

Medial Prefrontal Cortex Predicts Internally Driven Strategy Shifts

Highlights

- Some participants show uninstructed and spontaneous strategy changes
- MPFC signals allow prediction of strategy shifts ahead of time
- Otherwise suppressed signals are encoded in MPFC, allowing flexible task updating
- Unsupervised learning can trigger changes in cognitive control

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In Brief

Schuck et al. show that before humans spontaneously change to a novel strategy, medial prefrontal cortex begins encoding sensory information only relevant for the new strategy. This allowed predicting the spontaneous strategy change from neuroimaging data ahead of time.



Medial Prefrontal Cortex Predicts Internally Driven Strategy Shifts

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SUMMARY

Many daily behaviors require us to actively focus on the current task and ignore all other distractions. Yet, ignoring everything else might hinder the ability to discover new ways to achieve the same goal. Here, we studied the neural mechanisms that support the spontaneous change to better strategies while an established strategy is executed. Multivariate neuroimaging analyses showed that before the spontaneous change to an alternative strategy, medial prefrontal cortex (MPFC) encoded information that was irrelevant for the current strategy but necessary for the later strategy. Importantly, this neural effect was related to future behavioral changes: information encoding in MPFC was changed only in participants who eventually switched their strategy and started before the actual strategy change. This allowed us to predict spontaneous strategy shifts ahead of time. These findings suggest that MPFC might internally simulate alternative strategies and shed new light on the organization of PFC.

INTRODUCTION

Goal-directed behavior is a hallmark of intelligent behavior. To pursue a goal, we usually follow a particular strategy that we think will achieve our objective. This strategy, or behavioral policy, can in principle be any mapping between a state of the environment and actions that need to be taken in order to achieve a particular goal (Sutton and Barto, 1998). Imagine, for example, that you are leaving a New York subway station and need to find out which direction north is. Most likely, you will

be looking for the exit signs, which indicate the direction. The execution of such a strategy will cause you to focus on finding the exit signs in the busy subway station and to ignore all other, seemingly distracting, information. This ability to focus on the information that is relevant for an established strategy has the obvious advantage to make goal-directed behavior more efficient. At the same time, however, this focus might hinder the discovery of new—and potentially better—strategies. For instance, you could notice that the direction in which the cars are driving on the avenues also can tell you where north is. This new information may generate a superior strategy, which can achieve the same goal but is applicable to situations outside the subway and depends on cues that are easier to find.

The opposition between strategy exploitation and exploration creates a difficult dilemma for the brain. On the one hand, goal-directed behavior requires the neural processing of sensory information to become adjusted such that it makes the execution of a current strategy efficient (a process that is part of the more general concept of cognitive control; e.g., Miller and Cohen, 2001). On the other hand, discovering new strategies requires one to assess the potential usefulness of seemingly distracting information (strategy exploration, cf. Donoso et al., 2014).

Here, we asked how the brain could solve this dilemma and find a balance between cognitive control and strategy exploration. Despite the wide interest in related issues (Cohen et al., 2007; Hayden et al., 2011; Holroyd and Yeung, 2012; Kounios and Beeman, 2014; March, 1991; Reverberi et al., 2005), this question represents a major gap in our current understanding of prefrontal cortex (PFC) functioning. Many studies have shown that neural activity in PFC encodes components of currently active strategies (such as “task-sets,” rules, or relevant stimuli) (e.g., Reverberi et al., 2012; Sakai and Passingham, 2006; Sakai et al., 2002), and broadcasts a brain-wide bias that favors processing of task-relevant over task-irrelevant aspects (Dehaene et al., 1998; Desimone and Duncan, 1995; Dreisbach and Haider, 2008; Miller and Cohen, 2001). But how these cognitive control functions can coexist with functions that support strategy

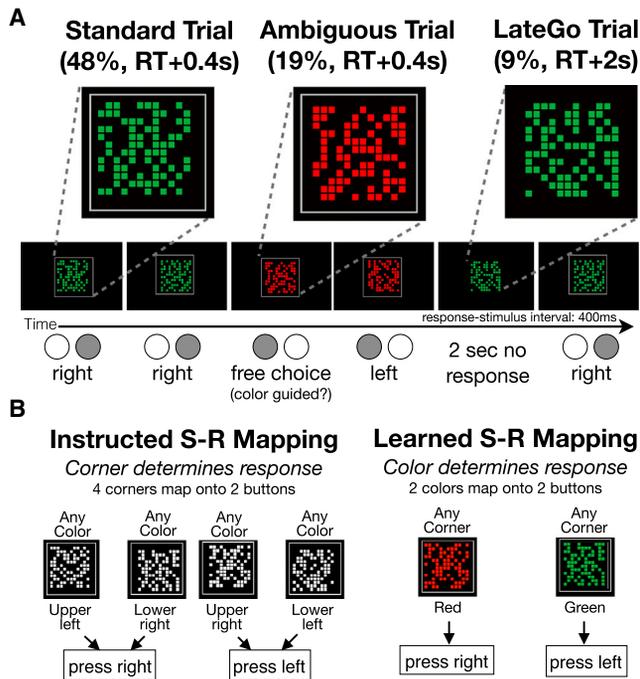


Figure 1. Spontaneous Strategy Switch Task

(A) An example sequence of trials in different conditions. The stimulus consisted of a white frame, which was partially filled with small, randomly distributed colored squares (all either red or green). In standard trials, the patch of colored squares was closest to only one corner of the white frame. In ambiguous trials, the patch was at equal distance to all corners of the frame. In Late Go trials, the white frame appeared with a delay of 2,000 ms. Numbers below condition names show trial proportions and durations.

(B) Participants were instructed to react to the corner of the patch within the white frame (left, S-R = stimulus-response). Alternatively, after the first 10 min, participants could detect the correlation between color and response and decide to use color to generate the answer (right).

explorations, remains unclear. In particular, existing studies have used experimental approaches that simplified the problem and therefore missed crucial aspects of the dilemma. For example, the alternative strategy/option is often not learned but instructed (Jepma and Nieuwenhuis, 2011; Kolling et al., 2012), or experimental interventions encourage strategy explorations (Daw et al., 2006; Hayden et al., 2011; Meiran, 1996; Monsell, 2003; Nassar et al., 2010; Yu and Dayan, 2005). Furthermore, prominent theories of PFC function have assumed that in the presence of a reliable strategy, alternative strategies are not explored (Donoso et al., 2014), or they have suggested that conflicts are the primary signal to trigger adaptations in cognitive control (Botvinick et al., 2001).

This study investigated spontaneous strategy improvements, which occur during the execution of a current strategy and therefore despite the presence of top-down cognitive control. We designed a more naturalistic task in which strategy discovery has to be based on learned environmental statistics and has to occur in parallel to the execution of the old strategy. No instructions about alternative strategies are given. We combined this novel experimental paradigm with multivariate pattern analysis of neuroimaging data, allowing us to track the neural encoding of task-

irrelevant information during a spontaneous strategy discovery and change. We expected stimulus features, which are irrelevant according to the current task strategy, to be mostly suppressed. Yet, learning mechanisms may trigger a change of strategy in a spontaneous, non-instructed manner. We predicted that such a change in strategy would be reflected in an increase in the encoding of task-irrelevant sensory signals in frontal cortex immediately before and after the strategy change.

RESULTS

Participants were instructed to respond manually to the location of a patch of small, colored squares within a square reference frame (Spontaneous Strategy Switch Task, Figure 1). While they were instructed to select a response depending on the position of the patch within the reference frame, we induced a deterministic relationship between the stimulus color (red or green) and the correct response (left or right) after 336 trials (~10 min). Learning this relationship did in principle allow participants to switch their strategy and rely on stimulus color rather than position (or both) to perform the task.

