Posterror slowing predicts rule-based but not information-integration category learning

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Abstract We examined whether error monitoring, operationalized as the degree to which individuals slow down after committing an error (i.e., posterror slowing), is differentially important in the learning of rule-based versus information-integration category structures. Rule-based categories are most efficiently solved through the application of an explicit verbal strategy (e.g., “sort by color”). In contrast, information-integration categories are believed to be learned in a trial-by-trial, associative manner. Our results indicated that posterror slowing predicts enhanced rule-based but not information-integration category learning. Implications for multiple category-learning systems are discussed.

Keywords Category learning · Category-learning models · Post-error slowing · PES

The abilities to learn new information and to adjust to changes in the environment are critically important at all stages of life. These skills are dependent upon the ability to utilize feedback to guide and shape future behavior (Holroyd & Coles, 2002; Ohlsson, 1996). Prominent theories of skill acquisition generally depict a multistep process that emphasizes an initial slow, declarative component to goal-oriented behavior (Anderson, 1982, 1987). Increased proficiency and automaticity are achieved via encoding an initial approximation of the desired behavior, gradually refining the behavior through error feedback, and finally compiling the multiple cognitive procedures into a single

procedure (Anderson, 1987; Logan, 1988). Hallmark characteristics of these models include heavy reliance on executive functioning, such as rule shifting and information updating (Miyake et al., 2000), in the development of skilled performance (Anderson, 1982; Logan, 1988).

One of the most frequently employed behavioral proxies used to index active error feedback processing is posterror slowing (PES), which refers to an increase in the response latency following an error. To control for individual differences in speed, PES has most frequently been quantified by taking the first correct reaction time after an error response and subtracting from it the average correct reaction time (Rabbitt, 1966, 1968).

Category learning

Organizing objects into categories is a critical skill. Categorization reduces information load, assists in language acquisition, and influences the formulation of inferences, predictions, and decisions that affects human behavior (Farrar, Raney, & Boyer, 1992). The ability to accurately categorize environmental elements into simple groupings—for instance, “safe/dangerous,” “same/different,” and “friend/foe”—has been perpetuated throughout evolutionary history (Smith, Chapman, & Redford, 2010), and emerges early in development (Huang-Pollock, Maddox, & Karalunas, 2011; Quinn, Doran, Reiss, & Hoffman, 2010), emphasizing its relevance to survival and fitness. We will focus on perceptual categorization learning and the associated COVIS model herein, after providing a brief review of the model for those unfamiliar with it (for a more complete description, see Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Paul, & Maddox, 2011).

COVIS (“competition between verbal and implicit systems”), a neurobiologically inspired multiple-systems model of category learning, posits the presence of at least two

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distinctive systems of category learning: an (explicit) verbal rule-based (RB) system and an (implicit) information-integration (II) associative-learning system (Ashby et al., 1998). Neuropsychological predictions based on COVIS have been validated in patients with Parkinson's disease (Ashby, Noble, Filoteo, Waldron, & Ell, 2003), Huntington's disease (Filoteo, Maddox, & Davis, 2001), amnesia (Maddox & Filoteo, 2007), anorexia nervosa (Shott et al., 2012), and attention deficit hyperactivity disorder (ADHD; Huang-Pollock, Tam, & Maddox, *in press*).

Verbal RB category learning is thought to be dependent on the anterior cingulate and prefrontal cortices. It operates via a hypothesis-testing procedure in which a verbalized rule is tested and updated until an optimal rule is identified (Ashby et al., 1998). Examples of verbalizable rules include single-feature (if-then), conjunctive (if-and-then), and disjunctive (if-or-then) rules, as well as rules with exceptions (if-then-except) (Minda, Desroches, & Church, 2008). Verbal skills, working memory, and attentional-control facilities play important roles in RB category-learning tasks (Ashby et al., 1998). In contrast, II categorization, mediated predominantly by the striatum, requires simultaneous assessment of multiple stimulus parameters in order to attain maximal accuracy, and its optimal "rule" is difficult to express verbally (Ashby et al., 1998). This system learns not by active hypothesis testing, but by automatically and gradually recognizing subtle covariations within the stimuli or environment, as well as which response or behavior to emit in response.

