

## Cognitive complexity effects in perceptual classification are dissociable

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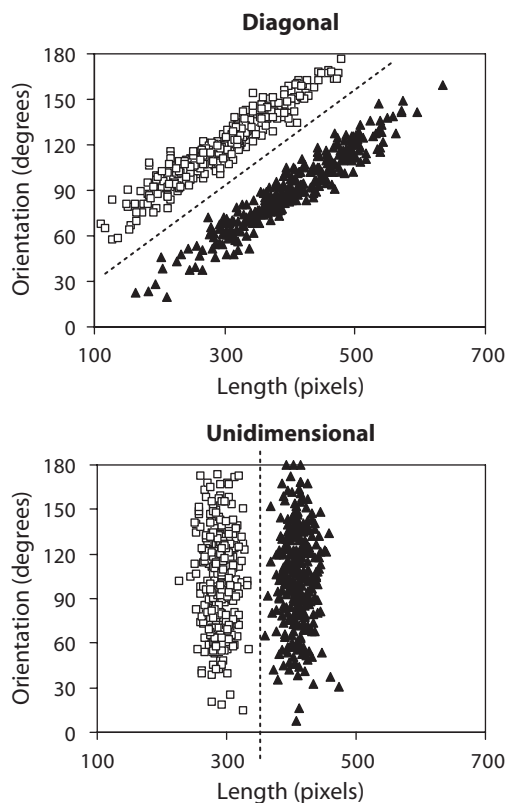
It has been proposed that a procedural-based classification system mediates the learning of information-integration categories, whereas a hypothesis-testing system mediates the learning of rule-based categories. Ashby, Ell and Waldron (2003) provided support for this claim by showing that a button switch introduced during classification transfer adversely affected information-integration but not rule-based performance. Nosofsky, Stanton and Zaki (2005) showed that increasing "cognitive complexity" can lead to button switch costs on rule-based performance. They argue that "cognitive complexity," and not the existence of separable classification systems, accounts for Ashby et al.'s empirical dissociation. The present study shows that experimental manipulations that increase "cognitive complexity" often have dissociable effects on information-integration and rule-based classification that are predicted a priori from the processing characteristics associated with the procedural-based and hypothesis-testing systems. These results suggest that manipulations of "cognitive complexity" can be dissociated, suggesting that "cognitive complexity" is not a unitary construct that affects a single psychological process.

Ashby, Alfonso-Reese, Turken & Waldron (1998) proposed a Competition between Verbal and Implicit Systems (COVIS) model of classification learning that assumes that a procedural-based classification system mediates the learning of information-integration categories, whereas a hypothesis-testing system mediates the learning of rule-based categories.<sup>1</sup> *Information-integration* category learning tasks are those in which accuracy is maximized only if information from two or more stimulus dimensions is integrated at some pre-decisional stage (Ashby & Gott, 1988). For example, Figure 1 presents a scatterplot of stimuli from a diagonal information-integration condition with two categories. Each point in the plot denotes the length and orientation of a single line that is displayed centered on the computer screen. Different symbols denote different categories. The diagonal broken line denotes the optimal decision bound. It has no verbal or rule-based analog because length and orientation are measured in different units. Although one can certainly state the rule as, "respond A if the orientation is greater than the length; otherwise respond B," it is unclear how to interpret the term "greater than" since the dimensional values are measured in different units, so this type of decision rule makes no sense to naive participants. The hypothesis-testing system is assumed to mediate the learning of rule-based categories. *Rule-based* category learning tasks are those in which the category structures can be learned via some explicit reasoning process. Figure 1 also displays a scatterplot of stimuli from a unidimensional rule-based condition with two categories. Frequently, the rule that maximizes accuracy (i.e., the optimal rule) is easy to de-

scribe verbally. In this example, the rule is unidimensional and requires the participant to respond A to "short" lines and B to "long" lines.

One source of evidence in support of the existence of the procedural-based learning system comes from a study by Ashby, Ell, and Waldron (2003) who incorporated into a category learning task a procedure originally developed by Willingham, Wells, Farrell, and Stemwedel (2000) to study serial reaction time. Willingham et al. (2000) showed that changing the location of the response keys interferes with serial reaction time learning, even when the sequence of stimulus positions is unchanged. Since the serial reaction time task is a classic measure of procedural learning, Ashby et al. reasoned that changing the location of the response keys during classification should adversely affect processing in the procedural-based classification system.

Ashby et al. (2003; Experiment 1) trained participants on a diagonal (information-integration) category structure or a unidimensional (rule-based) category structure (similar to those in Figure 1). All participants completed ten 50-trial blocks of training during which the response key on the left was assigned to category A, the response key on the right was assigned to category B, participants were given 5,000 msec to respond, and corrective feedback followed the response. Following training, participants completed two 50-trial blocks of transfer. In the *control transfer condition*, the category-response location mapping used during training was unchanged. In the *button switch transfer condition*, the category-response location mapping was reversed (i.e., the response key on the left



**Figure 1.** Scatter-plots of stimuli along with the optimal decision bounds from the diagonal and unidimensional conditions of Experiments 1 and 2. Open squares denote stimuli from category A. Filled triangles denote stimuli from category B.

was now associated with category B, and the response key on the right was now associated with category A). A response deadline of 1,500 msec was added during transfer to decrease the likelihood that participants would inhibit their initial response. Ashby et al. (2003) found that button switching led to a large performance cost in the diagonal condition, but had little effect in the unidimensional condition in support of their claim regarding multiple systems.<sup>2</sup>

