.

Transfer discrimination. Figure 11 shows PP and NP transfer task discrimination performance. Both discriminations were learned by both groups but, as previously, the performance of the BCD group was better than that of the TD group, especially in the NP condition. Analysis of the PP data produced a significant group x block x cue interaction, $F(1.6, 54.4) = 5.31, p < .05, \hat{\eta}^2_G = .02$. Simple interaction ANOVAs in each block produced highly significant cue effects in each block with the smallest F-value in block 1, $F(1, 33) = 133, p < .001, \hat{\eta}^2_G = .53$ but the cue x group simple interaction was not significant in any case. Analysis of the NP data produced a significant block x cue interaction and, importantly, a cue x group interaction ($F(1.6, 52.4) = 34.4, p < .001, \hat{\eta}^2_G = .18$ and $F(1, 33) = 4.97, p < .05, \hat{\eta}^2_G = .04$ respectively). Simple main effect analysis of the block x cue interaction showed that the cue effect was significant in all blocks with the smallest F-value occurring in block 1, $F(1, 33) = 44.9, p < .001, \hat{\eta}^2_G = .39$. For the cue x group interaction the mean proportions of trials with a response for CS- and CS+ in the BCD group were 0.2, and 0.9, respectively. The mean proportions of trials with a response for CS- and CS+ in the TD group were 0.35, and 0.89, respectively. Simple main effect analyses showed that the difference between the means for CS- and CS+ was significant in both groups ($F(1, 16) = 491, p < .001, \hat{\eta}^2_G = .82$ and $F(1, 17) = 72.2, p < .001, \hat{\eta}^2_G = .59$, for BCD and TD respectively) and that the group effect was significant for CS- but not for CS+ ($F(1, 66) = 8.06, p < .01, \hat{\eta}^2_G = .08$ and $F(1, 66) = 0.051, p = 0.82, \hat{\eta}^2_G < .01$ respectively).

Signal detection similarity validation. Figure 12 shows the data from the SDT using the similarity validation stimulus set. All panels show proportions correct. In the case of the high similarity condition (top panels) this is proportion of hits

whereas in the case of the medium and low similarity conditions (bottom panels) this is proportion of correction rejections. For the high similarity condition the proportion correct was lower in the 53ms condition than in the 80ms condition, lower in the compound-analysis tests than in the compound-detection tests (but both of these effects were less clear in session one than in session five), and lower in session one than in session five. ANOVA for the high similarity condition produced a significant main effect of test-type and session ($F(1, 33) = 8.6, p < .01, \hat{\eta}^2_G = .04$ and $F(1, 33) = 56, p < .001, \hat{\eta}^2_G = .17$ respectively). The effect of test-type was subject to an interaction with target duration and there was a three-way interaction involving test-type, target duration, and session ($F(1, 33) = 12.9, p < .01, \hat{\eta}^2_G = .02$ and $F(1, 33) = 9.76, p < .01, \hat{\eta}^2_G = .01$ respectively). Simple interaction analyses in sessions one and five produced a test-type x target duration interaction $F(1, 33) = 23.7, p < .001, \hat{\eta}^2_G = .04$ in session one only. The test-type by target duration interaction in session one was followed with simple main effect analyses of test-type at each duration and of duration at each test-type. The simple effect of test-type was significant only in the 80ms condition $F(1, 33) = 10.4, p < .01, \hat{\eta}^2_G = .15$ and the simple effect of target duration was significant only for the compound-detection test-types $F(1, 33) = 9.71, p < .01, \hat{\eta}^2_G = .06$).

For the medium and low similarity conditions the proportion correct was lower for the medium similarity tests than for the low similarity tests, lower in the 53ms than in the 80ms condition and, in the medium similarity tests, was lower in the compound-detection condition than in the compound-analysis tests. The proportion correct was also lower in session one than in session five and the BCD group improved more between sessions. ANOVA produced significant main effects of test-type, target duration, similarity, and session ($F(1, 33) = 10, p < .01, \hat{\eta}^2_G = .01$, $F(1, 33) = 5.15, p < .05, \hat{\eta}^2_G = .01$, $F(1, 33) = 81.3, p < .001, \hat{\eta}^2_G = .2$, and $F(1, 33) = 23, p < .001, \hat{\eta}^2_G = .05$ respectively). There were also significant two-way interactions between session and group, and between test-type and similarity ($F(1, 33) = 5.65, p < .05, \hat{\eta}^2_G = .01$ and $F(1, 33) = 9.59, p < .01, \hat{\eta}^2_G = .01$ respectively).

Simple main effect analysis for the effect of session for each group showed that the effect of session was significant for the BCD group only $F(1, 33) = 25.5, p < .001, \hat{\eta}^2_G = .12$ whilst the simple main effect analysis of group for each session failed to produce a significant group effect in either session. For the test-type x similarity interaction simple main effect analyses of test-type produced a significant effect only for the medium similarity condition $F(1, 33) = 18, p < .001, \hat{\eta}^2_G = .03$. In contrast the simple main effect of similarity was significant for both test-types ($F(1, 33) = 27.5, p < .001, \hat{\eta}^2_G = .18$ and $F(1, 33) = 56.4, p < .001, \hat{\eta}^2_G = .21$ for compound-analysis and compound-detection respectively).

Discussion

Experiment 3 demonstrated that the inclusion of filler trials in the TD condition did not cause the difference in performance between the TD and BCD groups on the transfer task. Furthermore we continued to find no evidence of performance differences between the groups on our SDT after further, similarity-based, validation. A similarity effect in the signal detection task was seen in better performance (more correct rejections) in the low than in the medium similarity condition. In the medium similarity condition there was better performance (more correct rejections) in compound-analysis than in compound-detection trials which is consistent with there being more similarity between target and probe on compound-detection trials. In the high similarity condition there was better performance (more hits) on the compound-detection trials than on the compound-analysis trials which is again consistent with greater target-probe similarity on compound-detection trials.

General discussion

In three experiments we replicated a result reported previously by Mehta and Russell (2009) and Melchers et al. (2005), namely that performance in NP transfer tasks is better after configural pre-training than after elemental pre-training. We hypothesised that pre-training effects could occur if pre-training increased the salience of configural information relative to element salience for the BCD condition

(Experiments 1-3) or if pre-training increased the salience of element information relative to configural salience for the TD condition (Experiments 2-3), but we could find no evidence of this occurring within 1-2s of the onset of stimulus compounds. This was not because our SDT was insensitive; in Experiments 2 and 3 we validated the test, showing it was sensitive to both configural information and similarity. Furthermore our tests were carried out under optimised conditions for finding group differences in that participants were given extensive experience with their discriminations and we selected those who had learned their discriminations well. Of course we have not proved the null hypothesis but we have conducted a thorough exploration of one hypothesis about the genesis of facilitative pre-training transfer effects. Our transfer results add to a now considerable body of evidence that indicates a broad range of manipulations can change the processing of stimulus compounds along a dimension running from elemental to configural (e.g. Melchers, Lachnit, & Shanks, 2008). Clearly this is incompatible with either-or theories of learning which propose that organisms process stimulus compounds either as elements or as configurations. Instead, the evidence shows that processing can be flexible in the configural dimension. There is currently limited understanding of the mechanism of flexible processing but our results shed some light on the psychological changes that occur when flexible processing is observed.