Behavioral Analyses

Our behavioral analysis aimed at revealing dynamics that were related to a strategy change that involved processing stimulus color (which was task-irrelevant according to the instructed task set). A post-experimental questionnaire indicated that eleven out of 36 participants (31%) had noticed and used the color information (henceforth, color users). On a general level, color users and corner users had comparable mean RTs (505 ms versus 562 ms, $p = 0.24$), and a marginally significant difference in error rates (4.2% versus 5.7%, $p = 0.07$). The analyses below will investigate potential differences in more detail. An online behavioral measure, in which position information was ambiguous (see Experimental Procedures), showed that the proportion of color-consistent choices in these trials indeed increased over time for color users (see Figure 2A, white line). Although this average time course of color use appears gradual, individual color users showed abrupt onsets. We thus determined large abrupt increases in color use (change-points) using the CUSUM method (Durstewitz et al., 2010) and aligned all time series to each participant's individual change-point (Figure 2B). Interestingly, color users changed their strategy spontaneously with no apparent relation to the elapsed number of trials—resulting in a temporal distribution of the change-points not significantly different from uniform (χ^2 test, $p = 0.16$). The remaining 25 participants (henceforth, corner users) did not report use of the color strategy in the questionnaire. Moreover, corner users did not show the abrupt onset of color use in ambiguous trials, which was apparent in color users (Figures 2A and 2B; Time \times Group: $F(10, 340) = 15.6$, $p < 0.001$; $\eta^2 = 0.8$). Further supporting the distinction between color and corner users, an analysis of standard trials showed that color users' RTs tended to transiently slow down before the change-point and speed up after it, whereas non-users did not show this pattern (Figure 2C; Time \times Group of RT slopes [lag 2]: $F(2.1, 136.6) = 3.0$, $p = 0.01$, $\eta^2 = 0.34$). Slight performance benefits resulting from the updated strategy were reflected in reduced errors after color

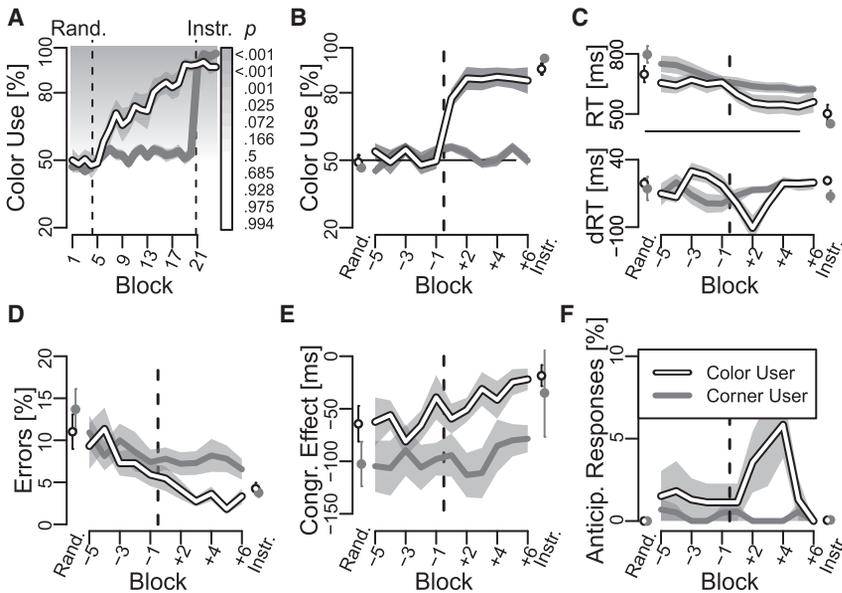


Figure 2. Behavioral Results

During the experiment, participants spontaneously separated into two groups of either color (white) or corner users (gray lines; group membership determined by questionnaire).

(A) Average percent of choices consistent with color when stimulus position was ambiguous across blocks (84 trials). The shaded areas on the left and right indicate blocks before color correlated with corner and blocks with instruction to use color, respectively. Background color indicates the binomial probability of choices assuming random behavior.

(B) Color users showed abrupt onsets of color use. For each participant, all data were aligned to the individual change-point (dashed line).

(C–F) Several independent behavioral markers showed significant Group \times Time interactions, including a transient RT slowdown before the switch ([C], upper panel shows RTs; lower panel lag-2 RTs; i.e., RT differences between blocks n and $n-2$), reduced errors and congruency effects following the switch ([D] and [E]), as well as increased anticipatory key-presses in delayed trials (F). All error bars/shadings represent mean \pm SEM. See also Figure S1.

users' change-point (Figure 2D; group comparison after switch, $t(32.5) = 2.73$, $p = 0.01$, $d = 0.69$; Time \times Group *ns.*). For color users, reduced reliance on spatial stimulus information during standard trials led to a decrease in the spatial congruency effect (Figure 2E) ($RT_{\text{congruent}} - RT_{\text{incongruent}}$, i.e., comparing trials in which horizontal stimulus position and response location did match versus did not match; t-test group comparison after switch, $t(31.3) = 2.56$, $p = 0.02$, $d = 0.62$; Time \times Group, *ns.*). At the same time, an increased amount of anticipatory (correct) key-presses in NoGo (= no response required) trials following color users' change-point (Figure 2F; Time \times Group, $F(5.7, 188.0) = 2.68$, $p = 0.02$, $\eta^2 = 0.71$) indicated a strengthened association between stimulus color and motor responses. Note that we found hints for group differences already before the onset of the color-corner correlation. Color users tended to have smaller congruency effects than corner user already during the random runs at the beginning of the experiment, ($t(32.86) = 1.72$, $p = 0.09$, $d = 0.48$). They also showed a trend for faster RTs ($t(29.9) = -1.67$, $p = 0.10$, $d = 0.51$). At the same time, there was no difference in error rates ($t(33.2) = -0.89$, $p = 0.41$, $d = 0.24$). Thus, conflict evoked in incongruent trials might not have been a driving force behind the task set update. In summary, the above results support the distinction between color and corner users in a number of independent behavioral markers. The emergence of group differences was in most cases related to the change-point and hence in accordance with the temporal dynamics as indicated by the choices in the ambiguous trials. In particular, color users showed reduced errors and congruency costs in standard trials after the task set change, and a transient increase in RTs before it. These results indicate that the processes that preceded the switch to the alternative strategy are associated with costs and result in performance benefits after the new task set has been established.

Decoding Information about Stimulus Features from Local Brain Activation Patterns

Representation of stimulus color was analyzed by a multivariate classification approach based on a support vector machine (SVM) with a linear kernel in combination with a searchlight approach (Haynes et al., 2007; Kriegeskorte et al., 2006). The data were divided into small time bins, and the SVM was trained and tested on parameter estimates ("betas") from a general linear model of red and green NoGo trials (see Experimental Procedures for details). To assess the representation of stimulus position (corner), a similar analysis was conducted based on betas of standard trials. The resulting time series of whole-brain accuracy maps was aligned to each participant's individual change-point and submitted to a univariate t-test. Most results refer to color users; see Figure S2 for corresponding analyses in corner users.

Consistent with our expectations, the analysis of color users' brain activity revealed several frontal brain areas in which we could decode color information only immediately prior to or after the change-point. Most interestingly, the stimulus became decodable from MPFC during the two blocks immediately before the change-point (Peak MNI Coordinates: 5/53/22, AAL Label: Frontal_Sup_Medial_R, duration of time window: 168 trials or about 5 min). After the strategy switch, color information emerged in lateral frontal brain areas, including the middle frontal gyrus (-36/11/33, Frontal_Mid_L) and the right Insula (42/-8/8, Insula_R). In contrast, mean color decoding across all time points (including early time points) was limited to visual cortex (clusters at 18/-87/-2 Calcarine_R, -22/-93/-2 Occipital_L, and 32/-72/-25 Cerebellum_Crust1_R; Figure 3). To formally test the different time courses of color encoding in medial and lateral frontal areas, we performed an interaction test between ROI (medial PFC versus lateral PFC/Insula; ROIs determined independently, see Experimental Procedures), Time (before,

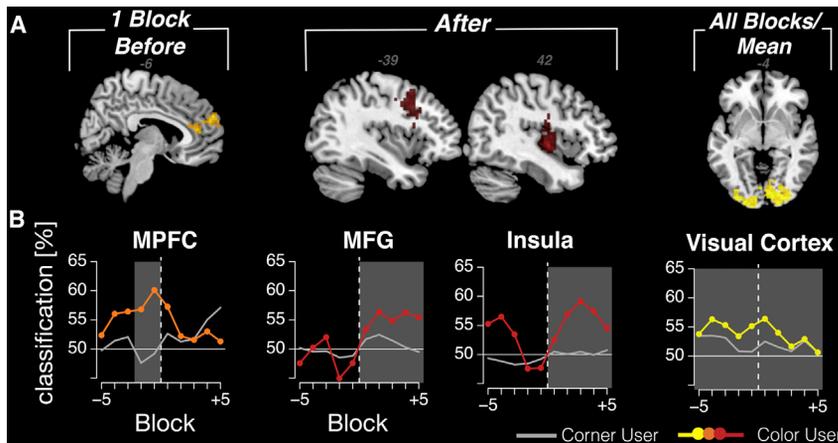


Figure 3. Stimulus Color Decoding

Classification accuracy was analyzed separately for either all blocks (mean) or only blocks immediately before the switch or after the switch (see gray shading in [B]; see also Figure S1).