Nosofsky, Stanton and Zaki (2005) offered an alternative explanation. They suggested that a procedural learning component is inherent in all classification tasks and that the button switch cost observed in the diagonal condition, but not in the unidimensional condition, might be due to the fact that the diagonal condition is more *cognitively complex* or *difficult* to learn than the unidimensional condition. They reasoned that a button switch can interfere with the procedural learning component inherent in all classification tasks, but that the cognitive complexity or difficulty of the task will determine whether the interference caused by the button switch will be *observable* in the data. If the task is simple, and the response deadline is long enough that the classification system can compensate then no effect of the button switch will be observed. On the other hand, if the task is complex and the response deadline is not long enough that the classification system can compensate then an effect of the button switch

will be observed. To test this hypothesis, Nosofsky et al. replicated Ashby et al.'s unidimensional control and button switch conditions but with a 750 msec and 400 msec response deadline. In addition, they constructed a "difficult" rule-based task (a biconditional structure). In all cases they observed a button switch cost.<sup>3</sup>

The present article tests the hypothesis that "difficulty" manipulations can have dissociable effects on rule-based and information-integration classification. We argue that "difficulty" is not a unitary construct that affects a single cognitive process, such as procedural learning (Nosofsky, Stanton, & Zaki, 2005). Rather, "difficulty" can affect processing differently depending upon whether the procedural-based learning system or the hypothesis-testing system is dominant at the time, and these processing differences can lead to dissociable effects on performance.

Following Ashby et al. (2003) and Nosofsky et al. (2005) we focus our investigation on the button switch paradigm. However, instead of manipulating the duration of the response deadline or the difficulty of the rule-based category structure, we manipulate the probability of a button switch on each transfer trial using diagonal and unidimensional category structures similar to those used in Ashby et al. As we will see shortly, this "difficulty" manipulation is predicted to have dissociable effects on processing in the procedural-based and hypothesis-testing classification systems.

## EXPERIMENT 1

The goal of Experiment 1 was to replicate and extend Ashby et al.'s (2003) examination of the effects of a button switch on diagonal information-integration and unidimensional rule-based classification. Ashby et al.'s (2003; Experiment 1) used structurally equivalent diagonal and unidimensional category structures that were related via a 45° rotation in the length-orientation space (see their Methods). They found better training performance for the unidimensional categories than for the diagonal categories. To address this difference in difficulty, Experiment 2 used the same category structures but increased the duration of diagonal condition training while decreasing the duration of unidimensional condition training. This procedure equated final training block performance across the two classification conditions, and continued to lead to a button switch cost in the diagonal but not the unidimensional condition.

In the present experiment we adjusted the separation between the two diagonal and two unidimensional categories so that training performance was equated with a fixed number of training trials (see Table 1 and Figure 1).

## Method

### Participants

Ninety-nine participants were solicited from the University community and received course credit or \$6 payment for participation. Monetary bonuses (\$1–\$2) were also offered for high accuracy. Following Ashby et al. (2003), participants whose performance fell below 70% during the final block of training were excluded. No more than four participants were excluded from any condition. The

**Table 1**  
**Category Distribution Parameters From Experiments 1 and 2**

Category	$\mu_l$	$\mu_o$	$\sigma_l$	$\sigma_o$	$cov_{lo}$
Diagonal					
A	300	400	83	83	6580
B	400	300	83	83	6580
Unidimensional					
A	300	350	18	116	0
B	400	350	18	116	0

Note— $\mu_l$ , mean length;  $\mu_o$ , mean orientation;  $\sigma_l$ , length standard deviation;  $\sigma_o$ , orientation standard deviation;  $cov_{lo}$ , covariance between length and orientation. Length is measured in pixels. Orientation values, in radians, were derived by multiplying by the scaling factor  $\pi/600$ .

number of participants who met the criterion was: diagonal control (22), diagonal button-switch (21), unidimensional control (22), and unidimensional button-switch (19).

**Stimuli and Stimulus Generation**

The stimulus on each trial was a static white line presented against a black background centered on a  $1,360 \times 1,024$  resolution computer screen. The category-distribution parameters are outlined in Table 1, and a scatter-plot of stimuli sampled from the diagonal and unidimensional conditions along with the optimal bound is displayed in Figure 1. Twenty-five unique stimuli were generated from each category (50 total) for both the diagonal and unidimensional category structures and were randomized separately for each block and participant.

**Procedure**

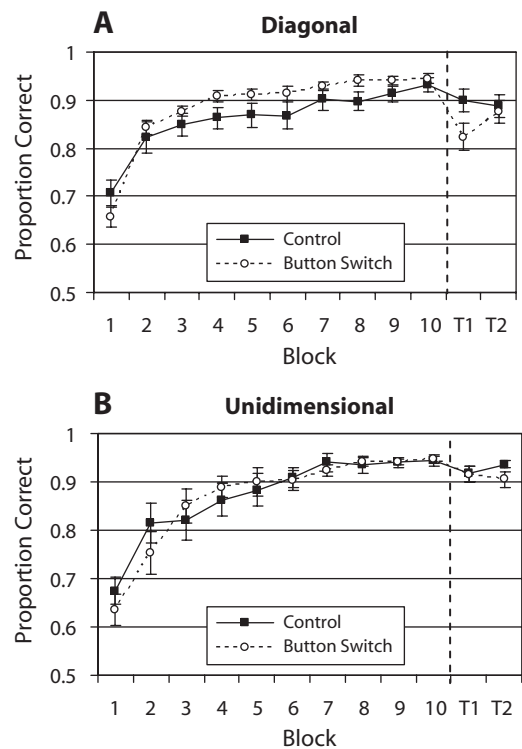
Participants were tested individually in a dimly lit room. They were informed that there were two equally-likely categories. Each experimental session consisted of the presentation of ten 50-trial training blocks and two 50-trial transfer blocks. During training participants were told to be as accurate as possible and were informed that they had 5,000 msec to respond. During transfer participants were told to be as accurate as possible and were informed that they had 1,500 msec to respond. When a participant failed to respond before the deadline they were prompted to respond more quickly, and the trial was discarded. In all conditions, participants used their left index finger to press the “Z” key and their right index finger to press the “/” key on a standard computer keyboard, and were given trial-by-trial feedback that consisted of the word “Correct” (along with a high pitch tone) or “Wrong” (along with a low pitch tone) and the correct category label. During training participants were told to press the “Z” key if they thought that the stimulus was a member of category A and to press the “/” key if they thought the stimulus was a member of category B. The transfer phase immediately followed the training. In the control condition the key assignments were the same as during training and in the button-switch condition they were reversed (i.e., the “Z” key was associated with category B and the “/” key was associated with category A). On each trial the letter “A” or “B” was displayed in the lower left or lower right of the computer monitor (depending upon the condition) to denote which response key (the “Z” key on the left or the “/” key on the right) was associated with which category.

