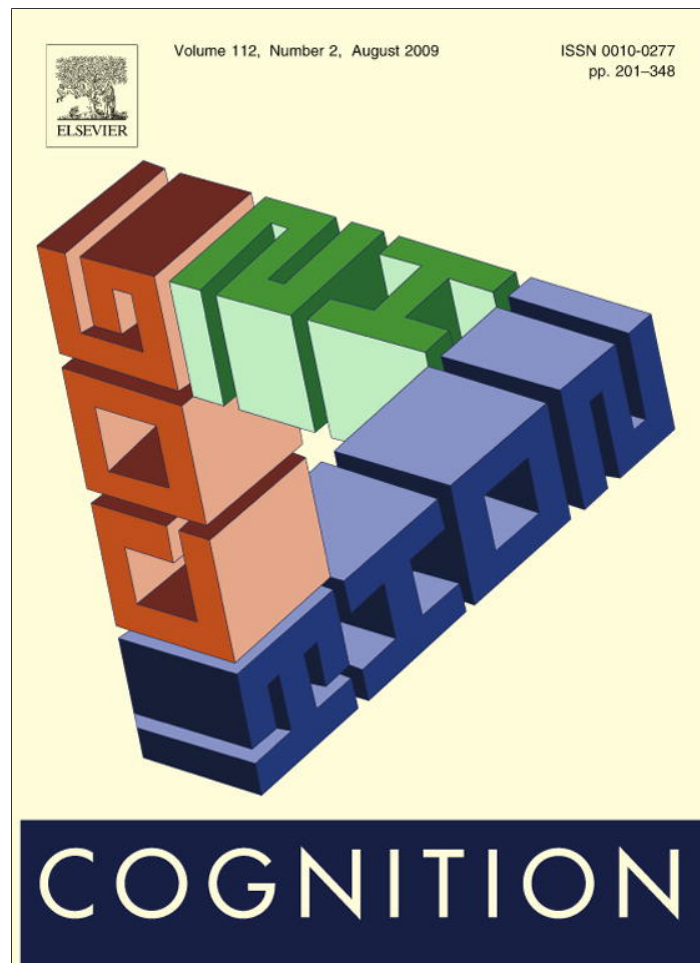


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Brief article

Errors, efficiency, and the interplay between attention and category learning

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ABSTRACT

Learning to identify objects as members of categories is an essential cognitive skill and learning to deploy attention effectively is a core component of that process. The present study investigated an assumption imbedded in formal models of categorization: error is necessary for attentional learning. Eye-trackers were used to record participants' allocation of attention to task relevant and irrelevant features while learning a complex categorization task. It was found that participants optimized their fixation patterns in the absence of both performance errors and corrective external feedback. Optimization began immediately after each category was mastered and continued for many trials. These results demonstrate that error is neither necessary nor sufficient for all forms of attentional learning.

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1. Introduction

Insofar as it is beneficial for an organism to complete a task as accurately and efficiently as possible, it is useful for it to ignore irrelevant information. Unless performance of the task is completely hard-wired, however, such *attentional optimization* must be learned, and so there will be significant differences in the optimization of novices and of experts. In humans, such differences have been demonstrated in tasks as diverse as X-ray image processing (Myles-Worsley, Johnston, & Simons, 1988), chess (Reingold, Charness, Pomplun, & Stampe, 2001), soccer (Williams & Davids, 1998), and driving a car (Underwood, Chapman, Brocklehurst, Underwood, & Crundall, 2003).