We examined above whether or not changes in the relative salience of configural and elemental cues could be detected early in the stimulus processing pipeline because this constitutes a test of one important idea on the origin of configural-cue information discussed by Hull (1945). Hull used the term 'afferent neural interaction' to describe a process in which two concurrently presented stimuli could interact, effectively with one altering perception of the other. This resembles very closely the way perceptually-based configural cues were described in the introduction and various proposals have been made to specify how such interactions might work. For example Kehoe and Graham (1988) suggested a mechanism for learning of configural discriminations involving a unique cue but also suggested that the unique cue encoding unit might inhibit the units representing each cue and that the extent of this inhibition would vary the amount of

generalisation between the compound and elements – a possible mechanism for configural learning transfer effects. Other elemental theories offer detailed accounts of configural cue mechanisms and suggest ways for understanding how configural learning could occur (Harris, 2006; McLaren & Mackintosh, 2002; Wagner, 2003). For example, Wagner's 2003 replaced elements approach incorporates a parameter (R) which allows the model to move along a continuum, from elemental to configural. Although there is no mechanism specified to control how this parameter might change with experience this is clearly one area for theoretical development; one possibility to explore would be a mechanism which adjusts R to minimise prediction error over a series of trials.

However, it is also clear that configural cue information can be extracted by integrating information across sensory modalities, and it is therefore also possible that changes in cue processing produced by pre-training may take place after the processing that initially takes place within a single sensory pathway (e.g. Delamater et al., 1999; Harris et al., 2008; Kehoe & Graham, 1988). This would not be incompatible with the different conceptualisations for the operation of configural cues mentioned above and the extension of these ideas to explain configural flexibility. It is merely necessary to assume that the representational units involved are 'higher-order' gnostic units (Konorski, 1967) rather than 'lower-order' features such as line segments. We have cited configural effects with multi-modal stimuli as a primary source of evidence for late extraction of configural information but it is also relevant to cite the work of Rescorla, Grau, and Durlach (1985). These authors presented evidence for late extraction of configural cue information in pigeons trained with unimodal (visual) stimuli in a NP procedure. After NP training the discrimination elements served as outcomes in a second-order conditioning procedure. That is, after A+, B+, AB- training second-order conditioning was undertaken with $X \rightarrow A$ and $Y \rightarrow B$ trials. A test was then presented with an XY compound which would be expected to activate central representations of A and B without activating their afferent pathways. Responding resembled that seen to the AB compound from the originally trained non-linear discrimination despite the fact that the second-order stimuli were physically distinct from those originally trained –

consistent with configuration of central representations rather than configuration of afferent perceptual inputs.

An alternative view that is applicable in the case of human learning is that problems involving cue configurations are solved by the application of verbal rules (Lachnit & Lober, 2001; Lachnit et al., 2001). For example, Lachnit et al. (2001) found interference effects when PP problems were learned before NP problems but not vice-versa. They explained this in terms of the rules participants used to solve the two different types of discrimination. PP was suggested to involve a cardinality rule 'respond to two items' that then interferes with the requirements of a NP task. On the other hand NP was suggested to involve a rule of the form 'compound and elements have opposite outcomes' which is equally applicable to both tasks. We can also envisage a process based upon practised application of an 'and-rule' during the course of BCD training. Practise makes such a rule readily available and could then facilitate performance in a NP transfer task where 'A and B no outcome' applies. Of course, such a rule-based system would represent a further level of information processing, beyond the integration of simple sensory inputs, and beyond the integration of information at the level of a central representation unit.

In summary, the transfer effects between biconditional discrimination and NP reported in the current experiments and previously (Mehta & Russell, 2009; Melchers et al., 2005) could be underpinned by changes in configural and elemental cue processing at multiple loci within an information processing pathway that begins with simple perceptual processes and progresses to rule-based mechanisms. We suggest that a rule-based mechanism would be relatively slow acting and therefore be unlikely to produce advantages over the 1-2s before participants made responses in our SDT. Furthermore, we imagine it quite plausible for a rule-based process to be activated over the 4s CS duration used in our learning tasks. Thus, the simplest explanation for the apparent discrepancy between the signal-detection and transfer tasks is that pre-training effects are produced at a relatively late point in stimulus information processing. Although we have provided a demonstration of flexibility in processing

strategy that does not seem to rely on early perceptual processes we do not rule out the possibility that different types pre-training may bias people towards the use of particular types of processing. For example, in our training procedure we randomised the left/right location of the stimulus elements. This does not change the fundamental difference between the TD and BCD conditions but it is possible that having many exemplars of perceptual configural cues could shift people towards use of a rule-based strategy. Furthermore, it is entirely possible that some perceptual processes could take more than 1-2s to develop and thus not be available for use in the SDT. Consistent with this Williams and Braker found that a speeded task disrupted configural processing as compared to an unspeeded task but did not find correlations between rule-following (assessed by post-experiment questionnaire) and response profiles. Further work exploring the parameters of learning, signal-detection, and transfer tasks will produce additional insights but at a general level, the data reported here and elsewhere document the involvement of flexible representational processes in associative learning (e.g. Alvarado & Rudy, 1992; Melchers et al., 2008).

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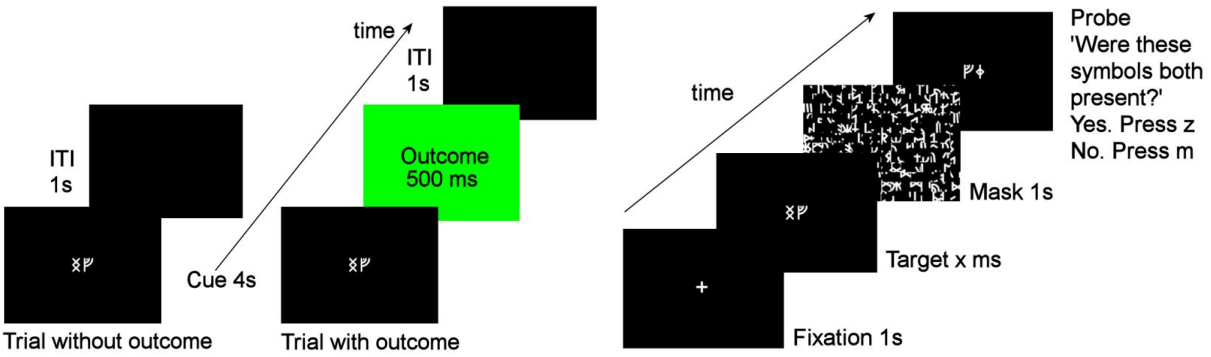

(a) Learning task trials. Two timelines were used. One for trials with and one for trials without an outcome. Cue presentation initiated both types. If the outcome was scheduled to appear the entire screen flashed green immediately after the offset of the cue. The ITI followed either the cue or outcome offset.

(b) Signal detection task trials. A target display of a pair of symbols was presented immediately after fixation. The target duration (x) was one of 53, 80, 93, or 107 varied according to experimental design. Targets were replaced by a mask and then the mask was replaced by the probe question. A response to the probe question initiated the next trial.

Figure 1. Timeline illustrations of computer screen displays in the learning and SDT. See Experiment 1, Design and procedure for additional details.