**Results**

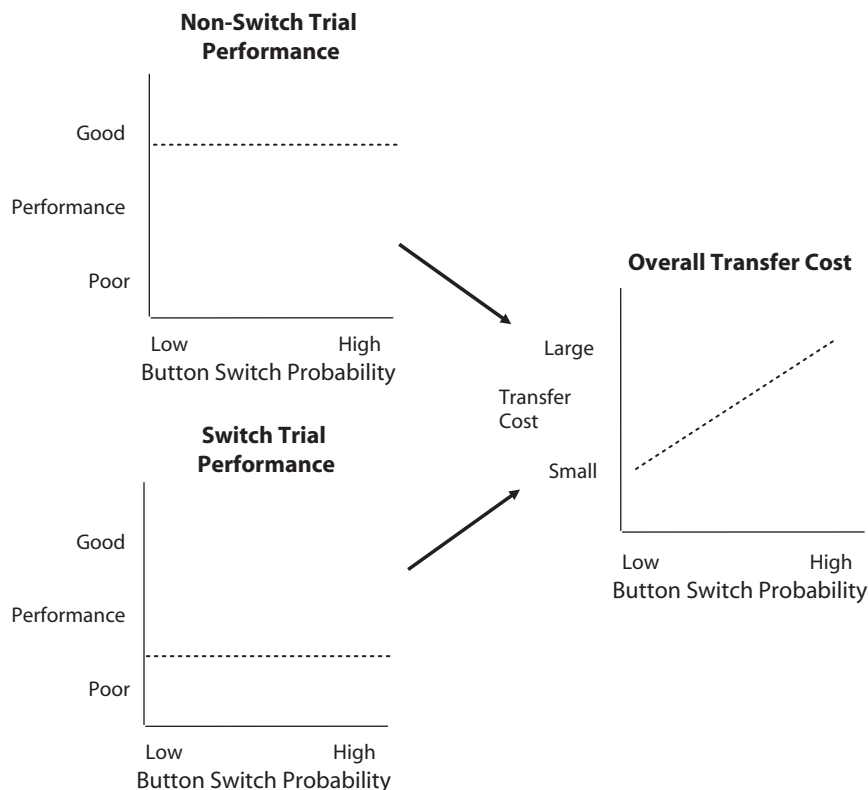
Figure 2 displays the proportion correct (averaged across participants) for the ten 50-trial training (1–10) and the two 50-trial transfer blocks (T1 and T2) for the diagonal (panel A) and unidimensional (panel B) conditions. To determine whether final block training performance was equated across the four experimental conditions, a category structure (diagonal vs. unidimensional) by button-

switch condition (control vs. button-switch) ANOVA was conducted. Neither main effect, nor the interaction was significant (all  $F$ s < 1.0).

We begin by comparing button-switch and control condition performance for the diagonal and unidimensional category structures across the final training, first transfer, and second transfer blocks (10, T1, and T2). For the diagonal condition, the block effect was significant [ $F(2,82) = 17.63, p < .001, MS_e = .004$ ], the button switch condition effect was not ( $F < 1.0$ ), but most importantly, the two-way interaction was significant [ $F(2,82) = 5.90, p < .01, MS_e = .004$ ]. This was characterized by a performance decline from the final training block to T1 in the button-switch condition ( $p < .001$ ) that was marginally significant in the control condition [ $F(1,21) = 3.15, p = .09, MS_e = .004$ ]. Importantly, the performance decline was significantly larger in the button-switch condition (.12) than in the control condition (.03) [ $F(1,41) = 7.81, p < .01, MS_e = .011$ ]. In the button-switch condition there was significant recovery from T1 to T2 ( $p < .005$ ), but a continued performance decrement in T2 relative to the final training block ( $p < .01$ ). For the unidimensional condition, the block effect was significant [ $F(2,78) = 4.32, p < .05, MS_e = .002$ ] suggesting a small performance drop during transfer, whereas the button switch condition effect ( $F < 1.0$ ) and the interaction [ $F(2,78) = 1.67, p = .195, MS_e = .002$ ] were not.



**Figure 2. Proportion correct (averaged across participants) from Experiment 1 along with standard error bars. The broken vertical line denotes the transition from training to transfer.**



**Figure 3.** Hypothetical pattern of performance predicted from the procedural-based system when the button switch probability ranges from a low to a high probability. The top left panel depicts the accuracy predicted on nonswitch trials, and the lower left panel depicts the accuracy predicted on switch trials. The right panel depicts the overall transfer cost predicted from the two left panels. The overall transfer cost is a function of nonswitch and switch trial performance, as well as the proportion of nonswitch and switch trials in each probabilistic button switch condition.

### Discussion

These results replicate the main finding from Ashby et al. that button switching had a large effect on diagonal classification but a small effect on unidimensional classification and extends it to diagonal and unidimensional category structures for which the amount of training and final training block accuracy was equated.