Our study explored attentional optimization in the context of category learning. Theories of categorization are computational in nature and come in many flavors: connectionist models (Gluck & Bower, 1988; DIVA: Kurtz,

2007), exemplar models (ALCOVE: Kruschke, 1992), rule-based models (RULEX: Nosofsky, Palmeri, & McKinley, 1994), prior-knowledge models (KRES: Rehder & Murphy, 2003), and hybrid models (COVIS: Ashby, Alfonso-Reese, Turken, & Waldron, 1998; ATRIUM: Erickson & Kruschke, 1998). Despite a healthy diversity of representational schemes, nearly all categorization models take error to be the essential ingredient in learning: prediction errors cause changes in the model that reduce the chance of future mistakes. Theories of categorization that incorporate mechanisms of learned attention extend this error-driven approach to attentional optimization as well. The most prominent examples are Kruschke's numerous influential models of categorization (ALCOVE: Kruschke, 1992; ADIT: Kruschke, 1996; EXIT: Kruschke, 2001; RASHNL: Kruschke & Johansen, 1999; ATRIUM: Erickson & Kruschke, 1998). Describing his EXIT model, Kruschke writes, "There is a single objective – error reduction – that drives all changes in attention and associative weights" (Kruschke, 2001, p. 489). Even neurologically-inspired models that describe attentional learning hold error-driven calculations at their

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core (LEABRA: Pauli & O'Reilly, 2008). Despite the obvious importance of error-reduction in guiding learning and the pleasing symmetry of using the same formulas for honing both associations and attention, direct evidence from a categorization task, either for or against this proposal, is hard to come by.

One problem is that attention is difficult to measure. The roles of attentional and associative changes are often not evaluated independently, but judged together based on the entire model's fit to participants' learning data (e.g., Kruschke, 2001). Some researchers have tried to improve inferences about how much attention participants pay to different stimulus features by using carefully chosen transfer tasks (Blair & Homa, 2005; Minda & Smith, 2002), but these measures are indirect, imprecise and provide no information about participants' attentional allocation on each trial.

Eye-tracking technology provides a partial solution, as it gives a precise measure of *overt attention* – muscular movements that orient an organism's sensory organs to selectively access information from the environment. It does not measure any of the variety of later *covert* processes that selectively bias the neural processing of particular streams of information (e.g., decisional attention; see Maddox & Dodd, 2003), and which may override the effects of muscular movements. Nevertheless, there are good reasons to think that, by and large, eye movements provide an accurate estimate of overall visual attentional allocation. Eye movements and covert visual attention shifting share functional and anatomical networks in the brain (Corbetta et al., 1998), and covert attention must be directed toward a location before an eye movement is made to this location (McPeck, Maljkovic, & Nakayama, 1999). More broadly, there is a significant penalty for failing to direct the fovea to objects of interest in the environment, since human visual resolution declines rapidly away from fixation. So unless there is good reason for neuronal attentional biases to be systematically opposed to eye direction, when averaged over many trials the direction of the eyes can be taken as a good indicator of what someone considers important in a scene.

Even more relevant to the present work, eye-tracking data has already been shown to correlate with attentional parameters in formal categorization models. Using fixation duration as a measure of attention, Kruschke, Kappenman, and Hetrick (2005) showed surprisingly consistent individual differences in attentional flexibility across tasks, and showed that these differences were related to the attentional shifting parameters generated through model fitting. Also, other studies show that participants cease to make eye movements to completely irrelevant dimensions (i.e., they have perfect attentional optimization; Rehder & Hoffman, 2005a), and that at both the group and individual level, the amount of time people spend looking at stimulus features correlates with attentional weights generated by fitting models to the response data (Rehder & Hoffman, 2005b). This ground-breaking work using eye-trackers to study attention in category learning provides a general recipe that we have modified to suit the present experimental goals.

In the present study we sought to test the hypothesis, encapsulated in formal models of category learning, that error is the necessary and sufficient condition for atten-

tional learning in categorization. We made several experimental design choices intended to elicit error-free attentional shifts (should they exist), and to improve our chance of measuring them. Previous findings suggest that simple categories lead to rapid attentional optimization and rapid reductions of performance error, making it problematic to distinguish them temporally (Rehder & Hoffman, 2005a). This is likely because in virtually any task with only two categories, attentional optimization is relatively easy, since any attentional allocation which allows one to efficiently identify members of one category can be used just as efficiently to identify members of the other category. The use of a complex four-category structure wherein the most efficient attentional allocations differed for different categories allowed us to slow down attentional optimization. In addition, we extended the task long after participants had ceased making errors in order to see if attentional optimization can continue over time. To eliminate the possibility that external feedback may be driving any attentional learning that occurs after task mastery, no external performance feedback was given after participants reached the learning criterion of 24 correct answers in a row. If error-driven accounts are correct, then we should see attentional optimization occurring prior to category mastery, when errors are plentiful, but no optimization afterwards, once errors have ceased.

