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Using transcranial Direct Current Stimulation (tDCS) to influence decision criterion in a target detection paradigm

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Abstract

In this paper we investigate how a psychological theory used to model perceptual learning and face recognition, can be used to predict that anodal tDCS delivered over the DLPFC at Fp3 site (for 10 mins duration at 1.5mA intensity) modulates the decision criterion, *C*, (and not d-prime, *d′*) in a *target detection task*. In two between-subjects and double-blind experiments (n=112) we examined the tDCS effects on *C* when subjects were engaged in a *target detection task*, in the first instance involving artificial checkerboard stimuli (Experiment 1a), and subsequently face stimuli (Experiment 1b). The results from both experiments revealed that in the sham/control groups a significantly higher *C* was used when detecting a target pattern (Experiment 1a) or face (Experiment 1b) presented on a familiar rather than a random background. Importantly, anodal tDCS significantly reduced/reversed this difference between *C* adopted for familiar and random backgrounds in both Experiment 1a and 1b without affecting *d′*. These results contribute to advance our understanding of the tDCS-induced effects on stimulus representation and to the literature regarding the modulation of *C*.

Key Words: tDCS; Perceptual Learning; Face Recognition; Signal Detection Analysis

Preamble

This paper is not about a task or experiment that can be said to be directly inspired by the work of Bob Rescorla. Nevertheless, it relies heavily on the approach to associative learning that Rescorla (and Wagner) pioneered in the early 1970s. It does this in two ways. Firstly, it uses an associative algorithm employing a pooled error term and an elemental approach to representation to explain the effects reported in the paper (e.g., Rescorla and Wagner, 1972; Rescorla, 1976). And secondly, it applies associative learning to a target detection task which might more commonly be thought not to involve that type of process. In this instance, it uses the Rescorla-Wagner model in a modified form to advance our understanding of some aspects of human visual search skills and how neuro-stimulation techniques can modulate these.

In doing this, we hope to make the point that associative learning has a ubiquitous role to play in human and other animal's task performance. Even when the task might not obviously lend itself to an associative analysis, there can still be room for (in this case admittedly small) effects that result from the operation of these processes "in the background" as envisaged in McLaren et al (2018). We think that this approach fits in rather well with Rescorla's (see Rescorla, 1988), in that it envisages a significant role for associative learning that goes well beyond standard Pavlovian conditioning.

Perhaps the final point to make here is that we cannot imagine taking the approach we have in this paper without having lived with Rescorla's contribution to psychology over several decades. It is not so much any individual piece of work that has inspired us here (though there are many we could refer to in that regard), but rather that he was one of the few psychologists of his time that set the context for the field, then and now. He played a more than significant role in defining what we do and how we think about what we do, and because

of this his influence is everywhere. We are grateful for this opportunity to acknowledge the intellectual debt that we owe him.

Introduction

In this introduction we start by outlining the evidence we have that a particular form of neurostimulation, tDCS (transcranial direct current stimulation) to Fp3, can modulate processes involved in perceptual learning. We also offer a theoretical interpretation of these results in terms of the McLaren, Kaye and Mackintosh (1989) model (and its later refinements henceforth referred to as MKM). This is necessary to arrive at the predictions we can make for the experimental paradigm employed in this paper, namely target detection against backgrounds containing similar stimuli that are familiar, when subject to the same neurostimulation manipulation. We begin with the basics of perceptual learning as applied to the face inversion effect typically studied using new/old recognition tasks.

Exposure to a set of stimuli generated from the same prototype-defined category can enhance individuals' performance when later asked to recognise new stimuli drawn from that category. The mechanism that leads to this enhanced performance is referred to as perceptual learning (Hall, 1980; McLaren, Leevers & Mckintosh, 1994). In the laboratory one of the most striking consequences of perceptual learning is the face inversion effect which refers to the reduced performance obtained when we try to recognise faces presented upside-down vs when presented in their usual upright orientation (Yin, 1969; Civile, McLaren et al., 2014; Civile, McLaren et al., 2016). This effect has been shown to be partly due to our expertise with faces, as demonstrated by studies that have used novel artificial stimuli to obtain a robust inversion effect after subjects had been exposed to these stimuli (e.g., Gauthier and Tarr, 1997 with Greebles; McLaren 1997 and McLaren & Civile 2011 with checkerboards). In 2014, Civile, Zhao et al adopted the *old/new recognition task* traditionally used to study the face inversion effect, to show how a similar effect can be obtained with stimuli that subjects had never experienced before entering the laboratory. Checkerboard stimuli were chosen because experience with them can be fully controlled and they are not monoorientated (i.e., do not have a predefined orientation). Subjects were first trained to categorize checkerboard exemplars (the pre-exposure phase) generated from two prototype-defined categories. Following this, subjects were asked to memorize a number of new checkerboards drawn from either the 'now familiar' categories or a novel category, half of which were presented upright (same orientation as in the categorization phase) and half inverted (turned upside down). Subjects were then tested for recognition of these studied exemplars. The results showed a better performance for upright vs. inverted chequerboards i.e., an inversion effect for exemplars drawn from a familiar category, that was absent for exemplars drawn from a novel category, suggesting that perceptual learning contributes to the inversion effect (Civile, Zhao et al., 2014).

The checkerboard inversion effect can be explained by the McLaren, Kaye and Mackintosh (MKM) model of perceptual learning (McLaren et al., 1989; McLaren & Mackintosh, 2000; McLaren et al., 2012) which predicts that pre-exposure improves performance because it results in the unique features of a stimulus becoming relatively more active during learning compared to the common features shared by the stimuli (which do not help in discrimination). To learn how to categorise exemplars of two different categories, subjects must associate the features that the category prototype and exemplars share with the correct category. The common features rapidly lose their salience because they are presented on every trial, becoming slow to form new associations. This produces perceptual learning because the features unique to each exemplar still have high salience due to less exposure and lower predictability. Thus, it is easier for the subjects to discriminate between exemplars because the salience of the common features is now low, whereas that of the unique features is still high. This process of *feature salience modulation* applies only to upright stimuli because we have little or no experience in seeing inverted stimuli and so performance on these is not aided by any significant amount of perceptual learning.

Other models would not predict the results obtained from the checkerboard inversion effect paradigm developed by Civile, Zhao et al (2014). For instance, McClelland and Rumelhart (1985) used the delta rule, an error correcting learning algorithm related to the Rescorla-Wagner (Rescorla and Wagner, 1972) model, in a connectionist network employing distributed stimulus representation to model categorization learning and recognition. The learning algorithm coupled with the activation function would lead to the features that are frequently co-activated to become more salient. Hence, it would be the prototypical features (i.e., common features) of a stimulus that would form the strongest links to an outcome. Thus, according to this model individuals pre-exposed to prototype-defined categories of stimuli (e.g., checkerboards) would then become worse at discriminating new exemplars drawn from the familiar categories due to the common features between the exemplars and the category prototype being the most salient. This would increase generalization rather than lead to the perceptual learning effect (indexed by the inversion effect) found in Civile, Zhao et al (2014).