(A) Color maps show areas in which stimulus color could be decoded ($p_{FWE} < 0.05$, cluster corrected). All three time windows showed distinct brain areas. Evidence for mean (time constant, see right) color representation was found in visual areas only, whereas color information emerged in MPFC immediately before the switch (left), and was at last found in the Insula and DLPFC (medial frontal gyrus, MFG, BA10).

(B) Time courses of decoding accuracy from shown clusters (smoothed with run. avg. of 2). See also Figure S2. Peak locations of individual subjects can be found in the Supplemental Information and Table S1.

immediately prior to, and after the switch) and Group (color users versus corner users). This analysis indicated an interaction that reflected the differential time courses of color encoding in lateral and medial frontal areas ($F(2, 68) = 4.5$, $p = 0.02$): in MPFC the amount of color coding did not differ between groups before or after the switch, whereas such a difference was evident immediately prior to the switch (p s for before and after: 0.16 and 0.48, p for immediately prior: < 0.01 , all p s are one tailed). In lateral PFC, in contrast, no difference could be found either before ($p = 0.39$) or immediately prior to the switch ($p = 0.94$), but a significant difference emerged after the switch ($p = 0.03$). Considering the same analyses only within the color user group showed comparable effects, as reflected in a Time X ROI interaction effect ($F(2, 20) = 5.4$, $p = 0.01$). We next analyzed the encoding of stimulus corner information in color users. This analysis revealed frontal areas in which corner could be decoded before but not after the change-point. In particular, we found high corner classification in superior frontal gyrus (23/9/53, Frontal_Sup_R), extending medially into the middle cingulate cortex (MCC, 9/17/43, Cingulum_Mid_R) and transient corner decoding in the superior parietal lobule (SPL, 23/-42/61, Postcentral_R). After the switch from instruction-based task processing (corner) to incidental learning-based task processing (color), no above-chance corner classification could be found (Figure 4).

Relation between Information Encoding in MPFC and the Use of Color Information

Our analysis revealed that activity patterns in medial prefrontal areas contained information about stimulus color before color-based response selection began. Next, we scrutinized the temporal relation between color encoding in MPFC and the behavioral change more directly. To this end, we tested if and when color-decoding accuracy would allow us to discriminate between color and corner users. Specifically, we extracted time courses from peak voxels within the PFC and applied a simple threshold classifier (participants with classification accuracy $> 50\%$ are classified as color users; voxel-selection and testing cross-validated; for details, see Experimental Procedures) (Figure 5A shows the peaks of the odd and even groups). Figure 5B shows that a significant proportion of the sample could

be classified correctly with this simple method, with above chance classification starting four blocks before and peaking at about one block before the switch (73%, $p = 0.01$). A ROC analysis over all possible thresholds confirms the best classifiability around the same time (see Supplemental Information). In addition, an analysis using non-time-locked data also confirmed the discriminability of both groups (see Supplemental Information; Figures S3 and S4). Hence, even an analysis that is completely agnostic to the switch decision and switch time points allowed us to predict participant's upcoming strategy change.

Relation between Information Encoding in MPFC and Conscious Knowledge about the Alternative Strategy

Finally, we explored the relation between the time point when participants gained conscious awareness of the color-corner relation and the onset of color encoding in MPFC. To address this issue, we analyzed the post-experimental questionnaire in which participants were asked to retrospectively assess the time when they became aware of the color-corner relation. These verbal reports correlate highly with the time of strategy change that was determined based on behavior ($r = 0.82$, $p = 0.002$). Importantly, however, the reported time points where temporally very close to the behavioral switch (mean difference: 0.14 blocks; t-test that the difference between verbal report and behavioral switch is different from 0: $p = 0.82$). Thus, conscious awareness presumably came after the onset of color encoding in MPFC (Figure 5), which started four blocks before (-4) and peaked one block (-1) before the switch. A t-test between the reported time of verbal knowledge and the earliest onset of color encoding in MPFC (-4) supports the notion that verbal knowledge came significantly later ($p < 0.001$). To further support these findings, we conducted a control experiment ($n = 23$) whose sole purpose was to refine the method with which the conscious awareness was assessed (the retrospective memory test was closer in time to the behavioral switch; see Experimental Procedures). Nine participants crossed the threshold for color use and where stopped right after their behavioral switch (see Experimental Procedures). As before, the given verbal report correlated highly with the behavioral switch ($r = 0.87$)

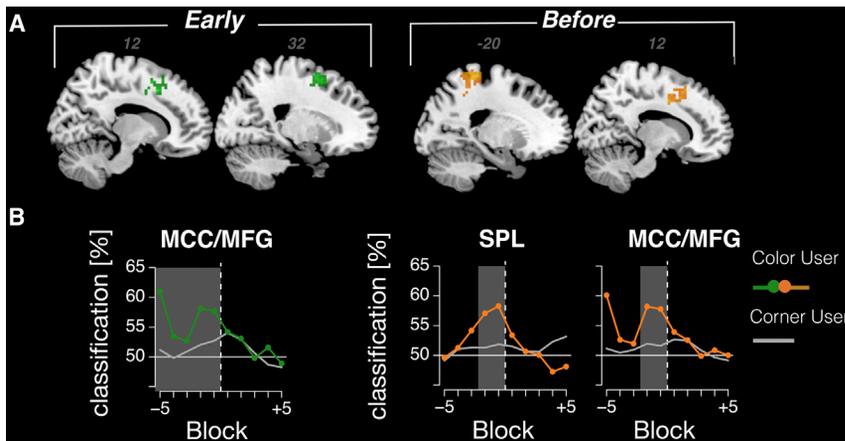


Figure 4. Stimulus Corner Decoding in Color Users

Corner classification was analyzed in separate time windows (indicated by the gray background areas on the time course plots; $p_{FWE} < 0.05$, cluster corrected). The presented results stem from time windows that included either all blocks before (–5 to 0, “Early”) or immediately before (“Before,” same as in Figure 3). Time windows after the switch did not show any significant results and hence are not shown (see also Figure S2).

(A) Evidence for corner representation could be found initially in frontal brain areas (medial frontal gyrus, MFG, BA10) as well as in middle cingulate gyrus (MCC) and transiently before the switch in superior parietal lobule (SPL).

(B) Time courses from shown clusters; gray background area indicates relevant time window. See also Figure S2.

and provided evidence that participants became aware after we could find significant MPFC decoding in our main experiment: a t-test between the reported time of verbal knowledge in this new experiment and the earliest onset of color encoding in MPFC (–4) again supported the idea that verbal knowledge came significantly later ($p < 0.002$).

DISCUSSION

When facing a complex task, we often don’t know if the current strategy is the best of all possible strategies. Information-rich environments often allow to use alternative strategies that can lead to the same goal, potentially in a more effective manner. At the same time, the efficient implementation of an existing strategy involves top-down control mechanisms, which degrade the representation of irrelevant information and hence make exploring such alternatives unlikely and difficult. Here, we studied the ability to spontaneously discover and implement new strategies. Our paradigm allowed, for the first time, the in-lab reproduction of this striking ability and the opportunity to track its neural underpinnings.

Participants were instructed with valid rules to perform a task based on the spatial location of a stimulus. Unmentioned but simple regularities in the task environment (stimulus color), however, could lead to a new strategy for reaching the same task goal. Although this regularity was very simple and repeated many times, most participants’ focus on the instructed sensory signal was so strong that it prevented them from discovering (53%) or using (16%) the alternative strategy. As a result, only 31% of participants changed to the new color-based strategy. Once it was triggered, however, the behavioral transition to the new strategy started abruptly and was completed within a few minutes. Importantly, we found that the neural encoding of color information was uniquely related to the behavioral switch in color users. Specifically, we revealed that in areas known to be involved in the representation of task sets, namely DLPFC and Insula (see Dosenbach et al., 2006, but note that other cognitive functions have been linked to these areas as well), color encoding emerged only after the behavioral change. Most interestingly, we found that the BOLD signal in MPFC started encoding color

information several minutes before the new strategy was actually applied. Based on this effect, we could predict which of our participants would apply the color strategy.