### EXPERIMENT 2

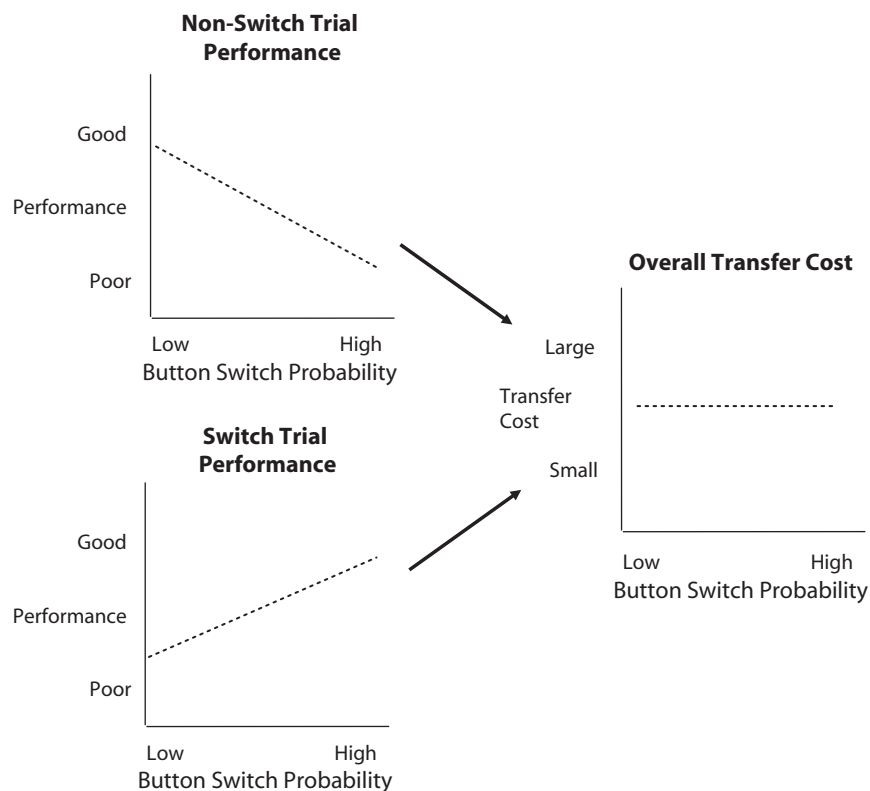
Experiment 2 examined the effects of an experimental manipulation that increases cognitive complexity, but for which dissociable effects on the procedural-based and hypothesis-testing classification systems would be observable. The introduction of three probabilistic button switch conditions during the transfer phase made this possible. The *training* phase of all conditions was identical to that of experiment 1. During the *transfer* phase the response keys and the “A” and “B” prompts displayed on the screen switched just as in the experiment 1 button switch condition, however, rather than switching on 100% of transfer trials they switched with probability .25, .50, and .75 for the *button switch 25 (BS25)*, *button switch 50 (BS50)*, and *button switch 75 (BS75)* conditions, respectively.

Information-integration classification is thought to be mediated by a procedural-based system that is relatively automatic, relies little on strategic control processes, and learns to map each category of stimuli to its respective response locations (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Ell, & Waldron, 2003; see also Maddox & Ashby, 2004). When this mapping is broken, as in the button switch condition, performance suffers. With respect to the probabilistic button switch conditions, this leads to three predictions (displayed schematically in Figure 3). First, on transfer trials when the buttons do not switch (referred to as *nonswitch* trials), performance should be relatively good, whereas on transfer trials when the buttons do switch (referred to as *switch* trials), performance should be relatively poor (see leftmost panels of Figure 3). This prediction follows directly from the fact that the procedural-based system learns to associate categories of stimuli with specific response locations. This mapping is broken on nonswitch trials and performance should suffer. Second, performance on nonswitch trials and on switch trials should be relatively constant across probabilistic button switch conditions. This prediction follows from the relative inflexibility and lack of strategic control in the procedural-based system. Finally,

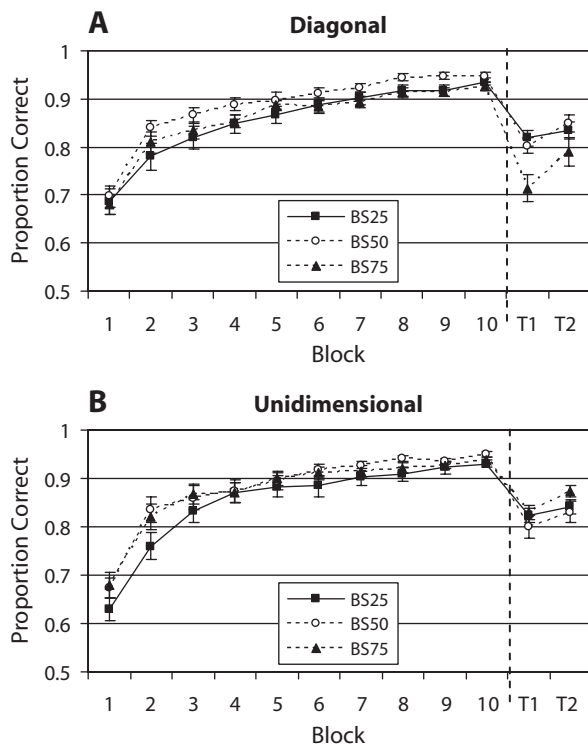
combining the first and second predictions leads to the final prediction that the magnitude of the overall transfer performance cost (i.e., averaged across nonswitch and switch trials) should *increase* as the probability of a button switch *increases*—that is, we should observe the smallest performance cost for the BS25 condition, an intermediate performance cost for the BS50 condition and the largest performance cost for the BS75 condition. This prediction follows because the ratio of switch to nonswitch trials increases as the probability of a button switch increases and can be seen in the rightmost panel of Figure 3.