With the aim to further strengthen the analogy between the inversion effect for checkerboards and that for faces, recent work has used tDCS to demonstrate that both inversion effects (for faces and for checkerboards) share the same causal mechanism. Civile, Verbruggen et al (2016) applied tDCS to the checkerboard inversion effect using the same old/new recognition behavioural task developed by Civile, Zhao et al (2014). The specific tDCS procedure used was adapted from Ambrus et al (2011)'s study which investigated the tDCS-induced effects on categorization learning task for prototype-defined categories of pattern stimuli (see also McLaren et al., 2016; and Kincses et al., 2004, for other examples of the tDCS procedure applied on categorisation learning tasks). Using a double-blind, between-subjects design, Civile, Verbruggen et al (2016) showed that anodal tDCS delivered over the dorsolateral prefrontal cortex (DLPFC) at the Fp3 site (for 10 mins at 1.5mA) while subjects are performing an old/new recognition task eliminates the robust inversion effect found for checkerboard exemplars. In particular, recognition for upright checkerboards taken from a familiar category that subjects had been pre-exposed to, was severely impaired compared to that in the sham group (Civile, Verbruggen et al., 2016). The results from the sham group replicated the robust checkerboard inversion effect for a familiar category previously used in the literature as index of perceptual learning (McLaren, 1997; McLaren & Civile, 2011; Civile, Zhao et al., 2014).

When the same anodal tDCS procedure was first extended to the face inversion paradigm by Civile, McLaren et al (2018), a significant reduction of the face inversion effect in the anodal group was found compared to the sham group. In this case as well, the reduction was mainly due to an impaired recognition performance for upright faces in the anodal vs sham group (Civile, McLaren et al 2018 Experiment 1 & 2). This result has been replicated across multiple studies and it is now an established finding (Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020; Civile, Quaglia et al., 2021; Civile, McLaren et al., 2021). Furthermore, Civile, McLaren et al (2018)'s Experiment 3 (the active control study) tested whether targeting a different brain area would result in the same effects obtained in Experiment 1 and 2. The right-Inferior Frontal Gyrus (rIFG) was selected because of its implications in previous studies that investigated the tDCS-induced effects on go/no go tasks (Cunillera et al., 2014, 2016). However, no study before had looked at the effects of tDCS delivered over the rIFG during a perceptual learning task. Civile, McLaren et al (2018) found no effect of tDCS over the rIFG (delivered for 10 mins at 1.5mA) on the face inversion effect. Civile, McLaren et al (2021) extended the tDCS active control to the P08 EEG-channel area where previous ERP studies have found the N170 component (i.e., a negative deflection happening at 170ms after a face stimulus onset) to be the largest (Civile, Ehlclepp et al., 2018; Civile, Waguri et al., 2020; Eimer 2011). However, no effects of tDCS at P08 were found (Civile, McLaren et al 2021). These active control studies showed that the tDCS-induced effects at Fp3 on perceptual learning and face recognition are not found by targeting any brain area.

The explanation proposed for the tDCS-induced effects on the inversion effect is based on the MKM model of perceptual learning which itself employs the pooled error term found in Rescorla-Wagner and the elemental type of representation used by Rescorla (1976) to explain generalisation. It is argued that the *feature salience modulation* normally generated by this model is disrupted by the tDCS procedure, so that instead of pre-exposure to a prototype-defined category enhancing the discriminability of exemplars drawn from that category, it now enhances generalization between them, essentially in a way akin to what would be predicted by the McClelland and Rumelhart (1985)'s model. Under tDCS the common features would become more salient making the faces look more "similar" and thus causing a reduction in the inversion effect because subjects' ability to discriminate between upright faces would be impaired. This explanation only applies to upright faces (or familiar upright checkerboards) because we have no experience in seeing inverted faces and so discrimination performance for them does not benefit from any significant amount of perceptual learning (Civile, Verbruggen et al., 2016; Civile, McLaren et al., 2018; Civile, Quaglia et al., 2021).

To date, the tDCS effects on perceptual learning and face recognition have been found always on recognition accuracy (reaction times were analyzed mostly to check for speed-accuracy trade-off and none was found). Hence, all the studies mentioned above have used as measure of face or checkerboard recognition discriminability, d-prime (*d'*) based on Signal Detection Theory (Stanislaw & Todorov, 1999). This is because popular old/new recognition tasks are yes/no tasks involving *signal* and *noise* trials. This approach assumes that responses are based on the value that a decision variable achieves in each trial. If this is sufficiently high, subjects respond *yes* otherwise they would respond *no*. The value determining what is sufficiently high is called the *criterion, C* (Macmillan, 1993; Macmillan & Creelman, 2005). Subjects compare decision variables (e.g., sense of familiarity with a face) to *C* to make their response. Hence, to advance our understanding of the mechanisms underpinning perceptual learning and face recognition, *C* becomes an additional important measure to use in the investigation. Interestingly, in Civile, Verbruggen et al (2016) and Civile, McLaren et al (2018)'s studies no effects of the tDCS procedure were found on *C*. However, several authors have argued that the use of a typical recognition task such as old/new recognition can preclude a detailed investigation of response criterion effects because it would tend to lead to a "balanced" effect on *C* that cancels out (see Macmillan & Creelman, 2005; Limbach & Corballis, 2016; Busch & Van Rullen, 2010 and later in this paper). Hence, previous studies that have used *C* as a main measure of performance have often used a *target detection task* although no applications of tDCS nor perceptual learning and face recognition skills have been investigated in these tasks to date (Ergenoglu et al., 2004; Mathewson et al., 2009; Roberts et al., 2014; Hanslmayr et al., 2011). Thus, to investigate the tDCS-induced effects on *C* we adapted the use of checkerboards and faces to a target detection task of the kind used in the literature regarding *C*.

In the current study, we aimed to extend the investigation on perceptual learning and face recognition by examining the effects of tDCS on *C* when participants are called upon to detect a target pattern presented on a background of either a familiar or a random checkerboard (Experiment 1a) or when detecting an upright face presented on an array of faces always shown in the same location i.e., a familiar background vs. an array of upright faces presented in random locations i.e., a random background (Experiment 1b). We used the same tDCS procedure as in previous studies on perceptual learning. However, this time in line with previous studies on *C*, we expected the *target detection task* design, which included equal numbers of target-present and target-absent trials, to allow us to modulate *C* but not discriminability *d'* with this procedure.

To arrive at this prediction, we employed a model of task performance that relies on two sub-components. The model allowed us to consider factors such as familiarity with the stimuli and the tDCS procedure employed, but it does not itself provide a mechanism for target detection, though it can function as a mathematical model of that ability. We assume that processes such as explicit comparison of the features in a presented stimulus to some memory of the to-be-detected target play a significant and, indeed, dominant role in determining the response given, and these are not included in the model except as somehow contributing to the difference between the signal and noise distributions, as we shall see later.

With that caveat in mind, one of the components is the MKM model of representation development as previously described, which details how in regular circumstances (i.e., no applications of tDCS) perceptual learning can occur because of experience with prototype-defined categories of stimuli (McLaren et al., 1989; McLaren & Mackintosh, 2000; McLaren et al., 2012). The other is a standard Signal Detection Theory approach based on the idea that some trace is established due to encountering a stimulus, and that the strength of the trace is then used as a basis for recognition (or detection) on the assumption that it will be greater for stimuli that have been recently encountered (or contain the target) than those that have not (Stanislaw & Todorov, 1999).We can now apply this second part of our model to earlier data. The results from previous studies (Civile, Verbruggen et al., 2016; Civile, McLaren et al., 2018) suggested that the effect of the anodal tDCS procedure applied to the Fp3 area can be interpreted as simply removing the enhanced discrimination consequent on experience with a class of stimuli, so increasing generalization between seen and unseen images in an old/new recognition paradigm and thus leading to a reduced *d′* value without affecting C to any great extent. In this context if we move the distribution for seen faces and that for unseen faces closer together that would lead to a reduced *d′*, however their crossover point does not move (assuming we shift each distribution by an equal amount) thus the calculation of C would remain the same (Figure 1a). This analysis illustrates how a "balanced" design can lead to a null effect on *C* as referred to earlier in our introduction. It also suggests how we can arrange things so that instead of changing *d′* we affect *C*. If we were to arrange for the two distributions to both shift in the same direction, then *d′* would not change but *C* would (see Figure 1b).

