Is Double-Dipping an Alternative to Double-Dissociation?: Sampling Two Representational Systems Using a Single Task

Jordan Richard Schoenherr (psychophysics.lab@gmail.com)
Guy Lacroix (guy_lacroix@carleton.ca)
Department of Psychology, Carleton University
1125 Colonel By Drive, Ottawa, ON K1S5B6 Canada

Abstract

Dual-process models of categorization posit dissociable implicit and explicit category learning systems. Evidence in favour of these accounts is typically obtained by examining how categorization responses differ over time, with differing category structures, and by changing task demands. If these two categorization systems are activated concurrently (e.g., COVIS) then both implicit and explicit representations can be examined over the course of learning even when one system dominates category response selection. In the current study, we used subjective measures of performance (i.e., confidence reports) to continuously sample from a participant's explicit representation of the category structure while also examining changes in these reports over the course of training. Using category structures that motivate the acquisition of either explicit or implicit representations, we observed differences in confidence reports that did not correspond to changes in categorization accuracy. These findings provide evidence for categorization systems that contain different representations.

Keywords: dual-process, categorization, confidence processing

Introduction

Dual-process models of categorization assume that information is processed by and represented in independent cognitive systems. For instance, one such model, RULEX (Nosofsky, Gluck, Palmeri, McKinley, & Glauthier, 1994), postulates that people categorize objects by using simple rules and by memorizing the exceptions to those rules. Similarly, another model, ATRIUM (Erickson & Kruschke, 1998) assumes that categorization involves the combination of rule-based and exemplar-based processes whose relative contributions are mediated by an attentional gating mechanism. An alternative account provided by Love, Medin, & Gureckis' (2004), SUSTAIN, assumes that instances of a category are stored as clusters of feature associations and these clusters are associated with a category in the context of both supervised and unsupervised learning. Moreover, the goals of the participant will also determine the nature of the representations that are formed (see the Conclusion for further discussion and implications).

Following from Logan's (1988) instance theory of automaticity, Ashby, Alfonso-Reese, Turken, and Waldron's (1998) COVIS model instead assumes that there is a competition between the verbal and implicit systems responsible for the categorization process. Evidence in favour of COVIS comes from double-dissociation paradigms which demonstrated feedback and a concurrent working memory load affect the implicit and verbal systems, respectively. In addition to predictions concerning categorization performance, COVIS also makes claims concerning post-decisional confidence reports. To our knowledge, the implications of these claims have not been examined. The present study is directed toward exploring this prediction: The correspondence between categorization accuracy and subjective confidence should change depending on the category structure that participants are required to learn.

COVIS Categorization Systems

COVIS has two main assumptions. First, categorization is assumed to rely on a multidimensional variant of signal-detection (SDT) referred to as general recognition theory (GRT; Ashby & Townsend, 1986). With the provision of feedback, the category boundary divides separable or integral stimulus dimensions into discrete regions of a categorical space (e.g., Ashby & Gott, 1988; Ashby & Maddox, 1992). If a stimulus consists of values along a dimension greater than those specified by the criterion, it is assigned to one category. If the values are less than that specified by the criterion, it is assigned to another category. Using curve fitting, Ashby and colleagues have demonstrated that by the end of training, participants performance is well described by an optimal classifier model that employs a category boundary.

The second critical feature of COVIS is the interaction of the explicit and implicit categorization systems during response selection (Ashby & O'Brien, 2005; Ashby et al., 1998). Initially, the hypothesis-testing system which uses executive function and working memory is assumed to dominate categorization as it can rapidly generate and test explicit, one-dimensional (rule-based) representations. Simultaneously, the implicit procedural learning system begins to associate regions of perceptual space with a category label though it does not yet dominate category response selection. As more instances of the categories are retained in memory, the process of retrieving the stimulus-response mapping within the implicit system becomes increasingly rapid. With sufficient training, the implicit system begins to dominate category response selection. Thus, in the absence of an executive load (e.g., Waldron & Ashby, 2001), participants will acquire rule-based category structures earlier in the course of the experiment relative to an information-integration category structures. These findings have been taken as evidence representing a *qualitative* change in responding rather than merely a *quantitative* shift in a category boundary location within a single implicit system (Ashby et al., 1998).