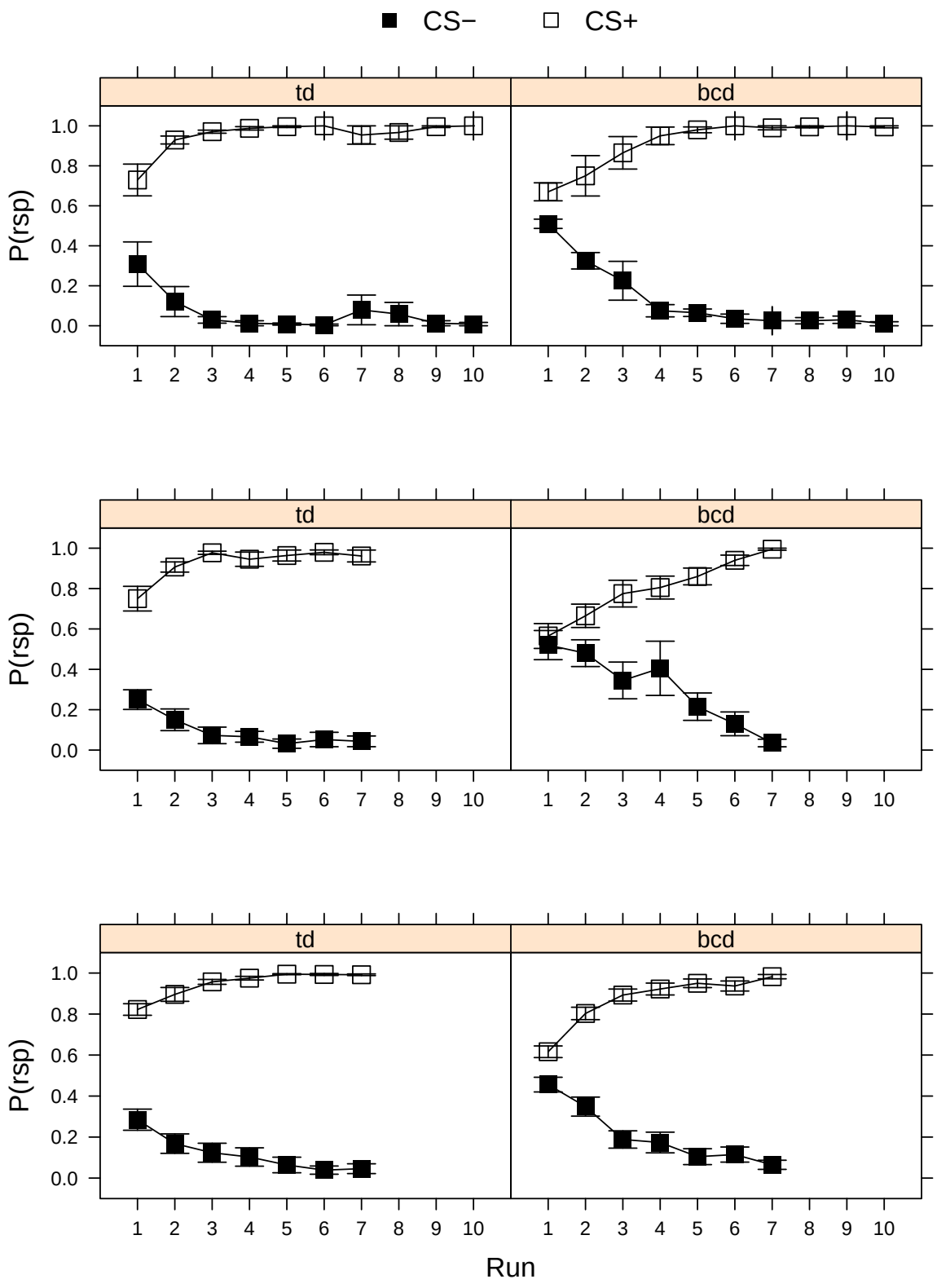

Figure 2. Top to bottom, Experiments 1, 2, and 3, learning task discrimination performance. The proportion of trials with an outcome prediction P(rsp) is plotted as a function of run, cue, and group.

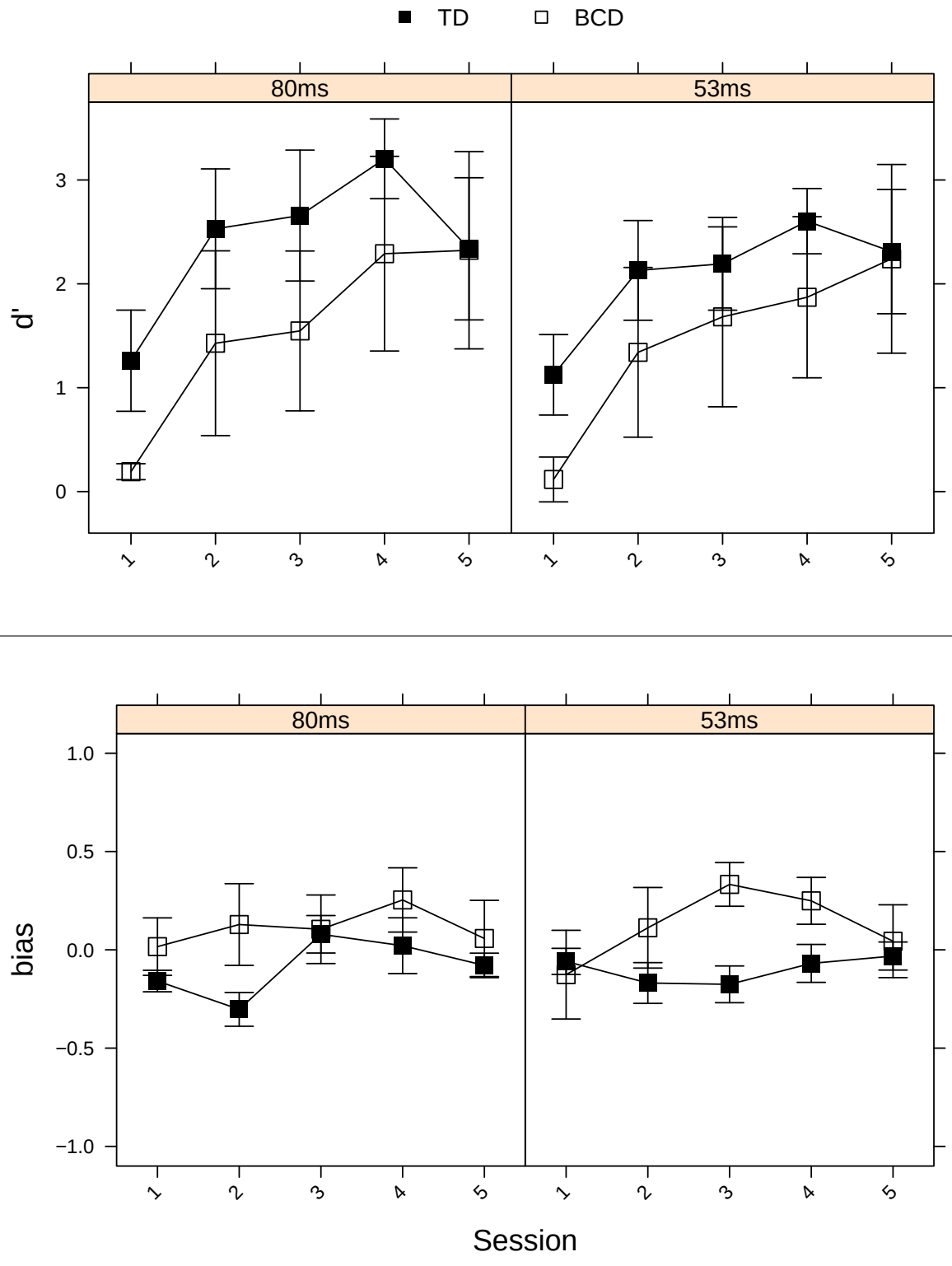

Figure 3. Experiment 1, SDT performance. d' and bias are plotted as a function of session, target duration, and group.