Why would it be important to do this? Because if we could predict such an effect based on the model and subsequently obtain it experimentally, then it would constitute a quite different test of the model to those employed to date, extending its application beyond simple recognition or matching studies to a whole new domain (as we will see). It would emphasise the general applicability of the model and the empirical manipulation that we use, making it clear that this approach does not just apply to a particular niche area concerning the inversion effect but has wider implications. It would also produce a novel empirical effect, in which we selectively impacted criterion rather than discriminability that might have other experimental applications. For these reasons it seemed to us that this was a good way to carry out a conceptual replication of the work conducted so far using this technique.

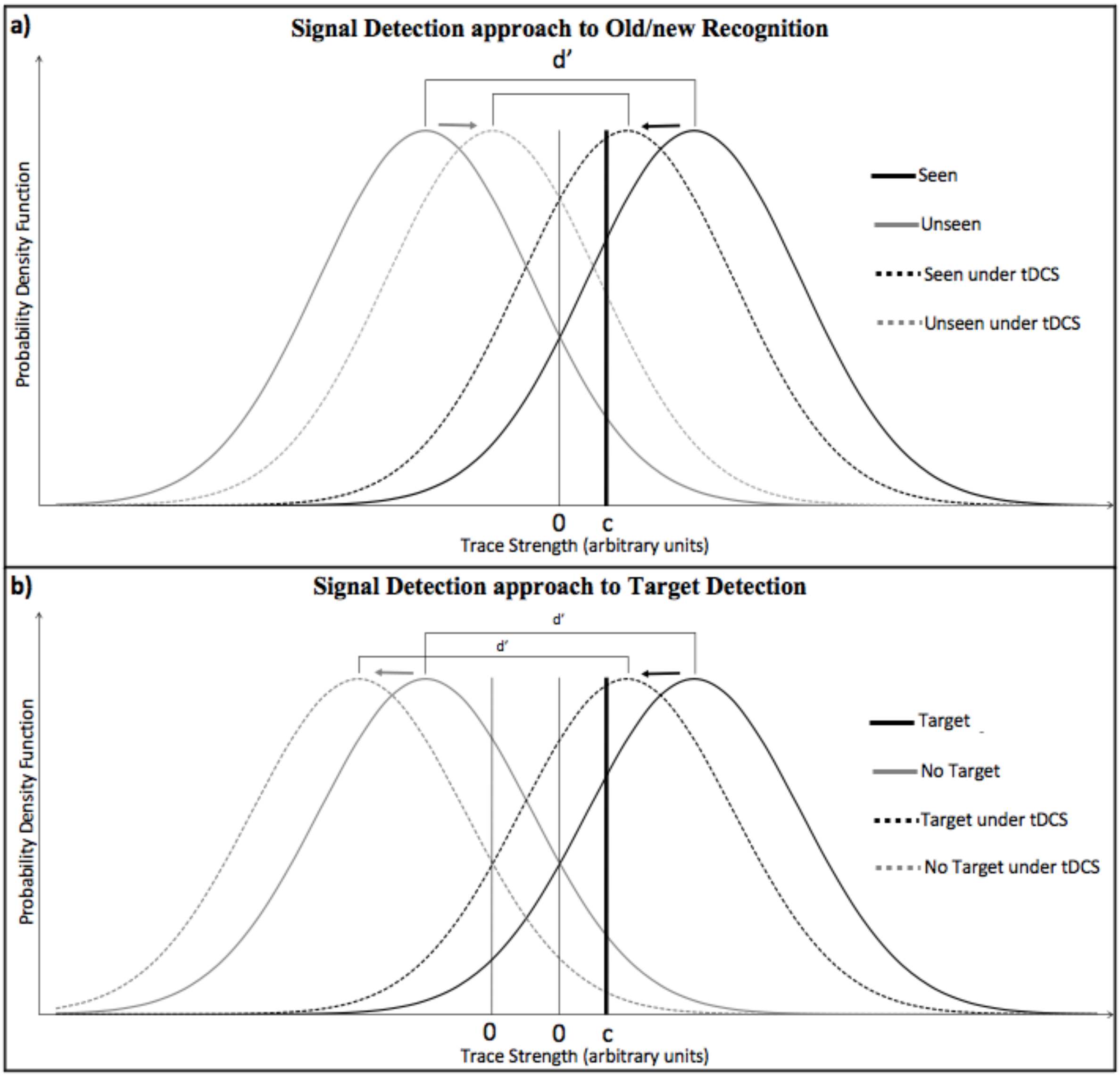

Figure 1. A signal detection analysis applied to an old/new recognition task (Panel a) and a target detection task (Panel b). The bold vertical line shows placement of the *C* used to decide if the stimulus is either seen (Panel a) or contains a target (Panel b). When a stimulus is presented, either the signal (Seen or Target) or noise (Unseen or No Target) distribution is sampled. If the trace has a value higher than *C* then the seen / target response is given. In ***Panel a*** the tDCS procedure is shown as shifting the two distributions inwards so that they become closer together (*d′* is less) but their crossover point does not move (hence the calculation of *C* remains the same). In ***Panel b*** the tDCS procedure is shown as shifting both distributions to the left, which has the effect of maintaining separation (*d′* unchanged) but

changing the calculation of *C* because the zero-point determined by distribution crossover for the two tDCS affected curves has also shifted to the left (0'). In this case, C would have increased.

How might such a shift be achieved in practice? The key consideration would be to arrange for the effect of tDCS on both signal and noise distributions to be the same. Based on previous studies on the inversion effect, we know that the tDCS procedure affects performance for familiar stimuli, or rather stimuli drawn from a familiar category. Specifically, it was suggested that the tDCS procedure increases the salience of the common features leading to an enhanced generalization. Hence, here we decided to use a target detection task that employed two different conditions. In Experiment 1a, subjects would have to detect a target pattern on a stable, familiar background that was repeatedly presented and was itself the prototype of a familiar category of checkerboards previously seen according to the same categorization task used in Civile, Zhao et al (2014) and Civile, Verbruggen et al (2016). In the other condition the background would be a random checkerboard that was drawn from a novel category (not previously seen in the categorisation task) and never repeated during the target detection task. Experiment 1b, was then designed to be like Experiment 1a but this time using upright face stimuli. Subjects had to detect a familiar (previously seen) face within an array of faces that had been repeated on multiple trials i.e., familiar 'background' vs an array of faces that changed on every trial i.e., random 'background'.

In the sham/control condition we expected an advantage in performance as measured by *d'* in the familiar background condition compared to the random background condition. This assumes that familiar background trials would share common features always presented in the same location and thus, according to the MKM model, they would tend to lose their salience leaving the salience of the unique features high. Critically, in the specific task used in the studies reported here, the target is the unique feature, because it would be the only feature being presented on a different location on every trial, thus it would maintain relatively high salience. This would make the target stand out and thus facilitate subjects' performance at detecting whether the target is present or absent. In the random background trials, all features would be equally salient because they would be potentially changing at every location on each trial. Hence no common features would be shared across all trials and so the background stimuli would not lose their salience and they would be as salient as the target. Thus, the target would not stand out and the participant's performance would be lower than in the familiar background trials. Importantly we did not expect anodal tDCS to affect this advantage in performance for familiar vs random background conditions. This is easiest to see for the random background condition, as here the tDCS manipulation would apply equally to background and target alike and so there is still no basis for target detection introduced as a consequence of the neurostimulation. In the familiar background condition tDCS can be expected to prevent the loss of salience consequent on familiarity for the background, and in fact the background features will now be more salient than for a novel stimulus such as the target (taken to be novel due to its appearing at a different location each time). Hence the difference in salience is still available as an aid to target detection, and so better performance can still be expected to a familiar background. What we can say is that the salience of the two different backgrounds (familar/repeated compared to random/changing) <u>will</u> be affected by tDCS. Without application of tDCS the salience of the novel, random background (higher error term on average for the units representing the features of this stimulus) would have been higher than that of the familiar repeated one (lower error). With tDCS this is reversed, as now the familiar background benefits from the stronger associations boosting unit activity and the salience of these units is not downregulated by modulation based on their lower error terms. But this also would not directly affect *d'*, because in both conditions it would, to a first approximation, affect the target and noise distributions equally and so simply shift them without changing their relative separation. But the shift could lead to changes in C as we will now demonstrate.