Our findings suggest an important role of MPFC in the spontaneous updating of mental programs. First, we showed that MPFC started encoding stimulus color of the current trial when participants were still pursuing the original (position-based) strategy. Strikingly, MPFC behaved as if it was involved in performing the task based on color, even though participants had not yet started doing so overtly. We speculate that MPFC is involved in planning and evaluating a future strategy shift by internally simulating the alternative strategy (Jeannerod, 2001; Sutton, 1990). This process takes place before a decision for the implementation of the alternative strategy is made, a process akin to counterfactual thinking (Barbey et al., 2009). Second, we showed that MPFC encoded a stimulus feature that was task-irrelevant according to the instructed task set. A large body of studies has shown that an important function of PFC is indeed to disadvantage processing of task-irrelevant information (e.g., Doll et al., 2009; Dreisbach and Haider, 2008; Duncan, 2001; Miller and Cohen, 2001). In support of this idea, our own findings showed that color processing was strongly impaired: the majority of participants did not notice the color-response relationship, despite its simplicity and the fact that the deterministic relationship could be observed in over 700 trials. Hence, the early encoding of color in MPFC in color users seems to reflect between-subject differences in the extent to which information processing excluded task-irrelevant information. Accordingly, our finding suggests that MPFC could escape the top-down bias. At the same time, in those participants who did not discover the color strategy, it remains an open question whether the instruction led to impaired learning of task-irrelevant information or only suppressed the effect irrelevant knowledge has on behavior (Doll et al., 2009; Gaschler et al., 2012; Zhao et al., 2013). In addition to our findings on color representation, we found largely absent or decreasing corner representation in color users (Figure 4). This contrasts with widespread corner encoding in corner users (Figure S2), although it is notable that the network employed to represent color in color users and corner in corner users did not overlap completely (see gray lines in Figure 2).

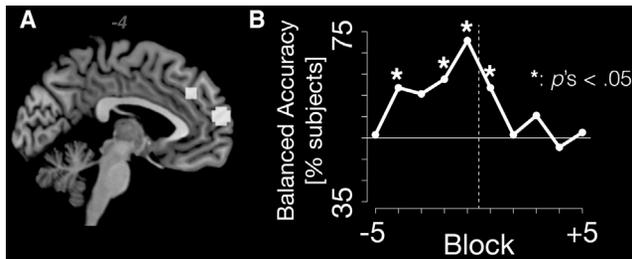


Figure 5. Relations of Information Encoding to Performance

(A and B) Evidence for color representation in MPFC could be used to determine group membership, even before participants showed behavioral signs of using the color. Time courses of color classification accuracy were extracted from brain areas encoding color during the switch (A) and used to classify subjects into color and corner users as a function of time ([B]; smoothing as in Figures 3 and 4). See also Figures S3 and S4.

Our findings relate to several studies that have previously offered accounts of MPFC function. Regarding the effects of changing a strategy, our findings agree with research that indicated that neurons in MPFC show abrupt and in some cases transient state transitions that accompany changes in the used rules/strategy (Durstewitz et al., 2010; Karlsson et al., 2012; Rich and Shapiro, 2009) or proposed that MPFC is involved in selecting a different action routine (Holroyd and Yeung, 2012). Other research suggested that ACC, a subregion of MPFC, processes conflict signals and evaluates the expected value of control (Botvinick et al., 2001; Shenhav et al., 2013), thus indicating a role of MPFC in cognitive control. Finally, the same brain area has also been linked to foraging (Hayden et al., 2011; Kolling et al., 2012; but see Shenhav et al., 2014) and exploration (Karlsson et al., 2012), suggesting that ACC encodes the “value of switching to a course of action alternative to that which is taken or is the default” (Kolling et al., 2012, p. 97). While our paradigm involves all of these components—strategy switching, adaptations in cognitive control, and deciding to explore novel courses of action—our approach allowed us to offer a new perspective on the functional role of MPFC in cognitive control and strategy switching. By showing that MPFC directly engaged in processing of stimulus features, our findings indicate that this brain area deals with the specific stimulus properties whose processing is affected by cognitive control (here: the color), rather than only “global” variables relating to the amount of necessary cognitive control (such as conflict, the value of control, or the value of foraging). Our interpretation of an internal simulation process could link our results to evidence of internally generated sequences in the rat hippocampus (Johnson and Redish, 2007) that reflect internal planning and influence activity in MPFC (Pezulo et al., 2014).

In addition to these commonalities, our findings represent challenging evidence for a recent theory of PFC function (Donoso et al., 2014), which prescribes a role of anterior and lateral frontal areas for exploring alternative strategies and assumes that exploration is related to the unreliability of the current strategy. Moreover, by not mentioning the alternative options, our approach contrasts with existing research (e.g., Kolling et al., 2012). Rather, our paradigm explored participants’ ability

to learn statistical relationships in the environment that could lead to the new strategy. This shows that incidental learning about features of the environment can interact with mechanisms that adjust cognitive control and drive spontaneous exploration of alternative strategies. Importantly, throughout the experiment the instructed task set remained veridical (and hence reliable), all participants made few errors, and our behavioral analyses did not show any positive relation between measures of conflict and the probability to discover and use the alternative rule. Thus, the observed exploration of alternative strategies does not seem to be driven by unreliability, conflict, or errors, as in previous studies (Botvinick et al., 2001; Collins and Koehlin, 2012; Daw et al., 2006; Donoso et al., 2014; Nassar et al., 2010). Rather, our findings would better relate with previous evidence showing the involvement of MPFC in deciding which task to perform in the future (Haynes et al., 2007; Momennejad and Haynes, 2013; Soon et al., 2013; Wisniewski et al., 2014). Note, however, that in the above-mentioned studies a (mostly a priori specified) rule was decoded from brain activity, whereas our study decoded stimulus features. Hence these existing studies were suited to answer questions about the representations of task sets/rules during or prior to their application, whereas the present study focused on the question how established task sets control which information is represented in prefrontal brain areas and how prefrontal representations of sensory information changes as a result learning about statistical relations in the environment. For this reason, the present experiment investigated the switch toward a strategy that was not specified by instructions, self-learned, and discovered despite the existence of an instructed and working rule.

MPFC was not the only region that encoded color. Following the strategy shift, we found that color information was present in the Insula and in the left DLPFC, while before the switch corner information was found in the right DLPFC. These findings are compatible with preceding proposals and evidence on the neural basis of cognitive control and the implementation of tasks (Koehlin et al., 2003; Reverberi et al., 2012; Sakai, 2008; Sakai and Passingham, 2006; Woolgar et al., 2011). Furthermore, they show how frontal cortex modifies the represented information depending on what is relevant in the current context (Freedman et al., 2001; Stokes et al., 2013). Recent research has also highlighted the importance of the adaptive representation of information that is relevant in the context of the current task (so called “task states”) for reinforcement learning (see Wilson et al., 2014). The present results are witness to the ability of frontal flexible coding and its potential interaction with learning.

One interesting question for future research is to assess the role of conscious and unconscious processes in the times before and during the changes in cognitive control and the applied strategy. While our own data indicate that the conscious realization of the color-corner relation occurs at the time of the behavioral switch (verbal reports of when participants realized the relation correlate to $r = 0.82$ with the behavioral switch time point and do not differ from each other, $p = 0.83$), our control experiment showed that 33% (3/9) of color using participants reported that they noticed the relation only because they had involuntarily started exploiting it (Frensch et al., 2003). Future research could thus employ more stringent methodology to assess conscious

knowledge and which neural processes relate to the transition from conscious to unconscious knowledge of environmental statistics (e.g., [Rose et al., 2010](#); [Schuck et al., 2013](#)). Note that our finding that participants' awareness of the alternative strategy arose mostly after we found the signal in MPFC also indicates that our results are not related to the possibility of insights or Aha moments. Although elucidating the role of insight for the spontaneous discovery of alternative strategies is an interesting question ([Kounios and Beeman, 2014](#); [Luo and Knoblich, 2007](#)), our task does not include a classic "problem" to solve and thus our results do not directly speak to this question.