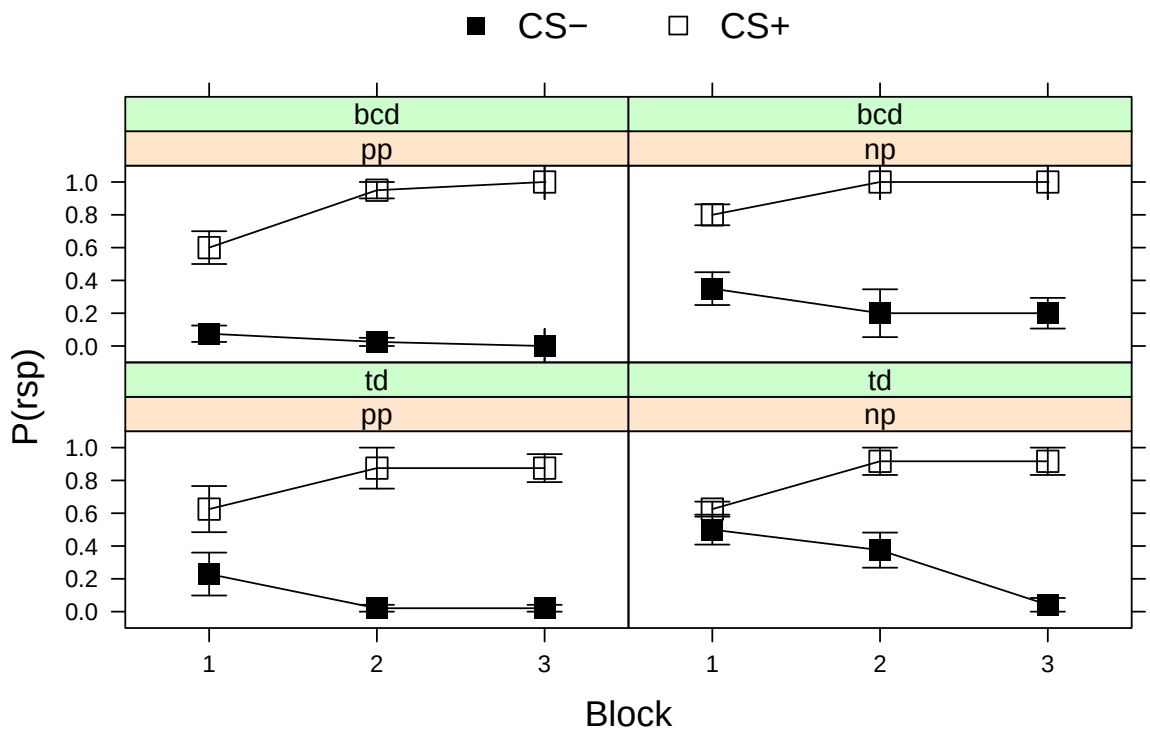

Figure 4. Experiment 1, transfer task discrimination performance. The proportion of trials with an outcome prediction P(rsp) is plotted as a function of cue, block, and group for each of the two transfer discriminations.

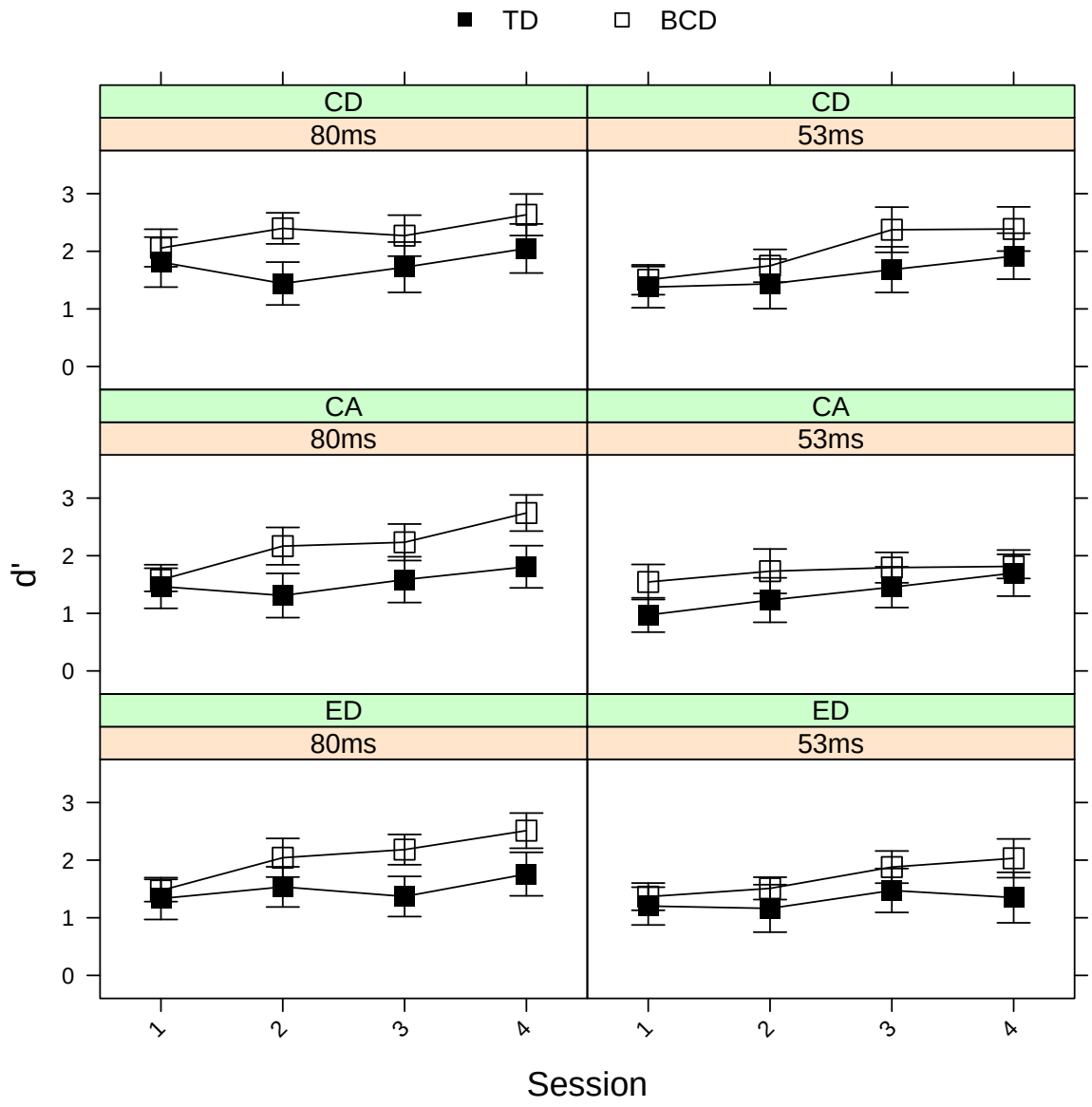

Figure 5. Experiment 2, signal-detection by session, test, and group (d') using training stimuli. Test-type ED=element-detection, CD=compound-detection, CA=compound-analysis.