If one criterion is used for both familiar and random background conditions (reasonable given that they are randomly intermixed), then the effects of tDCS on background salience should affect *C*. This conclusion follows from the assumption that people place the criterion at the same absolute value for both familiar and random conditions, and that the effect of tDCS will be to shift both signal and noise distributions in the same direction within conditions but, if our analysis is correct, in opposite directions between conditions. Thus, the logic is that this task will allow tDCS to affect *C* in a way that did not happen for the old/new recognition tasks used in previous studies.

The Study

Method

Subjects

In total, 112 naïve (right-handed) subjects (82 female, 30 male; Mean age = 20.6 years, age range= 18-29) took part in the two experiments. Subjects were students from the University of Exeter and were selected according to approved safety screening criteria. All methods were performed in accordance with the relevant guidelines and regulations approved by the CLES Psychology Research Ethics Committee at the University of Exeter. Informed consent was obtained from all subjects. The sample size for each experiment was decided based on previous studies that used the same tDCS experimental procedure (double-blind, between subjects) and the same montage to modulate perceptual learning and employed a full counterbalance for the stimuli (Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020; Civile, Quaglia et al., 2021; Civile, McLaren et al., 2021). **Experiment 1a** included 48 subjects randomly assigned to either sham or anodal tDCS groups (24 in each group). **Experiment 1b** included 64 subjects randomly assigned to either sham or anodal tDCS groups (32 in each group).

Materials

Experiment 1a employed checkerboards (256 x 256 pixels, presented at a resolution of 1680 x 1050 pixels) as previously used in previous perceptual learning studies (McLaren, 1997; McLaren & Civile, 2011; Civile, Zhao et al., 2014; Civile, Verbruggen et al., 2016). Category prototypes (16 x 16) were randomly generated with the constraint that they shared 50% of their squares with each of the other prototypes and were 50% black squares and 50% white. Exemplars were generated from these prototypes by randomly changing forty-eight squares and 128 (64 from each category) were presented in the categorization task (pre-exposure phase) at the beginning of the experiment. Importantly, one of the category prototypes (A or B, counterbalanced across subjects) was then used during the *detection task* phase of the experiment as the “familiar” background. A further set of 128 checkerboards was created by randomly allocating white and black cells within a 16 x 16 cell grid. This set of checkerboards was unrelated to categories A and B and each exemplar served once as the “random” background condition during the *detection task* phase of the experiment. A “target” pattern (80 x 80 pixels, 5 x 5 cell pattern, see Figure 2) was created so to be symmetrical and have similar numbers of black and white cells which would line up exactly with cells in the checkerboard exemplars. The position of the target within each checkerboard exemplar was determined by calculating the co- ordinates which would allow the target to line up exactly with the cells in each checkerboard. Subjects were counterbalanced across these target position types.

Experiment 1b used a set of 288 male and female faces, (5.63 cm x 7.84 cm, presented at a resolution of 1280 x 960 pixels) standardized to grayscale on a black background, previously used in the tDCS and perceptual learning literature (Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020). The original face images were selected from the Psychological Image Collection at Stirling open database, (https://pics.stir.ac.uk). All the images were cropped to a standardized oval shape, removing distracting features such as the hairline, and adjusted to standardize image luminance. Both Experiment 1a and 1b were run using SuperLab 4.0.7b. software (Cedrus Corporation, CA, USA) on an iMac computer. Participants sat about 70 cm away from the screen on which the images were presented.

The tDCS Paradigm

Both experiments adopted the same tDCS procedure previously used to modulate perceptual learning and face recognition skills (Civile, Verbruggen et al., 2016; Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020; Civile, Quaglia et al., 2021; Civile, McLaren et al., 2021). The stimulation is delivered by a battery-driven constant current stimulator (neuroConn DC- Stimulator Plus) using a pair of surface sponge electrodes (35 cm^2) soaked in saline water and applied to the scalp at the target areas for stimulation. A double-blind procedure reliant on the neuroConn *Study Mode* was used. A bilateral bipolar-non-balanced montage is used with one of the electrodes (anode) placed over the target stimulation area (Fp3) and the other (cathode) on the forehead over the reference area (right eyebrow). To identify the Fp3 area, from Cz we measured 7 cm anterior relative to the Cz and 9 cm to the left. In the anodal condition, direct current stimulation of 1.5mA is delivered for 10 mins (5s fade-in and 5s fade out). In the sham group, subjects experienced the same 5s fade-in and 5s fade-out, but with the stimulation intensity of 1.5 mA delivered for just 30s, following which a small current pulse is delivered every 550ms (0.1mA over 15ms) for the remainder of the 10 minutes to check impedance levels (Figure 2a). Once the experimenter started the stimulation (either anodal or sham) they would ensure that the subjects felt comfortable and were happy to continue with the study and start the behavioral task.

The Behavioural Task

In **Experiment 1a** subjects were first engaged in a *categorization task* (pre-exposure/familiarization phase) where a set of checkerboard stimuli was shown on the screen, one at a time in a random order. Subjects were asked to sort these exemplars into two different categories (A & B) by pressing two keys (1 or 2 on the numerical keypad). Subjects received immediate feedback according to whether their response was correct or not. If no response was made within 4s, they were timed out and received feedback saying, “too slow”. The presentation of each checkerboard was preceded by a fixation cross in the center of the screen presented for 500ms. Overall, 128 checkerboards were presented, 64 drawn from category A and 64 drawn from B. Following the categorization task, subjects were engaged in the *target detection task*. They were first presented with a target pattern and then instructed to find out if this target was in the checkerboards that they would subsequently see. The target could be presented anywhere on the background checkerboard, and it would be always of the same size and in the same orientation. Subjects pressed the “x” key if they thought the target was present or the “.” key if they thought the target was absent (the keys were counterbalanced across subject groups). Overall, the detection task included 256 checkerboards presented one at a time in random order, 128 with the target present (64 familiar and 64 random checkerboard backgrounds) and 128 with the target absent (64 familiar and 64 random checkerboard backgrounds). Each checkerboard was presented for 4s (and remained on the screen for whole duration), preceded by a fixation cross presented in the centre of the screen for 500ms. Subjects received immediate feedback according to whether their response was correct or not. If no response was made within 4s, they were timed out and received feedback saying, “too slow” (Figure 2b) (McLaren, Civile et al., 2020).