Taken together, the present study showed that MPFC is involved in the spontaneous exploration of irrelevant information that led to the discovery and implementation of a new strategy. Crucially, this change of strategy was self-initiated by participants and not cued by any experimental intervention. Hence, it is an example of self-driven and flexible goal-directed behavior. By showing that MPFC encoded aspects of the stimulus that eventually came to control behavior, our results highlight the role of MPFC in carrying out computations related to freely chosen exploration and adaptation of cognitive control. Finally, prediction of color use across subjects is, to our knowledge, the first demonstration that a future choice can be predicted from brain activity even when the experiment did not ask for a choice to be made at all. Our results shed new light on the computations carried out in MPFC and suggest that these processes are involved in initiating, rather than implementing, the spontaneous updating of the mental structures, which support goal-directed behavior.

EXPERIMENTAL PROCEDURES

Participants

Thirty-six volunteers (22 female, mean age 25.8 [21–31]) participated in the fMRI study in return for reimbursement (20 €/hr). Prior to recruitment, all potential participants were screened for MRI eligibility and provided informed consent to participation. The behavioral control experiment included 23 participants (14 female, mean age 22.9 [19–28]). The institutional review board at Humboldt University approved the study.

Task and Procedure

Behavioral and imaging data of the main experiment were recorded while participants performed a simple perceptual decision-making task (Spontaneous Strategy Switch Task). Participants were instructed to respond manually to the position of a patch of colored dots within a square reference frame ([Figure 1A](#)). They were asked to select one of two responses depending on which corner of the reference frame the colored squares were closest to. Participants held a button box in each hand and could press either left or right. Two opposite corners (along the diagonal) were mapped to the same response ([Figure 1B](#)). The main task during scanning included twelve runs with 168 trials each. In Runs 1 and 2 (Random Runs), the stimulus color was unrelated to the position of the stimulus and the response. In Runs 3–10 (Correlated Runs) the color had a fixed relation to the response (e.g., all upper-left and lower-right stimuli were green, the remaining ones were red) (see [Figure 1C](#)). Participants were not informed about this contingency, but could learn and apply it spontaneously. Hence, on the one hand, the instructions provided a functional set of rules to determine one's responses (based on stimulus position). On the other hand, an alternative rule based on the "irrelevant" feature color could also be used once color correlated with corner (and hence signaled the correct response). By the end of Run 10, all participants were informed about the existence of a fixed association between color and corner (without specifying the relation) and instructed to use the color from then on (Instructed

Runs). Each of the twelve runs of the main experiment lasted about 5 min and was followed by a short break. The experimenter monitored performance of participants. Written and oral feedback was given between runs if the error rate exceeded 20%. The response stimulus interval was 400 ms. To measure the learning and use of color information, we designed different trial conditions. In the standard condition (80 out of 168 trials/run), the patch of dots was presented for 400 ms and was closest to one of the four corners of the reference frame. Thus, a response could be selected as instructed based on stimulus position. Unmentioned to the participants, however, the stimulus was centered within the reference frame in some trials (ambiguous condition, 32/168 trials, display duration 400 ms; see [Figure 1A](#)). The ambiguous trials allowed for an online assessment of the tendency to use color because a participant can be expected to respond left or right at chance level to a centrally presented green stimulus—unless s/he has already learned that, for example, green stimuli are usually followed by a right response. Choices, which were more consistent with the color than expected by chance, thus reflect emerging knowledge about this contingency. A pilot experiment applying ambiguous trials only late in practice showed that the introduction of ambiguous trials neither evokes nor hinders color usage. To allow efficient measuring of BOLD responses related to color but not corner, the colored squares were displayed for 2,000 ms without a reference frame in some trials (48/168 trials). In two thirds of these trials, the task afterward continued with the next trial. Participants had to hold back any key press on the current trial (NoGo condition, 32/168). In the remaining one third of these cases, the frame was displayed after the initial 2,000 ms, and the participants had to react in a regular fashion (LateGo condition, 16/168, display duration of stimulus with frame: 400 ms). To ensure that the frame was indeed needed to make the correct choice, the stimulus always appeared at the same central location in each trial, whereas the location of the frame was changed from trial to trial. It was thus neither possible to ignore stimuli that lacked a reference frame nor to respond prematurely. The NoGo trials were used to study changes in the neural representation of color information. In these trials, color was displayed long enough to estimate a neural response. It was not confounded with spatial stimulus information and motor activation was suppressed. Finally, in eight trials of each run the screen remained black for 3,000 ms (baseline condition). Due to the duration of the hemodynamic response function, the fast design of the experiment resulted in event-related BOLD signals, which also contained a signal proportion that reflected brain activation caused by previous and following events. Because NoGo trials were central to the multivariate analyses (see below), we ensured that all trials in the 4 s preceding and following each NoGo trial were balanced. As we aimed at decoding color (red versus green), we ensured that for each red NoGo trial we had a green one with the exact same composition of preceding and following trials (i.e., color, corner, and condition). To ensure balancing of the last trials in each run, we generated balanced sequences of 168 trials and appended these with the first 12 trials of the sequence. Hence, from the 180 trials in each run, only the first 168 were analyzed. This procedure ensured that biases in the unwanted signal proportion were minimized. Additionally, we ensured representative frequency distributions of condition and color within windows of 42 trials. This allowed us to do analyses with a below-run temporal resolution, which still had minimal biases in the trial structure or signal.

Before entering the scanner, participants were instructed and trained in the task. The instructions described all conditions (except ambiguous trials). Participants were only told to press any key of their choosing in case they were uncertain about the stimulus location. The color of the stimuli was mentioned only in an unspecified manner ("A stimulus can be either red or green."). The response mapping was shown in all color combinations (a stimulus in each of the four corners was shown in both red and green during the instruction). In the training phase, participants were slowly accustomed to the short display durations (the display duration was successively shortened until it reached 400 ms). Feedback was given for all wrong and premature responses and time-outs (2,500 ms threshold). The color of the stimuli had no systematic relation to stimulus position during training. The training lasted at least 50 trials and ended when the participant made less than 20% errors in 24 consecutive trials. If the participant exceeded 168 trials without reaching the criterion, the training was restarted. Participants were further instructed that upon entering the scanner, no more feedback would be provided. After completion of the main

experiment, participants completed a questionnaire with the following questions: (1) "In the experiment, which you have just completed, each corner had one associated color. Did you notice this while you were performing the task?" [yes/no]. (1b) "If yes, *when* did you notice this (after what percentage of the experiment)" [participants had to mark their answer on a scale from 0% to 100%]. (1c) "Did you use this color-corner relation to perform the task, i.e. to choose which button to press?" [yes/no]. (2) "Please indicate now which color the stimulus had for each of the four corners. If you did not notice this relation during the experiment or you are uncertain, you can guess." The task employed for the control experiment was identical to the main experiment with the exception that it was automatically stopped once a participant showed the first clear signs of color use. Because its purpose was to shed light on the role of conscious awareness in our task and to reduce the concern that retrospective memory of longer time periods might be unreliable, we used this automatic stopping procedure to ask participants about their conscious knowledge at a time that was much closer to their behavioral switch. To determine the stopping criterion, we fitted a logistic regression to predict participant group (color users/no color user) based on the maximum overall percent of color use in ambiguous trials in the main experiment. The resulting threshold was 82% and correctly identified 91% (10/11) of color users while misidentifying only one corner user. Therefore, as soon as participants crossed this threshold (in the last two blocks over a running average), they were stopped in the control experiment. After the stop, participants were asked the same questions from the post-experimental questionnaire described above. Furthermore, we asked participants about four potential properties of insight: (1) whether they gained awareness suddenly, (2) whether the alternative strategy did seem obvious after they learned about it, (3) whether it they could not tell how they came to know about the alternative strategy, and (4) whether they have been very sure that the new strategy is valid for the whole task. Finally, we also asked them whether they initially started using the color involuntarily and only realized later that the colors could be used.