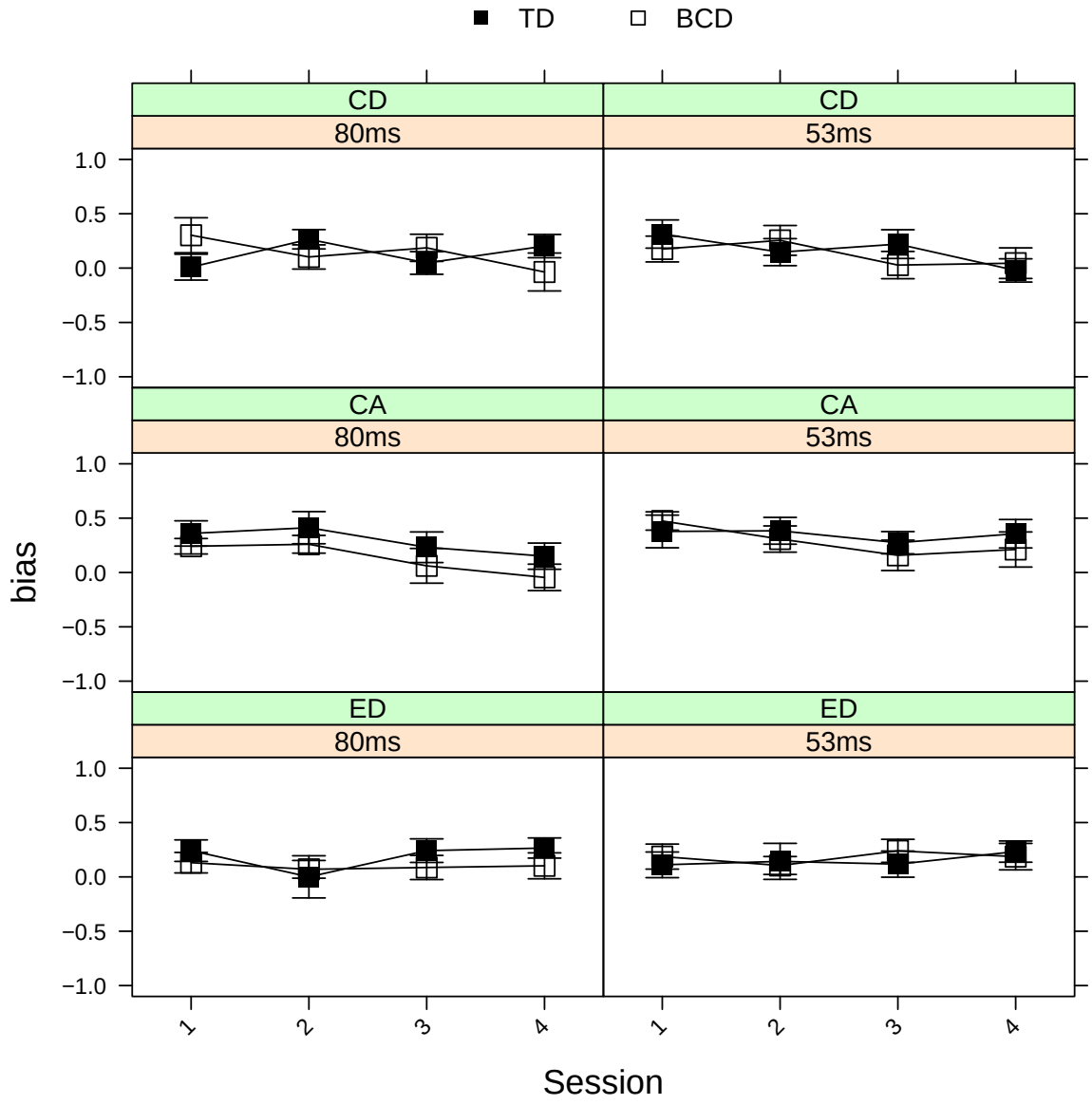

Figure 6. Experiment 2, signal-detection by session, test, and group (bias) using training stimuli. Test-type ED=element-detection, CD=compound-detection, CA=compound-analysis.

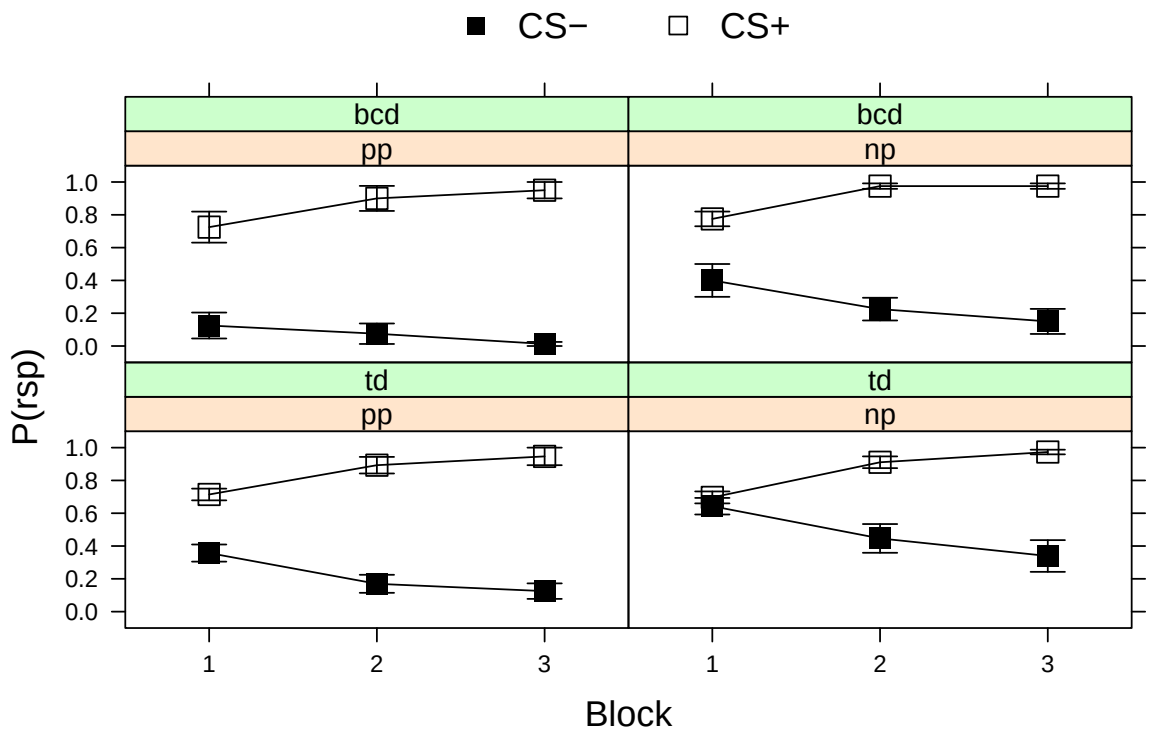

Figure 7. Experiment 2, transfer task discrimination performance. The proportion of trials with an outcome prediction P(rsp) is plotted as a function of cue, block, and group for each of the two transfer discriminations.