A critical observation concerning Ashby et al.'s (1998) dual-process account of COVIS is that although a single response results when presented with a stimulus, the resulting perceptual information activates both categorization systems. Later in training, when an implicit representation stored within the procedural-learning is used to produce responses, an explicit representation should still be produced by the hypothesis-testing system. If a method can be adopted to examine this explicit representation over the course of training, further evidence would be provided for a dual-process account of categorization. Confidence reports might be used to sample such an explicit representation over the course of learning.

Measures of Awareness of Performance

Confidence reports and related measures were among the earliest tools used in experimental psychology to assess participants' ability to consciously monitor their performance on a given task (for a review, see Baranski & Petrusic, 1998). Retrospective confidence reports are typically obtained by having an individual assign a numeric value corresponding to a subjective probability (e.g., 60%) in their belief that they have provided a correct response to a primary task. The degree of correspondence between a participant's mean accuracy and assigning a subjective probability to a response is referred to as *subjective calibration* (e.g., Baranski & Petrusic, 1994). Perfect calibration requires that the proportion correct (e.g., 0.6) and mean confidence are equivalent (60%). Typically, participants are observed to deviate from ideal performance as evidenced by miscalibration. Rather than presenting a random pattern, miscalibration occurs in a systematic form in terms of either over- or underconfidence. Overconfidence is observed when confidence exceeds accuracy. This pattern is typically observed when the task requires the use of either general or conceptual knowledge. Underconfidence is observed when accuracy exceeds confidence. This pattern is typically observed in perceptual tasks (for reviews see, Lichtenstein & Fischhoff, 1977; Kvidera & Koustaal, 2008). There is disagreement as to whether this pattern represents task dependencies (Lichtenstein & Fischhoff, 1977) or whether it is a result of differential accessibility of information within the systems when performing the task (Dawes, 1980).

A consideration of confidence models reveals the sources of this disagreement. The first formal models of confidence assumed a direct-scaling of primary decision information with a decisional-locus of confidence processing (e.g., Ferrel & McGooey, 1980; Gigerenzer, Hoffrage, & Kleinbolting, 1991; for recent models see, Pleskac & Busemeyer, 2010). On these accounts, confidence reports are based solely on information used by the primary decision process and consequently do not require any additional processing. Importantly for the present study, COVIS provides a similar model of confidence. Ashby et al.'s (1998) assume that confidence reports result from activation of the prefrontal cortex associated with the response alternative by the implicit system which they claim is supported by neurological studies examining cortical modulation (e.g., Frith, Friston, Liddle, & Frackowiak, 1991). Given the direct correspondence between the implicit representation used to categorize stimuli and that used to report confidence, Ashby et al.'s (1998) direct-scaling account of confidence predicts greater correspondence between accuracy and confidence reports in the information-integration condition. This pattern would result in high levels of confidence calibration.

Furthermore, if subjective confidence is determined by an implicit representation, then greater levels of miscalibration should be observed in the rule-based condition due to a difference between the representation used to categorize stimuli and that used to report confidence. Specifically, if an implicit representation is used to report confidence and that representation is inaccurate early in training then Ashby et al.'s (1998) account would appear to imply that underconfidence should be observed when learning rule-based category structures.

In contrast to this account, an alternative class of models assumes that confidence reports require an indirect-scaling of primary decision evidence requiring additional cognitive operations. Both a post-decisional locus (e.g., Audley, 1960; Vickers & Packer, 1980), or an alterable locus (Baranski & Petrusic, 1998) have been considered wherein participants process confidence following the primary decision or can additionally compute it concurrently with the primary decision. If confidence reports require a secondary set of operations, it is possible that they could be affected by information other than that available to the primary decision. This would follow from the observation that performance on any task is the result of explicit and implicit processes (Jacoby, 1991).