Both humans and nonhuman primates show a clear bias toward the RB system, even when the optimal strategy requires an II approach (Smith et al., 2011). This most likely occurs because RB learning follows a rational hypothesis-testing approach that leads to all-or-none mastery, which is faster than the incremental trial-and-error associative process of II learning. The transition in reliance from an RB to an II approach in the course of an II task has been proposed to occur when the RB system ceases its inhibition of the II system (Ashby & Crossley, 2010).

If PES reflects the recruitment of effortful attentional-control networks important in the acquisition of a new skill, we might expect PES to differentially predict both accuracy and strategy use in RB versus II category-learning tasks. Specifically, in RB tasks, PES should be positively associated with the adoption of the correct strategy, which would in turn predict performance accuracy (*Hypothesis 1*). In II tasks, though the initial bias toward the RB system might result in observable PES, PES would not be associated with either accuracy or the adoption of the correct strategy (or it might be negatively associated) (*Hypothesis 2*). Correct strategy use would predict accuracy in both types of learning, however.

Method

Participants

A group of 38 adults (15 male, 23 female) between the ages of 18 and 25 (mean age = 19.03 ± 1.44 years), with an average GPA of 3.32 ($SD = 0.45$), were recruited from the Department of Psychology Research Participant pool at Pennsylvania State University. Informed written consent was obtained for each participant, and course credit was granted for participation.

Procedures

Gabor patches were created by using MATLAB routines to randomly sample from two bivariate normal distributions of spatial frequency and line orientation (Maddox, Ashby, & Bohil, 2003). The spatial orientation and frequency stimulus parameters ranged from -2.65° to 81.82° and from 5.52 to 6.99 cycles/deg in the RB task, and from -14.62° to 89.16° and 2.52 to 8.52 cycles/deg in the II task (Fig. 1). All participants received the same randomized order of stimulus appearance, and each task was divided into five blocks of 80 trials (40 Category A and 40 Category B). The task was self-paced; participants were allowed to view the stimulus for as long as they deemed necessary. After each response, visual feedback ("correct" or "wrong") was presented for 500 ms. The next trial began immediately after the feedback period.

The conditions were either an RB task that could be solved using an explicit verbalizable rule based on spatial frequency, or an II task in which both spatial orientation and frequency information were needed in order to achieve optimal performance. The order of administration of these tasks was counterbalanced, and they were spaced one week apart. Participants were asked whether the images presented on the screen belonged in Category A or B (corresponding to the "z" and "/" keys, respectively), with stickers being placed over the appropriate keys. The participants were instructed that, although at first they might just be guessing, to try to be as accurate as possible and not to be concerned with speed. The task length was ~20 min.

Data analysis

For each task, a univariate repeated measures analysis of variance (ANOVA) with Block (five levels) as a within-subjects factor was run for three continuous dependent variables (accuracy, mean correct reaction times [RTs], and PES). A repeated measures logistic regression with block as the within-subjects condition was run on type of model use as a categorical variable. All anticipatory RTs (<140 ms) were excluded from the analysis, as they occurred too quickly to represent active decision-making behavior in

Fig. 1 Sample stimulus (a) and stimulus plots (b, c)

response to a stimulus (Eppinger, Mock, & Kray, 2009). Less than 1 % of the trials met this criterion. The mean correct reaction time (CRT) for each block was calculated by averaging the RTs for correct trials that followed a correct trial. To correct for individual differences in mean RTs (Leth-Steensen, King Elbaz, & Douglas, 2000), the PES for each participant was calculated as the mean RT of first correct responses after errors, minus the CRT for that block.

Because qualitatively different strategies can lead to identical accuracy rates, an analysis of accuracy alone cannot fully explain individual differences in skill acquisition. A number of models were fit to each participant's set of responses for each block in order to determine the type of strategy used. All models assumed that the participant partitioned the stimulus space into response regions (Ashby & Maddox, 1993; Maddox & Ashby, 1993) using either an RB or an II strategy. Each response region was assigned to a category, and the decision bound parameters were estimated from each participant's data.

Four models were applied to the RB data: (1) an RB unidimensional model based on the correct, frequency dimension; (2) an RB unidimensional model based on the incorrect, orientation dimension; (3) an II general linear classifier (GLC) model that partitioned the stimulus space using a linear decision bound that included both dimensions; and (4) a random-responder model. Four models were also applied to the II data: (1) an II GLC model, (2) an RB conjunctive model that partitioned the stimulus space into four perpendicular regions by frequency and orientation, (3) an RB unidimensional model (along either dimension), and (4) a random-responder model.