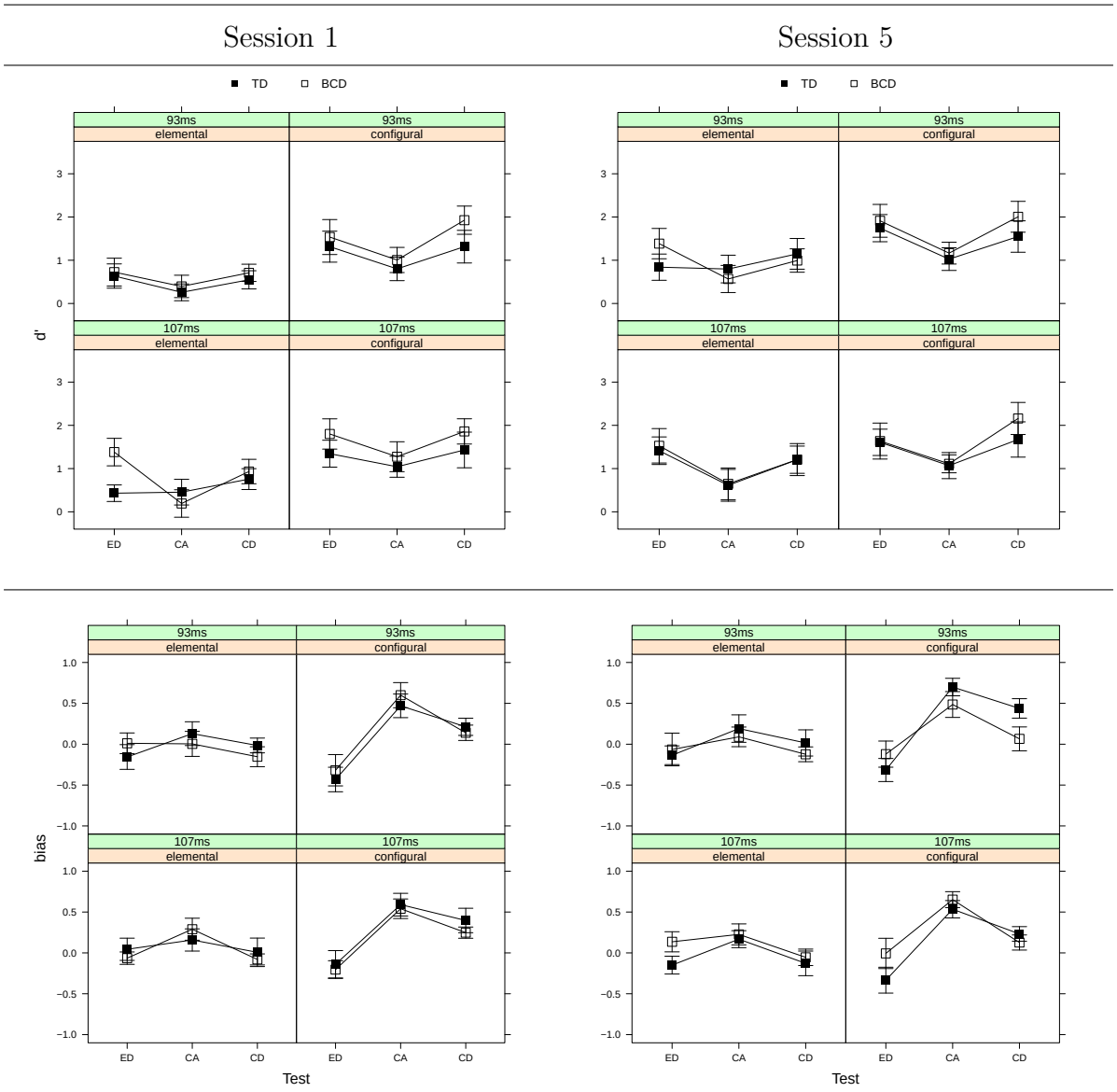

Figure 8. Experiment 2, signal-detection using configurality validation stimuli by session, test, group, and stimulus arrangement. d' is shown in the top row, bias in the bottom. Test-type ED=element-detection, CD=compound-detection, CA=compound-analysis.

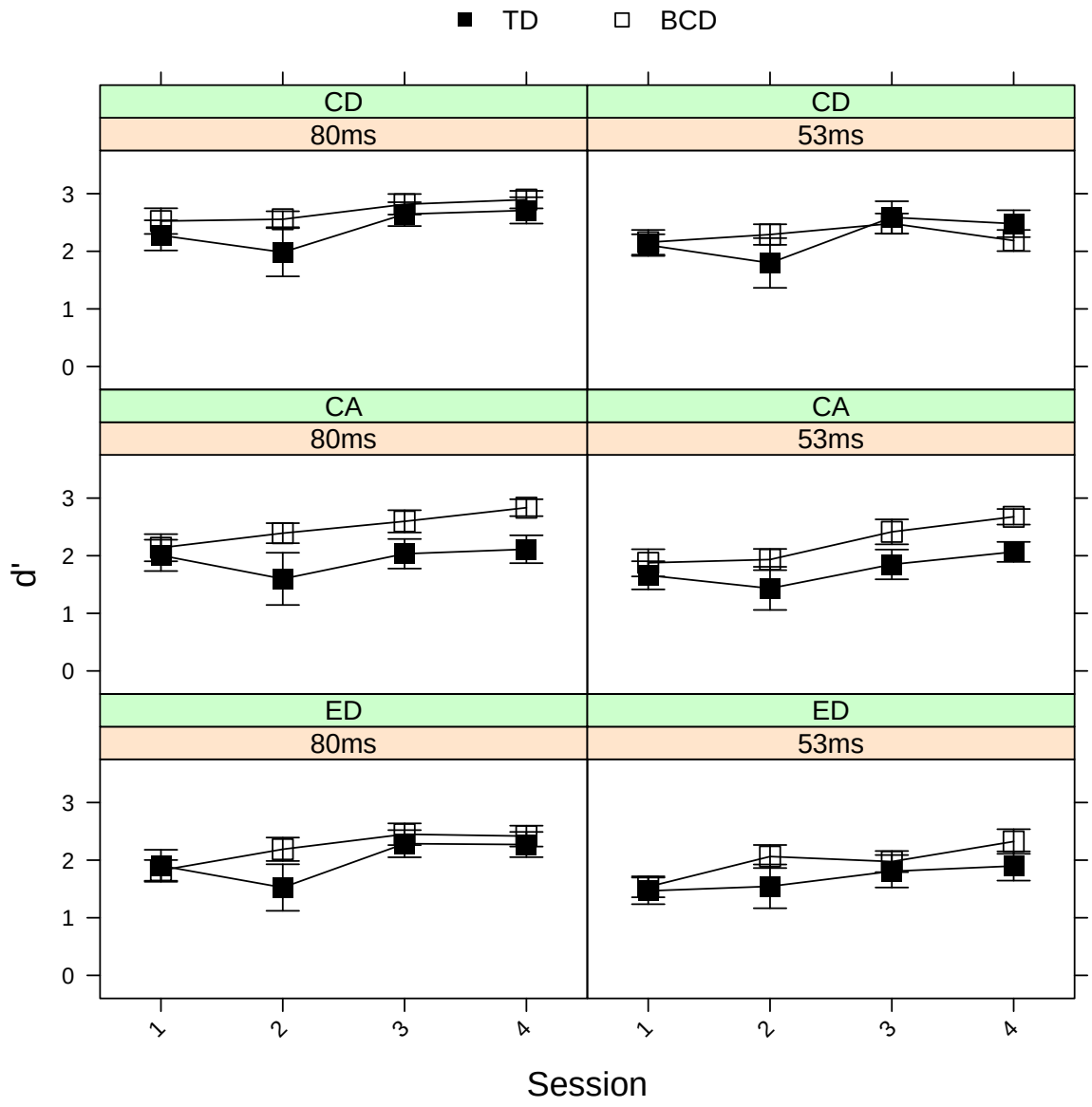

Figure 9. Experiment 3, signal-detection by session, test, and group (d') using training stimuli. Test-type ED=element-detection, CD=compound-detection, CA=compound-analysis.