In **Experiment 1b** subjects were engaged in a similar detection task as that used in Experiment 1a, however, this time we used face stimuli. Before the beginning of the task, subjects were presented with a target face on its own, and then with the same face within an array of 9 faces. The detection task included a set of 64 trials each showing an array of 9 faces (3 rows with 3 faces in each) presented on the screen for 4s (and remained on the screen for whole duration) followed by a mask for 1s (a blurred checkerboard). Subjects were instructed to press the key “x” to indicate the target face was present, or to press the key “.” to indicate the target face was absent (the keys were counterbalanced across subjects). If no response was made within 4s, they were timed out and received feedback saying, “too slow”. Half of the trials had a familiar background (16 target present, 16 target absent) and the other half were random background trials (16 target present, 16 target absent). In the familiar background trials, the same 9 faces appeared in the same location on every trial. Hence, in the target present trials, the target would appear at random replacing one of the 9 faces. In the random background condition, a different set of 9 faces appeared on every trial, and in the “present” condition the target face would appear in one of the 9 positions instead of a novel face (Figure 2c).

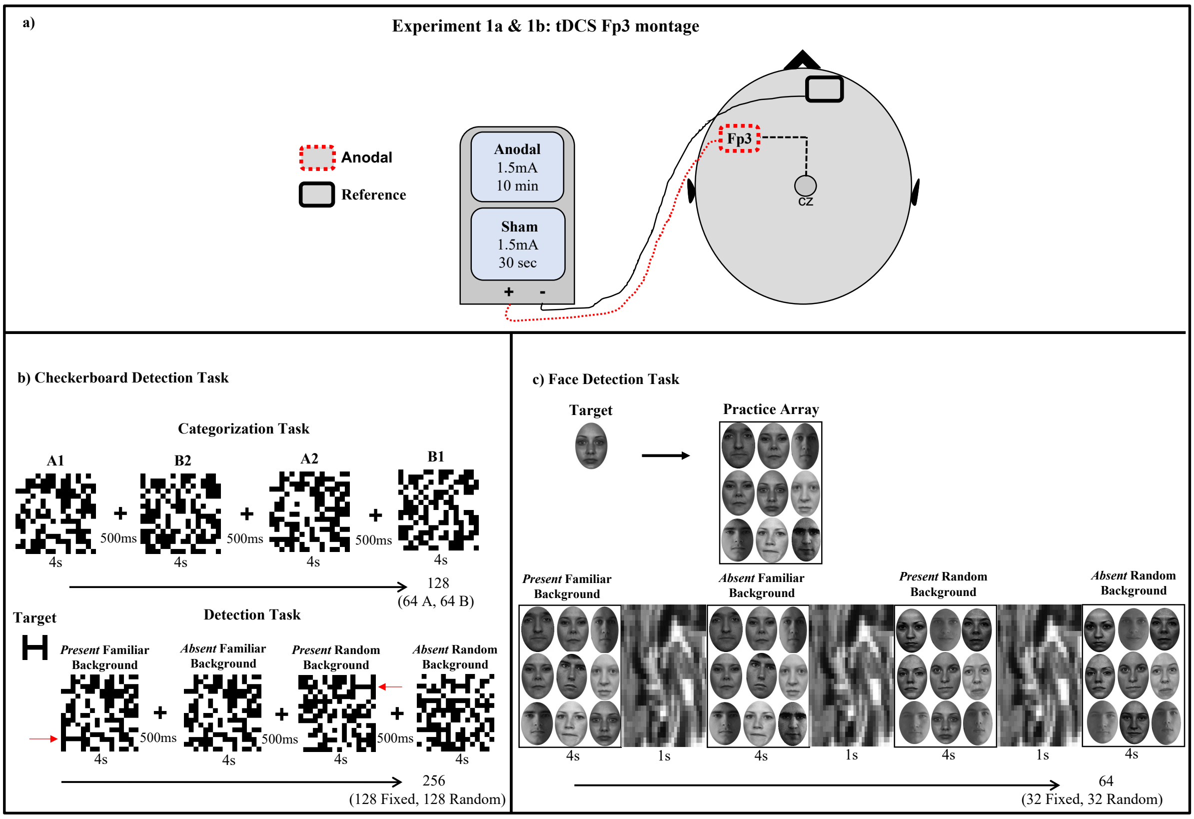

Figure 2. *Panel a* illustrates the tDCS Fp3 montage adopted in Experiment 1a and 1b. *Panel b* is a schematic representation of the checkerboard detection task adopted in the Experiment 1a. Through a trial-and-error task subjects first categorised a set of prototype-defined checkerboards drawn from two categories (64 from each category). Subjects were then engaged in a *target detection task* where they were instructed to detect a target pattern within the checkerboards that they would subsequently see. Overall, 256 checkerboards were shown, half of which had the target present (64 familiar and 64 random checkerboard backgrounds) and the other half with the target absent (64 familiar and 64 random checkerboard backgrounds). *Panel C* is a schematic representation of the face detection task used in Experiment 1b. Target face and background arrays were selected at random. Overall, 16 target faces were selected (8 male, 8 female). Each subject searched for only one of these target faces. Nine faces (4 male, 5 female) were selected for the familiar array and 288 were selected for the random arrays. The original face images were selected from the Psychological Image Collection at Stirling open database, (http://pics.stir.ac.uk).

Results

Data Analysis

As in previous studies (Civile, Verbruggen., 2016; Civile, McLaren et al., 2018; Civile, Cooke et al., 2020) in both experiments reported here, the accuracy data from all the participants in a given experimental condition was used to compute a *d′* sensitivity measure for the detection task (*present* and a*bsent* trials for each background type) where a *d′* of 0 indicates chance-level performance. To calculate *d'*, we used subjects' hit rate (H), the proportion of *present* trials to which the participant responded *present*, and false alarm rate (F), the proportion of *absent* trials to which the participant responded *present*. The statistic *d*' is a measure of this difference; it is the distance between the means of the signal + noise and noise alone distributions. Specifically, *d'* is the difference between the *z* transforms of the two rates: *d*' = z(H) – z(F) where neither H nor F can be 0 or 1. All the cases where H or F were 0 were adjusted by adding 1 divided by double the number of trials thus resulting in a number that was close to 0 but positive. To give an example, in Experiment 1b, 16 trials were presented in every condition, so if H or F was 0 then we calculated 0+ 1/32 = .03125. All the cases where H or F were 1 we adjusted them by subtracting from 1 the same value we would use in cases where H or F were 0. To give an example, in Experiment 1b, if either H or F was 1 then we calculated 1-(1/32) = .96875. Out of 704 H and F values (overall from both experiments) 103 were adjusted based on participants scoring 1 or 0. One consequence of this adjustment that should be borne in mind is the way that it constrains the maximum H and minimum F rates based on the number of trials used in a condition, and the effect this has on the maximum d' that can be obtained. As Experiment 1a has four times as many trials per condition as Experiment 1b (i.e., 64), its maximum *d′* is accordingly higher as H can be as high as .9921875 compared to .96875 for Experiment 1b. Thus, in Experiment 1b the maximum *d′* that can be obtained is 3.725, whereas in Experiment 1a it is 4.835. This should be borne in mind when comparing the experiments, and taking this into account it should be clear from Table 1 that performance in Experiment 1b is much closer to ceiling than in Experiment 1a, even though Experiment 1a has slightly higher *d′* values. This simply confirms that the experiment using faces was much easier than that using checkerboard, as might be expected.

Criterion, *C,* is calculated relative to where noise and signal distributions cross over (i.e., $\beta=1$) where neither response is favored. If the criterion is at this point it has a value of 0. Negative values of *C* indicate a bias toward responding *yes* (*C* is on the left of the neutral point), whereas positive values indicate a bias toward the *no* response (*C* is on the right of the neutral point). Specifically, the formula for *C* is the following: $C = -\,(z(H) + z(F)) / 2$.