There is considerable support that confidence reports involve a secondary set of effortful scaling operations that either integrate information from multiple sources (e.g., perceptual and conceptual) or manipulate this information in the process of scaling (Busey, Tunnicliff, Loftus, & Loftus, 2000; Schoenherr, Leth-Steensen, & Petrusic, 2010). For instance, Schoenherr et al. (2010) were able to alter subjective confidence independently of the primary decision. Studies investigating metamemory have also observed that subjective awareness appears to be determined by encoding and retrieval cues rather than the number of items recalled (e.g., Koriat, Sheffer, & Ma'ayan, 2002). Given that different sources of information can affect the primary decision and confidence reports, these studies suggest that a comparison of primary decision responses and confidence reports might be an alternative means to dissociate implicit and explicit categorization systems (see also Dienes & Berry, 1997).

In the context of indirect-scaling models, we can predict a different pattern of miscalibration. If we disregard the direct-scaling model adopted by Ashby et al. (1998) we can still adopt some of the assumptions of COVIS to predict an alternative pattern of overconfidence. If a hypothesis-testing system is not as dependent on feedback to learn a category structure as the procedural-learning system, negative feedback should exert less of an effect when learning rule-based category structures relative to information-integration category structures. Thus, in instances where there is category overlap which result in a performance asymptote, an explicit representation of the category structure that informs confidence reports would not reflect the proportion of negative feedback that results. This would lead to overconfidence. Greater calibration would be observed in the information-integration condition due to that system's reliance on feedback and absence of an explicit category structure to bias confidence reports.

Present Study

The present study starts from the assumption that the degree of correspondence between measures of accuracy and confidence can be used to infer the nature of representations used at different stages of the category learning process. To accomplish this, we adopted the randomization technique used by Ashby and colleagues and required participants to provide confidence report concerning the accuracy of their responses.

Two sets of predictions can be made concerning the relationship between accuracy and confidence depending on whether a direct- or indirect-scaling account of confidence is adopted. When adopting Ashby et al's (1998) direct-scaling model of confidence, we can expect participants to be well calibrated in the information-integration condition due to representational correspondence between the information used within the categorization system and that used to report confidence. Conversely, the rule-based condition should produce underconfidence due to the inaccurate implicit representation used to report confidence and an accurate explicit representation used to categorize stimuli.

An alternative set of prediction follows from indirect-scaling models of confidence (e.g., Baranski & Petrusic, 1998) should also be considered. First, when participants are incapable of obtaining 100% accuracy, such as when a performance asymptote is adopted, confidence should reach the equivalent subjective probability of this performance asymptote prior to categorization accuracy. Second, if the explicit system is not as dependent upon response feedback as the implicit system, then the proportion of negative feedback observed in the rule-based condition should not affect subjective confidence reports to the same extent as the implicit-condition. Following from this, participants should exhibit overconfidence when the category structure is readily verbalizable but category overlap is permitted. Thus, while we would expect the same comparatively high level of calibration in the information-integration condition as Ashby et al. (1998), we expect overconfidence in the rule-based condition. We also anticipate that the requirement of confidence should also increase categorization response time if it constitutes a secondary process and that these response times should be longer in the information-integration condition relative to the rule-based condition given the need for representational change. We do not report the successful observation of these findings here due to space limitations. Rather, we limit ourselves to changes in overconfidence bias across experimental blocks.

Experiment
Method

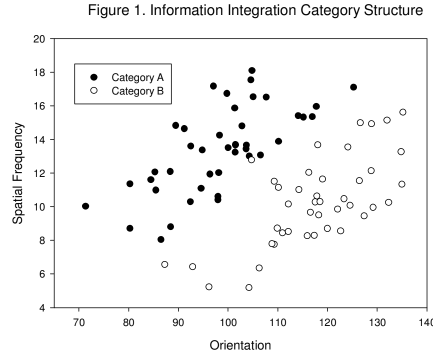
Participants

Eighty-eight undergraduate students participated in the study for course credit.