All models included a “noise” parameter that provided an estimate of the perceptual and criterial noise associated with classification. The model was fit using maximum likelihood procedures (Ashby & Maddox, 1992) and the Bayesian information criterion (BIC). The BIC statistic penalizes models for each additional free parameter, where $BIC = -2 * \ln(L) + n * \ln(80)$, where L is the maximum likelihood value, n equals the number of parameters, and $\ln(80)$ is the natural log of the number of trials being fit—in this case, 80 (Schwartz, 1978).

Regression analyses assessing sorting strategy (defined as the fit to the correct RB or II model, depending on the task) as a mediator to explain the relationship between PES and accuracy were conducted. Indirect effects were calculated using bootstrap confidence intervals as per Preacher and Hayes (2008). The results did not differ by sex and did not change when GPA (as a proxy for overall intellectual functioning) was used as a covariate. The results are thus reported without GPA as a covariate and without sex as a between-subjects variable.

Results

Preliminary analyses

We found no evidence for speed–accuracy trade-off effects (SATO) in either task. The correct and error RTs for both tasks were positively correlated (for all blocks, $r_s > .40$, all $p_s \leq .01$). RT was not correlated with error rate in the II task

(for all blocks, $p_s \geq .13$) or in Blocks 1–3 of the RB task (all $p_s \geq .63$), and it was positively correlated with error rates in Blocks 4 and 5 ($r_s > .37$, $p_s < .02$). We were therefore reassured that SATO effects were not present and that the RT and accuracy data could be validly interpreted.

RB category learning

As expected, main effects of block were found on accuracy, $F(4, 148) = 34.05$, $p < .001$, $\eta_p^2 = .48$, RTs to correct responses, $F(4, 148) = 10.46$, $p < .001$, $\eta_p^2 = .22$, and PES, $F(4, 148) = 2.38$, $p = .05$, $\eta_p^2 = .06$: Over time, accuracy increased, and RT and PES decreased. The main effect of block on the proportion of participants utilizing the correct RB strategy was not significant, Wald chi-square = 5.41, $p = .25$. Significant PES (i.e., >0) was only seen in Block 1, $t(37) = 2.07$, $p = .05$, as might be expected, since that is presumably the period in which the greatest amount of learning occurs (Fig. 2).

Block 1 PES was significantly and positively correlated with accuracy in that block, $R^2 = .12$, $\beta = 0.09$, $p = .03$. Adoption of the correct sorting strategy mediated the relationship between PES and accuracy in Block 1. Specifically, more PES was associated with a better fit to the optimal rule, $R^2 = .11$, $\beta = -9.13$, $p = .05$, which in turn was predictive of higher accuracy, $R^2 = .83$, $\beta = -0.01$, $p < .001$. The unstandardized indirect effect of PES on accuracy through sorting strategy, with bias-corrected confidence intervals calculated using 5,000 bootstrapping samples, was .08 (95 % confidence interval .003–.16). The results did not change when participants whose model fit showed ≥ 4 blocks of random responding ($N = 4$) were excluded from the analyses.

II category learning

Main effects of block were seen on accuracy, $F(4, 104) = 14.19$, $p < .001$, $\eta_p^2 = .35$, RTs to correct responses, $F(4, 104) = 5.16$, $p < .001$, $\eta_p^2 = .17$, PES, $F(4, 104) = 5.74$, $p < .001$, $\eta_p^2 = .18$, and model use, Wald chi-square = 10.43, $p = .03$. Specifically, accuracy and the proportion of participants using an II strategy increased, but RT and PES decreased over time (see Fig. 2). Significant PES (i.e., >0) was seen only in Block 1, $t(26) = 3.15$, $p = .004$. However, Block 1 PES was not associated with accuracy, $R^2 = .07$, $\beta = 0.08$, $p = .17$, or with the adoption of an II strategy, as measured by fit values to the II model, $R^2 = .03$, $\beta = -1.11$, $p = .92$. Adoption of the correct II approach was predictive of accuracy, as would be expected, $R^2 = .43$, $\beta = -0.003$, $p = .002$.