2. Method

2.1. Participants

Thirty-eight Simon Fraser University students with normal or corrected-to-normal vision participated for pay or for course credit.

2.2. Stimuli and category structure

Participants were asked to classify images of fictitious microorganisms. By modifying images of actual microorganisms, we created stimuli that had three binary-valued features (dimensions) but still had a rich photorealistic quality (see Fig. 1). The microorganisms were 25 cm when displayed, subtending 19° of visual angle. The features subtended 1.5–3°. The three distinct features in each stimulus could have one of two values. The assignment of physical feature to category was counterbalanced across subjects, as was the location at which the feature was presented. The features were always presented in the same location for each subject. The background of the image was shifted and flipped so that participants saw novel images on each trial, even when stimuli shared identical feature values. Participants learned to sort the stimuli into four categories. Categories A1 and A2 were defined by particular values of features 1 and 2, categories B1 and B2 by values of features 1 and 3, so each category had two relevant features and one irrelevant feature (see Table 1). This four-category rule-based structure, similar to a three-dimensional instantiation of the structures used by Maddox and Ing (2005) and Maddox, Ing, and Lauritzen (2006), allowed us to extend the active process of attentional allocation.

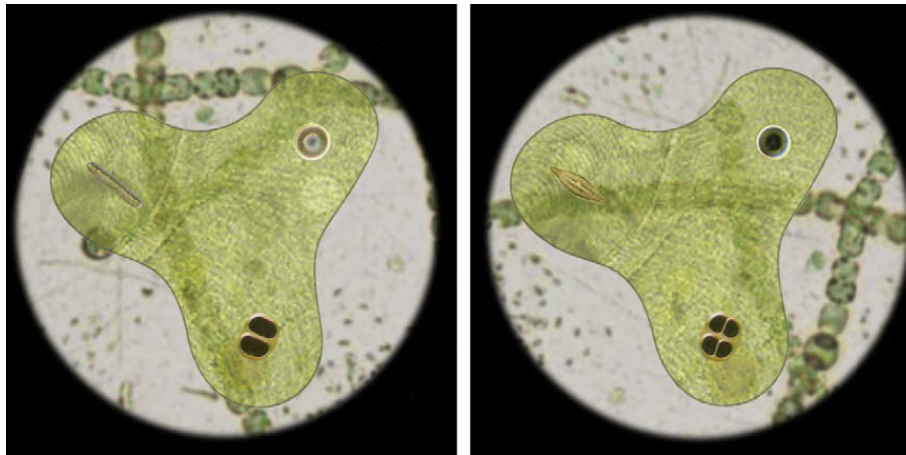


Fig. 1. Two example stimuli, illustrating each of the three features' two binary values. Feature locations were kept constant for individual participants throughout the session, and randomized across participants.

Table 1

Logical structure of the stimuli to be categorized. In an optimal strategy, participants will first determine if stimulus belongs to category A or B by checking F1, and then move either to F2 or F3 to determine complete category membership. In all instances, only two of the three features are relevant, though all three features are relevant for the entire task.