Materials

Stimuli consisted of Gabor patches varying in terms of spatial frequency and orientation. Replicating the method of earlier studies (e.g., Zeithamova & Maddox, 2007), 40 Gabor patches were created for each category for the training phase using the randomization technique by randomly sampling values from two normal distributions. Stimulus values were rescaled into stimulus dimensions with spatial frequency given by $f = .25 + (x_1/50)$ and orientation given by $o = x2(\pi/500)$. Using these values, stimuli were generated with the Psychophysics Toolbox (Brainard, 1997) using MATLAB R2008 (MathWorks, Matick, MA) with an 85% performance asymptote resulting from category overlap (see Figure 1). After a categorization response was provided and a confidence report was obtained, a feedback signal was presented to indicate a participant's accuracy in completing the task. Stimuli were presented to participants using E-Prime experimental software on a Dell Dimension desktop PC.

Figure 1. Information Integration Category Structure

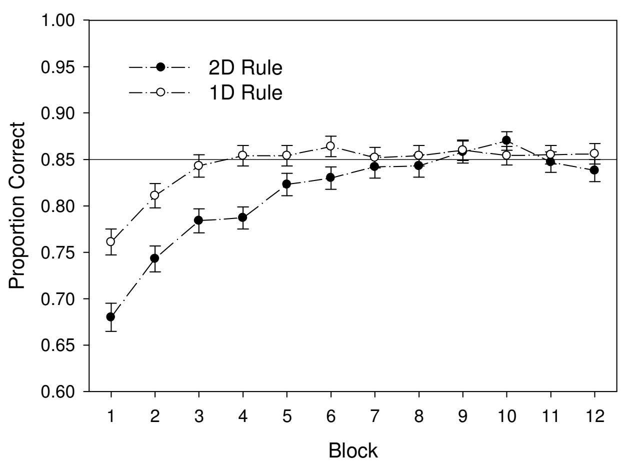


Procedure

The category task procedure used the randomization technique. A training phase consisted of 10 blocks of trials with 40 exemplars from each category, and a transfer phase consisted of 2 blocks with the same 40 exemplars from each category. Participants learned either a rule-based (1D) or an information-integration (2D) category structure. In the present experiment, participants were provided with both trial-to-trial and block feedback during the training phase. In the transfer phase, participants did not receive feedback. Before trial-to-trial feedback was provided, participants reported confidence on a 6-point Likert scale from 50 (guess) to 100 (certain) scale.

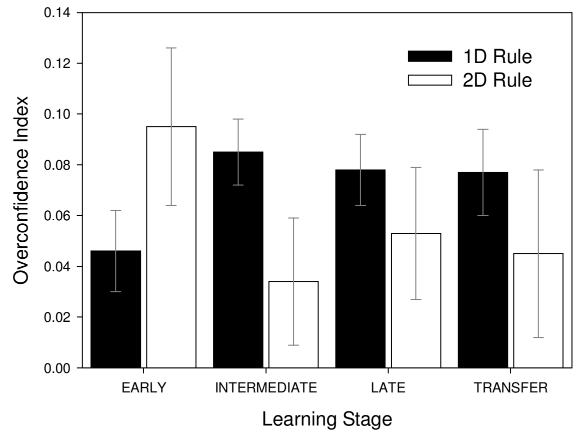
Results

Proportion Correct. As demonstrated in Figure 2, the results of categorization accuracy replicated earlier findings: 1D rules were learned in fewer blocks then 2D rules, $F(1, 83) = 6.317$, $MSE = .039$, $p = .014$, $\eta^2_p = .071$, and accuracy increased with the number of experimental blocks, $F(11, 913) = 49.167$, $MSE = .005$, $p < .001$, $\eta^2_p = .372$ The interaction between categorization rule and experimental block was also significant, $F(11, 913) = 6.891$, $MSE = .005$, $p < .001$, $\eta^2_p = .077$. We also found that the requirement of confidence affected category learning as it interacted with block, $F(11, 913) = 2.093$, $MSE = .005$, $p = .052$, $\eta^2_p = .025$. Although the requirement of confidence initially produced reduced performance in the first block ($M = .703$, $SD = .140$) relative to no confidence ($M = .738$, $SD = .131$), participants who reported confidence in the transfer phase were more accurate ($M = .866$, $SD = .112$) then those who did not ($M = .829$, $SD = .103$).



