

A Developmental Perspective on Order and Learning: Temporal Effects on Cued Attention

Joseph Burling (jmburling@uh.edu)

Department of Psychology, University of Houston, 126 Heyne Building
Houston, TX 77204-5022 USA

Hanako Yoshida (yoshida@uh.edu)

Department of Psychology, University of Houston, 126 Heyne Building
Houston, TX 77204-5022 USA

Abstract

The two experiments in this paper provide evidence for order effects obtained from adult and child populations. Experiment 1 compares different versions of base-rate and canonical highlighting tasks investigating the differences between visual processing of cues and inference based knowledge. Comparisons based on adults' individual performance are also addressed. Experiment 2 implements designs from Experiment 1 to investigate the nature of order effects on children ages 4-5-years-old.

Keywords: order effect; temporal factors; learning asymmetry; inverse base-rate; highlighting; selective attention; cue competition

Asymmetrical Learning

There are an infinite number of complexities involved when trying to provide explanations and descriptions of human learning ability; however, this adversity does not prevent experimenters from trying to search for answers. This ambitious problem has been confronted from many different perspectives, but one approach among many that provides a small glimpse into how humans acquire knowledge over time is to investigate behavioral anomalies that seem to contradict statistical expectation. Specifically, observing abnormal response patterns during decision making tasks may supply some answers that explain the processes involved in category formation.

The types of asymmetrical response patterns—responses that deviate from expectation—have been observed in a specific phenomenon known as the inverse base-rate effect (Medin & Edelson, 1988), or alternatively referred to as the highlighting effect due to the prominent role of rapid attentional shifts (Kruschke, 2003). These response biases seen in tasks involving the inverse base-rate effect are considerably robust across many different iterations of the experimental structure. Alterations in the proportion of objects pairs presented during training have shown consistent results in decision making patterns, in addition to dual-task implementations or time restrictions placed on outcome choice (Lamberts & Kent, 2007; Medin & Bettger, 1991; Shanks, 1992). Given the degree of stability across the different iterations, the validity of observed response biases is not under scrutiny; the existence of such response asymmetry is widely accepted. However, much contention is derived from the explanations provided to account for the

behavioral peculiarities. Medin & Edelson's (1988) original work placed considerable weight on base-rate knowledge, such as sensitivity to the frequency of presented cues. Over the course of experimentation on the issue, other influences have been shown to be of particular importance. One underlying factor that has been previously ignored—a factor that is integrated not only in base-rate information, but throughout all types of learning—is the order in which information is presented.

Temporal Factors

Order effects manipulating categorical representations can be accounted for by different models of explanation. These models propose different cognitive influences and may be divided based on their emphasis on either top-down or bottom-up processes. The proposed mechanisms based on higher-level inferences can take the form of explicit strategies implemented during a cost-benefit analysis (Medin et al, 1988), or rule-based processing, in which less familiar categories are actively eliminated as possible candidates during ambiguous forced-choice tasks (Juslin, Wennerholm, & Winman, 2001). An alternative viewpoint is that the patterns emerging over time that influence decision making are the result of shifts in attention away from erroneous cues inherent in the training structure, resulting in unequally weighted representations across different cue combinations (Kruschke, 1996).

Common to both paradigms is the reliance on certain sets of cues to be learned *before* later cue combinations; however, frequency theories place little importance on this factor. We believe that the order in which cues are presented is critical. In addition to the proposed mechanisms suspected of leading to variability in object representations, the nature of observing a subset of elements before others determines the fate of future learning for upcoming elements, which may contain some overlap in composition between time slices. The gradation of current knowledge sets the path for the identity and make-up of future knowledge. Taking the opposite perspective on temporality, prior experience and perceptual history accumulates in the form of stored memories. Not only does current knowledge matter in the way it affects future knowledge, one must also consider the current state of knowledge derived from one's entire history of learning. Invoking the necessary tools from the cognitive

toolbox that may be generally suitable for the task at hand, this in turn influences the kind of information processing during that given moment. Disparity in the contents of the individual's toolbox induces different methods for solving some yet unspecified problem.