	F1	F2	F3
A1	0	0	0
A1	0	0	1
A2	0	1	0
A2	0	1	1
B1	1	0	0
B1	1	1	0
B2	1	0	1
B2	1	1	1

2.3. Procedure

We used a Tobii X50 sampling at 50 Hz to collect direct and fine-grained spatial and temporal information about participants' gaze. The experiment consisted of a series of categorization trials. Participants began each trial by clicking a fixation cross that appeared in the center of the screen, after which a stimulus was displayed. Participants decided the category to which the stimulus belonged, then clicked the mouse button. This removed the stimulus and revealed response boxes in the four corners of the screen. The category labels (A1, B1, etc.) were randomly assigned to boxes in different corners on each trial to avoid biasing fixations during stimulus presentation. Once a box was clicked, it either turned green to indicate that the response was correct, or it turned red and the box with the correct category label turned green. The stimulus was re-displayed concurrently with the feedback and the participant could inspect it for as long as they wanted before clicking to begin the next trial. If the participant reached the learning criterion of 24 consecutive correct trials, an additional 72 trials were completed during which no external performance feedback was given. Participants were told they had properly learned the category structure, and that they would continue performing the same task but without feedback. To reduce random responding, participants were

also told that the experiment would finish sooner if they made fewer mistakes. If the participant had not met the learning criterion after 200 trials, the experiment concluded.

3. Results

Sixteen participants failed to reach the learning criterion. Learners reached criterion in an average of 99 trials of training. During the 72 post-criterion trials, errors were rare: 64% of participants made no errors, 27% of participants made only one error, and the remaining three participants made at most three errors.

Our measure of optimization ranges from -1 to $+1$ and indicates the relative importance of the relevant and irrelevant features on each trial. This measure is produced by subtracting the total time spent fixating on irrelevant features in a trial from the total time spent fixating on relevant features, and dividing the result by the total time spent fixating on all features. Because each stimulus has two relevant features, but only one irrelevant feature, total fixation times to relevant fixation features were halved. A score of 0 is obtained if a participant fixated equally on both relevant and irrelevant features, a positive number indicates that the participant fixated more on relevant than irrelevant features, and a negative number indicates the reverse. This measure accords with the intuition that when participants ignore features that are not predictive of a category on a particular trial, they are allocating attention optimally. While this measure is not derived from the assumptions of any particular model of category learning, it is true that models differ in the degree to which they can produce optimal attentional allocations.

Participants' average optimization score for the criterion and post-criterion trials is shown in Fig. 2. The first block contains the 24 trials during which participants met the learning criterion. The remaining three blocks contain trials during which no external feedback was provided. As shown in the figure, optimization rose from 0.31 to 0.47, reflecting a significant change: $t(21) = 3.64$, $p < 0.01$. The individual subjects' data, though noisier,

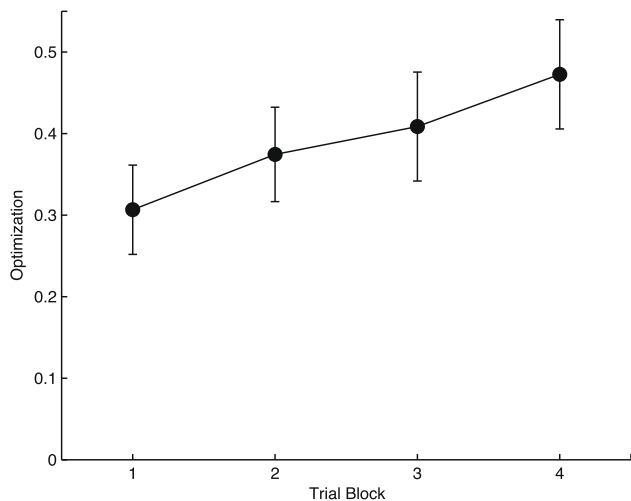


Fig. 2. Criterion and post-criterion attentional optimization. Each trial block is an average of 24 trials. The first block contains the criterion trials. The final three blocks contain the post-criterion trials during which no feedback was given. See text for details of the optimization measure. Error bars reflect the standard error of the mean.

reflects the aggregate trend of continuous, gradual improvement throughout the post-criterion trials.