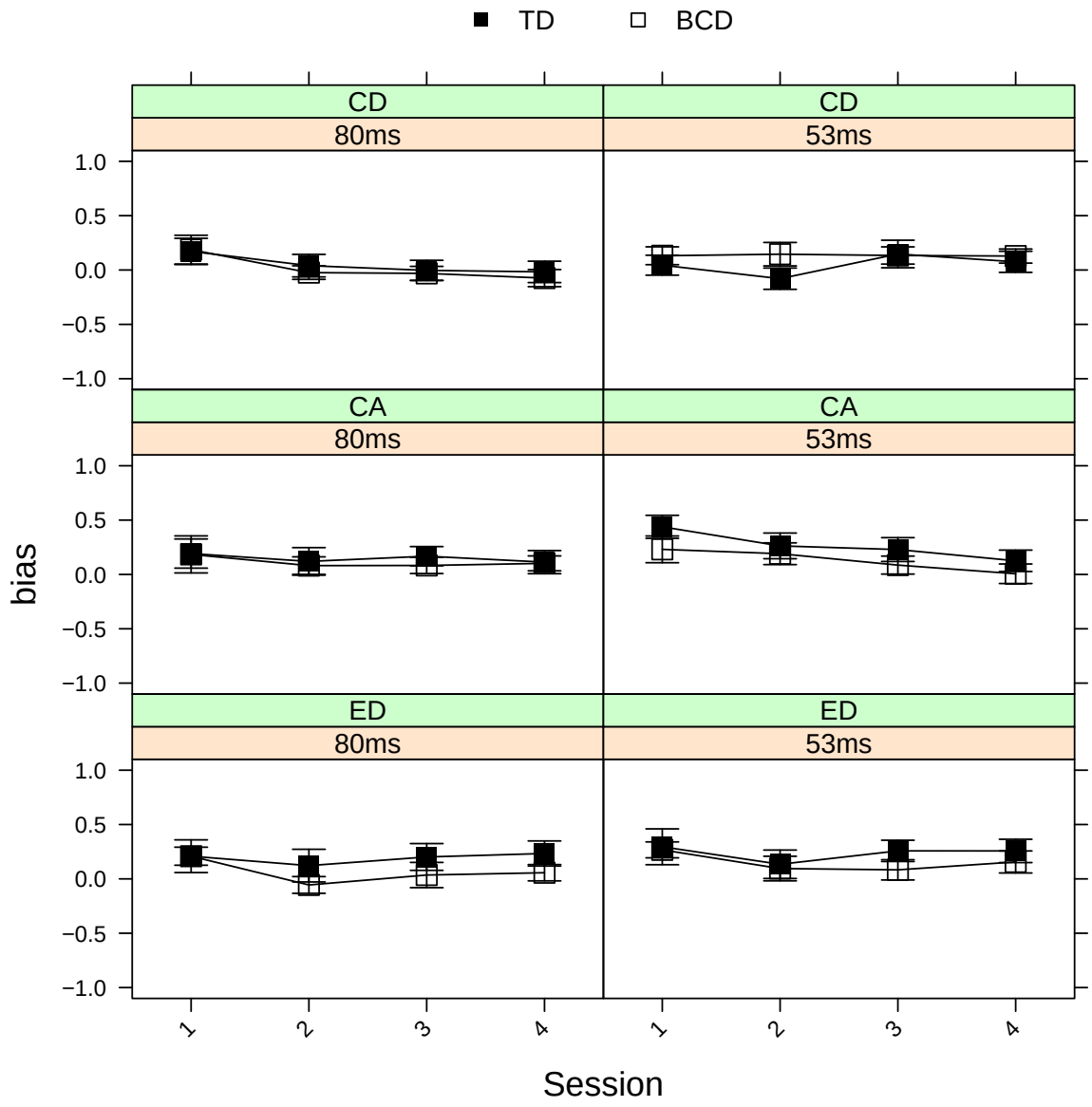

Figure 10. Experiment 3, signal-detection by session, test, and group (bias) using training stimuli. Test-type ED=element-detection, CD=compound-detection, CA=compound-analysis.

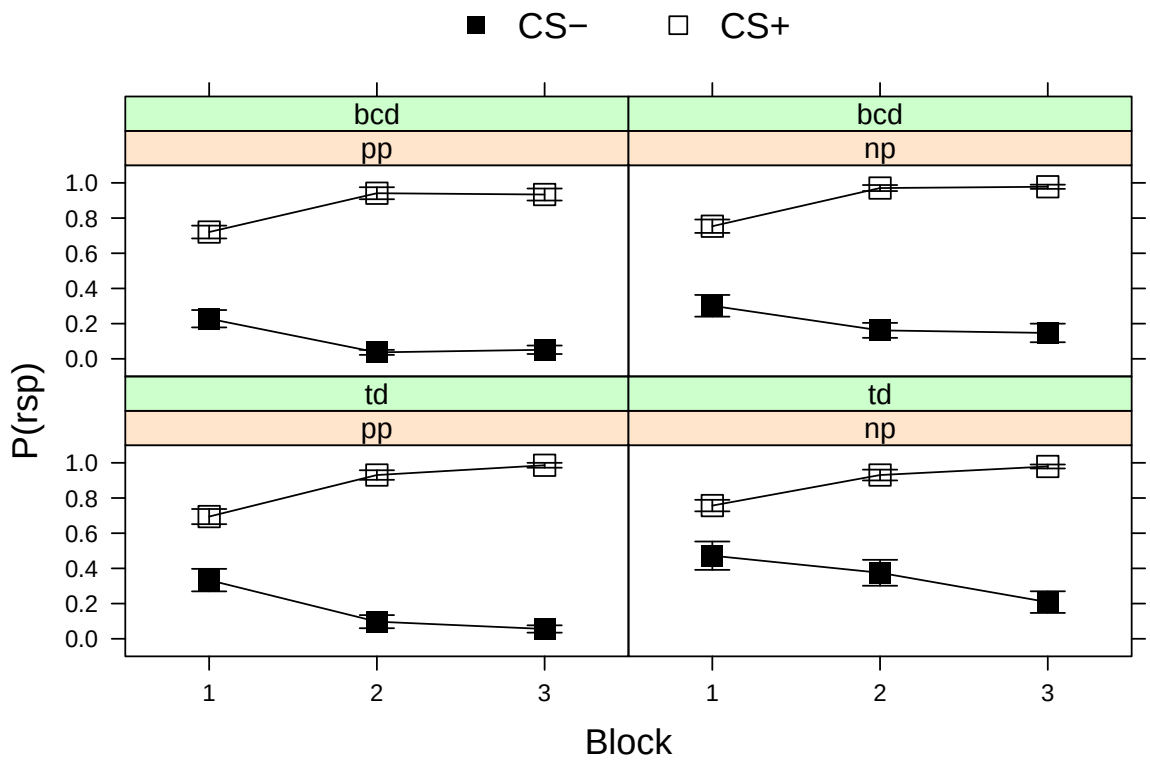

Figure 11. Experiment 3, transfer task discrimination performance. The proportion of trials with an outcome prediction P(rsp) is plotted as a function of cue, block, and group for each of the two transfer discriminations.