Order Effects and Children

What is considered relevant during a given moment depends on the timescale of observation. Specific tasks such as the highlighting paradigm can be thought of as a continuous learning trajectory over the course of training, each trial shaping the features of categorical representations along its path. A certain degree of categorical stability is maintained well into testing in order to display the types of response biases witnessed during the later assessment of cue preference. This notion poses two questions regarding development. Firstly, are children capable of reaching the same state of categorical stability, the type of stability seen in past adult literature which arises from unequally weighted representations and accounts for the behavioral outcomes? Secondly, how does the influence of order differ between young children and adults; i.e., what is the magnitude of temporal influence given two very different cognitive histories? The latter concern may address some of the necessary cognitive constraints required for this type of asymmetrical learning by assessing the likelihood of bottom-up and top-down mechanisms playing independent or interactive roles, as well as estimating the balance of bidirectionality between the two levels of processing.

Concerning the abilities of young children and detecting similar patterns of processing as adults, both constructs (either rule-based inferences or attentional shifting) can potentially lead to the same behavioral outcomes, yet only the rule-based approach posits that children are incapable of showing the same patterns in decision making due to their underdeveloped high-level reasoning skills (Winman, Wennerholm, Juslin, 2005). Winman et al (2005) found that only one third of the tested children aged 8-9-years-old showed a clear inverse base-rate effect, suggesting that the children within this age range are at the initial stages of acquiring the necessary cognitive abilities required for deductive reasoning. If the focus is shifted away from frequency evaluation of cues toward effects of temporal order, it is likely that the difficulties inherent in an inference-heavy task structure may not be a suitable measurement of order effects on conjunctive cue categorization for young children. It is suspected that different domains of processing may be required to possibly witness equivalent biases—the type of biases exhibited from adult judgments given a deductive reasoning task.

In this paper we propose an alternative approach that may be better suited for testing young children, with an emphasis on visual processing of predictive cues. This is achieved through the implementation of child-friendly imagery that serves as the basis for creating asymmetrical associations over time. Beforehand, using adults as controls we will make preliminary comparisons between learning paradigms

that place an emphasis on visual processing of cues versus typical designs investigating learning asymmetries. Specifically, we will compare a child oriented version of the highlighting task with and without base-rate information to a version focusing on the use of logic to draw conclusions about ambiguous cues. But first we introduce the implications of the highlighting effect as a domain-general learning mechanism as well as its potential application toward different types of tasks involving associative learning.

Developmental Perspective

The attention-shifting model is of particular interest from a developmental perspective. In opposition to the exclusive use of explicit top-down processes, this model is based on the deployment of basic cognitive mechanisms such as attention and memory. Its simplistic explanations can encompass many types of learning, including language acquisition, pattern recognition, and heuristics. Entertaining cognitive processes heavily based on an attentional framework—such that across time spans, asymmetrical representations are driven by cue competition—provides plenty of groundwork for potential application. This theoretical foundation is especially useful when investigating temporal learning theories at various developmental time slices. When trying to understand the nature of early learning, it is important to consider how temporal factors may interact with existing cognitive abilities at any given stage of development. Advantages for establishing the highlighting effect as an attentional byproduct is that across the entire lifespan, this model can provide explanations pertaining to the complex dynamics inherent in temporal learning theories. Its central focus is on attentional influence and the process of how attention is reallocated over the course of training, resulting in the formation of specific categories. In addition, it can be postulated that low-level mechanisms such as attentional control are sufficient in being able to account for the type of outcomes driven by order effects, given that young children are adequately capable of exploiting such mechanisms for this type of learning. By preschool age, children's attentional flexibility becomes evident in that they are capable of taking control over such mechanisms during this point of transition (Rueda, Posner, & Rothbart, 2005). However, relatively little is known about the interactive processes involved between temporal factors and attention in children, especially with regards to how the order of perceived information assists in constructing certain types of biases, and at the same time considering the underlying capacity for attentional flexibility at a given period in cognitive development.

Interactions between Cued Attention and Order

The structure of the highlighting paradigm allows for sets of items consisting of a conjunctive cue and its outcome to be learned symmetrically during initial stages of training. For example, conjunctive cue I.PE (I is one part of a pair of cues

and *PE* is the other) predicts the following event or concept represented as outcome *E*. Symbolic objects *I* and *PE* are paired cues that initially have equal associative weight in their predictability of outcome *E*. Order effects come into play with the later introduction of a new conjunctive cue *I.PL* predicting a distinct outcome *L*. Note that one specific element—cue *I*—was repeated across both sets, leading to the classification of such as an imperfect predictor of either outcome. Its repetitive nature has little informative value given its equal probability as a predictive cue; therefore cues *PE* and *PL* inherit the roles of certainty in predicting their respective outcomes. Given the timeline of early set *I.PE* → *E* and late set *I.PL* → *L*, attention is redirected away from potentially erroneous cues and reallocated toward more useful pieces of information. Due to its place in time, the association between cue *I* and outcome *L* is attenuated provided that attentional resources are actively being focused toward meaningful input, consequently strengthening or highlighting the link between *PL* and *L* considering it is no longer prudent to treat *I* and *PL* equally.