Because similar levels of PES were found in the II and RB tasks, exploratory analyses were conducted in order to better understand the source of these

Fig. 2 Accuracy, model use, and posterror slowing (PES) by blocks for the rule-based (RB) and information-integration (II) category-learning tasks

similarities. Significant PES (i.e., >0) was only seen in Block 1 among participants who had not adopted an II sorting strategy in the final block, $t(10) = 3.05$, $p = .02$. For those participants, PES in Block 1 was associated with neither accuracy, $R^2 = .04$, $\beta = -0.05$, $p = .53$, nor the adoption of an II strategy as measured by fit to the optimal model, $R^2 = .01$, $\beta = 4.5$, $p = .83$. PES was not observed in any block among individuals who were not sorting according to an II strategy in Block 5, $t(15) = 0.11$, $p = .11$. These results did not change when participants whose model fit showed ≥ 4 blocks of random responding ($N = 4$) were excluded from the analyses.

Discussion

We found significant main effects of block for both the RB and II category-learning tasks, in which participants improved their performance over time over a range of indicators. PES was observed in the first block of trials for both tasks, but consistent with a multiple-systems approach, it was only associated with performance in the RB task. Within the context of COVIS, unlike RB categorization, optimal performance in II category learning is an associative process that requires the simultaneous integration of multiple stimulus elements into a singular categorization decision (Ashby & Maddox, 2005). Thus, COVIS predicts that though the bias toward RB learning might lead to attempts at active hypothesis testing during the initial phase of skill acquisition in an II task, it would not be expected to result in improved performance for II category learning. This was, in fact, the pattern of results reported herein.

Other models of category learning could also account for the present data pattern. For example, ATRIUM proposes the existence of a verbal rule-based system as well as a second, exemplar-based system to account for performance in terms of graded category structures and frequency effects (Erickson & Kruschke, 2002). Similarly, SUSTAIN is a network-based model of category learning that represents categories as clusters of previously experienced stimuli and compares incoming stimuli to those clusters (Love, Medin, & Gureckis, 2004). If a simple rule-based cluster is not sufficient to solve the task, new clusters are dynamically recruited to improve the representation. If the category structure is complex enough, the clusters ultimately come to resemble an exemplar-like storage system. Neither ATRIUM nor SUSTAIN explicitly suggests that the exemplar-based system or clusters are less dependent on executive attention, but such a suggestion would not necessarily be incompatible with these theories, either. The logical extension of the COVIS model, however, would explicitly predict that posterror slowing, as a behavioral marker of the active recruitment of executive attentional processes, would be associated with performance in an RB but not an II category-learning paradigm.

Reinforcement-learning theories propose that PES represents the behavioral manifestation of comparing outcomes to expectations (Holroyd, Yeung, Coles, & Cohen, 2005), whereas conflict control theories view PES as an increased response threshold triggered by the presence of consecutive, parallel, discrepant streams of information (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Carter & van Veen, 2007). Regardless, both suggest that PES reflects the activation of some level of executive attentional process in the service of achieving a particular goal. Within this context, an argument could be made that, because PES indexes the triggering of the executive control system, we might have

expected greater PES to be associated with worse RB performance, due to the creation of a dual-task conflict. However, we did not observe that pattern of data, and the directionality of this hypothesis was not compelling, because any executive control exerted would be in the service of improving and solving the task, as opposed to distracting from it, as in more typical dual-task situations.

Though PES has historically been viewed as being reflective of engagement of higher-order executive processes (Botvinick et al., 2001; Carter & van Veen, 2007; Holroyd et al., 2005), others have more recently proposed that the phenomenon is a reflexive or automatic attentional-orienting response to a rare event (i.e., an error; Notebaert et al., 2009). Although it is difficult to completely rule out an orientating interpretation of PES, such an account seems unlikely here, because PES predicted accuracy and model use, and because PES did not increase as error feedback events became increasingly less frequent for participants in later blocks.

Why PES decreased over time is unclear. A less interesting answer might simply be that this reflects the general decrease in RTs that is typical of increased task mastery (Logan, 1988; Shiffrin & Schneider, 1977). A more interesting hypothesis would be that error reactivity decreases with increasing task mastery. In fact, some neurophysiological evidence supports the idea that event-related potential amplitudes associated with posterror processing decrease as participants become increasingly adapted to speeded RT tasks (Anguera, Seidler, & Gehring, 2009; Cavanagh, Frank, Klein, & Allen, 2010). COVIS also predicts that the explicit system only changes rules following negative feedback (Ashby & O'Brien, 2007), so PES would be expected to be greatest during early learning, when rule changing is most frequent. It is also possible that PES might have been observed beyond Block 1 if a response deadline had been used, which could be evaluated in future studies. Similarly, we defined PES in terms of the first correct response following an error because we were interested in understanding the cognitive processes involved in the successful resolution of conflict, and because this allowed for comparisons with the literature on error monitoring. However, other definitions of PES (e.g., the first response following an error) may produce different insights and could be followed up in future studies.