Rule-based classification is thought to be mediated by a hypothesis-testing system that is less automatic, but is more flexible than the procedural system because it relies on strategic control processes such as working memory and executive attention. However, because working memory and attention are limited capacity resources, if the task is one that places a high demand on working memory and attention, then rule-based performance decrements should be observed. When the button switch is probabilistic the participant must process the location of the A and B letter cues on the computer monitor to determine

which button location is associated with which category label. This extra processing takes time, utilizes working memory capacity and should negatively impact performance. Even so, as the participant gains knowledge that the buttons are more, less or are equally likely to switch locations, they can use this information to “bias” their responding in accordance with the probability of a button switch. With respect to the probabilistic button switch conditions, this leads to three predictions (displayed schematically in Figure 4). First, performance on nonswitch trials should decrease as the probability of a button switch increases (i.e., from the BS25 to BS50 to BS75 conditions). Second, performance on switch trials should increase as the probability of a button switch increases (see leftmost panels of Figure 4). Finally, combining the first and second predictions leads to the prediction that the magnitude of the overall transfer performance cost averaged across all trials (i.e., averaged across nonswitch and switch trials) should be approximately the same for the BS25, BS50, and BS75 conditions (see rightmost panel of Figure 4). Notice that all three of these predictions are different from those generated for the procedural-based classification system.



**Figure 4.** Hypothetical pattern of performance predicted from the hypothesis-testing system when the button switch probability ranges from a low to a high probability. The top left panel depicts the accuracy predicted on nonswitch trials, and the lower left panel depicts the accuracy predicted on switch trials. The right panel depicts the overall transfer cost predicted from the two left panels. The overall transfer cost is a function of nonswitch and switch trial performance, as well as the proportion of nonswitch and switch trials in each probabilistic button switch condition.



**Figure 5. Proportion correct (averaged across participants) from Experiment 2 along with standard error bars. The broken vertical line denotes the transition from training to transfer.**

## Method

### Participants

Two hundred forty-six participants were solicited from the University community. Participant compensation and performance criterion were identical to that from Experiment 1. No more than four participants were excluded from any condition. The number of participants who met the criterion were: information-integration BS25 (38), information-integration BS50 (39), information-integration BS75 (37), rule-based BS25 (38), rule-based BS50 (37), and rule-based BS75 (40).

### Stimuli and Stimulus Generation

The stimuli and stimulus generation was identical to that from Experiment 1. The assignment of stimuli to switch and nonswitch trials was randomized separately for each transfer block and participant with the constraint that the probability of a button switch in each transfer block was as close as possible to .25, .50, or .75, depending upon the condition.

### Procedure

The procedure was identical to that from Experiment 1 except for the transfer phases. During the *transfer* phase of the *button switch 25* (BS25), *button switch 50* (BS50), and *button switch 75* (BS75) conditions, the “A” was displayed on the lower *right* side of the screen (denoting the “/” key as relevant for A responses) and the “B” was displayed on the lower *left* side of the screen (denoting the “Z” key as relevant for B responses) with probability .25, .50, and .75, respectively, on each transfer trial. On the remaining trials the “A” and “B” were on the lower left and lower right of the screen, respectively.

## Results

We focus our analyses on the first transfer block, but second transfer block performance will be discussed briefly at

the end of the Results section. Three aspects of the data are examined. First, we compare final training block performance across the category structure and probabilistic button switch conditions to determine whether final training block performance was equated. Second, we compare the overall transfer performance cost (defined as final training block performance minus first transfer block performance) across the category structure and probabilistic button switch conditions. Finally, we examine the proportion correct during the first transfer block separately for nonswitch and switch trials as a function of category structure and probabilistic button switch condition.

### Final Training Block Performance

Figure 5 displays the proportion correct (averaged across participants) for the diagonal (panel A) and unidimensional (panel B) training and transfer blocks. To determine whether final training block performance was equated across the six experimental conditions, a 2 (category structure: diagonal vs. unidimensional)  $\times$  3 (probabilistic button switch: BS25 vs. BS50 vs. BS75) condition ANOVA was conducted. Both main effects [category structure,  $F < 1.0$ ; probabilistic button switch condition,  $F(2,223) = 2.48, p = .09, MS_e = .002$ ] and the interaction ( $F < 1.0$ ) were nonsignificant suggesting that final training block performance was equated.