There was no external feedback indicating errors during the post-criterion phase and therefore models of attentional learning that require an external error signal cannot account for the observed error-free optimization. It is possible, however, that an internally generated error signal might allow performance error a role in driving attentional change. If this were happening, then we would expect optimization to occur only in those participants who made performance errors during the post-criterion stage. To investigate this possibility we examined just the 14 participants who made no errors at all during the final 96 trials of the experiment. In those subjects optimization rose significantly from .31 to .52 between the first and last block: $t(13) = 3.11, p < .01$. This analysis confirms that neither external feedback nor performance error is necessary for continued attentional optimization.

Participants were already partially optimized at the criterion point. There are two possible explanations for this. In accordance with error-driven algorithms of attentional learning, it could be that attention shifted during category learning, when performance errors were most prevalent. However, learning the category structure in this experiment is a complex process that requires, at the very least, learning four separate categories. It seems unlikely that all these categories are mastered simultaneously. This raises the possibility that the pre-criterion optimization only occurs for categories that the participants have already mastered, which would conflict with error-driven accounts. To investigate this, we identified separate learning points for each category, and compared optimization on pre- and post-learning trials.

A learning point is defined as the first trial in a sequence of six correct responses to stimuli from a particular category. Note that these six trials are not consecutive, as there are trials of other categories interspersed throughout. An analysis of accuracy between learning points confirms that

each marks the development of mastery over a single category. Prior to the first learning point, mean accuracy is 26.9%, which is not significantly different from chance (25%). In between the first learning point and criterion, mean accuracy rises to 40%, which is significantly different from 25%: $t(21) = 18.4, p < .001$, so it may be that participants have learned *something* about some categories prior to their learning points. However, it is also possible that a learned category is not considered as a potential response on trials with stimuli from unlearned categories, in which case chance would rise to 33% between the first and second learning points, 50% between the second and third, and 100% between the third and fourth. The only case where the average accuracy on such trials is significantly different from these updated chances is between the third and fourth learning points, where it is 54%, far lower than 100%: $t(21) = 5.7, p < .001$. So, prior to learning points participants have either learned nothing or very little about the corresponding categories. Immediately upon reaching learning points, on the other hand, participants have completely learned the corresponding categories. Accuracy increases to 98% across trials where the presented stimuli are from categories for which the participant has reached a learning point. Thus learning points clearly mark a sudden achievement of mastery for individual categories.

We analyzed changes occurring around each subject's learning points by taking, for each category, the six trials of that category prior to the learning point, the learning point itself, and the six trials after the learning point. We averaged across all categories for which the subject had at least six pre-learning point trials, and then averaged across all subjects (six was chosen because there were some subjects who had no categories with seven pre-learning point trials). Fig. 3 shows the results.

Participants do not optimize their attention prior to learning each category. Average optimization over the six pre-learning point trials was not significantly different from zero: $t(21) < 1$. Mean optimization significantly increased from 0.06 (SD = 0.30) for the six pre-learning trials

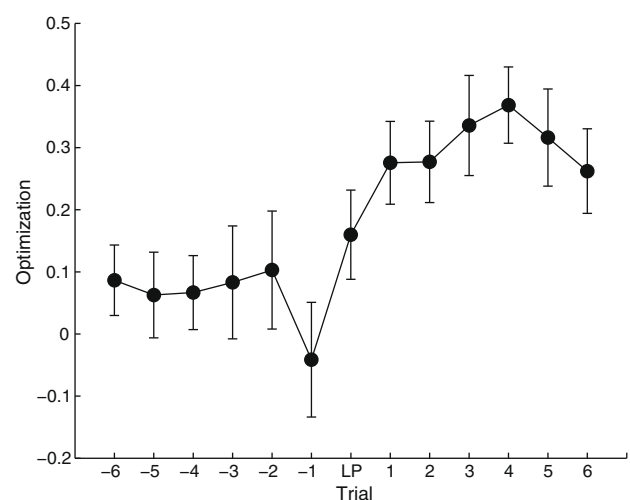


Fig. 3. Attentional optimization pre- and post-learning point. See text for details of how learning points were defined. Error bars reflect the standard error of the mean.

to 0.31 (SD = 0.29) for the six post-learning trials: $t(21) = 3.53$, $p < .01$. This jump in optimization centered on the learning point of each category is numerically larger than the increase in optimization shown in the entire post-criterion phase of the experiment. These results indicate that on trials where participants were presented with stimuli whose category membership they were unsure of, they did not optimize at all, but within one trial of learning a category they began optimizing to a significant extent.