Behavioral Analyses

Behavioral analyses were done using R (R Development Core Team, 2013). Time-out trials were excluded from all analyses and error trials from RT analyses. For each ambiguous trial, it was determined if the given response was the one predicted by the stimulus color or not (henceforth: "color use"). A participant was classified as a color user if s/he indicated a strategy switch in the questionnaire. These responses were 100% in line with a behavioral analysis, which determined if color use in the last run was at least 75% ($p < 0.005$, binomial test over all 32 ambiguous trials in this run). Remaining participants were classified as corner user. Six corner users reported having noticed the color-corner relation but that they had refrained from using it. For the behavioral and neural analyses, we divided the task into blocks of 84 trials each (half a scanner run). For each block, the median RT, mean percent of errors, and color use was calculated.

For the present experiment, it was important that we could determine when participants began using the color. To this end, we used the CUSUM method to determine the block when a color user started using the color. This method effectively detects the block where a participant started performing above her/his own overall mean level (i.e., the point in a time series where a large upward change occurs) (see [Durstewitz et al., 2010](#)). Because corner users per definition do not have a change point, we used the change points that were determined for color users and randomly assigned them to corner users. This resulted in an equal distribution of task experience before/after the change-points for both groups. The results can be seen in [Figure 2](#), where the dashed vertical lines indicate the change point.

In order to rule out that our results are dependent on the random assignment of switch-points to corner users, we applied the CUSUM algorithm to corner user's data. This is an interesting test because even if a data series does not have a clear switch point, the CUSUM algorithm will still find the point of greatest change and thus can serve as a conservative control. Indeed, the resulting time series of corner users shows an increase in color use around the change-point (an artifact of the algorithm), but importantly, this increase was still considerably smaller and more transient as compared to color users (interaction Time \times Group, $F(10, 340) = 9.4$, $p < 0.001$; see [Figure S1](#)). Hence, even in comparison to a stringent test, color user's showed larger change points than

corner users. In the analysis with change-point aligned data, we only consider time points with complete data from all subjects (if the earliest switch-point was at block 6, the maximum number of blocks before the switch was constrained to be five, etc.).

Scanning Protocol and Data Preprocessing

Acquisition of magnetic resonance images was conducted at the Berlin Center for Advanced Neuroimaging, Charité Berlin. We used a 3 T Siemens MagnetomTrio (Siemens) research-dedicated MRI scanner to acquire all data. T1-weighted structural images were acquired with an MP-RAGE pulse sequence with a resolution of 1 mm^3 . A T2*-weighted echo-planar imaging (EPI) pulse sequence was used for functional imaging ($3 \times 3 \times 3 \text{ mm}$ voxels, slice thickness = 3 mm, TR = 2,000 ms, TE = 30 ms, FOV = 192 mm, flip angle = 78° , 33 axial slices, descending acquisition). EPI slices were aligned to the anterior-posterior commissure axis. Field maps for distortion correction were acquired also using an EPI sequence. To allow for T1 equilibration effects, the experiment was started 6 s after the acquisition of the first volume of each run. fMRI data preprocessing was done using SPM8 (www.fil.ion.ucl.ac.uk/spm) and involved a correction for magnetic inhomogeneities using fieldmaps and spatial realignment.

Decoding

Whole-brain maps of parameter estimates from first-level subject-wise GLM analyses were subjected to multivariate pattern classification following a searchlight approach ([Haynes et al., 2007](#); [Kriegeskorte et al., 2006](#)). To obtain these parameter (beta) maps, we conducted two separate GLM analyses. For color classification, the GLM included two separate regressors for each block and condition (four regressors per block), two modeling all red, and two modeling all green NoGo trials (each regressor modeled four trials; duration each 2,000 ms). Regressors modeled half blocks instead of blocks to get better temporal resolution and to have more data for training/testing the classifier. The GLM also included six motion regressors and one intercept regressor per run, but no events from other conditions. For corner classification, the GLM included two separate regressors for each block and corner (modeling five trials per corner) plus six motion and one intercept (constant) regressor per run. We used a SVM with a linear kernel (cost parameter = 1) to classify patterns within spherical clusters centered on each voxel (LIBSVM; www.csie.ntu.edu.tw/~cjlin/libsvm) and the Princeton MVPA toolbox (<http://code.google.com/p/princeton-mvpa-toolbox>) for data organization. To analyze the representation of color, the classifiers were trained on the regressors modeling NoGo trials in the last two runs (i.e., eight red and eight green betas). In these runs, all participants showed strong color use; hence, brain activity in this time window reflects a task set that includes the use of color (see [Figure 2A](#)). The classifiers were then tested on betas from Runs 1–10. This resulted in one accuracy map for each block and subject, hence allowing us to analyze the time course of color representation within a given spherical cluster. We note that one potential confound of our findings is that color was fully correlated with responses and the classifier performance could have been based on sub-threshold response preparation (even in NoGo trials). Yet, in light of the very limited number of responses in NoGo trials (see [Figure 2F](#)), this interpretation seems unlikely. In addition, the classifier can only pick up a signal if participants prepare responses based on the color and hence increased classifier performance before a behavioral change would still hint at a mechanism for internal simulation of the alternative strategy. The analysis of corner representation was done by training the classifiers on standard trials in Runs 1 and 2 (in which color was uncorrelated to corner and hence brain activity should reflect the instructed task set based on corner) and testing the classifiers in Runs 3–12. To avoid results associated with motor responses during standard trials, this procedure was done separately for each set of two corners that were mapped to one hand: one set of classifiers was trained to distinguish between patterns associated with upper-left and lower-right standard trials, which were both associated with the right hand, and another set, classified upper-right and lower-left standard trials. The results of the two classifiers were averaged. For statistical inference on the group level, normalized and smoothed (2 mm FWHM) accuracy maps were submitted to second-level analyses in SPM. All time points were aligned relative to the individual change-point of color use. As mentioned above, the calculation of the change-points was derived from

behavioral data in a different condition (ambiguous trials) and hence was independent of the current analysis. Our main hypotheses regarded changes emerging immediately before and after the behavioral switch, and hence the possible blocks (−5 to +6; i.e., the relative time windows where data were available from all subjects) were divided into these categories. Maps containing the average classification within these time-windows (before, after, overall mean) were then submitted to separate t-tests. All resulting t-maps were thresholded at $p < 0.01$ with appropriate FWE cluster size correction ($p_{FWE} = 0.05$). To illustrate the precise development of representations within the above-threshold clusters, time courses of average accuracies (smoothed with moving average of length 2 blocks) in the identified voxels were extracted and shown separately. Time courses only serve to illustrate the temporal structure. The interaction test between ROI and time used cross-validated ROI definitions. Specifically, the analysis of color encoding immediately before and after was repeated for odd- and even-numbered participants. 7 mm spheres were centered on the resulting peak voxels (analysis constrained to prefrontal cortex (i.e., Brodmann areas 8–12, 24, 32, 33, and 44–47), which were, as in the main analysis, in medial (“switch contrast” peaks at −9/34/39, Frontal_Sup_Medial_L and 0/62/17, Frontal_Sup_Medial_L) and lateral PFC (“after contrast” peaks at 42/4/8, Insula_R and 45/-4/2 Insula_R). These spheres were used as ROIs for the ANOVA. The time effects involved the three factors: “Before,” “Immediately Before,” and “After,” which were defined as blocks −5, −4, −3; versus −2, −1, 0; and +1 to +5, respectively.

Classifying Subjects into Groups Based on Brain Data

To avoid peeking during the subject classification analysis, we split the color user group into two subgroups in which we selected voxels separately. In particular, for voxel selection, we repeated the t-test of mean color classification in the switch time window once with only odd- and once with only even-numbered color users. The resulting maps were masked with an anatomical mask of PFC (Brodmann areas 8–12, 24, 32, 33, and 44–47), and time courses were extracted from a spherical cluster around the peak voxel (radius 8 mm, the peaks of the odd and even groups are shown in Figure 5A; peak locations are marked in white). For each of the two resulting clusters, we used the time courses of color decoding accuracy of the remaining color users as well as half of the corner users (i.e., subjects not used for voxel selection) to classify subjects as either belonging to the color users or not (odd/even cross validation; i.e., the cluster defined in odd participants was used to test classification in even participants and v.v.). For classification with change-point-locked time courses, we used a very simple threshold classifier that assigned group status based on whether (rounded) decoding accuracy was $> 50\%$ (color user) or not (position user). The classifier performance was evaluated using the probability of the number of correct guesses under a hypergeometric distribution given the baseline probability and total number of guesses at each time point (the number of participants labeled as color users was not constrained and differed between time points). A control ROC analysis that shows how this effect behaves across different thresholds can be found in the Supplemental Information and Figure S3. Further supporting results from an analysis, which uses natural (not time-locked) data, can be found in the Supplemental Information and Figure S4.