### Overall Transfer Performance Cost

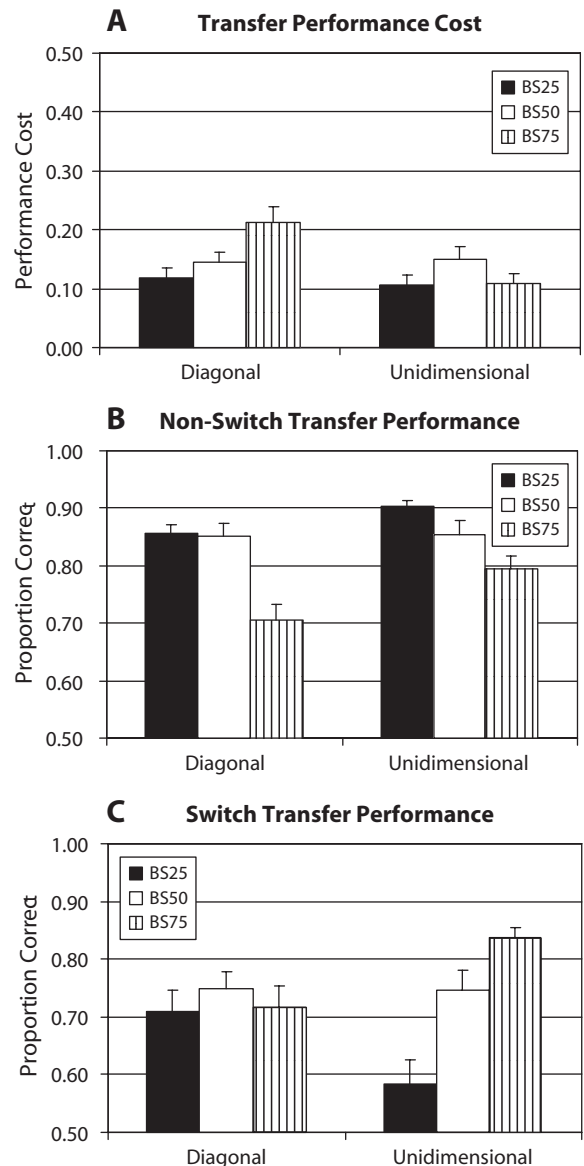
To determine whether there were overall transfer performance costs in each of the six experimental conditions, we conducted  $t$  tests comparing the observed performance cost with zero. In all six conditions, the transfer performance cost was significantly larger than zero (smallest  $t$  value = 6.16, all  $ps < .001$ ). To test for the predicted interaction between category structure and probabilistic button switch condition, we conducted a 2 (category structure)  $\times$  3 (probabilistic button switch condition) ANOVA on the transfer performance cost. These data are displayed in Figure 6A. There was a main effect of category structure [ $F(1,223) = 5.05, p < .05, MS_e = .015$ ] and a main effect of probabilistic button switch condition [ $F(2,223) = 3.21, p < .05, MS_e = .015$ ]. Most importantly, though, the interaction was significant [ $F(2,223) = 4.29, p < .05, MS_e = .015$ ]. To determine the locus of the interaction we conducted separate ANOVAs on the diagonal and unidimensional data. For the diagonal data, the probabilistic button switch effect was significant [ $F(2,111) = 5.28, p < .01, MS_e = .017$ ] and there was a monotonic increase in the magnitude of the transfer performance cost as the probability of a button switch increased. Post hoc Bonferroni tests suggested that the transfer performance cost was larger in the BS75 condition (.21) than in either the BS50 condition (.14;  $p = .08$ ) or the BS25 condition (.12;  $p < .05$ ). The transfer performance cost did not differ across the latter two conditions ( $p > .05$ ). For the unidimensional data, the probabilistic button switch effect was nonsignificant [ $F(2,112) = 1.66, p = .20, MS_e = .013$ ]. Interestingly, the transfer cost was larger (albeit not significantly) in the BS50 condition than in the BS25 and BS75 conditions.

Taken together these data provide support for the predicted interaction. As predicted the overall transfer performance cost in the diagonal condition increased as the probability of a button switch increased (i.e., as one goes from BS25 to BS50 to BS75), and there was no statistical difference in the magnitude of the overall transfer performance cost in the unidimensional condition.

**Nonswitch and switch transfer performance.** In this section, we examine nonswitch (Figure 6B) and switch (Figure 6C) transfer performance for the diagonal and unidimensional conditions.

*Diagonal condition.* Based on the processing characteristic associated with the procedural-learning based system we predict that nonswitch transfer performance should be better than switch transfer performance and that this should hold for all three button switch probabilities. In addition, we predict no effect of probabilistic button switch condition on nonswitch or switch trial accuracy. To test these predictions we conducted a 3 (probabilistic button switch condition)  $\times$  2 (stimulus type: nonswitch vs. switch) mixed design ANOVA. As expected, the main effect of stimulus type was significant [ $F(1,111) = 10.84, p < .001, MS_e = .032$ ] revealing that nonswitch trial accuracy (.80) was higher than switch trial accuracy (.72). However, this was qualified by a significant interaction [ $F(2,111) = 3.81, p < .05, MS_e = .033$ ]. To determine the locus of the interaction we compared nonswitch with switch trial accuracy for all three probabilistic button switch conditions. Nonswitch trial accuracy was significantly larger in the BS25 condition [ $t(37) = 4.09, p < .001$ ] and in the BS50 condition [ $t(38) = 2.67, p < .05$ ], but did not hold in the BS75 condition [ $t(36) = .25, n.s.$ ]. In addition, we compared nonswitch trial accuracy across probabilistic button switch conditions. Contrary to our prediction, a main effect was observed [ $F(2,111) = 14.95, p < .001, MS_e = .019$ ]. Post hoc Bonferroni tests revealed that the accuracy rate in the BS75 condition (.70) was lower than in either the BS50 condition (.85;  $p < .001$ ) or the BS25 condition (.86;  $p < .001$ ). Finally, we compared switch trial accuracy across probabilistic button switch conditions. As expected, there was no main effect ( $F < 1.0$ ).

*Unidimensional condition.* Because the hypothesis-testing system is under conscious control, and is highly flexible, we predict that nonswitch trial accuracy will decrease as the probability of a button switch increases, and that switch trial accuracy will increase as the probability of a button switch increases. To test these predictions we conducted a 3 (probabilistic button switch condition)  $\times$  2 (stimulus type: nonswitch vs. switch) mixed design ANOVA. Critically, the interaction was significant [ $F(2,112) = 27.23, p < .001, MS_e = .024$ ]. To determine the locus of this effect we conducted a 3 probabilistic button switch condition ANOVA separately on the nonswitch trial accuracy data and on the switch trial accuracy data. The effect of probabilistic button switch condition on nonswitch trial accuracy was significant [ $F(2,112) = 7.53, p < .001, MS_e = .015$ ] with nonswitch trial accuracy decreasing monotonically across the BS25 (.90), BS50 (.85), and BS75 (.80) conditions. Post hoc Bonferroni



**Figure 6.** (A) Overall transfer performance cost, (B) nonswitch transfer performance, and (C) switch transfer performance along with standard error bars from Experiment 2.

tests suggested that nonswitch trial accuracy was larger in the BS25 condition than in the BS75 condition ( $p < .001$ ) but that no other paired comparisons reached significance. The effect of probabilistic button switch condition on switch trial accuracy was also significant [ $F(2,112) = 15.88, p < .001, MS_e = .04$ ] with switch trial accuracy increasing monotonically across the BS25 (.58), BS50 (.75), and BS75 (.84) conditions. Post hoc Bonferroni tests suggested that switch trial accuracy was smaller in the BS25 condition than in the BS50 ( $p < .01$ ) and BS75 conditions ( $p < .001$ ).