Confidence Reports. Due to inter-block variability resulting from individual differences in the between-subject design, we collapsed blocks into learning phases. We examined overconfidence in early phases of training across two blocks (Blocks 1 and 2) in order to compare to the two transfer blocks (Blocks 11 and 12). Two other phases of training were also examined for comparison constituting and intermediate (Blocks 3 through 6), and late phases of training (Blocks 9 through 10).

Figure 3. Overconfidence Bias across experimental blocks.



Overall, we found that the overconfidence bias differed across the learning phases, $F(1,77) = 8.842$, $MSE = .085$, $p = .004$, $\eta^2_p = .103$. As expected, learning phase was also found to interact with category structure, $F(1,77) = 4.539$, $MSE = .085$, $p = .036$, $\eta^2_p = .\ 056$. As can be seen from Figure 3, overconfidence remained relatively constant in the information-integration condition suggesting that, in general, participants did not have access to the representation that guided their performance. In contrast, an increase in overconfidence was observed in intermediate phases of training in the rule-based condition. This finding suggests that once participants identified the 1D rule, they expected to have continual improvements in performance.

Conclusions

In the present study, we examined confidence reports as an alternative to double-dissociation paradigms. Using the randomization technique, we sought to replicate previous findings of the categorization literature such that participants would learn 1D categorization rules in fewer blocks then 2D categorization rules due to differences in the categorization systems that retain these representations. In a confidence rating paradigm, we had participants report trial-by-trial confidence after each categorization response and compared this to their accuracy. We examined whether the correspondence between accuracy and confidence (i.e., overconfidence bias) differed between category structures as well as whether this pattern changed across experimental blocks.

The results of our experiment replicate several earlier studies within categorization and confidence processing literature. Categorization performance was found to be affected by the category structure that participants learned. We observed that participants who were required to learn the rule-based category structure reached a performance asymptote faster than those who were required to learn the information-integration category structure (e.g., Ashby et al. 1998). Moreover, response latencies decreased in fewer blocks for participants in the rule-based condition relative to those in the information-integration condition indicating that participants could more readily acquire a stimulus-response mapping for rule-based categories relative to information-integration categories. Furthermore, these findings conform to the predictions of dual-process accounts of categorization such as COVIS (Ashby et al., 1998) allowing us to interpret the results obtained from confidence reports in a straightforward manner.

Our analysis of confidence reports also provides new evidence for dual-process accounts of categorization. In the experiment conducted here, we observed increased overconfidence in intermediate phases of training for those participants learning a rule-based category structure relative to those who learned the information-integration category structure. In general, the miscalibration observed here suggests that the representation used to report subjective confidence and that used to respond to categorize stimuli were informed by different sources of information. Greater overconfidence in the rule-based condition suggests that the category structure that participants were explicitly aware of did not contain the stimulus variability that resulted from category overlap. We would expect such a finding if the hypothesis-testing system were less reliant on feedback and could not incorporate exceptional exemplars into the explicit representation as a consequence.

Further support for the kind of representational dissociation that we predicted stems from the findings of greater calibration in the information-integration condition. In the absence of an explicit representation, the only explicit information available to participants is the proportion of feedback they have received on a trial-to-trial basis. Given that feedback is an accurate predictor of performance, less miscalibration is likely to result. Moreover, we should not expect perfect calibration if an explicit representation might be biasing confidence responses. This would occur if confidence reports incorporated multiple sources of information (Schoenherr & Logan, 2012) or if we additionally consider that any task is determined by both explicit or implicit processes (i.e., Jacoby, 1991).