SUPPLEMENTAL INFORMATION

Supplemental Information includes four figures and one table and can be found with this article online at <http://dx.doi.org/10.1016/j.neuron.2015.03.015>.

AUTHOR CONTRIBUTIONS

All authors contributed to designing the study. N.W.S., R.G., D.W., and J.H. conducted research. N.W.S. and C.R. analyzed the data. All authors contributed to interpretation of the findings and writing the manuscript.

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Supplemental Information

Medial Prefrontal Cortex Predicts

Internally Driven Strategy Shifts

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John-Dylan Haynes, and Carlo Reverberi**

Supplemental Figures

Figure S1, Related to Figure 2

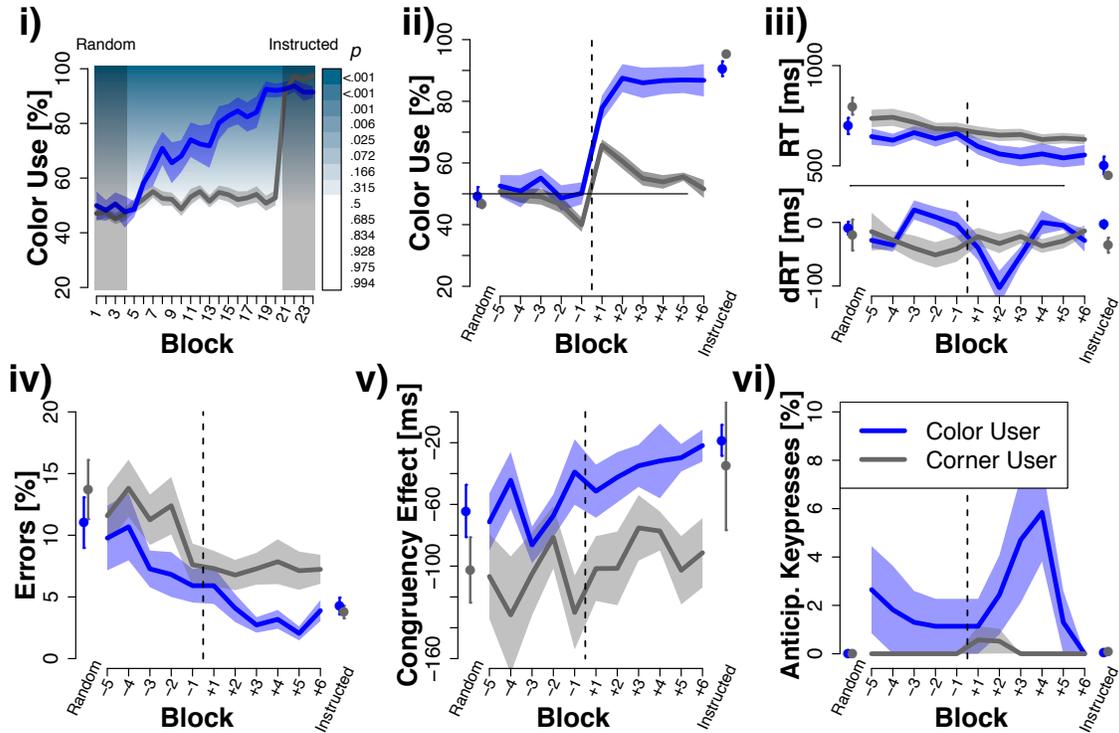


Figure S1. Behavioral results with alternative time locking of corner users. Instead of random assignment, corner users' switch-points were defined based on the CUSUM algorithm. Otherwise, the figure corresponds in all respects to Figure 2 of the main article. (i) Average percent of choices consistent with color when stimulus position was ambiguous across blocks (one block = 84 trials). (ii) Time locked color use data. In comparison to Figure 2, this shows that the sheer power of the CUSUM algorithm is able to cause a dip and increase in corner users' color use around the time of the switch. The increase in color use is transient and not as strong as in color users, however. (iii-vi) Importantly, the results of all other analysis on RTs or errors are qualitatively the same as compared to Figure 2.

Figure S2, Related to Figure 3

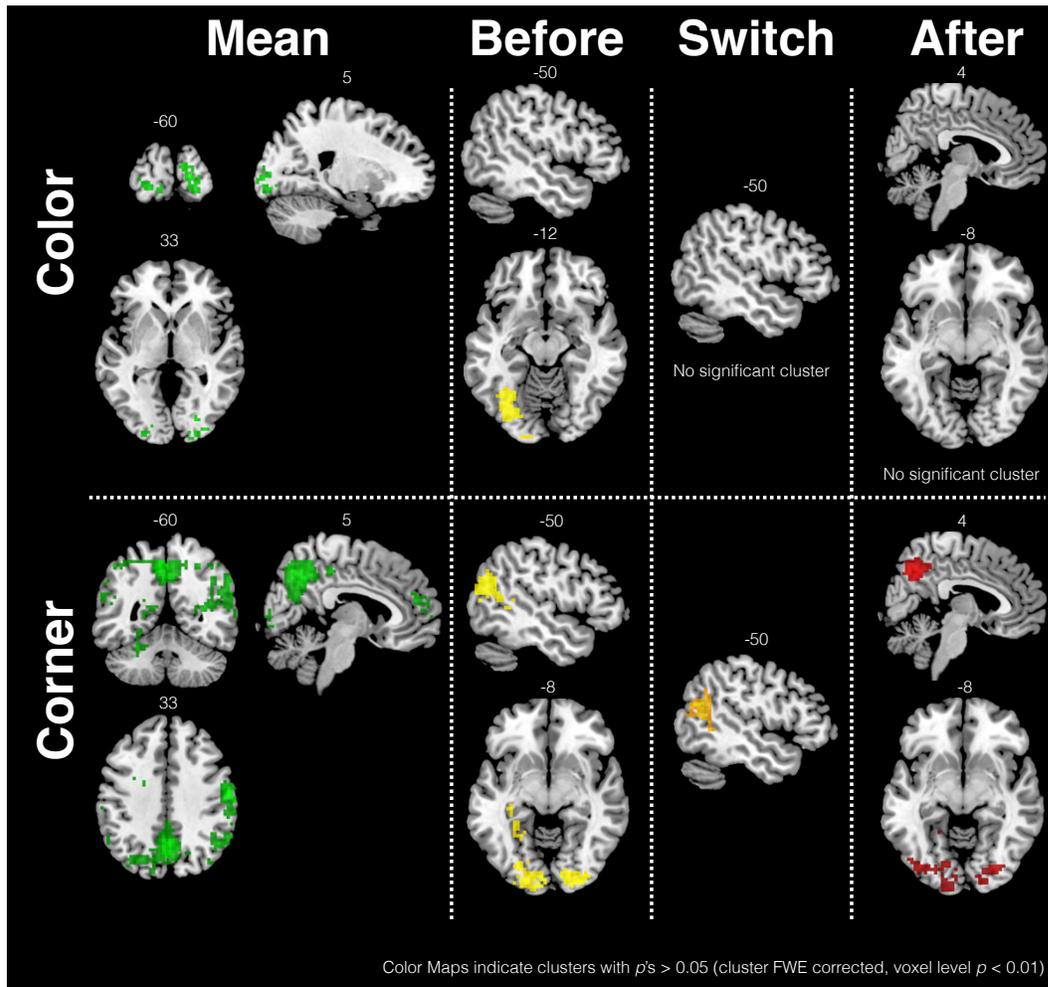


Figure S2. *Classification results for corner users.* The figure shows brain maps indicating significant color (upper row) and corner (lower row) classification among corner users. The analysis is complimentary to the analyses shown in Figs. 3 and 4 in the main paper (same time windows, and statistical threshold). The maps are divided into analyses considering the whole time series (*mean*, 1st column from left), all blocks before the switch (*before*, 2nd column), only the two blocks immediately before the switch (*switch*, 3rd column) and all blocks after the switch (*after*, 4th column). Corner users' switch was defined based on the switch points of color users (see Methods). Because the definition of time windows with this method might be noisy, the image showing the mean across all time points is the most easy to interpret, whereas other results have to be interpreted with caution. Empty brain images indicate that this respective analysis did not yield any significant results. In summary, we found that among corner users corner decoding worked well in all time windows and showed significant classification in visual cortex, precuneus, MPFC, lateral PFC and pre-and postcentral gyri, but color classification was much weaker throughout and confined to visual cortex.