Overall summary

In summary, and consistent with a multiple-systems model of category learning, we found evidence that PES reflects higher-order processing that is related to improved future performance for RB but not for II category learning. Our findings also support reinforcement-learning (Holroyd et al., 2005) and conflict control theories (Botvinick et al., 2001)

of PES as being representative of the recruitment of effortful attentional processes for goal-directed behavior.

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References

- Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review*, 89, 369–406. doi:10.1037/0033-295X.89.4.369
- Anderson, J. R. (1987). Skill acquisition: Compilation of weak-method problem situations. *Psychological Review*, 94, 192–210. doi:10.1037/0033-295X.94.2.192
- Anguera, J. A., Seidler, R. D., & Gehring, W. J. (2009). Changes in performance monitoring during sensorimotor adaptation. *Journal of Neurophysiology*, 102, 1868–1879. doi:10.1152/jn.00063.2009
- Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review*, 105, 442–481. doi:10.1037/0033-295X.105.3.442
- Ashby, F. G., & Crossley, M. J. (2010). Interactions between declarative and procedural-learning categorization systems. *Neurobiology of Learning and Memory*, 94, 1–12.
- Ashby, F. G., & Maddox, W. T. (1992). Complex decision rules in categorization: Contrasting novice and experienced performance. *Journal of Experimental Psychology*, 18, 50–71.
- Ashby, F. G., & Maddox, W. T. (1993). Relations between prototype, exemplar, and decision bound models of categorization. *Journal of Mathematical Psychology*, 37, 372–400. doi:10.1006/jmps.1993.1023
- Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, 56, 149–178. doi:10.1146/annurev.psych.56.091103.070217
- Ashby, F. G., Noble, S., Filoteo, J. V., Waldron, E. M., & Ell, S. W. (2003). Category learning deficits in Parkinson's disease. *Neuropsychology*, 17, 115–124. doi:10.1037/0894-4105.17.1.115
- Ashby, F. G., & O'Brien, J. B. (2007). The effects of positive versus negative feedback on information-integration category learning. *Perception & Psychophysics*, 69, 865–878.
- Ashby, F. G., Paul, E. J., & Maddox, W. T. (2011). COVIS. In E. M. Pothos & A. J. Wills (Eds.), *Formal approaches in categorization* (pp. 65–87). Cambridge: Cambridge University Press.
- Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, 108, 624–652. doi:10.1037/0033-295X.108.3.624
- Carter, C. S., & van Veen, V. (2007). Anterior cingulate cortex and conflict detection: An update of theory and data. *Cognitive, Affective, & Behavioral Neuroscience*, 7, 367–379. doi:10.3758/CABN.7.4.367
- Cavanagh, J. F., Frank, M. J., Klein, T. J., & Allen, J. J. B. (2010). Frontal theta links prediction errors to behavioral adaptation in reinforcement learning. *NeuroImage*, 49, 3198–3209.
- Eppinger, B., Mock, B., & Kray, J. (2009). Developmental differences in learning and error processing: Evidence from ERPs. *Psychophysiology*, 46, 1043–1053.
- Erickson, M. A., & Kruschke, J. K. (2002). Rule-based extrapolation in perceptual categorization. *Psychonomic Bulletin & Review*, 9, 160–168.
- Farrar, M. J., Raney, G. E., & Boyer, M. E. (1992). Knowledge, concepts, and inferences in childhood. *Child Development*, 63, 673–691.
- Filoteo, J. V., Maddox, W. T., & Davis, J. D. (2001). A possible role of the striatum in linear and nonlinear category learning: Evidence from patients with Huntington's disease. *Behavioral Neuroscience*, 115, 786–798.
- Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, 109, 679–709. doi:10.1037/0033-295X.109.4.679
- Holroyd, C. B., Yeung, N., Coles, M. G. H., & Cohen, J. D. (2005). A mechanism for error detection in speeded response time tasks. *Journal of Experimental Psychology: General*, 134, 163–191. doi:10.1037/0096-3445.134.2.163
- Huang-Pollock, C. L., Maddox, W. T., & Karalunas, S. L. (2011). Development of implicit and explicit category learning. *Journal of Experimental Child Psychology*, 109, 321–335.
- Huang-Pollock, C., Tam, H., & Maddox, W. T. (in press). Rule-based and associative perceptual category learning are impaired in children with Attention Deficit Hyperactivity Disorder.
- Leth-Steensen, C., King Elbaz, Z., & Douglas, V. I. (2000). Mean response times, variability, and skew in the responding of ADHD children: A response time distributional approach. *Acta Psychologica*, 104, 167–190.
- Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review*, 95, 492–527. doi:10.1037/0033-295X.95.4.492
- Love, B. C., Medin, D. L., & Gureckis, T. M. (2004). SUSTAIN: A network model of category learning. *Psychological Review*, 111, 309–332. doi:10.1037/0033-295X.111.2.309
- Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, 53, 49–70.
- Maddox, W. T., Ashby, F. G., & Bohil, C. J. (2003). Delayed feedback effects on rule-based and information-integration category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29, 650–662. doi:10.1037/0278-7393.29.4.650
- Maddox, W. T., & Filoteo, J. V. (2007). Modeling visual attention and category learning in amnesiacs, striatal-damaged patients and normal aging. In R. W. J. Neufeld (Ed.), *Advances in clinical cognitive science: Formal modeling of processes and symptoms* (pp. 113–146). Washington DC: American Psychological Association.
- Minda, J. P., Desroches, A. S., & Church, B. A. (2008). Learning rule-described and non-rule-described categories: A comparison of children and adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 34, 1518–1533.
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex “frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology*, 41, 49–100. doi:10.1006/cogp.1999.0734
- Notebaert, W., Houtman, F., Van Opstal, F., Gevers, W., Fias, W., & Verguts, T. (2009). Post-error slowing: An orienting account. *Cognition*, 111, 275–279. doi:10.1016/j.cognition.2009.02.002
- Ohlsson, S. (1996). Learning from performance errors. *Psychological Review*, 103, 241–262. doi:10.1037/0033-295X.103.2.241
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40, 879–891. doi:10.3758/BRM.40.3.879
- Quinn, P. C., Doran, M. M., Reiss, J. E., & Hoffman, J. E. (2010). Neural markers of subordinate-level categorization in 6- to 7-month-old infants. *Developmental Science*, 13, 499–507. doi:10.1111/j.1467-7687.2009.00903.x