We can also consider how these findings might be accounted for by models of categorization more generally. Although it is possible that with a sufficient number of parameters, a single-process model of categorization could account for the findings of the present study, it appears more principled to assume two independent learning systems. In terms of models that posit the retention of both rules and exemplars (e.g., Nosofsky, et al., 1994; Erickson & Kruschke, 1998) participants should be able to retain the optimal categorization rule as well as the exceptional exemplars. In the present study, one might expect that the retention of exemplars would ensure that participants would exceed the performance asymptote. There is little support for this pattern given that performance does not significantly differ from the performance asymptote (see Figure 2).

Given the inclusion of both a categorization and confidence processing component, COVIS provides a possible explanation of the findings of the present study. COVIS posits that the evidence accumulated within the information-integration condition should be used to report confidence. For this reason, the high level of subjective calibration in the information-integration provides evidence in support of such an account. Although it does not make explicit predictions concerning the rule-based condition, it would seem that participants should be quite accurate early in training due do rapid generation and testing of explicit rule. Participants should also exhibit underconfidence due to an inaccurate implicit representation that informs subjective confidence. As noted above, this was not observed. Thus, COVIS can account for the categorization results of the present study but does not provide a sufficient account of confidence processing. The basic assumptions of two categorization systems - one explicit and one implicit – are supported by our results.

Although in some respect similar to models that retain both rules and exemplars, SUSTAIN (Supervised and Unsupervised STratified Adaptive Incremental Network; e.g., Love & Medin, 1998; Love et al., 2004) might be better equipped to provide an explanation of the relationship between accuracy and confidence observed in the present study. A basic assumption of SUSTAIN is that clusters of features constitute a category and that there is response competition between clusters with a bias toward simple solutions. Unlike COVIS, SUSTAIN does not provide a comprehensive account of confidence processing. Love et al. (2004) note that the number of competing alternatives should reduce participant's subjective confidence. In the rule-based condition used in the present study there should be fewer clusters competing for response selection given that rule-based category structures can be identified relatively quickly. This would give rise to greater confidence. In contrast to this, the information-integration condition should have a larger number of clusters (constituting multidimensional rules) competing for response selection thereby reducing subjective confidence. On this account, however, it is not clear why exceptions would not affect confidence reports. Namely, exceptional exemplars should suggest the selection of alternative clusters thereby increasing competition and concomitantly decreasing confidence. Without a clear formulation of confidence processing within the context SUSTAIN, speculation on the adequacy of extension to accommodate our calibration results must be limited.

One promising feature of SUSTAIN is that it does allow for unsupervised learning and influences of participants' goals while learning. In our experiment we did find some evidence of better performance in the transfer phase with the requirement of confidence reports (see Figure 2). We might expect this pattern of results if participants were monitoring their performance and consequently desired a higher level of accuracy. Thus, when asked to provide confidence reports participants might be induced to attend to the task more so than they would otherwise.

References

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.

Ashby, F. G., & O'Brien, J. B. (2005). Category learning and multiple memory systems. *Trends in Cognitive Sciences*, 9, 83-89.

Ashby, F. G., & Gott, R. E. (1988). Decision rules in the perception and categorization of multidimensional stimuli. *JEP: LMC*, 14, 33-53.

Ashby, F. G., & Townsend, J. T. (1986). Varieties of perceptual independence. *Psychological Review*, 93, 154-179.

Baranski, J. V., & Petrusic, W. M. (1994). The Calibration and resolution of confidence in perceptual judgements. *Perception & Psychophysics*, 55, 412-428.

Baranski, J. V., & Petrusic, W. M. (1998). Probing the locus of confidence judgments: Experiments on the time to determine confidence. *JEP: HPP*, 24, 929-945.

Brainard, D. H. (1997). The Psychophysics Toolbox, *Spatial Vision* 10, 433-436.