Order effects are one influence among many that can govern the structure of categories. Factors such as memory capacity may influence the quantity of stored representations. Other factors might depend on feature characteristics of an individual stimulus, which might alter overall saliency of an object. But it is the interaction between selective attention and temporal components, in addition to these other factors, that give rise to unique patterns of associations over time. This complexity is beyond the scope of explanation provided by recency effects, in which the most current inputs are more accessible due to the nature of memory storage and retrieval. If this were in fact the case, a recency account would posit that independently observed cues *I* and *PL*—disregarding degree of predictability—will lead to responses of outcome *L* due to their later occurrence. However, when probing for a response to classify the imperfect cue, the attenuation of cue *I* during later learning leaves the individual with having to rely on previous knowledge about the nature of cue *I*, in which it was formerly categorized as belonging to outcome *E*.

It is this type of dynamic temporal interaction that may give rise to the accumulation of knowledge responsible for activating higher-level generalizations. A general learning mechanism responsible for building complex knowledge can serve as a bootstrap for explaining how complexity in behavior and cognition, whether manifesting itself as language, heuristics, or deductive reasoning, can be derived from a subset of highly influential underlying properties. Through the experiments conducted in this paper, observing similar learning patterns in young children can bridge the gap between adult cognitive literature and developmental literature, and account for what types of decisions children are capable of making given limitations in concrete top-down processing.

Experiment 1

The purpose of Experiment 1 is to evaluate the similarities between different variations of the highlighting paradigm. Adults participated in three tasks in which they were required to learn specific sets of conjunctive cues before others. The differences between each task are dependent on the use of base-rate information versus equal training of early and late cue sets, described in previous work as a canonical design (Kruschke, 2009). A direct comparison of performance on visual training of object pairs versus symptom training was made using a within-subjects design. It is expected that learning of the training sets will be analogous across the different types of tasks (visual object cues versus symptom diagnosis), and that ambiguous testing cues will elicit similar trends in performance across task type and structure (base-rate and canonical designs).

Method

Participants Fifteen adults participated in the visual task with objects as cues and with weighted base-rate information. Eleven different adults participated in both the visual task with equal base rate information and the symptom training task with equal base rates. Task order for this second sample was counterbalanced across conditions. All adults received partial class credit for their participation.

Visual object cues		Symptom cues		
Cues	I	PE	I	PE
Outcomes		+		"ear + "back aches" pain"
		↓		"Terrigitis"
			E	E

Figure 1: Examples of cues and outcomes for both the child and adult versions of the task.

Stimulus and Materials The visual implementation of the highlighting task consisted of a series of two-dimensional images presented on a touch screen monitor, which recorded the participant's responses. A total of 3 predictive cues were taken from a sample of 9 custom images to serve as items *I*, *PE*, and *PL*, while 2 cues from a sample of 6 served as outcomes *E* and *L*. The total number of available images allowed for the creation of different groups of stimuli consisting of cues *I.PE* → *E* and *I.PL* → *L*. From this, a total of 3 sessions were randomly compiled, exhausting all available images at the end of the last session. Predictive cues took the form of familiar objects, while outcomes were represented as known animals. Figure 1 illustrates the

quality of images used throughout the experiment. Each trial presented two conjunctive cues, which synchronously moved across the screen toward the animal, after which the objects disappeared. This animation lasted for a total of 2.5 seconds; probes during the testing phase were presented for the same amount of time; no time constraints were placed on outcome selection.

For the symptom cues experiment, text-based cues instead of images were programmed to be displayed from a touch screen monitor in a quiet room; all responses were collected via touch input. The terms for symptoms serving as predictive cues and names of diseases serving as outcomes were taken from Medin & Edelson (1988). Conjunctive cues were assigned from the array [I.PE, I.PL, I_O.PE_O, I_O.PL_O] and were centered toward the top of the screen one above the other while all possible outcomes [E, L, E_O, L_O] were presented equally spaced and in random order at the bottom of the screen. Time constraints were not implemented in this experiment.