In both experiments we assessed *d'* performance against chance to show that stimulus' conditions in both the tDCS sham and anodal groups were detected significantly above chance (for all conditions we found $p < .001$ for this analysis). We also analyzed the reaction time (RT) data which do not add anything to the interpretation of the results. However, for completeness we report the full analysis in the Supplemental Material file.

For both experiments, to analyse d' and *C* we computed a 2 x 2 mixed model design using, as within-subjects factor, *Background* (familiar or random), and the between-subjects factor *tDCS* (sham or anodal).

d' Results

Experiment 1a. Analysis of Variance (ANOVA) revealed a significant main effect of *Background*, $F(1, 46) = 24.31$, $p < .001$, $\eta^2_p = .34$, which indicated higher performance on familiar background trials (M = 3.72, SD = .72) vs random trials (M = 3.27, SD = .67). No significant interaction with *tDCS* was found, $F(1, 46) = 1.04$, $p = .310$, $\eta^2_p = .02$. There was also no significant main effect of the between-subjects factor *tDCS*, $F(1, 46) = 0.57$, $p = .812$, $\eta^2_p < .01$.

Experiment 1b. Analysis of Variance (ANOVA) revealed no significant main effect of *Background*, $F(1, 62) = .679$, $p = .413$, $\eta^2_p = .01$. No significant interaction was found, $F(1, 62) = 0.01$, $p = .988$, $\eta^2_p = .02$. There was also no significant main effect of the between-subjects factor *tDCS*, $F(1, 62) = 0.09$, $p = .760$, $\eta^2_p < .01$.

C Results

Experiment 1a. Analysis of Variance (ANOVA) revealed no significant main effect of *Background*, $F(1, 46) = 1.96$, $p = .307$, $\eta^2_p = .02$. A significant interaction between *Background* and *tDCS* was found, $F(1, 46) = 5.22$, $p = .027$, $\eta^2_p = .10$ (Figure 3a). No significant main effect of the between-subjects factor *tDCS* was found, $F(1, 46) = 0.13$, $p = .718$, $\eta^2_p < .01$. To investigate further the effect of *tDCS* on *Background* we conducted two paired-sample t-tests directly comparing the *C* values between familiar and random backgrounds. In the sham condition we found a significant difference, $t(23) = 2.54$, $p = .018$, $\eta^2_p = .21$. In the anodal condition no significant difference was found, $t(23) = 0.82$, $p = .417$, $\eta^2_p = .02$.

Experiment 1b. Analysis of Variance (ANOVA) revealed no significant main effect of *Background*, $F(1, 62) = .713$, $p = .402$, $\eta^2_p = .01$. A significant interaction between *Background* and *tDCS* was found, $F(1, 62) = 5.02$, $p = .029$, $\eta^2_p = .07$ (Figure 3b). There was no significant main effect of the between-subjects factor *tDCS*, $F(1, 62) = 0.23$, $p = .880$, $\eta^2_p < .01$. As for Experiment 1a, for the sham condition we found a significant difference, $t(31) = 2.38$, $p = .023$, $\eta^2_p = .15$. In the anodal condition no significant difference was found, $t(31) = 0.91$, $p = .356$, $\eta^2_p = .02$.

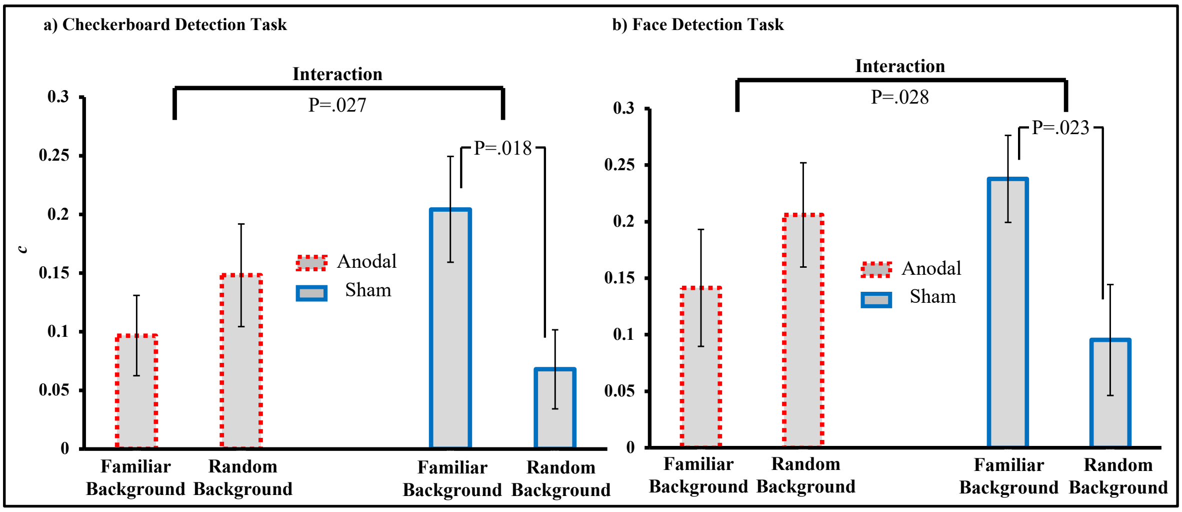

Figure 3 reports the results for *C* from both experiments. The *x*-axis shows the stimulus conditions, the *y*-axis shows *C*. Error bars represent s.e.m. *Panel a* shows the results for Experiment 1a. *Panel b* shows the results for Experiment 1b.

General Discussion

In the last six years research has shown that 1.5 mA anodal tDCS to Fp3 reduces both the inversion effect typically obtained with faces in recognition experiments and eliminates the inversion effect due to perceptual learning in checkerboards (Civile, Verbruggen et al., 2016; Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020; Civile, Quaglia et al., 2021; Civile, McLaren et al., 2021). Importantly, these studies provided evidence of this specific tDCS procedure modulating the discriminability index, *d'* in recognition tasks using either checkerboard or face stimuli, advancing our understanding of the role that perceptual learning plays in face recognition. In the two experiments reported here we extend previous work on perceptual learning and face recognition by examining the effects of the same tDCS procedure on a different task. Specifically, we applied the tDCS procedure with the intention to modulate the decision criterion, *C*, while subjects performed a target detection task (with checkerboards or faces) of the kind typically used in the literature to investigate decision making (Ergenoglu et al., 2004; Mathewson et al., 2009; Roberts et al., 2014; Hanslmayr et al., 2011). Our results provided some evidence for the tDCS procedure to influence the decision criterion in a target detection task. In both Experiment 1a and Experiment 1b we found that in the sham condition, the criterion used in detecting a checkerboard or face target presented on a familiar background was significantly higher than when the target was presented on a random background. Importantly, this effect was significantly influenced by anodal stimulation in both experiments, producing a numerically reversed effect that differed significantly from that in sham. Furthermore, as predicted based on the task we used, no effect of tDCS was found on *d'*, even though *d'* was affected by the familiarity of the background (significantly in Experiment 1a, only numerically in Experiment 1b where performance was near ceiling).

Before discussing the effects of anodal stimulation on *C*, we revisit the explanation for the main effect of Background on *d'* and the lack of significant tDCS effects on *d'*. As a precursor to doing that, it is important to remind ourselves that we take most of the performance on this kind of detection task to be due to explicit search for the target that either succeeds (=yes) or fails to find it (=no). Hence, what we are dealing with in the analysis we now offer is a relatively small modulation of performance due to associative processes. As described in the introduction regarding the interpretations of the results obtained in Civile, Zhao et al (2014) based on the MKM model, in normal circumstances because of exposure to stimuli, the common features (i.e., those presented on every trial) would tend to lose their salience. This is due to the strong associations formed to them from other features reliably predicting them and lowering their error. Hence, the same process of loss of salience can be applied to the familiar background stimuli used in our Experiment 1a and 1b. This is because on every trial the familiar background stimulus would have common features that would appear always in the same location. The target stimulus, by virtue of appearing at a different location in each trial, would not be suffer from reduced salience to anything like the same extent (we suspect there must be some loss of salience due to the repeated internal structure of the target but ignore this for now). Thus, according to this analysis, we might expect the target stimulus in our experiments to be relatively more salient when presented on the familiar background, and so to stand out and draw attention to itself. A random background stimulus would not confer this advantage because all the features within the stimulus would change location at every trial thus, no common features are shared across all trials. The random background stimuli would not lose their salience and stay equally salient to the target.