Figure S3, Related to Experimental Procedures

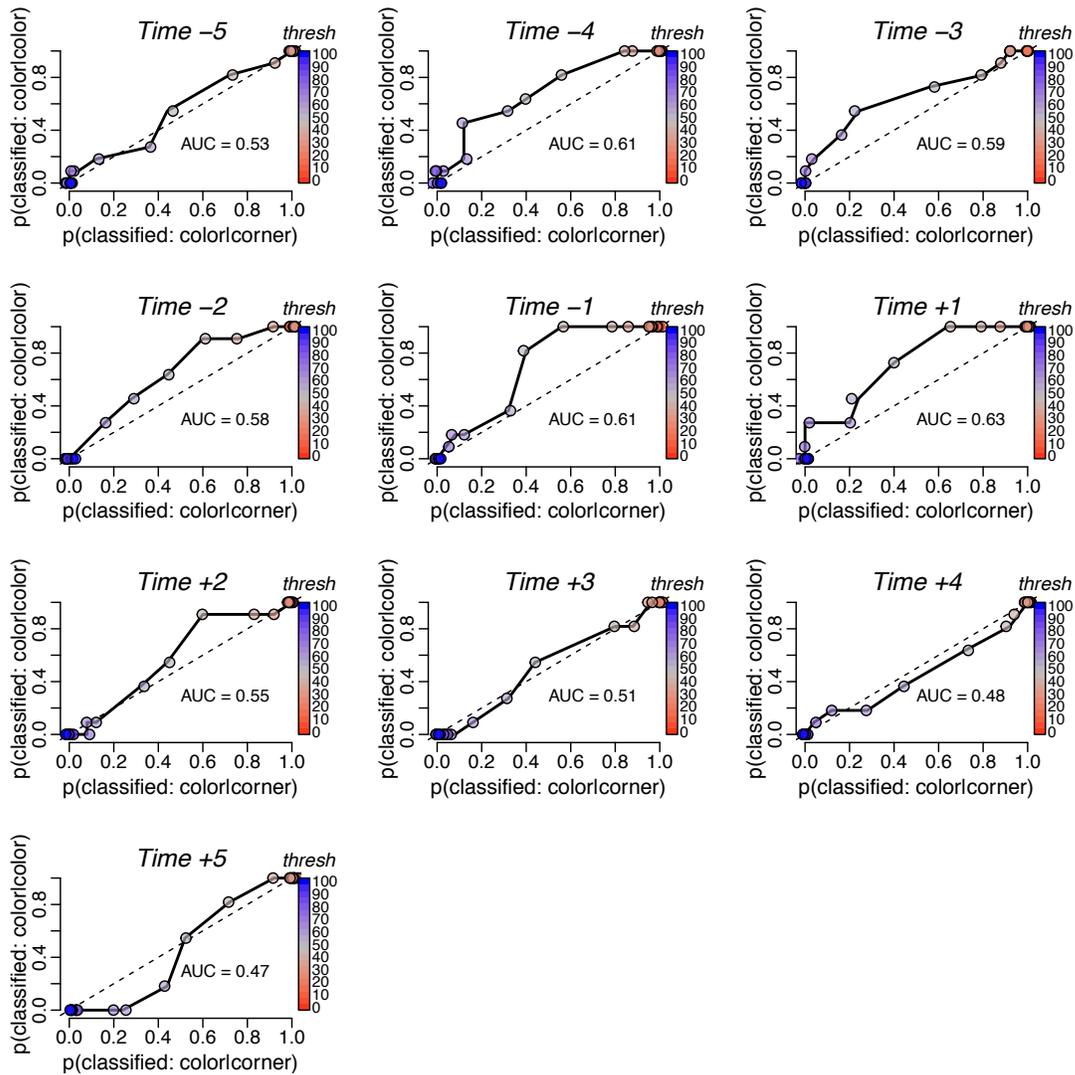


Figure S3. *Time resolved ROC analysis for classification of participants.* Each panel shows a receiver operating characteristic (ROC) curve for one block (see title of plot). This analysis is complimentary to the Experimental Procedures and Figure 5 in the main paper. In each ROC analysis, participant group (color or corner user) was predicted using different thresholds on the color classification accuracy within MPFC. As in the main analysis, the relevant ROIs were defined in a cross-validated manner and the analysis was run on time courses smoothed with a running average of 2 (see also Fig. 3, 4, 5). The sensitivity (proportion of subjects classified as color users, given that they are indeed color users, y-axis; $p(\text{classified: color} | \text{color})$) and specificity (proportion of subjects classified as color users, given that they are corner users, x-axis; $p(\text{classified: color} | \text{corner})$) are plotted as points within the graph, whereby different thresholds are color-coded. To better illustrate overlapping points, colors are semi transparent and jittered along the x-axis (Gaussian, $SD = 0.01$). As can be seen, the time-points around the switch allow the best classification across a range of thresholds.

Figure S4, Related to Figure 5

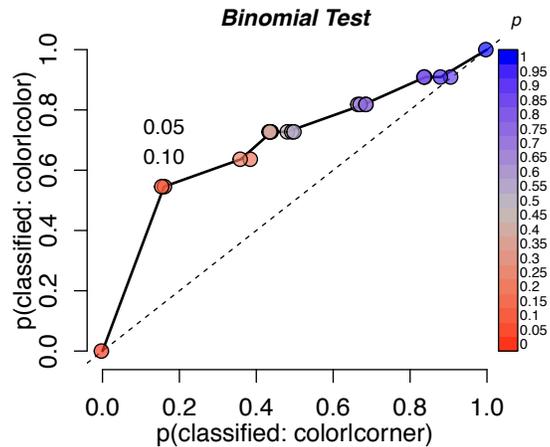


Figure S4. *Prediction of strategy switch without time-locking.* To test whether we could also predict participants' choice to switch strategy without knowledge about the switch-point, the classification was repeated without time-locking data. To this end, we applied a binomial test on the number of runs in which color classification was greater than 50%. The curve shows the sensitivity and specificity of this test if different thresholds are applied; see Fig. S3 (a ROC curve is shown for different thresholds of p). Best classification could be achieved using the conventional $p = .05$ or $.10$ thresholds (points overlap, see note in plot). ROI selection and time course smoothing as in Figs. 3, 4, 5 and S3.

Supplemental Tables

Table S1, Related to Figure 3

ID	Centroid MNI Coordinates			Max _{peak} (%)	No. Vox	Region	Dist (Vox)
	X	Y	Z				
1	3	56	22	93.3	45	Medial Frontal Gyrus (R)	2.8
2	3	56	40	91.1	5	Medial Frontal Gyrus (R)	4.3
3	12	59	16	85.2	9	Medial Frontal Gyrus (R)	4.8
4	9	44	19	89.2	45	Anterior Cingulate Cortex (R)	5.9
5	-3	41	22	87.3	60	Medial Frontal Gyrus (L)	6.9
6	-6	41	13	91.8	18	Anterior Cingulate Cortex (L)	9.1
7	-18	44	13	92.6	26	Superior Frontal Gyrus (L)	10.2
8	15	35	49	88.3	83	Superior Frontal Gyrus (R)	11.3
9	6	41	-23	83.8	8	Gyrus Rectus (R)	17.8
10	-6	2	28	94.1	18	Middle Cingulate Cortex (L)	19.4
11	-45	26	34	90.7	13	Middle Frontal Gyrus (L)	20.3

Note: *Characteristics of clusters with significant classification during switch for individual color using subjects.* The table is sorted by distance to the group peak and contains the locations (centroids), peak decoding accuracies, number of voxels, AAL atlas labels (Tzourio-Mazoyer et al., 2002) and peak-to-peak distances from the group result. To determine these clusters, we applied a threshold of 80.6% to the individual decoding accuracy maps ($p = .01$ according to empirical distribution of corner users, minimum cluster size: 5 voxels). Because the main purpose of this table is to shed some light on the individual clusters contributing to the group cluster, we list only the peak that is closest to the peak group result.