- Rabbitt, P. M. (1966). Errors and error correction in choice-response tasks. *Journal of Experimental Psychology*, 71, 264–272.
- Rabbitt, P. M. (1968). Three kinds of error-signalling responses in a serial choice task. *Quarterly Journal of Experimental Psychology*, 20, 179–188.
- Schwartz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, 6, 461–464. doi:[10.1214/aos/1176344136](https://doi.org/10.1214/aos/1176344136)
- Shiffrin, R. M., & Schneider, W. (1977). Controlled and automatic human information processing: II. Perceptual learning, automatic attending and a general theory. *Psychological Review*, 84, 127–190. doi:[10.1037/0033-295X.84.2.127](https://doi.org/10.1037/0033-295X.84.2.127)
- Shott, M. E., Filoteo, J. V., Jappe, L. M., Pryor, T., Maddox, W. T., Rollin, M. D. H.,... Frank, G. K. W. (2012). Altered implicit category learning in anorexia nervosa. *Neuropsychology*, 26, 191–201. doi:[10.1037/a0026771](https://doi.org/10.1037/a0026771)
- Smith, J. D., Ashby, F. G., Berg, M. E., Murphy, M. S., Spiering, B. J., Cook, R. G., et al. (2011). Pigeons' categorization may be exclusively nonanalytic. *Psychonomic Bulletin & Review*, 18, 414–421. doi:[10.3758/s13423-010-0047-8](https://doi.org/10.3758/s13423-010-0047-8)
- Smith, J. D., Chapman, W. P., & Redford, J. S. (2010). Stages of category learning in monkeys (*Macaca mulatta*) and humans (*Homo sapiens*). *Journal of Experimental Psychology: Animal Behavior Processes*, 36, 39–53. doi:[10.1037/a0016573](https://doi.org/10.1037/a0016573)