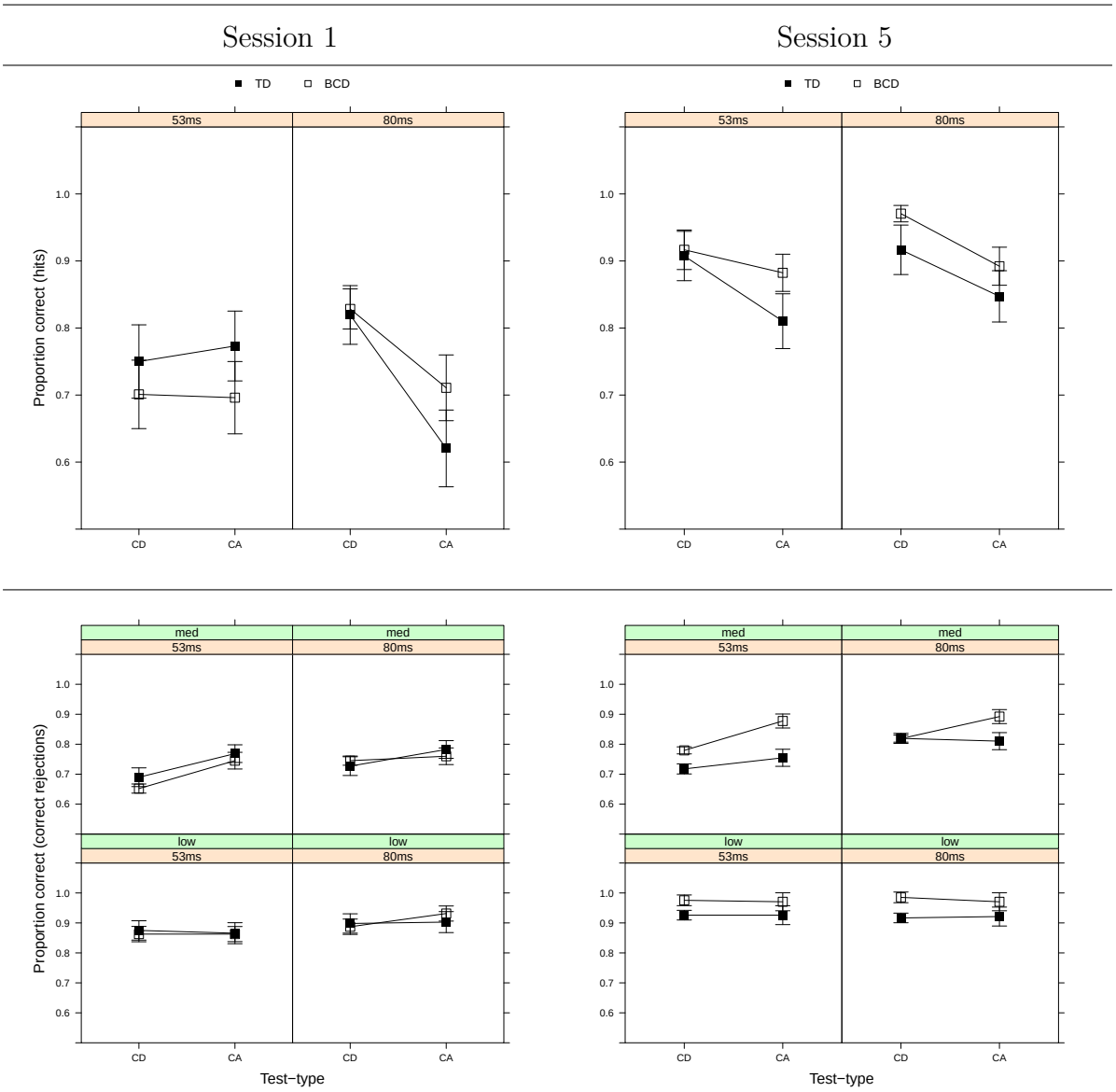

Figure 12. Experiment 3, signal-detection using similarity validation stimuli by test-type, target duration, similarity, group and session. Proportion correct for high (top row) and low/medium similarity conditions (bottom row). Test-type CD=compound-detection, CA=compound-analysis.

Table 1

Discrimination design summaries for Experiments 1-3. For the training discriminations each participant learnt two exemplars of either a true discrimination or a bi-conditional discrimination. For example the first TD exemplar consisted of AB+, BC+, CD-, and AD- trials and the second BCD exemplar consisted of EF+, FG-, GH+, and EH- trials. For the transfer discriminations each participants learnt one exemplar of a PP discrimination and one exemplar of a NP discrimination. +/- indicates which CS pairs predicted the US. + trials always occurred with the US, - trials never occurred with the US.

	Trial patterns			
Discrimination	Training			
True discriminations	AB+/EF+	BC+/FG+	CD-/GH-	AD-/EH-
Bi-conditional discriminations	AB+/EF+	BC-/FG-	CD+/GH+	AD-/ EH-
	Transfer			
Positive patterning	M-	N-	MN+	
Negative patterning	O+	P+	OP-	

Table 2

Design summary for similarity-based signal-detection validation in Experiment 3. Trial classification and numbers of trials in parentheses for one of the six different probe compounds (IJ). The other five probes (IK, IL, JK, JL, and LK) were treated in the same way to arrive at the 144 trials in each run of the validation task.

	Target		
Probe	compound-detection	compound-analysis	Similarity
IJ	IJ (4)	JI (4)	High
	IK (1)	KI (1)	Medium
	IL (1)	LI (1)	Medium
	KJ (1)	JK (1)	Medium
	LJ (1)	JL (1)	Medium
	KL (2)	KL (2)	Low
	LK (2)	LK (2)	Low

Table 3

Overall d' and bias values by test-type for signal-detection training stimuli in Experiment 2 and Experiment 3. ED=element-detection, CA=compound-analysis, CD=compound-detection.

	Test type		
	Experiment 2		
	ED	CA	CD
d'	1.61	1.66	1.89
bias	0.16	0.27	0.14
	Experiment 3		
d' TD group	1.84	1.84	2.32
d' BCD group	2.10	2.36	2.50

Table 4

Overall d' and bias values by test-type and stimulus arrangement for validation stimuli in Experiment 2. ED=element-detection, CA=compound-analysis, CD=compound-detection.

		Test type			
Arrangement		ED	CA	CD	$\overline{x}$
Elemental	d'	0.93	0.55	0.95	0.81
	bias	-0.06	0.16	-0.06	0.01
Configural	d'	1.66	0.99	1.69	1.45
	bias	-0.25	0.57	0.25	0.19
$\overline{x}$	d'	1.3	0.77	1.32	
	bias	-0.16	0.37	0.1	