### Second Transfer Block Performance

As expected, performance generally improved in the second transfer block relative to the first transfer block

(see Figure 5). Even so, the ordinal relations across conditions for nearly all of the relevant performance measures remained the same.

### Discussion

Taken together, these results provide support for the hypothesis that the probability of a button switch during transfer (.25, .50, or .75 in the present study) leads to dissociable effects on information-integration and rule-based classification. In the diagonal information-integration condition the overall transfer performance cost increased monotonically as the probability of a button switch increased, whereas in the unidimensional rule-based condition, the overall transfer performance cost remained relatively unchanged as the probability of a button switch increased. In the diagonal information integration condition, accuracy on switch trials remained relatively unchanged as the probability of a button switch increased, whereas in the unidimensional rule-based condition, accuracy on switch trials *increased* as the probability of a button switch increased. The only caveat was with the nonswitch trial data from the diagonal condition. In the diagonal information integration condition, accuracy on nonswitch trials was expected to remain relatively unchanged as the probability of a button switch increased. This held for the BS25 and BS50 conditions, but there was a substantial performance drop (of .15) for the BS75 condition. In the unidimensional rule-based condition, on the other hand, accuracy on nonswitch trials *decreased* as the probability of a button switch increased, as expected.

### GENERAL DISCUSSION

Ashby, et al. (2003) tested the hypothesis that a procedural-based classification system mediates the learning of information-integration categories, whereas a hypothesis-testing system mediates the learning of rule-based categories by showing that a button switch introduced during classification transfer adversely affected information-integration but not rule-based performance. Nosofsky, et al. (2005) showed that increasing "cognitive complexity" can lead to button switch costs on rule-based performance. They argued that "cognitive complexity" accounts for Ashby et al.'s empirical dissociation, and not the existence of separable classification systems. We hypothesized that some "cognitive complexity" manipulations are predicted from the processing characteristics associated with the procedural-based and hypothesis-testing systems, to have dissociable effects on information-integration and rule-based classification.

As a first step toward testing this hypothesis, we used a variant of the button switch paradigm introduced by Ashby et al. Instead of switching the buttons deterministically in the transfer phase, we introduced three probabilistic button switch conditions in which the buttons were switched with probability .25, .50, or .75 on each transfer trial. Based on an examination of the nature of the procedural-based classification system, we predicted that for diagonal category structures (1) the trans-

fer performance cost would increase as the probability of a button switch increases, (2) nonswitch trial performance would be high and constant across button switch probability conditions, and (3) switch trial performance would be low and constant across button switch probability conditions. Based on an examination of the nature of the hypothesis-testing classification system, we predicted that for unidimensional category structures (1) the transfer performance cost would be constant across button switch probability conditions, (2) nonswitch trial performance would decrease as the probability of a button switch increased, and (3) switch trial performance would increase as the probability of a button switch increased.

The transfer performance cost predictions were supported in the data. The cost increased in the diagonal condition and remained relatively constant in the unidimensional condition as the probability of a button switch increased. The nonswitch and switch trial predictions were all supported (with one caveat). For the unidimensional condition, nonswitch trial performance decreased and switch trial performance increased as the probability of a button switch increased. For the diagonal condition, performance was better on nonswitch trials than on switch trials. In addition, switch trial accuracy was relatively constant across button switch probability conditions. Finally, nonswitch trial accuracy was relatively constant across the BS25 and BS50 conditions, but dropped significantly in the BS75 condition. This finding was unexpected and we currently have no explanation for it. Even so, taken as a whole these data provide support for the hypothesis that experimental manipulations that increase cognitive complexity often have different effects on processing in the procedural-based and hypothesis-testing classification systems.

### Unitary Cognitive Complexity Effects Do Exist

Although the results from Experiment 2 suggest that cognitive complexity effects can be dissociable, we are not suggesting that unitary effects of cognitive complexity never exist. In fact, there is evidence for a unitary effect in the present data if one compares performance in the button switch condition from Experiment 1, with the probabilistic button switch conditions from Experiment 2. At the most basic level, the procedural-based system seems to predict that the overall transfer performance cost should be larger in the button switch condition from Experiment 1 than in the BS75 condition from Experiment 2, yet the overall transfer cost was .12 in the button switch condition from Experiment 1 but was .21 in the BS75 condition. When the button switch is probabilistic the participant must process the location of the A and B letter cues on the computer monitor to determine which button location is associated with which category label. This takes time away from processing the stimulus and leads to a general performance cost. Thus, the probabilistic button switch manipulation had the dissociable effect predicted from the hypothesis-testing and procedural-based systems, but also had a unitary effect on overall processing. It is likely that other manipulations intuitively defined as increasing cognitive complexity might also have both a dissociable and unitary effect on performance. Of course it is also pos-

sible that some manipulations have only a unitary effect. Perhaps the stringent response deadline used by Nosofsky et al. falls into this latter category.

What this discussion makes clear is the importance of defining "cognitive complexity" manipulations within each task. There is no reason to expect similar behavioral outcomes from different complexity manipulations within a task or from the same complexity manipulation across tasks. What is critical is to make detailed predictions regarding the outcomes of specific task manipulations. Without this level of rigor, terms like complexity and difficulty are vacuous.