Busey, T. A., Tunnicliff, J., Loftus, G. R., & Loftus, E. (2000). Accounts of the confidence-accuracy relation in recognition memory. *Psychonomic Bulletin & Review*, 7, 26-48.

Dawes, R. M (1980). Confidence in intellectual vs. confidence in perceptual judgments. In E. D. Lantermann & H. Feger (Eds .) *Similarity and Choice: Papers in Honor of Clyde Coombs* (pp. 327-345). Bern Hans Huber.

Dienes, Z., & Berry, D. (1997). Implicit learning: Below the subjective threshold. *Psychonomic Bulletin & Review*, 4, 3-23.

Erickson, M. A., & Kruschke, J. K. (1998). Rules and exemplars in category learning. *Journal of Experimental Psychology: General*, 127, 107-140.

Ferrel, W. R., & McGoey, P. J. (1980). A model of calibration for subjective probabilities. *Organizational Behaviour and Human Performance*, *26*, 32-53.

Frith, C. D., Friston, K. J., Liddle, E. E., & Frackowiak, R. S. J. (1991). Willed action and the prefrontal cortex in man: A study with PET. *Proceedings of the Royal Society of London*, *B*, 244, 241-246.

Jacoby, L. L. (1991). A process dissociation framework: separating automatic from intentional uses of memory. *Journal of Memory and Language*, 30, 513-541.

Koriat, A., Sheffer, L., & Ma'ayan, H. (2002). Comparing objective and subjective learning curves: Judgments of learning exhibit increased underconfidence with practice. *Journal of Experiment Psychology: General*, 131, 147–162.

Kvidera, S., & Koustaal, W. (2008). Confidence and decision type under matched stimulus conditions: overconfidence in perceptual but not conceptual *Decisions. Journal of Behavioral Decision Making*, *21*, 253–281.

Lichtenstein, S., & Fischhoff, B. (1977). Do those who know more also know more about how, much they know? *Organizational Behavior and Human Performance*, 20, 159-183.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review*, 95, 492-527.

Love, B. C., & Medin, D. L. (1998a). Modeling item and category learning. In M. A. Gernsbacher & S. J. Derry (Eds.), *Proceedings of the 20th Annual Conference of the Cognitive Science Society* (pp. 639–644). Mahwah, NJ: Erlbaum.

Love, B. C., Medin, D. L., Gureckis, T. M. (2004). SUSTAIN: A network model of category learning. *Psychological Review*, 111, 309–332.

Maddox, W. T., Ashby, F. G., & Bohil, C. J. (2003). Delayed feedback effects on rule-based and information-integration category learning. *JEP: LMC*, 29, 650-662.

Nosofsky, R. M., Gluck, M. A., Palmeri, T. J., McKinley, S. C., & Glauthier, P. (1994). Comparing models of rule-based classification learning: A replication and extension of Shepard, Hovland, and Jenkins (1961). *Memory & Cognition*, 22, 352-369.

Pleskac, T.J. and Busemeyer, J.R. (2010) Two-stage dynamic signal detection: a theory of choice, decision time, and confidence. *Psychological Review*, 117, 864–901.

Schoenherr, J. R. (2009). *Mapping Internal Representations of Confidence onto Scales Varying in Range, Interval, and Number of Response Categories*. Unpublished Manuscript.

Schoenherr, J. R., Leth-Steensen, C., & Petrusic, W. M. (2010). Selective attention and subjective confidence calibration. *Attenion, Perception & Psychophysics*, 72, 353-368.

Schoenherr, J. R., Logan, J., & Larose, C. (2012). Subjective confidence of acoustic and phonemic representations during speech perception. *Proceedings of the 28th Annual Meeting of the International Society for Psychophysics*, Ottawa, Ontario, Canada.

Waldron, E. M., & Ashby, F. G. (2001). The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. *Psychonomic Bulletin & Review*, 8, 168-176.

Zeithamova, D., & Maddox, W. T. (2007). The role of visuo-spatial and verbal working memory in perceptual category learning. *Memory & Cognition*, 35, 1380–1398.