Procedure After initial instructions, all tasks began by administering a training phase in which the participants learned or viewed early sets of cues before moving onto later cue sets. The testing phase consisted of probes of cue combinations that required a subsequent response to complete the trial and move to the next probe. Cues that were viewed in training as well as novel cue combinations were tested in order to observe outcome preferences.

For the visual object cue task with an unequally weighted training structure, a base-rate of 3:1 was assigned to the common and rare sets, resulting in participants viewing early common cue sets for a total of 15 times, while the late rare sets were watched for a total of 5 times. To account for order effects, the first 5 trials were always I.PE → E sets. Introduction of I.PL → L was present at the start of the sixth trial. The remaining training trials were randomized until a total of 20 trials was viewed, keeping in line with the base rate constraints. Only one set was assigned per phase (early versus late); participants were not required to learn multiple early sets and late sets simultaneously. Table 1 shows the cue combinations that were presented during testing for this particular design. Participants repeated the training and testing procedure for an additional two sessions with the remaining collection of images.

The canonical visual object cue task was identical to the previous task except for the removal of base-rate information. Overall, early sets were viewed at the frequency as late sets with a shift from early to late over the course of training. The total number of trials remained the same. Testing objects are presented in Table 1.

The symptom cue task's training structure was taken from previous literature implementing a canonical design, in which early sets of cues are learned before later sets, but at equal frequencies (for details over structure and number of training and testing trials see Kruschke, 2009). Late cue sets are gradually introduced over the course of training resulting in a difference of exposure by the time of testing,

while still maintaining total equality in presentation of early and late sets. Two different cue set configurations were learned simultaneously and classified as early training sets, while another two sets were learned at a further time point in training and categorized as late sets. For example, trials of set I.PE → E in addition to trials of I_O.PE_O → E_O were presented randomly during initial training; the 'O' subscript represents the 'other' cue of that type. Exposure to sets I.PL → L and I_O.PL_O → L_O was gradually increased over time. Participants were instructed to learn which pairs of symptoms predicted the appropriate disease, and that they were allowed to choose from all four possible outcomes (even though only 2 of the 4 diseases were relevant in the beginning), with the correct pairs of symptoms and diseases remaining constant throughout training. New symptoms were to be learned in the same manner. Feedback was given during training if they chose the wrong outcome based on the given predictive cues. During testing, they were instructed to choose which disease they thought best represented the set of symptoms presented on the screen. The types of testing probes were taken from Kruschke (2009) and tested, but due to the sake of comparison between the different types of tasks, only a subset is presented in Table 1.

Table 1: Response types and percentages collected from adults and children for each testing cue and each version of the highlighting task.

Cues	Adult						Child			
	Visual base-rate		Visual canonical		Symptom canonical			Visual canonical		
	E	L	E	L	E	L	E _O	L _O	E	L
I.PE	96.7	3.3	91.7	8.3	89.7	2.3	3.4	4.6	83.9	16.1
I.PL	3.3	96.7	9.8	90.2	12	85.5	1.2	1.2	11.1	88.9
I	74.4	25.6	65.9	34.1	70.5	15.9	6.8	6.8	48.6	51.4
PE.PL	40	60	40.2	59.8	44.2	41.9	4.7	9.3	33.3	66.7
PE	-	-	91.7	8.3	93.2	2.3	4.5	0	70	30
PL	1.7	98.3	9.1	90.9	2.3	88.6	0	9.1	22.2	77.8
I.PE.PL	-	-	48.5	51.5	45.2	40.5	9.5	4.8	42.1	57.9

Results

Performance across the different task variations was similar given the type of testing cues. A percentage comparison based on individual outcome choices can be viewed in Table 1 across all of the different formats. The left-most column shows the type of testing cue, while the rest of the columns show the proportion of responses for each possible outcome option. In assessing individual performance between the visual and symptom cue tasks, Table 2 shows the correlation value that a given participant made related response patterns during both versions of the canonical design. Analogous probes are presented in bold. Testing cues that evoked significantly consistent response behaviors from both versions were I.PL, PL, PE and PE.PL. Other

pairs showed high correlations but were not significant based on Pearson's correlation coefficient ($p < .05$). A chi-square test was conducted on critical testing probes which demonstrate response biases and a measure of order effects differentially influencing outcome preferences.