Previous work on perceptual learning and face recognition led to the idea that anodal stimulation delivered at Fp3 would affect feature salience modulation. Specifically, the tDCS procedure would cause the salience of the common features to be relatively high thus resulting in more generalization between stimuli instead of enhanced discriminability (Civile, Verbruggen et al 2016; McLaren et al., 2016; Civile, McLaren et al 2018; Civile, Quaglia et al 2021). Based on this interpretation we would predict that the change in feature salience modulation induced by the tDCS would affect the familiar backgrounds differently to the random backgrounds (whose salience would drop). But, of course, as we have already pointed out in the introduction, these effects would apply to both target and non-target trials, and so a change in *d'* is not necessarily predicted on this basis. It is important to note that in the sham condition the idea of target detection being better on the familiar backgrounds is based on the target "standing out" on that background by virtue of being novel and having higher error (i.e., higher salience). But this can still be the case in the anodal tDCS condition because the difference in novelty/error has not disappeared, even though its expression in terms of salience may well have altered because the target would now be relatively less salient than the familiar background. Thus, the difference will still be there and could be used to guide search.

Can other theories of perceptual learning provide a different explanation for the effects obtained on *d'* in our experiments? Previous studies not using tDCS, have demonstrated that in some circumstances perceptual learning simply involves subjects learning where to look rather than implying enhancement of stimulus discriminability (Wang et al., 2012; Jones and Dwyer, 2013). One may argue that the better performance at detecting the target in the familiar background condition vs the random background condition, would be due to subjects learning where to look for the target. Hence, having the location of the features staying the same trial after trial would help to learn where the target is. However, it is important to note that in the familiar background condition despite most of the features (either checkerboard features or faces presented at every trial with the array) not changing their location from trial to trial, the target does change its location on every trial. Thus, learning where to look for the trial in a specific location would not aid performance. We conclude that this alternative explanation would not suit the results here obtained based on the behavioural procedure used.

Now we turn to the interpretation of our results for *C*. Earlier, in the bottom panel of Figure 1 we created a hypothetical illustration of how the shift in distributions might affect *C* under tDCS without affecting *d'*. Our first step here, however, is to explain the difference in *C* computed for the familiar and random background conditions in the sham group for both Experiment 1a and 1b. In fact, the explanation is very similar and again involves one set of distributions being shifted relative to the other. Recall that the value of *C* is calculated relative to the crossover point of the two distributions which is taken to be 0. Imagine that we set some distributions for target (signal) and no target (noise) and a criterion for making the decision for the random background trial. If we leave the criterial value in the same place, but we shift the target and noise distributions leftwards because we are presented with a familiar background trial, also allowing for the fact that the mean difference between the two distributions is increased corresponding to the higher *d′* as observed in both experiments (at least numerically), then this will result in a smaller *C*, even though in reality the absolute value of the criterion used by subjects has not changed. This models our results for the sham condition, but the question must be why the distributions for the familiar background are shifted in this way relative to those for the random background.

In fact, there is a potential explanation for this shift. Consider as an example the case of Experiment 1a, where the familiar background condition is not just familiar because the category-prototype used as a background is drawn from one of the two categories seen in the pre-exposure phase (the categorization task), but also because it has a background that repeats from trial to trial. This means that there will be learning to that background, and we assume that this learning is governed by an associative algorithm using a pooled error term (as in Rescorla-Wagner, 1972, but using the continuous rather than trial-based approach adopted by McLaren, Kaye and Mackintosh, 1989[1]). As a random portion of the background is replaced by the salient target on "yes" trials, that portion replaced will not be associated with "yes", and the rest of the background will be overshadowed by the target in terms of associating with a "yes" response. The entire background will be associated with "no" on no-target trials. This means that, over time, the familiar background will become associated to some extent with a "no" response. This will not happen with the random background as it changes on each trial. The net result, then, to a first approximation is that the familiar background trials will have a bias towards "no", and the random background trials will not. In terms of Figure 1, this means that the familiar background distributions will be shifted to the

[1] Of course Rescorla has also raised the possibility that a pooled error term may not always be appropriate (see Rescorla, 2000), an issue that authors have grappled with (Le Pelley and McLaren, 2003; Le Pelley and McLaren, 2004). In this case, however, it is necessary to use a pooled error term when dealing with associations between stimulus elements as MKM does if we are to drive error-based modulation of salience, and parsimony then dictates that it is better to use the same algorithm to form other associations between stimuli.

left of the random background distributions, resulting in higher computed values for *C* for the familiar background - as shown in Table 1.

Table 1. Mean accuracy *d'* and C for Experiment 1a and Experiment 1b.

Stimulus Type		***d'***		***C***	
		Familiar Background	**Random Background**	**Familiar Background**	**Random Background**
EXPERIMENT 1a	SHAM	M = 3.79 SD = .55	M = 3.25 SD = .69	M = .20 SD = .22	M = .06 SD = .16
	ANODAL	M = 3.65 SD = .86	M = 3.30 SD = .67	M = .09 SD = .16	M = .15 SD = .21
EXPERIMENT 1b	SHAM	M = 3.02 SD = .52	M = 2.94 SD = .64	M = .23 SD = .21	M = .09 SD = .27
	ANODAL	M = 2.98 SD = .51	M = 2.91 SD = .69	M = .14 SD = .29	M = .20 SD = .26

This brings us to the results obtained in the anodal tDCS condition. There will continue to be no effect of this type on the random background, but the salience of the familiar background will be increased relative to the salience of the target when it is presented. This has the effect of reducing differential learning to the background, i.e., there will be less of an association with a "no" response, as it will now tend to pick up more of an association with "yes" on target trials. Therefore, the distributions for the familiar background shift rightwards compared to sham and compared to the random background, reducing *C*, as shown in Table 1. Note that this prediction only applies to the significant *Background x tDCS* interaction in both experiments, and to the finding that under sham conditions *C* is higher in the familiar background condition than in the random background condition. We are not able to explain any of the variation in the value of *C* for the random background given that this was not reliable (in Experiment 1a random anodal vs sham gives a p-value of .15 two-tail; In Experiment 1b p = .11 two tail) and is subject to a host of other possible factors. What we can be confident about, however, are the relative values for this measure in the two conditions, and it is this that is captured by our analysis.

After this analysis, the reader might well wonder if the associative learning postulated here could contribute to the basic background effect that we observe on *d'*. The answer is that it probably does, but only to a relatively minor extent. When the target replaces a region of the familiar background then there will be a loss of "no" associations resulting from that. This will contribute to *d'*, as the "no" associations will be higher for non-target trials than target trials when a familiar background is involved but this will not apply to a random background. But the target only accounts for 25 squares of the 256 square stimulus, so that roughly 10% of the associations will be affected. Contrast this with the fact that all of these associations contribute to the effect on *C*, and clearly the effect on *d'* must be an order of magnitude less than that for *C*, and any modulation of such a small effect by tDCS will be very hard to detect indeed.