The dip in optimization one trial before the learning point may be interesting. Optimization on this trial is significantly lower than the average of the five previous trials: $t(21) = 2.27$, $p < .05$. The definition of learning points guarantees that this trial will be incorrect, and it could be that before learning there is a very slight correlation between optimization and accuracy. Given the sample size, however, strong conclusions are unwarranted. Considering only the other five pre-learning data points, optimization is still not significantly different from zero: $t(21) = 1.30$, $p > .1$, so the dip one trial before the learning point is not the cause of the finding that no optimization occurs prior to category mastery.

4. Discussion

Attention influences learning and performance in many domains. The present work extends our understanding of learned attention with three important findings. First, we found that participants optimized their attention in the absence of both performance error and external feedback. Second, we found that participants did not optimize their attention before learning, but only once errors had been almost eliminated. Finally, we found that the initial burst of improvement in attentional allocation was concurrent with the mastery of individual categories.

Our data provide a significant challenge to error-driven accounts of attentional learning (e.g., *Kruschke, 2001*). According to such accounts, changes should be largest at the beginning of training when errors are most frequent and no change in attentional optimization should occur without error or external feedback. We found the exact opposite. There was no change in participants' attentional allocation when error rates were highest, consistent with *Rehder and Hoffman's (2005a)* finding that optimization lagged slightly behind error-reduction. Furthermore, unlike *Rehder and Hoffman*, we found significant changes in attentional optimization for many trials after errors had ceased and external feedback was removed, changes which likely would have continued had the experiment been longer. These findings demonstrate that neither error nor external feedback are necessary or sufficient for all forms of attentional learning.¹

How might attentional learning happen in the absence of error commission and external feedback? The past few

decades have seen tremendous advances in our understanding of the neurophysiology of attention. A number of prominent theories include an executive attentional network that is hypothesized to have access to goal information and to exercise endogenous control over other cognitive systems (for a review see *Posner & Petersen, 1990*). It has been speculated that this network is particularly involved in rule-based categorization tasks similar to ours (*Ashby et al., 1998*). The anterior cingulate cortex (ACC) is a key component in executive function (*D'Esposito et al., 1995; Posner & Dehaene, 1994; Posner & DiGirolamo, 1998*). The ACC was originally hypothesized to detect errors in performance but this function was later broadened to include detection of conditions conducive to error commission (*Carter et al., 1998*), conflict monitoring (*Botvinick, Braver, Barch, Carter, & Cohen, 2001*), evaluation of reward gains and losses (*Bush et al., 2002; Gehring & Willoughby, 2002*), the integration of action-outcome history (*Rushworth, Walton, Kennerley, & Bannerman, 2004*), expectancy violation (*Oliveira, McDonald, & Goodman, 2007*) and the adjustment of goal-directed behavior (*Botvinick, 2007; Holroyd & Coles, 2002*). In our study, these broader ACC functions may serve to optimize performance through internal, rather than external, signals for behavioral and attentional adjustments.

In the typical category learning experiment, participants generally have two distinct goals: to respond accurately to each stimulus, and to finish the experiment as quickly as possible. Fixations to irrelevant features may conflict with the goal of accuracy by increasing the chance of errors and with the goal of efficiency by increasing the overall amount of time it takes to complete the task, so the ACC would be expected to inhibit processes that lead to these fixations. However, our results show that while participants are focussed on improving accuracy, they do not make any progress towards optimizing their attention. This may be because during learning, the process of generating and testing hypotheses places a heavy load on the executive attentional system. Once a category has been mastered, however, the executive attentional system can devote more resources to increasing response speed. Thus, after errors cease, the executive attentional system might translate conflict information into attentional optimization of the sort we see in the present study. This is also consistent with our finding that attentional optimization happens after mastery of each individual category rather than after learning the entire task.