The results for the visual base-rate task show a strong effect for the ambiguous pair PE.PL and imperfect cue I, in that PE.PL → L and I → E were preferred associations, $\chi^2(1, N = 180) = 7.2, p < .01$, and $\chi^2(1, N = 180) = 42.29, p < .01$, respectively.

The results for the visual canonical design show similar patterns in choice preference in that PE.PL → L and I → E, with $\chi^2(1, N = 132) = 5.12, p = .023$, and $\chi^2(1, N = 132) = 13.36, p < .01$, respectively.

For the symptom cue version, a significant effect was only observed in the case of I → E, with $\chi^2(1, N = 38) = 15.15, p < .01$. Given the test case PE.PL, this did not elicit a significant effect with participants choosing outcome E slightly more often than outcome L ($N = 19:18$), with $\chi^2(1, N = 37) = .027, p < .869$.

Table 2: Correlation matrix comparing canonical versions of the symptom cue and visual cue tasks. Correlations are based on expected accuracy of outcome choices given previous literature. Significant correlations are marked with an asterisk.

		Visual cues						
		PE	PE.PL	I	I.PE	I.PE.PL	I.PL	PL
Symptom cues	PE	*0.83	-0.03	-0.15	0.01	-0.47	0.07	0.13
	PE.PL	0.31	*0.69	0.15	-0.42	0.20	-0.03	0.44
	I	0.30	-0.14	0.83	0.33	-0.57	-0.22	-0.20
	I.PE	*0.85	0.12	0.11	0.84	-0.24	0.11	-0.02
	I.PE.PL	0.19	0.57	0.29	-0.24	0.85	-0.35	0.13
	I.PL	0.59	0.08	-0.25	-0.31	0.32	*0.74	-0.03
	PL	*0.84	-0.23	-0.21	0.09	-.61	0.19	*0.88

Experiment 2

Experiment 1 showed that the visual cue version of the highlighting task with an equal base-rate design was successful in demonstrating order effects without relying on a highly conceptual task format. The use of stimuli generating visual object associations is sufficient in accounting for the presentation of predictive cues and outcomes. The question is whether or not children are capable of categorizing sets of visual cues and updating their categorical information over the course of training. This implies that children must perceptually separate conjunctive cues when necessary and implicitly consider the relevancy of individual items to target them as possibly being erroneous. Children are expected to implement such expectations through the process of selective attention in order to accommodate such inconsistencies in cue predictability.

Method

Participants 10 children ages 4- to 5-years-old participated in this version of the task (mean age = 56.3 months) and were included in the final analysis. The criterion for inclusion was that the children had to obtain at least 80% accuracy on the training cues. This led to the removal of 6 children who failed to learn during training. Table 1 and the Results section reflect the results obtained based on these criteria.

Stimulus, Materials, and Procedure The stimulus and materials used for this study were identical to the visual canonical task conducted in Experiment 1. The procedure was also identical except that the participants were instructed on how and when to respond to the training and testing phases of the experiment using the touch screen monitor.

Results

Outcome proportions are presented along with the adult data in Table 1. A chi-square analysis was conducted to assess response frequencies between testing cues and outcomes. Training cues I.PE and I.PL were adequately learned, with $\chi^2(1, N = 31) = 14.23, p < .01$, and $\chi^2(1, N = 36) = 21.78, p < .01$, respectively.

Perfect predictors PE and PL were also successful in individually representing their respective outcomes without the inclusion of the imperfect cue, with $\chi^2(1, N = 40) = 6.4, p = .011$, and $\chi^2(1, N = 36) = 11.11, p < .01$. The test statistic obtained for PL → L was higher than any other testing probe other than the training cues. There was a significant effect for the ambiguous cue PE.PL, with $\chi^2(1, N = 36) = 4, p = .046$.

Testing cues I, and I.PE.PL did not show significant differences in outcome preference, with $\chi^2(1, N = 35) = .029, p = .866$, and $\chi^2(1, N = 38) = .947, p = .330$, respectively.

General Discussion

The main argument from this paper is that order effects play a much larger role than previously given credit for in that they directly influence how information is categorized, which results in decision making behavior inconsistent with statistical expectancy. Experiment 1 demonstrated two points. One, whether given base-rate information or providing equal occurrences of training cues, the visual object version of the conjunctive cue task structure elicits similar effects. Visual learning seems to be just as effective in creating response biases, if not more so. Two, the comparisons made between the symptom cue and visual cue canonical designs showed similar trends. However, adults did not show a significant effect for the ambiguous cue for symptom version of the design. This may be due in part to the number of observations required for obtaining significant results using the chi-square distribution. Further analytical approaches must be considered in subsequent data

collection. Experiment 1 provides justification for studying order effects using primarily visually based stimuli.