Another issue about the effect of background on *d'* is that we only observed a significant effect in Experiment 1a, with checkerboards, and not in Experiment 1b with faces. One quite straightforward reason for this is that performance in the face version of this task was very high indeed and this made any differences harder to detect (see our comments about the asymptotic values of d' in the two experiments earlier). But another contributory factor may have been the nature of the target used in Experiment 1b compared to that in Experiment 1a. The target in Experiment 1a was deliberately chosen to be distinctive whilst blending in well with the background. This had the effect that when it replaced a section of the background it was bound to be different from it and so generate a large error score as discussed earlier. The target in Experiment 1b was just one chosen face amongst several faces. It is quite possible that this resulted in the stimuli containing a target in Experiment 1b being very similar to the non-target stimuli in the familiar background condition, because the face target was itself similar to the face it was replacing. This would lessen any "signal" due to the unexpectedness of that face at that location and reduce the benefit of the familiar background. The reason why this did not make that task difficult is that there were only 9 possible faces in 9 fixed locations, and so a serial search strategy was particularly easy to perform in both absent and present trials and was probably the default strategy employed by participants.

One may argue that the tDCS-induced effects on *C* shown in our Experiment 1a and Experiment 1b could be induced by the sensation experienced by our participants. Those assigned to the anodal condition would have experienced a different sensation to those assigned to the sham condition on this analysis, and this could have influenced their decision criterion. We cannot exclude this as a potential factor contributing to the results obtained here, however, our studies are between-subjects and the subjects recruited were naïve and had never experienced the tDCS before. Thus, they did not know how anodal and sham stimulations are supposed to feel. Another consideration regards the fact that the sham stimulation is programmed so to give subjects the sensation of being stimulated, although not for the whole 10 mins and the subjects do not know that the stimulation is supposed to last 10 min. Finally, previous work using the same tDCS procedure applied to the inversion effect, has consistently demonstrated how the effects of anodal tDCS are found only on the size of the inversion effect and specifically in modulating performance to familiar upright stimuli (e.g., faces or checkerboards). However, no effects of anodal tDCS have ever been found on overall performance nor on inverted stimuli (Civile, Verbruggen et al., 2016; Civile, McLaren et al., 2018; Civile, Obhi et al., 2019; Civile, Cooke et al., 2020; Civile, McLaren et al., 2020; Civile, Waguri et al., 2020; Civile, Quaglia et al., 2021; Civile, McLaren et al., 2021). Even if we allowed a potential explanation based on the sensation experienced in the anodal tDCS group vs sham, it hard to see why that would only systematically affect the inversion effect specifically via performance for upright stimuli. Furthermore, previous active control studies (Civile et al., 2018; Civile. McLaren et al., 2021) also mitigate against this possibility.

Overall, our results contribute to the literature by showing how a tDCS procedure developed in the perceptual learning and face recognition research and derived from a model of stimulus representation (i.e., the MKM model), can be applied to a quite different target detection task involving checkerboard or face stimuli and influence the decision criterion. Simply put, this suggests that it is not just some arcane effect on one task, but instead a more general reparameterization of learning and performance that can be applied to different tasks. Our results also contribute to the psychological literature on the modulation of *C*. To our knowledge, only one study in the literature has previously found effects of tDCS on *C*, and this was in depressed patients engaged in a working memory task (no perceptual learning or face recognition was involved). The authors adopted a double-blind and between-subjects design, where individuals diagnosed with depression, received either anodal stimulation over the left DLPFC with the reference channel placed over the right DLPFC, or sham while performing a working memory task (a *2-back task* involving letters). The results showed that tDCS increased both discriminability and the response criterion, which the authors suggested was evidence in support of subjects having a more liberal attitude towards responding (Oliveira et al., 2013). This result is not the same as ours, as we are able to influence *C* selectively, without an equivalent effect on *d'*.

In another recent study subjects were engaged in a detection task where they had to indicate whether a grey diamond-shaped target was present (50% of the trials) or absent (50% of the trials). No tDCS was used, but through EEG alpha-frequency band analysis, the authors found alpha power did not influence sensitivity to the target (i.e., no effects on d') but did affect the response criterion. Specifically, it was found that lower cortical excitability indexed by increased alpha power led to a more conservative response criterion (relative tendency for no responses) being adopted. During reduced power sates, which correspond to higher cortical excitability, the criterion was more liberal (Roberts et al., 2014). These results fit well with our demonstration of a selective effect on *C*, and our demonstration of such an effect increases our confidence in the model we have applied to the specifcic tDCS procedure and its effects on perceptual learning and face recognition.

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Author Note

Data and study materials are available upon request. The studies here reported were not preregistered.

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Supplemental Material for: Using transcranial Direct Current Stimulation (tDCS) to influence decision criterion in a target detection paradigm

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PART A: Additional Analyses on Reaction Time (RT) data

For completeness here we provide the additional statistical analyses of the RTs for Experiments 1a and 1b.

Experiment 1a. Analysis of Variance (ANOVA) with factors *Background* and *tDCS* revealed a significant main effect of *Background*, $F(1, 46) = 15.48$, $p < .001$, $\eta^2_p = .25$, which indicated faster performance on familiar background trials (M = 1000 ms, SD = 286.89) vs random trials (M = 1036 ms, SD = 291.73). No significant interaction with *tDCS* was found, $F(1, 46) = .281$, $p = .598$, $\eta^2_p < .01$. There was also no significant main effect of the between-subjects factor *tDCS*, $F(1, 46) = 1.58$, $p = .215$, $\eta^2_p = .03$.

Experiment 1b. Analysis of Variance (ANOVA) with the same factors revealed no significant main effect of *Background*, $F(1, 62) = .014$, $p = .906$, $\eta^2_p < .01$. No significant interaction was found, $F(1, 62) = 2.03$, $p = .158$, $\eta^2_p = .03$. There was also no significant main effect of the between-subjects factor *tDCS*, $F(1, 62) = .417$, $p = .521$, $\eta^2_p < .01$.

PART B:

Table 2: Mean accuracy (%) for Target Absent and Target Present trials

	Stimulus Type	Familiar Background		Random Background	
		Absent (%)	**Present (%)**	**Absent (%)**	**Present (%)**
EXPERIMENT 1a	SHAM	M = 97.73 SD = 2.35	M = 94.07 SD = 5.64	M = 94.25 SD = 4.97	M = 92.86 SD = 4.27
	ANODAL	M = 95.45 SD = 6.34	M = 94.42 SD = 4.89	M = 95.16 SD = 4.87	M = 92.01 SD = 5.10
EXPERIMENT 1b	SHAM	M = 97.65 SD = 6.49	M = 88.86 SD = 7.22	M = 94.33 SD = 7.83	M = 90.42 SD = 10.16
	ANODAL	M = 95.70 SD = 5.81	M = 89.84 SD = 10.25	M = 96.28 SD = 5.90	M = 87.30 SD = 13.23

PART C:

Table 3: Mean Hit and False Alarm Rates

	Stimulus Type	Familiar Background		Random Background	
		Hit	**False Alarm**	**Hit**	**False Alarm**
EXPERIMENT 1a	SHAM	M = .94 SD = .05	M = .02 SD = .02	M = .92 SD = .04	M = .05 SD = .04
	ANODAL	M = .94 SD = .04	M = .04 SD = .06	M = .92 SD = .05	M = .04 SD = .04
EXPERIMENT 1b	SHAM	M = .88 SD = .06	M = .04 SD = .05	M = .89 SD = .09	M = .07 SD = .06
	ANODAL	M = .88 SD = .09	M = .06 SD = .04	M = .86 SD = .12	M = .05 SD = .04