Though some aspects of *Rehder and Hoffman's (2005a)* findings were similar to ours, they postulated a different explanation. They found that participants only changed their patterns of attentional allocation after categories were learned and errors ceased, at which point they suddenly began ignoring irrelevant dimensions. *Rehder and Hoffman* related these findings to a multiple systems approach, wherein learning modules, representing different strategies or styles of learning (e.g., rule-based and exemplar-based) simultaneously learned the task, with the most successful module eventually dominating. *Rehder and Hoffman* postulated that participants may be performing a rule-based strategy but still looking at all dimensions in case the rule turned out to be incorrect and a new rule or

¹ Supervised algorithms have a long history of use in theories of learning, nevertheless there is recent interest in unsupervised learning. The possibility that attentional learning might be captured in computational accounts of unsupervised learning (or in more unified approaches; e.g., *SUSTAIN; Love, Medin, & Gureckis, 2004*) is an interesting possibility to explore.

strategy was needed. Once the rule was confirmed they were able to rapidly shift their attention to access only the necessary inputs. Because the learning module associated with the winning strategy will have been biasing stimulus information throughout training, their explanation seems to imply that the restriction of eye movements can be rapidly accomplished. Our data, on the other hand, show that attentional learning is sometimes a gradual process, slowly occurring over the experiment's final 72 trials. In other words, rather than being adjusted concurrent to category learning, attentional weights are not being optimized until after participants stop making performance errors. Given that we are still in the early stages of collecting data on attentional allocation, both Rehder and Hoffman's strategic account and our neuropsychological account will surely need further refinement, and testing. Indeed, these accounts may not necessarily be at odds with each other, as the ACC may play a role in the strategic shifts Rehder and Hoffman postulate.

Category structure will likely affect the relationship between attentional learning and category learning. Ashby, Maddox and colleagues have shown numerous examples of dissociations between performance on different types of structure and have tied these to different learning systems and attentional networks (for a review see Ashby & Maddox, 2005). They suggest that executive attention is involved in learning rule-based structures, but not in what they term "information-integration" structures. According to our account of learning without error, we would expect optimization to occur after learning mainly in those category structures that elicit heaviest involvement of the executive attentional networks and the ACC. Category structures learned through implicit systems would be more likely to show optimization prior to category mastery. It is unclear to what degree executive attentional networks might be involved in other structures such as memorization-based, linearly-inseparable, or family resemblance structures. Understanding how different category structures activate different learning systems and interact with attentional learning is obviously an important research goal.

Because our results are based on eye-tracking, there may be some residual worry that we have not measured attention in the way it is specified in categorization models, and have therefore failed to falsify the theoretical underpinnings of these models. We sympathize. It is critical to recognize, however, the notion of attention weights is a simplification. Attention weights in categorization theories stand in for the sum of all cognitive biases on incoming information. We cannot imagine any single measure of this sense of attention, because there is no single cognitive process to which this sort of "attention" corresponds. While attention weights are a useful stand-in for further theoretical and empirical work, they are completely free of detail, disconnected from anything that researchers have discovered about attention in recent decades. The proposed properties of attention in theories of categorization are difficult to falsify not because they are well-supported, but because they are *vague*.

The work presented here takes steps toward providing some specifics. We measure one important component of

attention (overt attention) carefully and accurately. By taking a closer look at one of the processes that are subsumed in these weights, we are not falsifying these models so much as trading in old, abstract placeholders for measurable human behaviors that reflect critical aspects of attentional allocation. We show that overt attention does not operate exclusively according to error-reduction principles. This provides strong impetus for important corrections of and extensions to extant theory. Beyond providing a basis for understanding the properties of this component of attention, this approach can be leveraged to better understand the remaining aspects of attention by controlling for otherwise unaccounted-for variance. We are hopeful that, in time, this approach can help to elucidate how attention, in all its rich behavioral and neural complexity, operates during category learning.

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