Experiment 2 showed that order effects do matter when certain sets of cues are presented before others; early and late learning created certain response biases in children during testing. When comparing performance in the visual task to adults, response frequencies were similar across both groups except for the I → E | L testing probe. Children were not able to significantly choose the early outcome when given the imperfect cue, in which they preferred both outcomes equally. It may be possible that children are sensitive to both types of temporal factors presented in this paper, in that recency effects of later cues as well as shifting attention away from erroneous predictors may dynamically play a role in decision making during this developmental stage. Failure to completely shift attention away from erroneous cues might lead to the imperfect cue garnering more attention than it should during later learning. Research addressing these factors individually should be taken into consideration. Experiment 2 also established the fact that children are highly capable of distinguishing and separating individual conjunctive cues as well as combining cue information across different stages of learning. This can be witnessed in the outcome preferences for the probes PE, PL, and PE.PL. Children are able to simultaneously process cue combinations as well as assess the predictability of these cues in absence of their conjunctive counterpart in order to make decisions about their respective categories. Further research must be conducted to understand the nature between the two equally probable cue sets, especially in regards to how they differentially influence object preferences.

In conclusion, the canonical visual implementation of the highlighting task distances itself from the use of higher-level knowledge required to show asymmetrical response patterns. Rules based on frequency of occurrence cannot be established given that training sets are equally presented, and that children and adults are not actively engaging in explicit processing of frequency and rule-based information over the course of training. They are merely observing sets of objects in a passive manner, with attentional mechanisms implicitly accounting for the differences in object categorization. If base rate information is critical for observing the typical asymmetrical patterns seen in previous literature, we would expect the canonical designs to deviate from such expectations. However, given that such patterns are observed in both designs, this is more consistent with an attentional shifting account. Testing certain cue combinations and witnessing asymmetrical behavioral outputs represents the type of associations created through visual processing of objects, without the initial goal of future application of those items. Participants ultimately relied on previous knowledge to make judgments based on visual categories, while the order in which this information was presented directly influenced their outcome preferences given ambiguous and individual cue combinations. Order effects do have an impact on multiple levels of processing

across different age ranges, in which the building of knowledge over time can be explained by basic properties inherent within all individuals.

Acknowledgments

This research is supported in part by a National Institutes of Health grant (R01 HD058620), the Foundation for Child Development, and University of Houston's Enhance and Advance Research (GEAR) program. We thank the children and parents who participated in this study.

References

Juslin, P., Wennerholm, P., & Winman, A. (2001). High level reasoning and base-rate use: Do we need cue competition to explain the inverse base-rate effect? *Journal of Experimental Psychology: Learning, Memory and Cognition*, 27, 849–871.

Kruschke, J. K. (1996). Base rates in category learning. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 22, 3-26.

Kruschke, J. K. (2003). Attention in learning. *Current Directions in Psychological Science*, 12, 171-175.

Kruschke, J. K. (2009). Highlighting: A canonical experiment. In: B. Ross (Ed.), *The Psychology of Learning and Motivation*, 51, 153-185.

Lamberts, K., & Kent, C. (2007). No evidence for rule-based processing in the inverse baserate effect. *Memory & Cognition*, 35(8), 2097–2105.

Medin, D. L., & Edelson, S. M. (1988). Problem structure and the use of base-rate information from experience. *Journal of Experimental Psychology: General*, 117, 68–85.

Medin, D. L., & Bettger, J. G. (1991). Sensitivity to changes in base-rate information. *American Journal of Psychology*, 104, 311–332.

Rueda, R. M., Posner, M. I., & Rothbart, M. K. (2005). The development of executive attention: Contributions to the emergence of self-regulation. *Developmental Neuropsychology*, 28, 573-594.

Shanks, D. R. (1992). Connectionist accounts of the inverse base-rate effect in categorization. *Connection Science*, 4, 3–18.

Winman, A., Wennerholm, P., Juslin, P., & Shanks, D. R. (2005). Evidence for rule-based processes in the inverse base-rate effect. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology*, 58A(5), 789-815.