### **A Single System Plus Cognitive Complexity Explanation of the Present Results**

The empirical aim of Nosofsky et al. was to show that a button switch cost can be observed in rule-based classification when cognitive complexity or task difficulty is high. That aim was achieved by using a stringent response deadline in transfer and by using a rule-based task with a complex verbal rule. Nosofsky et al. offer a post hoc interpretation of this result in which they extend a single-system exemplar model, the generalized exemplar-based random walk model (Cohen & Nosofsky, 2003), by adding onto the output of the model a procedural-learning component. In this section we apply this framework to the present results. Using Nosofsky et al.'s (2005) informal definition of cognitive complexity it seems reasonable to assume that probabilistic button switch conditions increase cognitive complexity. Based on the single-system model proposed by Nosofsky et al., the most reasonable a priori hypothesis would be that the pattern of effects observed across probabilistic button switch conditions should be the same for rule-based and information-integration category structures. More specifically, although the overall magnitude of the effects may be smaller or larger for one category structure or the other,<sup>4</sup> it should be the case that increasing the probability of a button switch should have the same ordinal effect on rule-based and information-integration performance. This prediction was not supported by the present data. Although Nosofsky et al.'s (2005) proposal does not account for the present data, it is possible that some other post hoc explanation could be generated.

Nosofsky et al. speculated that all perceptual classification tasks have a procedural learning component. Many multiple systems theorists would agree with this conjecture. In fact, in their seminal article that introduced COVIS, Ashby et al. (1998) hypothesized that the hypothesis-testing and procedural-based classification systems are both operative on every classification trial. Each generates an output, and in the current computational formulation of COVIS, they compete with each other to generate the response on each trial. Regardless of the nature of the category structure and the system that generally mediates its performance, it is expected that both systems will generate the response on some proportion of trials. In that sense, COVIS also predicts a procedural component in all classification tasks, but the implementation is much different from that proposed by Nosofsky et al. (2005).

### **Beyond the Single- Versus Multiple-Systems Debate in Perceptual Classification**

The present data provide evidence in support of the existence of a hypothesis-testing and a procedural-based learning classification system. This evidence is important, but in our view, the literature in support of multiple perceptual classification systems is overwhelming. Empirical support comes from a wide range of research areas including animal learning, neuropsychology, functional neuroimaging, and cognitive psychology (Ashby & Maddox, 2005; Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Erickson & Kruschke, 1998; Filoteo, Maddox, & Davis, 2001a, 2001b; Filoteo, Maddox, Salmon, & Song, 2005; Filoteo et al., 2005; Keri, 2003; Maddox & Ashby, 2004; Maddox & Filoteo, 2001; McDonald & White, 1993, 1994; Myers et al., 2003; Nomura et al., in press; R. M. Nosofsky, Palmeri, & McKinley, 1994; Packard & McGaugh, 1992; Poldrack & Packard, 2003; Poldrack, Prabhakaran, & Gabrieli, 1999; P. J. Reber, Stark, & Squire, 1998; Seger & Cincotta, 2002, 2005; Smith, Patalano, & Jonides, 1998). At this stage there is good behavioral, physiological, neuropsychological, and brain imaging evidence for the existence of at least four "systems." These include a fronto-striatal mediated hypothesis-testing system, a cortico-striatal mediated procedural-based system, a medial temporal lobe mediated exemplar system and a visual-cortical mediated perceptual representation system (for a review see Ashby & Maddox, 2005; Ashby & O'Brien, 2005). Although one may be able to construct a single system explanation for a pattern of data thought to support multiple systems, by postulating a post hoc adjustment of (single) system parameters, it is much more difficult to account a priori for the overwhelming body of results without concluding that there are multiple systems. In our view, the important question is not whether there is a single- or multiple-systems, but rather what systems do exist, what cognitive processes are associated with each, what are the qualitative properties of each system, and how do they interact? The present work begins to address these important issues, but much more work is needed.

### **Conclusions**

This study tests the hypothesis that an experimental manipulation that increases "cognitive complexity" or "task difficulty" can have dissociable effects on processing in the proposed procedural-based and hypothesis-testing classification systems. As predicted from a multiple systems approach, increasing the probability of a button switch during the transfer phase led to a different pattern of effects on (1) the overall transfer cost, (2) nonswitch trial performance, and (3) switch trial performance across a diagonal and unidimensional category structure. These results are in line with those predicted a priori from a model that assumes the existence of a hypothesis-testing and a procedural-based classification system. They provide important insights into the processing characteristics of these systems, and suggest that one needs to use caution before interpreting global accuracy deficits (such as transfer performance costs) across rule-based and information-integration category structures as evidence for single systems.

## AUTHOR NOTE

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## NOTES

1. Neuroscience evidence exists for at least three implicit classification systems (Ashby & Casale, 2003). These include a medial temporal lobe based declarative memory system (likely subserving exemplar-similarity processes) (Poldrack et al., 2001), a nondeclarative visual cortically based perceptual representation system (P. J. Reber, Gitelman, Parrish, & Mesulam, 2003), and a striatally mediated procedural-based classification system (Ashby, Alfonso-Reese, Turken, & Waldron, 1998).
2. Ashby et al. also included a hand-switch condition in which the hands were crossed during training so that the key on the left assigned to category A was pressed with the right index finger and the key on the right assigned to category B was pressed with the left index finger. During transfer, the hands were uncrossed on the response keys. Hand switching had no effect on rule-based or information-integration category learning suggesting that it was the shift in the response location and not the shift in the finger used to press the button that affected information-integration category learning.
3. Nosofsky et al. (2005) also included an "easy" information-integration task and found no button switch cost. Unfortunately, it is difficult to determine what classification learning system would be used to solve such a simple task as number verbal rules are possible.
4. Because training performance was equated across the unidimensional and diagonal conditions, there is also no reason to predict that the overall magnitude of the probabilistic button switch effect should differ across category structures.